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Improvements of sales forecasts in a Swiss small and medium enterprise (SME)



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Improvements of sales forecasts in a Swiss small and medium enterprise (SME)

DOCTORAL THESIS

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by

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from Lucens, VD

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The Faculty of Management, Economics and Social Sciences of the University of Fribourg (Switzerland) does not intend to either approve or disapprove the opinions expressed in a thesis; they must be considered as the author's own (decision of the Faculty Council of January 1990).

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1 Introduction

Businesses face many challenges in their day-to-day operations, and making the best decisions is not always simple. Despite the introduction of artificial intelligence and other new technologies, certain issues, such as sales forecasting, remain challenging. The aim of this project was to help a family business develop forecasting tools through various analyses, for sales forecasts themselves and, more generally, global analysis of the tools set up to improve internal communication between departments.

The company chosen for this work is a small and medium enterprise (SME) based in Canton Fribourg, Switzerland. Since the company has grown rapidly, it could not develop its tools at the same pace as its sales and turnover. For confidentiality reasons, certain company details cannot be disclosed.

The company's structure also changed during the course of this work due to a generational change in 2019. At the beginning of this work, the company structure included a chief executive officer (CEO) and the various departments identified in Figure 1.1 :

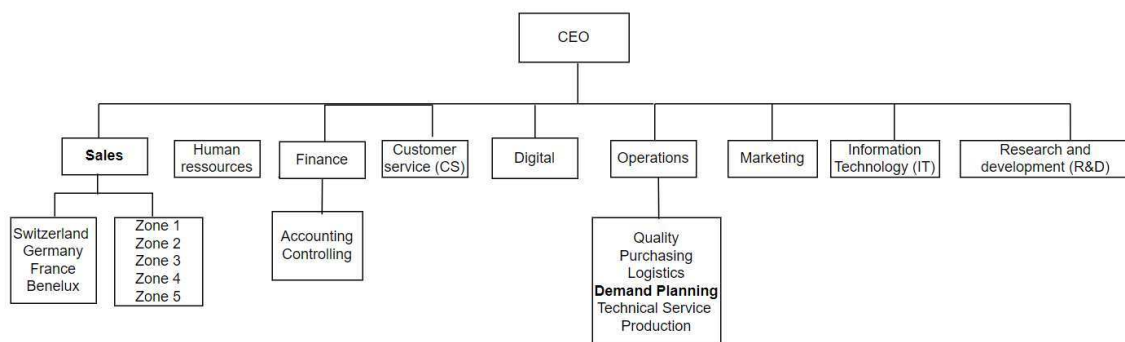


Figure 1.1: Diagram of the company's structure at the beginning of the project (designed by the author)

The sales department is the most complex. It is comprised of subsidiaries: Switzerland, Germany, France, Benelux¹ (Z0 in the Figure 1.2) and export markets (Z1 to Z5 in Figure 1.2).

¹ Benelux: Belgium, The Netherlands, and Luxembourg

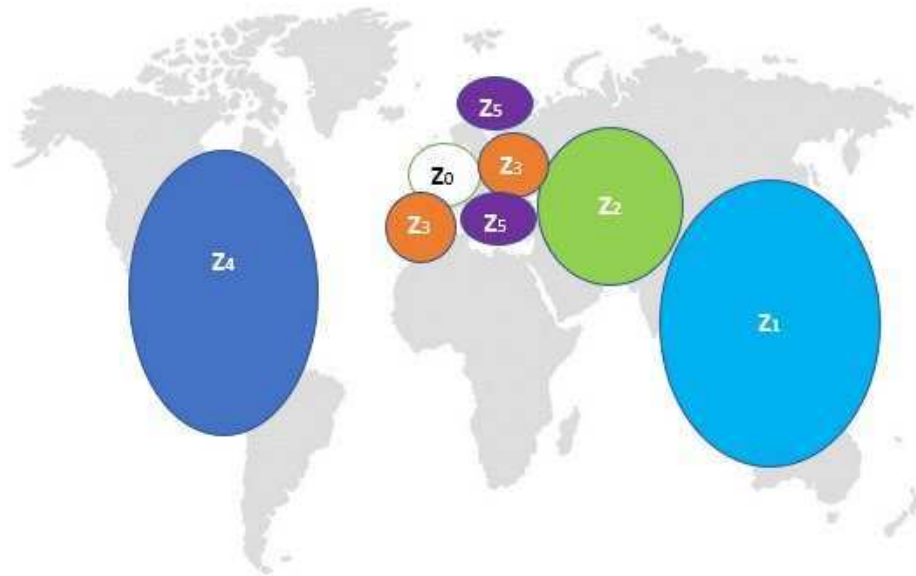


Figure 1.2: Zones mapping for the company (designed by the author)

Z0 contains five subsidiaries (Switzerland, France, Germany, Belgium, Netherlands, and Luxembourg) as well as the two internal direct sales departments of Customer Service (CS) and Digital. The CS and Digital departments have several particularities. They are considered separate sales channels because sales are made directly on the website for Digital and by phone for CS. The Digital department deals with websites from the countries in Z0 only. Websites from other geographical areas are outsourced and managed directly by resellers. The CS department only includes sales in Z0 because the department is based in Switzerland, although it also answers requests and questions from countries in other geographical areas.

The export markets are divided into five export zones composed of different countries: Z1 is the Asia-Pacific market (APAC, 8 countries); Z2 covers emerging markets in Asia (EEMA, 13 countries); Z3 contains six promising European countries; Z4 encompasses three countries in the Americas; and Z5 consists of 13 European countries with low but increasing potential. The company is active in a total of 50 different markets. The markets in Z0 are the most financially profitable, as shown in Table 1.1, and the company has aimed to further develop the export markets (Z1 to Z5).

Zones	Name of Zones	Number of countries	Percentage of the amount invoiced in 2019
Zone 0 = Z0	Subsidiaries CH, D, F, B, NL-LU, CS, Digital	(5 + 2) 7	76%
Zone 1 = Z1	APAC KR, SG, MY, TW, HK, JP, AU, CN	8	10%
Zone 2 = Z2	EEMA RU, KZ, UA, CY, IL, AE, BH, BY, KW, LB, TM, MA, MN	13	9%
Zone 3 = Z3	Promising European countries PL, TR, GB, ES, CZ, PT	6	3%
Zone 4 = Z4	The Americas US, CA, EC	3	1%
Zone 5 = Z5	European countries (with low potential) HU, IT, SE, AT, HR, DK, SI, NO, GR, RO, BA, FI, IS	13	1%
Total		50	100%

Table 1.1: Labels, composition, and percentage of amount invoiced in 2019 per zone (summarized by the author)

Since 2019, the company has been moving toward a co-CEO system. Each department was placed under the responsibility of one of the two CEOs depending on their respective expertise. The layout of the actual structure is represented in Figure 1.3.

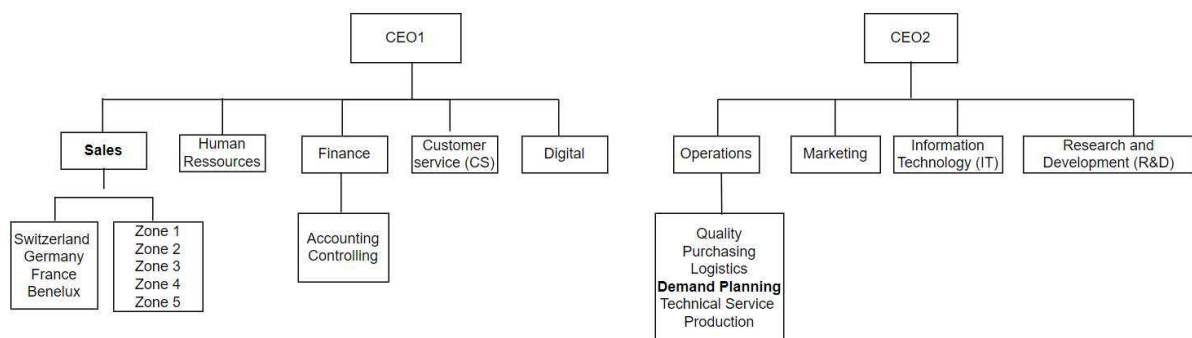


Figure 1.3: Final structure of the company (designed by the author)

To check the appropriateness of the distribution of departments between the two CEOs, Table 1.2 was created to summarize the key tasks performed in collaboration between departments. For each task, some departments have a bigger role than others, as shown in the chord diagram in Figure 1.4, where the width and darkness of the arrow corresponds to the degree of the department's impact in the associated task. For example, as Table 1.2 also shows, in conducting good sales and operations planning (S&OP), the Sales and Operations departments have greater roles than the other departments involved, such as Finance, Marketing, CS, and Digital; therefore, their arrow is bolder. Likewise, for the stock

management task, the Operations department has the highest impact, and thus the boldest arrow, but CEOs and Finance also help define suitable targets for the company.

Table 1.2 could help the company check if the division of the departments between the two CEOs is optimal. Based on an analysis of this chart, it seems that the separation was done in such a way that one CEO is responsible for the strategic parts of the company, such as Sales, Finance, and Human Resources (HR), while the other CEO is responsible for the technical and operational areas, such as Research and Development (R&D), Operations, and Information Technology (IT).

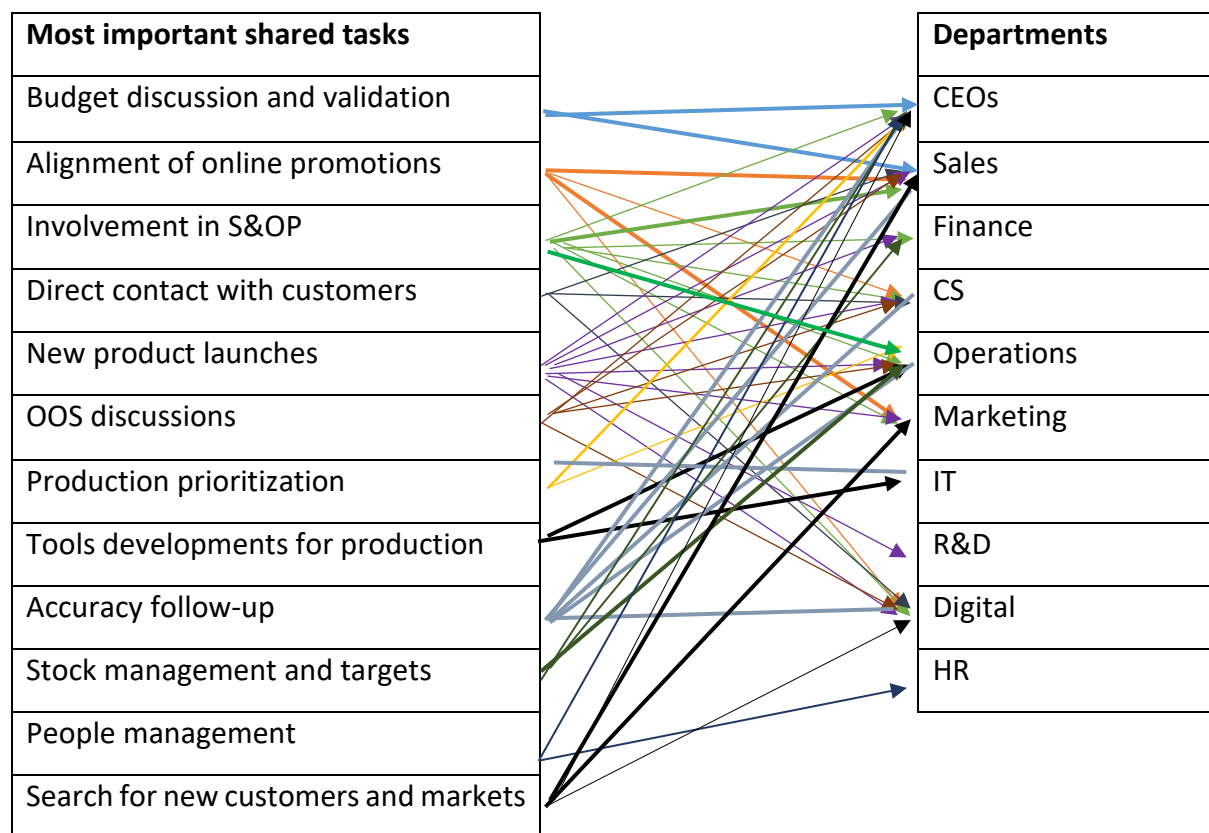


Table 1.2: Departments involved in the most important tasks of the company (designed by the author)

Figure 1.4 emphasizes those tasks, such as S&OP and new product launches, that require a higher number of departments. Furthermore, it highlights those departments that have a greater role in implementing the most important shared tasks between departments. It is visible that the Sales and Operations departments are frequently involved in tasks, which indicates that each has a valuable role in implementing the shared tasks.

This study focused on optimizing a small part of this structure, namely demand planning (sales forecasting), which is under the purview of the Operations department. This department is

considered the company's internal CS. It reacts closely and extensively with the Sales department, which is complex in this SME, as shown in the previous pages.

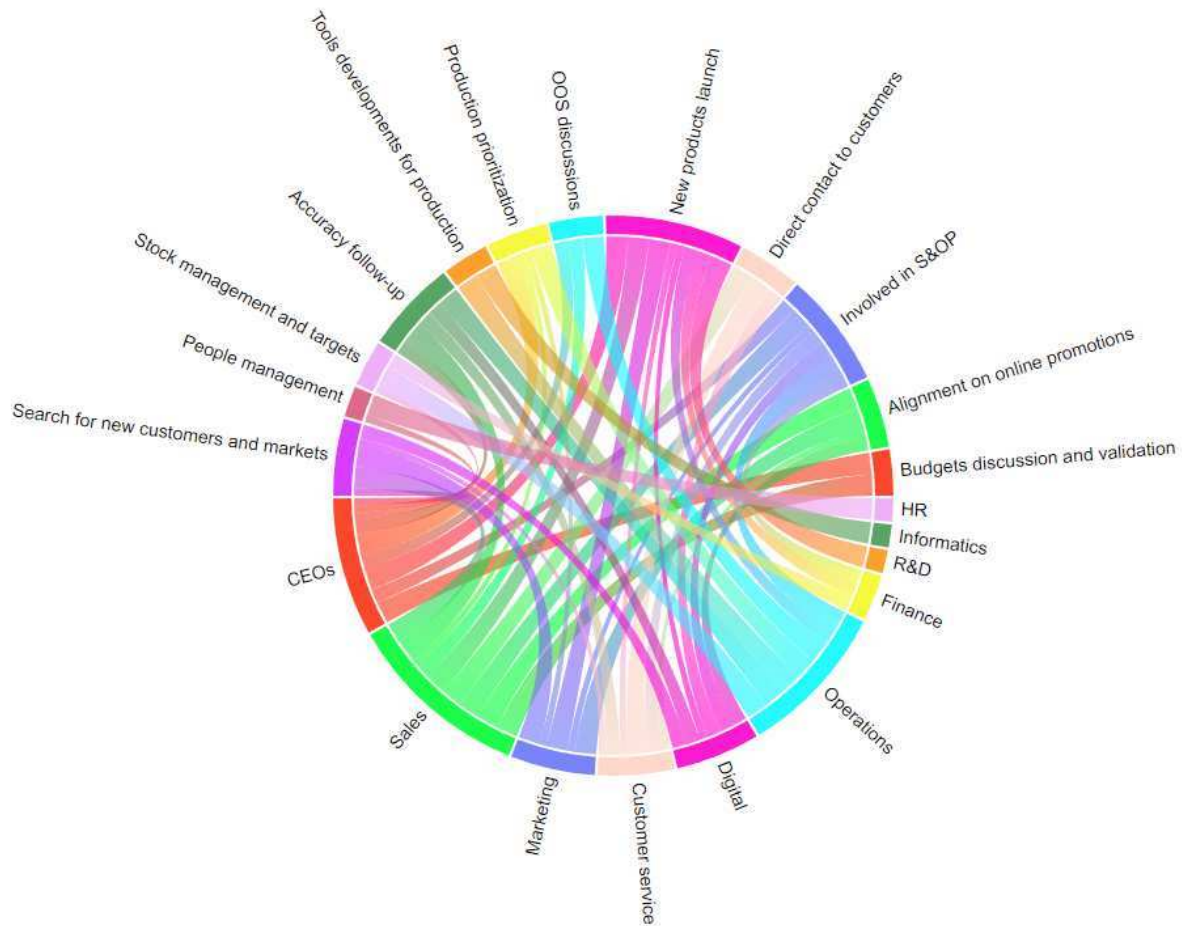


Figure 1.4: Chord diagram of department importance (designed by the author)

The reason for focusing on sales forecasting for this SME is simple: its sales forecasting was extremely underdeveloped. The first problem facing this SME was that sales forecasting was carried out by the Sales department. Since the salespeople did not necessarily have a passion or aptitude for sales forecasting, they tended to neglect it in favor of other tasks. Without good sales planning, the availability of merchandise could not be guaranteed.

In the initial process, illustrated in Figure 1.5 , the Sales department filled in Excel files with their requirements by market (for each subsidiary and for export countries). These files were then forwarded to the demand planning team, who acted only as an intermediary between the company and the subcontractor to whom production was outsourced at the start of the project. While the person in charge of demand planning in the Operations department should normally be able to challenge the Sales team on its forecasts, no analysis of sales history was carried out; they only reworked the figures provided by Sales to consolidate them and send the requirements to the manufacturer. As a result, the sales history was incomplete or non-existent.

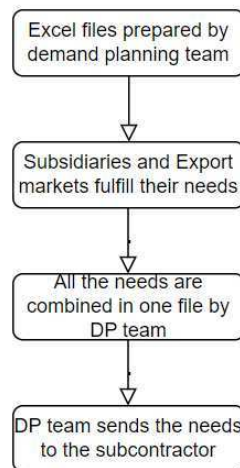


Figure 1.5: Flowchart of the initial forecasting process (designed by the author)

Figure 1.6 was created to obtain a simple view of sales evolutions. To supervise sales, most companies focus primarily on controlling promotional sales. Unfortunately, in the case of this SME, there was no monitoring of these sales.

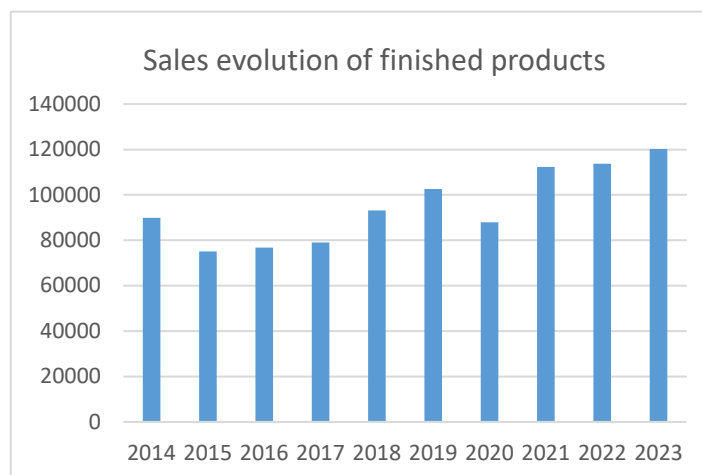


Figure 1.6: Overall trend in sales of finished products in units after construction of sales history (summarized by the author)

In addition, the establishment of a sales forecasting process was still unclear to the various departments in the company. In 2018, forecasts were made in the truly short term (three months), and even this truly short-term forecast was not fixed and was constantly changed. The Operations department would compile the so-called departure planning files (DP files) received from the Sales team and send the global requirements to the manufacturer who produced the final products. At the start of this project, the company was outsourcing the production to an external manufacturer. This external manufacturer was constantly receiving additional orders outside the planning process, or PP+ (production planning +). Sometimes, it also received last-minute order cancellations, or PP- (production planning -). The manufacturer reacted to satisfy the requests from Sales, and no initiative-taking analysis or reaction was made by this department.

To handle these variations, the company monitored accuracy for subsidiaries at Month-1 and Month-3. However, this accuracy was calculated at the global level without any weighting. The influence on sales accuracy differs depending on the quantities sold per product. For example, when the variation between the forecast and actual sales is three units, there is less of an impact on accuracy than when the difference is 300 units more. The influence on accuracy must therefore be weighted according to the gap in quantities between forecasts and actual sales. Weighting accentuates the impact of large forecast deviations.

Furthermore, the company's focus was on departure planning, which entailed tracking the departure date of goods from the warehouse to the customer. However, the focus should be on demand planning. Forecasts are improved by monitoring demand, which brings added value to the company.

Finally, there was a lack of item categorization. No item volatility was measured in relation to the weight of each item in the market. This dysfunction occurred because the weekly sales discussions did not include the person responsible for relations between the manufacturer and the company. In addition, his daily tasks concerned production planning and did not include sales forecasting. Here, the major underlying problem was the significant lack of communication among the various departments. Only one monthly meeting was held between the Sales and Operations departments, and it was regarded as a stock review meeting instead of an alignment meeting between the departments.

Given these issues, this study considered what this SME could do to improve its sales forecasting and how the company could be made aware of the need to act proactively to improve the tools it already had in place at a lower cost. It was necessary to address these questions to find the right solutions adapted to the needs of this SME.

Several tools are available to improve sales forecasting. However, it was important to first introduce the appropriate concepts within the company. In the future, the company will have to focus on demand forecasting and not only on loading planning.

The company needed to be informed about the different phases of S&OP, inspired by (Grimson J.A. & Pyke D.F., 2007), which are shown in Table 2.6 and explained further in Chapter 2.

The five stages of S&OP

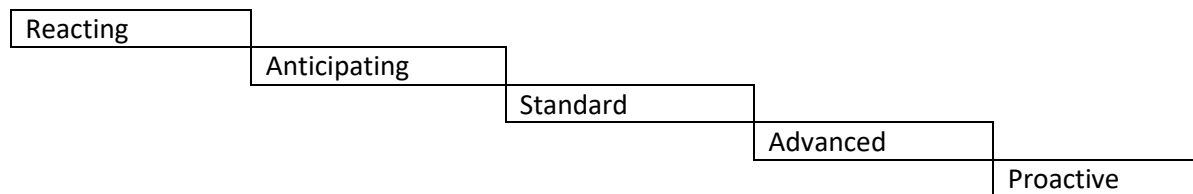


Table 2.6: The five stages of S&OP inspired by (Grimson J.A. & Pyke D.F., 2007)

At the start of this project, the company was in the first phase, Reacting. In this first phase, planning is done in the truly short term, and there is no control over sales forecasting. The aim was therefore to develop longer-term forecasting to move past the first phase, which is seen as purely reactive, and work in an initiative-taking direction.

To achieve this proactivity, it is important to differentiate between regular (or baseline) sales and promotional sales. Since the latter are larger in terms of quantity, it is necessary to have promotional plans for each market and, if possible, per customer. In this sense, it is possible to collaborate with customers to determine which merchandise leaves their stores during an action week (sell-out) compared to which merchandise they ordered for that action week (sell-in). With this information, post-promotional analyses can be conducted, which can provide the Sales, Finance, and Marketing departments with a good indication of the performance of promotion X compared to promotion Y.

Better monitoring of promotional quantities allows for more accurate sales forecasts. As it is also important to weight sales forecasts by market, category, or other factors, it is essential to ensure that all company stakeholders understand the concept of sales accuracy and to implement it as an objective in the Operations and Sales departments and even at the top management level.

However, implementing these processes is not so simple. Since the SME in this research is active in 50 markets, it was crucial for the company to segment markets. Each market

fluctuates differently, and it was highly likely that different solutions would be required for each market.

Before analyzing each market in detail, it was important to first improve the existing tools and gradually make up for the lacking components to avoid disrupting the SME.

Addressing the lack of communication between departments was considered the first objective of this improvement mindset. The company could quickly implement an S&OP process without upsetting employee habits, which would improve the transmission of information and promote collaboration between departments. To this end, the monthly meeting between the Sales and Operations departments could be maintained but extended to include more global topics or other departments, such as Marketing or Finance. In addition, the planner in the Operations department could be included in the weekly meetings of the Sales department. The planner could also have weekly conference calls with the subsidiaries, who account for most of the company's sales. Such measures could alleviate many dysfunctions in communication.

In summary, using the current organizational chart (Figure 1.3) as a starting point, communication between Sales and Operations was tackled first. More broadly, communication between Sales, Finance, Operations, Marketing, Digital, and CS would ideally be improved. Indeed, the Digital and CS departments in this SME are also involved in direct sales via the web shop and the call center, respectively. All sales-related departments (Sales, CS, and Digital) should analyze and pass on the right needs to the Operations department. The various promotions and activities that these departments propose should be compliant with the company's marketing strategy and with the budget set by Finance in terms of quantity and currency. The Operations department should ensure that everyone is aligned with the company's strategy and thus oversee the introduction of the S&OP.

In addition, the company could maintain the tools already in place at the head office, such as accuracy monitoring, but easily introduce the notion of weighting as a first step. In the second phase, the fluctuation of items was analyzed for subsidiaries to study their volatility in each market. Examining the volatility and weight of each item per market could make it easy to categorize these items and focus on those that are important in terms of weight, and which have high volatility.

Moreover, the SME was only monitoring this accuracy for subsidiaries. However, it would be highly useful to establish that monitoring for the most important export markets as well. After creating such files for exports, the company could include accuracy targets for subsidiaries and exports in its annual targets, thus emphasizing the importance of sales forecasting.

In conclusion, it was important for the Operations department to assume the role of sales forecast co-pilot, which has the functions of incorporating sales forecast analysis and questioning the figures given by the sales staff. In fact, this role must be revised to become a key position in the company to improve and monitor sales forecasts. The stagger chart is one Excel tool that could be quickly implemented by this department. The stagger chart is a metric table showing the evolution of sales forecast quantities over time. As illustrated in Chapter 5 of this thesis, the stagger chart can be a valuable tool for showing sales staff how their sales forecasts have changed from one month to the next.

Despite the additional short-term work (e.g., allocating additional resources, changing habits, implementing new tools) required for the company to realize all these improvements, the company was ready to accomplish it quickly because it was already planning a strategic change. Specifically, it was planning the construction of a new production site to begin manufacturing all its products itself instead of outsourcing the production. However, a major advantage of subcontracting is that the manufacturer suffers all the misfortunes of poorly managed sales and production forecast schedules. With this strategic change, the SME would have to bear all the consequences itself. Therefore, investing time and resources to make everyone's work easier and more efficient in the future was a necessity for the company.

Once the SME improved communication within its headquarters in Switzerland, it could minimize the aforementioned consequences by concentrating on communication and integration between the headquarters and the various markets, particularly the future production site, which is located abroad. The employees at this site are under the purview of a manager based at the production site as well as a manager at the company's Swiss headquarters. It was therefore important to integrate the production site team, share knowledge, and train staff in the company's new tools and processes. Relations between employees at the head office and those at the production site must also be monitored, and regular meetings and training are necessary to optimize collaboration between the two sites.

Given these circumstances, there was a real desire for a change of scope on the part of the SME, which was moving from a rather sales-oriented role to a much broader body of work that included the factory and production side. This underlines the importance of acting quickly to improve sales forecasts, which are at the heart of all the company's economic consequences.

This thesis is structured as follows. Following this introduction, Chapter 2 provides an overview of improvements in communication through S&OP. Subsequently, Chapter 3 discusses accuracy, and Chapter 4 introduces some of the applied methods. Chapters 5, 6, and 7 then explain what was done in the company to improve accuracy. Chapter 5 details the

stagger chart that was implemented, while Chapter 6 shows how product accuracy was improved by testing some time series methods and machine learning algorithms. Chapter 7 focuses on the improvement of accessories forecasts. The propositions in Chapters 6 and 7 were tested through time and a validation phase presented in Chapter 8. The final conclusion responds to the research questions that guided this work over the years:

1. How can the SME be made aware of the need to act proactively and improve the tools it already has in place at a lower cost?

2. How could this SME improve its sales forecasting?

2 Communication

As discussed in the introduction, it was crucial for the company to improve its sales forecasts before launching its own production site. The first area for improvement was the internal communication between the various departments. Clear, effective communication and coordination help synchronize the efforts of different departments and teams. A lack of good communication can lead to misunderstandings, duplications, or oversights that hamper productivity and performance. Through the exchange of information, communication ensures that the right items are produced at the right time, thus improving the company's forecast accuracy. Future sales depend on the company's ability to anticipate. Open, proactive communication is important to identify opportunities (e.g., new market segments, growth products) and warn of risks (e.g., falls in demand, increased competition). For these reasons, the implementation of S&OP within this SME was selected as the first area of work.

2.1 Sales and operations planning (S&OP)

Sales and operations planning (S&OP) is a monthly-based tactical planning process with the goal of aligning all business functions, including finance, sales, marketing, production, distribution, demand planning, and procurement, to support the same business plan and strategy. It is considered a cross-functional process within a planning horizon of typically one to two years (Mentzer J.T., et al., 1999). Sales and operations planning aims to align two components: sales planning, which is based on demand forecasting; and production planning, which involves capacity requirements, inventory level, and procurement (Wallace T.F., 2004). Although S&OP has become an important topic within companies, little research has focused on it. Practitioners (e.g., business managers, software vendors, consultants) have published five times more work on this topic than academics have (Tuomikangas N. & Kaipia R., 2014). The practitioner literature is based primarily on authors' opinions and personal experiences (Kreuter T., et al., 2021). (Adamczak M., et al., 2013) determined that the integration of S&OP has become a necessity for medium-sized enterprises.

The first empirical studies emerged in 1998 (Gianesi I.G.N., 1998). Table 2.1 summarizes some important contributions.

Authors	Year	Methodology	Contribution
(Gianesi I.G.N., 1998)	1998	Qualitative methods applied in different Brazilian companies.	The need to align different functional areas through S&OP.
(Vickery S.N., et al., 1999)	1999	Survey regarding marketing's knowledge of manufacturing processes.	Better product development when marketing has knowledge of manufacturing constraints.
(Olhager J., et al., 2001)	2001	Matrix emphasizing the common characteristics between manufacturing strategy and S&OP in terms of product and process.	Link between S&OP and manufacturing strategy for a long-term capacity management.
(O'Leary-Kelly S.W. & Flores B.E., 2002)	2002	Survey across multiple industries (primary metal, fabricated metal products, industrial machinery and equipment, electronic equipment, and transportation equipment) with a sample size of 789 firms.	Measure of the effects that both a firm's business strategy and environmental uncertainty have on the relationship between the integration of manufacturing and marketing/sales decisions and the organizational performance.
(Lapide L., 2005)	2005	Qualitative analysis of different S&OP applied in business companies.	Definition of an S&OP maturity model.
(Collin J. & Lorenzin D., 2006)	2006	Real case study within Nokia Networks with a strong customer-focused delivery process.	Importance of IT applications for ensuring that the right data are captured in the demand plans; importance of understanding customer needs and involving them in the agile process to improve planning.
(Grimson J.A. & Pyke D.F., 2007)	2007	Classification of the S&OP process into five stages based on a series of interviews with multiple companies.	Positive correlation between company size and S&OP maturity.
(Singhal J. & Singhal K., 2007)	2007	Analytical modeling for new products in a single firm.	Improvement of new product development process by incorporating the inputs of all cross-functions, such as marketing, manufacturing, and finance.
(Nakano M., 2009)	2009	Survey of Japanese manufactures to measure the degree of collaborative forecasting and planning (sharing resources, collaborative process operation, and collaborative process improvement); a proposed analytical model using structural equation modeling.	Positive relationships between internal and external collaborative forecasting and planning and a positive effect on relative logistics and production performance.
(Oliva R. & Watson N., 2011)	2011	Qualitative methods within a Californian enterprise; interviews of 25 leaders and participants in the S&OP process.	Identification of attributes of the planning process that can drive planning performance, information, procedural, and alignment quality.

Table 2.1: Main contributions in the literature, part 1 (summarized by the author)

Authors	Year	Methodology	Contribution
(Thomé A.M.T., et al., 2012)	2012	Qualitative methods regarding previous research in 271 papers.	The S&OP process is mostly used at the product family level or group level.
(Hulthén H., et al., 2016)	2016	Multiple case study of five companies from different industries based on data from 12 structured interviews.	A framework to measure the S&OP process, standardize measures, and enhance organizational transparency.
(Pedroso C.B., et al., 2016)	2016	Selection of companies in different stages of S&OP process with interviews conducted in different functional areas involved in S&OP; analysis of internal documents, visits to the plant, and offices to complete the characterization.	Characterization of success factors and barriers in S&OP implementation.
(Swaim J.A., et al., 2016)	2016	Survey of management-level participants in S&OP meetings to test four hypotheses.	Organizational integration positively influences a standardized S&OP process; both the S&OP process and priority lead to stronger organizational engagement in S&OP.
(Goh S.H. & Eldridge S., 2019)	2019	Survey method of 25 organizations supplemented by a qualitative analysis of comments from 568 respondents.	Organizational bricolage may be a coordinating mechanism of effective S&OP programs; managers should empower ambidextrous S&OP teams to maintain balance using self-governing, event-driven processes.
(Pereira D.F., et al., 2020)	2020	Analysis of mathematical modeling and summary of number of planning periods, time horizon, time granularity, level of detail (product/family), number of products/families, number of production locations, number of production stages, type of industry; categorization of analytical approaches.	Holistic framework depicting the overall S&OP; identification of parameters that have been modeled as uncertainty variables by researchers in the past based on 103 papers.
(Dittfeld H., et al., 2021)	2021	Multiple case study of seven organizations in the process industry using 17 in-depth interviews with high-ranking representatives, internal and external documents, and a group meeting with participating organizations.	Organizations proactively design their S&OP based on their main risk focus stemming from the planning environment; the design enables risk management activities in the monthly execution of S&OP.
(Seeling M.X., et al., 2021)	2021	A case study of a multinational manufacturing company, combining deductive logic from theory and inductive logic from field observation to elaborate on theory on global S&OP.	Standard set of KPIs beyond the standard S&OP five-step cycle; gradual evolution from tactic to strategic planning when global roll-up and global executive meetings are stimulated.

Table 2.1: Main contributions in the literature, part 2 (summarized by the author)

S&OP implementation and follow-up helps to improve sales accuracy for 20 to 30% (Smith L., et al., 2010). For an S&OP process to work, all employees need to be motivated and supported by management. The only thing to be gained is the awareness of the need to set up an alignment process between the various departments.

Only few enterprises consider their S&OP implementation as effective (Lapide L., 2005). Effectiveness of S&OP is measured through different maturity phases (Grimson J.A. & Pyke D.F., 2007). Maturity phases create a roadmap which aims to benchmark organizations (Poeppelbuss J., et al., 2011). A lot of enterprises have issues to switch from the first two phases which means an alignment of sales forecasts and production plan. (Grimson J.A. & Pyke D.F., 2007) saw no special link between the companies' size and the maturity of S&OP others as (Vereecke A., et al., 2018) think size of companies influence the maturity of S&OP owing to additional resources to invest in enterprise resource planning (ERP).

In the literature, the phases of maturity range from three to five dimensions, as reviewed in Table 2.2.

Stages of S&OP maturity	Literature
Three stages: (i) Integrated planning solution (ii) collaboration with trade partners (iii) network hub solutions.	(Wing L. & Perry G., 2001), (Feng Y., et al., 2008)
Four Stages: (i) Marginal process (ii) rudimentary process (iii) classic process (iv) ideal process	(Mentzer J.T., et al., 1999), (Lapide L., 2005), (Jacobs F.R., et al., 2011)
Five stages: (i) Reacting (ii) anticipating (iii) standard (iv) advanced and (v) proactive	(Grimson J.A. & Pyke D.F., 2007), (Tinker E.J., 2010), (Wallace T.F., 2011)

Table 2.2: Dimensions of maturity stages of S&OP (summarized by the author)

2.1.1 Analysis of S&OP maturity stages

To better understand the S&OP maturity stages, the following sections present the specific maturity models in more detail.

2.1.1.1 Wing and Perry's maturity model

The model proposed by (Wing L. & Perry G., 2001) consists of three stages (integrated planning solutions, collaboration with trade partners, network hub solutions) and two dimensions (information and integration technology), as summarized in Table 2.3.

The first stage, integrated planning solutions, occurs in a basic S&OP process with some integration in internal functions (e.g., Sales, Operations, Finance). The first goal is to align demand and supply planning with the organization.

The second stage, collaboration with trade partners, includes discussions with suppliers and distributors. The focus is on data sharing and enhancing forecasting impacts on the supply chain. The goal is to develop a collaborative relationship across the entire network.

The third stage, network hub solutions, is the most advanced stage. At this stage, organizations adopt a centralized network hub approach to manage S&OP across all stakeholders. The focus shifts to real-time data sharing and decision-making across the entire supply chain network, for which the companies need advanced technologies to respond quickly to changes in demand and supply conditions.

Dimensions	Stage 1: Integrated Planning Solutions	Stage 2: Collaboration with Trade Partners	Stage 3: Network Hub Solutions
Information	Aligns demand and supply within the organization	Extends integration to include collaboration with external partners; enhances visibility and responsiveness across the supply chain	Collaboration with external partners through a central hub approach
Integration Technology	Utilizes software tools for demand forecasting and inventory management	Enhances visibility and responsiveness across supply chain partners through the use of tools that support data sharing and collaboration	Enables real-time data sharing and decision-making across the network, which improves accuracy

Table 2.3: Summary of Wing and Perry's maturity model, based on (Wing L. & Perry G., 2001)

The principal criticism of (Thomé A.M.T., et al., 2012) is that the model reduces complex S&OP processes to just three stages, which may reduce the variations between organizations. In addition, the dimensions do not allow companies to correctly measure how to move from one stage to the next.

2.1.1.2 Lapide's maturity model

Lapide's maturity model is divided into four stages (marginal process, rudimentary process, classic process and ideal process) and three dimensions (meetings, processes, technology) as shown in Table 2.4.

The first stage, the marginal process, is an early stage with a high reactivity level. The focus of planning is usually short term. Data are often siloed, and there is limited collaboration across functions. Decisions about planning are made in response to immediate issues rather than for

strategic planning, and there is a lack of formalized processes for forecasting and demand planning.

In the second stage, the rudimentary process, companies start to anticipate demand and develop more formal planning processes. There are improvements in coordination between departments, and data sharing begins to take shape. Companies move toward forecasting and inventory management. Some efforts are made for demand planning, but these efforts are still largely functional and not integrated across the business.

In the third stage, classic process, companies attempt to improve collaboration across functions and departments. The planning becomes integrated, and companies start to make cross-functional decisions. The forecasting processes are more advanced, with greater accuracy and alignment between supply and demand. The strategic value of S&OP is finally apparent, and the focus is on both mid-term and long-term planning.

The fourth stage, the ideal process, is the highest stage of Lapide's maturity model. The S&OP is fully integrated in the entire organization, and companies operate in a proactive manner. The S&OP can drive the business because of real-time data availability, and there is a high level of collaboration across all departments.

Dimensions	Stage 1: Marginal Process	Stage 2: Rudimentary Process	Stage 3: Classic Process	Stage 4: Ideal Process
Meetings	Informal, sporadic meetings	Formal meetings, routine schedule	Formal meetings with full participation	Event-driven meetings to address imbalances
Processes	Disjointed, misaligned plans	Interfaced processes, reconciled plans	Integrated processes, alignment of supply and demand	Extended processes, internal and external collaboration with suppliers/customers
Technology	Heavy use of spreadsheets	Interfaced applications for demand planning	Integrated applications for demand and supply planning	Fully integrated technology, advanced collaborative software

Table 2.4: Lapide's maturity stages, based on (Lapide L., 2005)

The most significant criticism was expressed by (Pedroso C.B., et al., 2016), who argued that this model gives no indication of the metrics used to evaluate each stage of the S&OP process. Furthermore, the complexity of organizations is simplified into rigid stages that may not reflect the real-world fluidity. Another essential point is the lack of emphasis on external factors, such as market volatility or supplier disruptions.

2.1.1.3 Grimson and Pyke's model

(Grimson J.A. & Pyke D.F., 2007) proposed five stages of S&OP: reacting, anticipating, standard, advanced, and proactive. They aimed to help companies define the actions needed to improve their S&OP by first improving communication between Marketing, Sales, and Operations. The five stages progress from low integration of S&OP in the reactive stage to well-developed S&OP in the proactive stage. The model includes the five dimensions of frequency and pertinence of meetings, optimization of S&OP, timeline, measurements, and information technology, as shown in Table 2.5.

(Grimson J.A. & Pyke D.F., 2007) based their model on Lapide's model but added one stage and two dimensions. The model is the most widely known and frequently implemented in companies. The added stage and dimensions enhance the possibility to measure S&OP performance within companies (Jonsson P. & Mattsson S.A., 2006), thus overcoming the main criticism of Lapide's model (Pedroso C.B., et al., 2016).

In the first stage, reacting, S&OP knowledge is weak or non-existent. There is a low level of communication and a lack of meetings to share information between departments. The forecast horizon is mostly short term, and no measure of forecasts is done. The primary concern is whether the goods are delivered or not (departure planning), but there is no analysis of the impacts of these deliveries.

The second stage, anticipating, involves a process that is mainly guided by top management to align the sales and production plans with the financial objectives. This alignment is done for a short or medium period using spreadsheets for consolidation. There are no challenges from the Operations team yet at this stage. Sales are not aware of the production constraints because no executive meeting is in place.

In the third stage, standard, there is an awareness of the importance of S&OP. Several alignment meetings are held between departments. The S&OP leader is active in the Operations team and is usually the demand planning manager, who is the key person in aligning sales and production plans. The goal is to consider the sales demand and fulfill all production constraints. With the ERP in place and further analysis, the demand planning team can challenge the sales numbers to find a good consensus. Good key performance indicators (KPIs) are in place for all departments in line with the company objectives.

In the fourth stage, advanced, the plan integration is performed automatically through good planning tools. Advanced stock management is done, and the information is shared with all departments. An S&OP team is active, and the S&OP is a success thanks to suppliers and customers participating in the process.

The fifth stage, proactive, concerns the goals that companies have and have nearly reached (Grimson J.A. & Pyke D.F., 2007). The S&OP team is active within the departments of the company, and the suppliers and customers are always involved in the S&OP process. The tools used by the company are automatized, and the data are updated in real time. The principal criticism of this stage is the high cost of implementing it. Many companies cannot afford this cost, and the added value compared to stage three or four may not be worth it.

Dimensions	Stage 1 Reacting	Stage 2 Anticipating	Stage 3 Standard	Stage 4 Advanced	Stage 5 Proactive
Meetings	Silo culture Lack of meetings Low collaboration	Discussed at top level management meetings Focus on financial goals	Staff pre-meetings Executive S&OP Meetings	Supplier and customer data incorporated	Event-driven meetings Real-time access to external data
Optimization of S&OP Timeline	No S&OP focus Short-term forecasts	S&OP becomes a topic Short- and mid-term forecasts	S&OP function is part of another position Mid-long-term forecasts	Formal S&OP team Long-term forecasts	S&OP understood throughout the organization as a tool for optimizing company profit
Measurements	No measurements	Measure how Operations will meet the sales plan	Sales measures forecast accuracy Dashboard of KPIs	Operations gives inputs to inventor stock and sales promotions	Operations is involved in promotion plans and new launches
Information Technology	Own spreadsheets No consolidation of information	Many spreadsheets Some consolidation done manually	Centralized information Planning software ERP	S&OP workbench ERP	Integrated S&OP optimization software Real-time solver
S&OP Plan Integration	No formal planning Operations responsible for delivering orders (departure planning)	Sales plan driven Capacity utilization important only for Operations	Some plan integration between forecasts and production plan	Collaborative process Plan integrated	Seamless integration of plans

Table 2.5: Stages of S&OP, adapted from (Grimson J.A. & Pyke D.F., 2007)

2.1.2 The S&OP maturity stages of the analyzed SME

To understand where the SME stood regarding S&OP involvement, the stages of S&OP were adapted from (Grimson J.A. & Pyke D.F., 2007) as shown in Table 2.5. These five stages of maturity were chosen because the model is often used as a reference by academics and practitioners (Tuomikangas N. & Kaipia R., 2014). Furthermore, since the implementation of the S&OP process in this SME is a real-life practical case, it was necessary to select the most comprehensive model to cover all possible dimensions.

(Grimson J.A. & Pyke D.F., 2007) proposed a detailed model based on that of (Lapide L., 2005) to help companies define their maturity stage and underline the actions required to reach the next stage. The most important aspect of this maturity stage model is its inclusion of the notion of S&OP level measurement, as the lack of this notion in previous models was a major point of criticism (Pedroso C.B., et al., 2016). Moreover, it is possible that the SME may be between two stages in some dimensions depending on the level of implementation of each task (Thomé A.M.T., et al., 2012).

Table 2.5 is summarized in Table 2.6. As almost all chapters in this thesis concern the S&OP process, this table also appears in Chapters 3, 5, 6, and 7.

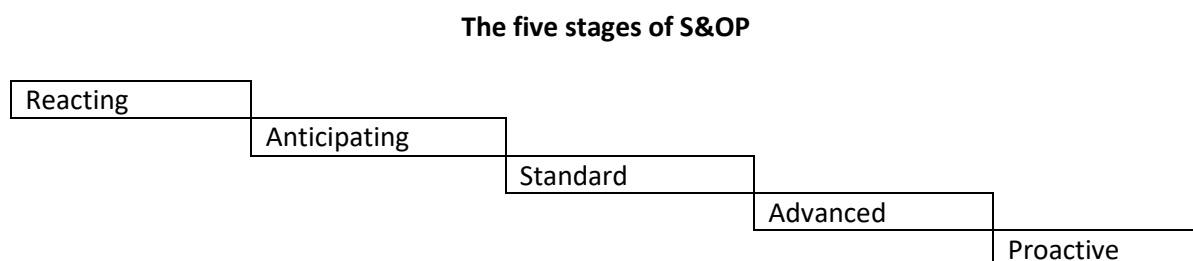


Table 2.6: The five stages of S&OP, inspired by (Grimson J.A. & Pyke D.F., 2007)

For (Grimson J.A. & Pyke D.F., 2007), communication is key for reaching the next stages of S&OP. It is beneficial in the long term for a company to not only improve the flow of communication across all departments of the parent company but also share this information with subsidiaries who are important stakeholders.

For successful S&OP, the involved departments of the SME must fulfill the following roles:

- CEOs
 - Provide ultimate decision-making when needed.
- Sales Management/Digital Management

- Set goals with the sales team to ensure sales according to the budget and work to improve forecast accuracy.
- Explain sales performance and accuracy within S&OP meetings.
- Know the actual performance versus the forecasted performance within the sales segmentation.
- Update sales forecasts monthly in the sales review.
- Marketing Management
 - Improve sales with adequate advertising aligned with Sales and Operations teams.
- Finance
 - Review the budget in terms of quantities and value.
 - Ensure a suitable stock level for the company.
 - Challenge other departments.
 - Follow up on actual monthly results compared to the budget.
- Customer Service
 - Review orders and due dates for delivery.
 - Communicate special promotions to customers.
 - Carry out direct sales.
- Operations Management
 - Ensure production and materials teams run the process according to the plan.
 - Perform inventory checks and follow-up on actual versus forecasted performance.
- Demand Planning Management
 - Present the demand plan in a readable format.
 - Ensure pre-plan analysis, collection of data, and demand planning.
 - Provide information about any issues in future forecasts.
 - Challenge the sales forecasts each month in the sales review.
 - Maintain a suitable safety stock level.

To implement the maturity model (Grimson J.A. & Pyke D.F., 2007) within the SME, it was important to follow a few essential steps. First, the company needed to evaluate its current S&OP level. This step involved understanding where the organization stood in regard to the five dimensions of (Grimson J.A. & Pyke D.F., 2007): meetings, optimization of the S&OP timeline, measurements, information technology, and an S&OP integrated plan. Then, it was important to set clear objectives for the improvements the company should achieve through the S&OP process. A roadmap could be developed to outline the necessary steps to move from the current maturity level to the desired state. Such a roadmap must include timelines,

resources, and the responsibilities of relevant stakeholders. In addition, to ensure strong collaboration across departments, it was essential to invest in appropriate technology to support the S&OP process improvements. Here, regular monitoring and review of S&OP implementation through KPIs is vital. However, success is dependent on the mindset of the stakeholders; therefore, it is worth implementing a culture of continuous improvements within the company (Grimson J.A. & Pyke D.F., 2007).

To measure the progress through the maturity levels in the model of (Grimson J.A. & Pyke D.F., 2007), KPIs for each maturity level were defined. Such KPIs could include metrics related to forecast accuracy, inventory level, and order fill rates, among other factors. To follow these KPIs, periodic assessments were conducted in a monthly meeting across departments, during which the KPI dashboard could be presented.

To apply the model of (Grimson J.A. & Pyke D.F., 2007), the first step was to determine the actual S&OP maturity level of the studied SME. When this project started at the end of 2018, the SME lacked a strong understanding of the importance of S&OP and of aligned demand planning. On average, the company was at the first, reactive maturity stage of S&OP, as shown in Figure 2.1. A goal was set to reach at least the third stage by the end of the project. Since the company was already customer oriented, the process of order management was quite well implemented. However, the KPIs and tools were not relevant to the forecasting process, or the key figures related to planning, and information sharing between departments was quite low.

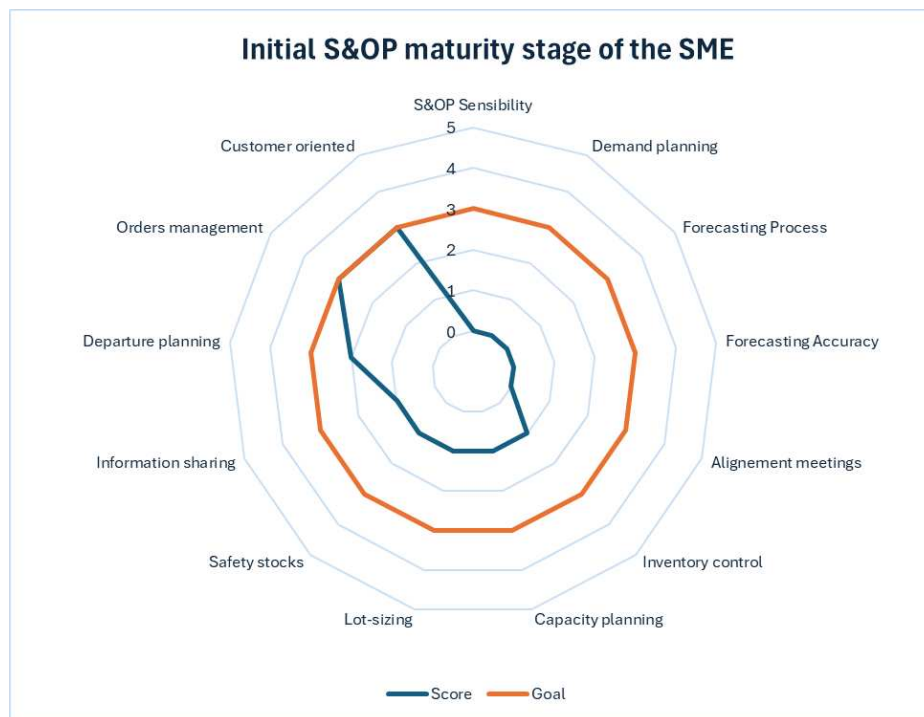


Figure 2.1: Summary of the S&OP stage for the SME at the start of the project (graphic by the author)

Several improvements were made to reach these goals. These improvements are described in the chapters of this thesis. As the first example, alignment meetings were established between Sales, Marketing, and Operations (demand planning), as explained in Section 2.2.

The recurrent alignment meetings were proposed as described below to improve communication and the S&OP process within the company.

- Week 1: Alignment meeting between Operations and Sales with a focus on subsidiaries as a starting point.
- Week 2: Global meeting to align departments.
- Week 3: Review of gaps in sales at month-1 and month-3 and discussion of opportunities and threats.
- Week 4: Presentation of results and KPIs, including out-of-stock (OOS) impacts and main monthly accuracy impacts.

To implement the best objectives and KPIs to improve the S&OP process of the SME according to (Grimson J.A. & Pyke D.F., 2007), a roadmap was made to outline the necessary improvements and timeline, as represented in Table 2.7. The tasks within the roadmap are presented in different sections of this thesis; for example, the implementation of a stagger chart is detailed in Chapter 5.

The goal of reaching the third stage of maturity was successfully achieved. The departments learned about the importance of S&OP, and various meetings were introduced to align goals, sales forecasts, and inventory control. Forecast accuracy was a KPI for Sales as well as for the Operations team. Safety stocks were discussed and defined by the different departments, such as Sales, Operations, and Finance, once per year. Stock level was also discussed and aligned.

Figure 2.2 shows the state of S&OP maturity in the company by the end of the project in 2024. Stage 5 had not yet been reached because it requires substantial technology investments that can be difficult for an SME to make (Tuomikangas N. & Kaipia R., 2014).

The following sections elaborate on the actions taken within the company to reach the defined S&OP goals.

Final S&OP maturity stage of the SME



Figure 2.2: Summary of the S&OP stage of the SME by the end of the project (graphic by the author)

S&OP process implementation within the SME				
Tasks done	Department involved	2019	2020 to 2022	2022 to 2024
1. Raising awareness of S&OP process 2. Monthly alignment meetings with subsidiaries, Finance, Marketing 3. Building a sales history 4. Follow-up of sell-in/sell-out sales 5. Construction of an accuracy measurement on Excel for subsidiaries 6. Implementation of a stagger chart 7. Sales forecasts extended from 6 to 12 months	Operations Operations, Sales, Finance, Marketing, CS, Digital Operations Operations, Sales, CS, Digital Operations Operations Operations, Sales, CS, Digital	From stage 1 Reacting to stage 2 Anticipating		
8. Extend accuracy measurement to the export market 9. Start to automate accuracy measurement directly in Qlikview/ QlikSense 10. Implementation of production KPIs 11. Improvement and development of customer sales dashboards 12. Valuation of components + finished goods inventory 13. Long-term planning over 18 months 14. Annual check of pallet (PAL) serial numbers in stock 15. Review of safety stocks continuously	Operations, Sales, CS, Digital Operations, IT Operations Operations, Sales, CS, Digital Operations, Finance Operations, Sales, CS, Digital Operations Operations, Sales, CS, Digital, Finance, Marketing	From stage 2 Anticipating to stage 3 Standard		
16. Automatization of KPIs in Qlikview/ QlikSense 17. Automate accuracy measurement directly in Qlikview/ QlikSense 18. Data from key customers and suppliers actively integrated 19. A formal S&OP team exists 20. Improvements of product and accessories accuracy	Operations, IT Operations, Sales, CS, Digital, IT Operations, Sales, CS, Digital, Finance, Marketing Operations, Sales, CS, Digital, Finance, Marketing, IT Operations, Sales, CS, Digital			From stage 3 Standard to stage 4 Advanced

Table 2.7: Roadmap of the S&OP process for the SME (designed by the author)

2.2 Monthly demand planning-sales meeting

At the start of the project, the only meeting held between Sales and Operations was a stock review meeting based on an Excel file. The aim was to maintain this meeting but to broaden it to give it added value. This meeting became the monthly alignment meeting between the departments (Sales, Operations, Marketing, Finance, CS, and Digital). This extension enabled the review of stock levels as well as a greater focus on more global themes, such as the various projects underway between the departments and the next steps in those projects and their implementation. The presence of each department was necessary for the proper dissemination of information to bring added value to the meeting.

2.3 Monthly calls with subsidiaries

At the start of this project, Operations had almost no communication with the subsidiaries. However, the subsidiaries account for significant figures in terms of profitability and volume. Therefore, a monthly conference call was held at the beginning of each month. During these conferences, participants discussed topics such as forecasting accuracy, promotional plans, upcoming activities, and product performance in each market. They also mentioned stock levels and production issues (e.g., component availability, line capacity). In fact, a stock file was sent to the whole company. Inventories were also reviewed in greater detail for each market. The highlights of these discussions could be shared at the monthly alignment meeting mentioned in Section 2.2.

The objectives of these meetings can be summarized as follows:

- Raise awareness of information transfer between the subsidiaries and the parent company.
- Discuss and implement promotional plans.
- Share information regarding inventory issues and discuss product launches in each market.
- Share reports on these discussions with the company's top management.
- Visit subsidiaries to support them in developing their sales planning.
- Create trust and mutual support between parent company and subsidiaries.
- Facilitate information sharing and have the parent company show support for subsidiaries by creating specific tools for each market.

Overall, the mentioned alignment meetings were a crucial component of the S&OP process because they ensured that all key stakeholders were working together toward common business objectives.

2.4 Conclusion and next steps regarding S&OP

As noted, strong implementation of S&OP can improve sales accuracy by up to 30% (Smith L., et al., 2010). However, such improvement requires significant alignment between various departments. Strong S&OP helps organizations align future demand and production needs, which in turn reduces shortages and overstock. Throughout the S&OP maturity stages, it is crucial to advance cross-departmental collaboration and information sharing to improve accuracy and enhance decision-making processes. Sections 2.2 and 2.3 illustrated the importance of monthly alignment meetings to enhance the effectiveness of S&OP and move the company to the second stage (anticipating), as shown in the roadmap in Table 2.7.

The next chapters (3 to 7) present other improvements that were made as part of the S&OP process. These improvements helped the company progress through the maturity stages outlined in the model of (Grimson J.A. & Pyke D.F., 2007) and the roadmap in Table 2.7.

3 Accuracy

3.1 Introduction

This chapter addresses several elements of the roadmap presented in Table 2.7. Each element helped the company improve its sales forecasts and evolve through the S&OP stages represented in Table 2.6. These elements consisted of the following:

- Construction of an accuracy measurement in Excel for subsidiaries to progress from the first stage (reacting) to the second stage (anticipating), as represented in orange and blue in Table 2.6 (Section 3.2).
- Extension of the accuracy measurement to the export market to progress from the second stage (anticipating) to the third stage (standard), as represented in blue in Table 2.6 (Section 3.2).
- Automation of the accuracy measurement directly in Qlikview/QlikSense to progress from the second stage (anticipating) to the third stage (standard) or even the fourth stage (advanced), as represented in blue and green in Table 2.6 (Section 3.2).
- Annual check of pallet (PAL) serial numbers in stock to progress from the second stage (anticipating) to the third stage (standard), as represented in blue in Table 2.6 (Section 3.3).
- Improvement and development of customer sales dashboards to progress from the second stage (anticipating) to the third stage (standard) or even the fourth stage (advanced), as represented in blue and green in Table 2.6 (Section 3.4).

The aim of this Chapter is to highlight the importance of communication for improving accuracy, as discussed in Chapter 2. The following sections describe how the company evolved from the first stage to the third or fourth stage of S&OP maturity, as shown in Table 2.6.

The five stages of S&OP

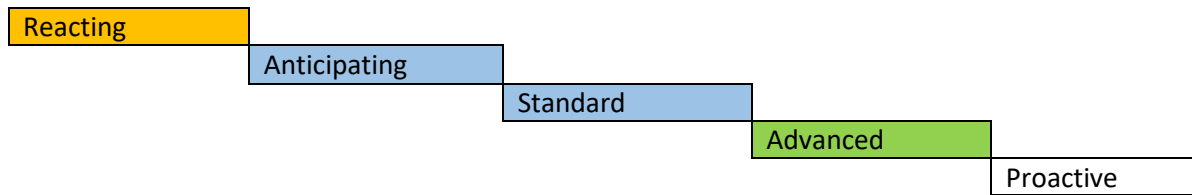


Table 2.6 The five stages of S&OP, summarized from (Grimson J.A. & Pyke D.F., 2007)

3.2 Accuracy follow-up

Improving accuracy was important for the analyzed SME. The SME outsourced its production until end of 2019, at which point it decided not to renew the contract with the manufacturer and instead start building its own production site. For this reason, the company needed help with improving its accuracy.

When the project started, the company did not perform any follow-up on accuracy. To advance from the first stage (reacting) to the second stage (anticipating) of the S&OP process (Table 2.6, Section 2.1.2), it was decided to focus first on improving sales accuracy for the subsidiaries only, as shown in the roadmap in Table 2.7 (Section 2.1.2). The improvements needed to be accomplished quickly in the first step because the company wanted to build its own production site. From the beginning of 2019 to the end of 2020, the efforts were focused on improving demand planning and production planning, which involved the following actions:

- On-site follow-up on the building of the factory, especially for demand planning tools and the buildup of production.
- Check with the actual manufacturer to produce products for different countries in advance since the new factory would need certifications for each country before selling the goods. The manufacturer contract ended in December 2019, and the new production started in January 2020.

Table 3.1 displays the certification deadlines that were introduced for each appliance plug. These deadlines were initially defined by the company and discussed between the quality manager of the SME and an external certification expert of International Organization for Standardization (ISO). When the production started in January 2020, the only countries for which the company could start producing directly were the CH/EU plugs. Because of special regulations, production for other countries, such as China, Korea, and the US, would not be

possible for up to six or seven months. Therefore, the company would have to anticipate the demand for the mentioned countries and have the manufacturer produce goods in advance at the end of 2019.

New factory certification deadlines per countries in 2020	Jan	Feb	Mar	Apr	May	June	July
CH/EU plugs							
UK plugs							
Russia plugs							
Malaysia/Singapore plugs							
China plugs							
Korea plugs							
USA plugs							

Table 3.1: Certification deadline for the new factory

This part presented some difficulties due to a lack of communication and alignment between Sales and Operations. In addition, there were seasonal sales in November for Black Friday, a key promotion of the company that leads to twice as many sales in November as in other months. Therefore, anticipation of the demand for the first semester of 2020 and the end of 2019 sales was made 9 to 12 months in advance. For this, stock building was discussed with finance and top management to ensure that deliveries to customers would be made in time.

Despite all these efforts, the company could not anticipate the impacts of the COVID-19 pandemic starting in March 2020. The SME was heavily affected from March to May and even later due to impacts on the delivery time of components. Since the electronical components came from China, the production and distribution were complicated during the first semester of 2020. The initial speed of production also posed a challenge. Since the company had decided to hire operators step by step, the daily quantities that were produced at the beginning were quite low. Alignment between HR, Operations, and top management had to be done to anticipate hiring of the workforce.

The anticipation conveyed to the manufacturer at the end of 2019 was necessary during this time to ensure the delivery of orders to customers. The improvements of accuracy achieved in the first phase of the project (from the end of 2018 to 2020) were helpful for making the right decisions (+30%).

To achieve these improvements in accuracy, the first step was to collect data and build up accuracy for the year 2018. Since it had not been measured correctly by the company, and it had to be implemented quickly, a spreadsheet template was created for comparing the forecasts with the real sales for each country. In the same file, illustrated in Table 3.2, an accuracy follow-up was performed for each country, and a consolidation of all subsidiaries and

export countries was carried out in a second step. This consolidation was helpful in establishing a common accuracy goal for the sales team and demand planning team. After a few meetings, the importance of accuracy was demonstrated to the top management and all stakeholders, and all parties agreed to the common goal of increasing accuracy to a range of 50 to 60% in the first year.

When important deviations between forecasts and real sales were observed, the key account managers (KAMs) had to make a comment in the accuracy file, as shown in Table 3.2. These comments were addressed during the pre-monthly alignment meetings between Sales and the demand planning team to understand the origins of the gaps. Then, they discussed common adaptations for the future months. As a result, the demand planning team began to challenge the quantities given by Sales.

Accuracy targets were set separately for the subsidiaries and for the export markets because of the safety stock in place for subsidiaries, especially for final products. In contrast, for the export markets, the process was “make-to-order.” Production was usually set once the payment by export markets was complete. The first semester of 2020 was an exception to this, as the demand had to be anticipated because of the certification deadlines for the new manufacturing site (Table 3.1). The “make-to-order” approach is quite utopic. All export countries require the goods in the first week of each month, and production does not have the capacity to produce the full quantities in one week. Therefore, some quantities must be anticipated. When the customer does not take the goods as expected, it negatively impacts accuracy, which was the case almost every month for the company. At the same time, some emergent countries had volatile demand and sold higher quantities than anticipated. Therefore, Operations had to find solutions to produce more quantities than planned each time. For all these reasons, monitoring of sales and accuracy is helpful.

SWITZERLAND		January 2020									
	Firm order	Real	R vs F	R vs F %	R vs F% abs	Accuracy per item	Weight	Accuracy	Comments	PP+/PP-	
	Product 1	140	107	-33	-24%	24%	76%	0.43	76%		
	Product 2	90	13	-77	-86%	86%	14%	0.05	14%	Quantities taken in December	
	Product 3	180	129	-51	-28%	28%	72%	0.52	72%	Quantities taken in December	
	Total First type of product	410	249	-161	-39%	39%	54%	0.24	71%		
	Product 4	0	0	0	0%	0%	100%	-	100%		
	Product 5	0	0	0	0%	0%	100%	-	100%		
	Product 6	0	-2	-2	0%	0%	0%	-0.01	0%		
	Product 7	0	0	0	0%	0%	100%	-	100%		
	Product 8	0	0	0	0%	0%	100%	-	100%		
	Product 9	0	0	0	0%	0%	100%	-	100%		
	Product 10	250	195	-55	-22%	22%	78%	0.64	78%	Performance less than expected	
	Product 11	270	112	-158	-59%	59%	41%	0.37	41%		
	Product 12	0	0	0	0%	0%	100%	-	100%		
	Total Second type of product	520	305	-215	-41%	41%	80%	0.30	65%		
	Product 13	22	35	13	59%	59%	159%	0.73	63%		
	Product 14	132	13	-119	-90%	90%	10%	0.27	10%		
	Total Third type of product	154	48	-106	-69%	69%	84%	0.09	49%		
	Product 15	257	367	110	43%	43%	143%	0.32	70%	High sales due to winter promotions	
	Product 16	66	266	200	303%	303%	403%	0.23	25%	Not planned, to check with customer	
	Product 17	0	0	0	0%	0%	100%	-	100%		
	Product 18	0	0	0	0%	0%	100%	-	100%		
	Product 19	44	8	-36	-82%	82%	18%	0.01	18%		
	Product 20	88	361	273	310%	310%	410%	0.31	24%	Not planned, to check with customer	
	Product 21	0	0	0	0%	0%	100%	-	100%		
	Product 22	0	0	0	0%	0%	100%	-	100%		
	Product 23	44	32	-12	-27%	27%	73%	0.03	73%		
	Product 24	66	87	21	32%	32%	132%	0.08	76%		
	Product 25	66	26	-40	-61%	61%	39%	0.02	39%		
	Total Fourth type of product	631	1147	516	82%	82%	147%	0.37	45%		
	Total all Products	1715	1749	34	2%	2%	91%	1.00	57%		

Table 3.2: Example of deviation follow-up in place in the company

Table 3.3 shows how the follow-up on accuracy was first set up in an Excel spreadsheet.

Monthly forecast Accuracy and last 3 Months accuracy							
Evol. Quantities	Jan 2020	Feb 2020	Mar 2020	Apr 2020	May 2020	Jun 2020	Jul 2020
Q Difference First type of products	-161	-214	-141	-267	-324	204	48
Q Difference Second type of products	-215	-15	-270	58	-15	312	-62
Q Difference Third type of products	-106	-191	-26	122	-166	110	27
Q Difference Fourth type of products	516	-268	-433	-425	-253	778	85
Total First type of products (%)	71%	65%	60%	15%	10%	36%	79%
Total Second type of products (%)	65%	24%	42%	86%	54%	36%	42%
Total Third type of products (%)	49%	56%	73%	17%	51%	0%	24%
Total Fourth type of products (%)	45%	66%	33%	30%	49%	71%	54%
Sums of deviations	34	-686	-870	-512	-758	1'404	98
Accuracy per month	57%	59%	45%	27%	40%	67%	54%

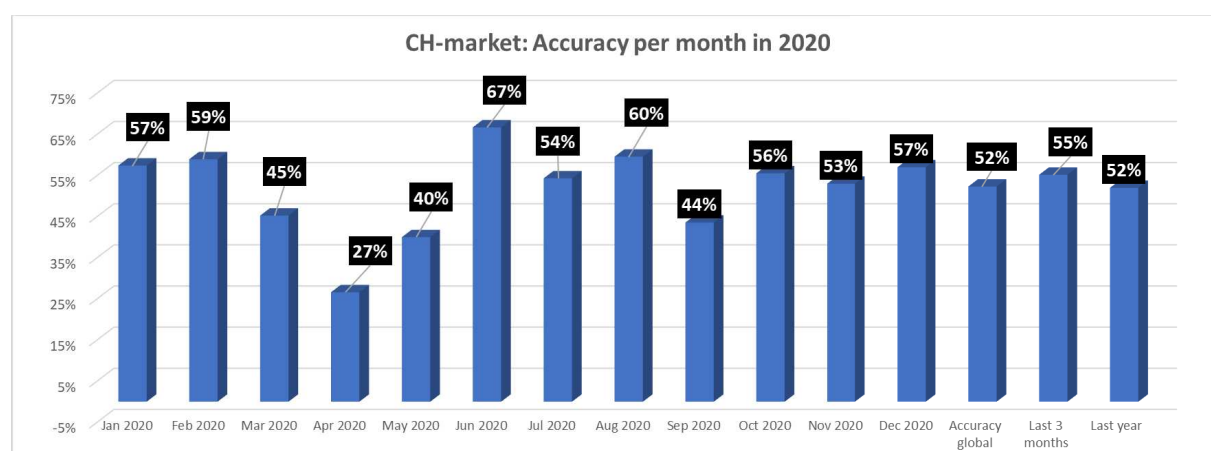


Table 3.3: Accuracy follow-up in spreadsheets (designed by the author)

As seen in Table 3.3, the initial file was a rather simple visual summary of the accuracy each month, in the last three months, and in the previous year, which facilitated comparison. A target was defined for each subsidiary and set as a target for the company from the year 2019. It helped the SME reach the second stage of S&OP by requiring the departments to collaborate more in the same direction to improve negative forecasting impacts. Once the accuracy monitoring with the subsidiaries was in place, the project was extended to export countries. Accuracy monitoring was introduced for the export countries with a 100% target since the export countries must theoretically accept the full quantities they forecasted and paid for. Of course, this is not always the case, as the situation may be influenced by external factors, such as COVID-19 in 2020.

In the second step to proceed from the second stage (anticipating) to the third stage (standard) of S&OP, a project was started with IT to automatize the forecast accuracy follow-

up in QlikView,² a tool that was already being used by the company and constantly developed to integrate data and analytics.

To automatize the forecast follow-up, the source of the data provenance needed to be specified together with all formulae for computing the accuracy. Table 3.4 presents a simplified example of the calculation used for the accuracy to automatize the tool and the accuracy follow-up. In this table, firm orders (forecasted quantities) are compared to real sales per item. A weight is given to the quantities sold by item, and the accuracy is automatically calculated at the end.

Monthly forecast accuracy			
		févr. 21	Total
Firm order (D3)	Smart	400	400
	Lift	1136	1136
	Total	1536	1536
Real (E3)	Smart	377	377
	Lift	693	693
	Total	1070	1070
Accuracy per item (I3)	Smart	0.94	0.94
	Lift	0.61	0.61
	Total	0.70	0.70
Firm orde (D3) / real (E3)	Smart	1.06	1.06
	Lift	1.64	1.64
	Total	1.44	1.44
Pondération	Smart	0.26	0.26
	Lift	0.74	0.74
	Total	1.00	1.00
Accuracy	Smart	0.94	0.94
	Lift	0.61	0.61
	Total	0.70	0.70

Source XLS, fichier Agneta Comparaison_xxx

Accuracy per item :
SIEPPEUR(ABS(SI(D3=E3;100%;E3/D3)),0)
D3 = Firm order
E3 = Real

Accuracy :
ABS(SI(I3>100%;D3/E3;I3))
I3 = Accuracy par article
D3 = Firm order
E3 = Real

Pondération :
Firm order item code / Firm order item code group

%
Accuracy * pondération

Table 3.4: Screenshot of an example of accuracy calculation in QlikView set up in the SME

To build Table 3.4 automatically, the data must be available in QlikView. To ensure this availability, work was done to define which data needed to be extracted. Table 3.5 summarizes the source of the required information for the real sales data.

² [Qlik Data Integration, Data Quality, and Analytics Solutions](#)

Source Dashboard Sales				
Champs Excel	Source QV	Builder QV	Data QV	Remarques
Type	Ls\ls_sales_dashboard	Item code		Recherchev(item code, 'product Info';3;0)
Subtype	Ls\ls_sales_dashboard	Item code		Recherchev(item code, 'product Info';4;0)
Data Conc	Ls\ls_sales_dashboard	Year + Month		Concatener (month, "", year)
Date	Ls\ls_sales_dashboard			Recherchev(Data Conc, 'Month format';3;0)
Country	Ls\ls_sales_dashboard	Territory	Territory Group	Recherchev(Territory, 'country mapping'!A:B;2;0)
Whse Ship	Ls\ls_sales_dashboard	Territory	Territory Group	Recherchev(Territory, 'country mapping'!B:C;2;0)
Business	Ls\ls_sales_dashboard	Centr de coût		Recherchev(centre de cout,'country mapping'!H:I;2;0)
Q total	Ls\ls_sales_dashboard	Q total		

Table 3.5: Screenshot of Sources of data needed to extract real sales values specific to the SME

The sales data were easily extractable because they were already in another dashboard in QlikView. For the forecasted quantities, the demand planning team and IT must find a link between the ERP, Oracle (used by the Operations teams, in which the forecasting quantities are visible), and QlikView. For this purpose, mapping was done for the forecasted quantities as well, as shown in Table 3.6.

Source Dashboard Sourcing				
Champs Excel	Source QV	Builder QV	Data QV	Remarques
Type	Sourcing\ls_sourcing	Analysis Forecasts	Items	Recherchev(item code, 'product Info';3;0)
Subtype	Sourcing\ls_sourcing	Analysis Forecasts	Items	Recherchev(item code, 'product Info';4;0)
Data Conc	Sourcing\ls_sourcing	Analysis Forecasts	Year, Month	Concatener (month, "", year)
Date	Sourcing\ls_sourcing	Analysis Forecasts	Year, Month	Recherchev(Data Conc, 'Month format';3;0)
Country	Sourcing\ls_sourcing	Analysis Forecasts	Forecast designator	Recherchev(Territory, 'country mapping'!A:B;2;0)
Whse Ship	Sourcing\ls_sourcing	Analysis Forecasts	Inventory Name	Recherchev(Territory, 'country mapping'!B:C;2;0)
Business	Sourcing\ls_sourcing	Analysis Forecasts	Inventory Name	Recherchev(centre de cout,'country mapping'!H:I;2;0)
Q total	Original QTY (Forecasts.ORIGINAL_FORECAST_QUANTITY)	Sourcing_all	MRP_FORECASTS	

Table 3.6: Screenshot of Sources of data needed to extract forecasted values specific to the SME

In summary, the accuracy calculation is based on the deviation between real sales and forecasts. A weight is assigned automatically to each product forecast depending on the quantity of sold products.

To emphasize the improvements and move to the fourth stage of S&OP maturity as shown in Table 2.6, products were also classified with volume and volatility for each subsidiary. The goal was to reduce the negative impacts of accuracy on products with high volume and high volatility, which requires demand planners to focus on these items when challenging the forecasts. The illustration in Figure 3.1 represents the classification of the main products in terms of volume and volatility for the Swiss market. Given that the company should focus on products with high volume and volatility ($> +15\%$), the figure indicates that products 1, 4, 6, and 7 could be good focuses for the Swiss market.

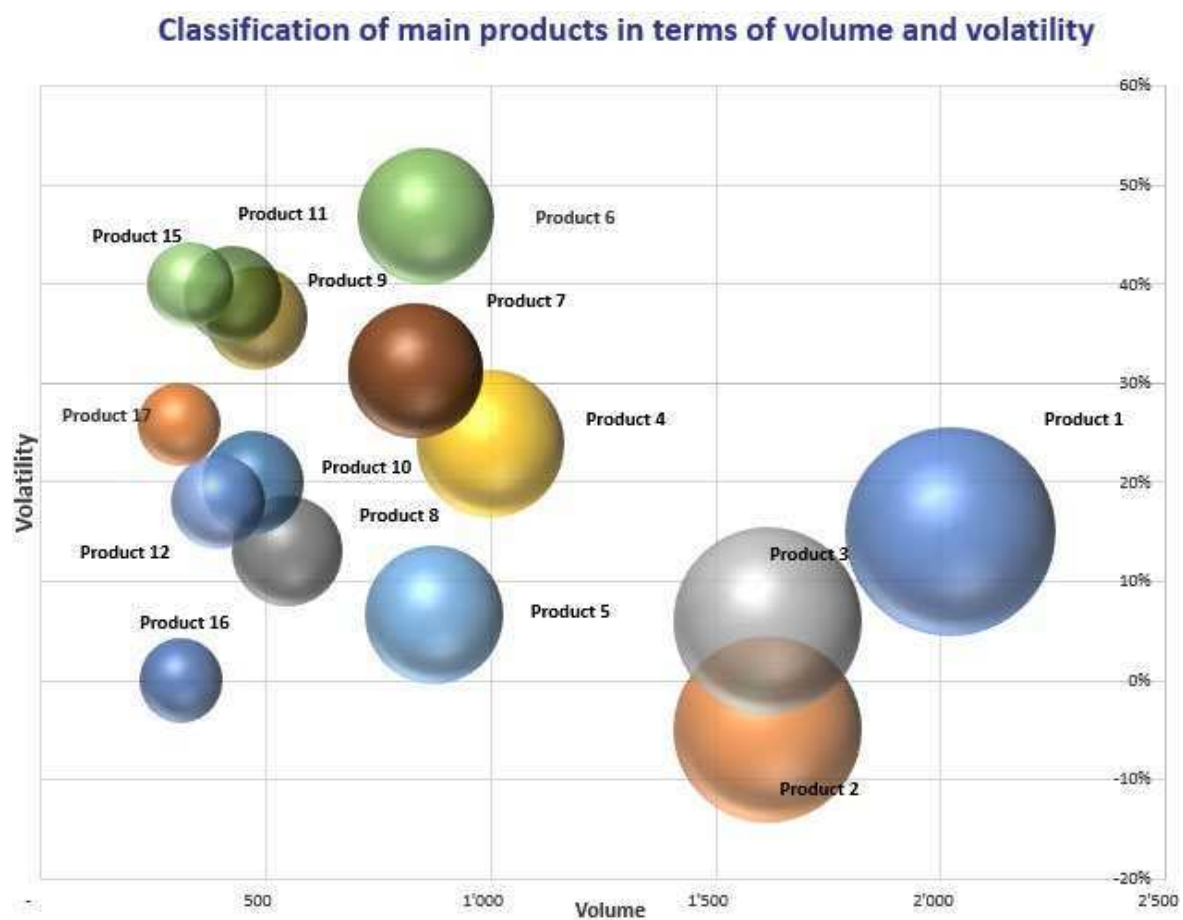


Figure 3.1: Classification of products in terms of volume and volatility (designed by the author)

The markets were also classified in terms of the amount invoiced and quantities sold. The company is active in more than 50 markets. Markets 1 to 7 are considered subsidiaries by the company. Zone 1 is composed of markets 8 to 15, Zone 2 includes markets 16 to 28, Zone 3 encompasses markets 29 to 34, Zone 4 is comprised of markets 35 to 37, and Zone 5 contains markets 38 to 50. Figure 3.2 shows that markets 2, 3, and 5 are the largest markets in terms

of amount invoiced, and market 1 is the largest in terms of quantities sold. Thus, the company sells more expensive goods, such as final products, in markets 2, 3, and 5, whereas more accessories are sold in market 1.

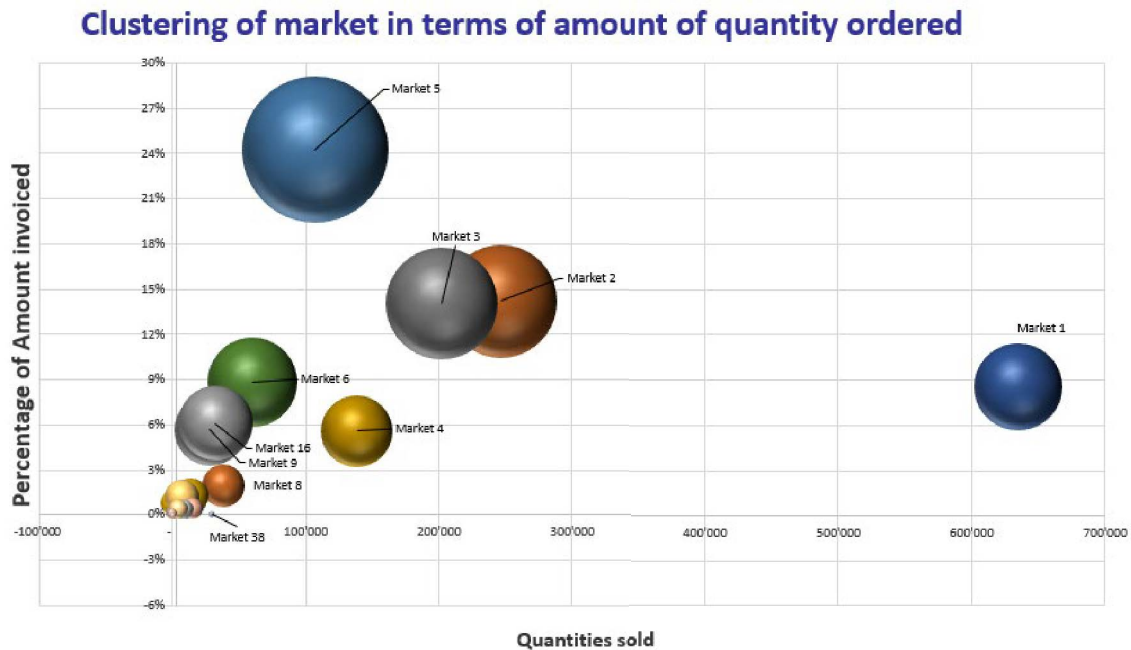


Figure 3.2: Classification of sales per country (designed by the author)

With this analysis, the impacts of COVID-19 on accuracy were easily identified in 2020. For example, the Swiss market was impacted most heavily in April 2020, when there was a 30% decrease in the accuracy level (Figure 3.3).

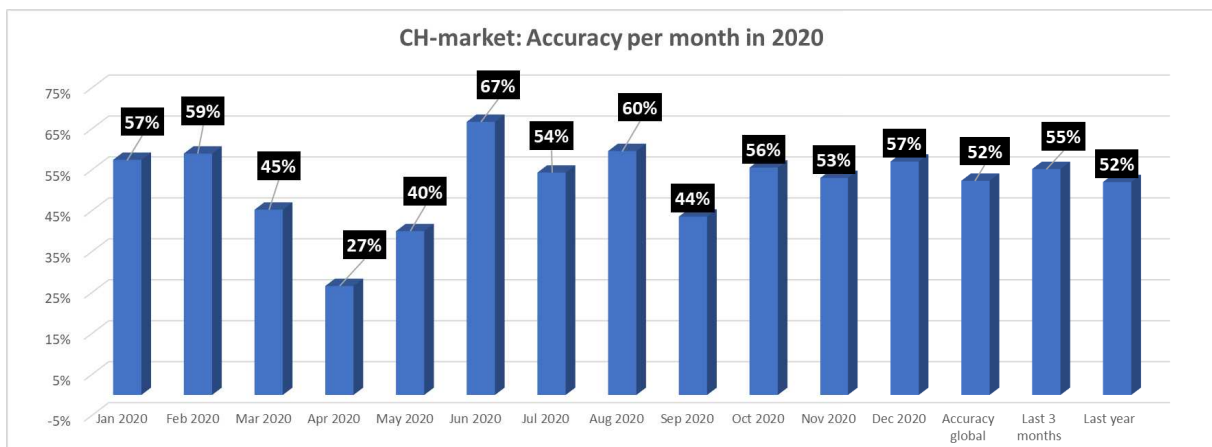


Figure 3.3: Accuracy values of the Swiss market in 2020 (designed by the author)

Figure 3.4 summarizes the accuracy improvements in the company from 2018 to 2023. The improvements at the beginning of the project were the most significant with an increase of 30% from 2018 to 2019.

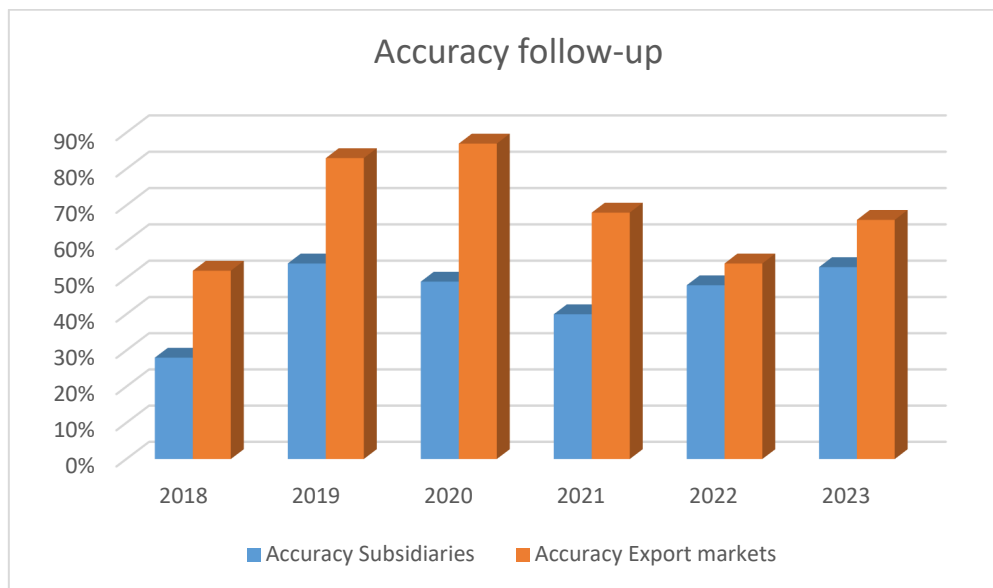


Figure 3.4: Summary of accuracy follow-up (designed by the author)

Many tools were implemented to improve the accuracy, including stagger charts (see Chapter 5), inventory control, S&OP, improved product and accessory forecasts (see Chapters 6 and 7), and customers sales follow-ups. However, COVID-19 had a substantial impact on the accuracy improvements. Another factor that could explain the stability in accuracy is the variety of changes made within the company. First, with the change of cap by the company, it began self-producing rather than outsourcing the production. Therefore, the workforce had many tasks to attend to, which impacted accuracy. When a company has its own manufacturing company, top management pushes for additional orders in production when possible. Such orders might have been refused by the original equipment manufacturer (OEM). Even though additional orders are good for the business, they have an adverse effect on accuracy measurement. Yet another possible factor is the turnover of employees within Operations and Sales, which could lead to less significant efforts.

Nevertheless, the accuracy of this company improved considerably compared to other domestic device companies. The order fill rate also remained stable, as shown in Figure 3.5. Despite stagnating accuracy, the company managed to deliver to customers on time in almost 97% of cases, which was the delivery target set by the company.

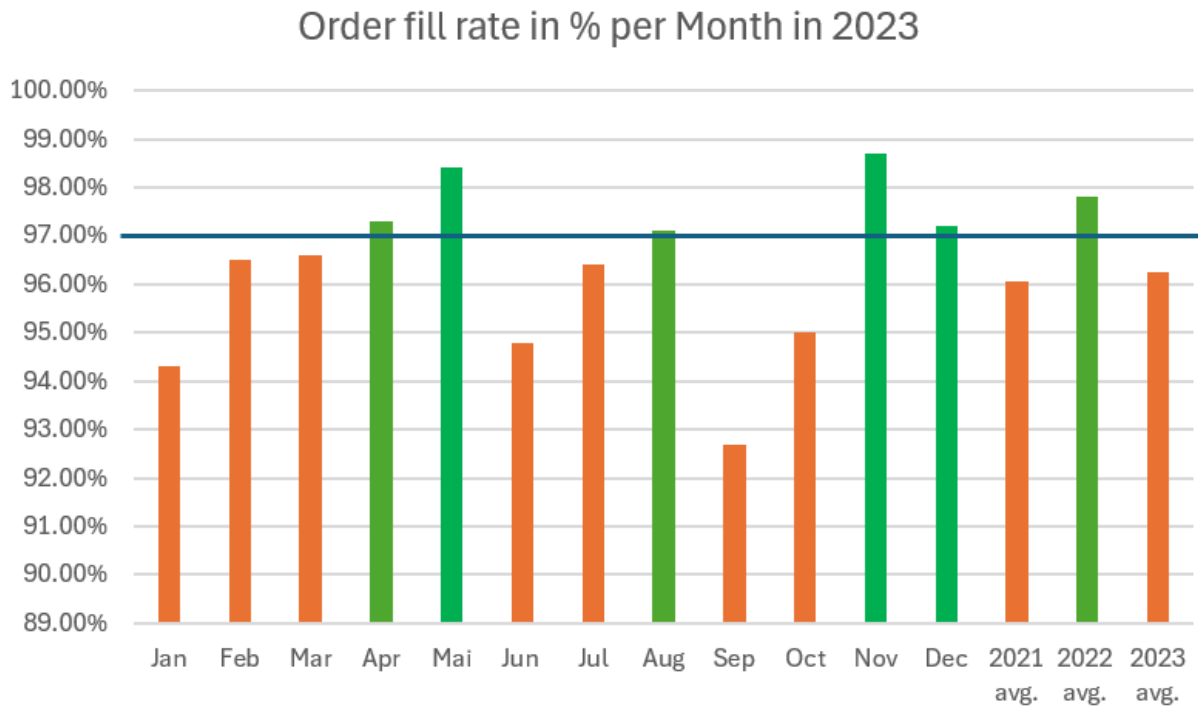


Figure 3.5: Order fill rate in % of the company, internal KPI put in place in the company

3.3 Internal storage stock follow-up

At the start of the project in 2018, many stock movements were carried out manually, even when the company had already implemented the ERP, Oracle, for some functions of the business. Therefore, stock cleaning was also a goal of the project. To this end, the two warehouses of the company were checked, and the logistics team had to check all serial numbers for final products. For each pallet, they checked the serial number of at least one item and sent it for review. For example, in March 2021, the oldest production for item 520.000.0301 (item description removed to ensure confidentiality) was from 2019, as shown in Figure 3.6.

Item	Item Description	Stellplatz	Serial Number
520.000.0301		44-A-10	210323 193484
		45-C-18	210323 193425
		45-D-16	210323 193350
		45-D-18	210322 193280
		46-C-17	210322 193250
		46-C-18	210323 193462
		46-C-19	210322 193111
		46-D-16	~ 193203
		46-D-17	~ 193173
		46-D-18	210323 193387

Figure 3.6: Example of serial number checks for one product within the company

After submitting the list for each product in stock and for both warehouses, the old productions were highlighted and sent to top management for further action. The actions were discussed together in a weekly stock meeting. For instance, old items could be refurbished by the company and subsequently sold as new products.

This check was put in place for the first time at the beginning of 2019, when many products were marked as “old products needed to be updated.” A yearly check was conducted thereafter to avoid any issues in the future. Such small actions were part of the project to improve the company’s processes and awareness of supply chain issues before starting its own production site.

3.4 Customers stock follow-up

This section explains the positive impact of alignment and information sharing between the various departments. First, to move from the second stage (anticipating) to the third stage (standard) of S&OP as shown in Table 2.6, it was important to help the company use the information provided by the customers directly. In certain subsidiaries, such as Switzerland, Germany, and France, some significant customers reported on the stock situation of each product every week or month, but the company was not using this information because it did not recognize the importance of S&OP.

As an example, every Monday, one of the top three retailers in the Swiss market reported on the weekly stock situation of the company’s products in more than 200 stores. To use this information in an optimal way and challenge the customer on its sell-in orders, a compiled file was created with an Excel macro to analyze the quantities sold in each retailer’s store. The format of the file received by the customer was sorted into several .csv files (around 200 files per week). At the start of the project, to analyze this data, an employee opened every file and copy-pasted all information into a main file, Consolidation.xlsx, with an appropriate layout. This took 45 seconds per file. There was a significant risk of committing a mistake due to missing information or files. The goal of this small part of the project was to automatize this process and reduce the treatment time.

3.4.1 “.csv” file structure

Every file had same title structure, MmINVRPT202001066196.csv (Figure 3.7), in which MmINVRPT was Customer1 INVeNtory RePorT, 20200106 was the date of the exported data, and 6196 was an incremental number.

The requested data for the analysis were cell B2 for the subsidiary’s name, cells C3 to C15 (in this example) for the EAN Code of the related product, and cells O3 to O15 (in this example) for the quantity of the sold items. While the columns were always the same, the row quantity was variable across files.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	HEADER	LRS		RBCH10151	11					7.9078E+11					
2	PLACE	4.3353E+12													
3	DETAIL		1	7.9078E+11											0
4	DETAIL		2	7.9078E+11											3
5	DETAIL		3	7.9078E+11											4
6	DETAIL		4	7.9078E+11											0
7	DETAIL		5	7.9078E+11											0
8	DETAIL		6	7.9078E+11											3
9	DETAIL		7	7.9078E+11											4
10	DETAIL		8	7.9078E+11											4
11	DETAIL		9	7.9078E+11											3
12	DETAIL		10	7.9078E+11											3
13	DETAIL		11	7.9078E+11											1
14	DETAIL		12	7.9078E+11											1
15	DETAIL		13	7.9078E+11											6

Figure 3.7 : The .csv file structure

3.4.2 The Consolidation.xlsx file structure

The Consolidation.xlsx file contained several tabs for handling the data. The relevant tabs for this project were Mapping Subsidiary (for mapping the subsidiary’s name and country to the code in the .csv file; Figure 3.8), and Mapping Item (for mapping the EAN code from the .csv file to the item number, item description, and user item type; Figure 3.9). Both of these tabs were necessary to complete the table in the Data tab (Figure 3.10).

The table in the Data tab was organized as follows.

- Column A: The date when the .csv file was exported (Section 3.4.1)
- Column B: The .csv file name without extension
- Column C: The subsidiary’s number (taken from the contents of the .csv file)
- Column D: The subsidiary’s name (mapped from Mapping Subsidiary)
- Column E: The EAN Code (taken from the contents of the .csv file)
- Column F: The item number (mapped from Mapping Item)
- Column G: The item description (mapped from Mapping Item)
- Column H: The user item type (mapped from Mapping Item)

- Column I: The item quantity (taken from the contents of the .csv file)
- Column J: The subsidiary's country (mapped from Mapping Subsidiary)

All these data were used to analyze the selling quantities and improve the forecasts.

	A	B	C
1	EAN-code	Interne Bezeichnung	Land
2	4335347759004	MS Verwaltung Schweiz	Schweiz
3	4335347760000	MM Chur	Schweiz
4	4335347761007	MM Crissier	Schweiz
5	4335347762004	MM Dietikon	Schweiz
6	4335347763001	MM Dietikon	Schweiz
7	4335347764008	MM Granges-Paccot (Fribourg)	Schweiz

Figure 3.8: Consolidation.xlsx – Mapping_Subsidiary file structure

	A	B	C	D
1	EAN code	Item	Item Description	User Item type
2	790776004684	520.000.0101	Product a	Finished Good Buy
3	790776001287	521.000.0101	Product b	Finished Good Buy
4	790776010661	800.000.0101	Product c	Finished Good Buy
5	790666010739	805.000.0101	Product d	Finished Good Buy
6	790776004585	510.000.0103	Product e	Finished Good Buy
7	790776001102	511.000.0103	Product f	Finished Good Buy
8	790776001263	512.000.0103	Product g	Finished Good Buy
9	790776001799	731.000.0103	Product h	Finished Good Buy
10	790776001812	735.000.0103	Product i	Finished Good Buy

Figure 3.9: Consolidation.xlsx – Mapping_Item file structure

	A	B	C	D	E	F	G	H	I	J
1	Date	File	Subsidiary	Subsidiary Name	EAN code	Item	Item Description	User Item type	Quantity	Country
2	19.09.2019	MmiINVRPT201909191444	4335347331544	S. Hamburg	790776001287	898.302.7800	accessory a	Buying good sellable	3	DE
3	19.09.2019	MmiINVRPT201909191444	4335347331502	S. Hamburg	790776010661	898.302.7800	accessory b	Buying good sellable	4	DE
4	14.10.2019	MmiINVRPT201910148529	4335347308506	S. Hamm	790666010739	898.139.0008	accessory c	Buying good sellable	1	DE
5	14.10.2019	MmiINVRPT201910149115	4335347019503	S. Bocholt	790776004585	898.7820.145	accessory d	Buying good sellable	1	DE
6	14.10.2019	MmiINVRPT201910148421	4335347176708	M. Donauworth	790776001102	712.512.7805	accessory e	Buying good sellable	1	DE
7	14.10.2019	MmiINVRPT201910148421	4335347176708	M. Donauworth	790776001263	525.502.7800	accessory f	Buying good sellable	1	DE
8	14.10.2019	MmiINVRPT201910148421	4335347176708	M. Donauworth	790776001799	525.109.7801	accessory g	Buying good sellable	1	DE
9	14.10.2019	MmiINVRPT201910148421	4335347176708	M. Donauworth	790776001812	898.145.7820	accessory h	Buying good sellable	1	DE

Figure 3.10 : Consolidation.xlsx - Data file structure

3.4.3 First improvement

The first improvement was the reduction of the process duration and human error through a macro implementation in .vba that opened .csv files and extracted the needed values. Then, these data were pasted into the Consolidation.xlsx file. The formulae for the mapping of other values and the extraction of the data from the .csv file were already defined in the Data tab. With this improvement, an employee is requested to start the macro and update the file, and it takes only 1.5 seconds per file. The risk of error is low because of the control of existing files in the macro. Nevertheless, there are two disadvantages: first, the macro is included in the

Consolidation.xlsx file, and this configuration leads to a file-opening time of 35 seconds; second, the computer is busy when the macro is working.

3.4.4 Second improvement

The second improvement was made by editing a script in Java that obtained the needed values from the .csv files and filled an array with the mapped data (from subsidiary and item) in the same layout as the Consolidation.xlsx file. The Java script is independent, works on any computer that has Java installed, and is able to generate an historic of data. With this improvement, an employee is required to start the macro and update the file, which takes 0.2 seconds per file. Additionally, the risk of error is low because of the control of the existing file and moving the added file from one directory to another. The disadvantages are that the free license version of the plugin limits the maximum handled files to 90 .csv files at a time, and an advisory tab appears when the update of Consolidation.xlsx is done.

3.4.5 Summary

Table 3.7 shows a comparison of the discussed possibilities.

	Copy-Paste	Macro VBA	Java Script
Automatization	No	Yes	Yes
Risk of errors	High	Low	Low
Time per file	45 seconds	1.5 seconds	0.2 seconds
Time per week (200 files)	150 minutes	5 minutes	0.66 minutes
Resources busy per week	150 minutes	5.5 minutes	0.75 minutes

Table 3.7: Comparison of possibilities

3.4.6 Use of the file by demand planning and sales teams

As the data compilation was improved by the macro, another improvement was proposed to the company to simulate the sell-ins of customers. In this example, the retailer only reported its stock situation and not the quantities it really sold to end-customers (sell-ins). In simulating the sell-ins, the company knew the stock of month M, which was aggregated from weeks to

month, and the stock of month M-1 of the retailers. It also knew the M-1 sell-out of the retailer (i.e., what the company sold to the retailer during M-1). The compiled data of the retailer could be used in a crosstab within Excel to easily add a calculation. Once the crosstab was done, the sell-ins of the retailer could be calculated in the tab “dynamic crosstab analysis” – calculation – fields elements. The sell-ins of customer MMS in this example, shown as *Stock 12.2018 – (Stock 11.2018 + Sales out 11.2018)* in Table 3.8, were extracted from the Excel file build to analyze this customer.

<i>Champ calculé</i>		
Ordre de résolution	Champ	Formule
1	MMS Sales 11.2018	= 'Stock 12.2018' - ('Stock 11.2018' + 'Sales 11.2018')
2	MMS Sales 12.2018	= 'Stock 01.2019' - ('Stock 12.2018' + 'Sales 12.2018')
3	MMS Sales 01.2019	= 'Stock 02.2019' - ('Stock 01.2019' + 'Sales 01.2019')
4	MMS Sales 02.2019	= 'Stock 03.2019' - ('Stock 02.2019' + 'Sales 02.2019')
5	MMS Sales 03.2019	= 'Stock 04.2019' - ('Stock 03.2019' + 'Sales 03.2019')
6	MMS Sales 04.2019	= 'Stock 05.2019' - ('Sales 04.2019' + 'Stock 04.2019')
7	MMS Sales 05.2019	= 'Stock 06.2019' - ('Stock 05.2019' + 'Sales 05.2019')
8	MMS Sales 06.2019	= 'Stock 07.2019' - ('Stock 06.2019' + 'Sales 06.2019')
9	MMS Sales 07.2019	= 'Stock 08.2019' - ('Stock 07.2019' + 'Sales 07.2019')

Table 3.8: Screenshot of the sell-in calculation field in the crosstab

Knowing the sell-ins of the customer would help the company’s sales team challenge the five retailers on which the company obtained the data to make such an analysis. The SME could also challenge the retailer’s stock if it is visible that a product is working well. In this case, the company could ask the retailer to order more stock to avoid OOS. Another issue identified with this analysis was stock entry problems to customers. Since the SME acquired a tool to determine what a customer has in stock and what it sells, it could directly contact retailers and ask them to double check stock errors if any were identified, which can help avoid unsold product issues in the future.

Table 3.9 contains a screenshot of the tool provided through a crosstab. First, the company could choose between an analysis for finished goods (final products), accessories, or even spare parts. The SME could also choose the country since some retailers were active in different countries. For each product, it has the stock of M-1 (01.2023), the sell-out of M-1 (01.2023), the calculated sell-in of M-1 (01.2023), and the stock at the beginning of month M (02.2023 in the example below).

With the macro described above, the data are updated each month. Therefore, the crosstab can also be updated effortlessly each month. Since the calculation was added in the crosstab, it is simple to follow up on the sell-ins of the retailers’ month by month. To add further value to the tool, the demand planning team provided monthly comments to the sales team to

direct their attention to specific products or sales. The sales team discussed these comments directly with the retailers when necessary.

User Item type	Finished Goods			
Country	Switzerland			

Item_Description	Stock 01.2023	Sell-out 01.2023	MMS Sales 01.2023	Stock 02.2023
Product 1	0	0	0	0
Product 2	37	38	-23	52
Product 3	57	9	-11	55
Product 4	75	57	-49	83
Product 5	0	0	0	0
Product 6	5	0	0	5
Product 7	6	0	-2	4
Product 8	76	13	-19	70
Product 9	11	0	-5	6
Product 10	1	0	-1	0
Product 11	46	15	-13	48
Product 12	9	9	-4	14
Product 13	0	0	0	0
Total général	323	141	-127	337

Table 3.9: Screenshot of the tool provided through a crosstab

3.4.7 Recap

The Java script was helpful for automatizing this operational task. It reduced the resource time by 99.5% (from 2.5 hours to less than 1 minute), and the crosstabs provided a quick and easy tool that the company could use to challenge the monthly sell-out orders of retailers. It supports a simple visualization of what happened to a retailer and can be shared with that retailer to discuss further promotions or future orders. This step could help the company move from the third stage (standard) to the fourth stage (advanced) of S&OP, as shown in Table 2.6, by keeping the company on track with its S&OP improvement goals and including customer inputs within S&OP.

3.5 Conclusion

As described in this Chapter, the accuracy significantly improved at the beginning of the project but stagnated in the last three years. However, the stagnation had no negative impact on the order fill rate, which remained on target at 97%. The automation with the tools described above, particularly through Excel macros or on the QlikView platform, avoids human error. Notably, QlikView was replaced by Qlik Sense³ in 2023. Both platforms have the same objective of data visualization, but Qlik Sense supports data visualization that is live and much quicker than in QlikView.

³ [Moving from QlikView to Qlik Sense | Qlik Sense for administrators Help](#)

4 Sales Forecasting Methods

Chapters 2 and 3 explained how the project helped the company globally improve communication within departments and the exchange of information. These elements are key to improving forecast accuracy. The accuracy measurement became weighted, and certain KPIs were put in place, particularly accuracy follow-up (Figure 3.4) and order fill rate (Figure 3.5). To further advance in the S&OP stages, it was necessary to investigate different forecasting methods to evaluate which could be implemented in the SME.

4.1 Demand components

Sales forecasts are important for all companies to make the right strategic decisions. Even if perfect forecasts do not exist, every company should regularly and continually review its forecasts to reduce the impacts of poor forecast reliability.

Demand forecasts are based on the following six main components (Batyrrshin I., 2007), as summarized in Figure 4.1:

- Average demand: The total demand for a given period t divided by the number of weeks or months during that period t .
- Trend: The projection of a change in some direction (increase, decrease, stable).
- Seasonality: Fluctuations that occur during the same period each year.
- Cyclic elements: Elements that commonly follow a curve from a low value to a high value (Landry R., 2005).
- Random variation: The variability of sales forecasts caused by irregular factors.
- Autocorrelation: An indicator representing the degree of dependence between two successive observations.

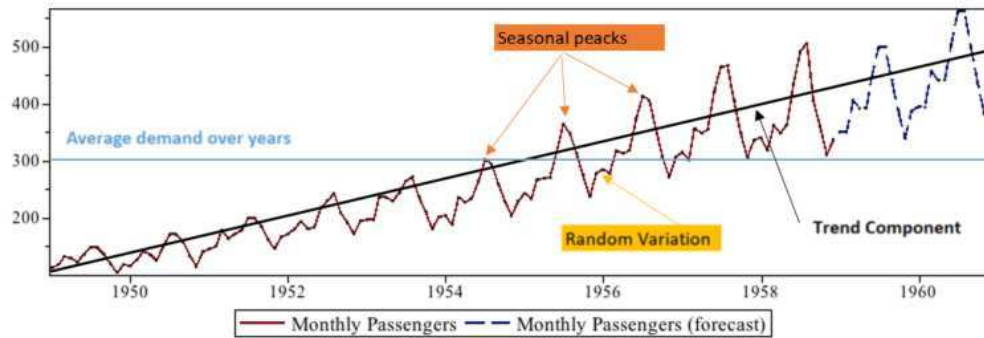


Figure 4.1: Demand components (Box G.E.P., et al., 2015)

Forecasts are usually classified into four basic categories: qualitative methods, time series analysis, causal relationships, and simulations (Makridakis S. & Wheelwright S.C., 1977).

4.2 Qualitative methods

Qualitative methods are based on the judgments or knowledge of experts who provide input to determine future demand. They are particularly useful when launching new products for which no historical information exists. To determine future demand, qualitative methods rely on information such as the future number of points of sale (POS), sales trends for comparable products, customer habits, and the amount of marketing support allocated to the product launch.

Companies using qualitative methods can conduct market research to track customer habits. They can also organize sample panels within the company, which encourages the different departments to participate in sales forecasts and collectively determine the future demand. It is also possible to use historical analogy to determine future sales forecasts by observing the sales trend of a comparable existing product and applying that trend to the forecast for the new product.

For greater reliability, the Delphi method can be used. This method involves a structured process that aims to reach a consensus through the argumentation or opinions of panel participants who are known experts. The main stages of the Delphi method are described as follows (Jacobs F.R. & Chase R.B., 2018).

- a. A panel of experts is selected based on their skills and knowledge within the field of study. These experts may come from a variety of disciplines to ensure a diversity of viewpoints.

- b. The participants fill out a questionnaire with the estimated forecasts. Each expert answers the questionnaire independently and anonymously to limit social influence and group bias.
- c. The results of the forecasts are summarized in one place and distributed to all participants along with appropriate new questions. The experts are invited to adjust their answers in light of the other participants' opinions and arguments. Anonymity is guaranteed to avoid social pressure.
- d. The results from the questions are summarized again, and a new questionnaire is developed. This process can be repeated over several rounds until a consensus is reached or the responses stabilize. At each iteration, the experts are informed of the overall results and can adjust their points of view.
- e. Once a consensus has been reached or responses stabilize, the results are analyzed in detail, and a final report is drawn up. This report presents the forecasts, decisions, or recommendations developed during the process.

One limitation of qualitative methods is that they are subjective. They are not based on calculations and may be open to different interpretations. Furthermore, they can be time-consuming and costly depending on the number of turns. Nevertheless, these methods could have added value, especially in short-term forecasts (Ramosaj A., et al., 2022).

4.3 Time series analysis

Time series analysis is based on historical sales data. It assumes that future sales can be based on previous observations. Past data may include seasonal or promotional trends. A characteristic of this type of forecast is the use of short-, medium-, and long-term periods. A short-term forecast spans less than three months and is usually used for tactical decisions, such as filling inventory or employee timetables. It is also a good measure for variability and current accuracy, which can be good indicators for defining safety stock. A medium-term forecast is used to build a strategy for the next 6 to 18 months and is useful for observing seasonal effects, while a long-term forecast covers more than two years and is suitable for detecting trends. Time series methods are summarized in Table 4.1.

Forecasting methods	Historical data	Data models	Forecast Horizon
Simple moving average	6 to 12 months; weekly data often used	Stationarity only (no trend or seasonality)	Short-term
Weighted moving average and exponential smoothing	At least 5 to 10 observations to start	Stationarity only	Short-term
Exponential smoothing with trend	5 to 10 observations to start	Stationarity or trend	Short-term
Linear regression	10 to 20 observations	Stationarity, trend, and seasonal	Short to medium or long term
Trends and seasonality	2 to 3 observations per season	Stationarity, trend, and seasonal	Short to medium or long term

Table 4.1: Time series type, adapted from Jacobs and Chase (Jacobs F.R. & Chase R.B., 2018)

4.3.1 Simple moving average

A simple moving average reflects the average demand over a certain recent period. This period can be defined by the week or month depending on the reliability of the forecast. The ideal time window for a simple moving average in sales forecasts depends on the type of data being analyzed, the sales volatility, and forecasting objectives. It is often useful for testing several windows to determine which offers the most accurate forecasts. If sales fluctuate significantly from one period to another, it is safer to use a longer window (6 to 12 periods) to smooth out temporary peaks and obtain a more stable view of the trend. The disadvantage of this method is that it does not account for seasonality or product sales trends. This type of forecast will be more reliable if demand is stable and non-volatile.

$$F_t = \frac{A_{t-1} + A_{t-2} + A_{t-3} \dots + A_{t-n}}{n} \quad (1)$$

F_t is the forecast for instance t , and A_t is the actual sales (referred to as real sales throughout this section).

Taking the data from Table 4.2, the forecast for May would be evaluated as follows based on actual sales from January to April:

$$F_{\text{May}} = (130 + 125 + 90 + 100) / 4 = 118$$

4.3.2 Weighted moving average

The weighted moving average is a forecasting method that places greater emphasis on recent data. This method includes a weight for each forecast. As a general rule, more recent periods are given a greater weight because they are considered more relevant to future forecasts. However, if the data are known to be seasonal, the weights should be established accordingly (Jacobs F.R. & Chase R.B., 2018). In any case, the sum of all weights must equal 1. An advantage of this method compared to a simple moving average is that it varies the importance of the past data. A disadvantage is that the weights are often chosen arbitrarily, and the results may depend heavily on the choice of weights, which may not always optimally reflect the actual dynamics of the data. The formula is as follows:

$$F_t = w_1 A_{t-1} + w_2 A_{t-2} + \dots + w_n A_{t-n} \quad (2)$$

In Table 4.2, the Forecasts column contains indications of sales forecasts made for each month. The Real Sales column displays the actual sales made by the company, and the Weights column shows the given weight for each value. For example, the May forecast would be calculated as follows:

$$F_{\text{May}} = (100 \cdot 0.2) + (90 \cdot 0.2) + (125 \cdot 0.3) + (130 \cdot 0.3) = 114$$

Months	Forecasts	Real sales	Weights
January	150	130	0,3
February	120	125	0,3
March	95	90	0,2
April	105	100	0,2
May	?		

Table 4.2: Example of forecasts (made by the author)

4.3.3 Exponential smoothing

A limitation of the two quantitative methods above is that they are only effective for stationary data. For data that include a trend or seasonality factor, exponential smoothing is preferred. This method is the most widely used in sales forecasting. It requires the following data: the most recent forecast (F_{t-1}), current/actual demand for the same period as the forecast (A_{t-1}), and a smoothing constant alpha (α). The smoothing constant determines the level of smoothing and the speed of reaction between the forecast and the actual sale for a

given period. Alpha (α) is a parameter between 0 and 1. If it is close to 1, more importance is given to recent estimations; if it is close to 0, older observations are assigned more weight. Experts sometimes estimate alpha (α) based on their knowledge of the data and the context. A general rule is to start with $\alpha = 0.1$ or $\alpha = 0.2$ for relatively stable time series and $\alpha = 0.5$ or higher for highly volatile series or in the event of rapid change (Jacobs F.R. & Chase R.B., 2018). The formula is as follows:

$$F_t = F_{t-1} + \alpha (A_{t-1} - F_{t-1}) \quad (3)$$

Taking the data for April from Table 4.2, where the forecast was 105, actual sales were 100, and $\alpha = 0.2$, the forecast for May would be calculated as follows:

$$F_{\text{May}} = 105 + 0.2 (100 - 105) = 104$$

4.3.4 Exponential smoothing with trend

Exponential smoothing with trend has the same basis as the previous method but includes a trend factor (δ). FIT_t represents the forecast including the trend for period t , while FIT_{t-1} represents the forecast including the trend for the prior period. The trend factor (δ) is close to 1 if the trend adapts quickly to recent changes and close to 0 if the trend is stable, which favors past changes.

The formulae are as follows:

$$F_t = FIT_{t-1} + \alpha (A_{t-1} - FIT_{t-1}) \quad (4)$$

$$T_t = T_{t-1} + \delta (F_t - FIT_{t-1})$$

$$FIT_t = F_t + T_t$$

For example, assuming a trend of 5, $\alpha = 0.2$, and $\delta = 0.3$, the forecast for May would be calculated as follows:

$$F_{\text{May}} = 105 + 0.2 (100 - 105) = 104$$

$$T_{\text{May}} = 5 + 0.3 (104 - 105) = 4.7$$

$$FIT_{\text{May}} = 104 + 4.7 = 108.7$$

The determination of α and δ is a limitation of exponential smoothing and exponential smoothing with trend. Determining these parameters is not straightforward, and assuming

these two values incorrectly can lead to significant errors. The alpha constant (α) and the trend (δ) can be determined by testing different values, by optimization (minimization of the error), or by using statistical tools (e.g., Excel, R, Python).

4.3.5 Linear regression analysis

Linear regression analysis is typically used for medium-term forecasts. The assumption is that future forecasts are linear with past sales. The form of this linear regression line is expressed as:

$$Y = a + bx \quad (5)$$

Where Y is the value of the dependent variable computed with the regression equation, a is the Y intercept, b is the slope of the line, and x is the value at each data point.

Past data and future projections are assumed to fall on this straight line. The coefficients a and b are calculated from the data to obtain the best line that fits the scatterplot. A common method for obtaining these values is the least squares method (LSM), which minimizes the sum of the squares of the deviations between the observed points and the line (Jacobs F.R. & Chase R.B., 2018). The equations for calculating a and b are:

$$a = \bar{y} - b\bar{x} \quad (6)$$

$$b = \frac{\sum_i x_i y_i - n\bar{x}\bar{y}}{\sum_i x_i^2 - n\bar{x}^2} \quad (7)$$

Where $\bar{y}$ is the average of all y_i , $\bar{x}$ is the average of all x_i , x_i is the value x at each data point, y_i is the value y at each data point, and n is the number of data points.

4.3.6 Trend and seasonal models

Seasonal trends are easy to define even without a mathematical formula. It is important to compare different data over several years and seasons. For example, a simple assumption is that the demand for ice cream or water will increase in the summer, and sales of these two products will therefore be much higher in the summer than in the winter. The seasonal factor is characterized by a period of the year with some special activities. In short, trend and seasonality models are used to model time series that evolve regularly (seasonality) and in a general direction (trend).

4.4 Causal forecasting relationships

Causal forecasts use independent variables to predict future values and assume that demand is linked to underlying factors (the explanatory variables) in the environment. This method is not based on the analysis of historical data such as purely statistical methods, but it tries to identify and analyze the cause-and-effect relationships between explanatory variables and predictor variables. It is often based on econometric models which attempt to quantify the relationship between the explanatory variables and the dependent variable (Jacobs F.R. & Chase R.B., 2018). For example, we might expect umbrella sales to increase in the event of prolonged periods of rain.

4.5 Simulation models

Simulation models are tools for reproducing and studying the behavior of a complex real system by simulating it within a virtual environment. Simulation models can be used to develop several hypotheses and tests to define forecasts. The principle is to modelize a situation through an ordinary differential equation (ODE) to simulate the output based on different initial conditions and select the one that is the closer to the reality.

4.6 Methods applicable to the SME

Of the methods described above, those that could be quickly applied to the company were chosen. Since the company needed to change its production site, the most favorable and easily implemented methods were simple moving average, weighted moving average, and exponential smoothing. These methods were tested as described in Chapter 5. Factors such as trend and seasonality were also considered. The results obtained through these methods are presented in later chapters. Causal forecasting relationships and simulation models were discarded because they are more difficult to set up and require more investment to implement. They are also less suited to the data of this SME.

4.7 Summary of the presented methods

Forecasting methods can be used to anticipate the future development of a variable and support decision-making. The choice of methods depends on several factors. Quantitative methods are preferred if the data are reliable or abundant, whereas qualitative methods are more appropriate when data are limited. The effectiveness of a method depends on the context and the type of data that are available for the forecasted products. An appropriate method for one product may not be suitable for others, and the parameters applied to each method must be analyzed and calculated for each product independently. A method that is adequate today may not be adequate tomorrow according to the evolution of sales by product. Therefore, some methods are considered more sophisticated to implement in industry.

Implementation is particularly difficult in SMEs because they may not have sufficient historical or well-organized data to effectively apply quantitative methods, and they do not have the same financial flexibility as multinational companies. Furthermore, the lack of a rigorous system for data collection and storage can limit the effectiveness of forecasting models. It takes time to set up a forecasting tool using one or more of the models described above, and SMEs generally lack the time and skilled resources to implement such a tool. For this reason, it is important to offer SMEs a simpler tool for tracking their sales and forecasts. Once their needs and capabilities increase, SMEs can start to gradually progress toward more complex forecasting techniques.

5 Introduction of the Stagger Chart

Unlike large companies, SMEs often have limited resources in terms of qualified staff or budget to invest in forecasting solutions. As traditional forecasting methods seem more complicated to implement in the short term, the idea of the stagger chart was developed. This visual tool could be shared by different departments. It is also easy to implement and update on a weekly or monthly basis depending on the company's needs.

The concept of the stagger chart first appeared in 1983 in Andrew Grove's book *High Output Management* (Grove A.S., 2005). At the time, Grove was the CEO of Intel, which was considered the best company in the technology industry. In his book, Grove explained specific management tools, such as the stagger chart and the complexity-uncertainty and ambiguity factor (CUA), and more general concepts, such as management by objectives (MBO) and task-relevant maturity (TRM).

In the literature, the stagger chart does not appear to be commonly used in operations management, although it was featured in some articles, such as Heizer's "Forecasting with Stagger Charts" (Heizer J., 2002). (Weedon R., et al., 2015) also presented the stagger chart and tried to improve it for airline fleet planning using an advanced approach based on a genetic algorithm. However, they did not consider actual sales or the evolution of forecasts over time.

According to (Grove A.S., 2005), the stagger chart is a tool for better forecasting future demand. The chart contains all information on when the forecasts are made and the real sales by month for each product or category of products. Depending on the type of product or market, it must be updated weekly, monthly, or yearly with additional, recent information. A stagger chart commonly includes input of qualitative forecasts. It is often used in finance to predict and anticipate cash flows but can also be used to predict future sales and, accordingly, future production needs.

The goal of using a stagger chart is to visualize the evolution of forecasts from one month to another. For example, a stagger chart can show the sales trend of one product or one category of products. If a product is more successful than anticipated, the forecasts can be directly adjusted accordingly.

The stagger chart originally introduced by Grove is depicted in Table 5.1. The first column shows when the forecasts were made and to which months they are related. The forecasts in this chart follow a four-month rolling plan.

The forecasts for September were evaluated as follows. At the beginning of July, 34 real sales were forecasted for September. The forecasts were reduced to 33 at the start of August and then to 30 at the beginning of September. However, the number of real sales in September was 29. The black line in Table 5.1 separates the forecasts from the real sales, which are marked with an asterisk.

Grove presents a basic case of how a stagger chart can be used.

Forecast made in	July19	Aug19	Sept19	Oct19	Nov19	Dec19	Jan20	Feb20	Mar20	Apr20	May20
July19	22	28	34	29							
Aug19	*23	27	33	31	29						
Sept19		*21	30	30	35	33					
Oct19			*29	32	32	32	29				
Nov19				*27	32	31	32	31			
Dec19					*27	27	31	30	40		
Jan20						*26	28	29	39	30	
Feb20							*24	30	36	32	34

Table 5.1: Stagger chart, inspired by Grove (Grove A.S., 2005)

The stagger chart has several similarities with the rolling-horizon planning concept described by Fleischmann Bernhard, Meyr Herbert, and Wagner Michael in Stadtler and Kilger's book (Stadtler H. & Kilger C., 2002). It explains how the planning is divided into periods (e.g., months) and how the new planning horizon overlaps with the previous one (Figure 5.1). Brown et al. (Brown G., et al., 2001) also used a rolling horizon and explained how the period, period $t+1$, becomes period t one month later.

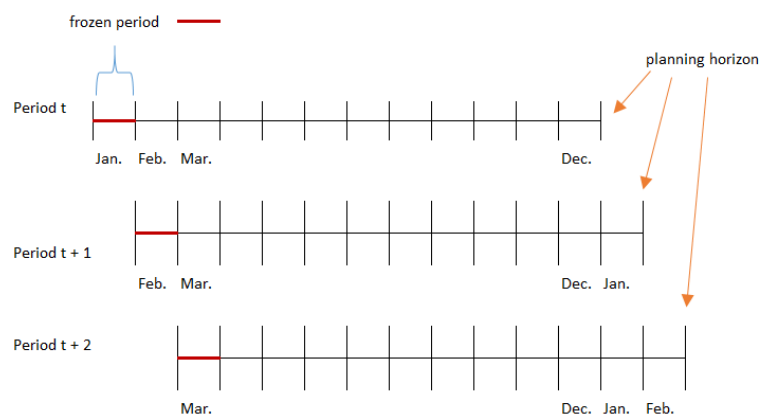


Figure 5.1: Planning on a rolling horizon basis, inspired by (Stadtler H. & Kilger C., 2002)

As an illustration of a rolling plan horizon, consider the example of an electronic product company with a 12-month production plan that it reviews monthly. In January 2024, the company plans for the period from January to December of 2024. In February 2024, it updates its plan to cover February 2024 to January 2025 and adjusts its forecast based on the results of the previous months. In March 2024, the company reviews its plan once again to cover March 2024 to February 2025. In this way, the company continually adjusts its objectives to stay in line with market realities.

The previous cases used the same stagger chart as Grove, even when they concerned cash flows predictions, sales, or production forecasts. However, Heizer used a stagger chart in an interesting way to compare forecasts with the average sales, the budget plan, and the actuals (recent sales) of a product family (Heizer J., 2002). Heizer utilized the visual facility of the stagger chart to validate the forecast accuracy. For example, he compared the accuracy of forecasts made three months in advance (in January for April), two months in advance (in February for April), and one month in advance (in March for April). The results proved that the forecast that was made one month ahead had better accuracy than those made two and three months in advance. His stagger chart served more to validate the forecast accuracy than to develop a real tool for the company to better forecast the future demand.

The simplicity of Grove’s stagger chart is both an advantage and a limitation of the tool. A stagger is provided globally, but Grove’s introduction to the tool does not explain what happens if few markets and products are considered.

With respect to the five stages of S&OP (Grimson J.A. & Pyke D.F., 2007) in Table 2.6, the stagger chart could help the company move from the first stage (reacting, in orange) to the second stage (anticipating, in blue) or the third stage (standard, in blue) depending on the development done to the tool.

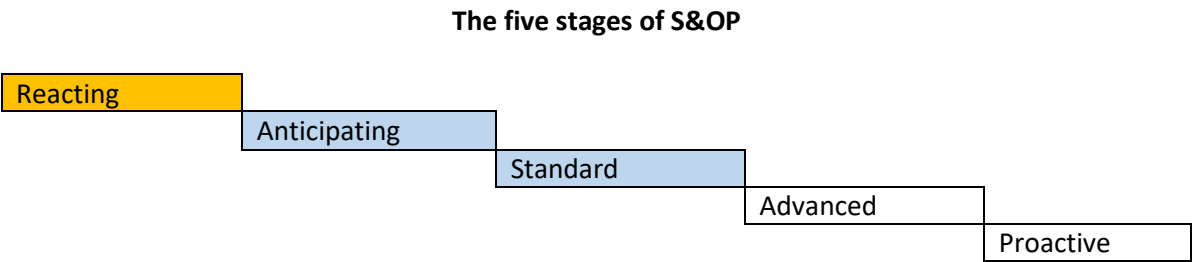


Table 2.6: The five stages of S&OP, inspired by (Grimson J.A. & Pyke D.F., 2007)

5.1 Stagger chart in SME context

Forecasting has been a major topic of interest for several decades, especially in multinational companies. Lately, it has attracted more attention from SMEs in search of relevant, efficient, and relatively low-cost tools. Applying traditional models usually requires companies to invest in new tools or hire specialized employees. Since SMEs often cannot afford those extra costs, they must find inexpensive tools that can help them improve their vision in forecasts. The stagger chart is one such tool.

From what is known, a stagger chart mainly concerns one product. In this case study, the SME must foresee sales for more than 40 countries around the world, all of which have different products, ways of ordering, and so on. Therefore, a consolidation of the forecasts for all markets was done through a pivot table, which enabled the selection of the market, the product, or the family product.

At this point, two questions arise:

- Is it feasible to implement a simple stagger chart in this company?
- Is it possible to integrate all products and markets into this simple stagger chart?

The following section answers both of these questions.

5.2 Case study

The first idea was to develop the stagger chart based on Grove's inputs. The SME in the present case study used qualitative methods of forecasting. A stagger chart could provide a visual comparison of the qualitative forecasts and the real sales.

Figure 5.2 illustrates the compilation of all the company's data in a pivot table. The SME could compare the forecasts it obtained each month through qualitative methods (in grey) and the real sales (i.e., what was sent to the customers, in blue). This representation is already useful for the company to "visualize" the forecasting errors and sales trends. All these modifications are visible in the first tool that was proposed to the company to monitor their forecasts (Figure 5.2).

Market	Switzerland
Type	Type 5
SKU	Item 1

Qualitative methods Real sales

Forecast made in	01.01.2018	01.02.2018	01.03.2018	01.04.2018	01.05.2018	01.06.2018
01.11.2017	200	200	400	350	350	
01.12.2017		200	400	350	400	400
01.01.2018	245		400	350	300	200
01.02.2018		20		200	44	400
01.03.2018			49		88	200
01.04.2018				35		200
01.05.2018					109	
01.06.2018						121
Forecast Accuracy Against Actual						
3 months ahead			-716%	-900%	-175%	-231%
2 months ahead			-716%	-900%	60%	-65%
1 months ahead			-716%	-471%	19%	-65%

Figure 5.2: Stagger chart comparison of qualitative methods and real sales (designed by the author)

The main difference between this chart and the stagger chart proposed by (Grove A.S., 2005) is that the SME worked with two-month rolling orders. For example, in November 2017, they received the final orders for January 2018 and a four-month rolling forecast horizon.

With this chart, every sale or operations manager could see where the variations came from. They could select the market of interest (e.g. Switzerland), the type of products (e.g. Type 5), or even the stock-keeping unit (SKU) to observe the forecasting trend and readjust future forecasts as needed based on higher or lower sales of one or more products.

5.3 Methodology

In the second step, the goal was to assess the suitability of the qualitative techniques used by the company to forecast and, accordingly, whether the SME could use quantitative techniques to improve its forecast accuracy. To this end, some of the quantitative methods described in Chapter 4 were tested. These tests are summarized in Table 5.2 (Jacobs F.R. & Chase R.B., 2018).

Forecasting methods	Special feature	Parameters
Simple moving average	Calculates the average demand over the most recent periods	A _t : Demand of period t F _t : Forecast of period t n: Number of periods
Weighted moving average	Generally, it assigns more importance to recent periods	A _t : Demand of period t F _t : Forecast of period t n: Number of periods w _t : Weight associated to the demand
Exponential smoothing	Determines the level of smoothing and the speed of reaction between the forecast and the actual sale	A _t : Demand of period t F _t : Forecast of period t n: Number of periods α: Smoothing constant

Table 5.2: Quantitative methods tests – features and parameters, summarized from (Jacobs F.R. & Chase R.B., 2018)

The tested methods—simple moving average, weighted moving average, and exponential smoothing—are classical methods in forecasting. As in the data, several high variations were detected; therefore, a fourth method was developed to consider seasonality.

The first step of this seasonal method was to compare the sales of month t over the four previous years (2015 to 2018). The formula below was used for the first estimation of forecasts for year 2019 and month t.

$$F'_t = \frac{1}{4} * (A_{t-12} + A_{t-24} + A_{t-36} + A_{t-48}) \quad t \in \{1, \dots, 12\} \quad (8)$$

Then, it was necessary to find a seasonal factor for each month to readjust the forecast F'.

$$\text{Factor: } f_t = \frac{F'_t}{\sum_{i=1}^{12} F'_t} \quad (9)$$

Once the seasonal factor was defined, the forecast could be readjusted for month t.

$$F_t = f_t * \frac{1}{12} \sum_{i=1}^{12} (A_{t-i}) \quad (10)$$

These four methods were used as the basis for estimating and improving the forecast accuracy of the SME. However, to better readjust them, further elements could be considered.

Other factors, such as promotional factors, were also defined. For this, the first step was to analyze whether the past data could be used to determine which months were impacted by

promotional sales. The promotional factor was identified by tracking the promotional sales per item and calculating the average of the promotional quantities sold per item. Then, the past sales were cleaned up by removing the promotional quantities. The impact of these promotional quantities was compared to the total quantities, and a factor was determined as the promotional factor. To obtain the promotional factors, Excel Solver was used to minimize the mean absolute deviation (MAD). The promotional factors considered promotions made in the same months in different years.

Another estimated element was the trend factor (δ). Based on past data, this factor provides information about the sales tendency (increase, decrease, or stability). This factor can be quantified by comparing past similar data. For this, the Excel formula “trend” was used.

The factors above were applied to refine the method and optimize the result for each product. Since the company’s data are considered confidential, they cannot be published in this thesis. Therefore, the MAD was chosen as the indicator to compare the results of the methods and show the efficiency of the proposed quantitative techniques. The MAD was calculated for each method and each dataset (Jacobs F.R. & Chase R.B., 2018).

$$MAD = \frac{\sum |A_t - F_t|}{n} \quad (11)$$

5.4 Results

The obtained results depend on the characteristics of the product types. Overall, it was found that the quantitative methods always yielded better results than the qualitative method that the company was using. This section provides a detailed analysis of the results that led to this finding.

For the comparison, the MAD (*column C* in Table 5.3) was used over time for all methods and SKUs (from 4 to 12 months). The data available for this comparison were from five products (*column A*). For four of those products, data were available over four years. Only two years of data were available for the fifth product since it was launched on the market later (*column B*). Table 5.3 summarizes the results.

First, the MAD was calculated for the qualitative method used by the company (*column D*). This result was then compared to the MAD of the first quantitative technique that was tested (simple average). This comparison was done for 6, 12, and 24 months (*columns E to G*). Table

5.4 shows that the simple average technique improved the MAD compared to the qualitative method (*column 4*). Higher improvement was found for product 3, which, depending on the period, increased up to 167%. However, the technique did not improve the results for product 5, which is most likely because that product was launched later, and its sales history was therefore smaller than the sales histories of the other four items.

Then, the weighted moving average with the defined factors of 0.1 for $t-3$, 0.3 for $t-2$, and 0.6 for $t-1$ (*column H*) was applied. The results were better (Table 5.3) than those obtained using the qualitative method (*column D*). To further improve the MAD, a solver was used to readapt the factors for 3, 4, 6, and 12 months (*columns I to L*) to observe whether the MAD would decrease. It was found that the best forecast was obtained when calculating for the last 6 months. Furthermore, in Table 5.4 (*column 5*) shows improvements of up to 1497% for product 4 and up to 91% for product 5 compared to the company's qualitative method when calculating the MAD for 4 months. These results prove that the short-term forecasts provided better results than the long-term forecasts (6 or 12 months).

Subsequently, the exponential smoothing technique was used for $\alpha = 0.1$, $\alpha = 0.6$, and α as defined by a solver (*columns M to O* in Table 5.3). The objective for the solver was to minimize the MAD by changing the value of the α factor using the generalized reduced gradient (GRG) nonlinear solving method. The results provided by the solver were the best results. Table 5.4 shows improvements in *column 6* compared to the qualitative method. While improvements were generally observed for all products except product 5, the improvements were less significant than those observed with the weighted moving average technique.

Another approach was to assess the possibility of considering seasonal factors. For example, January 2015, January 2016, January 2017, and January 2018 were compared, and a factor was determined and applied to January 2019 to forecast the sales for that month (*column P*, in Table 5.3). Compared to the qualitative method, the results significantly improved only for product 3 (Table 5.4, *column 7*).

As all these methods were evaluated separately, the next question to consider was whether the MAD would be improved when combining methods.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Models	Datas	MAD	SME Qualitative methods	Simple average 12 months	Simple average 6 months	Simple average 24 months	Weighted Moving Average (3 months)	Weighted Moving Average with solver (3 months)	Weighted Moving Average with solver (4 months)	Weighted Moving Average with solver (6 months)	Weighted Moving Average with solver (12 months)	Exponential smoothing ($\alpha = 0.1$)	Exponential smoothing g ($\alpha = 0.6$)	Exponential smoothing ($\alpha = \text{over}$)	Seasonality factors	Seasonality exponential smoothing	Promotional factors	Promotional factors and trends	Promotional factors and seasonality
Product 1	4 years	MAD (4 months)	186.00	152.38	124.75	148.92	159.98	126.78	99.61	74.92	63.00	144.99	159.05	142.62	182.15	180.79	58.50	78.52	102.37
Product 1	4 years	MAD (6 months)	142.83	121.40	101.83	118.37	137.83	105.16	99.63	71.07	39.82	116.71	139.57	116.55	129.54	128.33	55.73	79.12	57.14
Product 1	4 years	MAD (12 months)	98.50	114.96	109.07	116.20	132.77	111.62	112.92	93.56	78.97	113.56	131.34	111.66	98.90	97.72	93.29	115.16	60.73
Product 1	2 years	MAD (4 months)	186.00	152.38	124.75	144.64	159.98	119.25	99.60	74.92	31.62	148.27	159.05	142.67	171.95	172.02	99.60	63.76	108.77
Product 1	2 years	MAD (6 months)	142.83	121.40	101.83	115.11	137.83	98.42	113.89	73.71	38.41	118.75	139.57	116.96	122.93	122.82	60.01	71.73	86.88
Product 1	2 years	MAD (12 months)	98.50	114.96	109.07	110.90	132.77	111.62	110.70	95.55	76.07	113.99	131.34	111.66	100.37	99.51	78.34	66.17	69.95
Product 2	4 years	MAD (4 months)	105.50	58.56	64.58	62.17	76.33	49.91	30.36	7.70	5.37	59.51	75.66	55.18	76.07	90.38	49.93	68.52	50.07
Product 2	4 years	MAD (6 months)	79.00	69.72	86.30	72.96	118.25	68.51	41.76	27.20	17.64	66.39	114.68	52.12	74.57	107.08	56.05	72.13	57.14
Product 2	4 years	MAD (12 months)	94.75	85.85	93.89	82.04	111.44	107.73	87.87	81.67	67.51	83.80	110.51	75.56	98.57	107.90	102.70	68.68	57.14
Product 2	2 years	MAD (4 months)	105.50	58.56	64.58	63.24	76.33	50.87	31.85	7.78	28.30	59.53	75.66	55.00	66.01	68.57	49.91	67.03	54.26
Product 2	2 years	MAD (6 months)	79.00	61.47	84.22	67.89	118.25	52.98	41.76	27.01	40.49	66.54	114.68	52.04	54.55	55.68	67.90	52.43	57.03
Product 2	2 years	MAD (12 months)	94.75	85.85	93.89	79.78	111.44	95.10	87.99	82.63	67.69	83.80	110.51	100.30	92.84	90.38	78.13	60.92	46.66
Product 3	4 years	MAD (4 months)	50.50	18.92	23.38	18.89	28.53	11.55	8.42	6.39	9.41	19.44	25.13	14.08	17.85	21.40	11.40	57.96	36.72
Product 3	4 years	MAD (6 months)	47.50	27.32	28.36	26.86	29.60	21.51	18.75	19.61	14.75	24.66	27.41	15.95	23.56	25.14	22.63	48.39	29.55
Product 3	4 years	MAD (12 months)	28.67	22.20	22.85	24.72	22.63	22.08	18.66	18.73	14.37	22.94	20.95	13.07	20.38	19.59	22.92	30.04	27.05
Product 3	2 years	MAD (4 months)	50.50	18.92	23.38	19.35	28.53	11.10	6.37	6.92	5.45	19.41	27.99	19.28	24.27	24.29	8.92	2.90	41.07
Product 3	2 years	MAD (6 months)	47.50	27.32	28.36	27.21	29.60	18.74	18.63	23.51	12.92	26.88	28.81	24.03	24.61	24.73	5.01	16.70	37.24
Product 3	2 years	MAD (12 months)	28.67	22.20	22.88	22.69	22.63	18.96	18.82	21.83	13.46	21.87	22.19	20.34	16.91	17.01	11.32	14.91	81.73
Product 4	4 years	MAD (4 months)	157.00	119.08	143.63	119.76	122.00	24.63	18.29	9.83	16.60	126.11	122.97	24.05	165.21	162.24	9.63	56.59	83.22
Product 4	4 years	MAD (6 months)	154.50	138.89	162.83	135.86	124.12	98.18	97.47	104.40	82.88	140.88	126.98	46.88	153.21	151.03	64.19	115.19	68.62
Product 4	4 years	MAD (12 months)	114.83	91.16	130.44	111.61	114.42	106.97	106.94	89.30	74.74	113.56	115.56	54.40	107.78	108.70	93.11	115.47	56.78
Product 4	2 years	MAD (4 months)	157.00	119.08	143.63	114.68	122.00	9.74	9.54	25.45	6.02	114.77	122.97	100.89	140.07	141.10	9.74	32.98	87.31
Product 4	2 years	MAD (6 months)	154.50	138.89	162.83	134.17	124.12	97.90	97.46	101.44	88.44	138.47	126.98	97.93	131.08	132.85	84.55	53.04	75.57
Product 4	2 years	MAD (12 months)	114.83	108.03	129.50	117.89	114.42	106.87	111.55	101.62	87.83	111.87	115.56	109.69	109.62	111.83	74.70	88.39	79.82
Product 5	2 years	MAD (4 months)	37.50	54.67	78.08		78.88	61.63	57.72	19.59	23.23	55.15	78.57	47.85	35.88	37.65	28.88	20.36	23.89
Product 5	2 years	MAD (6 months)	30.33	76.69	95.69		73.65	18.90	43.46	33.08	14.06	79.60	72.61	41.20	38.89	47.18	34.44	42.97	20.02
Product 5	2 years	MAD (12 months)	42.75	77.60	76.21		78.94	67.03	62.53	47.75	46.25	72.73	76.51	55.07	70.99	75.39	38.36	48.30	49.11

Table 5.3: The MAD for the tested quantitative methods (designed by the author)

Since the results were not satisfying, *column Q* (Table 5.3) was included as a mix of seasonal factors and exponential smoothing methods previously given in *columns M to O*. However, for products 2 and 4, the MAD was even worse than that obtained with the qualitative method.

The last approach tested was the determination of promotional factors (Table 5.3, *column R*). These promotional factors were applied to the method that produced the best results (weighted moving average). Table 5.4 shows the improvements compared to the qualitative method used by the company (*column 8*). From a quick comparison between *columns 5* and *8*, it can be observed that the improvements for products 1, 3 and 4 were even higher when considering promotional factors, which suggests that these products were promotionally driven products. The improvement was significant for products 2 and 5, but better results were obtained from the weighted moving average without considering the promotional factors.

1	2	3	4	5	6	7	8	9	10
Compared to the company's forecasts/ Qualitative methods			Classical Methods			Developped Method	Factors		
Products	Data	MAD	Simple average 12 months	Weighted Moving Average with solver (6 months)	Exponential smoothing (α = solver)	Saisonaliti factors	Promotional factors	Promotional factors and trends	Promotional factors and saisonaliti factors
Product 1	4 years	MAD (4 months)	22%	148%	30%	2%	218%	137%	82%
Product 1	4 years	MAD (6 months)	18%	101%	23%	10%	156%	81%	150%
Product 1	4 years	MAD (12 months)	-14%	5%	-12%	0%	6%	-14%	62%
Product 1	2 years	MAD (4 months)	22%	148%	30%	8%	87%	192%	71%
Product 1	2 years	MAD (6 months)	18%	94%	22%	16%	138%	99%	64%
Product 1	2 years	MAD (12 months)	-14%	3%	-12%	-2%	26%	49%	41%
Product 2	4 years	MAD (4 months)	80%	1270%	91%	39%	111%	54%	111%
Product 2	4 years	MAD (6 months)	13%	190%	52%	6%	41%	10%	38%
Product 2	4 years	MAD (12 months)	10%	16%	25%	-4%	-8%	38%	66%
Product 2	2 years	MAD (4 months)	80%	1256%	92%	60%	111%	57%	94%
Product 2	2 years	MAD (6 months)	29%	192%	52%	45%	16%	51%	39%
Product 2	2 years	MAD (12 months)	10%	15%	-6%	2%	21%	56%	103%
Product 3	4 years	MAD (4 months)	167%	690%	259%	183%	343%	-13%	38%
Product 3	4 years	MAD (6 months)	74%	142%	198%	102%	110%	-2%	61%
Product 3	4 years	MAD (12 months)	29%	53%	119%	41%	25%	-5%	6%
Product 3	2 years	MAD (4 months)	167%	630%	162%	108%	466%	1638%	23%
Product 3	2 years	MAD (6 months)	74%	102%	98%	93%	849%	184%	28%
Product 3	2 years	MAD (12 months)	29%	31%	41%	70%	153%	92%	-65%
Product 4	4 years	MAD (4 months)	32%	1497%	553%	-5%	1531%	177%	89%
Product 4	4 years	MAD (6 months)	11%	48%	230%	1%	141%	34%	125%
Product 4	4 years	MAD (12 months)	26%	29%	111%	7%	23%	-1%	102%
Product 4	2 years	MAD (4 months)	32%	517%	56%	12%	1512%	376%	80%
Product 4	2 years	MAD (6 months)	11%	52%	58%	18%	83%	191%	104%
Product 4	2 years	MAD (12 months)	6%	13%	5%	5%	54%	30%	44%
Product 5	2 years	MAD (4 months)	-31%	91%	-22%	5%	30%	84%	57%
Product 5	2 years	MAD (6 months)	-60%	-8%	-26%	-22%	-12%	-29%	52%
Product 5	2 years	MAD (12 months)	-45%	-10%	-22%	-40%	11%	-11%	-13%

Table 5.4: Comparison of results (designed by the author)

Since the promotional factors seemed to give good results, it was decided to add further parameters to observe their positive or negative influence on these factors. For *column S* (Table 5.3), the basis was the same as the that of the previous column (*column R*), but a trend factor (δ) was added. *Column 9* in Table 5.4 shows that the results were not as good as those obtained in *column 8* or *5*.

As Table 5.3 (*column T*) shows, when the promotional factors and the seasonality trend were used simultaneously, the MAD improved significantly for most products compared to the qualitative method; however, the observed improvements (Table 5.4 *column 10*) were lower than those in *column 5* or *8*. These observations confirm that the results were better when seasonal factors were not considered, which indicates these products do not have a marked seasonality. The promotional factor seems to be more important than the seasonal factor.

In the case study, the quantitative methods led to better results for all types of products compared to the results of the qualitative method used by the SME. The quantitative methods, which gave a lower MAD, were also dependent on the product's volatility, as highly volatile products tended to have better results when promotional and seasonality factors were considered (Table 5.4).

The testing of these quantitative techniques provided inputs for the company indicating that it should use the stagger chart in a different way by replacing its forecasting method with quantitative techniques that yield better results. However, since not all methods gave good results for all products, Table 5.5 was made to summarize the characteristics of each product and identify the best and worst quantitative methods.

For all products, weighted moving average was the best quantitative method. For products 1, 3, and 4, combining this method with a promotional factor led to further improvement, which implies that these three products were promotionally driven. For product 5, data were available only for two years, as summarized in Table 5.5. This product did not seem to be driven by promotions, probably because it had a different positioning and a more affluent target audience.

Table 5.5 shows that the simple moving average and seasonal method produced the worst results for all product types. Therefore, these two methods should be excluded. The results suggest that promotions have a stronger impact on the company's sales figures compared to seasonal effects.

Products	Characteristics	Best quantitative method	Worse quantitative method
Product 1	4 years of data history No seasonality Promotionally driven	Promotional factor with weighted moving average	Seasonal method
Product 2	4 years of data history No seasonality Low promotions impact	Weighted moving average	Seasonal method
Product 3	4 years of data history Little seasonal effect Promotionally driven	Promotional factor with weighted moving average	Simple average
Product 4	4 years of data history No seasonality Promotionally driven	Promotional factor with weighted moving average	Seasonal method
Product 5	2 years of data history No seasonality Not promotional driven	Weighted moving average	Simple average

Table 5.5: Summary of characteristics per product (generated by the author)

5.5 Application of results

After defining weighted moving average as the most suitable quantitative method to forecast the company's future demand, the results of the method were added to the stagger chart and visually compared to the forecasts made by the company through qualitative methods and the real sales of each product.

The stagger chart in Figure 5.3 illustrates that the quantitative methods (in yellow) gave better results than the qualitative methods (in grey) when comparing the real sales (in blue). To add value to the tool, a graphic history (Figure 5.4) was integrated into the stagger chart tool to allow the company to view the forecast deviations in a simple visual way. This easy tool could be highly useful for sales managers in challenging distributors or subsidiaries on their forecasts. It can be used at monthly meetings and as a basis for the company to better follow the sales accuracy of each subsidiary and important export market. It also helps to picture the sales trend per product and quickly adjust the forecasts if needed.

Nevertheless, as mentioned, perfect forecasting does not exist. Even if this decision support tool can improve forecasts, it is up to the sales managers to see the customers and market behavior. Therefore, the stagger chart offers a good foundation for forecasting, but it should be readapted to the company's future needs if additional information becomes available. Furthermore, as seen in Figure 5.3, forecasts are sometimes lower than the real sales. For this reason, safety stock must also be considered for each item.

	Qualitative methods				Real sales		Quantitative methods			
Forecast made in	01.01.2018	01.02.2018	01.03.2018	01.04.2018	01.05.2018	01.06.2018	01.07.2018	01.08.2018	01.09.2018	01.10.2018
01.11.2017	200	200	400	350	350					
01.12.2017		200	400	350	400	400				
01.01.2018	245		400	350	300	200	200			
01.02.2018	221	20		200	44	400	200	200		
01.03.2018		85	49		88	200	200	88	176	
01.04.2018			57	35		200	200	88	176	400
01.05.2018				107	109		400	200	200	400
01.06.2018					150	121		300	200	400
01.07.2018						116	391		200	400
01.08.2018							352	266		400
01.09.2018								266	89	
01.10.2018									114	329
01.11.2018										328

Forecast Error with Qualitative method										
3 months before			716%	900%	175%	231%	49%	67%	125%	22%
2 months before			716%	900%	60%	65%	49%	25%	125%	22%
1 months before			716%	471%	19%	65%	2%	13%	125%	22%

Forecast Error with Quantitative method										
3 months before			604%	227%	100%	245%	43%	67%	75%	22%
2 months before			604%	227%	71%	72%	43%	25%	75%	22%
1 months before			116%	87%	41%	72%	14%	13%	75%	22%

Forecast value added (FVA)										
3 months before			113%	673%	75%	-14%	6%	0%	50%	0%
2 months before			113%	673%	-11%	-7%	6%	0%	50%	0%
1 months before			600%	385%	-22%	-7%	-11%	0%	50%	0%

Figure 5.3: Comparison of qualitative and quantitative forecasting methods through a stagger chart (generated by the author)

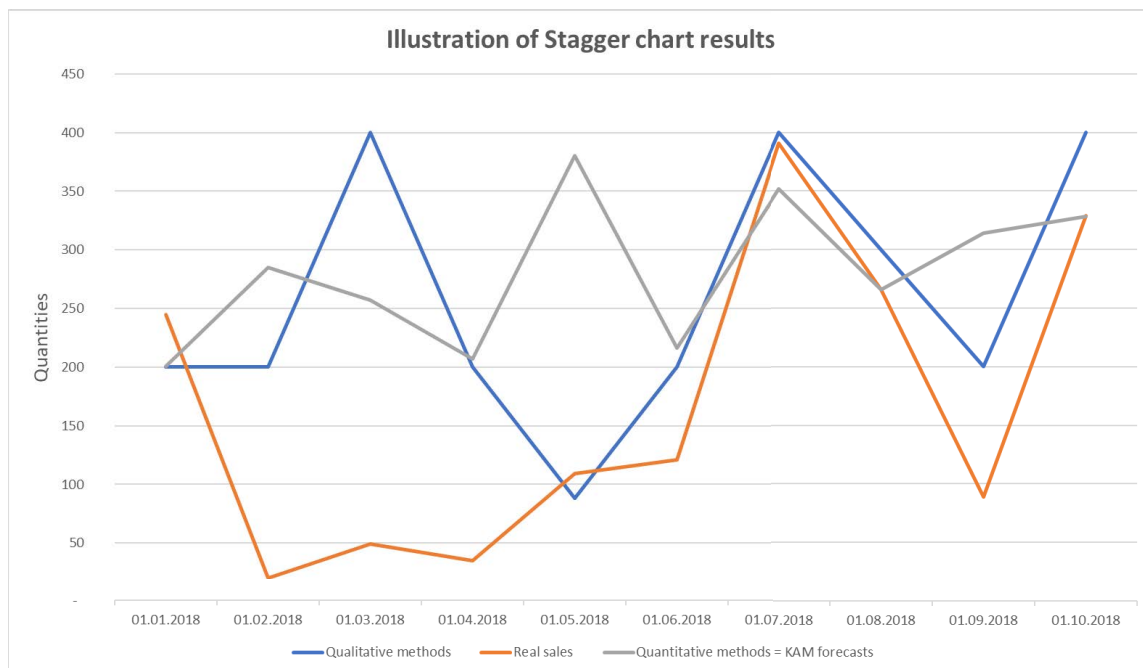


Figure 5.4: Graphic illustration of the stagger chart forecasts (generated by the author)

The forecast value added (FVA) at the bottom of Figure 5.3 reveals that the quantitative method proved to be more accurate than the qualitative method for most months and lead times. The FVA focuses on the forecasting process and its contributions (Gilliland M., 2013). In this case study, the FVA is the added value in percentage of the forecasts with quantitative methods compared to the qualitative method used by the company. The formula is as follows:

$$FVA = \varepsilon_{quali} - \varepsilon_{quanti} \quad (12)$$

Where:

ε_{quali} = is the forecast error with the qualitative method, calculated with the relative absolute error (RAE) = $\left| \frac{\text{Qualitative forecast} - \text{Real sales}}{\text{Real sales}} \right|$,

and ε_{quanti} = is the forecast error with quantitative method, calculated with the relative absolute error (RAE) = $\left| \frac{\text{Quantitative forecast} - \text{Real sales}}{\text{Real sales}} \right|$.

If the FVA is greater than 0, the method improved the forecasts. If it is lower than 0, the method deteriorated the forecasts.

5.6 Automatization

At the beginning of this project, Sales was providing the forecasts through Excel files for different markets (about 20 files in total). All these files were combined into the stagger chart including the real sales figures and the best quantitative method, as shown in Figure 5.3. This tool made it possible to improve the efficiency of the forecasting. However, to build the stagger chart, an employee must copy-paste all data from the forecast files to the Stagger Chart.xlsx file. This takes 120 seconds per file, and the risk of committing a mistake due to missing or false information is significant.

The goal was then to automatize the data collection and reduce the treatment time. To this end, a Java script was used. This Java script is independent, works on any computer with Java installed, and is able to generate a data history. With this improvement, an employee is required to start the macro and update the file. It takes only 0.6 seconds per file, and the risk of error is low due to the control of the existing file and moving the added file from one

directory to another. The disadvantage is the free license version of the plugin since an advisory tab appears when the update of Stagger Chart.xlsx is done.

Table 5.6 shows the comparison of the possibilities.

	Manual Copy-Paste	Java Script
Automatization	No	Yes
Risk of errors	High	Low
Time pro file	120 seconds	0.6 seconds
Time pro month (20 files)	40 minutes	0.2 minutes

Table 5.6: Comparison of possibilities (designed by the author)

The Java script is a good improvement for this operational task, as it can reduce the resource time by 99.5% from 40 minutes to 12 seconds.

5.7 Conclusion

To conclude, the development of this tool provides the advantage of gaining a better view of the company's sales forecasting and a quick visual understanding of trends and variations, which could expedite the company's reactions to improve the tendency. It remains legible and easy to interpret. However, it may lack information for very detailed analyses that require numerical precision or numerical comparisons between items.

This tool is focused on sales forecasting for the SME, but it could also be applied on the production side to better plan for the spare parts needed for future manufacturing demand. This part of the project was implemented between 2019 and 2020. Since then, the tool has evolved through the incorporation of more graphic elements, as shown in Figure 5.4. The stagger chart initially done in Figure 5.3, may require additional explanation to interpret the data if the audience is not accustomed to analysis. By comparison, Figure 5.4 is easier to interpret and understand.

6 Accuracy Improvements for Products

6.1 Introduction

The previous chapters demonstrated ways to improve the S&OP process and accuracy within the SME from a simple, medium-term perspective. This Chapter and Chapter 7 introduce the advanced analysis performed to improve the automatization of accuracy, as shown in Chapter 3. These two chapters describe some analyses and tools that were implemented within the SME to move from the third stage (standard) in blue to the fourth stage (advanced) in green of the maturity model by (Grimson J.A. & Pyke D.F., 2007) in Table 2.6.

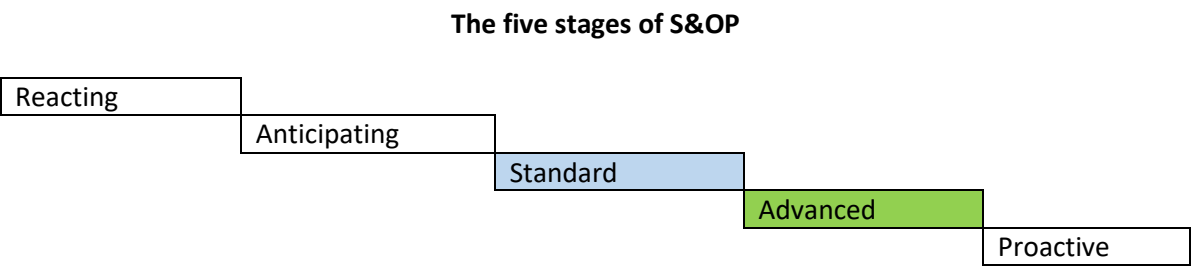


Table 2.6: The five stages of S&OP, inspired by (Grimson J.A. & Pyke D.F., 2007)

As discussed, sales forecasting is becoming an important subject even in small and medium enterprises (SMEs). Poor predictions have several negative impacts for companies, including overstock (immobilization of cash flow) or stockout and lack of components. Improving sales accuracy also improves the company’s future business projections (Haberleitner H., et al., 2010).

For decades, it has been repeatedly proven that quantitative forecasting methods provide better results than qualitative forecasting methods (Ramosaj A. & Widmer M., 2020). The most well-known quantitative method is time series forecasting, in which historical observations are collected and analysed to develop an applicable model. The goal of time series forecasting is often to improve forecast accuracy (Siami-Namini S., et al., 2018). Time series methods have been applied to improve different areas, such as forecasting the power load for the electricity market (Bozkurt O.O., et al., 2017), wind energy production (Hui L., et al., 2012), food retail demand (Pereira Da Veiga C., et al., 2014), road and traffic optimization

(Zhao Z., et al., 2017), cryptocurrency exchange rates (Chen W., et al., 2021), COVID-19 infection rates (Wang P., et al., 2020), air pollution levels (Rani Samal K.K., et al., 2019), and warranty demand (Xie W., et al., 2017).

More recent efforts to improve forecasting accuracy have employed hybrid methods, such as auto-regressive integrated moving average (ARIMA) and artificial neural network (ANN) combined with empirical mode decomposition (Büyükşahin, Ü.Ç. & Ertekin, Ş., 2019). Hybrid models such as long short-term memory (LSTM) are often compared with ARIMA (Chen W., et al., 2021). However, comparisons have also been made between ARIMA and Facebook Prophet (Taylor S.J. & Letham B., 2017) and even between ARIMA, LSTM, and Facebook Prophet (Chikkakrishna N.K., et al., 2019). Many articles (e.g., (Weytjens H., et al., 2019)) have compared ARIMA and Facebook Prophet with LSTM multi-layers for cash flow prediction or demand forecasting (Abbasimehr H., et al., 2020).

This Chapter describes the evolution through the S&OP process presented in Chapter 2. The goal was to improve the sales accuracy of the final products sold by the analysed Swiss SME by first using different time series forecasting models. Sales forecasts and real values were considered for the 44 months from January 2018 to August 2021. These data contain the sales in approximately 50 markets and 150 stock-keeping units.

The first model used was the well-known ARIMA, which is composed of auto-regressive models, and moving average (MA). The November sales of the SME were more significant every year because of Black Friday promotional activations. As these promotions took place in the same week every year, they were considered to have a seasonal effect within the next analysis presented in this Chapter. Therefore, seasonal auto-regressive integrated moving average (SARIMA) provided better results than ARIMA. The SARIMA predictions were compared with those of exponential smoothing and Facebook Prophet. In parallel, a neural network was developed using LSTM.

After comparing the four models, a new factor was introduced through the KAMs. Several KAMs were responsible for different sales markets, and each KAM was responsible for at least one market. The KAMs were responsible for the sales and work on the front line for obtaining a better overview of the sales by receiving all purchase orders from all markets. With the information provided by the KAMs, or the “KAM forecasts,” the models could be consolidated and improved by adding weight to the KAM forecasts and the different predictions by the tested models.

6.2 Existing forecasting models

This section compares and describes the four models (exponential smoothing, SARIMA, Facebook Prophet, and LSTM) to approximate the forecasts of the dataset. The models were tested over the 12 months prior to t (today), and the rest of the dataset was used for the training.

6.2.1 Exponential Smoothing

Exponential smoothing is the most frequently used forecasting method (Stadtler H. & Kilger C., 2002), as noted in Section 4.3.3. This method requires only three types of data to forecast the value for period t (F_t): the exponentially smoothed forecast made for the previous period (F_{t-1}), the actual demand in the previous period (A_{t-1}), and a smoothing constant alpha (α), which provides the weight of the committed error. The formula is given by Equation (3) in Chapter 4.3.3 and repeated below.

$$F_t = F_{t-1} + \alpha (A_{t-1} - F_{t-1}) \quad (3)$$

6.2.2 SARIMA

The ARIMA forecasting method has been frequently used for reliable forecasts (Ho S.L. & Xie M., 1998). The principal limitation of ARIMA is that it assumes that time series are linear (Adhikari R. & Agrawal R.K., 2013). It is one of the most widely used approaches for time series forecasting by describing the autocorrelation in the data (Hyndman R.J. & Athanasopoulos G., 2018). The initial parameters used are the order $ARIMA(p,d,q)$, which capture the key elements of the model (auto-regression [AR], integrated [I], and moving average [MA]) by, for example, associating the key to the parameters by $AR(p)$, $I(d)$, and $MA(q)$. The value of each parameter can be explained using tools such as the auto-correlation function (ACF), partial ACF, and the stationarity of the dataset measured by the p-value (the time series should be differentiated when the result is $> 5\%$).

Equation (13) demonstrates how ARIMA can be written.

ARIMA (p,d,q):

$$\underbrace{(1 - \phi_1 B)}_{\text{Non-seasonal AR(1)}} \underbrace{(1 - B)}_{\text{Non-seasonal difference}} y_t = \underbrace{(1 + \theta_1 B)}_{\text{Non-seasonal MA (1)}} \varepsilon_t \quad (13)$$

where p is the order of the auto-regressive part, d is the degree of the first differencing involved (I), and q is the order of the MA part.

To include the seasonality of the dataset, a seasonal ARIMA model was developed by including additional seasonal terms in the ARIMA, such as seasonal order (P, D, Q , Seasonality), as mentioned in SARIMA (Hyndman R.J. & Athanasopoulos G., 2018).

SARIMA can be expressed as written in Equation (14).

$$\text{SARIMA} \quad \underbrace{(p,d,q)}_{\text{Non-seasonal part of the model}} \quad \underbrace{(P,D,Q)s}_{\text{Seasonal part of the model}} \quad (14)$$

where s is the number of observations in which uppercase notation could be observed and defined as the seasonal parts (s) of the model, as depicted in Equation (15).

$$\begin{array}{ccc} \text{Seasonal AR(1)} & \text{Seasonal difference} & \text{Seasonal MA (1)} \\ \uparrow & \uparrow & \uparrow \\ \underbrace{(1 - \phi_1 B)}_{\text{Non seasonal AR (1)}} & \underbrace{(1 - \phi_1 B^s)(1 - B)}_{\text{Non-Seasonal difference}} & \underbrace{(1 + \theta_1 B^s)(1 + \Theta_1 B^s)}_{\text{Non-seasonal MA (1)}} \end{array} y_t = \varepsilon_t \quad (15)$$

In training SARIMA on the different product categories, the values of parameters d and D remained 0 because of the stationarity of the dataset. During the training, parameters $p, q, P,$

and Q were applied and fine-tuned, and seasonality was given by the ACF. The ACF and partial ACF (PACF) were used to identify parameters $AR(p)$ and $MA(q)$ for the model. The autocorrelation (or correlation of the time series with itself) is the key statistics in time series analyses. The ACF measures the extent of the linear relationship between two variables and is used as a tool to explore the time series before forecasting, which helps check for seasonality, cycles, and other time series patterns. The PACF measures the degree of association between two variables that have no direct correlation.

P, D, Q and p, d, q are set based on the best Akaike's Information Criterion (AIC). The AIC is defined as: $AIC = -2\log(L) + 2K$, where L denotes the likelihood, and K represents the number of parameters estimated by the model. As the AIC penalizes models with many parameters, it favors simpler models when selecting the best model. Note that the AIC has little meaning on its own and it is only useful in comparison to the AIC value of another model fitted to the same dataset (Makridakis S., et al., 2008).

6.2.3 Facebook Prophet

Prophet is an open-source framework used by Facebook for time series forecasting (Wang P., et al., 2020). It has three main components: trend, $g(t)$; seasonality, $s(t)$; and holidays, $h(t)$ (Taylor S.J. & Letham B., 2017). These components are combined in Equation (16).

$$y(t) = g(t) + s(t) + h(t) + \epsilon(t) \quad (16)$$

where $\epsilon(t)$ is the error term. This model has gained attention for its potential usefulness with seasonal datasets.

6.2.4 Long short-term memory (LSTM)

Long short-term memory (LSTM) is the most commonly used model in recurrent neural networks (RNNs). One of its most known advantages is the ability to memorize the data sequence (Siarni-Namini S., et al., 2018). The model was proposed by (Hochreiter S. & Schmidhuber J., 1997). The initial common parameters are the hidden layer called LSTM containing four neurons, and a single output with 12 predicted values. The training is done on 250 epochs, and the train set should not be shuffled. Figure 6.1 presents an overview of the implementation of the LSTM predictor.

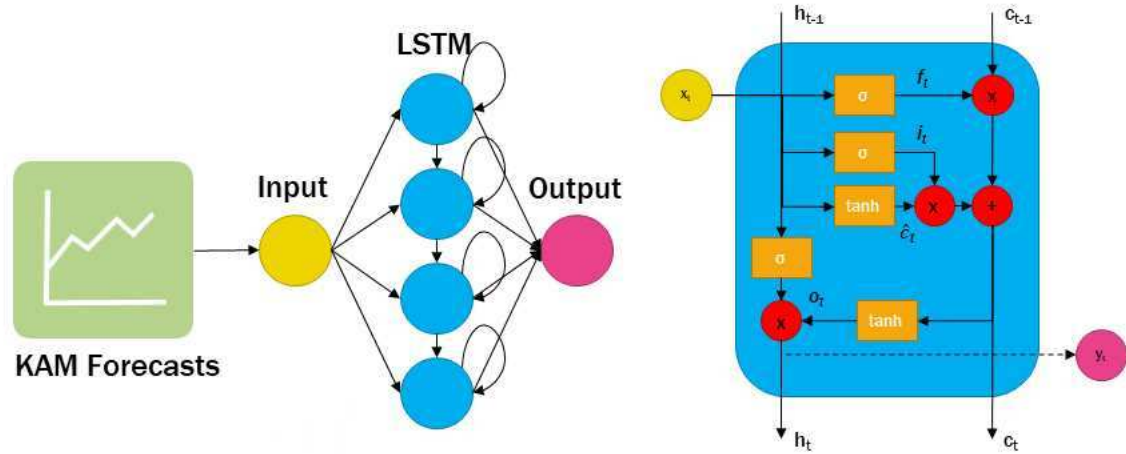


Figure 6.1: Overview of LSTM with KAM forecasts (designed by the author)

The LSTM model can be divided into three parts, known as gates, which perform individual functions. The first part, the forget gate, checks whether the incoming information is relevant or irrelevant. If it is irrelevant, it can be forgotten; otherwise, it must be remembered. The second part, the input gate, tries to learn new information from the input of the cell and decides which information from the current step could be added. In the third part, the output gate, the current period provides the updated information to the next period. The output gate finalizes the next hidden state.

The notations are as follows:

x_t : The input value of the current period

f_t : The forget gate of the current period

h_t and h_{t-1} : the hidden states for the current and previous periods, representing the short-term memory

c_t and c_{t-1} : The cell states for current and previous periods, representing the long-term memory

σ : Sigmoid activation function, a mathematical function with an S-shaped curve characteristic

$\tanh$: Non-linear activation (allows multiple layers of neurons to learn the error)

i_t : Input gate for the current period

$\hat{c}_t$: Value generated by $\tanh$

o_t : Output gate for the current period

y_t : Output value for the current period

Forget gate

The forget gate decided which information in the sequence is useful. If the information is useful, it should be kept; otherwise, it should be forgotten. The equation of the forget gate is presented in Equation (17).

$$f_t = \sigma(x_t \times W_f + h_{t-1} \times w_f) \quad (17)$$

where W_f is the weight matrix between the forget and input gates, and w_f is the weight associated with the input between the forget and input gates.

A sigmoid function is applied to the current input x_t and hidden state h_{t-1} . The hidden state represents the output of an LSTM cell. The sigmoid function generates values between 0 and 1. If the value is closer to 1, the old output is necessary; if it is close to 0, the output is irrelevant and can be ignored.

Input gate

Through the input gate, the importance of the information can be quantified. The function of the input gate is presented in Equation (18).

$$i_t = \sigma(x_t \times W_i + h_{t-1} \times w_i), \quad (18)$$

where W_i is the weight matrix between the input and output gates and w_i is the weight associated with the input between the input and output gates.

The new information passes through the cell state (representing the internal cell of the LSTM, which is not an output), with the function presented in Equation (19):

$$\hat{c}_t = \tanh(x_t \times W_c + h_{t-1} \times w_c) \quad (19)$$

where W_c is the weight matrix between the cell state information and the output gate and w_c is the weight associated with the input between the cell state information and output gate.

With the tanh value, new information between -1 and 1 can be obtained. If the $\hat{c}_t$ value is positive, it is added to the cell state; otherwise, it is subtracted.

The next step is to decide if the information should be stored in the cell state. For this, the following equation can be used:

$$c_t = f_t \times c_{t-1} + i_t \times \hat{c}_t. \quad (20)$$

The new cell state is determined by multiplying the cell state of the previous period by the forget gate of the current period, which is added with the value generated in the input gate multiplied by the generated tanh value. If the outcome is 0, then the values are dropped from the cell state.

Output gate

The output gate provides information about the values of the next hidden state. The hidden state is used for predictions. The functions are presented in Equations (21) and (22).

$$o_t = \sigma(x_t \times W_o + h_{t-1} \times w_o) \quad (21)$$

$$h_t = o_t \times \tanh(c_t) \quad (22)$$

where W_o is the weight matrix of the output gate and w_o is the weight associated with the input of the output gate. The LSTM model helps learn the forecast errors made by the KAMs.

6.3 The proposed methodology

To improve the current forecasts, the sequential methodology shown in Figure 6.2 was applied as follows.

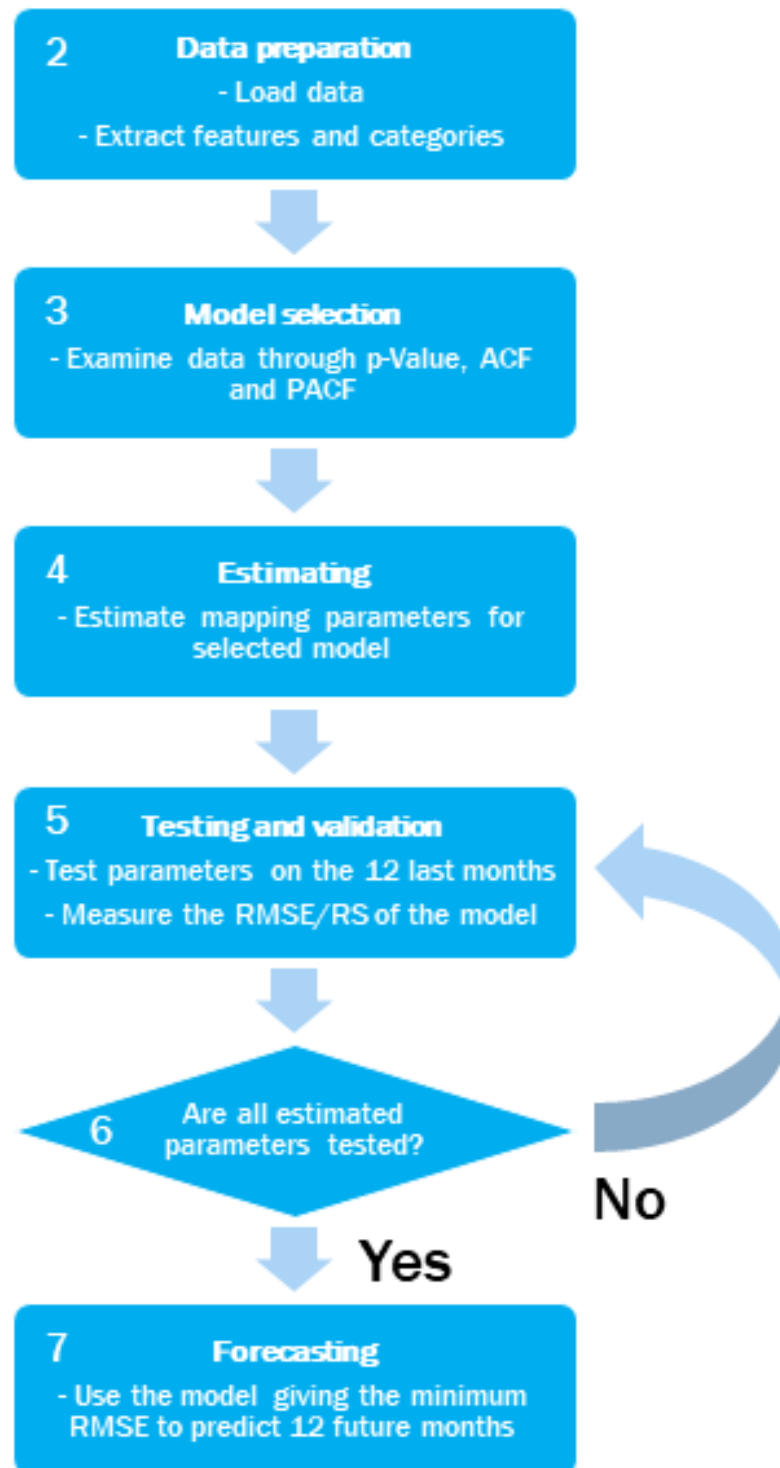


Figure 6.2: Analysis process (designed by the author)

(1) The data used for the evaluation of the different methods were provided by the Swiss SME. The sales history was available for the period from January 2018 to August 2021.

(2) The sales history was filtered to obtain time series according to a global view and then deeper according to product category. Features such as the real sales and KAMs forecasts were also extracted.

(3) The purposed time series were evaluated using the ACF, partial ACF (PACF), and p-value to identify the parameters to be assigned in the model. The ACF computes and presents how the autocorrelation evolves through the lags. As a complement, the PACF allows for the suppression of the influence of the lag between lag_0 and lag_t . The stationarity of the dataset was evaluated with the p-value by a critical step of 5%. Over this step, the time series should be differentiated.

(4) In the next step, the mapping of hyperparameters was estimated for each chosen model. The hyperparameters were configuration parameters that were external to the model and, whose values could not be estimated from the data. They were set before the training was started. The hyperparameters were used for defining the higher-level properties of the mapping function and learning process to inspect the performance on the data.

(5) The dataset was split into a train set and a test set. The test set contained the most recent sales values, with 12 values representing one year of sales forecasting. The model trained the train set with the given hyperparameters and forecasted the sales.

(6) The operation was repeated until all combinations of the hyperparameters were visited. The metric root mean square error (RMSE), defined in Equation (23), was computed for each combination and helped define the optimal hyperparameters for the model by using the hyperparameters from the min (RMSE).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \text{ where } n \in [1, \dots, n] \quad (23)$$

Where n is the number of data points or observations, Y_i is the observed values (test set), and $\hat{Y}_i$ is the predicted values.

(7) The model with the best hyperparameters was used to make the forecasts, and the residual stock (RS), defined in Equation (24), was computed for each timestamp (every month), to qualify the model as too optimistic or too pessimistic. A model that is too optimistic is of interest when the current stock is low and the company wants a margin of stock, whereas a model that is too pessimistic is of interest when the current stock is high, and the company wants to reduce the stock of the product.

$$RS = \sum_{i=1}^n (\hat{Y}_i - Y_i) \text{ where } n \in [1, \dots, n] \quad (24)$$

$\hat{Y}_i > Y_i$ yields a too optimistic forecast, whereas $\hat{Y}_i < Y_i$ yields a too pessimistic forecast.

Further investigation

(8) The KAM forecasts were more accurate than the forecasts made by the models over the short term (today + 3 months). A combination of the two forecasting methods is relevant when using a set of weights given an important ponderation of the KAM forecasts in the short term and an important ponderation of the model in the long term. The sum of both weights should be equal to 1.

(9) A deeper approach is to combine the KAM forecasts and the so-called LSTM model forecasts to learn the error on the KAM forecasts and predict an adjustment of the KAM forecasting.

6.4 Experimental setup and results

Three statistical time series forecasting methods (exponential smoothing, SARIMA, and Facebook Prophet) and one neural network (LSTM) were considered to evaluate the performance of the proposed approach. All models were implemented in Python. Exponential Smoothing, SARIMA and Facebook Prophet were executed and optimized using the statsmodels package, while LSTM was performed using Keras. To compare all models, the RMSE and RS metrics were used.

6.4.1 Performance of the models

The statistical time series forecasting methods were benchmarked through the process detailed in Section 6.3. The results are illustrated in Section 6.4.4. The main observation was that SARIMA remained the best choice for the purposed dataset by providing the best RMSE for all product categories. Exponential smoothing and Facebook Prophet did not satisfy the request of the dataset, because they provided too optimistic or too pessimistic RS.

6.4.2 Evaluation with the residual stock

Visualization by RS was interesting to observe over the months when the selected model was too optimistic or pessimistic. The main challenge was to provide a good forecast for the month of November, because of the promotional days during this month, (e.g., Black Friday, Cyber Monday, and Singles Day), the selling was difficult to predict. The KAM forecasts were a valuable input for identifying the more accurate model by, for example, correcting the gap between the real and model-predicted sales.

6.4.3 Introduction of the KAM forecasts

The KAMs were better at predicting short-term sales. They maintained contact with the retailers and knew the needs of each market because of the orders they received. However, they made optimistic forecasts when examining RS only on the basis of their forecasts, in which cases, the RS was always observed to be high. Awareness of this information allowed for adding the KAM forecasts as “feedforward” for the prediction by a simple weighting or learning method.

6.4.3.1 The KAM forecasts and statistical time series forecasting methods

The first approach integrated the KAM forecasts and the time series forecasting method by giving a weight to each forecast. The weight was given on both curves for each timestamp. A high weight was assigned to the KAM forecasts in the short term, and the rest of the weight was given to the statistical time series forecasting methods. For the long term, a high weight was given to the statistical time series forecasting methods, and the rest of the weight was assigned to the KAM forecasts. The results of the combination of the two curves were analyzed using the RMSE and RS metrics.

In the present case, consider the weights as the predictions from the different forecasting models and KAM forecasts. The forecasts were improved in terms of RMSE. The weight applied was $0.9 \cdot \text{KAM} + 0.1 \cdot \text{prediction_model}$ for the forecasts for the first three months, $0.3 \cdot \text{KAM} + 0.7 \cdot \text{prediction_model}$ for the forecasts for months 3 to 6, and $0.1 \cdot \text{KAM} + 0.9 \cdot \text{prediction_model}$ for the forecasts for months 6 to 12. The accuracy of the RS analysis was improved by combining the prediction models and the KAM forecasts.

6.4.3.2 The KAM forecasts and learning method LSTM

This second approach consisted of learning the KAM curve through an RNN called LSTM. This neural network was trained by the history of the KAM forecasts and labeled by the real sales. The timestamp values were predicted using LSTM.

6.4.3.3 The KAM forecasts, statistical time series forecasting methods and learning method LSTM

Both of the previous methods were performed in the last method presented, which combined the KAM forecasts, statistical time series forecasting methods, and learning methods. The principle of this approach was to train the real sales history through a statistical time series method and predict the future based on the trained models. It provided an additional “feedforward” to the learning methods by creating for each timestamp a tuple of the KAM forecast value and value obtained using the statistical time series forecasting method. A tuple is an ordered and unchangeable collection in Python. Each list of tuples was trained on LSTM, and the model was used to predict future sales.

6.4.4 Results

The following sections present the results in order of the steps of the development.

6.4.4.1 Statistical time series forecasting methods

When using only the canonical forecasting method, it was observed that the model made good forecasts when the variation was lower than the average, but it could not reveal high seasonality peaks. By comparison, the KAMs knew the market better in the short term, but they did not make good long-term forecasts.

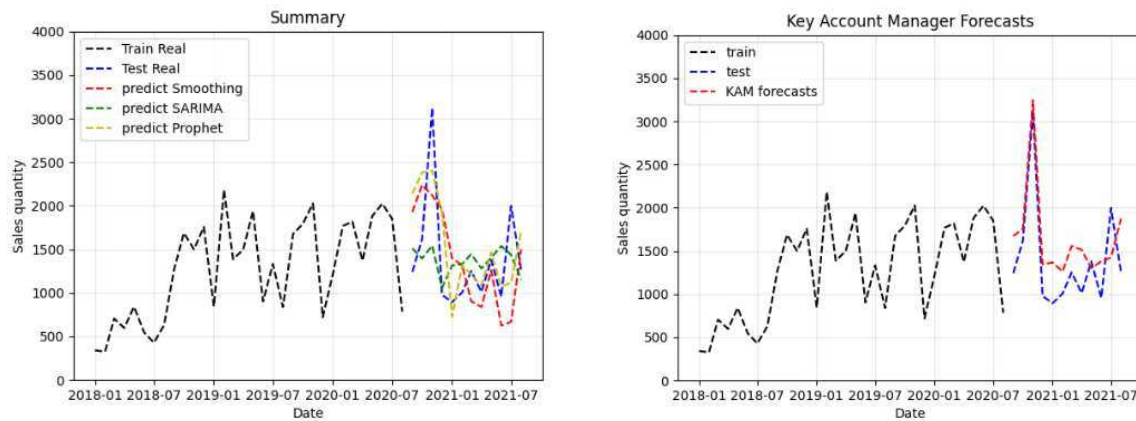


Figure 6.3: The left graph presents the canonical model of forecasts, and the right graph presents KAM forecasts (designed by the author)

6.4.4.2 The KAM forecasts and statistical time series forecasting methods

When combining the KAM forecasts and models by assigning a weight to each, a weak RS variation was predicted for the first months. The plus value was observed in the medium-long term, especially with SARIMA, which presented the best potential to forecast this type of dataset.

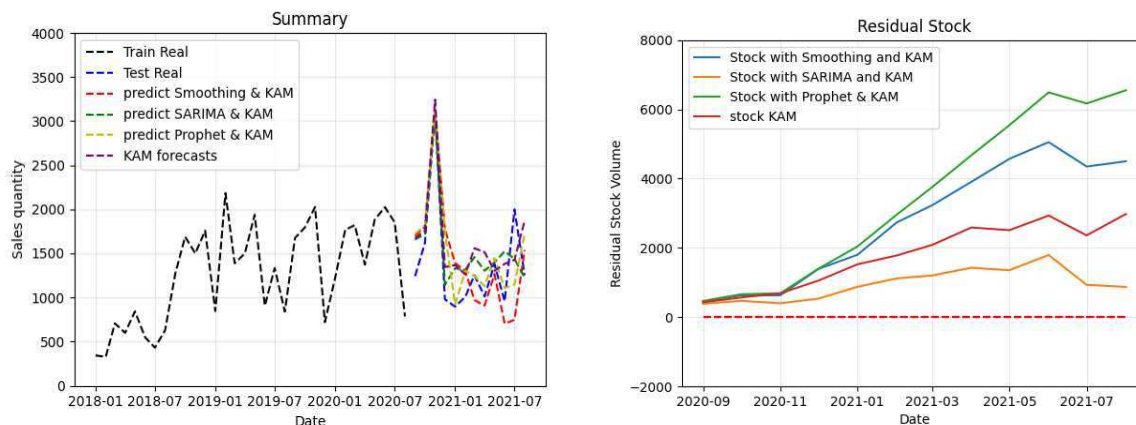


Figure 6.4: The left graph presents the prediction models combined with the KAM forecasts, and the right graph presents the RS of the predictions (designed by the author)

6.4.4.3 KAM forecasts and learning method LSTM

As only the KAM forecasting and KAM behavior was too optimistic or too pessimistic, this strategy consisted of an error learning of the KAM forecasts to adjust the prediction and increase accuracy.

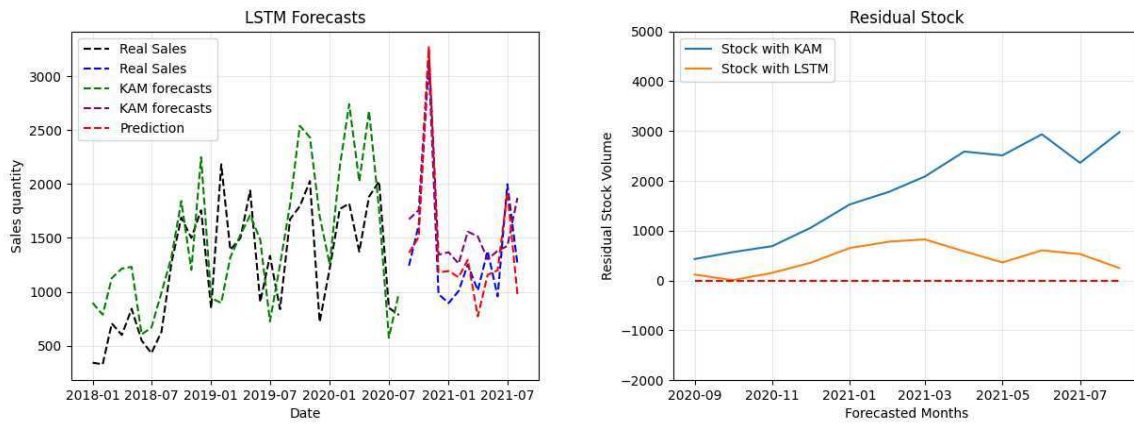


Figure 6.5: The left graph presents the prediction by learning the error of the KAM forecasts, and the right graph presents the RS of the predictions (designed by the author)

6.4.4.4 KAM forecasts, statistical time series forecasting methods and LSTM learning method

The deeper approach combined the KAM forecasting and forecast models, such as SARIMA, through LSTM. It also consisted of a prediction model that fine-tuned the previous method.

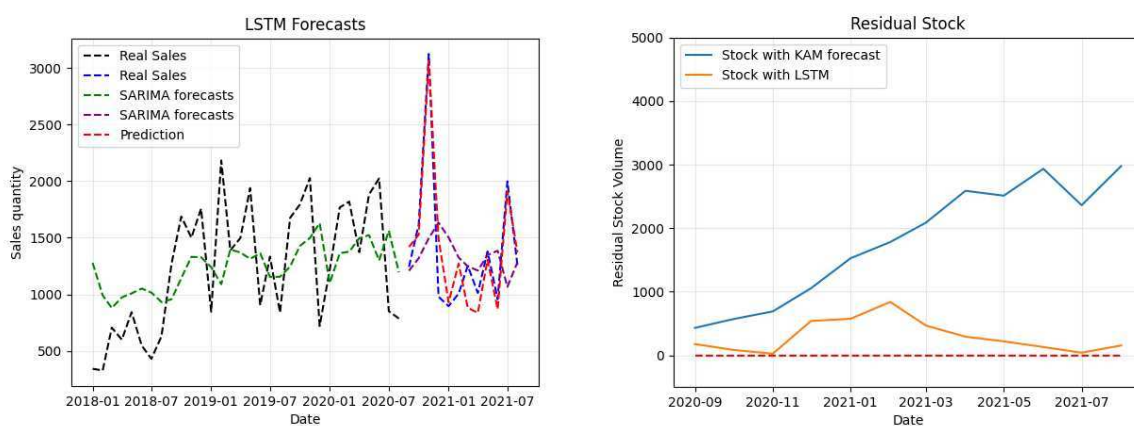


Figure 6.6: The left graph presents the prediction by learning the error of the KAM forecasts and SARIMA prediction, and the right graph presents the RS of the predictions (designed by the author)

6.4.4.5 Results summary

SARIMA remained the best starting point for predicting a sequence from the presented dataset. The KAM forecasts helped increase the prediction accuracy over the short term, whereas canonical forecasting methods were preferable for medium to long-term predictions. Using LSTM and error learning avoided the use of self-defined weights for KAM forecasts and forecasting methods, and LSTM provided better accuracy for the presented dataset, as demonstrated in Table 6.1.

Quantitative or qualitative method	Overall quantity (in units)	Delta with real	RMSE	Overall quantity (incl. KAM) (in units)	Delta with real (incl. KAM)	RMSE (incl. KAM)
Real sales	16'718	0%	0			
KAM	19'695	+17.8%	176.58			
Exponential Smoothing	21'172	+26.6%	194.56	21'217	+26.9%	204.09
SARIMA	16'161	-3.3 %	109.71	17'593	+5.2%	153.47
Facebook Prophet	24'025	+43.7%	237.18	23'268	+39.1%	231.59
LSTM & SARIMA	17'236	+3.1%	108.18	16'885	+1.0%	98.14

Scale in %; -10% to 0%; 0% to 10%; 10% to 20%; >20%

Table 6.1: Summary of results

6.5 Real application

This application was created to help the company improve its finished goods sales forecasts using the best methods that emerged from the analyses presented in this Chapter (SARIMA and LSTM). The tool was designed to be simple and easy to implement in the SME.

6.5.1 Environment preparation

The visualization tool for forecasting products was written in Python. It uses a standalone executable that embeds useful libraries to compute the forecast.

The installation folder contains the document, as shown in Figure 6.7, and can be placed anywhere.

Name	Date modified	Type	Size
.streamlit	06/08/2024 08:16	File folder	
data	18/07/2024 16:48	File folder	
app.exe	30/07/2024 17:30	Application	523'367 KB
forecast_products.py	30/07/2024 18:19	Python File	17 KB

Figure 6.7: Directory of the application to forecast products

The .streamlit folder contains the settings to launch the visualization, the data folder contains the related sales and forecasts, app.exe is the executable to launch by double-clicking on it, and forecast_products.py is the toolbox to compute the forecasts. Only the data folder can be edited by adding some files of data.

6.5.2 Starting the application

Double-clicking on app.exe starts the application. A shortcut can be created by right-clicking on app.exe and selecting the option to create a shortcut. After launching the application, a terminal window opens. After a few seconds, the web browser opens a new tab with the application, as seen in Figure 6.8. It contains the option to open a .csv file with the Browse files button. Windows Explorer opens and can be used to navigate to the desired file.

Product Analysis

Choose a CSV file to handle



Drag and drop file here
Limit 200MB per file

Browse files

Figure 6.8: Start page of the application

6.5.3 Application's main page

Once a file has been loaded, the main page of the application appears as in Figure 6.9. The types of products can be edited with the banner, and the canvas displays the main information about the forecasts.

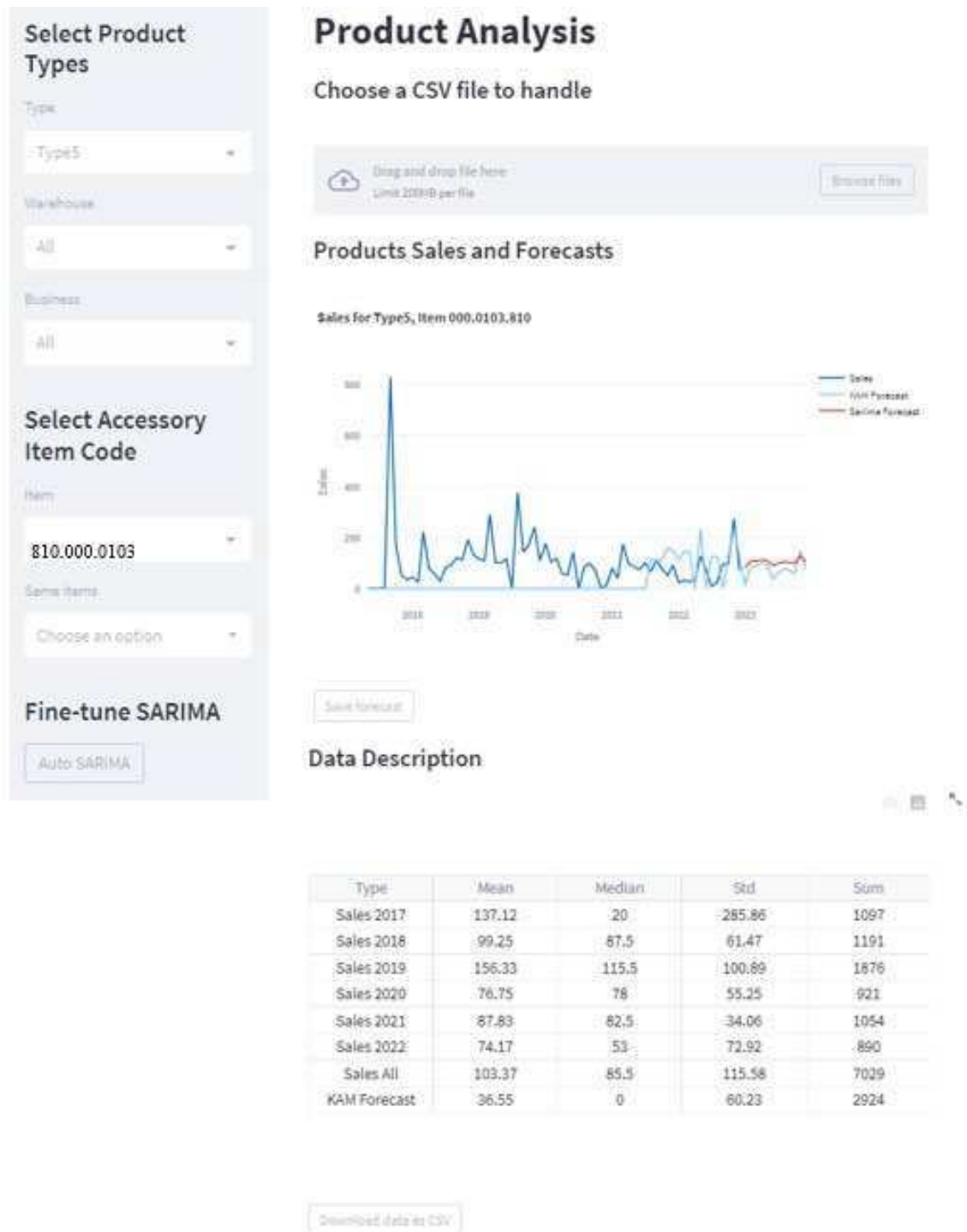


Figure 6.9: Main overview of product application

The banner makes it possible to filter for the subtype of the products (Type1, Type2, Type3...), the warehouse (War1, War2, War3), and the business (Market 1, Market 2...). Once the filter for the subtype has been set, the item code can be associated.

On the canvas, there is a dynamic graph to represent the data (Sales, KAM Forecasts, SARIMA and LSTM forecasts). It is possible to zoom or filter the data. If the forecasts are validated, the Save forecast button can be pressed, and another item can be analyzed. The Data Description section shows a table of statistics for the item with the mean, median, standard deviation, and sum for the different years. Finally, the Download data as CSV button can be used to export the forecasted data into the Downloads folder.

6.5.4 Making and saving forecasts of final products by LSTM

To make a forecast, the needed parameters should be set on the banner, as illustrated in Figure 6.10. In this example, three elements are circled: (1.) the choice of Type 5 as the type, (2.) the selection of item code 810.000.0103, and (3.) the Save forecast button for saving the forecasts.

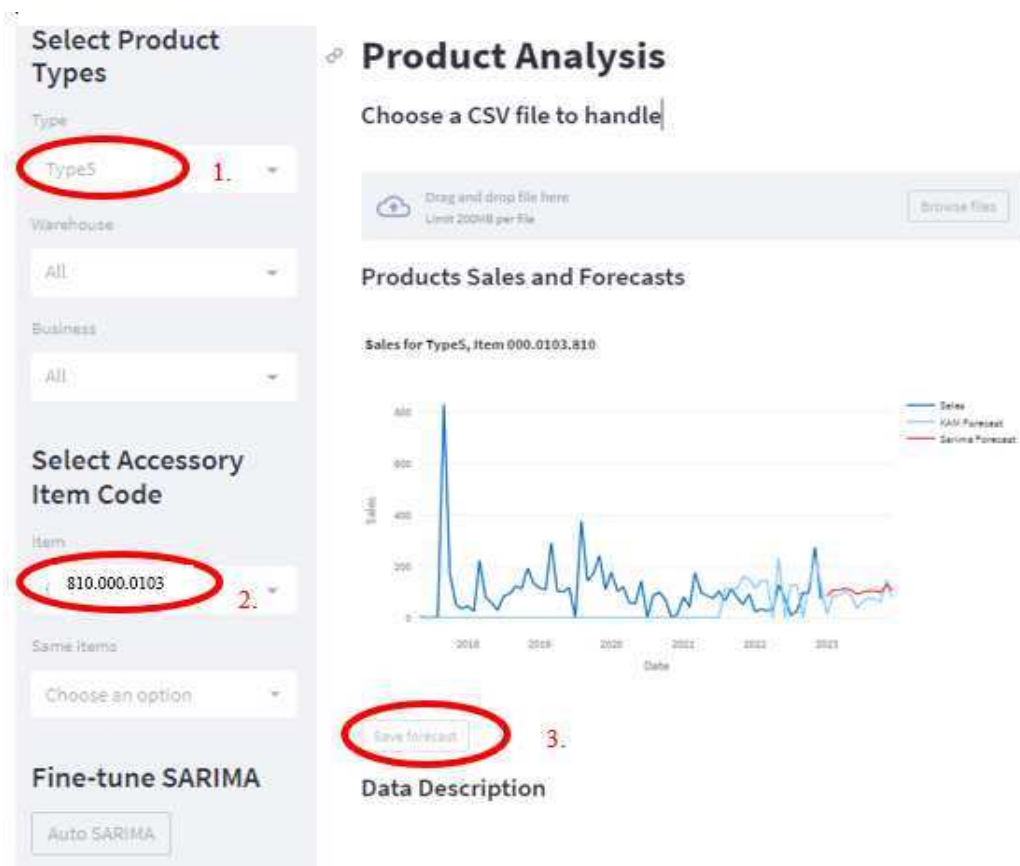


Figure 6.10: Options to make forecasts by LSTM

Once the forecasts are done, it is possible to use the Download data as CSV button to export all data to the Downloads folder on the computer, where it will appear in a file called products.csv. The new saved data can be found by opening this file and scrolling to the end, as depicted in Figure 6.11.

index	Measure	Date Conc	Date	Country	WHSE SHI	Business	YEAR	Month	ITEM CODE	ITEM_DES	Q TOTAL
52363	SARIMA	janv.23	janv.23	Switzerland	All	All	2023	January	810.000.0103	Type5	83
52364	SARIMA	Feb-23	Feb-23	Switzerland	All	All	2023	February	810.000.0103	Type5	107
52365	SARIMA	mars.23	mars.23	Switzerland	All	All	2023	March	810.000.0103	Type5	107
52366	SARIMA	Apr-23	Apr-23	Switzerland	All	All	2023	April	810.000.0103	Type5	112
52367	SARIMA	May-23	May-23	Switzerland	All	All	2023	May	810.000.0103	Type5	109
52368	SARIMA	juin.23	juin.23	Switzerland	All	All	2023	June	810.000.0103	Type5	91
52369	SARIMA	juil.23	juil.23	Switzerland	All	All	2023	July	810.000.0103	Type5	99
52370	SARIMA	Aug-23	Aug-23	Switzerland	All	All	2023	August	810.000.0103	Type5	104
52371	SARIMA	sept.23	sept.23	Switzerland	All	All	2023	September	810.000.0103	Type5	103
52372	SARIMA	oct.23	oct.23	Switzerland	All	All	2023	October	810.000.0103	Type5	98
52373	SARIMA	nov.23	nov.23	Switzerland	All	All	2023	November	810.000.0103	Type5	128

Figure 6.11: Data in the products.csv file

6.6. Conclusion

The main contributions of this Chapter can be summarized as follows.

- Short-term forecasts (less than 3 months) were clearly improved with KAM inputs. Weighting short-term KAM forecasts and time series models for long-term forecasts provided better results compared to the tested models. Additionally, RS could be an added value metric to decide which time series model to apply for long-term forecasts.
- SARIMA and LSTM were good choices for handling the dataset, but LSTM had the advantage of greater efficiency in error learning on KAM forecasts.

Further investigation is needed to consider the KAM forecasts, which were more accurate than the forecasts by the models for the short term (today + 3 months). The combination of the two forecasting methods is relevant when using a set of weights with an important ponderation of the KAM forecasts in the short term and of the model in the long term. The sum of the two weights is equal to 1. Changing the ratio of the KAM forecasts to the LSTM model can reduce the RMSE, thereby increasing the forecast accuracy.

7 Improvements of Accuracy for Accessories

7.1 Introduction

The previous Chapter focused on the improvement of product forecast accuracy for the Swiss SME. It identified certain methods that are suitable for improving product forecasting accuracy. This Chapter discusses how forecasting accuracy can be improved for accessories and spare parts as well. The difference between final products and accessories is that final products are household products, while accessories are goods that are necessary for the household products to be used. Accessories include spare parts, esthetic elements, and even maintenance products. Poor forecasting for spare parts can negatively impact decisions about supply, additional storage, maintenance costs, destruction, and more.

In a continuation of the previous Chapter, this Chapter describes the efforts to help the SME consolidate improvements to move from the third stage (standard) in blue to the fourth stage (advanced) in green in the maturity model of (Grimson J.A. & Pyke D.F., 2007) as seen in Table 2.6.

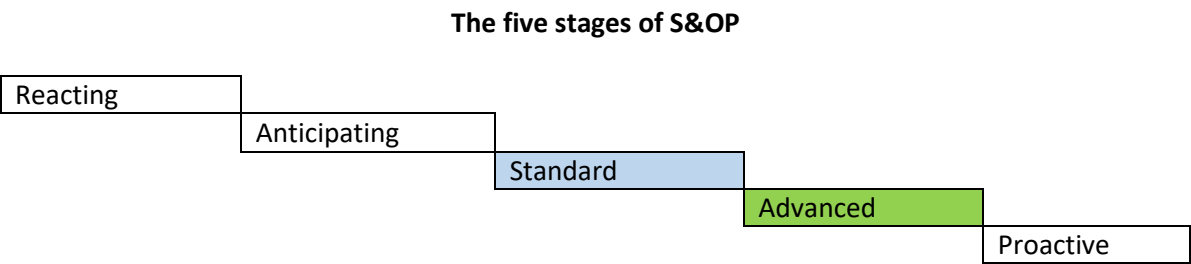


Table 2.6: The five stages of S&OP, inspired by (Grimson J.A. & Pyke D.F., 2007)

There are noticeable differences between forecasting methods for final products and those for spare parts (Morris M., 2013). Various studies have been carried out to improve spare parts forecasting. Most tried to reduce inventory costs (Romeijnders W., et al., 2012), but others attempted to make connections between poor accuracy and inventory obsolescence (Teunter

R.H., 2011). Likewise, different forecasting approaches have been applied to improve the accuracy of spare parts orders. An interesting review of the field by (Pinçea C., et al., 2021), split spare parts forecasts into three categories: (1) time-series methods; (2) a combination of contextual approaches and statistical forecasting techniques; and (3) comparison of traditional and alternative demand forecasting methods.

The consumption of spare parts varies greatly and is therefore challenging to forecast. Some research has investigated the gap between research and practice in spare parts management based on case studies (Bacchetti A. & Sacconi N., 2012) or focused on statistical analysis (Hemeimat R., et al., 2016). An interesting paper by (Arvan M., et al., 2019) introduced human adjustments to quantitative forecasts, while another study made links between judgmental adjustments and statistical methods (Van den Broeke M., et al., 2019). (Hu Q., et al., 2018) addressed spare parts classification by defining criteria such as the repairability, lead time, and obsolescence of spare parts. Most studies used historical data to determine the best way to improve spare parts and applied models such as ARMA, auto-regressive integrated moving average (ARIMA) (Sheng F. & Jia L., 2020), autoregressive integrated moving average with exogenous values (ARIMAX), and seasonal autoregressive integrated moving average with exogenous values (SARIMAX) (Arunraj N.S., et al., 2016). Others have further compared statistical and machine learning (ML) methods, such as k-nearest neighbors (k-NN) or even random forest (RF) models (Spilitotis E., et al., 2020). Most studies have used accuracy to measure the performance of forecasting, but some have shown that inventory performance yields more realistic benchmarks (Teunter R.H. & Duncan L., 2017).

One aim of the present study was to improve the forecasting of accessories for the SME by using time-series models and ML algorithms. Following (Xie M., et al., 2013), it was decided to add exogenous variables to SARIMA. The objective was to check the impacts of different exogenous values on the SARIMA model and compare the results with ML algorithms. The models and algorithms that were used and described in this Chapter are the following: exponential smoothing, SARIMA, SARIMAX (SARIMA with exogenous variables), and some ML algorithms, such as least absolute shrinkage and selection operator (LASSO), k-NN, RF, and linear regression.

To outline the performance of the results, it was decided to combine traditional forecasting measures, such as mean absolute error (MAE) and root mean square error (RMSE) with residual stock (RS) metric, to check the inventory impacts, as suggested by (Teunter R.H. & Duncan L., 2017).

7.2 Existing forecasting models

7.2.1 Exponential smoothing

As explained in Chapter 6, exponential smoothing is the most frequently used forecasting method (Tuomikangas N. & Kaipia R., 2014). This method is explained in Section 4.3.3 and the formula is represented in Equation (3).

7.2.2 SARIMA

ARIMA is frequently used in spare parts forecasting (Jiafu R., et al., 2009). The initial parameters used in ARIMA (p, d, q) are auto-regression [AR(p)], integrated [I(d)], and moving average [MA(q)].

The difference between ARIMA and SARIMA is that the latter includes seasonality effects (Hyndman R.J. & Athanasopoulos G., 2018). The equations of ARIMA and SARIMA are given in Chapter 6 and in (Ramosaj A., et al., 2022). The methods are explained in detail in Section 6.2.2.

7.2.3 SARIMAX

SARIMAX can be applied to include the effect of demand influencing factors. This model is a combination of the SARIMA model with an X factor that represents an exogenous value (Arunraj N.S. & Ahrens D., 2015). This exogenous value, X, is an external factor that impacts the accuracy of the forecasts. SARIMA can be expressed by (p,d,q) (P,D,Q)s (Ramosaj A., et al., 2022). To move from SARIMA to SARIMAX, the additional external factor X is added and modeled by multi-linear regression equation:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_k x_{k,t} + \omega_t \quad (25)$$

where y_t is the time series dependent variables, $x_{1,t}$ to $x_{k,t}$ are the external variables, β_0 to β_k are the correlation regression coefficients, and ω_t is a stochastic residual independent of the input series. ω_t can be formulated as follows:

$$\omega_t = \frac{\theta_q(B)\theta_Q(B^S)}{\phi_p(B)\phi_p(B^S)(1-B)^d(1-B^S)^D} \varepsilon_t \quad (26)$$

where $\theta_q(B)$ is the non-seasonal MA, $\theta_Q(B^S)$ is the seasonal MA, $\phi_p(B)$ is the non-seasonal AR, $\phi_p(B^S)$ is the seasonal AR, $(1-B)^d$ is the non-seasonal difference (I), $(1-B^S)^D$ is the seasonal difference (I), and ε_t is the remaining error.

The general formula of SARIMAX can be obtained by substitution, by placing Equation (26) in Equation (25) as follows (Arunraj N.S., et al., 2016):

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \dots + \beta_k x_{k,t} + \frac{\theta_q(B)\theta_Q(B^S)}{\phi_p(B)\phi_p(B^S)(1-B)^d(1-B^S)^D} \varepsilon_t \quad (27)$$

Each exogenous value is appropriate to each accessory forecasted. The following exogenous variables were selected to use in this study:

- Month sales: Indication of the months; for example, January is 1 and August is 8.

- Mean sales: Mean of all August months for the four years of data; for example,

$$\frac{\text{Sales. August 2018} + \text{Sales. August 2019} + \text{Sales. August 2020} + \text{Sales. August 2021}}{4}$$

- KAM: The given KAMs' forecasts.

- Mean KAM: The mean of all August months predicted by the KAM for the four years of data; for example,

$$\frac{\text{KAM. August 2018} + \text{KAM. August 2019} + \text{KAM. August 2020} + \text{KAM. August 2021}}{4}$$

- Last year KAM: The KAM forecasts of the preceding year based on rolling values for 12 months.

- Regression KAM: Linear regression on all KAM predictions used to find the values of forecasts for the next year.

7.2.4 Machine learning models

Machine learning in forecasting uses algorithms to learn from past sales to predict future events. While statistical methods use linear processes to forecast, ML uses non-linear algorithms. Machine learning methods have become popular with the increase in interest in artificial intelligence (AI) (Makridakis S., 2018). For the data set used in this study, the most common ML algorithms were used (LASSO, k-NN, RF, linear regression).

7.2.4.1 LASSO

LASSO regression measures the relationship between variables. The goal is to find a balance between the best accuracy and overfitting by adding a penalty term to the traditional linear regression models (Sethi J.K. & Mittal M., 2021). The parameters are close to zero if the influence on the prediction model is low. LASSO is helpful when a model includes many variables that are not all relevant (Ranstam J. & Cook J.A., 2018).

The objective function is to minimize the following equation:

$$J(w) = \frac{1}{2m} [\sum_{i=1}^m (\hat{y}_i - y_i)^2 + \lambda \sum_{j=1}^n |w_j|] \quad (28)$$

where y_i is the observed values (test set), and $\hat{y}_i$ is the predicted values.

The equation is based on two parts.

First part:

$$\frac{1}{2m} \sum_{i=1}^m (\hat{y}_i - y_i)^2$$

Second part:

$$\lambda \sum_{j=1}^n |w_j|$$

The goal of the first part is to minimize the prediction error. The goal of the second part is to minimize the value of the parameters, where λ is a constant and $|w_j|$ is the L_1 -norm of the coefficient vector. λ is a regularization parameter which is a hyperparameter between 0 and 1. It refers to the degree of penalty that is assigned to each parameter of the model.

7.2.4.2 k-NN

k-NN regression is a nonparametric method, which means it does not make any assumptions about the underlying data. It bases its prediction on feature similarities. This type of regression is used when data are labeled or noise-free. k-NN is considered a “lazy learner” because it does not learn from the training set immediately.

The parameter k refers to the number of nearest neighbors to include in most of the processes. Choosing the right k value is important for accuracy. A suitable value for k is typically chosen using cross-validation.

To obtain the nearest neighbors, the Euclidean distance was calculated between the given point and all points of the training set. The following formula was used:

$$Euclidean = \sqrt{\sum_{i=1}^k (x_i - y_i)^2} \quad (29)$$

where x_i and y_i are the two points for which the distance is calculated.

7.2.4.3 Random Forest

An RF is built by taking a collection of multiple random decision trees. Because it uses several different decision trees, RF is less sensitive to the training data than other ML models. The sample of each tree is taken randomly by bootstrapping (Tugay R.S. & Ogüsügü S.G., 2020), which is a procedure for estimating the distribution of the estimator by resampling. Bootstrapping is used to create subsets of the original dataset with replacement.

The following steps were taken to build the RF.

- Subsets of the original data were created, as shown in Figure 7.1. Rows and columns were selected through replacement.
- An individual decision tree was created for each subset.
- The decision trees all gave a different output.
- In a regression problem, the random forest’s final prediction is the average of the outputs from all trees.

More variation among the trees leads to better accuracy. A benefit of the RF algorithm is that it can reduce overfitting and bias (Mei J., et al., 2014). To set up the RF, parameters must be set for the node, size, number of trees, and number of features.

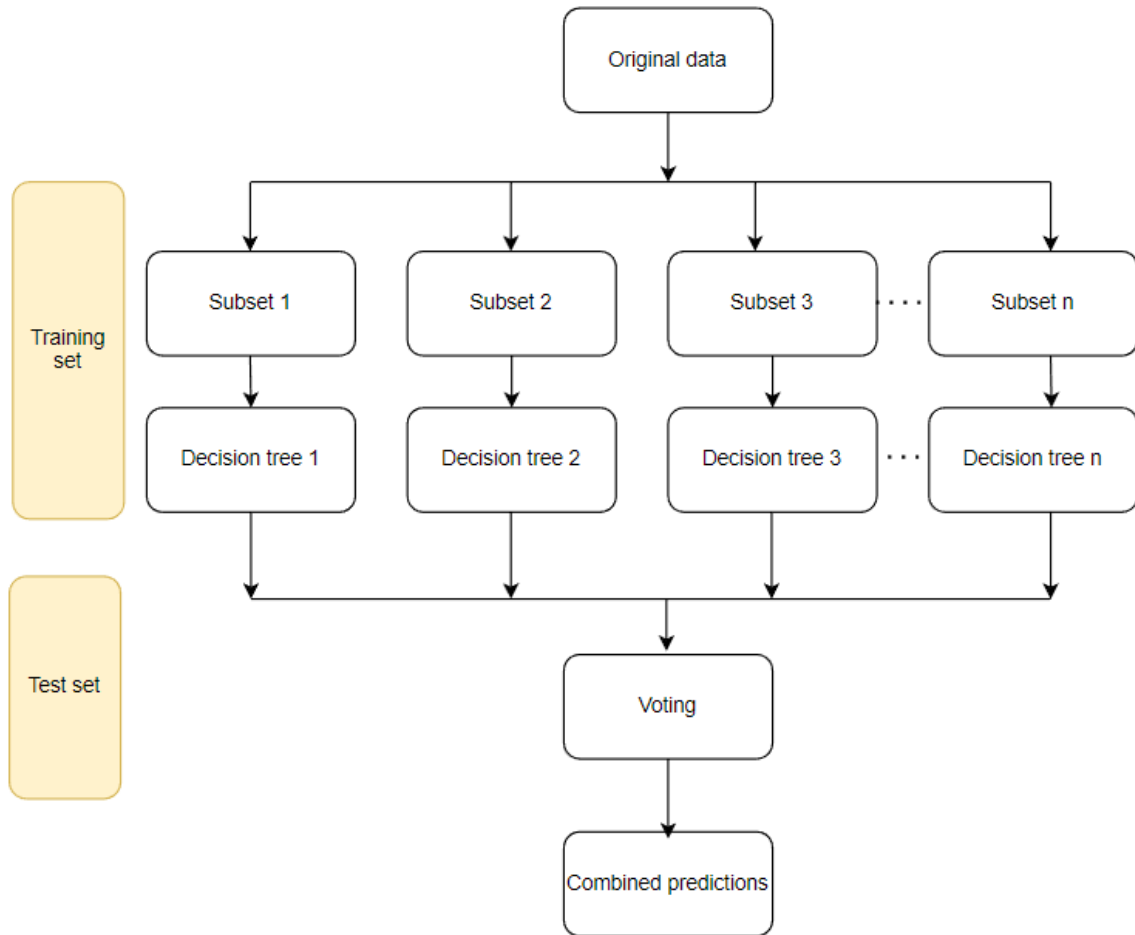


Figure 7.1: Random Forest structure (designed by the author)

The RF algorithm is built through the following steps (Nourreen S., et al., 2019).

- a. For $s = 1$ to $S = \text{forest size}$
 - Draw a bootstrap sample Z of size n from the training data, as shown in Figure 7.1.
 - Grow an RF tree T_s to the bootstrapped data. To grow the tree, it is necessary to repeat the following steps at each node until the minimum node size n_{min} is reached.
 1. Select the number of randomly chosen factor r from the p variables.
 2. Pick the best p among the r .
 3. Split the node into two sub-nodes.
- b. Output the ensemble of the trees $\{T_s\}_1^S$.

To make a prediction at a new point, x , the following formula, based on the average, was used for the RF algorithm based on regression:

$$\hat{f}_{rf}^S(x) = \frac{1}{S} \sum_{s=1}^S T_s(x) \quad (30)$$

Random forests improve the variance reduction of bagging by reducing the correlation between the trees without overly increasing the variance. Bagging is a technique for reducing the variance within a noisy dataset. It is possible to achieve it in the tree-growing process with a random selection of the inputs. Hence, when a tree is growing on a bootstrapped dataset, a check must be made before each split to determine the selected factor $r \leq p$ of the input variables.

$$\rho\sigma^2 + \frac{1-\rho}{S}\sigma^2 \quad (31)$$

Where ρ is the positive pairwise correlation and σ^2 is the variance.

7.2.4.4. Linear regression

Linear regression is an important algorithm that assumes a linear connection between the independent variable x_i and the dependent variable y_i . It uses this linear connection to assume a relationship between these two variables (James G., et al., 2013). Linear regression aims to find the best value for a and b , which means the error between the predicted value and the independent variable should be as low as possible.

$$y_i = a + bx_i + e_i \quad (32)$$

where y_i is the predicted value, a is the regression constant, b is the regression coefficient, x_i is the independent variable or observed variable (i.e., the variable expected to influence y), e_i is the error, and i is $1, \dots, n$.

7.2.4.5 Standardization

The goal of data standardization is to convert the data into a common format to enable better processing and comparison (Arner D.W., et al., 2019). Data standardization can enhance accuracy and help with selecting the most relevant forecasting model (Grannis

S.J., et al., 2019). Therefore, standardization is carried out as a data pre-processing step before using data in a time-series model or ML model. To standardize the data, the following criteria must be observed:

- Numerical data should be on a consistent scale.
- The categories should be consistently named.
- The data value should be in a consistent format.
- A uniform approach must be taken to deal with undefined or missing values.

Zero-normalization (z-norm) is the most common method of standardizing data. The formula is as follows:

$$x' = \frac{(x-\mu)}{\sigma} \quad (33)$$

where:

x' is the standardized value.

x is the observed value.

N_{train} is the number of sales values used to train the model.

$\mu = \frac{1}{N_{train}} \sum_{n=1}^{N_{train}} x_n$ is the average deviation for the given feature.

$\sigma = \sqrt{\frac{1}{N_{train}} \sum_{n=1}^{N_{train}} (x_n - \mu)^2}$ is the standard deviation for the given feature.

After standardization, all features have a mean of 0 and a standard deviation of 1 and the same scale (Milligan G.W. & Cooper M.C., 1988).

7.2.4.6 Dataset preparation

To make a prediction with an ML model, it is necessary to process the time-series into a matrix of history. To do so, multiple retrospective observations must be defined, and a target value must be labeled, such as the next month after the history of observations is considered. Conversely, statistical models are based only on the time-series itself and do not require any processing. However, in both cases, the temporal aspect of the series must be preserved to obtain the best predictions. Figure 7.2, Table 7.1 and Table 7.2 are illustrative examples. The chart presents the time-series as a temporal chart, and the data are organized by date from January 2018 to December 2022. The window of observations was defined as 12, and the matrix was built as shown in Table 7.1. The observations from

January 2018 to December 2018 were kept and the value that the ML model needed for the training in column $F(t+1)$ was stored, where F is the forecast, t is the current time, and 1 is the next month. Then, the process continued with the second row, where the window moves from 1, it reperformed the process until the whole time-series had been parsed. The dataset was subsequently shuffled by rows, and the ML model was trained.

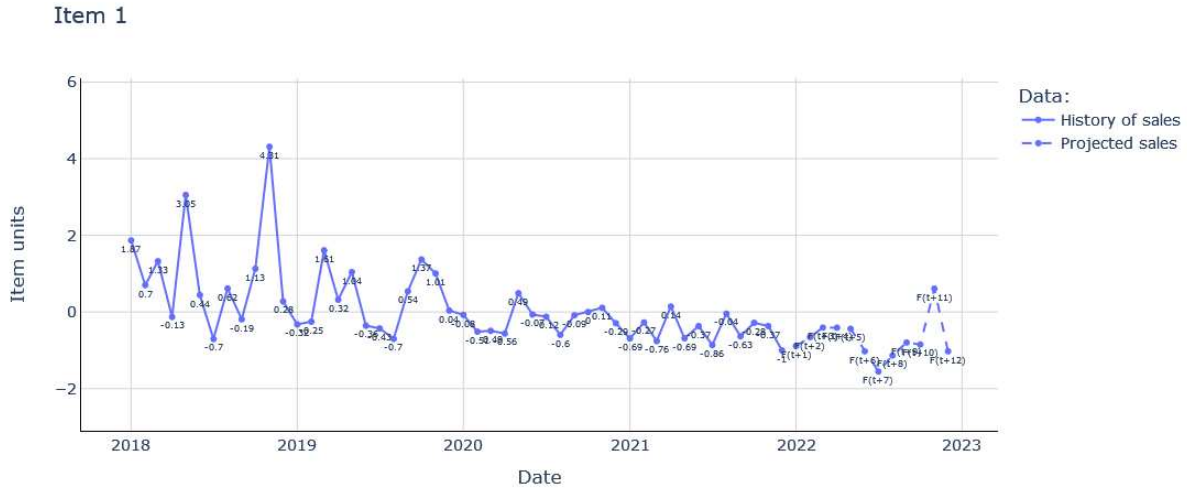


Figure 7.2: Normalized time-series for item 1 with displayed values

	hist1	hist2	hist3	hist4	hist5	hist6	hist7	hist8	hist9	hist10	hist11	hist12	$F(t+1)$
1	1.87	0.7	1.33	-0.1	3.05	0.44	-0.7	0.62	-0.2	1.13	4.31	0.28	-0.32
2	0.7	1.33	-0.1	3.05	0.44	-0.7	0.62	-0.2	1.13	4.31	0.28	-0.32	-0.25
3	1.33	-0.1	3.05	0.44	-0.7	0.62	-0.2	1.13	4.31	0.28	-0.32	-0.25	1.61
4	-0.1	3.05	0.44	-0.7	0.62	-0.2	1.13	4.31	0.28	-0.32	-0.25	1.61	0.32
5	3.05	0.44	-0.7	0.62	-0.2	1.13	4.31	0.28	-0.3	-0.25	1.61	0.32	1.04

Table 7.1: Dataset created for the use of ML models based on Figure 7.2

Once the ML model was trained, it was ready to make predictions for the future. However, the ML model could only predict the next month, and the objective was to predict the next 12 months. Therefore, the predictions were resumed to predict the future. Table 7.2 shows the process of making predictions for the next 12 months. The predictions were based on a rolling window that considered a history as 12 months and predicted 1 month ahead. After completing 12 iterations of predictions, the forecasts for the next 12 months were returned and could be compared through metrics.

	hist1	hist2	hist3	hist4	hist5	hist6	hist7	hist8	hist9	hist10	hist11	hist12	F(t+1)
1	-0.69	-0.27	-0.76	0.14	-0.69	-0.37	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)
2	-0.27	-0.76	0.14	-0.69	-0.37	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)
3	-0.76	0.14	-0.69	-0.37	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)
4	0.14	-0.69	-0.37	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)
5	-0.69	-0.37	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)
6	-0.37	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)
7	-0.86	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)	F(t+7)
8	-0.04	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)	F(t+7)	F(t+8)
9	-0.63	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)	F(t+7)	F(t+8)	F(t+9)
10	-0.28	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)	F(t+7)	F(t+8)	F(t+9)	F(t+10)
11	-0.37	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)	F(t+7)	F(t+8)	F(t+9)	F(t+10)	F(t+11)
12	-1	F(t+1)	F(t+2)	F(t+3)	F(t+4)	F(t+5)	F(t+6)	F(t+7)	F(t+8)	F(t+9)	F(t+10)	F(t+11)	F(t+12)

Table 7.2: Predictions of the ML model based on a rolling window

The performances were also benchmarked by using the KAM forecasts in the same way to increase the number of experiments for training the ML model (only in Table 7.1).

7.2.4.7 Model adaptation

To fit a statistical or ML model, the data must be adapted to preserve the integrity and consistency of the time-series. The data processing, model building, and estimation of the metrics were carried out using the Python libraries Scikit-learn and Statsmodels. The model fitting was still based on data from January 2018 to December 2021. The data from January 2022 to December 2022 were set aside for evaluation of the forecasts.

Regarding the exponential smoothing model, the data were considered in a time-series format, the alpha parameter was auto-adjusted, and the series was directly given to the model.

In the SARIMA model, the data were preserved in a time-series format, and the parameters, such as p,d,q for the ARIMA model, P,D,Q, and s for the seasonality, were set based on the best AIC computed on the training set and a mapping of the previously mentioned parameters. The model with the lowest AIC was used to make the forecasts. The same method was used for SARIMAX as for SARIMA except that the exogenous values were added to the model during the training and forecasts.

The different ML models required the matrix with the history of the 12 values to forecast the next month (Table 7.1) as input. The ML models were trained by searching for the best parameters based on the training set itself, which consisted of cross validating the training

set to find the best parameters for the model. The method involved splitting the dataset into batches, also known as folds, performing the training on the number of folds minus 1 and forecasting on the one remaining fold. This process was repeated in the same number of iterations as the number of folds. In the present case, five folds for all items and all ML models were considered; hence, for every item, five iterations per parameter were mapped through different values.

For instance, the LASSO model needed to be fitted through the alpha parameter only, and the alphas to map were 0.001, 0.01, 0.1, and 1. For every parameter's value, five training rounds were required to match the quantity of folds, which resulted in 20 iterations for the four mapped values ($4 \times 5 = 20$).

The complexity increased when using the k-NN model, for which two parameters were mapped, the number of neighbors and the methods to compute the distance. The number of neighbors consisted of three values (2, 3, 5), and the distance could be Manhattan or Euclidean (1 or 2). We kept the number of folds at five. Because of the mapping of the parameters, we had six couples of parameters to test by item, which resulted in 30 iterations to select the best model ($3 \times 2 \times 5 = 30$).

For the RF, the number of parameters increased again when considering the number of trees or estimators with five values (5, 10, 15, 20, 25) to map, the maximum depth of the tree with a mapping between five values (2, 4, 6, 8, 10), the minimum number of samples required to split a node to map at three values (2, 3, 5), and the bootstrap. Bootstrapping method uses the entire dataset to train all trees at once, or the dataset is split proportionally to the number of trees so that every tree is trained with unique data. The bootstrap is mapped as two values (true or false). Based on the previous calculation, the RF needed 750 iterations to find the best parameters for the model ($5 \times 5 \times 3 \times 2 \times 5 = 750$).

Finally, the linear regression model did not need to search for the best parameters of the model because it minimized the residual sum of squares without any restrictions or constraints. The ML models could be trained with an enlarged dataset thanks to the KAM forecasts, which were added to the training set.

After finding the parameters for the ML models, the final model could be trained based on the entire training set, and the forecasts could be made as illustrated in Table 7.2. Metrics were applied to measure the performance of the models.

7.2.5 Metrics

To measure the performance of the models, RMSE, MAE, and RS have been chosen as the metrics. Using RS enabled the inventory impacts to be checked, as suggested by (Teunter R.H. & Duncan L., 2017).

7.2.5.1 Root mean square error

As seen in Section 6.3, Equation (23), RMSE measures the magnitude of the error, and better models have a lower RMSE (Bakay M.S. & Agbulut U., 2021). Equation (23) is given as follows:

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}} \quad (23)$$

Where n is the number of data points or observations, y_i is the observed values (test set), and $\hat{y}_i$ is the predicted values.

7.2.5.2 Mean absolute error

The MAE is the sum of the absolute residual error. The formula is as follows:

$$MAE = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \quad (34)$$

7.2.5.3 Residual stock

Residual stock measures whether the forecasts are too optimistic (high stock level) or pessimistic (OOS) (Ramosaj A., et al., 2022). The formula is in Section 6.3 and is repeated as follows:

$$RS = \sum_{i=1}^n (\hat{y}_i - y_i) \quad (24)$$

$\hat{y}_i > y_i$ yields a too optimistic forecast, whereas $\hat{y}_i < y_i$ yields a too pessimistic forecast.

7.3 Methodology

The methodology was used to define the most suitable model to forecast sales of accessories. The dataset was composed of 27 items with the weekly sales from 2018 to 2023 for every item. However, three items were end of life (EOL), which meant the company was selling the remaining stock, and would not order them anymore. Therefore, those items were excluded from the dataset. Of the remaining 24 items, 11 showed large accuracy impacts, because they were seasonally driven, had high volatility, or for another reason. The KAM forecasts were either too optimistic or too pessimistic.

The methodology started with the raw data, which were divided into two subsets: the monthly sales and the KAM forecasts. These subsets were grouped by items and months to create a monthly time-series for every item. Then, every sales time-series was standardized, and the computed mean (μ) and the computed standard deviation (σ) of the defined item were reused to standardize the equal item with the KAM forecasts.

Once the standardization was complete, the time-series were split into two subsets. The first contained the sales values used to fit the model, and the second consisted of the last 12 sales values, which helped compute the metrics. The KAM values were also split into the data used for the fitting and the data used computation of the metrics. This process resulted in two subsets, called the train set and test set, for the sales and KAM forecasts.

The train set of sales was used with most of the model categories (exponential smoothing, SARIMA, SARIMAX, ML, and ML with KAM) to fit the model to make predictions for the next 12 months. These predictions were compared to the real sales from the last 12 months, or the test set of sales, using the two metrics of the RMSE and MAE. The third metric, RS, was used at the end to compare the RS of the KAM with the best selected model. The train set of the KAM could also be used with specific model categories, such as SARIMAX and ML, with the KAM predictions. The test set of the KAM was used to measure the error between sales and KAM forecasts over the last 12 months. All RMSE and MAE results were collected to compute the average and median for each item through the errors of the statistical and ML models. This step defined the selection criteria for a model to make acceptable predictions for the time-series. The count by statistical and ML models was plotted with a histogram. The most suitable models were those that were more accurate than the KAM forecasts for each criterion, and they were ranked by largest occurrence.

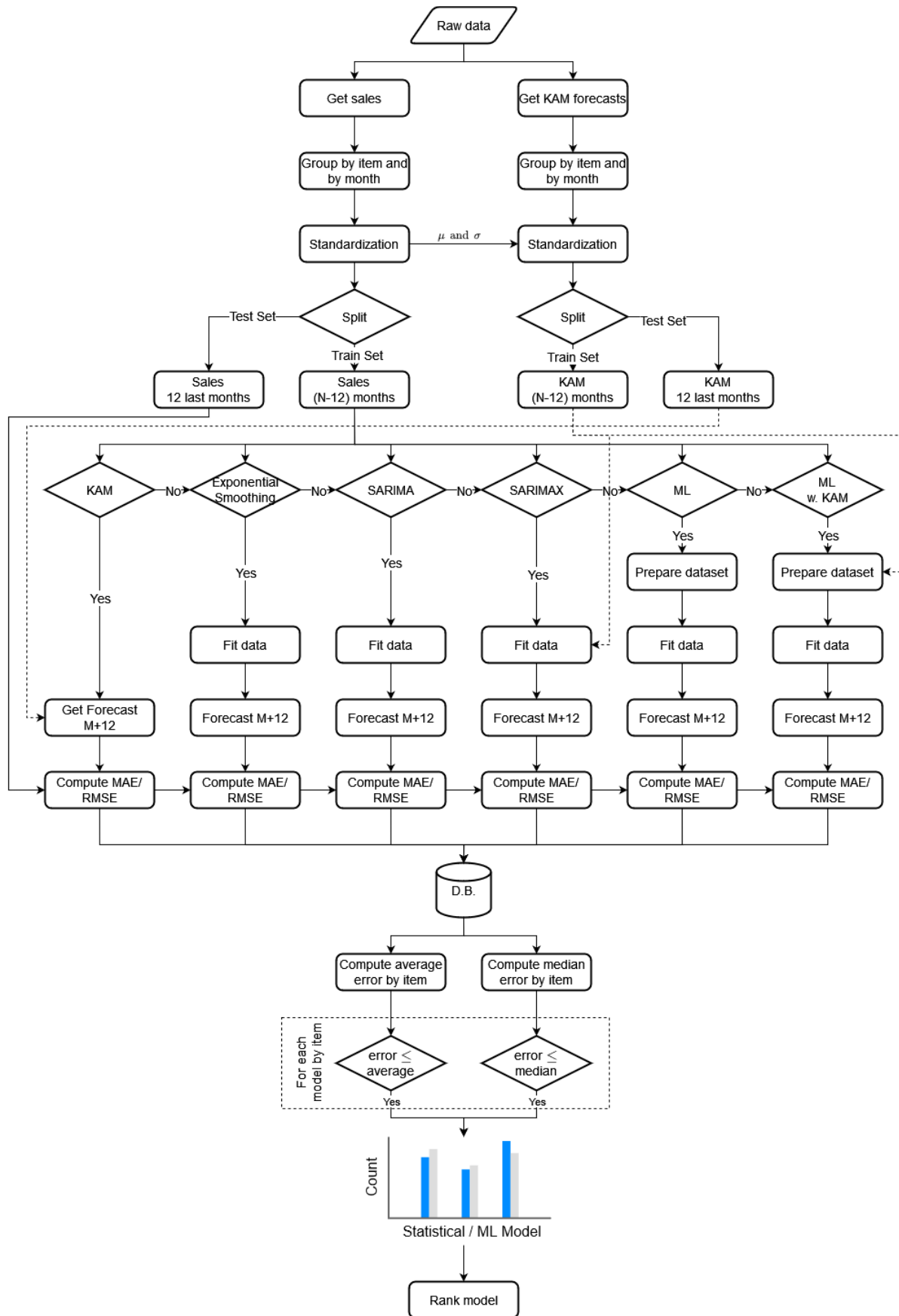


Figure 7.3: Methodology (designed by the author)

7.4 Results

The results are presented in the following sections in order of the steps of the development.

The following explanations are given for the differences between MAE and RMSE:

- RMSE gives more weight to large values; ability to handle outliers.
- MAE treats errors equally; unsensitivity to outliers.
- RMSE and MAE are interpretable and have same unit as the data.
- Lower RMSE and MAE indicate a better fit of the model.

The first step of the methodology was to obtain the sales and KAM forecasts from the raw data and represent them by months. Figure 7.4 contains an example of the sales and KAM forecasts represented as a time-series.

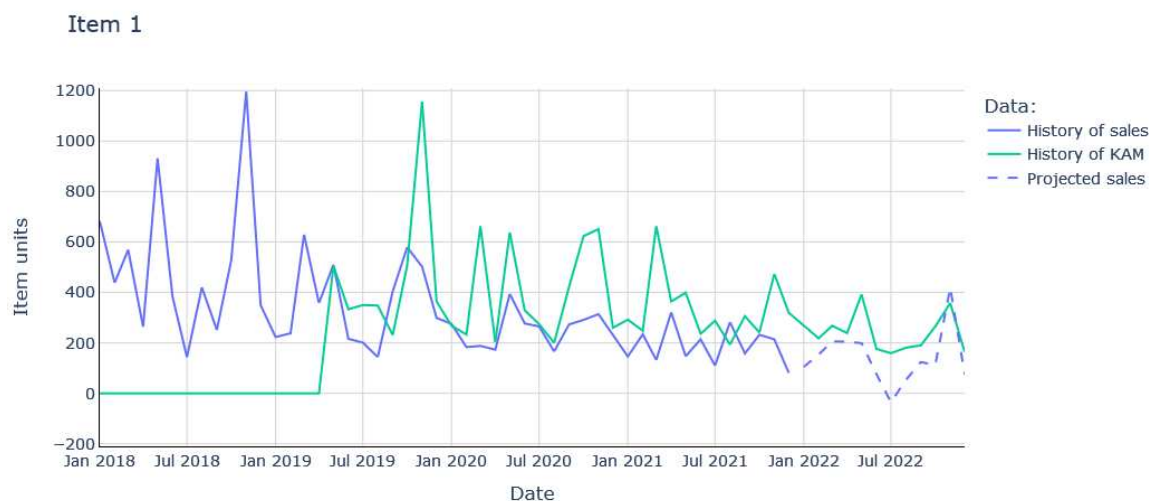


Figure 7.4: Presentation of the sales and KAM forecasts as a time-series

Once the time-series for sales and KAM forecasts were formed, the sales values were standardized for every item individually. The mean (μ) and standard deviation (σ) of each item were also used to standardize the same item with the KAM forecasts. Figure 7.5 shows the standardization of the sales and KAM forecasts illustrated in Figure 7.4. The standardization allowed for retaining the distribution of the data and for bringing the mean to 0 and the standard deviation to 1. The forecasts are in the same layout in Figure 7.4 and Figure 7.5; the difference is that the data were processed on a common scale.

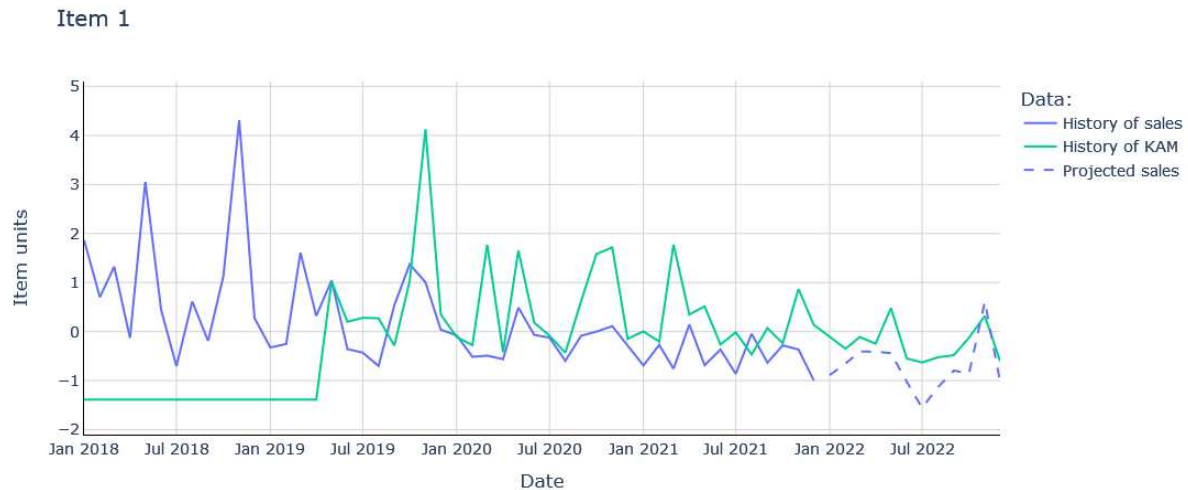


Figure 7.5: Standardization of the sales and KAM forecasts

After the statistical and ML models were performed and the error was computed, the count of models with an error less than or equal to the selection criteria was presented. The maximum value of counts was 24.

Of the 16 models, 13 performed better than or as well as the KAM with the average criterion (Figure 7.6), and 14 performed better than the KAM with the median criterion (Figure 7.7) with the MAE metric. Additionally, 15 models performed better than the KAM with the average criterion (Figure 7.8) and the median criterion (Figure 7.9) with the RMSE metric.

The models that demonstrated better performance than the KAM forecasts were deemed the most suitable models. These were the SARIMAX model coupled with the monthly mean of the KAM forecasts, the SARIMAX model associated with the last year of the KAM forecasts, and the SARIMAX model without exogenous values regarding the MAE metric. With respect to the RMSE metric, all models presented an acceptable performance with the exception of the SARIMAX model with the average of the monthly sales as exogenous values.

As shown in Figure 7.6, where the average of the MAE by item was the selection criterion, nearly all models gave predictions that were better than the KAM forecasts. Only the exponential smoothing model and SARIMAX models with the average of the monthly sales were globally less accurate than the KAM forecasts. The model that was generally better than the KAM forecasts in most cases was the SARIMAX model with KAM forecasts for the last 12 months.

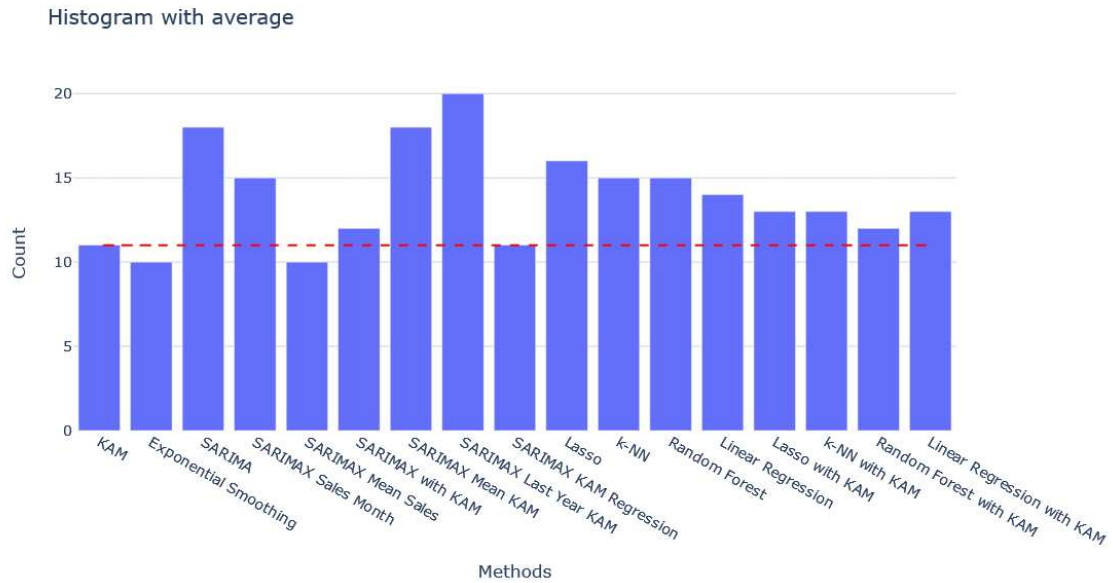


Figure 7.6: Histogram of the best statistical and ML models relative to the KAM count (red dashed line) based on the average of the MAE by item

When using the MAE median by item as the selection criterion, as illustrated in Figure 7.7, almost all models presented better or equivalent predictions relative to KAM forecasts. The exceptions were the SARIMAX models with the average of the monthly sales and the SARIMAX models with the KAM forecasts fitted through linear regression. The model with the best performance was the SARIMAX model with the last 12 months of KAM forecasts.

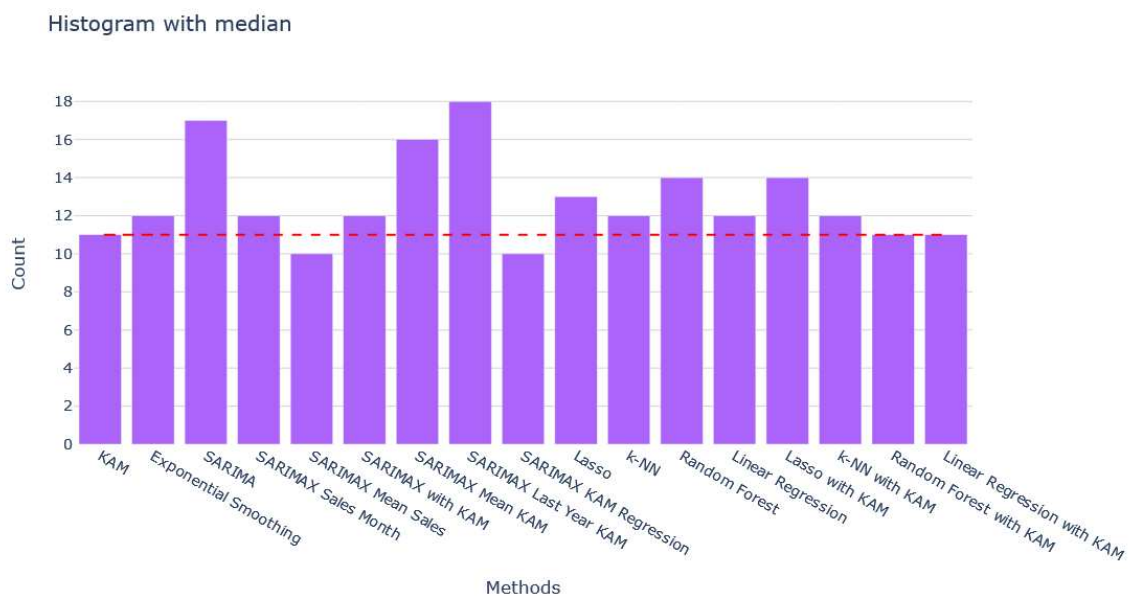


Figure 7.7: Histogram of the best statistical and ML models relative to the KAM count (red dashed line) based on the median of the MAE by item

A ranking of the statistical and ML models based on the average and median criteria was subsequently performed and highlighted the best models by criterion. Table 7.3 shows the best models by metric. The three models that performed the best were the SARIMAX model with the last 12 months of KAM forecasts, the SARIMA model, and the SARIMAX model with the average of the monthly KAM forecasts.

Rank	Based on the average criterion		Based on the median criterion	
	Model	Count	Model	Count
1	SARIMAX last year KAM	20 / 24	SARIMAX last year KAM	18 / 24
2	SARIMA	18 / 24	SARIMA	17 / 24
3	SARIMAX mean KAM	18 / 24	SARIMAX mean KAM	16 / 24

Table 7.3: Ranking of the three best models by selection criteria (average, median) and their related counts with MAE

When considering the average of the RMSE by item as the selection criterion (Figure 7.8), almost all models produced better forecasts than the KAM forecasts. Only the SARIMAX model with the average of the monthly sales was globally less accurate than the KAM forecasts. The models that were generally better than the KAM in most cases, were the SARIMAX model with the last 12 months' KAM forecasts and the SARIMAX model with the average of the monthly forecasts.

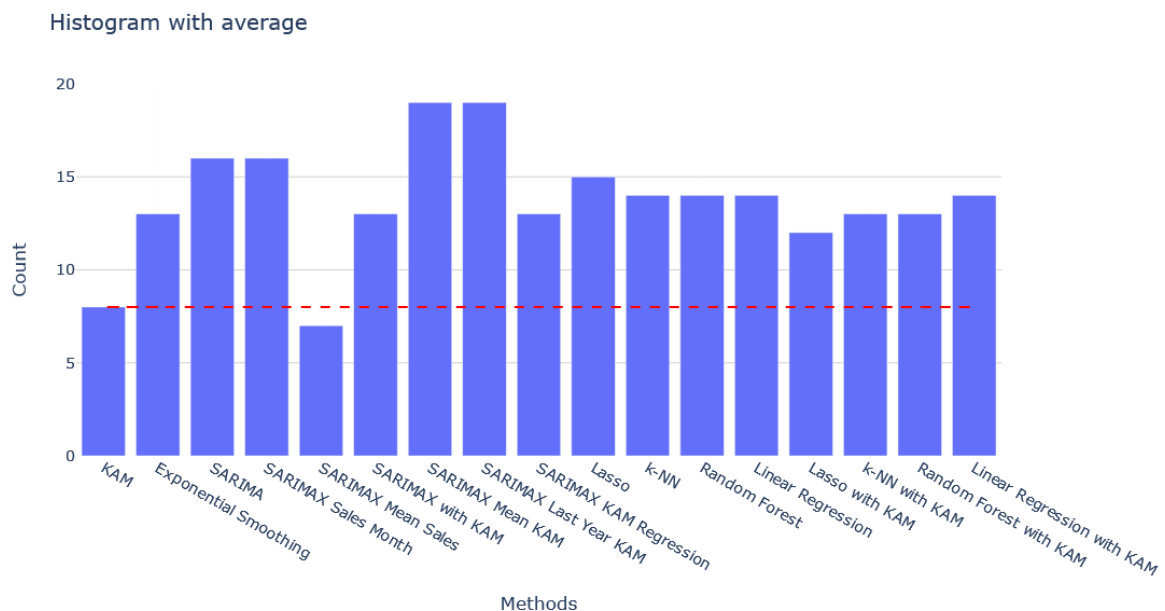


Figure 7.8: Histogram of the best statistical and ML models relative to the KAM count (red dashed line) based on the average of the RMSE by item

Figure 7.9 shows the RMSE median by item as the selection criterion. All models presented predictions that were better than or equal to the KAM forecasts. The top-performing model was the SARIMAX model with the average of the monthly KAM forecasts.

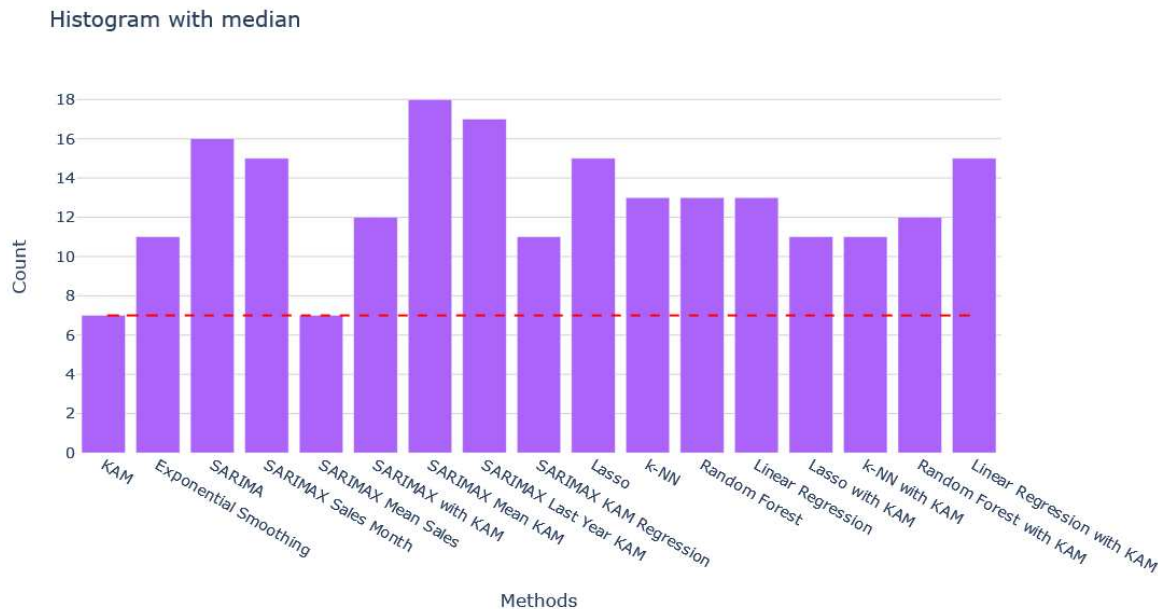


Figure 7.9: Histogram of the best statistical and ML models relative to the KAM count (red dashed line) based on the median of the RMSE by item

The ranking for the metric RMSE indicated that the three best models were the SARIMAX model with the average of the monthly KAM forecasts, the SARIMAX model with the last 12 months of KAM forecasts, and the SARIMA model with the average and median criteria. Table 7.4 shows the ranking and number of occurrences.

Rank	Based on the average criterion		Based on the median criterion	
	Model	Count	Model	Count
1	SARIMAX mean KAM	18 / 24	SARIMAX mean KAM	18 / 24
2	SARIMAX last year KAM	18 / 24	SARIMAX last year KAM	17 / 24
3	SARIMA	16 / 24	SARIMA	16 / 24

Table 7.4: Ranking of the three best models by selection criteria (average, median) and their related counts with the RMSE

Overall, the most suitable models for forecasting the next 12 months for all items by using a single type of statistical or ML model remained the SARIMAX model with the last 12 months of KAM forecasts as exogenous values, the SARIMAX model with the average of

the monthly KAM forecasts as exogenous values, and the SARIMA model. These models presented better forecasts than the other models based on the presented method of analysis by giving an overall reduced MAE. Thus, they demonstrated a reduction in prediction errors and an ability to handle outliers well with a higher reduction of the RMSE compared to the other models.

To confirm the suitability of these models, RS was used with different items presented during the test period for which the KAM forecasts were made one year ago, and the last 12 month of sales were registered. A typical result is shown in Figure 7.10, where the red line represents the limit to avoid an OOS situation. Considering the RS of the KAM forecasts on 01.01.2022 without knowing the sales for the year 2022, the RS of the SME would have increased by 1184 units, whereas the statistical model would have increased the RS by only 585 units. Moreover, there would have been no stock shortages.



Figure 7.10: Residual stock for “item 1” by comparing the RS with the KAM forecasts vs. the statistical model SARIMAX with the 12 last months of KAM forecasts as an exogenous value

Finally, the RS after 12 months by considering the KAM forecasts only or by using a statistical model was reported, as illustrated in Figure 7.11. The RS showed that the results when using the 12 months of KAM forecasts as an exogenous value were better 16 over 24 times. It was also observed that the statistical model would reduce the forecasting error when the KAM was too extreme.

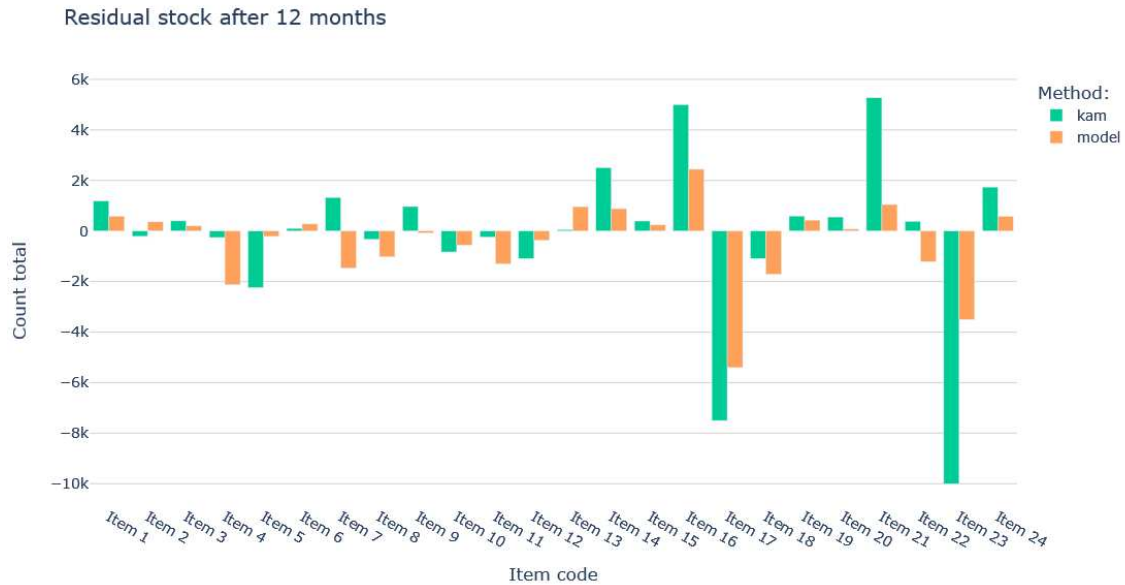


Figure 7.11: Residual stock for all items after 12 months when considering the KAM forecasts for the next 12 months of operation or considering the statistical model SARIMAX with the last 12 months of KAM forecasts as an exogenous value

The same analysis could be made for the SARIMAX model with the average of the monthly KAM forecasts as an exogenous value. This solution also presented better RS for many items but tended to be more pessimistic and deliver negative stock in the long-term, thus posing the risk of stock shortages. Figure 7.12 presents the RS of item 1. The RS stays in a range of 40 to 318 units through the months for the statistical model opposite to the KAM forecasts, which reflect a continuous increase in stock level. The red line represents the limit to avoid an OOS situation.



Figure 7.12: Residual stock for "item 1" by comparing the RS with the KAM forecasts vs. the statistical model SARIMAX with the average of the monthly KAM forecasts as an exogenous value

Considering all items and the RS after 12 months, as reported in Figure 7.13, it emerged that 14 out of 24 forecasts made with the statistical model yielded better results than the KAM forecasts. It was observed that the statistical model SARIMAX with the average of the monthly KAM forecasts increased the risk of a stock shortage.

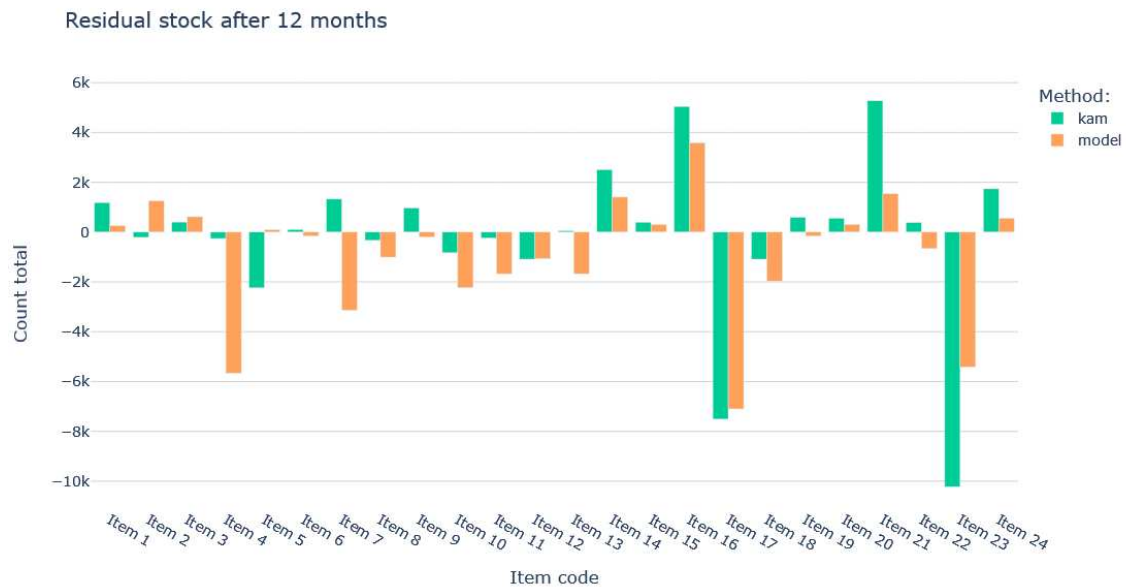


Figure 7.13: Residual stock for all items after 12 months when considering the KAM forecasts for the next 12 months of operation or considering the statistical model SARIMAX with the average of the monthly KAM forecasts as an exogenous value

Finally, the analysis was made with the SARIMA model. This model showed poor RS because it tended to deliver negative stock during the evaluated period, which would risk a stock shortage. Figure 7.14 presents the RS of item 1. The RS stays in a range of -92 to 240 units through the months for the statistical model (orange), which implies good accuracy but also some risk. The green line represents the KAM forecasts, which indicate continuous growth in the stock. The red line represents the limit to avoid an OOS situation.

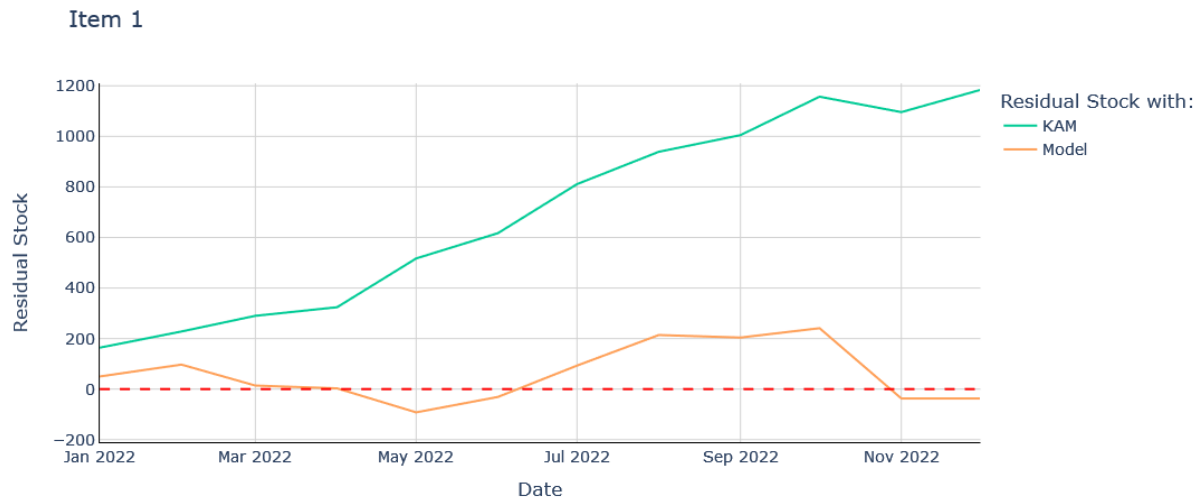


Figure 7.14: Residual stock for “item 1” by comparing the RS with the KAM forecasts vs. the statistical model SARIMA

When considering all items and examining the RS after 12 months, as shown in Figure 7.15, 14 of the 24 forecasts produced with the statistical model outperformed the KAM forecasts in terms of accuracy. However, the statistical model SARIMA posed a large risk of stock shortage.



Figure 7.15: Residual stock for all items after 12 months when considering the KAM forecasts for the 12 next months of operation or considering the statistical model

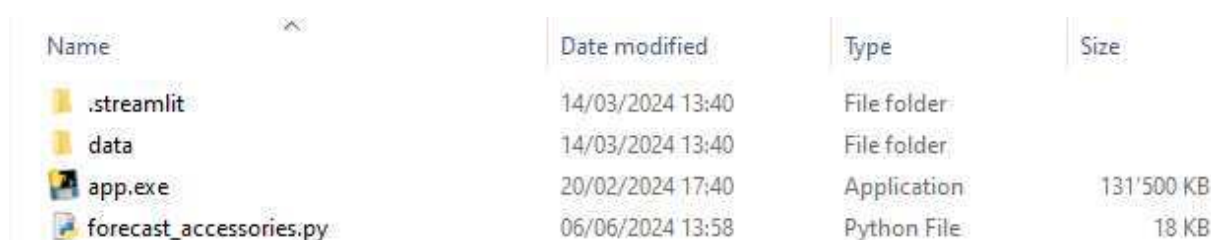
In general, the SARIMAX model with the last 12 months of KAM forecasts as an exogenous value was the most suitable for the provided dataset of accessories. The model would improve the forecasts for 2022 for 16 of the 24 items, and the risk of stock shortage would be present for only 10 items, which is equivalent to the risk when considering only the KAM forecasts. SARIMA and SARIMAX models with the monthly average of the KAM forecasts models created a higher risk of OOS for the company. In the long-term, the RS could be useful for defining the safety stock needed for each item. The RS seemed to stabilize after a few months, as shown in Figure 7.12.

7.5 Real application

This application is similar to the one proposed in Section 6.5. The previous Chapter focused on improving forecasts for finished products, whereas this Chapter analyzes the best methods for improving forecasts for accessories. The accuracy of finished products was improved first since stock shortages for finished products have a greater impact on the company. In its final stage, this project sought to improve forecasts for accessories as well. The tool created for this purpose, as mentioned in Section 6.5, would be easy for the company to implement and use in its daily business.

7.5.1 Environment preparation and start

The visualization tool for forecasting accessories was written in Python. It uses a standalone executable that embeds useful libraries to compute the forecast. The installation folder contains the document, as shown in Figure 7.16 and can be placed anywhere.



Name	Date modified	Type	Size
.streamlit	14/03/2024 13:40	File folder	
data	14/03/2024 13:40	File folder	
app.exe	20/02/2024 17:40	Application	131'500 KB
forecast_accessories.py	06/06/2024 13:58	Python File	18 KB

Figure 7.16 : Directory of the application to forecast accessories

The .streamlit folder contains the settings to launch the visualization, the data folder contains the related sales and forecasts, app.exe is the executable to launch by double-clicking on it, and forecast_accessories.py is the toolbox to compute the forecasts. Only the data folder can be edited by adding some files of data.

7.5.2 Starting the application

Double-clicking on app.exe starts the application. A shortcut can be created by right-clicking on app.exe and selecting the option to create a shortcut.

Once the application has been launched, a terminal window opens. After a few seconds, the web browser opens a new tab with the application, as seen in Figure 7.17.

A .csv file can be opened by clicking the Browse files button. Windows Explorer opens and makes it possible to navigate to the desired file.



Figure 7.17 : Start page of the accessory forecasting application

7.5.3 Main page of the application

Figure 7.18. displays the main page of the application once a file has been loaded. The banner allows for editing the types of accessories, and the canvas displays the main information about the forecasts.

The banner makes it possible to filter by accessory subtype (e.g., Subtype1, Subtype2, Subtype 3), warehouse (War1, War2, War3), and business (e.g., Market 1, Market 2, Market 3). After setting the filter for the subtype, an item code can be associated. The Auto SARIMA button activates the algorithm to find the best parameters for predicting the sales.

The canvas displays a dynamic graph to represent the data (Sales, KAM Forecasts, and SARIMA forecasts). It is possible to zoom or filter the data. If the forecasts are validated, the Save

forecast button can be pressed, and another item can be analyzed. The Data Description section shows a table of statistics for the item with the mean, median, standard deviation, and sum for the different years. Finally, the Download data as CSV button can be clicked to export the forecasted data to the Downloads folder.

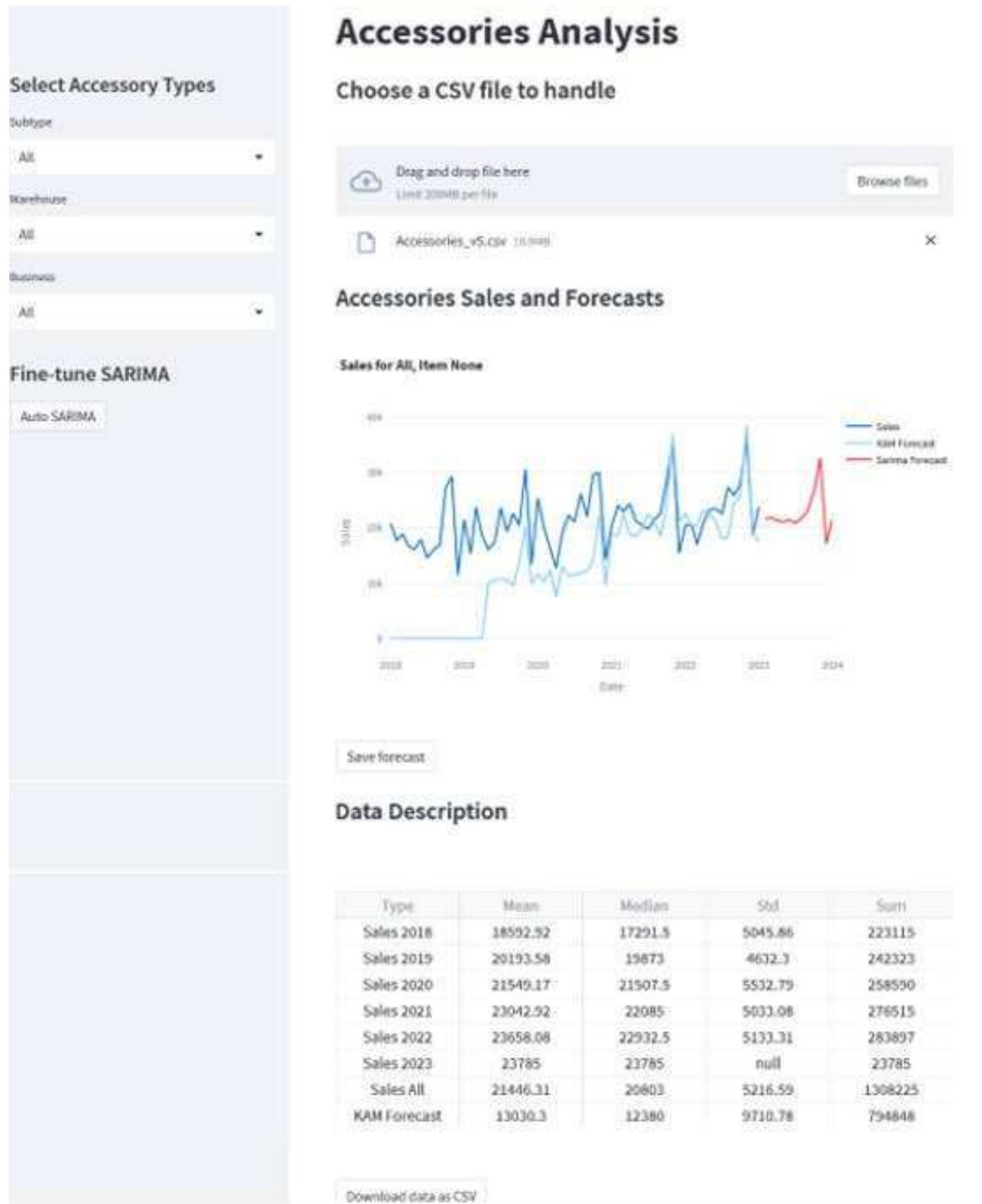


Figure 7.18 : Main overview

7.5.4 Saving forecasts

To make a forecast, parameters must be set on the banner, as illustrated in Figure 7.19. In this example, four aspects are circled: (1.) Subtype1 was chosen as the subtype, (2.) the item code 898.142.0001 was selected, (3.) the Auto SARIMA has been pressed, and (4.) the forecasts have been saved with the Save forecast button.

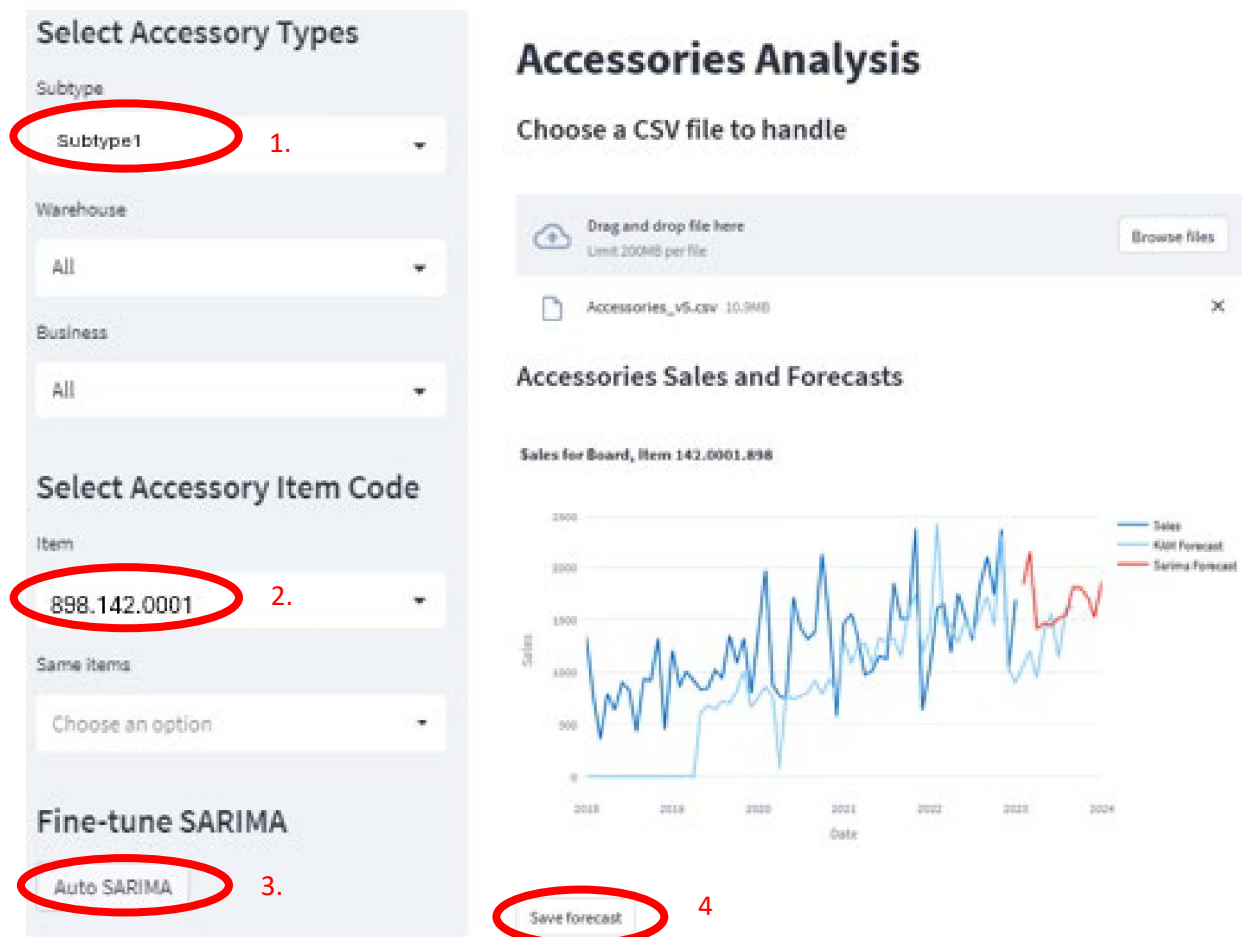


Figure 7.19 : Options for making forecasts

After generating the forecasts, the data can be exported by clicking the Download data as CSV button. The exported data are saved to the Downloads folder on the computer, where they appear as a file called accessories.csv. The new data can be found by opening this file and scrolling to the end, as presented in Figure 7.20.

index	Measure	Segment	Type	Date Conc	Date	Country	WHSE SHL	Business	YEAR	Month	ITEM CODE	ITEM_DESI	Q TOTAL
63150	SARIMA	Purchased	Accessory	juil.23	juil.23	Switzerland	All	All	2023	July	898.142.0001	Subtype1	1429
63151	SARIMA	Purchased	Accessory	Aug-23	Aug-23	Switzerland	All	All	2023	August	898.142.0001	Subtype1	1558
63152	SARIMA	Purchased	Accessory	sept.23	sept.23	Switzerland	All	All	2023	September	898.142.0001	Subtype1	1861
63153	SARIMA	Purchased	Accessory	oct.23	oct.23	Switzerland	All	All	2023	October	898.142.0001	Subtype1	1533
63154	SARIMA	Purchased	Accessory	nov.23	nov.23	Switzerland	All	All	2023	November	898.142.0001	Subtype1	1940
63155	SARIMA	Purchased	Accessory	Dec-23	Dec-23	Switzerland	All	All	2023	December	898.142.0001	Subtype1	1177
63156	SARIMA	Purchased	Accessory	janv.24	janv.24	Switzerland	All	All	2024	January	898.142.0001	Subtype1	1456
63157	SARIMA	Purchased	Accessory	Feb-24	Feb-24	Switzerland	All	All	2024	February	898.142.0001	Subtype1	1878
63158	SARIMA	Purchased	Accessory	mars.24	mars.24	Switzerland	All	All	2024	March	898.142.0001	Subtype1	1669
63159	SARIMA	Purchased	Accessory	Apr-24	Apr-24	Switzerland	All	All	2024	April	898.142.0001	Subtype1	1343
63160	SARIMA	Purchased	Accessory	May-24	May-24	Switzerland	All	All	2024	May	898.142.0001	Subtype1	1393
63161	SARIMA	Purchased	Accessory	juin.24	juin.24	Switzerland	All	All	2024	June	898.142.0001	Subtype1	1491

Figure 7.20 : Data in the file accessories.csv

7.6 Conclusion

This Chapter has detailed the testing of multiple methods. The results demonstrate that the company's forecasting is not completely independent of human factors. Therefore, like in Chapter 6, the human factor was combined with the best tested methods. The statistical models were generally found to perform better than ML models for accessory forecasts. Of the 16 models that were tested, 13 performed better than the KAM forecasts. The most suitable models that outperformed the KAM forecasts were the SARIMAX model coupled with the monthly mean of the KAM forecasts, the SARIMAX model associated with the last year of KAM forecasts, and the SARIMAX model without exogenous values regarding the MAE and RMSE metrics.

Residual stock helped measure the remaining stock of the best selected model compared to the KAM forecasts. It was noted that the KAM forecasts were always more optimistic than the forecasts of the models; therefore, they would result in excessively high stock levels, which would increase additional costs. Since it was observed that the RS stabilized after a few months when applying a statistical model to the forecasts, RS could also help the company define safety stocks.

8 Validation

8.1 Introduction

As seen in previous chapters, sales forecasts have a major influence on the management of a company. However, a forecast is only useful if it is reliable and relevant. Long-term forecasting presents several challenges. First, there is a great deal of uncertainty linked to the evolution of economic, social, and technological variables. Forecasting methods need to be adapted to account for seasonal trends, changes in consumer behavior, and unforeseen events, such as economic crises or supply problems. Indeed, the studied SME faced several supply issues due to the COVID-19 pandemic in 2020 and the start of the war in Ukraine in 2022.

As demonstrated in Chapter 2, good communication and information exchange are essential. Chapters 5, 6, and 7 presented different methods for improving the company's sales forecasts for final products and accessories. The methods were observed and validated over time. The previous chapters showed that the improvement of forecast accuracy is not completely independent of the human factor, as also suggested by (Ramosaj A., et al., 2024). In this context, this chapter discusses the validation of the best methods for the company's product ranges. This validation was carried out over a 12-month period and was crucial to ensure that forecasts are realistic and adaptable to changing market conditions. By comparing the generated forecasts with actual observed data, we were able to assess the models' accuracy and detect biases or systematic errors.

8.2 Methodology and metric

To validate the models proposed in Chapters 6 and 7, a comparison was done between the qualitative method used by the company through the KAMs' incentives and the quantitative methods of the top-performing models. The validation entailed a process repeated at the beginning of each month over the validation period. Figure 8.1 illustrates the ongoing tasks that were carried out each month to obtain the key information in this process, which is shown in the example in Table 8.1. These tasks consisted of (1) reporting the real sales of the previous month to use as a basis for the next forecast, (2) obtaining the KAM forecasts (qualitative

method) for the same period in the next year, which gave the trend for the next forecasts, and (3) applying the forecasts with the selected model. To validate the model, the operation was repeated over 12 months, and the FVA seen in Chapter 5 was applied to evaluate the performance and stability of the model over time. The formula for the FVA is presented in Equation (12), Section 5.5 and repeated below:

$$FVA = \varepsilon_{quali} - \varepsilon_{quanti} \quad (12)$$

where ε_{quali} is the forecast error with the qualitative method, calculated with the relative absolute error as $(RAE) = \left| \frac{\text{Qualitative forecast} - \text{Real sales}}{\text{Real sales}} \right|$,

And ε_{quanti} is the forecast error with the quantitative method, calculated with the relative absolute error as $(RAE) = \left| \frac{\text{Quantitative forecast} - \text{Real sales}}{\text{Real sales}} \right|$.

The FVA quantifies the improvement (or deterioration) brought about by a specific intervention in the forecasting process—in this case, by a comparison between the qualitative forecasts of the KAMs and the best quantitative method that was tested. If the FVA was greater than 0, the tested methods improved the forecasts; if it was lower than 0, it deteriorated the forecasts. As seen in Section 5.5, this metric focuses on the forecasting process and its contributions (Gilliland M., 2013).

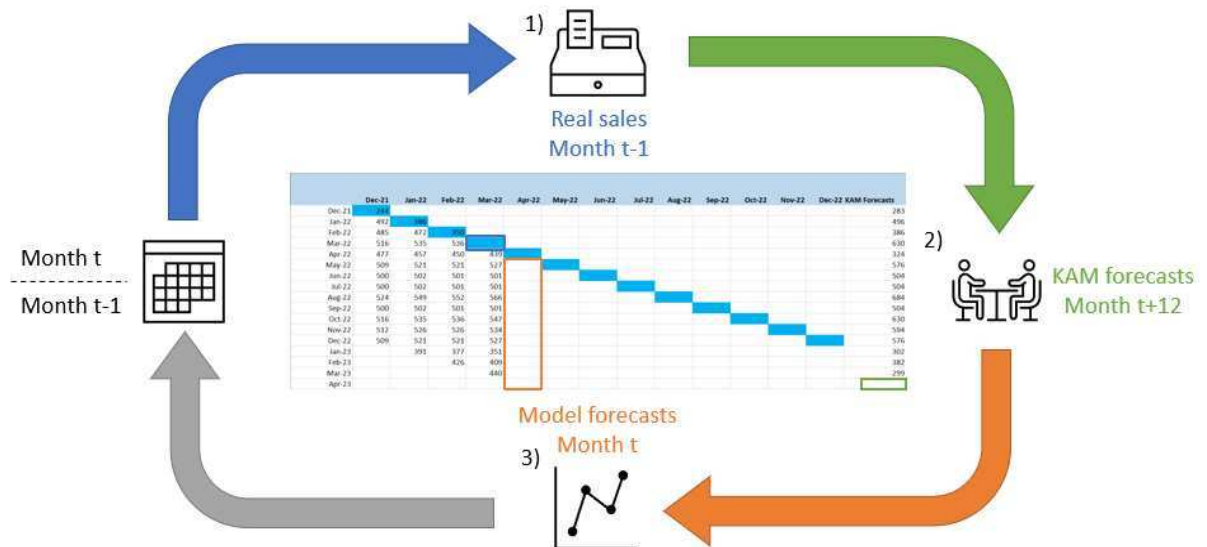


Figure 8.1: Validation process methodology (designed by the author)

8.3 Model validation for final products

As demonstrated in Chapter 6, several forecasting methods for final products were tested on 150 SKUs in the 50 markets in which the company is active. The two methods giving the best results were SARIMA and LSTM (Section 6.4.4.5). Data from 2018 to 2020 were used for the train set, and data from 2021 were used for the test set. The best model, LSTM, was tested again for the following years, 2022 and 2023, to observe if it still yielded better results compared to the KAM forecasts.

The aim of generating the comparative tables (Table 8.1 to Table 8.4) was to compare the accuracy of the forecasting methods (qualitative, based on KAM's incentives, and LSTM) for each product. To this end, the FVA was calculated for each month. If the FVA was positive, the forecasts were improved by LSTM compared to KAM forecasts; if the FVA was negative, the forecasts deteriorated.

The FVA revealed that LSTM significantly improved the forecasts for all 150 SKUs. To demonstrate this improvement, four volatile products were selected from the various markets (Table 8.1 to Table 8.4). In the comparative tables, the actual sales are identified in blue. The KAM forecasts are displayed in KAM Forecasts column, and the LSTM forecasts are given to the left of the actual sales.

For the first product, the FVA was positive in all months but September (-1%), and the best improvement was 39% (Table 8.1). For the second product, the FVA was negative in February 2022 (Table 8.2). It seems that the company had negative sales that month. Negative sales are only possible when customers return goods, which is difficult to predict, even with the best models. For the same product, there was an improvement of 1064% in April 2022, which confirms that LSTM gave better results overall compared to the qualitative forecasts from the KAMs. For the third product, the FVA remained positive, with an improvement of up to 333% in July 2022 (Table 8.3). The FVA also remained positive for the fourth product, with an improvement of up to 83% in May 2022 (Table 8.4).

It is clear from this analysis that the LSTM model improved final product forecasts for this company over time. It is therefore a useful tool if the company wishes to move from the third stage to the fourth stage of S&OP (Table 2.6).

Months	Dec.2021	Jan.2022	Feb.2022	Mar.2022	Apr.2022	May.2022	Jun.2022	Jul.2022	Aug.2022	Sep.2022	Oct.2022	Nov.2022	Dec.2022	KAM Forecasts	Forecast error with Qualitative method	Forecast error with LSTM	FVA
January 2022	492	386												496	28%	27%	1%
February 2022		372	350											386	10%	6%	4%
March 2022			536	238										630	165%	125%	39%
April 2022				319	229									324	41%	39%	2%
May 2022					512	339								576	70%	51%	19%
June 2022						498	296							504	70%	68%	2%
July 2022							501	207						504	143%	142%	1%
August 2022								597	482					684	42%	24%	18%
September 2022									508	282				504	79%	80%	-1%
October 2022										578	484			630	30%	19%	11%
November 2022											552	495		594	20%	12%	8%
December 2022												529	152	576	279%	248%	31%

Table 8.1: First product, item number 756.000.0333

Months	Dec.2021	Jan.2022	Feb.2022	Mar.2022	Apr.2022	May.2022	Jun.2022	Jul.2022	Aug.2022	Sep.2022	Oct.2022	Nov.2022	Dec.2022	KAM Forecasts	Forecast error with Qualitative method	Forecast error with LSTM	FVA
January 2022	198	95												284	199%	108%	91%
February 2022		189	-16											257	-1706%	-1281%	-425%
March 2022			174	190										264	39%	8%	31%
April 2022				191	11									308	2700%	1636%	1064%
May 2022					183	13								264	1931%	1308%	623%
June 2022						119	16							132	725%	644%	81%
July 2022							116	104						132	27%	12%	15%
August 2022								189	114					264	132%	66%	66%
September 2022									312	361				308	15%	14%	1%
October 2022										333	323			308	5%	3%	2%
November 2022											320	380		308	19%	16%	3%
December 2022												176	385	176	54%	54%	0%

Table 8.2: Second product, item number 501.000.0104

Months	Dec.2021	Jan.2022	Feb.2022	Mar.2022	Apr.2022	May.2022	Jun.2022	Jul.2022	Aug.2022	Sep.2022	Oct.2022	Nov.2022	Dec.2022	KAM Forecasts	Forecast error with Qualitative method	Forecast error with LSTM	FVA
January 2022	109	24												113	371%	354%	17%
February 2022		100	33											144	336%	203%	133%
March 2022			100	27										144	433%	270%	163%
April 2022				26	34									0	100%	24%	76%
May 2022					71	127								234	84%	44%	40%
June 2022						130	74							0	100%	76%	24%
July 2022							96	9						126	1300%	967%	333%
August 2022								94	24					126	425%	292%	133%
September 2022									110	96				0	100%	15%	85%
October 2022										102	96			126	31%	6%	25%
November 2022											243	274		234	15%	11%	3%
December 2022												113	72	126	75%	57%	18%

Table 8.3: Third product, item number 810.000.0103

Months	Dec.2021	Jan.2022	Feb.2022	Mar.2022	Apr.2022	May.2022	Jun.2022	Jul.2022	Aug.2022	Sep.2022	Oct.2022	Nov.2022	Dec.2022	KAM Forecasts	Forecast error with Qualitative method	Forecast error with LSTM	FVA
January 2022	165	158												150	5%	4%	1%
February 2022		166	103											178	73%	61%	12%
March 2022			205	193										264	37%	6%	31%
April 2022				214	212									264	25%	1%	24%
May 2022					286	186								440	137%	54%	83%
June 2022						265	271							264	3%	2%	0%
July 2022							84	77						132	71%	9%	62%
August 2022								292	280					264	6%	4%	1%
September 2022									161	455				132	71%	65%	6%
October 2022										329	201			440	119%	64%	55%
November 2022											165	187		264	41%	12%	29%
December 2022												131	112	132	18%	17%	1%

Table 8.4: Fourth product, item number 511.000.0103

8.4 Model validation for accessories

As seen in Chapter 7, SARIMAX (SARIMA with the exogenous value of the last 12 months of KAM predictions) gave the best results for forecasting accessory sales. Data from the years 2018 to 2021 were used as the train set, and data from 2022 were used as the test set. This section presents a validation of this method for 2023. As noted, the 24 accessories were sold in 50 different markets.

The aim of generating the comparative tables (Table 8.5 to Table 8.8) was to compare the accuracy of the forecasting methods (qualitative, based on the KAMs' incentives, and SARIMAX) for each accessory. To this end, the FVA was calculated for each month. When the FVA was positive, the forecasts were improved with SARIMAX compared to the KAM forecasts; when the FVA was negative, the forecasts deteriorated.

To demonstrate the improvement, 4 of the 24 accessories are represented in Table 8.5 to Table 8.8. In these tables, the actual sales are identified in blue. The KAM forecasts are listed in the KAM Forecasts column, and the SARIMAX forecasts are displayed to the left of the actual sales.

For the accessory in Table 8.5, the FVA was positive for each month. The greatest improvement was 106%, and the lowest improvement was 2%. For the accessory in Table 8.6 and the accessory in Table 8.7, the FVA was always positive, with improvements of up to 70% and 149%, respectively. Such improvement was also visible for the accessory in Table 8.8, with a positive FVA of up to 77%.

Based on this validation, SARIMAX obviously remains a model that significantly improves sales forecasts for this company's accessories compared to their qualitative method (KAM forecasts).

The implementation of this SARIMAX method enable the company to go further in the S&OP stages (Table 2.6) and reach level 4 (Advanced).

8.5 Conclusion

From the validation of the methods tested for this company's products and accessories, it can be concluded that the best models presented in Chapters 6 and 7 are still relevant today. The LSTM model remains the most suitable model to apply to the final products sold by the company, although SARIMA also produced good results. The LSTM model makes possible to learn from the forecasting errors made by the KAMs and avoid replicating them. This method also seems to be effective over time. The FVA was positive in all months in every case apart from the month affected by an external factor (the return of goods). For accessories, SARIMAX (SARIMA with the KAM forecasts for the last year as an exogenous value) remains the most suitable model. The FVA was positive in every month in every case despite the observed volatility of certain accessories. As mentioned, the implementation of LSTM for final products and SARIMAX for accessories can support the company's progress through the S&OP stages (Table 2.6) to the fourth stage (advanced).

Months	Dec.2022	Jan.2023	Feb.2023	Mar.2023	Apr.2023	May.2023	Jun.2023	Jul.2023	Aug.2023	Sept.2023	Oct.2023	Nov.2023	Dec.2023	KAM Forecasts	Forecast error with Qualitative method	Forecast error with SARIMAX	F/A
January 2023	6194	5771												4698	19%	7%	11%
February 2023		5954	4628											10357	124%	29%	95%
March 2023			5669	5542										10519	90%	2%	88%
April 2023				6103	6271									12603	101%	3%	98%
May 2023					6211	5485								11836	116%	13%	103%
June 2023						6525	5304							11052	108%	23%	85%
July 2023							6479	5171						10364	100%	25%	75%
August 2023								6853	4627					11756	154%	48%	106%
September 2023									6312	5860				10808	84%	8%	77%
October 2023										7294				6917	19%	15%	4%
November 2023											8561			8511	13%	8%	5%
December 2023												8116	7549	5038	58%	56%	2%
													4980				
													3187				

Table 8.5: First accessory, item number 898.302.7800

Months	Dec.2022	Jan.2023	Feb.2023	Mar.2023	Apr.2023	May.2023	Jun.2023	Jul.2023	Aug.2023	Sept.2023	Oct.2023	Nov.2023	Dec.2023	KAM Forecasts	Forecast error with Qualitative method	Forecast error with SARIMAX	F/A
January 2023	1603	1709												898	47%	6%	41%
February 2023		1904	1023											2497	144%	86%	58%
March 2023			1724	1490										2348	58%	16%	42%
April 2023				1468	1169									2284	95%	26%	70%
May 2023					1745	1801								2891	61%	3%	57%
June 2023						1668	1776							3126	76%	6%	70%
July 2023								1542	1645					2276	38%	6%	32%
August 2023									1907	1910				3210	68%	0%	68%
September 2023										2169	1755			3256	86%	24%	62%
October 2023											1898	2120		1862	12%	10%	2%
November 2023												2469	2552	2367	7%	3%	4%
December 2023													1414	1679	53%	29%	24%
													1099				

Table 8.6: Second accessory, item number 898.142.0001

Months	Dec.2022	Jan.2023	Feb.2023	Mar.2023	Apr.2023	May.2023	Jun.2023	Jul.2023	Aug.2023	Sept.2023	Oct.2023	Nov.2023	Dec.2023	KAM Forecasts	Forecast error with Qualitative method	Forecast error with SARIMAX	FVA
January 2023	100	66												178	170%	52%	118%
February 2023		506	464											515	11%	9%	2%
March 2023			430	374										460	23%	15%	8%
April 2023				301	303									419	38%	1%	38%
May 2023					357	191								384	101%	87%	14%
June 2023						290	184							374	103%	58%	46%
July 2023							374	334						448	34%	12%	22%
August 2023								318	331					368	11%	4%	7%
September 2023									368	239				724	203%	54%	149%
October 2023										424	666			406	39%	36%	3%
November 2023											537	561		1086	94%	4%	89%
December 2023												369	332	467	41%	11%	30%

Table 8.7: Third accessory, item number 898.155.0001

Months	Dec.2022	Jan.2023	Feb.2023	Mar.2023	Apr.2023	May.2023	Jun.2023	Jul.2023	Aug.2023	Sept.2023	Oct.2023	Nov.2023	Dec.2023	KAM Forecasts	Forecast error with Qualitative method	Forecast error with SARIMAX	FVA
January 2023	894	1531												582	62%	42%	20%
February 2023		925	1031											1236	20%	10%	10%
March 2023			900	1007										1336	33%	11%	22%
April 2023				926	935									1118	20%	1%	19%
May 2023					990	814								1617	99%	22%	77%
June 2023						1503	1902							1408	26%	21%	5%
July 2023							2101	2050						2102	3%	2%	0%
August 2023								1586	1131					2146	90%	40%	50%
September 2023									1366	1365				1384	1%	0%	1%
October 2023										1458	1667			1290	23%	13%	10%
November 2023											1973	2198		1893	14%	13%	1%
December 2023												1716	1832	2020	10%	6%	4%

Table 8.8: Fourth accessory, item number 143.0001.898

9 Global Conclusion

The study carried out in this thesis was essentially concerned with improving the sales forecasts of a Swiss SME. It demonstrated that accuracy is crucial to enhance the internal management of processes and relations with various stakeholders. The two objectives defined for this work were achieved.

The first objective was to determine how to make the company aware of the need to act proactively and improve the tools it already has in place at a lower cost? A key step toward achieving this goal was for the company to strengthen collaboration between departments through the implementation of regular meetings and greater transparency in the exchange of information. In addition, the development of more automated tools can enable real-time monitoring of sales data and forecasts for support more proactive decision-making. The stages of S&OP that the SME has reached over time reflect this proactivity (Figure 2.2). At the start of the project, S&OP implementation was non-existent; by the end of the project, after six years of collaboration, the company had reached stage 3 or 4 of S&OP (Table 2.6) depending on the area. As seen in Chapter 2, the fifth and final stage of S&OP (proactive) is quite difficult for SMEs to reach because it requires significant technology investments that are sometimes not feasible for SMEs (Tuomikangas N. & Kaipia R., 2014).

Another important element for the company to consider improving and acting proactively was the change in its production strategy. While the company previously outsourced manufacturing, it switched to producing its own products in 2020. This change made it necessary to monitor accuracy more closely (Chapter 3). Accuracy improved by 30 points since the start of the project (Figure 3.4). Since 2021, the improvement has stagnated at around 54% accuracy, which is largely due to the residual impacts of the COVID-19 pandemic and the effects of the war in Ukraine, which has hindered the arrival of raw materials. Nevertheless, if the SME's accuracy for domestic devices is compared with the accuracy of similar companies, the results are positive. For example, a multinational company that is more advanced in the S&OP process had an accuracy of 44.6% in 2023 for its domestic devices,⁴ whereas the

⁴ Confidential data provided by a multinational company based in Switzerland

analyzed SME had an accuracy of 54% for the same period. Therefore, it is possible to conclude that the SME is indeed doing well.

The second objective was to determine how the SME could improve its sales forecasting. In this regard, the introduction of tools such as the stagger chart (Chapter 5), accuracy measurement, and automated customer stock tracking can definitely help (Chapter 3). The results of the analyses showed significant progress when the company used quantitative methods instead of its qualitative method based on the KAM incentives. A literature search (Chapter 4) was carried out to identify forecasting models that could be applied to the company, and the defined models were integrated into the company's stagger chart (Chapter 5). Advanced models, such as LSTM, SARIMA, and SARIMAX, gave very good results (Chapters 6 and 7). The FVA was used as a key indicator to demonstrate the added value of the quantitative models compared with the company's qualitative model over time (Chapter 8).

The improvement in forecast accuracy was more rapid in the first three years of the project, during which existing tools were automated, and S&OP was implemented. The company's various departments were made aware of the importance of exchanging information to improve accuracy. A good sales forecast is positive for all departments, which seemed to be understood by all employees.

In conclusion, the efforts deployed in this project enabled the company to achieve several S&OP milestones. The improvements contributed not only to greater accuracy but also to more proactive anticipation of production and inventory requirements. The progress in the S&OP stages provides a solid foundation for the company's future growth. Efforts to help the company consolidate its sales forecasting tools will continue even after the conclusion of this thesis, as an internal meeting is already planned to continue monitoring the tools that were put in place during the six years of fruitful collaboration on this project.

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