Development of an Improved Demand Planning Process

A Case Study at KåKå

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Abstract

Title	Development of an Improved Demand Planning Process - A Case Study at KåKå
Authors	Emma Hall & Clara Kronberg
Contribution	This thesis has been a complete elaboration between the two authors. Each author has been involved in every part of the process and contributed equally.
Supervisor	Jan Olhager, Faculty of Engineering - Lund University Malin Berghult, Project Consultant - KåKå, Project Management Office
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Background	Operations planning and control has undergone an extensive shift from an individual company focus to a complete supply chain focus which has required a new common approach for supply chain planning and control to evolve. Increasing competition and globalization has created complexity in supply chain planning and integration since it requires a new cross-functional approach. To handle such complexity and difficulties, the cross-functional planning process Sales and Operations Planning (S&OP) can be used. However, to create a successful S&OP process the first step: demand planning that creates the work base for all S&OP activities, must be performed properly. To do so, forecasting activities must provide necessary input to the demand planning phase. This study aims to identify solutions to an improved demand planning phase in order to overcome the difficulties that supply chain planning and integration implies.
Purpose	The purpose of this thesis is to improve the demand planning phase of KåKå's S&OP process to create better conditions for more efficient operations.
Research Questions	RQ1: How is the current demand planning process at KåKå designed and how does it perform? RQ2: How can bakery products be categorized, based on characteristics, to simplify the forecasting and demand planning process? RQ3: How can forecast methods be selected to fit different demand patterns?

Methodology A single case study with an abductive research approach, conducted by utilizing both quantitative and qualitative data.

Findings To summarize the findings of this thesis, the main identified issues of KåKå's demand planning process are related to forecasting and product management. The use of one single forecast method for all products along with inadequate parameters, results in poor forecast accuracy. Also, the lack of clear processes, a large product assortment and product management being performed on an individual SKU level causes difficulties for both forecasting and demand planning. To face these issues, several potential solutions were identified in the analysis. Primarily, products can be categorized for forecasting based on their demand model to be able to allocate appropriate forecast method to each group, where the methods of simpler type resulted in the most robust and accurate forecasts. Secondarily, due to different grouping purposes, products can be categorized for demand planning by utilizing an ABC-XYZ analysis. The analysis should be based on two important demand planning characteristics in order to identify critical categories.

Key words Sales & Operations Planning, Demand Planning, Forecasting, Product Categorization, Non-manufacturing, Bakery Industry

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Abbreviations

Important abbreviations for the readers understanding of this master thesis are presented below.

AE - Absolute Error

APE - Absolute Percentage Error

CoV - Coefficient of Variation

ERP - Enterprise Resource Planning

IBP - SAP Integrated Business Planning

KPI - Key Performance Indicator

MAE - Mean Absolute Error

MAPE - Mean Absolute Percentage Error

ME - Mean Error

MPE - Mean Percentage Error

MSE - Mean Squared Error

OFI - Orkla Food Ingredients

S&OP - Sales and Operations Planning

SKU - Stock Keeping Unit

WAPE - Weighted Average Percentage Error

WMAPE - Weighted Mean Absolute Percentage Error

1 Introduction

This chapter introduces the background of the master thesis, the case company and the identified problem the thesis aims to solve. Further, this chapter also presents the research purpose, questions, focus and delimitations.

1.1 Background

Over the last 50 years, operations planning and control has undergone an extensive shift from an individual focus to a supply chain focus. During the century shift, it became clear that companies could no longer compete on a global market whilst only focusing on internal operational efficiency (Olhager 2013). Instead of competition arising between companies Olhager (2013) explained that it began to arise between supply chains, which required a new common focus on supply chain planning and control.

Due to the increase in competition and globalization, supply chain planning and integration is becoming more difficult to manage. The increase creates new opportunities as well as challenges for companies to manage when aiming to integrate their evermore complex supply chains. Oliva & Watson (2011) argue that a fundamental aspect to be able to manage and plan a more complex supply chain is a well-defined cross-functional reach. However, Wagner et al. (2014) states that many companies struggle to implement such a cross-functional reach and comprehensive business plan due to a lack of standardized, structured and continuous processes that are used as the base for all future planned activities. As a consequence to the inability to align cross-functional activities and future plans, an imbalance between supply and demand may arise.

A process that is commonly used to enable a balance between supply and demand is Sales and Operations Planning (S&OP). Lapide (2007) claims S&OP to be the most ubiquitous cross-functional process since it creates a cross-functional team consisting of managers from functions such as sales & marketing, manufacturing, operations, logistics, supply chain, and procurement. S&OP is characterized as the long-term planning between the sales and operations functions (Olhager 2013; Olhager et al. 2001). The main role of the collaborative planning process is to facilitate master planning, which focuses on the supply side of an organization, and demand planning, that focuses on the customer-facing functions of an organization, as well as the flow of information between the two (Oliva & Watson 2011).

Demand planning is one of the main processes in the S&OP process and is a set of processes that enables a company to efficiently manage challenges with supply and demand in the supply chain. One of the main activities in the demand planning process is forecasting which, even though is deemed to be of great importance, is not the only activity in the process (Świerczek 2019). Other activities such as data gathering and communication of demand predictions are also performed. The main goal of demand planning is to achieve a balance between supply and demand. However, as stated by Świerczek (2019) this goal is not to be achieved through increasing sales but rather by creating superior value through a thorough understanding of market requirements and supply capacity.

1.2 Company Presentation

KåKå is a supplier of bakery ingredients and accessories that was founded in 1927 (KåKå nd). The assortment KåKå offers consists of frozen, cold and dry items, including ingredients such as flour, sugar and yeast, as well as bake-off products, beverages, service articles and much more. According to Supervisor at KåKå (2023a), KåKå distributes approximately 5 000 different stock keeping units (SKUs) to 2 500 different customers and the company's main customers are bakeries, patisseries and the bakery industry in Sweden. In addition to supplying a broad assortment of products, KåKå also offers its customers support with recipes, concept advice and marketing activities. This goes in line with their slogan: *"We are more than a supplier of products - KåKå is a partner that helps you succeed"* (KåKå nd).

KåKå currently has two main warehouses, located in Lomma and Örebro, that handle a majority of their total volume and when additional capacity is required an external warehouse in Bjuv and an additional rented warehouse in Örebro are utilized (Supervisor at KåKå 2023a). The main office is located next to the warehouse in Lomma and Supervisor at KåKå (2023a) states that this is where most of the company's 165 employees are located. One of the latest transformations in the main office is the initiation of a new Project Management Office, which runs various improvement projects in logistics.

Since 1999, KåKå is a part of the Orkla Group, which entails access to an extensive production of bakery products and ingredients (KåKå nd). Orkla is a company that supplies concept solutions and branded consumer goods with a turnover of NOK 50,4 billions and a total of 21 400 employees (Orkla nd). KåKå is divided into three different Business Areas, one of them being Orkla Food Ingredients (OFI), responsible for manufacturing, selling and distributing bakery, sweet and plant-based ingredients to the customers throughout Europe and this is the business area that KåKå belongs to (Orkla nd). In 2021, OFI's turnover reached above NOK 12 billions, whereof KåKå constituted with SEK 1 billion and a contribution margin of SEK 232 million (Supervisor at KåKå 2023c). However, Supervisor at KåKå (2023c) mentioned that the organizational structure contains one additional hierarchical level between the bakery cluster of OFI and KåKå. This is the business unit group called KåKå Group that consists of three different individual companies, whereof KåKå is one. The complete organizational structure, from Orkla and all the way down to KåKå, is summarised in Figure 1.

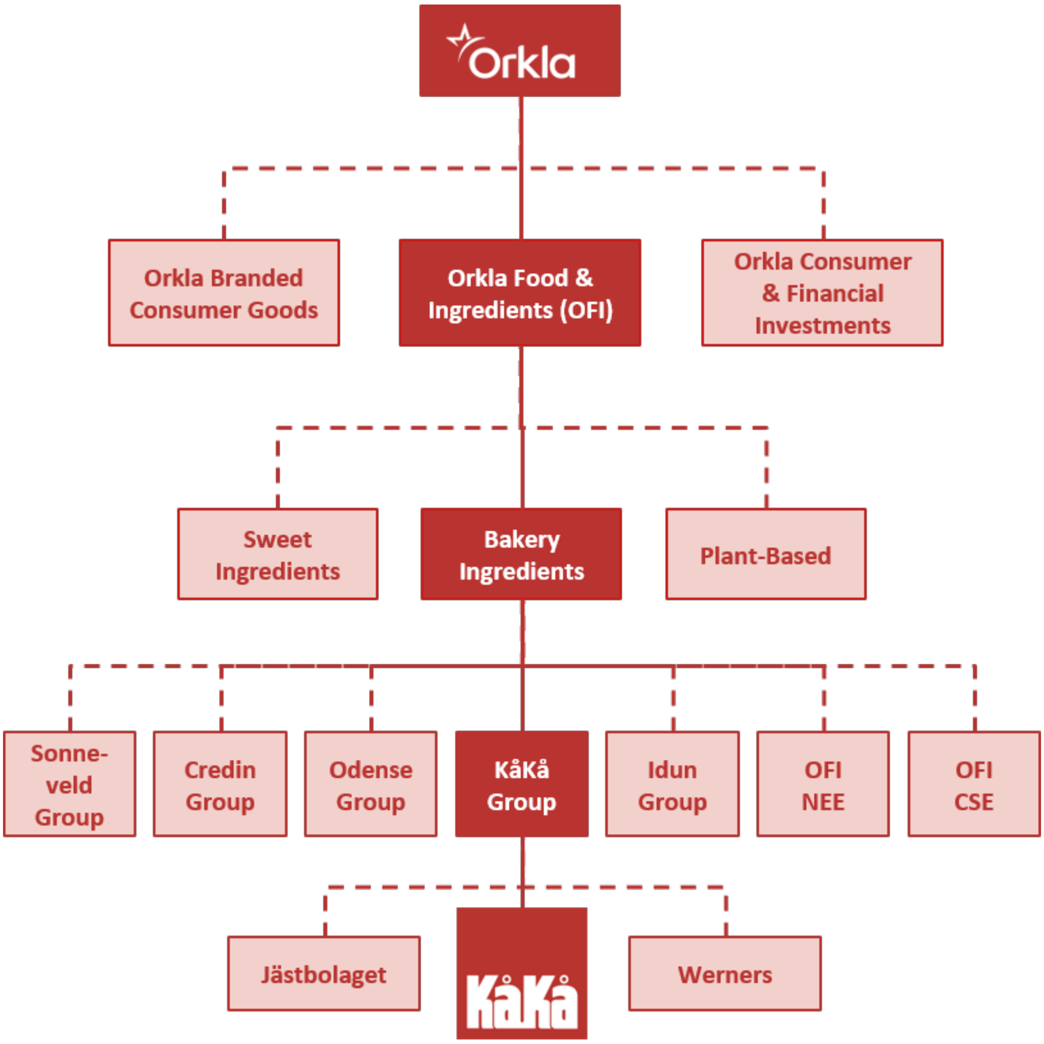

Figure 1: KåKå's organizational position

1.3 Problem Description

KåKå faces a big challenge in managing its complex environment, with many different customers and a large variety of different SKUs, in an efficient way. To handle the consequences of such a complex system, necessary theoretical knowledge is required and is, as of now, lacking at KåKå. Due to this, there is a desire to simplify the consequences to a level that is manageable for all, no matter the level of competence.

A main challenge in the complex system is to gain control of the volumes in stock whilst ensuring that the right products are available at the right moment in time. KåKå runs a monthly S&OP process to address this challenge, but they were still forced to discard SKUs with a total value of SEK 3,5 millions year 2022 (Supervisor at KåKå 2023b). This indicates that there is an imbalance between supply and demand which is not addressed by the current S&OP process.

One distinct problem with today's S&OP process is that employees perceive that the forecast fails to reflect the actual demand. A root-cause of this issue is that the demand planning is based on inadequate statistical forecasts and limited by poor collaboration between different functions. As of today, the same forecasting method, *Triple exponential smoothing*, is applied to all different SKUs and no grouping of products is performed. Furthermore, functional silos constrain the input of qualitative data to the demand planning process since obtained information about customers' changing buying patterns is poorly reported back to the people responsible for making manual adjustments to the statistical forecasts. This results in a misleading demand planning which causes a lack of trust among employees and a lot of manual adjustments as well as double handling. Another issue is that the purchasing department currently owns the responsibility for the forecasting process which excludes the sales department's involvement in the process.

1.4 Purpose

The purpose of this thesis is to improve the demand planning phase of KåKå's S&OP process to create better conditions for more efficient operations.

1.5 Research Questions

To solve the challenges the company is facing and to fulfill the purpose of this thesis, the following research questions will be analyzed and answered:

RQ1: How is the current demand planning process at KåKå designed and how does it perform?

RQ2: How can bakery products be categorized, based on characteristics, to simplify the forecasting and demand planning process?

RQ3: How can forecast methods be selected to fit different demand patterns?

1.6 Focus and Delimitations

The focus of this thesis will primarily be the demand planning phase of the S&OP process since this is where KåKå's main problems have been identified. An important criteria for the proposed approach to fulfill is that it must be manageable for all employees, no matter the level of competence. To make the demand planning process manageable for all, one important aspect is to categorize the products that withhold similar characteristics. The identification of product characteristics that will be used as a base for categorization will therefore be defined in the thesis. Thereafter, the main focus of this master thesis will be to identify and propose a forecasting approach that will improve the possibility of ensuring that the right quantity is available at the right time. The thesis will be limited to identifying appropriate forecasting methods for different groups of products, which means that each SKU will not be analyzed from an individual perspective. Another limitation in this thesis is that campaigns will not be taken into consideration within the demand planning process since KåKå does not utilize campaigns to a greater extent as of today.

1.7 Target Group

This master thesis is mainly directed to the Project Management Office at KåKå since it aims to provide an insight in the current demand planning process, the correlated challenges and recommendations for improvement. Furthermore, the thesis is also directed to the Faculty of Engineering at Lund University, especially the department of Mechanical Engineering Sciences, since the thesis is performed to complete the authors' studies within this department. Lastly, the thesis is also directed to all others that are interested in or that are experiencing difficulties in their demand planning process.

1.8 Thesis Structure

In order to accomplish the defined goals for this master thesis and provide well-prepared answers to the chosen research questions, multiple steps will be performed. This thesis will be initiated by creating a thorough understanding of the current problems KåKå is facing. Once the problem definition is in place, the thesis will proceed to identify and present the chosen thesis methodology. During this section, the authors will thoroughly describe relevant research methods, approaches, and data types, to then motivate the chosen method, approach and data types for this thesis. The authors will also present the methods and procedures that utilized for data collection and to analyze the data needed to perform the thesis. Thereafter, the thesis will proceed to execute an extensive literature review that will begin by describing S&OP in order create a common understanding of the process. The thesis will then continue to present relevant theory on the main focus areas: demand planning and forecasting. Once the necessary theory has been presented, the thesis will proceed to the empirical study, where the authors will thoroughly describe the current situation at KåKå. Following this section is the analysis, which will present the key findings from the empirical study by comparing knowledge obtained from the literature review with KåKå's current situation. The section will then proceed to present the analysis which will consist of a three parts: a forecasting-, demand planning- and S&OP analysis. Finally, the thesis findings and analysis will be concluded and a final recommendation will be presented for KåKå. The overall thesis structure is presented in Figure 2 below.

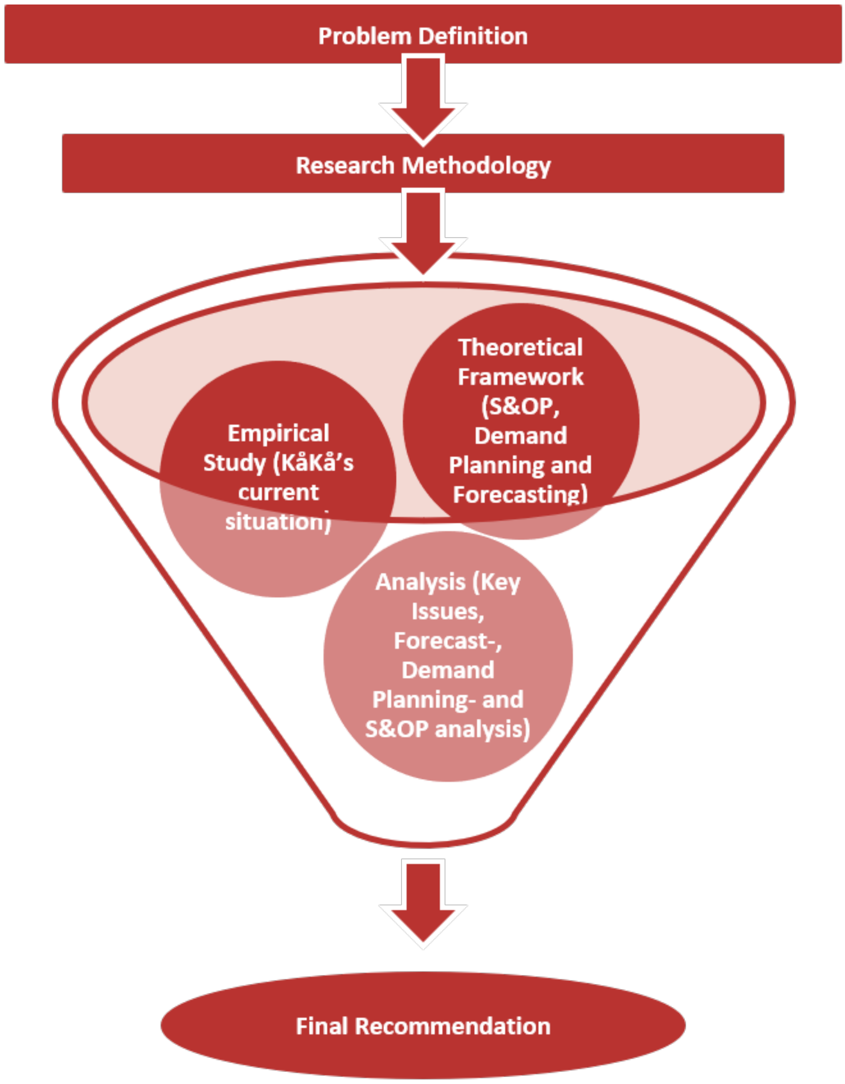

Figure 2: Thesis Structure

2 Methodology

Research is an investigation to describe, explain, predict and control a phenomenon in a systematic way, where the phenomenon is an expression for the concept being studied (Olhager 2023a). In this thesis, the identified phenomenon is demand planning at a bakery supplier and in order for this to be studied in a systematic and effective way, appropriate research methodology has been applied. The research methodology specifies the framework and forms the guidelines of how to proceed to achieve the objective of the research (Höst et al. 2006). This chapter will present the methodology of this thesis, including the research method, research approach, data collection, data analysis and research credibility.

2.1 Research Method

When conducting research, there are several different methods to follow and Höst et al. (2006) imply that the decision of the most suitable method is dependent on and influenced by the purpose and characteristics of the research. The general purpose of the study can be descriptive, exploratory, explanatory or problem solving (Höst et al. 2006):

- A *descriptive* study aims at identifying and describing how something works.
- An *exploratory* study aims at building a more thorough understanding of a phenomenon.
- An *explanatory* study aims at discovering causations of how something is done.
- A *problem solving* study aims at finding a solution for an identified problem.

Höst et al. (2006) describe four different research methods that are of high relevance when conducting a thesis and state that each of them are most suited to one of the four purposes presented above:

- *Survey* is a suitable method to use when the general purpose of the study is *descriptive*. It is often applied to describe and summarise a broad issue and is conducted by asking questions to a population, or a representing sample, to make it possible to draw conclusions regarding the entire population.
- *Case study* is a method to apply for *exploratory* studies since it entails a deep analysis of one or multiple different cases. This method describes a contemporary phenomenon and it can be conducted in an organisation to improve the understanding and knowledge of a certain concept. When conducting a case study, the conclusions should not be generalized to phenomenon based on other conditions since the findings are related to the specific case and purpose. It is common to use both interviews, observations and archival analysis to collect data in a case study.

- *Experiment* is an appropriate method to use in an *explanatory* study where a more controlled approach is necessary to identify and describe the causations of a phenomenon. The design of an experiment is fixed and it is based on a hypothesis, different variables and subjects, if applicable.

- *Action research* is a method to use when the purpose is *problem solving.* This method can sometimes be included as one type of case study and it follows a course of actions that start with an observation, followed by a proposed solution and ends with an evaluation. The design of an action research method is flexible, similarly to the design of a case study.

Compared to the point of view raised by Höst et al. (2006), Yin (2018) suggests that each method can be applied to studies with different purposes and it is rather three key-conditions that affect which research method to use in different situations, see Table 1. The first condition regards the form of the research question, which is categorized into who, what, where, how and why questions. The second condition regards whether the research requires control over behavioural events or not. Lastly, a distinction is made between research focusing on contemporary events and research focusing on historical events.

Table 1: Relevant conditions for different Research Methods (Adapted from Yin (2018))

	Form of Research Question?	Requires control over Behavioural Events?	Focuses on Contemporary Events?
Experiment	How, Why?	Yes	Yes
Survey	Who, What, Where, How many, How much?	No	Yes
Archival Analysis	Who, What, Where, How many, How much?	No	Yes/No
History	How, Why?	No	No
Case Study	How, Why?	No	Yes

What formed questions can be divided into two different types where the first alternative is an exploratory question where all methods mentioned in Table 1 can be applied and the second option is rather a type of *how many* or *how much* questions where a survey or an archival analysis is favorable (Yin 2018). Similar to the latter type of *what* question, Yin (2018) points out that a survey or an archival analysis is also more suitable for *who* and *where* questions. In contrast, research questions formulated with *how* or *why* phrases are better addressed by an experiment, a history or a case study. To further distinguish which method is the most applicable in different scenarios, Yin (2018) advocates looking into whether the study requires control over behavioural events or not, as well as whether the study focuses on contemporary events or not.

To decide upon which research method to use in this thesis, the theoretical perspectives from both Höst et al. (2006) and Yin (2018) were taken into consideration. Primarily, from Höst et al. (2006)'s description of four research methods related to different purposes, the case study was found to be the most applicable method in this thesis. A survey was excluded since it is not of interest to describe and summarise a broad issue and an experiment was not relevant since the main purpose is not to describe causations of the phenomenon. The objective with this thesis is rather to thoroughly study the demand planning process at a bakery supplier and propose relevant solutions of how this process can be improved, which indicates that the purpose is both exploratory and problem solving. However, the proposed solutions will not be implemented and evaluated due to the time limit of the thesis and consequently a complete action research method was not possible to apply. When looking at the three conditions that Yin (2018) brings up to identify a relevant research method, the case study was the most suitable for this thesis since the research questions are *how* formed, the study does not require control over behavioural events and the focus is on contemporary events. Furthermore, the thesis was conducted in an organisation and multiple sources have been used for data collection. A final justification of the appropriateness of conducting this thesis as a case study was supported by Meredith (1998) description of a significant advantage with a case study method: *"The phenomenon can be studied in its natural setting and meaningful, relevant theory generated from the understanding gained through observing actual practice"*. With this in mind, the chosen research method for this thesis was a case study.

Number of cases

The unit of analysis in a study can be an organization or a group within an organization but it is also possible that an event, multiple events or a specific incident constitute the unit of analysis (Olhager 2023a). Meredith (1998) states that the number of units of analysis influences what type of study is appropriate and whether a single or multiple case study should be chosen. When designing case study research it is important to distinct between single- and multiple case study designs and, at an early stage, make a decision on the number of cases to use (Yin 2018; Voss et al. 2002). The single case study is appropriate in several situations and Yin (2018) mentions five reasons to choose this research design. Yin (2018)'s first motive for a single case study is when a *critical* case is selected and the theory is questioned. The second motive for choosing a single case study is when the case is *unusual* while the third motive represents the opposite, a *common* case, which is about capturing an everyday situation again and providing social benefits related to theory (Yin 2018). The fourth reason is a *revelatory* case where a new phenomenon is observed that has not been subject to social science investigations previously (Yin 2018). The last motive for a single case study is described by Yin (2018) as the *longitudinal* case where the same concept is studied at multiple points in time and according to Voss et al. (2002) this is a common application of single case studies. With these five motives in mind it appears that the single case study is justified to use in several different situations and this is further strengthened by the fact that Yin (2018) mentions that their might even be more rationales than these five. Furthermore, Voss et al. (2002) state that whether a single case study is suitable or not depends on the amount of resources available and the desired depth of analysis. With the same amount of resources available, a single case study would allow for more in-depth observations than multiple case studies. However, with a single case study there is an increased risk of biases and that a single event is misjudged, which is a risk that would be mitigated if a multiple case study would be conducted (Voss et al. 2002). Another benefit with a multiple case study is that it increases the possibility to generalize the findings made (Meredith 1998; Voss et al. 2002).

In this thesis, the single unit of analysis is KåKå as an organization and thus a single case study was chosen. This was motivated by the fact that a multiple case study would require resources and time beyond what was viable in this thesis. Additionally, it was of interest to conduct in-depth observations and analyses of the demand planning process at KåKå and this was possible by conducting a single case study.

2.2 Research Approach

When conducting a research study, the research approach must be chosen and, as Kotzab et al. (2005) states, the appropriate approach depends on the phenomenon at hand. Depending on whether or not the phenomenon is well-known, the chosen research approach may vary between a qualitative-, quantitative-, or balanced approach. These research approaches are also commonly known as inductive-, deductive-, or abductive approaches (Spens & Kovács 2006) and can be illustrated as seen in Figure 3.

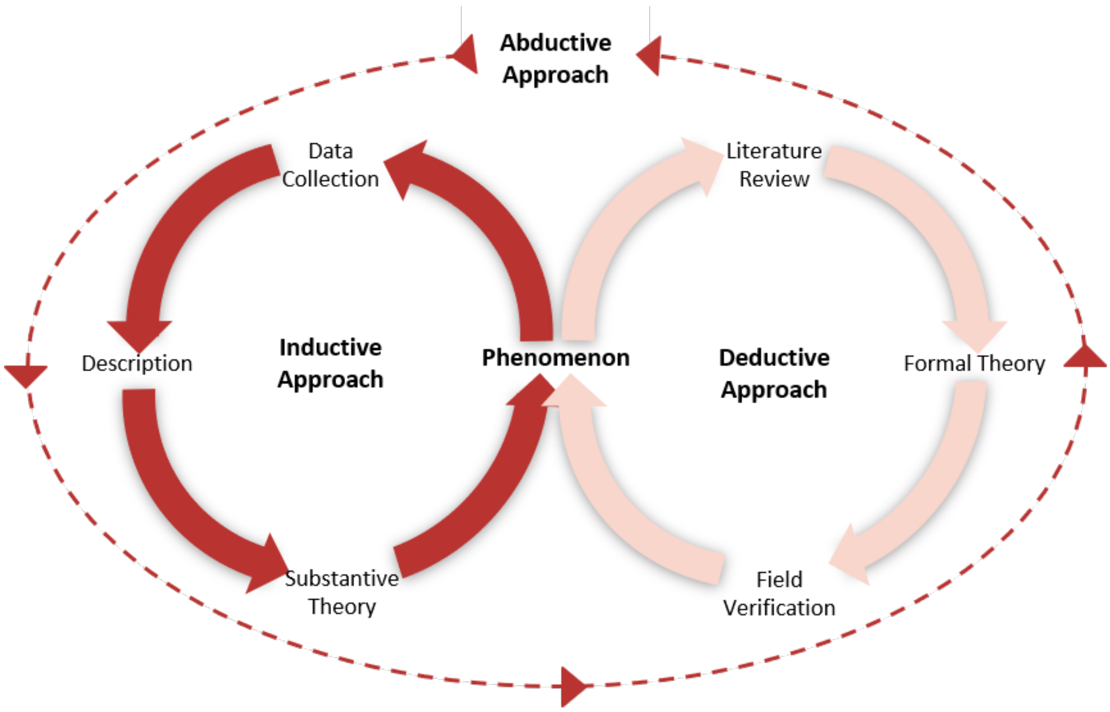

Figure 3: The balanced approach model (Adapted from Woodruff (2003))

2.2.1 The Inductive Research Approach

As stated by both Kotzab et al. (2005) and Olhager (2023a), the aim of the inductive approach is *"to understand the phenomenon in its own terms"*. Spens & Kovács (2006) further explain that the aim of the inductive approach is to develop more generalized theory about the studied phenomenon rather than testing existing theory. This approach is therefore commonly chosen, as argued by Kotzab et al. (2005), when the phenomenon is new, complex and relevant information is not available to thoroughly understand the phenomenon. Furthermore, Kotzab et al. (2005) also motivate the inductive research approach for such phenomena since it helps create a detailed understanding of the new phenomenon and the belonging complexity by performing field data collection. Research that applies an inductive approach often begins with the question "How?" or "What?" and proceeds with an aim to describe a certain process.

The inductive approach is presented, by both Kotzab et al. (2005) and Olhager (2023a), as a continuous process that consists of three steps. The first step in the process is data collection, which can be conducted by performing field visits with the purpose to observe the studied phenomenon in its natural environment (Kotzab et al. 2005; Olhager 2023a; Spens & Kovács 2006). Within this step, the use of relevant literature is continuously embedded rather than occurring as an individual step. The second step is to describe the studied phenomenon according to the observations collected from the field visits. The third step entails the creation of a substantive theory, i.e. a theory of the phenomenon. This theory is typically created by using descriptive data which is analyzed inductively and, as

Olhager (2023a) explains, through inductive reasoning from the usage of detailed and general perspectives.

2.2.2 The Deductive Research Approach

The aim of the deductive research approach is, as stated by Kotzab et al. (2005), Olhager (2023a) and Spens & Kovács (2006), to add to the existing phenomenon knowledge by developing formal theory that explains, predicts and controls the phenomenon. Kotzab et al. (2005) and Spens & Kovács (2006) therefore describe the deductive approach to be the exact opposite to the inductive. Kotzab et al. (2005) explain that a deductive research approach is commonly chosen when the studied phenomenon is well-known, well-documented and well-researched. In such cases, the research can be performed by using known variables in order to identify gaps in the current understanding of the phenomenon and thereafter proceed to develop measures necessary to reduce the gaps. Research that applies this approach tends to aim to answer questions such as "Why?" or "To what extent?". This approach is also known to be predominant when researching phenomena within logistics and supply chains (Kotzab et al. 2005; Spens & Kovács 2006).

The deductive approach is also seen as a continuous process in the same manner as the inductive approach. Kotzab et al. (2005), Spens & Kovács (2006) and Olhager (2023a) state that the first step of this process consists of reviewing relevant literature and possessing a strong understanding of the phenomenon in order to develop a conceptual framework. The framework is developed by identifying relevant variables and the expected relationships between them. As in the first step of the inductive approach, the researcher can perform field visits. However, the purpose of the visits is to clarify variables and relationships between them and not to develop the conceptual framework. The second step uses deductive reasoning based on the findings from the previous step in order to develop a formal theory, which includes predictive statements that can be contradicted by using real-time phenomenon data (Kotzab et al. 2005; Olhager 2023a). Before performing the data collection, hypotheses for the research questions are formed deductively. This means that the researcher begins with a more general view to later proceed to the details in the data. The third and final step of this approach is field verification and includes the collection of data by using carefully selected measurement instruments in either field experiments or surveys. Olhager (2023a) explains that the purpose of this step is to verify the formal theory developed in the second step.

2.2.3 The Abductive Research Approach

Since supply chains are of complex nature, a phenomenon within that area can, despite being well-known, require research to firstly gain a thorough understanding of the complex or dynamic phenomenon, i.e. applying an inductive approach (Kotzab et al. 2005). Once the thorough understanding has been built, the researchers can proceed to evaluate relationships in the identified variables, i.e. applying a deductive approach. Applying both research approaches is also known as a balanced or abductive research approach (Kotzab et al. 2005; Olhager 2023a). Spens & Kovács (2006) explain that an abductive approach is based on real-life phenomena where researchers apply new theory or frameworks to an already existing phenomenon. The research can be based on cases where a deviation from expectation has occurred. This approach is also well-suited for borrowing theory from similar research fields. The authors proceed to explain that during this approach, the data collection and theory building phases overlap in aim to develop new theory.

The abductive research process, is as the others, a continuous process. In this case, the research process begins in the same manner as the inductive, i.e. by reviewing existing theoretical knowledge or by performing observations, and proceeds into a learning loop between the theoretical and empirical study. The process then continues to develop hypotheses or propositions that are applied in empirical studies for testing the theory and creating new knowledge of the phenomenon (Spens & Kovács 2006). Due to the characteristics of the abductive research approach, Spens & Kovács (2006) argue that this approach is mostly suited for action research but also well-suited for case studies. An *abductive research approach* was therefore selected for this thesis since it allowed the researchers to develop both a theoretical and empirical understanding of the phenomenon before presenting and empirically testing a solution. This research approach also aligned well with the selected research method being a case study.

2.3 Data Collection

In order to conduct the thesis, perform an analysis and present a result, data collection was required. The data collection process can be performed in various manners depending on the type of data at hand. The two types of data that this thesis consists of are presented below, along with the various sources of data that were exploited.

2.3.1 Quantitative and qualitative data

Data required to perform research can be of two types: quantitative or qualitative. Höst et al. (2006) describe quantitative data as data that can be calculated, such as numerical information, and classified, such as colours, percentages, weights and lengths. To analyze and develop a more thorough understanding of such data, statistical methods are most commonly used (Höst et al. 2006; Rosengren & Arvidson 2002). Qualitative data is instead described by Höst et al. (2006) as data consisting of words, phrases and descriptions and that is rich in details. The analysis of qualitative data is normally a flexible and iterative process which typically consists of analyzing documents such as transcribed interviews or archival documents (Höst et al. 2006). In more complex cases, Höst et al. (2006) argue that a combination of both qualitative and quantitative data is preferable since the two can complement and support each other to strengthen statements. This is also motivated by Kotzab et al. (2005) that explain that quantitative and qualitative data cannot substitute one another since they observe and explain different aspects of the same phenomenon.

The data required to perform research can originate from many different sources and the sources can depend on the type of data being collected. Qualitative and quantitative data are commonly collected in different ways. To collect qualitative data, interviews and observations can be performed as well as examining existing documents (Kotzab et al. 2005). Quantitative data can also be collected through interviews, but more common data collection methods for this data type is by using measurement instruments in field surveys or experiments (Kotzab et al. 2005). Yin (2018) highlights the six most commonly used sources for all case study data regardless of the type: documentation, archival records, interviews, direct observations, participant-observation and physical artifacts. The author proceeds to emphasize that no single data source can be seen to have complete advantage over another source and that it is important to note that most sources are rather complementary. This indicates that multiples sources are necessary to strengthen a case study and since a case study was conducted in this thesis, multiple sources were used and are presented below.

2.3.2 Theoretical review

A literature study was included in this thesis since it plays an important role for the researchers as well as the thesis audience. Höst et al. (2006) state that a well-performed literature study supports the purpose and goal of developing already existing knowledge whilst ensuring to minimize the risk of overlooking previous lessons. Furthermore, the author explains that the audience is more likely to understand the origin and context of the thesis if relevant literature sources are presented. The main purpose of the theoretical review is stated by Olhager (2023b) and Höst et al. (2006) to be to build a thorough understanding of the phenomenon, theoretical concepts and terminology. Once the thorough understanding was established and the research questions and limitations were defined, the researchers could proceed to increase their understanding by performing more specific studies of relevant literature. Both Olhager (2023b) and Höst et al. (2006) agree that the theoretical review should later be used to analyze and compare the thesis results with the findings of others to enable the possibility to identify the thesis credibility.

Höst et al. (2006) describe theoretical reviewing as an iterative process that includes activities such as keyword decision, searching, selection, assessment and compilation. In order to understand which literature is needed, an understanding of the phenomenon and focus area is required. When searching for relevant literature, Olhager (2023b) presents two search strategies that can be used:

1. *Citation pearl growing* is a search strategy that implies going from a few to many sources. The researcher applying this strategy starts with a few documents and then uses identified keywords within the documents to find more relevant literature.

2. *Successive fractions* is the opposite search strategy to citation pearl growing and instead implies going from many sources to only a few. This is done by increasing the number of sub-keywords within the documents with the aim to eliminate those that are less relevant.

In the beginning of the thesis it is common to apply a wider search approach in order to identify sources that are relevant to the thesis phenomenon (Höst et al. 2006). At the beginning of this thesis, literature was collected through the thesis supervisor who had thorough insight in which sources that were of relevance to the topic. Proceeding forward, the researchers used the list of references in relevant articles and books in order to identify sources of information within the focus area. Another way of searching for literature used in this thesis was through databases. The primary database that was used was *Web of Science*, where it was possible to perform keyword-based searches. Some keywords that were used were *Demand Planning, Non-manufacturing, Food industry, Bakery industry, Forecasting, Sales and Operations Planning, Product Grouping, Product Categorization and Demand Patterns* and the keywords were also combined in the searches to retrieve more specific results. The successive fractions search strategy was mostly utilized in the beginning of the thesis since the approach with the theoretical framework of this thesis was to gather a broad understanding of the focus area to later gather a more in-depth and specified understanding. Once the broader knowledge was identified and applied in the framework, the citation pearl growing strategy was applied in order to find an increased number of sources with more specific information of the focus area.

When performing the literature study in this thesis, it was also important to review the credibility of the chosen sources. To do so, Höst et al. (2006) present multiple questions that should be asked and answered by the researcher and that have been utilized throughout the literature study in this thesis:

- Has the literature been reviewed and if so, by whom?
- Who can guarantee the credibility?
- Has the results of the study been confirmed or been used in other credible contexts?

Related to the first question presented by Höst et al. (2006) is whether or not the literature has been reviewed. In this thesis, scientifically reviewed sources such as journals and shorter papers have been utilized frequently. Other non-scientific sources such as textbooks, websites and organizational information have been utilized.

2.3.3 Empirical study

In the empirical study performed in this thesis, multiple sources of data have been utilized according to the first principle of data collection presented by Yin (2018): *Use Multiple Sources of Evidence.* Yin (2018) argues that a major strength of case studies is the possibility to use multiple data sources since this can lead to an improved quality of the study and in-depth understanding of the phenomenon. The aim of using multiple sources is to result in convergent evidence, which implies that the multiple sources used will provide the same findings through multiple measures of the same phenomenon (Yin 2018). The main sources that have been used to fulfill the convergent evidence in this empirical study are three of the six sources of case study data highlighted by Yin (2018): documentation, interviews and observations. In Figure 4, the convergence of evidence is presented for this empirical study.

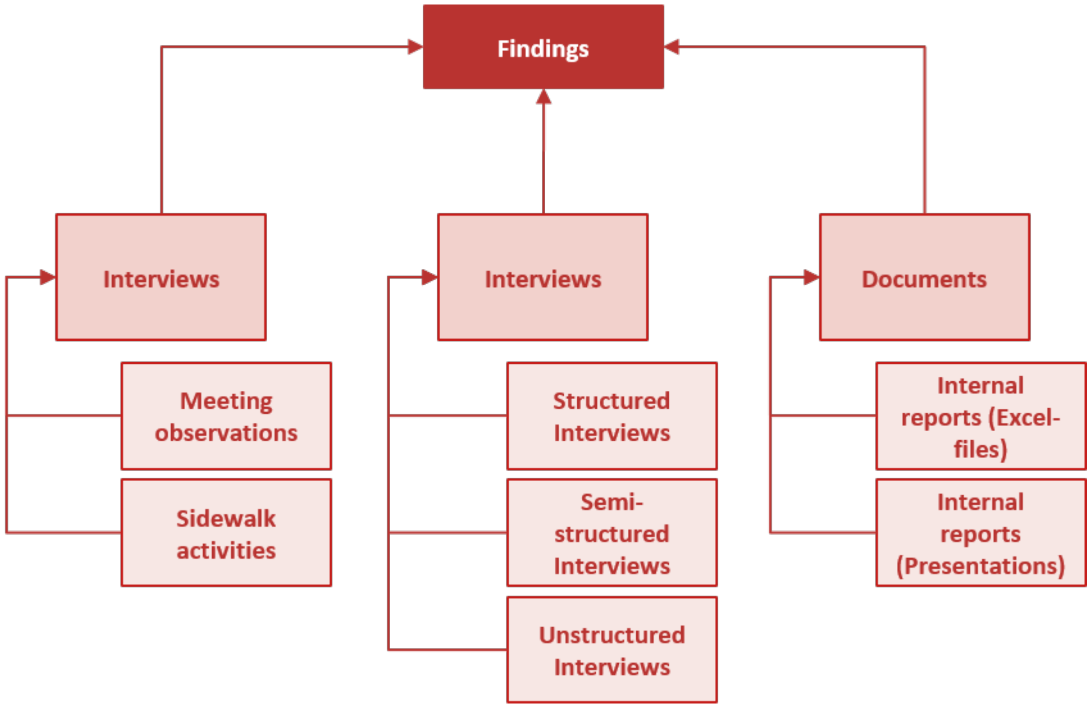

Figure 4: Convergence of Evidence for the empirical study (Adapted from Yin (2018))

Documentation

The first source of data listed by Yin (2018) and used in the empirical study of this thesis is documentation. This source of data provides information that can take many forms such as formal studies, administrative documents, internal reports, letters and e-mails. This type of information is commonly accessed through the Internet today which entails that usage of such information must be pursued with precaution due to the risk of them being imprecise or biased (Yin 2018). In this empirical study, the main data from documentation that has been utilized was in the form of internal reports. In order to access information about historical and forecasted sales quantities, discarded SKUs, and forecasting accuracy, internal reports in form of Excel-files and PowerPoints were received from KåKå.

Interviews

The second source of data used in this empirical study and listed by Yin (2018) to be one of the most important sources of case study evidence was interviews. Interviews can be used in the beginning of a thesis with the purpose to gather background information and views on the focus area (Höst et al. 2006). When utilizing interviews as a source of data, three types of interviews can be used: prolonged-, shorter- and survey interviews (Yin 2018):

1. *Prolonged interviews* can require multiple hours, either at once or distributed over time, in order to gather all necessary information. During such interviews, information such as employee interpretations, opinions, explanations and other interviewee suggestions can be retrieved.

2. *Shorter interviews* normally require one hour or less. The main purpose of such interviews may be to confirm findings gathered in prolonged interviews or in the empirical study. These interviews tend to be of a more determined nature compared to the prolonged interviews that are more open-minded.

3. *Survey interviews* are based on the use of structured questionnaires and aim to produce quantitative or qualitative results that can be used as data in the study.

Apart from the three types of interviews above, different interview structures are discussed in literature (Höst et al. 2006; Olhager 2023b) and are: structured-, semi-structured and unstructured interviews:

1. *Structured interviews* consist of well-prepared questions that are asked in a certain order.

2. *Semi-structured interviews* are interviews that are a balance between structured- and unstructured interviews. Preparations are performed beforehand in form of chosen focus areas, whilst specific questions are formulated depending on the response from the interviewee.

3. *Unstructured interviews* are the opposite of structured interviews and are instead based on more general conversation. The questions are typically not prepared beforehand and instead arise depending on the dialogue held between the interviewer and interviewee.

In the empirical study of this thesis, interviews have been utilized during multiple occasions. The type of interviews that have been chosen were dependent on the purpose of the interview. To begin with, prolonged and unstructured interviews have been utilized when interviews were performed with the thesis supervisor at KåKå as well as KåKå's Supply and Demand Manager. These interviews did not exceed two hours within one sitting and rather reoccurred at different moments in time. The purpose of these interviews was to gather an overall understanding of the perceived problems and underlying causes. During these interviews it was of great importance to gather an understanding of KåKå as an organization, the demand planning process and the parties involved. Thereafter, a shorter and semi-structured interview was held with KåKå's Demand Planner. The interview was semi-structured since the authors had built an initial understanding of the demand planning process, the perceived problems and causes and aimed to build a more in-depth understanding of the causes. The focus area was therefore prepared beforehand together with some rather general questions, but all questions were not decided upon before the interview and were instead formulated depending on the dialogue held with the demand planner. Furthermore, multiple shorter, structured interviews were performed with an aim to gather a broader understanding of KåKå's employees opinions and experiences of the current demand planning process and forecasts. These interviews were also performed in order to gather opinions from multiple departments to ensure that an inclusive group of interviewees had been chosen. All interviews performed during the thesis are presented below in Table 2 together with information regarding the interview type, interviewee's role as well as the date and length of each interview.

Table 2: Information regarding the interviews performed in this thesis

Interview type	Role of interviewee	Date of interview	Duration
Unstructured	Project Consultant	Recurring weekly	60 min per session
Unstructured	Supply and Demand Manager	2023-01-23	60 min
Semi-structured	Demand Planner	2023-01-23	60 min
Structured	Chief Operations Officer	2023-03-21	60 min
Structured	Sales Manager	2023-03-22	60 min
Structured	Team Leader Internal Sales	2023-03-22	60 min
Focus group	Project Consultant, Supply and Demand Manager, Chief Operations Officer, Sales Manager, Manager of Project Consultants	2023-05-02	60 min

All of the interviews previously presented were performed as individual interviews, i.e. only one person was interviewed during each session. Apart from the individual interviews, a type of group interview was also utilized during this study. A group interview, also known as a focus group or group discussion, is defined by Saunders et al. (2007) to be all non-standardized interviews that are performed with two or more people. A focus group can also be defined as a group interview where the topic is clearly defined and there is a main focus on enabling interactive discussions between the involved parties (Saunders et al. 2007). The number of participants can vary depending on the complexity of the topic at hand, the skills of the interviewers and the nature of the participants. In more complex cases, the number of participants is normally smaller than in other, less complex cases. When choosing the group interview participants, a specific purpose is normally developed and it is common that the interviewers choose such participants that can contribute to the lessons learned (Saunders et al. 2007). In this thesis, a focus group was performed together with the participants presented in Table 2 above which were chosen due to the understanding that they would be able to provide the interviewers with relevant guidance on a particular topic. Each of the participants possess years of experience and knowledge within KåKå and specifically within the topic of this thesis and were therefore identified as important participants for the focus group. The purpose and topic of the focus group was clearly defined prior to the meeting and was communicated to the chosen participants per e-mail. The main topic of the focus group was the analysis section of this thesis and the purpose was to discuss and retrieve input regarding the choice of KåKå specific parameters that were necessary to perform the analysis.

When conducting interviews, the field researchers need to withhold the necessary skills-set in order to attain the full potential and purpose of the interview. Olhager (2023b) presented that the skills-set should, first and foremost, include having a firm understanding of the phenomenon being studied. Another ability that Olhager (2023b) states as important is the ability to ask good, relevant questions and thereafter being able to interpret the answers correctly. Additionally, the ability to be adaptable and flexible to new circumstances is of great importance in order to see changing situations as opportunities and not threats. Lastly, it is also vital to withhold the skill of being unbiased by pre-conceived notions since this may otherwise affect the researchers interpretations skills.

Direct observations

The last source of data used in this empirical study was direct observations, which can be used to observe the phenomenon (Höst et al. 2006). Yin (2018) explains that case studies create the opportunity to use this source of data since they occur in the real-world. Direct observations can consist of observing meetings, sidewalk activities and organizational work. The observers can be categorized into four categories depending on the degree of interaction of the observers and awareness of the observed group (Höst et al. 2006). When interaction and awareness are high the observers are observing participants. On the other hand, when interaction and awareness are low the observers are complete observers. The remaining categories of observers are the complete participant, where interaction is high but awareness is low, and participant observer, where interaction is low but awareness is high. In this thesis, the researchers will be *participant observers*, which implies that the observed groups will be aware of the observers presence whilst the observers interaction will be kept to a minimum. Direct observations were utilized in this empirical study in multiple forms. Firstly, the authors participated in an observation of the warehouse and office operations by a walk-through. Secondly, both authors participated in observations of the monthly and weekly S&OP meetings at KåKå. Lastly, two observations were performed in form of sidewalk activities. One of the sidewalk activities took place with an Operational Purchaser whilst the other took place with KåKå's Demand Planner.

2.4 Data Analysis

As presented in Section 2.3, this thesis has used both quantitative and qualitative data to enable an in-depth understanding of the case company's current situation and problems at hand. To be able to design appropriate and useful solutions, the collected data had to be analyzed. Höst et al. (2006) also states that when using data that has been collected in different ways, analyzing the data becomes increasingly important to be able to understand what it shows. Since both quantitative and qualitative data has been collected and utilized in the empirical study, the data types require different analysis methods. The methods required and utilized in this thesis are presented in more detail below.

2.4.1 Qualitative analysis

When conducting qualitative data analysis, Miles et al. (2014) recommend to cycle back and forth between the analysis and data collection. They state that this iterative way of working encourages the testing of new hypotheses that arise in the analysis as well as the possibility of filling gaps that occur in the data collection. Miles et al. (2014) describe several possible courses of action when conducting qualitative data analysis, where data coding and pattern development are two common approaches to include. These approaches are also mentioned by Höst et al. (2006) as two of four steps that constitute the process of qualitative analysis. The overall four-step process should be flexible and iterative, and is further described below (Höst et al. 2006):

1. *Data collection* is the primary phase where various qualitative methods are used to obtain relevant information to analyze.

2. *Coding* is about marking and highlighting important data obtained from e.g. an interview. It can be single keywords or entire statements that contain relevant information.

3. *Grouping* involves pattern development of coded segments, which e.g. could be to gather different opinions on the same topic into one place and identify patterns. The patterns can be illustrated graphically.

4. *Conclusions* are drawn based on the grouped data and it is important that it is possible to track how the conclusions were drawn.

In this thesis, data analysis and data collection were performed simultaneously as the findings that were made required, in some cases, new data to be collected.

The iterative way of working is further reflected by the choice of an abductive research approach. In addition to the iterative procedure, which is well aligned with the theoretical recommendations, the qualitative data analysis was carried out in accordance with the four-step process mentioned by Höst et al. (2006). The qualitative data obtained from interviews and observations was coded by highlighting the most relevant and important take-aways from each occasion. Thereafter, the highlighted information was gathered and summarised in one single document to be able to compare statements from different people on the same topic. Finally, conclusions were drawn based on the gathered information containing all different perspectives.

2.4.2 Quantitative analysis

Quantitative analyses are commonly performed when quantitative data has been collected and requires an analysis to create an in-depth understanding of the content. Analysis methods that are used in quantitative analyses are normally of statistical nature and therefore include various methods from both statistics and mathematics (Höst et al. 2006; Kotronoulas et al. 2023). Kotronoulas et al. (2023) state that it is first when an analysis of quanitative data is performed that the data becomes useful evidence or results. Both Höst et al. (2006) and Kotronoulas et al. (2023) explain that quantitative analysis methods can be of two types, either descriptive in order to gain an improved understanding of the data or inferential in order to prove relationships between variables. Inferential statistical analyses are of great importance in quantitative data analysis since, as argued by Kotronoulas et al. (2023), they are able to prove if observed relationships, effects and variations are random findings or if they are actually likely to occur in reality. Descriptive statistics are instead used to describe what the data sample looks like and can be used to present frequencies in either tables or graphs.

To identify and prove connections between quantitative data, different statistical methods can be of use. Höst et al. (2006) presents the calculation of correlation coefficient and hypothesis testing as two common methods for this purpose. Kotronoulas et al. (2023) further present the use of measurement averages, dispersion, confidence intervals and other inferential statistics. Inferential statistics are used to test hypotheses in order to return the probability about whether or not a relationship, effect or difference is likely to occur (Kotronoulas et al. 2023). Many statistical tests exist for hypothesis testing, such as the following that are presented by Kotronoulas et al. (2023):

- *Chi-square test* - A test that compares variables that can only obtain two values.

- *Student's t test* - A test that compares the means between two independent groups.

- *Analysis of variance* - An analysis that is utilized when one desires to compare the mean of two or more independent groups.

- *Regression analysis* - An analysis that, when performed, shows the effect one variable has on another.

In this thesis, both descriptive and inferential analysis methods have been utilized to analyze the collected quantitative data. When descriptive analyses were performed, scatter graphs were most commonly utilized to visualize the data at hand and in some cases to identify frequencies. Inferential analyses were performed throughout the thesis analysis and multiple tests were utilized. The thesis has used linear regression analysis to identify product trends and then combined the regression analysis with Wald's test in order to test whether or not identified trends were significant. Wald's test is a statistical method that is used to identify if a group of independent variables is collectively significant or not and can be used when performing an regression analysis (Sundell 2012). This analysis was necessary in order to be able to identify which trends must be considered when choosing appropriate forecast methods for different demand models, i.e. when answering RQ3.

2.5 Research Credibility

One important aspect when conducting research is that the findings are good and trustworthy, but there are many possible terms and definitions on this subject. Validity, reliability and generalizability are three common categories when evaluating the credibility of research (Höst et al. 2006). These categories will be further described in the subsections below, together with a discussion of how the research credibility of this thesis will be achieved.

2.5.1 Validity

One of the most important aspects in research credibility is that empirical concepts agree well with the theoretical concepts, which indicate that the research is valid (Rosengren & Arvidson 2002). There are several ways to define research validity but one common definition is that a valid measurement actually measures the right thing (Olhager 2023b; Rosengren & Arvidson 2002; Höst et al. 2006). Another definition mentioned by Rosengren & Arvidson (2002) is that validity reflects the absence of systematic errors in a measurement. Höst et al. (2006) states that a potential way to increase the validity is by applying triangulation, meaning that multiple methods are used to study the same concept. Triangulation can also involve using multiple types of data or letting several people study the same object (Höst et al. 2006). Olhager (2023b) describes triangulation as a way of increasing the quality of a study by using different perspectives and states that there are four different types of triangulation, distinguished by where the different perspectives are coming from: method triangulation, data triangulation, evaluation triangulation and theoretical triangulation. In this study, the method of data triangulation was utilized to increase the study's validity which implies that multiple data sources are used to strengthen the study's quality. Multiple sources of data were used for both the theoretical review and the empirical study, as described in Section 2.3. Additionally, several people at KåKå were interviewed regarding the same concepts and phenomenon to get a comprehensive picture of what is being studied. To further strengthen the validity, all material was evaluated by both authors throughout the report and a lot of input from the supervisors was taken into consideration.

2.5.2 Reliability

When conducting research it is critical that the data collection and analysis is reliable and not depending on random variations (Höst et al. 2006; Miles et al. 2014). This represents the research reliability and it is similarly defined by Rosengren & Arvidson (2002) as the degree of trustworthiness of a study, which corresponds to the absence of random error in measurement. With this in mind, one major difference between validity and reliability is that validity relates to the systematic error while reliability is about the random error. Olhager (2023b) declares that a reliable study is characterized by the fact that the same result will be obtained if the study is repeated. To achieve a high level of reliability, it is important to manage data thoroughly and clearly describe the course of action throughout the study (Höst et al. 2006). With this in mind, all data collected in this study was structured in a database and thoroughly managed to increase the reliability. For example, both authors attended all interviews and the notes were crosschecked and compiled immediately afterwards. Another way of increasing the reliability of a study is by using triangulation, like how increased validity is achieved (Olhager 2023b). Similar to evaluation triangulation, Höst et al. (2006) mention the possibility of letting a colleague review the data collection and data analysis as another way of increasing the research reliability and identifying potential weaknesses. The fact that both authors evaluated all material, with input from supervisors, did not only increase the validity but also the reliability of this thesis. Furthermore, the thesis is subject to opposition from other students at least twice which is also favorable from a reliability perspective.

2.5.3 Generalizability

The generalizability of research is reflected by the possibility to generalise the findings made and this is influenced by the sample that was used to obtain the result (Höst et al. 2006). This concept may also be referred to as representativity or external validity (Meredith 1998; Höst et al. 2006). According to Meredith (1998), there are three ways of increasing the generalizability:

1. By including independent variables to the greatest extent possible.
2. By including several populations in the original study.
3. By testing the theory on different populations.

One important aspect mentioned by Höst et al. (2006) is that case studies typically are not possible to generalise, but if similar conditions are obtained it is more likely that the findings are possible to imitate. Also Meredith (1998) states that the results from case research are only valid for that specific situation and thus the generalizability is limited, but it is possible to extend the generalizability with significantly more effort by conducting a multiple case study. Due to the time limit of this thesis, it was not possible to include several populations or conduct multiple cases which limits the generalizability of the study.

3 Theoretical Framework

In this chapter the S&OP concept will be introduced in more detail together with a description of the different process steps. Further, demand planning, product classification and forecasting will be of focus due to the purpose of the thesis.

3.1 Sales and Operations Planning

S&OP is a term that has gained attention and has been used more frequently in recent years. Olhager (2013) explains that the increase in recognition for the S&OP functionality occurred in parallel with the switch from Material Requirements Planning II (MRP II) to Enterprise Resource Planning (ERP) systems during the 1990s. The popular term, S&OP, is characterized as the long term planning of production and sales based on forecasted demand and capacity availability (Olhager et al. 2001; Olhager 2013). The S&OP process is described by Wallace & Stahl (2014) as a set of business processes that aim to maintain a balance between demand and supply in a company.

S&OP is, as stated by Lapide (2007), a cross-functional process that helps break down functional silos by creating a team of managers from both customer facing and supply facing departments. Lapide (2007) explains that the cross-functional team acts as a bridge between supply and demand, which can help decrease the imbalance between the two functions. Other authors, such as Wagner et al. (2014), also agree that introducing S&OP allows for improved integration and collaboration between sales and operations. Therefore, the introduction helps decrease the consequences of the operational silos that otherwise arise such as uncoordinated reactions within the company and insufficient flexibility. One of the main benefits from S&OP identified by Wagner et al. (2014) is therefore the possibility to align sales and operations vertically and horizontally to enable a continuous balancing of supply and demand.

The S&OP process generates a long term plan for the planning object that is commonly applied to product groups, which entails the grouping of products that withhold similar product characteristics (Lapide 2007; Olhager 2013). The long term planning horizon enables a long term perspective, which makes it possible to evaluate investments that are costly and require a long time to acquire with respect to the long term plans for sales, operations and inventories (Olhager 2013). One of the main objectives of the S&OP process is to integrate operational plans with financial plans to ensure that financial and operations activities are aligned within the company. Wallace & Stahl (2014) present two other main objectives of S&OP which are:

1. To balance demand and supply
2. To align volume and mix

3.1.1 Balancing demand and supply

Balancing demand and supply is of great importance in companies since negative consequences such as stock outs, unsatisfied customers and lost sales can occur if demand exceeds supply. However, negative consequences do not only occur when demand exceeds supply since they may also occur if supply exceeds demand. Such negative consequences can be excess inventory which binds capital and can lead to problems with cash flow (Wallace & Stahl 2014). With regard to the consequences that can occur due to an imbalance, it is of importance to actively monitor demand to be able to identify imbalances as soon as possible. When potential imbalances in demand and supply are identified, actions can be put in place to reduce or eliminate the imbalance and avoid the accompanying consequences.

3.1.2 Aligning volume and mix

Another main objective of S&OP is to align volume and mix within a company, where volume refers to an aggregate issue and mix refers to the details. Volume is also known to create the big picture and is often expressed in product groups whilst the mix refers to individual products or customer orders (Wallace & Stahl 2014). When deciding a company's volume, the question to be answered is *"How much?"* compared to the question of *"Which ones?"* when deciding the mix. Wallace & Stahl (2014) state that companies tend to see volumes as less important and less urgent than the mix. However, as demand is the driver of supply, Wallace & Stahl (2014) argue that volume should be seen as the driver of mix. When setting volume plans, the rates and levels of activity that occur within the mix are also set. It is therefore of importance to focus on forecasting and planning the volumes to ensure that the correct mix is in place.

3.1.3 The Sales and Operations Planning Process

The planning horizon of S&OP is usually around 15-18 months with a monthly planning period (Olhager 2013). Many researchers and practitioners suggest that the monthly S&OP process consists of the following five steps: Data Gathering, Demand Planning, Supply Planning, Pre-Meeting and Executive meeting (Grimson & Pyke 2007; Wagner et al. 2014; Wallace & Stahl 2008). However, Olhager (2019) states that the first step, data gathering, is commonly included in the demand planning-step and thus the process is nowadays considered to consist of four steps, as seen in Figure 5.

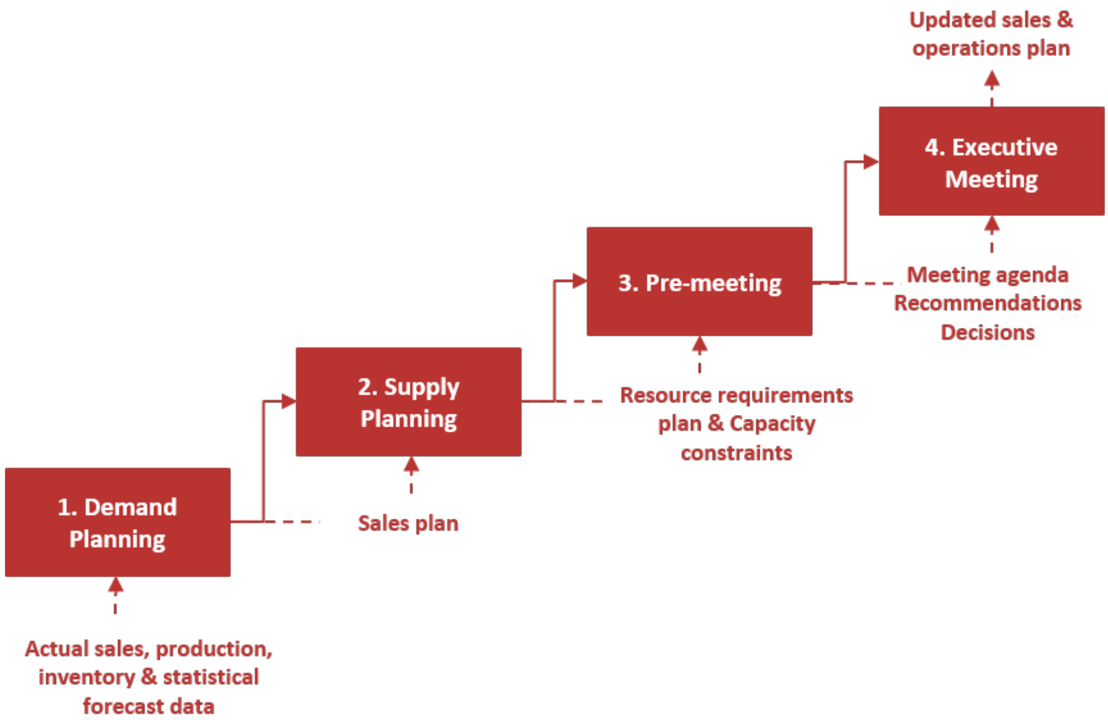

Figure 5: The S&OP process

Step 1: Demand Planning

The first step in the monthly S&OP process is the demand planning phase. During the first part of this step, data gathering is performed and consists of updating files with the actual sales, production and inventory data. The data is generated to enable the development of new and more accurate future forecasts (Wallace & Stahl 2014). Throughout the demand planning phase, Wallace & Stahl (2008) and Wagner et al. (2014) state that it is the people working with sales and marketing as well as those working in product development that should be involved. The final output from this first step is a sales plan without regards to capacity constraints that is used as a base for the following steps (Olhager 2019).

Step 2: Supply Planning

The second process step is about supply planning and this is where resource and capacity constraints are taken into consideration (Olhager 2019; Wagner et al. 2014). As described by Olhager (2019), the sales plan generated in the previous step is reviewed with regard to available capacity of e.g. production, distribution, suppliers and logistics. The sales plan is also compared to the actual stock level and backlog orders. Further, Olhager (2019) states that the planning of critical resources within the planning horizon is executed and the output from this step is a business plan including production plans, capacity plans and stock plans. This step of the monthly S&OP process is performed by people working in the operations function (Wallace & Stahl 2008; Wagner et al. 2014).

Step 3: Pre-Meeting

When the demand- and supply planning are complete, the next step is a meeting where all affected functions participate and the plans are commonly reviewed (Olhager 2019; Wagner et al. 2014). All product groups are discussed and potential problems or disagreements are raised and solved, if possible. If the problems cannot be solved, Olhager (2019) claims that they are prepared to be further discussed during the executive meeting. In general, this pre-meeting is about preparing and setting the agenda for the final executive meeting (Olhager 2019; Wagner et al. 2014).

Step 4: Executive Meeting

The last step of the monthly S&OP process is the executive meeting where management get their handle on the business, as described by Olhager (2019). Decisions are taken about the plans for all product groups and to ensure that this is possible to do effectively, it is important that the previous steps have been performed properly (Olhager 2019). When all decisions are taken, the output from this meeting is a sales and operations plan agreed upon by all involved functions (Olhager 2019; Wagner et al. 2014).

3.1.4 Barriers to successful S&OP

An important aspect that often hinders the implementation of S&OP is the extensive change that the implementation implies on the company. Grimson & Pyke (2007) explain that implementing S&OP requires companies to not only change their business processes but also to undergo a cultural change within the company. The cultural change entails that functional silos must be eliminated since S&OP requires a cross-functional team of managers that previously focused on independent incentives and now must cooperate to reach aligned objectives (Grimson & Pyke 2007; Jacobs et al. 2011). By breaking down the traditional functional silos, Ling & Goddard (1988) state that S&OP guarantees improved teamwork. Building teamwork is also stated by Ling & Goddard (1988) as a key element of S&OP since it provides the opportunity for each function to participate in the process. The increased participation allows for experience and knowledge sharing, which can lead to an increased feeling of involvement and value in the team. A prerequisite for performing S&OP is therefore known to be the commitment and people aspect since it is only through commitment of the executive team that other key participants will commit their time and resources to the process (Ling & Goddard 1988). The prerequisites of commitment, people, and teamwork are of importance throughout the whole S&OP process. Each step of the process requires collaboration between the involved functions, and the involvement must be present from the first step. The first step of the S&OP process, demand planning, requires necessary demand data to be provided in order to create the desired output: updated forecasts and a sales plan. During this step, the prerequisites are of great importance since the required data cannot be provided from one single function.

Pedroso et al. (2016) states that another important aspect that, if not implemented, can hinder the successful implementation of S&OP is the lack of training with all process participants. Without necessary training for the change that is to occur, employees may lack understanding of why the change is occurring as well as what is required of them to facilitate the change. The lack of understanding from employees can hinder the elimination of functional silos since there is a lack of knowledge as to how they should redirect their focus to shared incentives and cooperate cross-functionally to achieve them.

3.2 Demand Planning

Demand planning is, as presented above, the first step in the S&OP process. Since this is the first step of the process, it is important that the correct input information is accessible in order for the outputs to be useful. As the outputs from the demand planning phase are used as inputs in the following steps, the quality of the first step will determine the quality of the remaining process steps. Lapide (2004) also presents the baseline demand forecast, which is the output from the demand planning phase previously mentioned as the sales plan, as one of the main success factors for S&OP since this creates the initial working draft that is used in all following activities. Therefore, ensuring that the demand planning phase is performed correctly is of great importance for all companies implementing S&OP.

The demand planning phase can be divided into three different parts which form the basis of the monthly sales plan that is generated and sent out to stakeholders (Olhager 2019):

1. *Product portfolio:* The first part is about reviewing the product portfolio, which involves taking decisions about phase ins of new products as well as phase outs of old products.

2. *Forecasts:* Secondly, forecasts of the different product groups are updated. It is important to take into consideration that potential new products may need to be handled in a particular way when generating the forecasts. The same applies to products that are to be phased out and products that are undergoing a shift in their product life cycle.

3. *Market knowledge:* In the third and last part, the statistical forecasts are reviewed and adjusted taking planned campaigns, prices changes and the current situation with competitors and economy in general into account.

Those working in the sales and marketing department carry the responsibility of overriding the generated statistical forecasts and making appropriate adjustments by using existing knowledge in the field. It is also important to include those working in product development due to their important knowledge about the timing of new product launches (Wallace & Stahl 2008). Other relevant roles that are typically included in the demand planning team are e.g. Demand Manager, Forecast Analyst, S&OP Process Owner, Salesperson, Sales Manager, Product

Manager and Supply Chain Manager (Wallace & Stahl 2008). During the demand planning phase, demand planning meetings can be held with the demand planning team. The demand planning meetings can be of formal structure, which Wallace & Stahl (2008) state are more common in larger companies who may conduct multiple meetings in order to be certain of the forecast. Smaller companies are less common to have formal meetings and may instead conduct multiple smaller and less formal meetings such as face-to-face sessions.

3.2.1 Product groups

As S&OP planning is an aggregate planning tool, this implies that the planning object is most often focused on selected product groups rather than individual SKUs (Wallace & Stahl 2008; Grimson & Pyke 2007; Chapman 2006; Tavares et al. 2012; Ling & Goddard 1988). Since demand planning is one of the steps in the S&OP process, this implies that this process also focuses on product groups instead of SKUs. Ling & Goddard (1988) explain that the motivation for using product groups is to increase and achieve effective input and control from management. This is further strengthened by Kampen et al. (2012) who explain that if companies handle a large variety of SKUs, this typically causes difficulties in control of the production and inventory systems. Due to such difficulties, Kampen et al. (2012) state that defining a limited number of SKU classes, i.e. product groups, based on the SKU characteristics is advantageous since it allows the company to base decision making on a product group level rather an on an individual SKU level. The main purpose of product classification is presented by Kampen et al. (2012) to be to identify similarities in products regarding different properties in order to systematically classify the products. In many cases product classification is not the main purpose but is instead utilized in order to achieve another purpose, e.g. using product classification to reduce inventory levels (Kampen et al. 2012). Therefore, product classification is frequently used in inventory management and forecasting as a basis for decision making (Kampen et al. 2012).

The choice of product groups is a common challenge that many companies face in the S&OP process, and therefore also within the demand planning phase. A reason for this is that the use of too many product groups causes companies to struggle with maintaining an effective planning process (Wallace & Stahl 2008). The negative effect that too many product groups has on the planning process is argued by Wallace & Stahl (2008) and Ling & Goddard (1988) to be due to S&OP being a decision making process for top management. Too many product groups implies more details for top management to understand, which can be time-consuming and may therefore lead to an ineffective process. If the S&OP process is to be effective, top management must have an active participation and be hands-on in the decision making for each product group (Wallace & Stahl 2008). Obtaining more than a dozen product groups is therefore not desirable due to the risk of increased time-consumption. Wallace & Stahl (2008) presents that an optimal number of product groups ranges between six to twelve product groups. By staying within this range of product groups, companies are able to maintain active engagement from top management and an overall effective process.

Another reason for the need to aggregate products into product groups is connected to forecasting. Product classification is commonly used in the forecasting field since selecting the correct forecasting method for each product class enables companies to balance inventory costs and stock-out risks (Kampen et al. 2012). An important characteristic in the forecasting field is the demand pattern of the product group since this influences the level of performance of the chosen forecast method (Kampen et al. 2012). Chapman (2006) also explains that the forecasting accuracy tends to increase when based on an aggregate level rather than on individual products. When aggregating products into product groups, Chapman (2006) highlights the importance of the general rule which is to aggregate as far as possible without excluding useful information. The level of aggregation should allow for useful plans to be made.

When selecting the product groups, Wallace & Stahl (2008) state that an important question that companies must ask themselves is what the purpose of their product groups are. By answering this question, identification of the product group characteristics can be facilitated. Product group characteristics that are used to structure the product groups are numerous. Wallace & Stahl (2008) presents the following methods for structuring the product groups: product type, product characteristics, product size, market segment, distribution channel or customer. Kampen et al. (2012) have identified the four most common characteristics used for product classification in their study which are: demand volume, product, customer and timing. Once the product groups based on identified relevant characteristics are decided, different analysis methods can be used to identify which group a product should belong to.

3.2.2 ABC-XYZ matrix

The ABC analysis is a one-dimensional classification model that has been used widely in inventory management (Kampen et al. 2012; Flores & Whybark 1986). Stojanović & Regodić (2017) explain that the significance of the ABC classification model is due to it enabling monitoring of inventories and therefore being able to identify those inventories that do not contribute to the company's objectives. When applying the ABC classification model, products are grouped into A-, B- and C-categories depending on their contribution to a predetermined objective. The classification follows the Pareto-principle, also known as the 80-20 rule, which implies that 20% of the e.g. sold products should contribute to 80% of the sales results (Stojanović & Regodić 2017). Such products are placed in the A-category whilst products that contribute with 15% and 5% are placed in the B- and C-categories respectively. An example of the ABC classification curve is presented below in Figure 6. Once the classification has been performed, Flores & Whybark (1986) state that management's attention should mainly be placed on the A-category in order to maximize effectiveness.

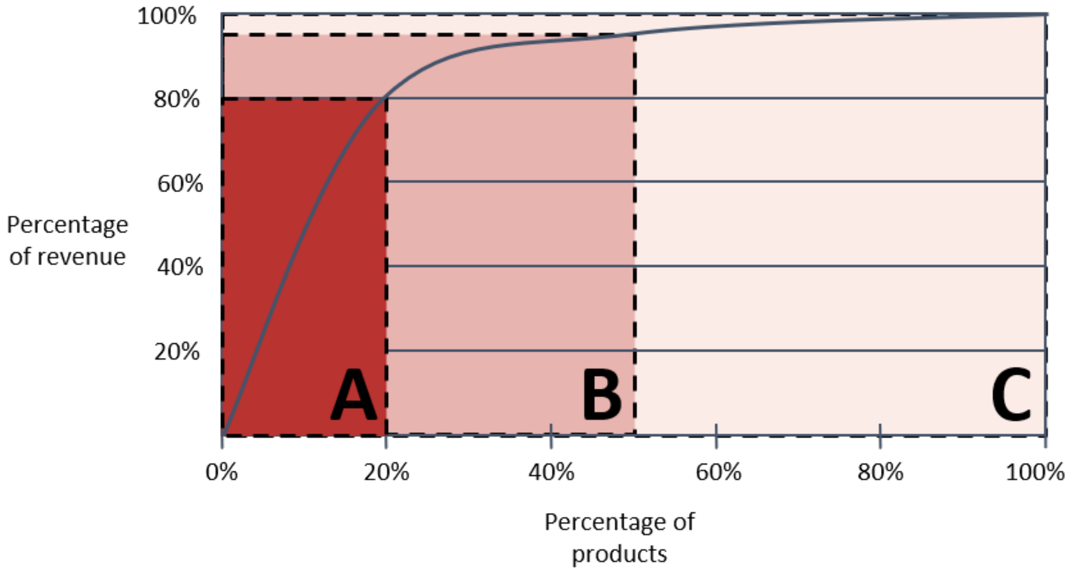

Figure 6: The ABC Classification Curve

The classifications used can vary depending on the purpose of performing the ABC-analysis since the purpose often determines the relevant criterion. The use of a single criterion creates a simplicity that the ABC-analysis is well-known for. However, this simplicity is also the basis of critics towards the classification method (Stojanović & Regodić 2017). Due to the critics, (Stojanović & Regodić 2017) explain that the need of encompassing several criteria has been acknowledged and widely accepted. Therefore, the ABC-XYZ classification model has been developed and enables the possibility to encompass multiple criteria in product classification. The XYZ-dimension of the product analysis is commonly utilized to categorize products according to the demand variability. Stojanović & Regodić (2017) and Calisir et al. (2019) present a common definition of the categories, where the X-category consists of products with continuous demand with minimal variations. Products with fluctuating demand patterns are commonly placed in the Y-category whilst products with large variations in demand and infrequent sales patterns are placed in the Z-category. There is also a correlation between the XYZ-categories and forecasting since the forecasting accuracy increases when demand is more stable. This implies that the forecasting accuracy should generally be highest for X-category products and lowest for Z-category products. When combining the two dimensions, i.e. ABC and XYZ, it is possible to obtain nine different product characteristics. Within the nine categories, Calisir et al. (2019) state that four of the categories can be seen as extreme, and obtain the following characteristics:

- *AX:* These products are of high value and are easy to forecast due to low demand variability.
- *CX:* These are less important products in terms of value and are relatively easy to forecast.

- *AZ:* Compared to AX products, these products are of high value but rather difficult to forecast due to high demand variability.
- *CZ:* Compared to CX products, this category includes products that are of low value but difficult to forecast due to high demand variability.

These four categories are classed as extreme, as stated by Calisir et al. (2019), since they are found in either the highest or lowest parts of the spectrum. Even though all nine categories are not as extreme, each category obtains certain characteristics that can be used in order to facilitate the categorization. A general example of the product characteristics for each of the nine categories in the ABC-XYZ-model is presented in Table 3. These categories are, in this example, based on the value of sales compared to the demand variability.

Table 3: The ABC-XYZ-classification model (Adapted from Stojanović & Regodić (2017))

	A	B	C
X	High value, continuous demand & high forecast accuracy	Medium value, continuous demand & high forecast accuracy	Low value, continuous demand & high forecast accuracy
Y	High value, fluctuating demand & medium forecast accuracy	Medium value, fluctuating demand & medium forecast accuracy	Low value, fluctuating demand & medium forecast accuracy
Z	High value, irregular demand & low forecast accuracy	Medium value, irregular demand & low forecast accuracy	Low value, irregular demand & low forecast accuracy

Depending on the classification the product receives, different strategies are possible to apply. An example of inventory strategies per product category is provided by Stojanović & Regodić (2017) and presented below in Table 4. The strategies are based on the classifications presented in Table 3. An advantage of the ABC-XYZ classification model is that it can therefore be used for strategic purposes in supply and inventory control in multiple industries, such as the food industry (Calisir et al. 2019). Another advantage of the ABC-XYZ classification model is that it enables the integration of products with similar characteristics (Scholz-Reiter et al. 2012).

Table 4: The ABC-XYZ-classification strategies (Adapted from Stojanović & Regodić (2017))

	A	B	C
X	Low inventory	Low inventory	Medium inventory
Y	Low inventory	Medium inventory	High inventory
Z	Medium inventory	High inventory	High inventory

3.2.3 Demand Planning in Non-Manufacturing Companies

General theory regarding demand planning is commonly based on the manufacturing industry. Even though previous research and theory does not put emphasis on the non-manufacturing industry, the need for demand planning in such companies is of great importance. Non-manufacturing companies, such as retailers and distributors, normally supply their customers with a large variety of products. Ulrich et al. (2022) explain that the demand of the products that non-manufacturing companies offer to their customers are high in diversity in regards to demand quantities, demand frequencies and demand variations. Due to the diversity in demand patterns, demand forecasting and planning is of great importance for non-manufacturing companies in order to enable increased forecast accuracy. Ulrich et al. (2022) explain further that the diversity in demand patterns within the product assortment also creates difficulty in demand forecasting since it is improbable that all products can obtain the same forecast model. The authors highlight the need for demand forecasting in non-manufacturing companies in order to understand the product assortment and thereafter identify relevant product categories. It is first once these factors are in place that the corresponding forecasting model per category can be identified in order to increase the forecasting accuracy.

Demand forecasting is also stated by Bai (2022) to have become an essential part of non-manufacturing operations in recent years since it provides an increased understanding of the current market and product planning activities such as distribution, pricing and promotions. The importance of demand forecasting for non-manufacturing companies is further motivated by Bai (2022) and Ulrich et al. (2022) to be due to the financial consequences that arise when an imbalance between supply and demand occurs. Demand forecasting is an important aspect of all decision making activities, both short term decisions regarding inventory levels and long term decisions regarding the company's strategy (Bai 2022; Veiga et al. 2016). The role of demand forecasting in decision making is therefore equally relevant in the manufacturing industry as in the non-manufacturing industry.

3.2.4 Demand Planning in the Food Industry

Demand planning is also highly important when handling perishable goods that deteriorate rapidly (Huber & Stuckenschmidt 2020; Huber et al. 2017). When handling such time sensitive goods, it is important that the supplier is able to provide the right quantity at the right time. If the supplier is not able to do so, Huber & Stuckenschmidt (2020) and Huber et al. (2017) explain that the perishable goods will become waste and create unnecessarily high costs for the company. It is therefore important to increase the demand forecast accuracy in order to reduce high safety stocks and the number of products that are discarded. Huber & Stuckenschmidt (2020) also proceed to motivate the importance of demand forecasting in the bakery industry, which is subject to many special days, i.e. public holidays and days before as well as after such holidays, and seasonal patterns. Demand patterns on special days within the bakery industry deviate from the demand on otherwise normal days since customer routines change depending on the type of day. Due to this, the demand can either be higher or lower on special days compared to normal days depending on how the days fall during the week (Huber & Stuckenschmidt 2020). Another challenge that the bakery industry is subject to and that is strongly connected to special days is the fact that some special days do not fall on the same weekday every year. Huber & Stuckenschmidt (2020) explain that this causes difficulties in quantifying the effect that the specific day entails.

Demand forecasting within the food industry is also affected by the input of managers' experience (Huber et al. 2017). When ordering perishable goods, Huber et al. (2017) explain that the order quantities tend to be determined by managers experience rather than from forecasts based on historical demand. Since baked goods and the corresponding ingredients are classed as perishable goods, these products have a short shelf-life as well as a high number of sales (Huber et al. 2017). Due to this, the main cost factor that arises for such products is due to excessive stock levels that lead to products being discarded or marked down (Huber et al. 2017; Huber & Stuckenschmidt 2020). Inaccurate forecasts, i.e. an under- or overestimation of the demand, is also presented by Huber et al. (2017) to be a main cause to the occurrence of such negative financial costs. In order to reduce the occurrence of costs due to inaccurate forecasting and the accompanying effects such as excessive stock levels, improving the company's demand planning is essential.

3.3 Forecasting

The general purpose of forecasting in a company is described by Olhager (2019) as increasing profitability by improving the understanding of demand and using this knowledge to plan in advance. Forecasting can result in shorter delivery times, more steady capacity utilization and better inventory control (Olhager 2019), which is equal to having the right quantity of items in stock at the right time in order to obtain the desired service level. Both Olhager (2019) and Hyndman & Athanasopoulos (2018) state that short term forecasts are important to maintain production- and inventory control while long term, aggregated forecasts are necessary to dimension the amount of capacity needed in production and logistics. According to Olhager (2019), one general fact about a forecast is that it is very difficult to get it exactly right and thus a forecast is usually wrong. Hyndman & Athanasopoulos (2018) mean that it differs from one thing to another regarding how easy it is to forecast and that the predictability is dependent on three different aspects:

- How well understood the influencing factors are
- The amount of data available
- Whether the forecast itself actually affects the output of what is being forecasted

3.3.1 The forecasting process

There are several aspects to take into consideration when a forecast is to be used as a basis for decisions related to production and logistics. Two of these aspects regard identifying what time horizon and level of detail that is necessary in order to support the decision making (Olhager 2019; Hyndman & Athanasopoulos 2018). As illustrated in Table 5, the purpose, level of detail and decision area of a forecast differs between various time horizons.

Table 5: The use of forecasting across different time horizons (Adapted from Olhager (2019))

	Short term *(1-12 weeks)*	Mid term *(3-24 months)*	Long term *(1-5 years)*
Purpose	Operational planning and control of production, inventory, purchasing and staffing	Allocation of resources	Planning of resource acquisition
Item level	Final products	Product groups	Total sales per business area
Decision area	Master planning, distribution- and purchasing planning	S&OP, product portfolio planning	Capacity- and facility planning, technology investment

In the area of identifying an appropriate item level for the forecast, Wallace & Stahl (2008) discuss ten possible levels of aggregation to use when conducting forecasts and these are illustrated in Figure 7. The highest level of aggregation is on a company level, which implies that forecasts will be done for the company as a whole. The consequences of such a high level of aggregation are, as stated by Wallace & Stahl (2008), that the results will not provide enough detail to base sales and operations plans on. On the other hand, the lowest level of aggregation, SKU by customer by location, contains all necessary details needed which can be used to aggregate upwards in different ways. However, performing forecasts at this aggregation level may contain too much detail that can instead cause forecast errors. Wallace & Stahl (2008) argue in line with Chapman (2006)'s statement that the aggregation should be at such a detailed level that allows for accurate forecasting and planning.

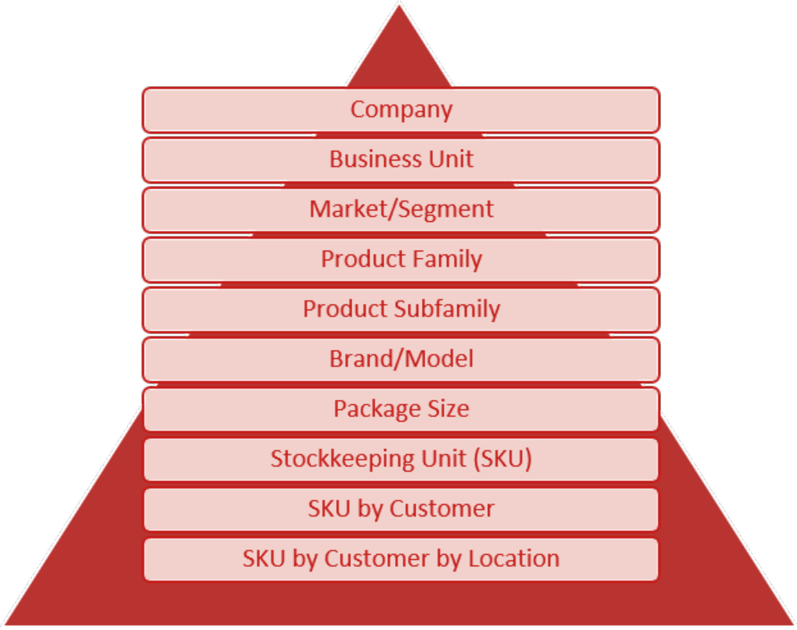

Figure 7: The aggregation pyramid (Adapted from Wallace & Stahl (2008))

It is also important to consider the number of objects to forecast to determine whether a lot of effort should be put into each forecast or if a standardized process is more appropriate (Olhager 2019; Hyndman & Athanasopoulos 2018). Furthermore, Hyndman & Athanasopoulos (2018) state that the frequency of which forecasts should be produced is important to take into consideration, as forecasts that have to be produced very often should preferably be made in an automated system. Another important aspect mentioned by Olhager (2019) is to consider who will use the forecast and thus also how it should be presented. All of these aspects are part of the problem definition phase, which is the first of the five steps that are typically involved in the forecasting process (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998):

1. *Problem definition* - It is important to get a thorough understanding of how, who and where the forecasts will be used.

2. *Gathering information* - Both statistical data and input from people that are collecting data and using the forecasts is necessary.

3. *Preliminary analysis* - Graph the data to identify patterns, such as trend, seasonality and cycles, as well as outliers that need further explanation from people with expert knowledge.

4. *Choosing and fitting models* - Which forecast model is best to use depends on the historic data and the relationships with explanatory variables, but also the way the forecast should be used affects the choice.

5. *Using and evaluating a model* - Once a model and its parameters have been chosen and put to use it is of high importance to evaluate the performance and make adjustments if needed.

Olhager (2019) describes the forecasting process in a similar manner but mentions the following steps: Identify demand model, Choose forecasting method, Decide parameter values, Set initial values and Perform continuous follow-up. In this context, the problem definition, gathering of information and initial analysis of data is included in the first step. Furthermore, the fourth step in Hyndman & Athanasopoulos (2018) and Makridakis et al. (1998) five step model includes the three steps of choosing method, deciding parameters and initial values that are kept separate by Olhager (2019). With this in mind, these authors mention the same activities in their description of a forecasting process but have divided the steps in various ways.

3.3.2 Demand models

The choice of forecast method depends on what the demand model looks like (Olhager 2019; Hyndman & Athanasopoulos 2018). As expressed by Olhager (2019), a demand model describes the process generating the demand and it is estimated from historic demand, while a forecast method is used to estimate future demand. To identify the demand model is part of the second and third step in Hyndman & Athanasopoulos (2018) five step process described above, since it requires information and preliminary analysis.

The time series representing historic demand can be described with five different components: level, variation, cycle, trend and seasonality (Olhager 2019).

- The *level* is represented by the average demand, excluding trend, seasonality and cycle.
- The *variation* include the random, inexplicable deviations that do not follow any clear pattern.
- The *trend* is the successive increase or decrease in demand.
- The *seasonality* is the recurring deviations, often on yearly basis.
- The *cycle* represents patterns that returns after several years, often reflecting the general economic conditions.

Axsäter (2006) discusses three demand models that involve various of the above mentioned parameters and thus are of different complexity. The first and most simple demand model that is brought up is a *constant model* where the demand in a certain period is represented by the random deviation from an average value, which includes the first two time series components: level and variation. This model is, according to Axsäter (2006), suitable to use for products that are in a mature stage of their life cycle and have stable demand. The second model addressed is a *trend model* that extends the constant model by also taking a linear trend into consideration, which is suitable when there is a systematic increase or decrease in the demand (Axsäter 2006). The last and most complex model described is a *trend-seasonal model*. In addition to the components of the previous model, this model also takes the seasonality into consideration and is thus appropriate for items with seasonal demand variations (Axsäter 2006). The *trend-seasonal model* is more general than the other two and results in a need to estimate more parameters, which usually is very difficult (Axsäter 2006). With this in mind, the author states that it is often more efficient to use a simple model with fewer parameters and that a general model should be avoided when there is no clear evidence that the generality is beneficial.

Coefficient of variation

A characteristic that can be used to describe the variation of a demand model is the demand variability. This can be evaluated using the Coefficient of Variation (CoV), which is described by Makridakis et al. (1998) as a measurement of the relative dispersion of a data series. This is calculated by dividing the standard deviation (σ) by the mean (μ) (Makridakis et al. 1998), as presented in Equation 1. Considering the fact that the measurement is relative to the mean, it is possible to compare demand variability of products with distinct differences in demand volume.

$$CoV = \frac{\sigma}{\mu} \tag{1}$$

D' Alessandro & Baveja (2000) have performed a study where the CoV is used to examine demand patterns at a chemical company named Rohm and Haas. The study was carried out over three years with the goal to examine and redesign Rohm and Haas' precepts, as the company faced problems with increased competition and lower profit margins. The study resulted in millions of dollars saved and a more structured operation unit, through e.g. a segregation of products which were assigned different production and inventory policies.

To segregate products into different groups, D' Alessandro & Baveja (2000) analyzed the demand variability. They applied the Pareto principle of 80/20% to separate products with high demand variability from low variability products. D' Alessandro & Baveja (2000) motivate the use of the Pareto principle by the fact that several sources of literature encourage this method for segregating products. In this case, they were able to capture 20% of the products by setting a upper bound of the CoV equal to 0,52. This means that the products with a CoV between 0 and 0,52 is set to be low variability products while the remaining 80%, with a CoV above 0,52, is named as high variability products. Furthermore, D' Alessandro & Baveja (2000) produced a matrix, with demand variability on the y-axis and demand volume on the x-axis to obtain four different product groups based on the four quadrants. They measured the demand volume in weekly average demand and the bound between high and low demand volume was obtained by analyzing the production yields. The design of the matrix is illustrated in Figure 8.

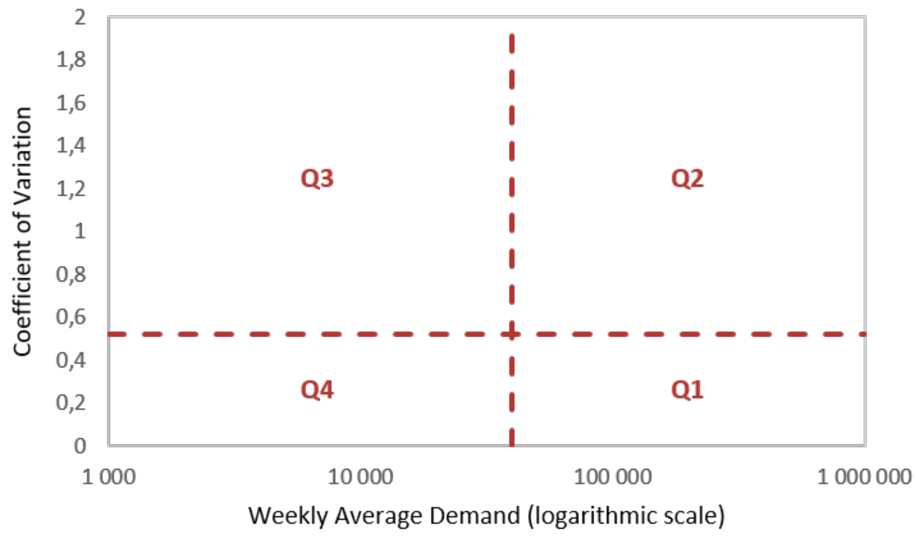

Figure 8: Demand variability matrix (Adapted from D' Alessandro & Baveja (2000))

The first quadrant, Q1, represent the products with high volume and low variability, and these are the most predictable products. The second quadrant, Q2, holds the high volume products with high variability. The third quadrant, Q3, contains the products with low volume and high variability, and this is the group where most of the products ended up in Rohm and Haas' case. Lastly, Q4 is the quadrant representing low volume and low variability products. In the study conducted by D' Alessandro & Baveja (2000), no products ended up in Q4 and only a few were represented in Q2, so these were treated as Q1-products. With this in mind, they ended up with two different groups, Q1 and Q3, which were assigned different strategies for manufacturing, storing and service. The products in group Q1 were assigned a make-to-stock policy based on a demand forecast, while the Q3-products where not subject to demand forecasting as they were to follow a make-to-order policy.

3.3.3 Forecast methods

Once the basic time series components of a demand model have been identified, the forecasting method that is able to capture the pattern of demand should be chosen (Olhager 2019; Hyndman & Athanasopoulos 2018). As stated by Olhager (2019), it is important to select an appropriate forecast method in order to identify the systematic variations and disregard the random occurrences. A forecast can be of qualitative or quantitative nature and the most suitable nature depends largely on the amount of historic demand data available (Olhager 2019; Hyndman & Athanasopoulos 2018). A completely qualitative forecast is a subjective assessment which is appropriate to use when there is a lack of available quantitative data or when the relationship between history and future data is difficult to model (Olhager 2019; Hyndman & Athanasopoulos 2018). This type of forecast is based on intuition or judgements and examples of qualitative methods are the Delphi method, Expert opinions and Sales force estimations. This can be compared with an objective, quantitative forecast, which is useful when historic data is available and it is probable that the future will continue to follow some part of the historic pattern (Olhager 2019; Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). Quantitative forecasting methods can be divided into two subtypes, where the first is time series methods and the second is causal, also called explanatory, methods (Olhager 2019; Makridakis et al. 1998). As stated by Olhager (2019), time series method is the most common type of quantitative forecast and it is based on the fact that time series data from one certain variable is used to forecast the future demand of the same variable, for example *Moving Average* and *Exponential Smoothing*. Olhager (2019) also mentions causal methods where the forecast is related to the history and the development of other variables, for example *Regression* and *Econometrics*. Regardless of the subtype, most quantitative forecasting methods have certain parameters and initial values that need to be determined and this should be done to minimize the forecast error (Olhager 2019; Hyndman & Athanasopoulos 2018). Except quantitative and qualitative forecasts, Makridakis et al. (1998) mention a third category, unpredictable forecast, which applies when little or no information is available to conduct a forecast.

Both in terms of qualitative and quantitative forecast methods, there are a lot of different alternatives to choose from when determining what method to apply. To further complicate this issue, Ulrich et al. (2022) state that in an organisation with a wide range of SKUs with different characteristics, it is unlikely that one single forecast method is the most appropriate across all SKUs. This is strengthened by the fact that the forecast method should be chosen based on the demand model and that the demand of different SKUs within the same organization can be very different. Furthermore, even for one single demand model there are multiple forecast methods that could be suitable, but the satisfaction may differ. The familiarity, satisfaction and use of major forecasting methods, both qualitative and quantitative alternatives, are discussed by Makridakis et al. (1998) and they have made several observations based on surveys among forecasting users. The highlights of these observations are:

1. *Familiarity*: More than 70% of the respondents are very familiar with the qualitative methods Jury of executive opinion, Sales force composite and Customer expectations as well as the quantitative methods Moving average, Straight-line projection, Exponential smoothing and Regression. The method of lowest familiarity was Box-Jenkins, with a total of 65% of the respondents being completely unfamiliar with this method.

2. *Satisfaction*: The three methods that are used with the highest level of sat-

isfaction are Regression, Exponential smoothing and Moving average with 58% or more of the respondents being satisfied. The methods with the lowest satisfaction are Box-Jenkins and Straight-line projection. Notable is that all qualitative methods investigated are ranked in the middle in terms of satisfaction.

3. *Area of use*: The qualitative forecast methods that are mentioned are used across all forecasting time horizons. Exponential smoothing and Moving average are most commonly used for the short term with a horizon of up to three months, while Regression is most often used for longer forecast horizons.

The three forecast methods used with the highest level of satisfaction will be presented in more depth below.

Moving average

One useful approach when conducting a quantitative time series forecast is to split the time series into different components of the pattern representing trend, seasonality and cycles (Hyndman & Athanasopoulos 2018). However, the trend and cycle are usually integrated into one single component and an additional component called error, irregular or remainder is used to describe the difference between the trend-cycle and seasonality patterns and the actual data (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). This is called time series decomposition and Hyndman & Athanasopoulos (2018) and Makridakis et al. (1998) state that one fundamental element when methods apply this approach is moving average.

Moving average is a simple forecast method that has existed for a long time and it is used to estimate the trend-cycle of a time series by using smooth historic data (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). This method is generally stable, reacts slowly to systematic changes and it is given as follows (Olhager 2019):

$$F_{t+1} = \frac{D_t + D_{t-1} + ... + D_{t-N+1}}{N} = \frac{1}{N} \sum_{i=t-N+1}^{t} D_i \tag{2}$$

where F_{t+1} = forecast of period t+1, conducted in period t
D_t = observed demand in period t
N = number of observations included in the average

The choice of number of observations to include in the moving average, also called the order, depends on the demand model and whether it is considered to be stable or not (Olhager 2019). A larger number of observations results in a smoother and more stable trend-cycle and increases the probability that random deviations are eliminated. However, fewer observations result in a more flexible trend-cycle that take bumps or cycles that are of interest into consideration (Makridakis et al. 1998; Olhager 2019).

Exponential Smoothing

Another forecast method that is easy to use and quickly provides reliable forecasts for a wide range of time series is Exponential Smoothing (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). In contrast to moving average where all past observations are weighted equally, the weights of the past observations decrease exponentially as they get older (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). This indicates that the most recent observations are assumed to provide the best guidance and thus these are weighted higher. The most simple version of this forecast method is called *Simple Exponential Smoothing*, which is suitable when the demand model does not contain any clear trend or seasonal pattern (Hyndman & Athanasopoulos 2018). The forecast is given by the following formula (Olhager 2019):

$$F_{t+1} = \alpha D_t + (1-\alpha)F_t \tag{3}$$

where F_{t+1} = forecast of period t+1, conducted in period t
D_t = observed demand in period t
α = the smoothing parameter, $(0 \leq \alpha \leq 1)$

The value of the smoothing parameter determines whether more weight is given to the previous forecast, and thus the more distant observations, or if more weight is given to the recent observations (Hyndman & Athanasopoulos 2018). A higher value of the smoothing parameter results in a forecast that quickly adapts to changes but is more sensitive to random events (Olhager 2019). Olhager (2019) states that the smoothing parameter is most commonly set between 0,05 and 0,3 in practice and that the value is determined to minimize forecast error.

The simple exponential smoothing method can be extended to allow forecasting of data with trends and this extension is called Holt's linear method, but it can also go by the name *Double Exponential Smoothing* (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). This forecast method uses two smoothing constants and three equations (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998; Axsäter 2006):

$$\textit{Level}: a_t = \alpha D_t + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{4}$$

$$\textit{Trend}: b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{5}$$

$$\textit{Forecast}: F_{t+k} = a_t + b_t k \tag{6}$$

where F_{t+k} = forecast of period t+k, conducted in period t
a_t = estimated level of the series at time t
b_t = estimated trend of the series at time t
D_t = observed demand in period t
α = the smoothing parameter for the level, $(0 \leq \alpha \leq 1)$
β = the smoothing parameter for the trend, $(0 \leq \beta \leq 1)$

The Holt's linear method can also be extended to capture seasonality in data and this extended method is called Holt-Winters' Trend-Seasonal Method or *Triple Exponential Smoothing* (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998;

Axsäter 2006). This method includes three smoothing constants and four equations, but there are two different variations of the method that depend on whether the seasonal component is modeled in an additive or multiplicative way (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). As stated by Hyndman & Athanasopoulos (2018), the additive method should be used when the seasonal variations are fairly constant no matter the level of the series, while the multiplicative method should be used when the seasonal variations are proportional to the level. This indicates that the seasonal component in the additive method is expressed in absolute terms while the seasonal component in the multiplicative method is stated in percentages, a relative term. As described by Hyndman & Athanasopoulos (2018) and Makridakis et al. (1998),the additive method is given by:

$$\textit{Level}: a_t = \alpha(D_t - c_{t-s}) + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{7}$$

$$\textit{Trend}: b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{8}$$

$$\textit{Seasonal}: c_t = \gamma(D_t - a_t) + (1-\gamma)c_{t-s} \tag{9}$$

$$\textit{Forecast}: F_{t+k} = a_t + b_t k + c_{t-s+k} \tag{10}$$

where F_{t+k} = forecast of period t+k, conducted in period t
a_t = estimated level of the series at time t
b_t = estimated trend of the series at time t
c_t = estimated season of the series at time t
D_t = observed demand in period t
α = the smoothing parameter for the level, $(0 \leq \alpha \leq 1)$
β = the smoothing parameter for the trend, $(0 \leq \beta \leq 1)$
γ = the smoothing parameter for the season, $(0 \leq \gamma \leq 1)$
s = length of the seasonality

The multiplicative method is given by (Hyndman & Athanasopoulos 2018) and (Makridakis et al. 1998):

$$\textit{Level}: a_t = \alpha\frac{D_t}{c_{t-s}} + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{11}$$

$$\textit{Trend}: b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{12}$$

$$\textit{Seasonal}: c_t = \gamma\frac{D_t}{a_t} + (1-\gamma)c_{t-s} \tag{13}$$

$$\textit{Forecast}: F_{t+k} = (a_t + b_t k)c_{t-s+k} \tag{14}$$

where F_{t+k} = forecast of period t+k, conducted in period t
a_t = estimated level of the series at time t
b_t = estimated trend of the series at time t
c_t = estimated season of the series at time t
D_t = observed demand in period t
α = the smoothing parameter for the level, $(0 \leq \alpha \leq 1)$
β = the smoothing parameter for the trend, $(0 \leq \beta \leq 1)$

γ = the smoothing parameter for the season, $(0 \leq \gamma \leq 1)$
s = length of the seasonality

The main advantage with these smoothing methods is the fact that they are simple and come at a low cost (Makridakis et al. 1998). As discussed by Makridakis et al. (1998), there are other, more complex methods that could potentially result in better forecast accuracy but exponential smoothing methods are often the only ones that are fast enough to achieve an acceptable implementation when there is a need to forecast thousands of items. With this in mind, Makridakis et al. (1998) suggest that exponential smoothing methods are appropriate for short term forecasting on the operating level of an organization.

Regression

In comparison to the previously mentioned methods, a forecast can also be of explanatory type, where the outcome is expressed as a function of several influencing factors (Makridakis et al. 1998). For example, the weather might be an influencing factor that affects the outcome when forecasting the demand of ice cream. The method is called *Simple regression* if a variable that is subject to forecast only depends on one single explanatory variable, which can be compared to *Multiple regression* where more than one explanatory variable is involved (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998). As described by Hyndman & Athanasopoulos (2018), the most simple case of regression is when there is a linear relation between the influencing variable and the forecast variable. In case of simple regression and a linear relation, the method is given by (Hyndman & Athanasopoulos 2018; Makridakis et al. 1998):

$$Y = a + bX + e \tag{15}$$

where Y = the forecast variable
X = the influencing/explanatory/predictor variable
a = the intercept
b = the slope
e = the error

3.3.4 Forecast error

The last part of the forecasting process is about evaluating the performance of the used forecast method. As described by Olhager (2019), it is of great importance to continuously follow up the forecast accuracy and make adjustments if necessary. The forecast error is defined as (Olhager 2019; Makridakis et al. 1998):

$$e_t = D_t - F_t \tag{16}$$

where e_t = forecast error in period t
D_t = observed demand in period t
F_t = the forecast of period t

If there are observations and forecasts from several time periods, then there are many error terms that can be used to measure the forecast accuracy. Three commonly used statistical measures of the forecast error are Mean Error (ME), Mean Absolute Error (MAE) and Mean Squared Error (MSE), which are defined as (Makridakis et al. 1998):

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t \tag{17}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t| \tag{18}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \tag{19}$$

Of these three, ME is the only measure that identifies whether the forecast is higher or lower than the actual demand. On the other hand, positive and negative values can offset each other, which result in a small value in total. Makridakis et al. (1998) state that ME should only be used to identify the forecast bias, which indicates if there is a systematic under- or over-forecasting. In comparison, the errors are made positive in MAE and MSE to get a better indication of the size of the errors. Makridakis et al. (1998) mean that an advantage with MAE is that it is easy to understand and explain, while a benefit with MSE is that it is easy to handle mathematically. MSE results in large values when there is a significant error, in comparison to MAE. Olhager (2019) also describes MAE to be the most commonly used measure in practice. All these three statistical measures of the forecast error are dependent on the size of the sample and do not give any relative measure that can be compared across time series based on different conditions (Makridakis et al. 1998). To make such comparisons, it is necessary to use relative or percentage error measures, where two common types are Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) (Makridakis et al. 1998):

$$MPE = \frac{1}{n}\sum_{t=1}^{n} \frac{D_t - F_t}{D_t} * 100 \tag{20}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} |\frac{D_t - F_t}{D_t} * 100| \tag{21}$$

Another way of measuring forecast accuracy is by weighting the error by the total sales, which is called Weighted Average Percentage Error (WAPE) (Riva 2021):

$$WAPE = \frac{\sum_{t=1}^{n} |D_t - F_t|}{\sum_{t=1}^{n} |D_t|} \tag{22}$$

As discussed by Das et al. (2020), WAPE emphasizes the accuracy of items with high demand and it can be used to evaluate series containing items with varying demand. This is justified by the fact that the sum of the absolute error is normalized by the total demand. If the forecast of a product with high demand deviate by a few percentages, this will correspond to a larger absolute error than if a product with low demand deviate with the same proportion. However, it is not possible to assign different weights or priorities to different products when using WAPE or any of the previously mentioned measurements. To achieve this, the Weighted Mean Absolute Percentage Error (WMAPE) can be used instead and this is calculated as follows (Riva 2021):

$$WMAPE = \frac{\sum_{t=1}^{n} (w_t|D_t - F_t|)}{\sum_{t=1}^{n} (w_t|D_t|)} \tag{23}$$

where $w_t =$ the weight in period t

3.3.5 Success factors of forecasting

To achieve a forecasting process that results in as low forecast error as possible, there are several aspects that need to be in place in an organisation. Moon et al. (1998) have conducted an extensive research program that resulted in seven identified keys that generate better forecasting and these keys are presented below:

1. *Understanding what forecasting is and is not*: It is important to understand that sales forecasting is a management process and not just a computerized program. Many computer systems cost huge amounts of money and resources but actually fail to deliver accurate forecasts. The originators have to understand how and why numbers are generated from the system to use the system and tools properly. With this in mind, an organization should be put in place to manage the forecasting process and not just manage a system. Another important aspect in order to avoid confusion in forecasting is to understand how the forecasts relate to the organization's plans and goals.

2. *Forecast demand, plan supply*: The initial forecasts should result in predictions that are not restricted by capacity. It is important to identify where the capacity does not meet the demand forecast to know when it is necessary to expand capacity. To forecast the actual demand will help an organisation take long term decisions.

3. *Communicate, cooperate & collaborate*: It is critical to obtain input from different functions of an organisation to generate effective forecasts. However, employees are often unwilling to work across functions and with this in mind it is important to establish a cross-functional approach and collaboration when conducting forecasting activities. This results in more accurate forecasts, less double handling and forecasts that are trusted along the organization.

4. *Eliminate islands of analysis*: It is common that distinct areas in an organisation perform similar activities and this can also be the case when it comes

to forecasting. As a result of mistrust, different functions might create their own forecasts, but the problem is that these are often based on different assumptions and the result is inaccuracy and inconsistency. To solve this, a single "forecasting infrastructure" should be established and employees should be trained to get an understanding of the overall process.

5. *Use tools wisely*: One key to achieve more effective forecasting is to include both quantitative and qualitative tools. However, these tools must be well understood to know where each tool works and where they do not work.

6. *Make it important*: The importance of the forecasting function should not only be understood by senior management and certain individuals, it should be a consensus among the whole organisation. To achieve this, it is important to incorporate forecasting performance measures in individual performance plans. Furthermore, people should be trained to understand the consequences of poor forecasting to ensure that developers take it seriously.

7. *Measure, measure & measure*: A system for measuring performance, including setting targets, is of utmost importance to identify if the forecast is contributing to the success of the business. Sources of errors can be identified and subject to improvement.

4 Empirical study

This chapter will present all empirical data that has been collected and used in the upcoming analysis to be able to answer the research questions described in Section 1.5. The chapter begins with a description of the sources used to collect the data. Thereafter, KåKå's role in the supply chain is presented, followed by an in depth description of how KåKå currently works with S&OP, demand planning and forecasting. Lastly, some key product characteristics are presented.

4.1 Data sources supporting the empirical study

The information described throughout this empirical study has been provided by KåKå and both quantitative and qualitative types of data have been used. Several interviews have been conducted with employees from different parts of the company. The interviewees represent different functions in the current S&OP process at KåKå, including sales, supply- and demand planning, supply chain and top management, see Table 6. The interview guide that was used during the interviews is available in Appendix A. A second way of collecting empirical information was through observations, both by supervising people involved in demand planning in their daily work as well as observing the ongoing warehousing operations. Another type of observation conducted was to attend meetings that are part of KåKå's current S&OP and demand planning processes to see how they are performed in practice. In addition, internal documentation and quantitative information obtained from KåKå's information systems was used to get a comprehensive picture of the current situation.

Table 6: List of interviewees in the empirical study

Function	Employee title
Top management	• Chief Operations Officer • Sales Manager
Supply chain	• Project Consultant (Internal)
Demand & Supply planning	• Supply and Demand Manager • Demand Planner
Sales	• Sales Manager • Team Leader Internal Sales

4.2 KåKå's role in the supply chain

As previously described in Section 1.2, KåKå supplies 2 500 customers with bakery ingredients and accessories. Since KåKå is a non-manufacturing company, their suppliers are of great importance in order to fulfill customer demand. All of the products in KåKå's product assortment are purchased from approximately 300 suppliers, which implies that the main operational activity that KåKå performs is warehousing. Due to this, the main focus of the S&OP process at KåKå is the warehousing operations and not manufacturing operations, which is the most common case in theory. When supplying customers with the demanded products, some products are directly transported to the customer whilst the majority pass through at least one of KåKå's four warehouses. The deliveries of products to KåKå's four warehouses can occur in two ways, either directly from the supplier or through a so-called loop. A loop implies that a product delivery is performed by transporting products from one warehouse to another, e.g. from the warehouse in Lomma to the one in Örebro. These loops are performed multiple times during a working week and can occur between all four warehouses, in all directions. KåKå's current supply chain setup is presented in Figure 9.

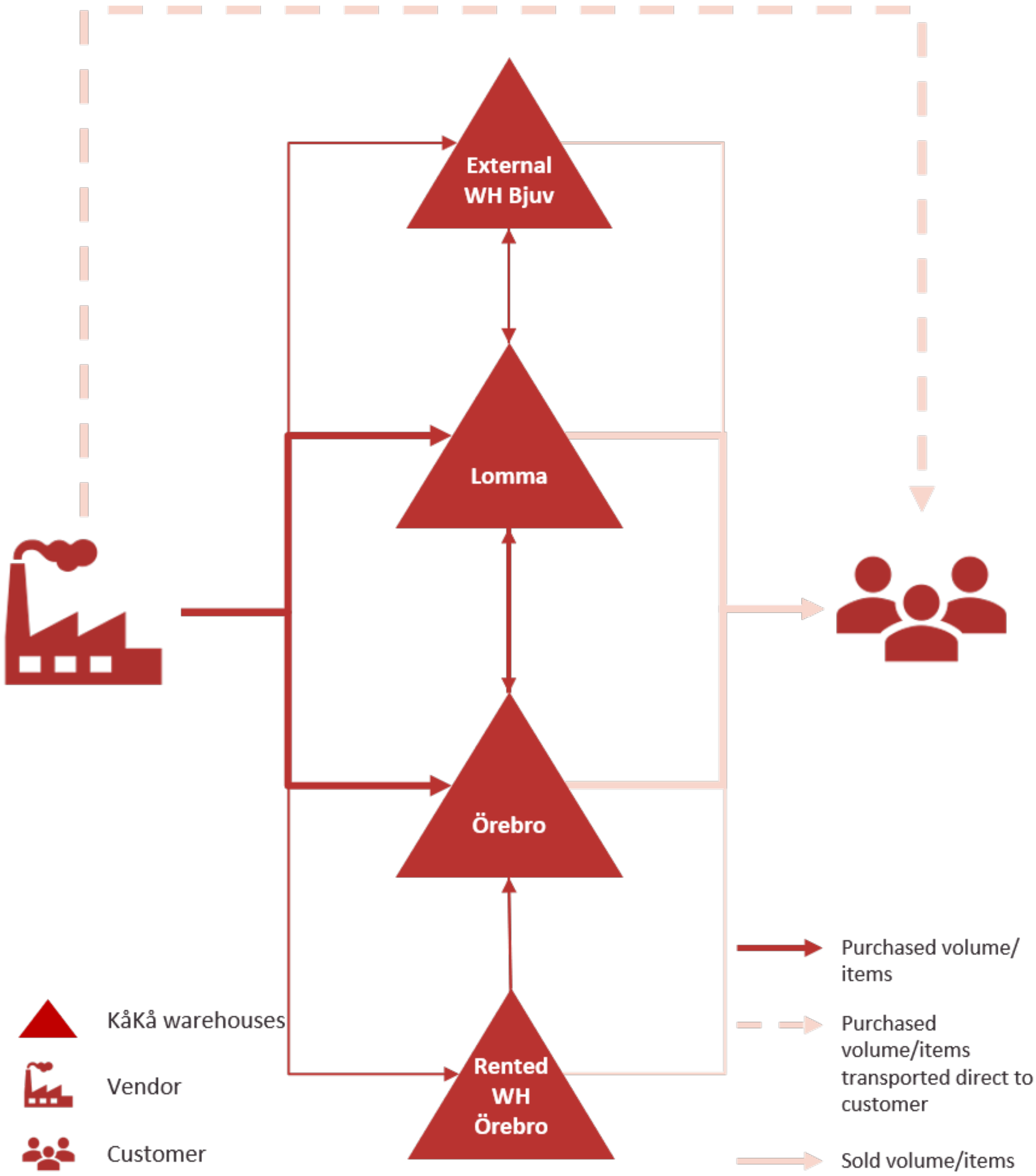

Figure 9: KåKå's current supply chain

At KåKå, the main company mission is to: *"Strengthen the customers profile, profitability and contribute to sustainable growth in the market."*. In order to fulfill the company mission, KåKå emphasizes the need to be flexible and offer short lead times to customers. The company also emphasizes the need to obtain the ability to transfer their customers' desired complexity to the company itself. An example of how KåKå offers the ability to acquire their customers' complexity was presented during an interview. The interviewee explained that their offer of branded non-food goods, such as packages, reduce the complexity for their customers since they must be ordered in such large volumes from the manufacturer in order to be allowed to print the customers' brand on the products. These large volumes normally correspond to at least a year's worth of their customers' consumption. This would, in general, require their customers to have a large stock of such branded products, which is not possible for most customers due to lack of storage capacity. Instead of losing customers due to the producers conditions, KåKå offers to stock their customers' branded products in exchange for a storage fee, which enables KåKå to continue to offer branded products despite strict manufacturer constraints. The company's mission to provide flexibility and take on customer complexity is also strongly reflected in the service level target of 98,5% that the company has set. From the interviews, it has also become clear that there is an overall understanding that the short lead times KåKå offers is one of their main strengths when achieving a high service level since it allows them to respond quickly to new or changed demand.

4.3 Supply chain information systems at KåKå

All employees at KåKå are in contact with information systems in their daily work and the ERP system Microsoft Dynamics 365 (Dynamics 365) is widely used throughout the company. This system influences all business processes by offering several functions that support e.g. sales, customer service, marketing, warehousing and logistics operations. This is also where all transactions of orders, pickings and invoices occur. In addition to the ERP system, KåKå uses SAP Integrated Business Planning (IBP) for demand planning activities. This is a system that offers multiple solutions for various supply chain issues, but as of today it is only utilized for statistical forecasts at KåKå. IBP is integrated with the ERP system in such a way that the master data from Dynamics 365 is continuously sent to IBP, where forecasts are calculated and the information about the forecasts is thereafter sent back to the ERP system. A third information system used at KåKå is Microsoft Power BI (Power BI), which is utilized to produce reports and get comprehensible overviews of data. Similar to IBP, Power BI is integrated with the ERP system and accesses master data from Dynamics 365, but there is no integration between Power BI and IBP. Lastly, KåKå uses Microsoft Excel (Excel) for various supply chain activities supporting the daily operations.

4.4 The Sales and Operations Planning process at KåKå

KåKå has been working with S&OP for four years, but due to unforeseen circumstances the implementation has been interrupted several times since the initiation. The Covid pandemic was one event that occurred with poor timing and obstructed the implementation of a proper S&OP process. Moreover, the process was very dependent on certain individuals and thus the process collapsed when these were no longer available to drive the work forward. Another issue that made it difficult to achieve the desired structure of the S&OP process was the fact that a new ERP system was implemented in parallel. However, despite the difficulties with the implementation, there is an incorporated routine for a monthly S&OP process established at KåKå today. Prior to the monthly S&OP process, KåKå had a weekly S&OP process which to some extent resembled the theoretical monthly process but was carried out on a weekly basis. The main problem with this process was that most meetings were not fully utilized, which caused the final executive meeting to become a long and inefficient discussion meeting. The final meetings could, in some cases, lead to decision making but this was not the case in general. From interviews, the main cause of the previously inefficient weekly S&OP process was assumed to be due to a lack of understanding of each meetings' purpose.

The major component in the current S&OP process at KåKå is a monthly meeting where several different functions are represented. The people attending this meeting have the following positions: Chief Operations Officer, Supply and Demand Manager, Project Consultant, Demand Planner, Sales Manager, Sales Director, Warehouse Manager, Strategic Purchaser and Team Leaders from the internal sales department. The internal Project Consultant is the one who leads and calls the others to the meeting as well as the one responsible for preparing the data file in Power BI that is used as input. This file is used to identify trends, seasonalities and campaigns, and it includes data of the sales history from the products with the highest turnover. It is filtered to show products with sales values above SEK 25 000 on an annual basis where the difference in sales in recent weeks compared to the same period last year exceeds 10%, which usually results in between 300-400 rows. The file is sent to the internal sales department before the monthly meeting to get their input on whether future sales are expected to increase or decrease. The other participants generally do not have any preparatory tasks, but provide input based on their insights during the meeting, where they go through the following agenda:

1. Actions from last meeting
2. Trend last month
3. Upcoming seasonality
4. Product deviations and customer changes

Moving forwards, campaigns are intended to be included to a greater extent in the S&OP meetings as KåKå plans to utilize campaigns more in the future. The output from the monthly S&OP meetings are decisions on how to act on the products discussed and the responsible person for each action point is determined during the meeting. Lastly, the demand planner uses the information discussed in the meeting as input to perform manual adjustments of the sales forecasts. The monthly S&OP meeting is illustrated in Figure 10 below.

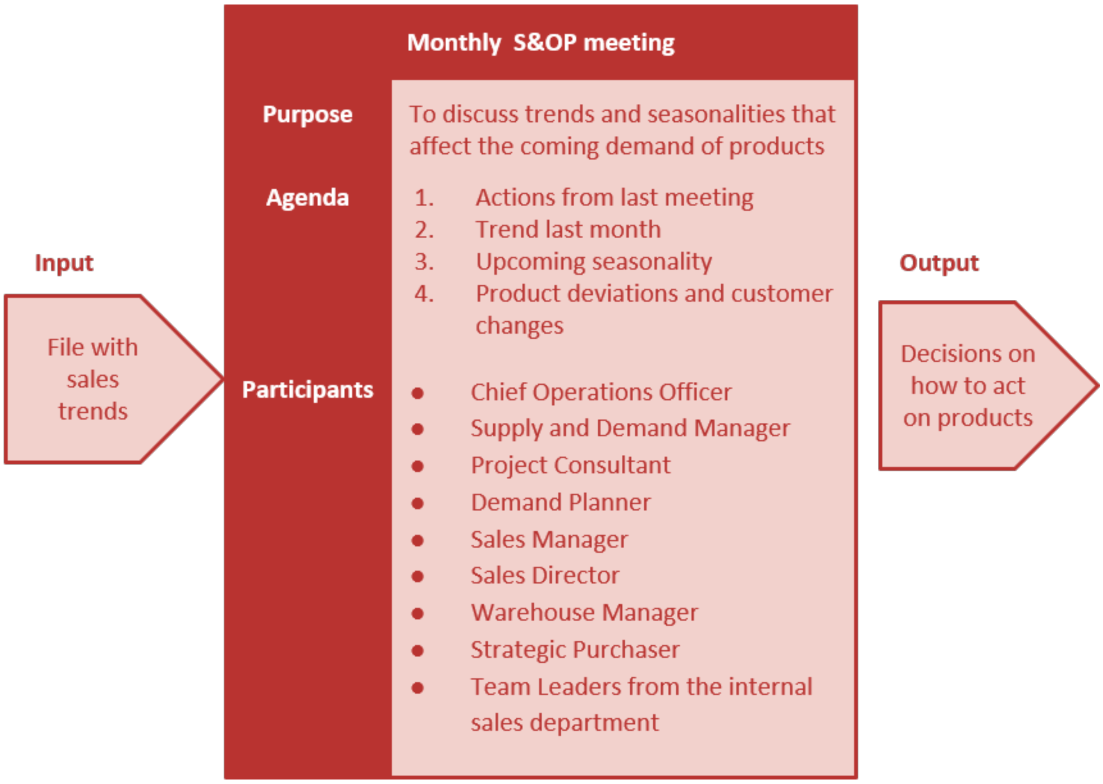

Figure 10: The S&OP process at KåKå

4.4.1 Sales and Operations Planning focus

The focus of the S&OP meeting has changed back and forth since the implementation. Initially, the focus was very broad in order to cover everything, then it changed to a more narrow and seasonal based perspective, whereas it now has changed back to a broader perspective with specific focus points. However, discussions tend to occur around individual problem items which often take up a large amount of time during the meetings. The discussions occur with a monthly time horizon and the reason why a longer period is not taken into consideration is explained by interviewees to be due to the lack of ability to manage a longer time horizon. One interviewee implied that since the current S&OP process with a time horizon of one month does not perform as desired, the company cannot attempt to expand the time horizon. An interviewee also explained that using such a short time horizon implies a risk that the company and their suppliers do not obtain a common perspective since their suppliers typically obtain a much longer time perspective.

4.4.2 Opinions on Sales and Operations Planning

During the interviewing process, a common perspective of the S&OP process was obtained in all interviews. The common perspective is that the purpose of the S&OP process is not clearly communicated throughout the company, which results in the functions lacking an understanding of the potential benefits that may be obtained from a well-implemented process. Some of the interviewees implied that the S&OP process is given lower priority by certain parts of KåKå and this is seen as an obstacle to the development of the process. It is also expressed that the organization has not kept up with the changing surroundings and that the structure required to match new challenges is lacking. Furthermore, an opinion raised during multiple interviews was the understanding that the current S&OP process obtains a reactive nature, which results in the S&OP meetings being used to ascertain the sales patterns that have occurred. The interviewees also agreed that the process does not necessarily facilitate the work with sales and demand for the company.

A problem that the majority of the interviewees mention regarding the current S&OP process is the lack of collaboration between different functions. Different functions blame each other for arising issues instead of taking on the responsibility themselves. Some mean that there is a lack of understanding of what consequences the actions from one department can have on another department or the company as a whole. One interviewee believes that the lack of collaboration is a result of poor understanding and an unclear process. The different departments within KåKå possess important information that could be vital inputs in the S&OP process. However, due to the lack of collaboration and communication, the importance of this input for the company as a whole is not realized. One interviewee explained that information often gets lost in the gaps between organizational units due to the lack of collaboration and therefore never reaches the right forum or person.

Despite the lack of comprehensive S&OP knowledge and cross-functional collaboration, some of the interviewees have implied that the S&OP process has resulted in improvements and highlights that this is one of very few forums where different parts of the company actually connect with each other and have the possibility to discuss issues from multiple perspectives. Another improvement that the S&OP process has resulted in occurred during the pandemic, where approximately SEK 5 million was saved in terms of decreased levels of discardment due to weekly, proactive S&OP meetings. Even though most interviewees state that the S&OP process is not very successful as of today, there is a common belief that it could be possible to obtain benefits if the process was improved. Such benefits have been expressed by an interviewee to be the possibility to minimize manual labor, increase the service level and decrease the number of products being discarded. Another benefit that is thought to be obtained from an improved S&OP process in the future is the willingness to embody ownership of certain actions, i.e. activities that are identified as necessary during the S&OP meetings and that need to be performed rapidly. A need for more firm directions provided to those who obtain ownership was also identified to be necessary for an improved S&OP process.

4.5 The demand planning process at KåKå

Even though KåKå is actively working with S&OP, the company does not have a pronounced demand planning process that is utilized. This implies that there are no reoccurring demand planning meetings and the demand planning within the company is rather unstructured. However, even though there is no pronounced process, KåKå still performs demand planning activities. The demand planning activities are mainly performed by KåKå's Demand Planner, who dedicates all working time towards demand planning activities. Since KåKå's demand planning is rather unstructured, the Demand Planner receives instructions from the Supply and Demand Manager as well as the internal Project Consultant approximately 80% of the time. During the remaining 20% of the time, the Demand Planner has creative freedom in terms of identifying necessary activities to perform. The main objective of performing these activities and demand planning as a whole is to improve the forecasting accuracy and reach the company's forecast accuracy target that is currently set to 80%, which is also defined as a maximum forecast error of 20%.

4.5.1 Data gathering

The demand planning activities that are performed at KåKå are related to data gathering, product portfolio, forecasting and market knowledge. In order to perform the demand planning activities, the necessary data must be accessible to the Demand Planner. At KåKå, most of the quantitative data required to perform demand planning activities is retrieved from Dynamics 365 through internally created Excel-files and reports generated from Power BI. The data retrieved from Dynamics 365 consists of information such as each product's status, shelf life, lead times, sales history and financial aspects. All data provided through these data sources is on an individual product level and not based on any product categories. However, the Demand Planner does have the possibility to overview products on a customer or supplier level if this is observed as necessary when performing demand planning activities.

4.5.2 The product portfolio

When performing demand planning activities that regard the product portfolio, i.e. product phase ins and phase outs, the data gathering methods mentioned above are utilized. However, before using those data sources, the product phase ins or phase outs must be initiated. The phase in of a new product can be initiated in various ways such as through customer desires, identified gaps in the current product assortment or changes in the suppliers' assortment. Once the initiation has occurred, the process can require the participation of multiple departments depending on the product and can include the Assortment Manager as well as representatives from the sales-, product development- and strategic purchasing departments. Once the decisions have been made regarding the new product, the Product Administrator handles all technical aspects and makes the product available in the ERP system. This aspect is crucial since the product cannot undergo forecasting until it is available in Dynamics 365.

The Demand Planner typically receives information regarding product phase ins and phase outs through an Excel-file called Product Deviations. New products that are to be phased in to the company's product assortment are provided in this file once the initiation of the phase in is completed as explained above. The information in this file is mainly provided by Strategic Purchasers and can regard the phase in of a new product as well as substitutes for already existing products. Information regarding the phase out of products that will no longer be available for sales is also retrieved from this file. The process for phasing out products is not perceived to be as structured as the phase in process. To phase out a product, the status of the product must be changed in Dynamics 365, which implies that no purchase proposals will be generated. Since no purchase proposals will be generated, the new product status will be received in IBP and the product will no longer be forecasted. There is no active process to completely remove products that have been phased out from IBP since the historic forecasting data might be desirable to review at a later stage.

4.5.3 Market knowledge

Information regarding market knowledge is gathered in a similar manner as for the product portfolio, i.e. through Excel-files and Power BI. Market knowledge that KåKå takes into consideration is price changes, competitors and customer behavior as well as the current situation in the world. Over the past three years, worldwide situations such as the pandemic, war and the economic recession have been important aspects to consider since they have had a large impact on supply and demand. Market knowledge regarding customer behavior is provided to the Demand Planner through a Customer Changes Excel-file that is provided by the sales department. This file consists of deviations in order frequency and volumes.

Using market knowledge within demand planning at KåKå has also led to the need for new meetings. The Demand Planner currently attends weekly meetings that are held in order to discuss potential sales deviations. These meetings are rather new at KåKå and are not intended to be permanent in the future. The main purpose of creating these meetings is due to the troubled environment that is currently occurring and impacting sales. Previously, sales at KåKå were rather stable and did therefore not require separate meetings to discuss sales deviations and decide upon necessary actions. During this temporary meeting, the following employees participate: Sales Managers, Sales Directors, Operational Purchasers, Demand Planner and an internal Project Consultant. The agenda for the meeting is to identify products that have a shelf life of less than 100 days and whose forecast for the next month has deviated with 80-100% compared to the sales data from the month prior. Thereafter, the desired output is to provide the Demand Planner with guidance on how to handle these deviations in the forecasts.

4.5.4 Forecasting activities

The two Excel-files presented above, i.e. Product Deviations and Customer Changes, are both used as input to KåKå's forecasting activities within demand planning. These files are used to help indicate which forecasts need to be examined by the Demand Planner to ensure that the forecasts are accurate. The forecasting activities performed at KåKå are impacted by all of the above mentioned demand planning activities, i.e. product phase ins, phase outs and market knowledge. The forecasting process at KåKå will be described in more detail in Section 4.6 below in order to provide more insight in how each demand planning activity impacts the forecasts.

4.5.5 Opinions on Demand Planning

Due to the non-existence of a pronounced demand planning process at KåKå, the responses obtained from the interviews about this process were rather limited. Most of the interviewees did not have much insight into the demand planning activities. All interviewees knew who performed the demand planning activities and that the activities require input from various departments. When asked about product phase ins and phase outs, the majority of the interviewees could not provide detailed answers regarding the processes that are performed and how information is received. One of the interviewees is, however, responsible for gathering participants when necessary to discuss market knowledge. The interviewee explained that these meetings are of ad hoc nature and also expressed that the company is rather quick at adapting to large changes, such as the pandemic, but performs inferior in regards to the daily routines connected to utilizing market knowledge. In general, most interviewees interpreted demand planning as the forecasting process, which implies that knowledge regarding what demand planning entails and the purpose of such a process lacks.

4.6 The forecasting process at KåKå

All forecasting activities that are performed at KåKå are exclusively performed in IBP. The forecasting activities typically use a time horizon of one year but this can vary depending on the product at hand. The variation in time horizon can depend on the lead time for the specific product because if the lead time is longer than the one year forecasting period, then important details risk being overlooked. An overview of the forecasting process at KåKå is presented in Figure 11 below.

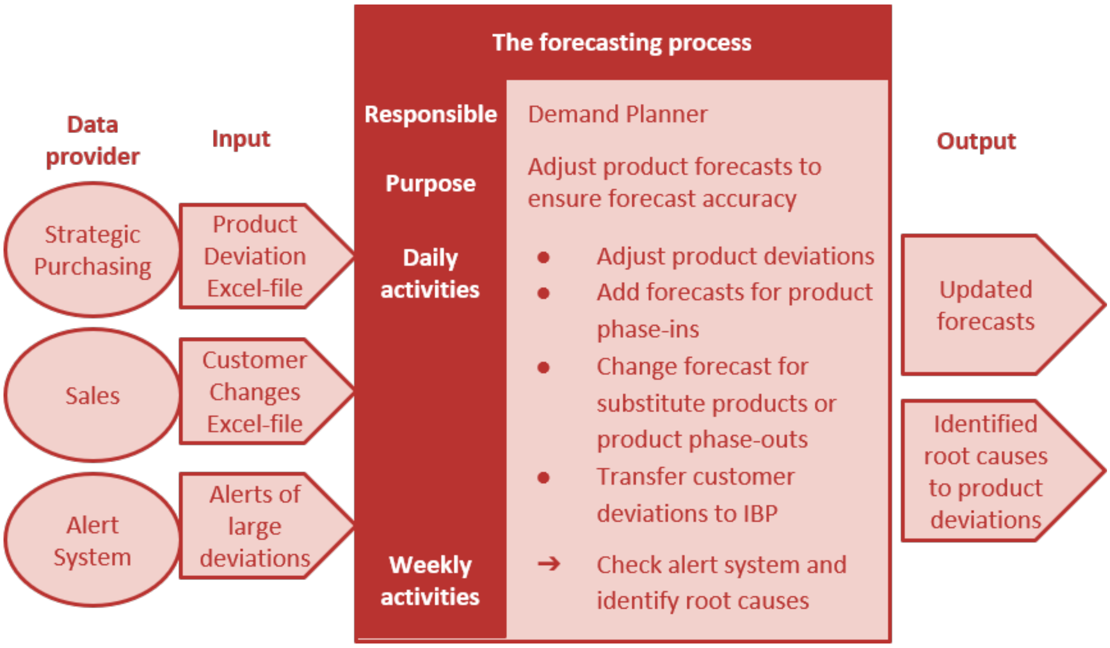

Figure 11: The forecasting process at KåKå

The Demand Planner has both daily and weekly assignments to perform connected to forecasting. As previously mentioned, all of the demand planning activities are closely related to forecasting and therefore also the Demand Planner's assignments. To begin with, the Demand Planner reviews the Product Deviation Excel-file in order to identify necessary adjustments. If information is provided for a new product phase in, the Demand Planner must receive an expected forecast from the Strategic Purchaser who provided the information about the phase in. This information is typically provided in the Excel-file but in some cases the Demand Planner must contact the Strategic Purchaser directly. The necessary information about the new product must contain the product ID that the Product Administrator entered into the business system, the date for the phase in and the expected sales volume within the first six months of sales. Once the Demand Planner obtains this information, the forecast for the new product is added manually in IBP. If the information regards a product substitute instead of a phase in, then the Demand Planner must enter the substitute product in IBP. When performing this activity, the Demand Planner must transfer the old products' historic and future forecast to the substitute product. Thereafter, the old products' forecasts must be reset to zero in order to complete the transaction.

Another daily assignment performed by the Demand Planner and related to forecasting is to examine the Customer Changes Excel-file. When deviations in customer orders occur, the deviations are presented in this file by the sales department. The deviations need to be transferred to IBP in order to ensure that the forecast is accurate according to the new information available. The deviations are transferred to IBP by adding a percentual increase or decrease, adding marketing or sales input in pieces as a unit or through a manual input from the Demand Planner. Performing such changes must be done forwards in time to ensure that the forecast accuracy does not decrease due to misinformation. Lastly, the Demand Planner performs weekly assignments that arise due to an alert system created by KåKå. This alert system has been created in order to identify products whose forecast accuracy is less than 30% the last couple of weeks. These alerts have been defined on chosen customer segments. If an alert occurs, the Demand Planner explores further to identify a possible explanation. If an explanation is identified but difficult to interpret, the Demand Planner can request input from the sales department.

4.6.1 Forecasting method

As mentioned above, KåKå currently utilizes IBP for all forecasting activities that are performed. In IBP, the company has the possibility to choose between multiple forecasting algorithms and the associated variables. Firstly, the time setting is set which includes the decision of the periodicity, i.e. the time unit used to define the forecasting period, which KåKå has chosen to be *weeks*. The chosen periodicity is then used when defining the historical and future forecast periods, which are then defined in number of weeks. The historical period is defined as the number of weeks that KåKå wants to use as the input for their forecasts, currently set to *104 weeks*, while the forecast period is defined as the number of weeks KåKå wants to forecast in the future, which is set to *52 weeks*. This implies that KåKå takes two years worth of historical data into account when forecasting one year forwards for each product. The item level on which forecasting is performed is per SKU by location and after that the forecasts are allocated down to SKU by location by customer.

Thereafter, the overall parameters are decided for the forecasting algorithm, which includes deciding the main input for the forecasting steps. The main input is selected as *Clean Historical Sales*, which is extracted from the business system. Once these decisions are in place, the forecasting algorithm can be chosen. KåKå has decided to apply *Triple exponential smoothing* to all products in their assortment. When applying this algorithm, the number of periods in a season must be decided and KåKå has set this parameter to *52 week*s and to be of the *additive type*. In the formula for Triple exponential smoothing, the three parameters presented in Equations 7, 8 and 9 must be decided by the system user. KåKå's choice of these parameter values is presented in Table 7 below.

Table 7: The parameters used by KåKå in their Triple Exponential Smoothing forecast method

α	0.35
β	0
γ	0.99

From the performed interviews with the Demand Planner, Supply and Demand Manager and the internal Project Consultant, it appears that the chosen forecasting method has not been clearly motivated, nor has the chosen settings of the associated variables. The choice to apply this forecasting algorithm to all products has not been motivated either. Due to this, it has been expressed that a thorough understanding of the used forecasting system lacks which also leads to a lack of trust in the system. Furthermore, since all products do not follow the same demand pattern, the interviewees express that choosing the same forecasting algorithm for all products does not seem logical. These factors have led the users to express a lack of trust in the forecasts provided by the system.

4.6.2 Forecast error

To measure the performance of the forecasts, KåKå analyzes the forecast error of the system. To do so, *WAPE* is used to retrieve a sum of the absolute error in the forecasts, which is normalized by the total demand. From the performed interviews, the choice of measurement was motivated due to KåKå's large assortment of products and that the volume per product is, in many cases, considered to be in the smaller range. It was argued that this is a way to prioritize the accuracy of products with higher demand over products with lower demand. The interviewee implies that this measurement takes these factors into consideration better than others through the weighting factor that is used. However, the weighting factor in WAPE is the same for all products and it is not possible to assign different priorities to different products when using this measurement. The current target that KåKå has set is to achieve a forecast error of a maximum 20%, however, this target is not reached as of today. Another validation of the high forecast error is the fact that the operative purchasers only accept the purchase proposition from the forecast 25% of the time. The other 75% of the propositions from the forecast are either completely neglected or in some way adjusted to become more accurate according to the purchasers' knowledge or experience.

4.6.3 Opinions on Forecasting

From the interviews performed, a common view on the current forecasting process at KåKå is that it does not result in a high forecast accuracy and therefore requires a lot of manual labor. The manual labor is performed by the Demand Planner as well as the Operative Purchasers. The low forecast accuracy is further explained to be due to the lack of important input information regarding sales variations as well as the reactive nature of the S&OP process. These factors imply that KåKå does not identify changes or deviations early enough to be able to identify the cause and plan accordingly. Instead, once the variations have occurred, the causes are discussed after the occurrence. Due to the lack of trust towards the forecasting process, all interviewees expressed that there is a need to improve the process and that an improvement would imply significant benefits for KåKå. The benefits were commonly expressed as the possibility to decrease the amount of manual labor, decreasing the number of Operative Purchasers and increasing efficiency. The interviewees also expressed that the lack of trust for KåKå's forecasts does not only occur internally, but also externally. Customers have experienced stock outs of demanded products during certain seasons due to KåKå's high forecast error which has caused customers to stock up prior to these seasons. By increasing the forecast accuracy, interviewees expressed a belief that the company's trustworthiness from their customers would increase and therefore also their faithfulness towards KåKå.

4.7 Product characteristics

As of today, KåKå has a total of 4 695 active products in their assortment whereof a majority are kept on stock whilst some are purchased on demand due to their low turnover rate. Additionally, products that are inactive and no longer sold to customers are still visible in Dynamics 365. There are also products with a status somewhere in between the active and inactive ones, e.g. products that are about to be active or about to be inactive. The accurate amount of products with different statuses in the ERP system is presented in Table 8. One common opinion obtained from the interviews is that KåKå has too many SKUs in their assortment and that many of these should be possible to remove since they are only bought by a few customers or because there are very similar alternative products available in the assortment.

Table 8: Number of SKUs at KåKå

Status	Unique Item IDs
Active	4695
New article, not yet active	23
Temporarily inactive	28
Inactive	2150
About to be inactive	157
Total	**7053**

Furthermore, the products have different characteristics that affect how they are handled throughout KåKå and the rest of the supply chain. Four product characteristics that are of high importance for KåKå are: temperature requirements, shelf life, lead time and demand pattern. These characteristics will be described further below.

Temperature requirements

The temperature requirement is a very important product characteristic of food and bakery ingredients as it is necessary to ensure sufficient quality of the items. Regardless of which of KåKå's warehouse the products are stored in, they are divided into three different storage areas depending on their temperature requirements. The warehouses have one area for frozen items, one for cold items and lastly an ambient/dry area, and the inventory management differs between the three categories.

Shelf life

Another product characteristic that is important in KåKå's industry and is related to quality assurance is the shelf life. This characteristic is important to ensure that items are not forced to be discarded due to expired dates of shelf life. In 2022, KåKå discarded products with a total worth of 3,5 MSEK due to short expiry dates, but their target is to stay below 200 000 SEK in scrap each month. Some of KåKå's SKUs are not edible and therefore have an endless shelf life, which is noted as 999 999 days shelf life in KåKå's systems. The shelf life is given from the producer of each article and then there are agreements on what proportion of the total shelf life that can be consumed by the supplier, by KåKå themselves and by their customers. The most common agreement is one third of the shelf life to the supplier, one third to KåKå and one third to the customer, but there are some deviations between different suppliers and different items. The goods reception at KåKå checks the remaining shelf life when they receive the goods and then a best before and an expiry date is entered in Dynamics 365. With this in mind, there are three possible inventory statuses for KåKå's SKUs with regard to the shelf life. These indicate in which period the SKU is, either normal, best before or expired, where the middle one indicates that KåKå's agreed shelf life has run out and the latter indicates that the total shelf life has expired. In Figure 12 below, a distribution of KåKå's products and their shelf life is presented. The figure is based on all currently active products in KåKå's assortment and by discarding products with a shelf life of either zero or over 9 999 days. These products are discarded since they either have no shelf life to consider, e.g. non-food products, or have a shelf life that is so long that KåKå does not need to take it into account, e.g. sugar. These products are provided an abnormally long shelf life since Dynamics 365 requires a value of each product's shelf life.

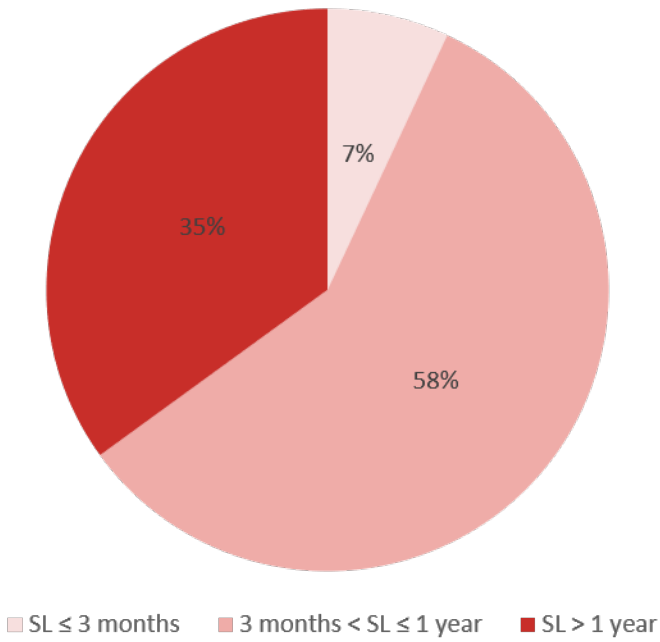

Figure 12: Shelf life (SL) for active items

Lead time

The lead time is another product characteristic that differ between SKUs in KåKå's assortment. As they are not conducting any manufacturing activities themselves, their lead time to customers is very dependent on the lead time received from their suppliers. Their purchasing lead time to Lomma ranges between one and 180 days and the average purchasing lead time of the active products is approximately 21 days. The proportion of products in Lomma with a lead time of less than one week, less than one month and above one month is presented in Table 13 below. The products that are looped from the other inventories to Lomma are excluded in these calculations since this does not count as a purchasing lead time for Lomma. When looking at the second main inventory, in Örebro, the purchasing lead time is similar to the lead time to Lomma. It might differ a few days due to slightly different transport lead times and slightly different items being bought from suppliers versus looped from other inventories.

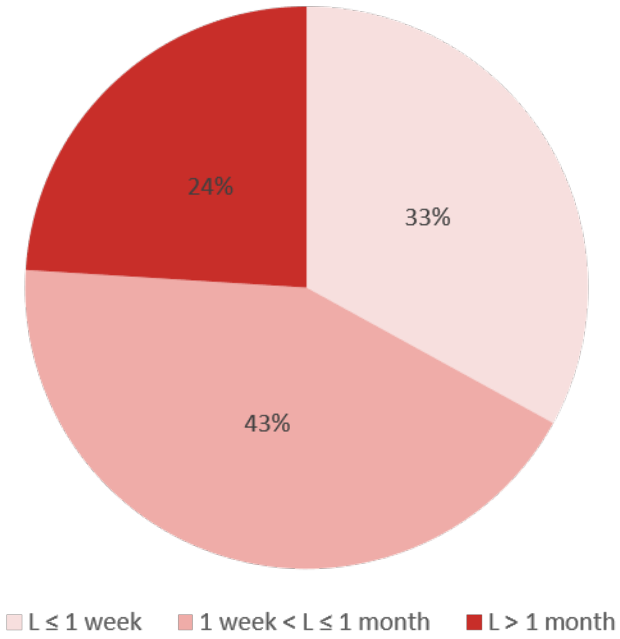

Figure 13: Purchasing lead time (L) for active products in Lomma

Demand pattern

With regard to KåKå's broad assortment, with a lot of different products and several different customers, the demand patterns differ from one SKU to another. Some of their products face a high turnover and are sold on a daily basis, whilst others are sold as infrequently as once a year. Flour is an example of a product in KåKå's assortment that is sold to many different customers with a very high frequency as it is a commonly used bakery ingredient, while a customer branded carton is an example of a product that is sold very rarely. The frequency of which a product is bought is one of several factors influencing how stable the demand is perceived. The stability of a products demand can also be described by the size of the deviations from an average value. The deviations can be explained by trend or seasonality that influence the demand, but it can also be a result of more random factors that are difficult to explain. The demand of several products at KåKå is largely influenced by seasons, where public holidays and time of the year affect the sales significantly. For example, the demand of ingredients that are included in the traditional Swedish "semla" peaks in the beginning of the year, while products such as ice cream-bases increase in sales prior-to and during the summer. KåKå has identified seven seasons in which they categorise products that face a significant increase in sales when the specific season occurs. The different seasons and the amount of products included in each is presented in Table 9.

Table 9: KåKå's seven seasons

Season	Number of SKUs
Cinnamon bun's day	21
Father's day	10
Christmas & New Years	32
"Semla"	14
Easter	14
Late spring	41
Ice cream	25

The products at KåKå are also subject to trends. Changed patterns of behaviour and increased awareness of health and climate are examples of aspects that might affect whether a product faces an increasing or decreasing trend. For example, KåKå has experienced increasing demand of vegan products in the last couple of years whilst a Sales Manager expressed a new trend of increasing demand of semi-finished goods to facilitate customers' production.

4.8 Product categories

The perception obtained from the interviews is that KåKå has categorized their products on several different levels, but the categories mentioned during the interviews differed slightly from one person to another. It was also understood that several employees believe that there is a need to restructure the categories as there are far too many and incorrect subcategories. However, the most consistent opinion of the current product categories is that the top level corresponds to KåKå's six business areas: bakery, patissery, bake-off, non-food, ice cream and food & beverage. Another categorization that is frequently mentioned is based on the purchasing department's distribution of responsibilities. This contains 21 different categories, as well as subgroups to each one of these. Most of these categories represent different types of food, but there is also one large category for non-food items that e.g. includes different sizes of packaging printed with their customers' logos. Import commodities is another group that contains a large variety of products, but the common denominator is that these are customer unique items. One additional group that is distinguished from the others is Acquisition Martin, which represent acquisition items from one specific supplier. All 21 categories and the corresponding amount of active SKUs that belong to each are presented in Table 10.

Table 10: Number of active SKUs in each product category

Category	Number of SKUs
Masses	58
Chocolate	146
Flour	116
Powder	154
Baking aid	37
Filling	45
Sugar/Syrup	82
Ice cream	187
Jam/Fruit/Berries	69
Yeast	15
Vanilla cream	7
Margarine	101
Dairy/Vegetable	166
Sandwich food	205
Beverage	131
Acquisition Martin	70
Separation oils	22
Import commodities	151
Bake-off	184
Non-food	2646
Other	147

5 Findings and analysis

This chapter begins with a detailed description of the key identified issues at KåKå and will proceed into a three-part analysis. Firstly, a forecast analysis is performed in order to identify the best forecast models for the identified forecasting groups. Secondly, a demand planning analysis is performed to be able to provide a product categorization process that facilitates and improves the demand planning process. Lastly, a S&OP analysis is performed to provide guidance to how the S&OP process can be designed to fulfill it's purpose and achieve the set targets.

5.1 Key issues identified in the empirics

Several key issues have been identified in the empirical study as there are multiple areas where KåKå's course of action contradicts theory. These issues correspond to four different problem areas: forecast method, product management, information sharing and S&OP process design, which are described further below.

5.1.1 Forecast method

As described in Section 4.6.1, KåKå currently applies the same forecast method, *Triple Exponential Smoothing*, to all products in their assortment. By applying the same forecast method as well as using the same parameter values within the chosen method, all of KåKå's products are assumed to have similar demand patterns in terms of e.g. trend and seasonality. However, as Ulrich et al. (2022) states, it is rather unlikely that all of an organizations SKUs withhold the same characteristics, which means that the demand pattern may vary between each individual product. This implies that forecast methods ought to be chosen depending on the demand for a specific product and should therefore be chosen depending on the product at hand. The choice of applying one forecasting method to all products is further contradicted by Olhager (2019) who states that it is of great importance to choose an appropriate forecast method for each product if one desires to identify systematic variations and to be able to neglect any random occurrences. In other words, if one single forecasting method is applied to all products despite different product characteristics and varying demand patterns, an organization may fail to identify product specific trends and seasonalities that will affect the forecast.

In addition to this, the trend-seasonal model chosen by KåKå can be seen as a rather complex forecast model since it requires the identification of multiple parameters. In this case, it is important to acknowledge that estimating more parameters when using a trend-seasonal model becomes increasingly challenging and it is therefore important to reflect on whether or not the complexity of such a model is beneficial, as Axsäter (2006) explains. If the complex model is not identified to be necessary, Axsäter (2006) motivates the use of a simple model with fewer parameters since it is commonly more efficient to apply to products that do not have clear need for a trend-seasonal model. Furthermore, when discussing the choice of the parameter values in KåKå's current forecast model, no clear motivations could be identified. It has also been identified that the current parameter values are not found in the ranges provided in theory which raises further uncertainty in the choice of values. Due to the issues discussed above regarding the selection of appropriate forecast methods and parameter values, KåKå's current choice of forecast method is highlighted as a key issue that has been identified in the empirics.

5.1.2 Product management

Within both forecasting, demand planning and S&OP, KåKå conducts activities and discussions on an individual product level. At the same time, they have a broad assortment with thousands of different products that are very time consuming to handle one by one. With this in mind, it could be beneficial to conduct activities and discussions on a product group level instead of an individual product level in order to achieve more efficient processes. As described by Kampen et al. (2012), using product groups based on suitable characteristics is advantageous to enable decision making on a higher level than on an individual SKU level. During the interviews, the employees at KåKå has mentioned several different product categories used within the organization. However, the mentioned categories are not applied within forecasting, demand planning or S&OP. Meanwhile, theory presented in Section 3.2.1 states that it is advantageous to aggregate products into groups within all of the three areas previously mentioned. With this in mind, a key issue identified in KåKå's current set up is the lack of product groups within the three areas: forecasting, demand planning and S&OP.

Another issue related to product management raised by multiple employees is the perception that KåKå currently has too many products in their assortment. There is currently multiple products in the assortment that are seen to be substitutes to other products which causes the product assortment to increase unnecessarily. Multiple employees expressed that they see the possibility to remove some products from the assortment since the number of available substitutes are too many. The large product assortment and high number of substitutable products indicates that the process for phasing out old products does not work as intended. From the empirics, it was possible to identify a rather structured phase in process for both completely new and replacement products. However, the phase out process is not equally structured, which is also the perception of multiple employees who lacked knowledge in how this process is currently performed.

5.1.3 Information sharing

Throughout the current S&OP process at KåKå, the information sharing across different functions or departments is highlighted as a problem by multiple interviewees. When analyzing the lack of information sharing, it has been identified to have two main root-causes: lack of collaboration and inadequate understanding of S&OP. The lack of collaboration throughout the company has been expressed by multiple interviewees. KåKå is an old and traditional company, where many departments have always had independent departmental incentives. Due to this, cross-functional collaboration has not been the norm. Implementing a cross-functional S&OP process often requires a cultural change in order to eliminate functional silos in the organization, as explained in Section 3.1.4. Without cross-function collaboration, the S&OP process is difficult to implement successfully. The fact that the employees at KåKå experience poor communication and collaboration indicates that the organisation has not undergone the necessary cultural change when implementing S&OP. Without the necessary cultural change and desired cross-functionality, the functional silo mindset remains and hinders collaboration across the organization. The function silo mentality is also discussed by Stone (2004) to be affected by the lack of communication and knowledge of how to communicate. The effectiveness of communication is, as stated by Stone (2004), affected by both experience and background of those communicating since these factors influence how things are said and perceived. If communication skills are improved, Stone (2004) states that more open and effective communication can be achieved across the organization. Through effective communication, the functional silo mentality and the lack of understanding of how one department's actions can affect another department or even the organization as a whole, can be decreased. Therefore, communication and effective information sharing is an important aspect in the process of eliminating function silos, establishing cross-functional collaboration and implementing S&OP.

From the empirical study it was also possible to identify that another main cause of the functional silos and poor information sharing is the inadequate theoretical understanding of S&OP and demand planning. As stated by Pedroso et al. (2016), the lack of relevant training, and therefore also understanding, impedes the success of S&OP. This also has a significant affect on the demand planning process since market knowledge, particularly in terms of customer changes, is not communicated to the Demand Planner who is responsible for adjusting the statistical forecasts based on qualitative information. To obtain input from different departments of the organisation is also mentioned by Moon et al. (1998) as a critical success factor to obtain effective forecasts. Due to the effect inadequate information sharing has on the demand planning process and the S&OP process as a whole, it has been identified as a key issue at KåKå.

5.1.4 Sales and Operations Planning process design

The S&OP process that is currently conducted at KåKå is identified from the empirics to be inadequate. One of the identified challenges with the S&OP process today is that it is not highly prioritized within the organization. The low prioritization of S&OP is a also acknowledged by KåKå's employees as a main obstacle to the success of S&OP within the organization. Connected to the low prioritization is the need for a more firm directing hand since there is currently an experienced lack of willingness to obtain ownership for S&OP activities. Since there is no clear direction from top management to the employees to prioritize their S&OP activities, these are rarely prioritized by the activity owner. These problems are identified as a large challenge for the success of the S&OP process at KåKå since the level of priority from the organization and engagement of top management is two important prerequisites to be able to perform S&OP and succeed. As Ling & Goddard (1988) explained, the commitment of the executive team is one of the most important factors for the S&OP process since without it, other key participants will not be willing to commit their own time and resources to the process.

Furthermore, the current S&OP process does not follow the structure of the S&OP process described from theory in Section 3.1. In Section 3.1.3, the theoretical monthly S&OP process is presented as a four step process, where each step has a specific purpose and is strongly connected to the steps prior and later. The first problem identified with the S&OP structure is related to these four steps. As described in Section 4.4, KåKå currently has a monthly S&OP process with the main component being one single monthly meeting. When KåKå's monthly S&OP process is compared to the four step process presented in theory, it is possible to identify that the process is inadequate in multiple areas. Firstly, the process is meant to include at least four steps, which is not the case at KåKå since they only have one monthly S&OP meeting. This entails that the structure of the current S&OP process is inadequate according to theory. Secondly, from the observations performed during the empirics, the monthly meeting obtains characteristics that are equivalent to the fourth and final step in the S&OP process presented in theory, i.e. the executive meeting. This identification is based on the fact that the discussions held and decisions made during these meetings aligns with the theory presented on the purpose and what the desired output ought to be from an executive meeting. As Olhager (2019) states, the desired output regarding decision making is only possible to perform effectively if all of the three previous steps are performed correctly. With this in mind, the lack of the three steps prior to KåKå's monthly S&OP meeting indicates that the monthly meeting cannot be performed effectively, as desired.

The S&OP process has also been identified to obtain a more reactive nature than a proactive nature as originally desired for the planning process. An S&OP process is desired to provide supply and operation plans for a longer planning horizon. Compared to the planning horizon of 15-18 months, as presented by Olhager (2013), the planning horizon at KåKå is one month. The reason behind the short horizon being the lack of ability to manage a longer planning horizon is a strong indicator of an S&OP process that is not performed correctly. As mentioned, the short planning horizon forces KåKå to react to unidentified changes in the market instead of being able to identify such changes ahead of time and take them into account when creating the S&OP plans. The lack of an adequate S&OP structure has a large impact on the performance of the S&OP process as a whole and therefore also the planning horizon. If the first three steps were performed more accurate, detailed and long-term demand and supply plans would be possible to obtain. With this in mind, it is possible to identify KåKå's S&OP process design as a key issue that is causing the problems described and affecting the performance of the process.

5.1.5 Summary of key issues

As described above, KåKå is experiencing problems within multiple areas. To summarize the key issues identified in the empirics, Table 11 presents the four problems areas: forecast method, product management, information sharing and S&OP process design, together with the main issues for each problem area.

Table 11: Identified problem areas and corresponding main issues

Problem area	Main issues
Forecast method	One single method to all products
	Inadequate parameters
Product management	All products managed on individual SKU level
	Too many products in the assortment
	Lack of clear phase out process
Information sharing	Lack of collaboration
	Inadequate understanding of S&OP and the consequences
S&OP process design	One single meeting
	Inadequate time horizon
	Low priority within the organization

5.2 Analysis approach

The analysis has been divided into three different parts that are related to the identified problem areas and the research questions of this thesis. As KåKå's forecast method was identified as a main problem area, this will be addressed in the first part of the upcoming analysis. The purpose of the forecasting analysis is to identify relevant forecasting product groups, present the product grouping process and identify appropriate forecast methods for each product group. Since forecast methods are based on demand models, such models have been used to identify appropriate forecasting groups. This part will partially address the second research question, but the main focus is on the third research question which concerns selecting forecasting methods to different demand models.

In the second part of the analysis, the attention will be lifted one level higher from forecasting to demand planning, as seen in Figure 14. This part is related to the identified problems with product management and information sharing, and the main focus is to address research question two about categorizing products. It has been decided that two separate product grouping processes are necessary, one for forecasting and one for demand planning. The product groups used for forecasting have not been identified to fulfill the purpose of using product groups in demand planning in general. One of the reasons to use product groups in S&OP, and thus also in demand planning, is to achieve more effective input and control from management (Ling & Goddard 1988). The product groups should facilitate the discussions and decision making during the demand planning meetings as well as ensure that the focus on these meetings is directed to the most critical groups. The perception obtained in this study is that groups based on demand models would not fulfil this purpose at KåKå. There are other product characteristics, such as shelf life and sales value, that can facilitate the identification of critical products for demand planning more effectively and thus will be used in product grouping process. Once the critical product groups are identified, the product groups presented in Table 10 will be used in order to aggregate the products on a level manageable for effective demand planning. Following the analysis on demand planning product grouping, the remaining key issues, product planning management and information sharing at KåKå, are discussed.

Lastly, the attention is lifted one additional level and the focus of the analysis is S&OP, as illustrated in Figure 14. As presented in Section 1.6, the main focus of this thesis is the demand planning phase of the S&OP process, with forecasting being the primarily focus within demand planning. However, during the course of this thesis, several issues in KåKå's general S&OP process have been identified and will be subject to analysis. This analysis has been identified as necessary to perform, even though it is not the main focus of this thesis, since KåKå has expressed the need of guidance regarding how their current process can be improved. With this in mind, a more theoretical discussion is held in order to provide guidance as to how KåKå should design their S&OP process more correctly and effectively according to theory. This discussion will provide information regarding how to increase collaboration and restructure the process.

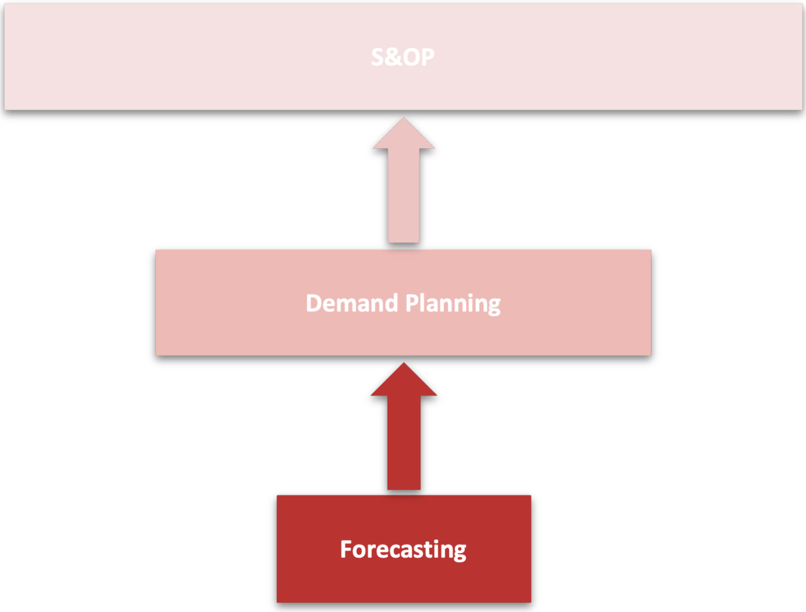

Figure 14: The relationship between forecasting, demand planning and S&OP

5.3 Forecasting analysis

As of today, KåKå uses forecasts to gain operational planning and control of purchasing and inventory in short term. With regard to the theory presented in Table 5, KåKå's purpose of forecasting indicates that it is reasonable with a weekly forecasting period and an item level per SKU by location. A reason why it is appropriate with such a low item level is that the operational purchasing is performed per product and warehouse, and thus the forecasts can support this process in a proper way. However, it is not necessary to allocate the forecasts down further to include customers as this factor does not influence purchasing or inventory activities. Since KåKå has a lot of historic data available, and have products in their assortment that are subject to yearly seasonality, it is suitable to include two years of data as input for their forecasts. As the time horizon of KåKå's forecasting and demand planning activities is short, it could be argued that they do not need to forecast up to a year forward. However, they have some products with a long lead time that need to be purchased far in advance and the forecasts are automatically generated by IBP so there are no clear benefits to obtain by shortening this.

The perception obtained from the empirical study was that some of KåKå's products are subject to seasonality and trend, but this was not the case for the entire assortment. With this in mind, the demand model, which determines what forecast method to apply, is of different nature for different products. One potential demand model is of a constant demand, where the variation is low and no significant trend or seasonality can be identified. Another possible model is where the demand is subject to trend due to a successive increase or decrease, but no seasonality pattern is identified. Thirdly, the demand model can contain seasonality patterns in terms of recurring deviations, but no significant signs of trend. The fourth possible demand model is the one where both patterns of trend and seasonality can be identified. Lastly, the demand model can be characterised by high variations and intermittent data such that none of the previous models are applicable. This results in five different demand models which are applicable for KåKå's assortment and these were used to establish forecasting product groups. The groups together with their characteristics in terms of demand variability, trend and seasonal are presented in Table 12.

Table 12: Forecasting product groups

	Group 1 - Intermittent	Group 2 - Constant	Group 3 - Trend	Group 4 - Seasonal	Group 5 - Trend-Seasonal
Demand variability	High	Low	Low	Low	Low
Trend	-	No	Yes	No	Yes
Seasonal	-	No	No	Yes	Yes

5.3.1 Forecasting product grouping process

When determining which of the five potential forecasting groups presented above that a product belongs to, there were several aspects to take into consideration. The first step was to gather the necessary data to be able to identify the demand model of each product in KåKå's assortment. To do so, two years of historical data regarding the weekly demand on a product level was utilized. This data was retrieved for the two main warehouses, Lomma and Örebro, and was separated since forecasts are currently performed per warehouse as well. Together with KåKå, a decision was made to disregard the other warehouses and only focus on the two main warehouses throughout the forecasting analysis. Since these are handling a significant majority of the demand volume, this is where the forecasting is of greatest importance. Thereafter, data filtering was performed in order to obtain the products that are active and subject to forecasting as of today, which resulted in a total of 2002 products at the warehouse in Lomma and 2060 products in Örebro. This data was then used to identify demand variability, trend and seasonality patterns for each product, which is necessary to determine the appropriate forecast product group. The identification and analysis of each of these three aspects are presented in more detail in the following sections.

Demand variability

The first aspect of the demand history that was analyzed was the demand variability. The reason why this was analyzed first was to separate the products that are possible to forecast from the ones that have very high variations and intermittent demand and thus are difficult to forecast properly. This means that the products that belong to Group 1 were to be identified and separated from the other four groups. In this case, the CoV was used to evaluate the demand variability and the analysis was inspired by the study at Rohm and Haas made by D' Alessandro & Baveja (2000), which was presented in Section 3.3.2. Similar to their approach, a matrix with demand variability on the y-axis and demand volume on the x-axis was used to obtain four different quadrants containing products with different characteristics. To separate products with high demand variability from low variability products, the Pareto principle of 80/20% was applied and this resulted in a limit in terms of CoV at 0,645 for products at the warehouse in Lomma and 0,564 for products in Örebro. With the given bounds, 80% of the products in each warehouse ended up with a high demand variability and the remaining 20% constituted the low variability products. The bound between low and high weekly average demand was obtained from discussions during the focus group with several different employees at KåKå. The guide that was utilized as a basis for discussion during the focus group can be found in Appendix B. It was determined that an average weekly demand of five units should constitute the limit between high and low demand, for both warehouses. This limit is motivated by the fact that KåKå's system cannot properly handle products with a weekly demand of less than five. The forecasts in IBP are made on a weekly level, but when transferred to their ERP system, Dynamics 365, they are split down to a daily level to support the operational purchasing. When the system converts the forecasts from a weekly to a daily level, the values are divided by five and rounded to the closest integer. This indicates that a weekly value of two or one will always be rounded to zero and thus the forecast does not fulfil any purpose. On the other hand, a forecast of three or four units will always be rounded up to one per day and thus the forecast will always be exceeded by at least 25%. With a demand limit of at least five per week, the daily values in the ERP system will represent the actual forecasted value more accurately. With this in mind, all products with an average weekly demand of less than five units are set to be low demand products, while the others are considered to be products with high demand. The matrices, including the bounds of the CoV and average weekly demand, for both warehouses are presented in Figure 15 and Figure 16.

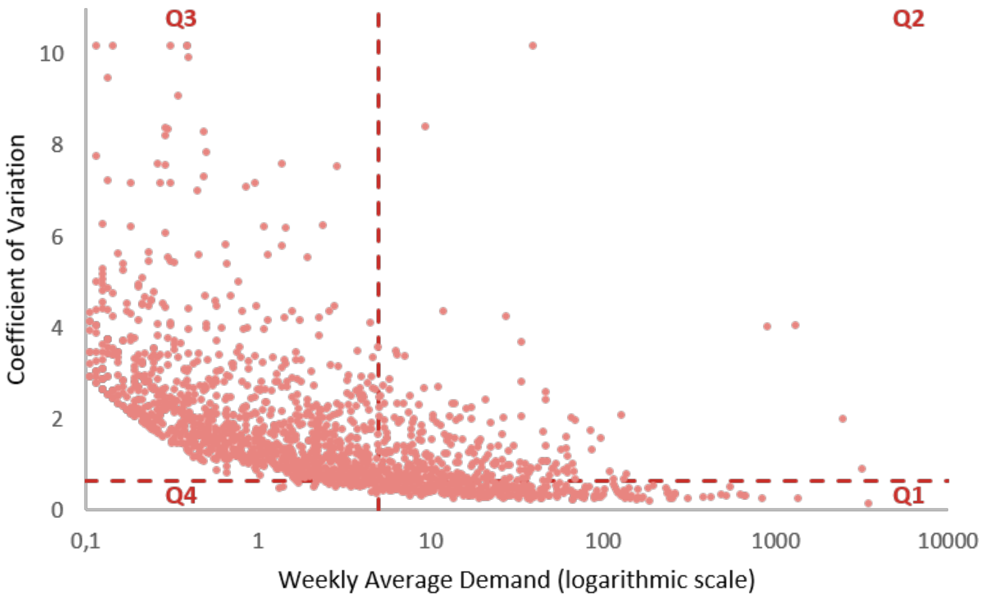

Figure 15: The demand variability matrix for the warehouse in Lomma

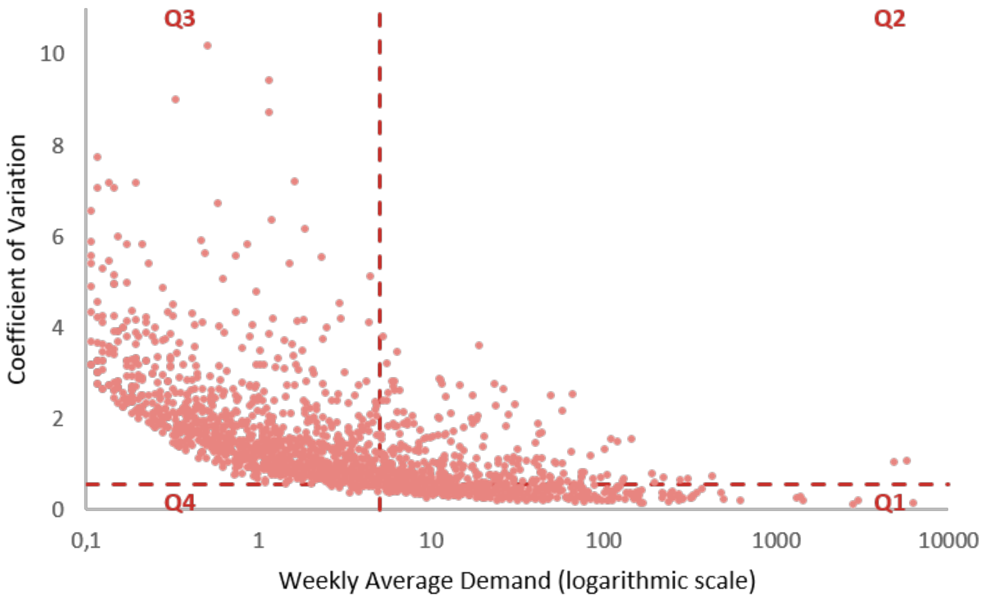

Figure 16: The demand variability matrix for the warehouse in Örebro

As illustrated in the figures above and discussed in section 3.3.2, the matrices result in four quadrants that correspond to four different groups of products. In both cases, the third quadrant, Q3, holds a majority of the total number of products. This implies that most of the products that are forecasted today are represented by a high variability and low average weekly demand which is similar to the result obtained in the Rohm and Haas case performed by D' Alessandro & Baveja (2000).

On the other hand, the fourth quadrant holds a low number of products in both Lomma and Örebro, and this differs from the Rohm and Haas case where Q4 was empty. In the study conducted by D' Alessandro & Baveja (2000), Q1 and Q2 were treated as one group and thus they only had two different groups that were assigned different strategies. As presented earlier, the strategy they ended up with was a make-to-stock policy based on demand forecasting for Q1 and Q2 products while the products in the third quadrant, Q3, were not subject to demand forecasting as they were assigned a make-to-order policy. A similar approach was applied to identify the products in KåKå's assortment that are currently kept on stock and subject to forecasting, but perhaps should be assigned a different strategy. The products that ended up in quadrant Q3, with a high variability and low demand, were therefore assigned to Group 1 due to their intermittent demand model. A total of 1 316 products ended up in Q3 for the warehouse in Lomma and 1 296 products in Örebro, when the products that ended up on the boundary line between Q3 and Q2 were assigned to quadrant Q2. When analyzing the type of products belonging in this category, it is clear that a majority of these are non-food products. In Lomma, around 54% of the products in Q3 are non-food items and the corresponding number in Örebro is 62%. The distribution of the items in the four quadrants according to the categories mentioned in Section 4.8 is displayed in Table 13. The employees that attended the focus group expected a majority of non-food items in this category and thus they were not surprised by these numbers. Furthermore, the perception obtained from the focus group was that a minimum demand of five per week is requested by KåKå for forecasting to make sense and with this in mind, the few products ending up in Q4 were also directed to Group 1. Due to the difficulty with forecasting the products in these two quadrants properly, they should be handled with a more manual approach.

Table 13: Products in each category and quadrant

	Lomma				Örebro			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Masses	4	19	3	0	2	21	3	0
Chocolate	13	15	87	4	19	18	79	0
Flour	24	15	20	2	30	15	15	1
Powder	30	19	65	7	27	18	58	2
Baking aid	8	3	11	2	7	2	10	1
Filling	1	10	17	0	2	13	11	0
Sugar/Syrup	12	12	17	0	15	10	15	0
Ice cream	13	30	98	0	6	28	91	0
Jam/Fruit/Berries	14	17	20	1	20	16	14	0
Yeast	2	2	1	0	2	1	0	0
Vanilla cream	2	1	0	0	2	1	0	0
Margarine	16	2	7	2	14	4	6	0
Dairy/Vegetable	7	2	4	1	9	3	1	0
Sandwich food	45	15	46	5	49	22	41	2
Beverage	26	0	36	5	24	5	48	1
Acquisition Martin	0	0	0	0	0	0	0	0
Separation oils	1	2	9	0	22	1	2	0
Import commodities	18	29	67	2	20	32	29	1
Bake-off	67	31	48	4	66	45	38	3
Non-food	43	52	716	22	59	86	805	10
Other	10	9	44	0	13	13	30	1
Total	**346**	**285**	**1316**	**55**	**388**	**354**	**1296**	**22**

With the first aspect of the demand model analyzed, Group 1, holding products with intermittent demand, was identified as the quadrants Q3 and Q4. However, there is a possibility that products with a significant trend or seasonality ended up in quadrant Q3 or Q4 but still should be subject to forecasting. Products with a recent increase in trend may have an average weekly demand above five when looking at a shorter period of history than two years. Similarly, seasonal products may have a significant demand in the period of the season but no demand at all in the other weeks, which would result in an average demand below five on a two year horizon. With this in mind, all products were subject to the trend and seasonality analysis and thereafter an additional review of the products belonging to multiple groups was conducted.

Trend

The second aspect that was analyzed from the historical demand was the trend. To identify a trend, the method of linear regression, which is commonly used to estimate the parameters of a straight line (Sundell 2012), was applied on the historical weekly demand data. The parameters that are estimated by linear regression are found in the straight lines equation presented by Sundell (2012) and that can be seen in Equation 24:

$$y_i = \beta_0 + \beta_i \cdot x_i + e_i \tag{24}$$

where y_i = The outcome variable for observation i
β_0 = The estimation of the mean value of y_i when x_i is zero
β_1 = The estimation of the average change in y_i when x_i increases by one unit
e_i = The difference between the actual value of y_i and the predicted value of y_i

The purpose of applying this method was to retrieve the estimation of the straight lines gradient for each demand data point, i.e. the parameter β_i in the equation above. The estimation of this gradient provides how the demand has changed on average per time period over a chosen amount of time which can also be interpreted as a trend. One method that can be used to obtain the trend gradient is the Least Square Method (LSM), which finds the best fitted line for a given set of data points by minimizing the error (Seber & Lee 2003). When applying this method, it was decided that 12 weeks of data points should be utilized to calculate the trend coefficient. The choice of a shorter period as input was decided upon in collaboration with KåKå and was motivated by the fact that trends tend to change rather rapidly and it is therefore not relevant to consider trends that have occurred prior to the latest 12 week period. Such trends will most likely not be relevant to consider in future planning but would effect the output from the LSM and it was therefore decided that an input from the most recent 12 weeks would be most appropriate. The procedure is exemplified by the following: *to calculate the trend coefficient for week 13 in year 2023, the demand data for weeks 1-12 in year 2023 was used as the input to the LSM.*

Once each product's most recent trend coefficient had been identified, it was important to analyze if the trend was actually relevant to consider in forecasting. To do so, the trend was tested for statistical significance. Testing for statistical significance can be done in multiple ways, one of them being by utilizing Wald's test, which calculates the squared relation between the trend coefficient and it's standard deviation (Sundell 2012). The exact formula is presented in Equation 25 below. Sundell (2012) stated that the squared quota (W) follows a chi-squared distribution with one degree of freedom. To check whether the trend is significant or not, the answer from the squared quota is compared to the given value from a chi-squared distribution table for one degree of freedom and the chosen significance level, which is presented in Appendix C. If the calculated value is greater than the value identified from the chi-squared distribution table, then the trend can be identified as significant.

$$W_i = (\frac{\beta_1}{\sigma})^2 \tag{25}$$

where β_1 = Trend coefficient
σ = Standard deviation of the trend coefficient

In this case, Wald's test was utilized in order to identify if any products in KåKå's assortment follow a significant trend. To begin with, the trend coefficient for the most recent week of demand data was calculated by using the demand data points from the 12 previous weeks, as described above. Thereafter, the standard deviation had to be identified in order to perform Wald's test. To be able to calculate the standard deviation, the trend coefficient for each of the 12 previous weeks was calculated. The standard deviation of the trend was then obtained through the following equation (Makridakis et al. 1998):

$$s = \frac{\sum_{i=1}^{n}(x_i - m)^2}{(n-1)} \tag{26}$$

where s = Estimated standard deviation
x_i = Trend coefficient in period i
m = The sample mean
n = The number of observations

Once the standard deviation of the trend coefficient is known, it was possible to perform Wald's test for each product's trend coefficient. A significance level of 99% was chosen since this decreases the risk of a product that does not have a significant trend being identified as significant. In this case, it was preferred that a product with a smaller trend was not identified as a significant trend since forecasting trend products requires more complex forecast models and should therefore only be utilized when necessary. To identify the significant trends, the chi-squared distribution table was utilized to obtain the critical value for the chosen significance level and one degree of freedom, which in this case resulted in a value of 6,63. The W value previously calculated was then compared to the value obtained from the distribution table and if W was greater than or equal to the critical value, then the trend was identified as significant according to Wald's test. Otherwise, the trend was not identified to be significant. The significance test resulted in 61 significant trend products in Lomma and 39 in Örebro.

Seasonality

The identification of products that are subject to seasonality is rather complex in the bakery industry. As described by Huber & Stuckenschmidt (2020) in Section 3.2.4, the bakery industry is subject to many special days in the form of public holiday, days before and after such holidays and other seasonal patterns. At KåKå such special days tend to result in the same seasonal pattern each year, but with one difficulty - at different times throughout the year. The special days can fall around the same time of year each year but commonly fall on different dates and in some cases even on different weeks. Due to the complexity in the special days and seasonality that KåKå's products are subject to, the seasonality of their products was not identified mathematically. Instead, KåKå's previous experience and knowledge regarding seasonality was used as the main input for identifying seasonal products. Since KåKå has been working with seasonailty for many years, their insight in the subject was seen to be more adequate than applying any mathematical model. Therefore, an Excel-file of seasonal products provided by KåKå was utilized in the identification of seasonal products. When only the products that are subject to forecasting were considered from the provided seasonal file, the resulting number of seasonal products in Lomma and Örebro was 136 and 134 respectively.

Products belonging in multiple groups

When the demand variability, trend and seasonality of all products had been identified, there were several products that belonged in multiple groups. These products required further analysis to determine which of the groups that was the most suitable. Primarily, an analysis was conducted on the products that were subject to both a significant trend and seasonality to determine whether the trend pattern was a consequence of the seasonality or if these products actually contained both characteristics. There were six products in Lomma and four products in Örebro with a significant trend that were also included in the list of seasonal products. Considering the small amount of products, these were analyzed manually by plotting the demand history in a scatter plot. One of the products that was subject to this analysis was *Marzipan Yellow 2,5kg* and the scatter plot of this item is presented in Figure 17. As seen in the figure, this product does not show any obvious trend pattern when observing a longer historical period than 12 weeks and it therefore appears as if the significant trend is rather a consequence of the products seasonality, Easter, occurring at the moment. When all products had been analyzed it was identified that only one had a significant trend while the other trends were all a consequence of seasonality. Thus, only one single product contains trend-seasonal characteristics and is relevant for Group 5. Considering this result, it was determined to exclude Group 5 completely moving forwards since it is not worth the complexity of handling one additional group when only one product belong there. With this in mind, the products with a significant trend that were also subject to seasonality were all removed from the trend-group.

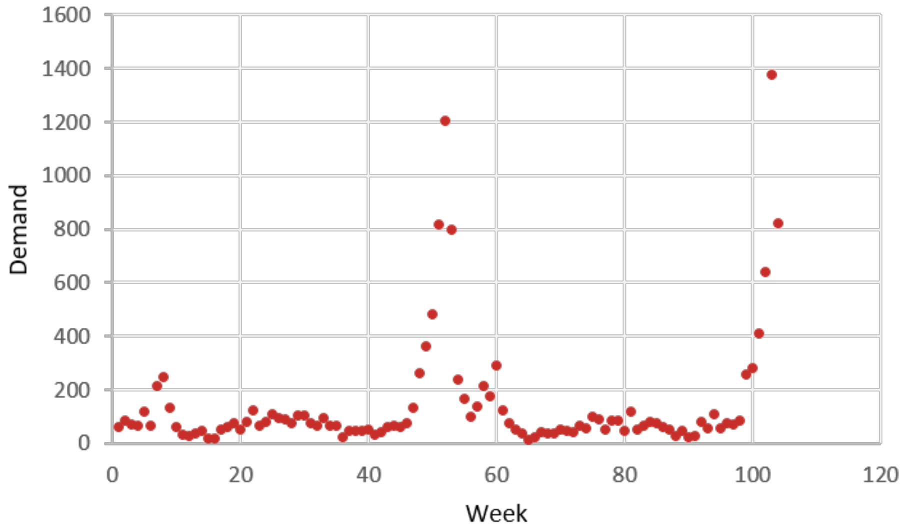

Figure 17: Scatter plot of Marzipan Yellow 2,5kg

Once the products that ended up in both Group 3 and Group 4 had been reviewed, the next step was to analyze the products in Group 1 and Group 3. This concerned a total of 42 products in Lomma and 29 products in Örebro. These were the products whose demand model was both intermittent and contained a significant trend. The analysis was conducted by reviewing the number of weeks during the trend period of 12 weeks where the demand was at least five units. The purpose was to identify whether the products had an increasing trend in the last period that resulted in a weekly demand above five or if the product still did not exceed this weekly demand limit and thus should not be forecasted. The limit was set for the products' demand to reach five units per week at least 50% of the weeks included in the trend period, which corresponds to six weeks, in order to be forecasted and excluded from Group 1. If a product's demand did not reach five units in six weeks or more, they were excluded from the trend group and were not subject for forecasting after all. The obtained result was that only one product in Lomma and none in Örebro had a weekly demand that reached five or more in a majority of the weeks in the actual trend period and these were therefore removed from Group 1 and stayed in Group 3. The others were removed from Group 3.

Lastly, the products that ended up in both Group 1 and Group 4 were analyzed to determine whether these should be in the intermittent group or if they should end up in the seasonal group. In total, there where 45 products in Lomma and 33 products in Örebro that were subject to this analysis. As the number of products to analyze was quite large, it was not possible to analyze each product manually and a more general course of action was necessary. With this in mind, a similar approach as the one previously described was conducted where the number of weeks with a demand of at least five units were identified. In contrast to the previously described analysis, the reviewed period in this case included the complete two years of historic demand. The idea was to identify if the demand exceeded five units per week in a majority of the weeks included in the products seasonality. By plotting the demand history in a scatter plot for a few products, it was possible to identify what limit, in terms of number of weeks with a demand of at least five, should be used to distinguish between products that should belong in the seasonality group and the intermittent group. The limit was set to ten weeks, which indicates that those products with a demand of five or more units during at least ten weeks within the last two years were removed from Group 1 while the others were removed from Group 4. The obtained result was that 34 products in Lomma and 26 products in Örebro were removed from the intermittent group and stayed in the seasonal group. The remaining products were solely assigned to the intermittent group.

Final forecasting product groups

Lastly, the remaining products that were not identified as intermittent, trend or seasonal products were identified as constant products and were therefore placed in Group 2. To summarize, the final forecasting product groups that have been identified and discussed above are presented in Table 14 below.

Table 14: Products categories in each forecasting product group

	Lomma				Örebro			
	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
Masses	3	10	2	11	3	10	1	12
Chocolate	78	26	2	13	67	36	0	13
Flour	22	39	0	0	16	45	0	0
Powder	70	43	0	8	60	138	0	7
Baking aid	13	10	0	1	11	8	0	1
Filling	14	3	2	9	11	4	1	10
Sugar/Syrup	17	22	1	1	15	24	0	1
Ice cream	92	19	0	20	82	21	0	22
Jam/Fruit/Berries	19	26	2	5	14	30	1	5
Yeast	1	4	0	0	0	3	0	0
Vanilla cream	0	1	0	2	0	1	0	2
Margarine	9	13	1	4	6	14	0	4
Dairy/Vegetable	5	7	0	2	1	10	0	2
Sandwich food	50	56	1	4	43	67	0	4
Beverage	39	26	0	0	49	29	0	0
Acquisition Martin	0	0	0	0	0	0	0	0
Separation oils	9	3	0	0	2	3	0	0
Import commodities	67	43	0	6	29	47	0	6
Bake-off	47	84	1	18	37	96	1	18
Non-food	737	92	3	1	815	143	1	1
Other	44	16	0	3	31	22	1	3
Total	**1336**	**543**	**15**	**108**	**1292**	**651**	**6**	**111**

5.3.2 Forecasting method identification

With three different product groups identified to be subject to forecasting, the next step was to evaluate which forecast method to assign each group in order to fit the demand model. This corresponds to the fourth step, *Choosing and fitting models*, in the forecasting process described by Hyndman & Athanasopoulos (2018) and Makridakis et al. (1998), which was presented in Section 3.3.1. The general approach for this analysis was to move back three months in time and calculate forecasts using a number of different forecast methods and parameter values, to then compare the outcome with the actual sales in the corresponding periods. The forecasts were calculated in IBP together with the supervisor at

KåKå as this system has the functionality to perform calculations with different methods within a reasonable amount of time. It is also possible to assign filters to get the products into different groups when using IBP. Thereafter, the comparison with actual sales and calculations of forecast error were performed in Excel. The perception obtained from a discussion with employees at KåKå was that the forecast accuracy should be measured in months, despite the fact that the forecasting period is weeks. This is argued by the fact that KåKå works with coverage times, meaning that they aim to have enough items on stock to cover for a number of weeks' demand. For most products, the coverage time is between three to four weeks and thus it is inessential if the forecast is right one specific week as long as the monthly accuracy is sufficient. With this in mind, the idea was to calculate the forecast error on a monthly time period, but since all data was given in weeks it was translated to a period of four weeks.

When choosing which methods to use for the different groups, the approach was to select as simple methods as possible that are applicable for the specific group's demand model and available in IBP. As discussed by Makridakis et al. (1998), simple forecast methods generally perform at least as good as more complex ones. With a complex method there is a bigger risk of over-fitting a model to the time series data, which means that random and extraordinary patterns are captured by the forecast but do not occur again in the future (Makridakis et al. 1998). On the other hand, Makridakis et al. (1998) state that simple methods are robust and estimate the future time series pattern more appropriately when randomness, that cannot be predicted, occurs in the data. The choice of using simple methods in this analysis was further motivated by the fact that the theoretical knowledge about forecasting is limited among employees at KåKå and as stated by Moon et al. (1998), one of the success factors of forecasting is about the organization's understanding of the forecasts. The use of simple methods will facilitate the understanding of the forecasts among the employees and thus increase the chance of successful forecasting. With this in mind, two different forecast methods of simple nature were chosen for all three product groups and the methods were tested with several different parameter values when possible.

The number of different values tested for each individual parameter was limited to three so that the calculations could be carried out within a reasonable amount of time. Though, when applying an Exponential smoothing method it is possible to let IBP decide the most suitable values of the included parameters SAP (nd). This will be noted as a parameter value *Chosen by system* hereafter and was applied in addition to the three manually chosen values when an Exponential smoothing algorithm was used. The specific methods and parameters that were chosen for each group will be further described in the sections below. Each group was also forecasted using KåKå's current method, Triple exponential smoothing, to be able to compare the forecast error. Additionally, there is an available method in IBP named *Automated exponential smoothing* which automatically identifies the most applicable algorithm of exponential smoothing, including the most suitable coefficients, and applies this when calculating the forecast (SAP nd). This method was also applied for all three groups. For the methods that consider seasonality, the number of periods in a season was set to 52 weeks and the seasonality was set to be of additive type. The number of periods was motivated by the fact that KåKå's products are subject to seasonality on a yearly basis and the seasonality was set to be of additive type through discussions with KåKå.

Once the forecast had been computed, the error of each method was calculated to enable a comparison. The Absolute Error (AE) and the Absolute Percentage Error (APE) were calculated for each product, and these values were later used when calculating the final measurements of each group's forecast error. As APE was obtained by dividing AE by the actual demand, the demand had to be greater than zero. However, in this case there were several products whose demand was zero in the analyzed period and thus APE was set manually for these products. If both the demand and forecast were zero, then APE was set to zero as the forecast was accurate. On the other hand, if the forecast was greater than zero while the demand was zero, APE was set to one, which correspond to a 100% error. As presented in Section 3.3.4, there are several different measurements that are possible to use when evaluating forecast accuracy. In this case, it was of interest to identify the size of the errors rather than if there was a systematic under- or over-forecasting. Furthermore, as multiple groups were analyzed, it was of interest to use a relative or normalized measure since this enables a comparison across time series with different conditions (Makridakis et al. 1998). With this in mind, the measures MAPE, WAPE and WMAPE were the most applicable measures of those presented in Section 3.3.4.

There are pros and cons with all three measures and they provide different insights to the situation. MAPE is a measurement that is commonly mentioned in theory and it emphasizes the forecasting error of all products equally as no weighting factor is applied. In contrast, WMAPE makes it possible to assign different priorities to different products. With this in mind, both measures were used in the analysis to evaluate if the result differed when the products of highest priority are assigned a greater weight. The understanding obtained from discussions with employees at KåKå was that it is of highest importance to obtain accurate forecasts for products with high demand. This is motivated by the fact that a relative forecast error of these products has a greater economic impact than an equivalent relative error of a product with low demand. With this in mind, the weight in WMAPE was set to correspond each product's proportion of the group's total demand. Further, as WAPE is the measure that KåKå uses today, this was also included in the analysis. KåKå argues that this measure was chosen to decrease the impact of products with a lower demand. However, if the main objective is to obtain high forecast accuracy of items with high demand, this would be measured more appropriately by using WMAPE and assigning weights based on sales volume. In addition to these three measures, MAE was used to obtain one measurement that reflects the accuracy in number of units instead of a relative percentage and it is also stated by Olhager (2019) that this is the most commonly used measure in practice. However, as this is not a relative measure, it is important to keep in mind that it should mainly be used to evaluate the performance of different methods applied to the same forecast group as these are based on the same time series.

During the analysis it was found that some forecast results, and therefore also errors, were significantly effected by single outliers. Due to this, an investigation was performed on each method and group to identify potential outliers and their root-cause. The analysis was conducted by comparing the value of MAE when the greatest value of the AE was included and when it was not included. It was also analyzed how MAPE changed when the greatest value of the APE was included and excluded. In most cases, the greatest value of the AEs in a group only effected the MAE by a few units. Similarly, the greatest value of the APEs in a group only effected the MAPE by a few percentages. However, there were a few cases were a single value had a significant effect on the MAE and MAPE. In these cases, the demand history of the product causing the outlier was analyzed to ensure whether the outlier in the forecast could be explained or not. If it was found that it was a result of an inexplicable outlier in the demand history, the outlier in the forecast was dampened as this demand spike should not have been used as a basis for the forecast. On the other hand, if it was not found that the outlier was caused by inexplicable patterns in the demand history, it was concluded that the outlier was rather caused by an inaccurate forecast. How individual outliers within the different groups were handled will be presented further in the following sections.

Group 2 - Constant

Primarily, the products in Group 2 were forecasted using four different forecast methods. The methods that were chosen for this group, in addition to KåKå's current method and Automated exponential smoothing, were *Single exponential smoothing* and *Simple moving average*. These are two simple methods that are suitable for stable demand models. When using Single exponential smoothing, it is necessary to assign a value between zero and one to the smoothing parameter, as described in Section 3.3.3. As presented by Olhager (2019), this parameter is most commonly set between 0,05 and 0,3 in practice. On the other hand, SAP (nd) state that it typically ranges between 0,1 and 0,5. Similarly, it is necessary to determine the number of periods to include in the average when applying the method Simple moving average, as presented in Section 3.3.3. For both methods, three different values for each parameter were tested to evaluate which values result in the best forecast accuracy. In addition, the parameter value was also set to be chosen by the system as an additional test with the Single exponential smoothing method. Each method, parameter value and its forecast error in terms of MAE, MAPE, WAPE and WMAPE for Group 2 are presented in Table 15. The lowest forecast error, and thus the highest accuracy, of each measure is marked green, the three subsequent are marked yellow and the rest are kept red.

Table 15: Forecast error with the different methods and parameter values applied to Group 2

	Forecast method	Parameter values	MAE	MAPE	WAPE	WMAPE
Group 2 Constant	Single exponential smoothing	Alpha (α) = 0,1	85	54%	38%	15%
		Alpha (α) = 0,3	118	46%	53%	24%
		Alpha (α) = 0,5	151	56%	67%	35%
		Chosen by system	163	63%	73%	52%
	Simple moving average	Periods (N) = 3 weeks	149	48%	66%	31%
		Periods (N) = 12 weeks	93	49%	41%	17%
		Periods (N) = 26 weeks	104	75%	46%	28%
	Automated exponential smoothing	-	182	185%*	81%	58%
	KåKå's current method	-	198	89%	88%	82%

***Value has been obtained without excluding the identified outlier**

The method and parameter value that resulted in the lowest forecast error for Group 2 in three of four measures was Single exponential smoothing with the smoothing parameter set to 0,1. Second best was the method Simple moving average with the number of weeks set to 12. As described by Axsäter (2006), there is a relation between the value of the smoothing parameter, α, in Single exponential smoothing and the number of periods, (N), in Simple moving average. This relation is described by the following formula (Axsäter 2006):

$$\alpha = \frac{2}{(N+1)} \tag{27}$$

This implies that a value of the smoothing parameter set to 0,1 corresponds to 19 weeks in Simple moving average terms. This value was not used in these tests but, according to the theory discussed by Axsäter (2006), using 19 weeks as the parameter value should result in a similar accuracy as with Single exponential smoothing and the smoothing parameter set to 0,1.

In this group, one outlier that affected MAPE with 104% was identified when applying the method Automated exponential smoothing. However, no reasonable explanation for this could be found when the demand history was analyzed and it was therefore assumed to be caused by a poor forecast method. This means that the outlier was not removed and is thus included in the resulting MAPE.

Group 3 - Trend

With the constant group analyzed, the next step was to forecast the products in the trend group. Once again, KåKå's current method and Automated exponential smoothing were applied. In addition to these two, Group 3 was forecasted with *Double exponential smoothing* and *Simple linear regression*. Similar to the reasoning above, these were chosen based on the fact that they are two methods suitable for this demand model that are of the simpler type. Double exponential smoothing contains one additional smoothing parameter, a trend parameter, in addition to the smoothing parameter for the level that appears in Single exponential smoothing. This is further described in Section 3.3.3. Similar to the smoothing parameter for the level, SAP (nd) state that the trend parameter typically ranges between 0,1 and 0,5. Three different values of each parameter, within this range, were tested and this resulted in nine different combinations of parameter values in addition to the alternative where the parameters were chosen by the system. On the other hand, no parameter value had to be determined when using the method Simple linear regression. Each method, parameter value and its forecast error in terms of MAE, MAPE, WAPE and WMAPE for Group 3 are presented in Table 16.

Table 16: Forecast error with the different methods and parameter values applied to Group 3

	Forecast method	Parameter values	MAE	MAPE	WAPE	WMAPE
Group 3 Trend	Double exponential smoothing	Alpha (α) = 0,1 Beta (β) = 0,1	65	61%	49%	28%
		Alpha (α) = 0,1 Beta (β) = 0,3	94	72%	71%	62%
		Alpha (α) = 0,1 Beta (β) = 0,5	96	75%	72%	67%
		Alpha (α) = 0,3 Beta (β) = 0,1	84	68%	64%	55%
		Alpha (α) = 0,3 Beta (β) = 0,3	109	60%	82%	62%
		Alpha (α) = 0,3 Beta (β) = 0,5	80**	55%	61%**	68%
		Alpha (α) = 0,5 Beta (β) = 0,1	96	75%	73%	70%
		Alpha (α) = 0,5 Beta (β) = 0,3	114	75%	86%	87%
		Alpha (α) = 0,5 Beta (β) = 0,5	114	84%	86%	93%
		Chosen by system	115	85%	87%	89%
	Simple linear regression	-	39**	55%	29%**	23%
	Automated exponential smoothing	-	129	83%	97%	70%
	KåKå's current method	-	99	78%	74%	62%

*****Values have been obtained by excluding the identified outlier***

The lowest forecast error of all four measures was obtained when using the method Simple linear regression. In this group, two outliers were identified and analyzed. One outlier was obtained when using the method Double exponential smoothing with the smoothing parameter for the level set to 0,3 and the smoothing parameter for the trend set to 0,5. When analyzing the demand history for the product with the outlier it was identified that the demand had a significant spike in one week while the demand in all other periods was zero. As this significant peak is inexplicable considering the other periods' non-existent demand, it is assumed that this spike should have been highlighted and not included as a basis for the forecast. Therefore, the forecast outlier was dampened and this product was excluded in the accuracy calculations. The other outlier was obtained when using the Simple linear regression method. It was identified that this outlier was caused by the same product as previously discussed and this means that the outlier was dampened for this method as well. Considering the fact that the same product caused a significant outlier for two of the methods, it was further analyzed how this affected the other methods in this group. However, it was concluded that this product did not cause any significant effect on the accuracy of other methods and parameter values such that the result when comparing the different methods changed.

Group 4 - Seasonal

The third and last group that is subject to forecasting is Group 4 which contains the seasonal products. Apart from KåKå's current method and Automated exponential smoothing, the products in this group were forecasted using *Triple exponential smoothing* and *Seasonal linear regression*. When using Triple exponential smoothing, the trend parameter was set to zero as the products in this group do not contain any significant trend pattern in their demand. As seen in Equation 5 presented in Section 3.3.3, this means that the estimated trend is not updated and kept as the initial value. The initial value is identified automatically by IBP and it is assumed that this will be close to zero as no significant trend patterns were identified for these products in the forecast grouping process. However, the smoothing parameter for the level and the seasonal smoothing parameter were tested with three different values. Similar to the other smoothing parameters, the seasonal parameter is commonly ranged between 0,1 and 0,5 (SAP nd). The method Seasonal linear regression follows the approach of a Simple linear regression before adding a seasonality by multiplying the forecasted values with seasonal indexes that are identified automatically in IBP (SAP nd). With this in mind, there are no parameter values that have to be set manually when using this approach. Each method, parameter value and its forecast error in terms of MAE, MAPE, WAPE and WMAPE for Group 4 are presented in Table 17.

Table 17: Forecast error with the different methods and parameter values applied to Group 4

	Forecast method	Parameter values	MAE	MAPE	WAPE	WMAPE
Group 4 Seasonal	Triple exponential smoothing	Alpha (α) = 0,1; Beta (β) = 0; Gamma (γ) = 0,1	140	75%	55%	52%
		Alpha (α) = 0,1; Beta (β) = 0; Gamma (γ) = 0,3	138	75%	54%	51%
		Alpha (α) = 0,1; Beta (β) = 0; Gamma (γ) = 0,5	135	75%	53%	50%
		Alpha (α) = 0,3; Beta (β) = 0; Gamma (γ) = 0,1	214	88%	84%	89%
		Alpha (α) = 0,3; Beta (β) = 0; Gamma (γ) = 0,3	214	88%	84%	89%
		Alpha (α) = 0,3; Beta (β) = 0; Gamma (γ) = 0,5	214	88%	84%	89%
		Alpha (α) = 0,5; Beta (β) = 0; Gamma (γ) = 0,1	224	89%	88%	93%
		Alpha (α) = 0,5; Beta (β) = 0; Gamma (γ) = 0,3	224	89%	88%	93%
		Alpha (α) = 0,5; Beta (β) = 0; Gamma (γ) = 0,5	224	89%	88%	93%
		Chosen by system	233	93%	94%	97%
	Seasonal linear regression	-	58	88%	23%	10%
	Automated exponential smoothing	-	229	97%	90%	84%
	KåKå's current method	-	217	88%	85%	90%

In three of four measures, the lowest forecast error was obtained when using the method Seasonal linear regression. No outlier value was identified for any of the methods used.

Summary of chosen methods

In all three groups, it has been identified that the method that resulted in the best forecast accuracy was one of the simple methods with manually chosen parameters. The best method for each group, including the accuracy obtained using this method, is presented in Table 17. The methods of Exponential smoothing and Regression are presented by Makridakis et al. (1998) as two of the methods that have attained the highest level of satisfaction by the users, which further strengthens the motivation for using these methods.

Table 18: The methods that resulted in best forecast accuracy for each group

	Forecast method	Parameter values	MAE	MAPE	WAPE	WMAPE
Group 2 Constant	Single exponential smoothing	Alpha (α) = 0,1	85	54%	38%	15%
Group 3 Trend	Simple linear regression	-	39	55%	29%	23%
Group 4 Seasonal	Seasonal linear regression	-	58	88%	23%	10%

One consistent result is that WMAPE is the measure resulting in the best relative accuracy level, followed by WAPE and lastly MAPE. Of these three measures, WMAPE is the one where the least weight is devoted to the products with low demand and thus it can be concluded that there are products with a low demand that increases the total forecast error when using MAPE and WAPE. This indicates that the products with a high demand generally obtain higher forecast accuracy than products with lower demand. With KåKå's current forecast accuracy target of 80%, the error should stay below 20% and if WMAPE is used to measure the error this target is reached in two of three forecast groups. If WAPE is used, which is KåKå's current measure, the target is not reached in any of the groups. However, the gap between actual performance and the target is significantly smaller than it is using KåKå's current forecast method.

A notable result is that the method Automated exponential smoothing performed inferior to most of the other methods that were used in all three groups. Further, the methods where the parameter values were automatically chosen by the system did also perform poorly. The simple methods that were manually chosen outperformed these despite the fact IBP had chosen methods and/or parameter values based on demand history for each individual product to optimize performance. One potential reason behind this result is that the phenomenon of over-fitting has occurred since the demand of KåKå's products is subject to some randomness. This phenomenon is also a potential explanation to why the forecast accuracy obtained with KåKå's current method is worse than the accuracy obtained with the methods presented in Table 18. Furthermore, the parameter values in KåKå's current Triple exponential smoothing method was identified as a main issue with their current method and thus this is another potential reason behind the obtained result.

5.4 Demand Planning analysis

As previously explained, the forecasting and demand planning processes require different product groups. For demand planning, the identification of critical product groups is based on an ABC-XYZ analysis of two important product characteristics. The product characteristics were determined in collaboration with the thesis supervisor at KåKå and with participants from the focus group. The first identified characteristic is shelf life, which has been identified as important since it can have a large impact on the level of products that are discarded. The degree of the impact is also strongly connected to the forecast accuracy at KåKå, since the level of discarded products may increase if products with a short shelf life are forecasted incorrectly. As the company is not achieving their current target level for the value of discarded products or the forecast accuracy, this further motivates the need of product groups based on shelf life.

The other product characteristic that has been identified as important for product grouping is sales value. The distribution of sales value should indicate where a company directs their main focus and resources. Products that account for a large share of the company's total sales value should receive a lot of focus since smaller deviations can resemble a large portion of the total value. This characteristic also has an impact on the engagement from different departments. At KåKå, there is a current lack of understanding for the need of information sharing and input to the demand planning process. Discussing products in terms of sales value is believed to attract the attention of more demand planning participants and therefore also increase the information sharing.

Once the characteristics were identified they were utilized as a base for performing the ABC-XYZ analysis. The purpose of performing an ABC-XYZ analysis was to identify which products that KåKå should focus their resources on regarding demand planning. However, the groups that are retrieved from the analysis cannot be directly utilized as demand planning groups since they do not provide a clear indication of which products are in each category. Therefore, the product categories presented in Table 10 were utilized in combination with the ABC-XYZ analysis to create the demand planning products groups. The process for product grouping is presented in detail below.

5.4.1 Demand planning product grouping process

To perform the demand planning product grouping process, data regarding product shelf life and sales value were utilized. The sales value was calculated manually using information provided from an Excel-file regarding each product's cost price.

Depending on the unit, some products' cost prices were recalculated in order to attain the correct cost price per unit value. For example, some products' cost prices were per 1 000 units and the cost was therefore divided by 1 000 to achieve the correct value. Once the cost price per unit was correctly calculated, the total cost price per product was calculated. This was done by multiplying the cost price per unit for a product by the demanded sales volume for the same product. The demanded sales volume was for the year of 2022 since this was the only year in the Excel-file that provided a whole years worth of demand data. The annual sales value per product was then retrieved and could be used for the product grouping process.

The shelf life utilized in this product grouping process was retrieved from an Excel-file provided by KåKå. The file consisted of all products in KåKå's assortment, their product status and shelf life period in days. Data filtering was performed to select those products that have an active status since these are the only products that will be included in the product grouping process. Products with a status that reflects a product phase in or out will be discussed more in Section 5.4.2 and not considered in the demand planning product grouping process presented in this section. Another data filtering was performed in order to remove all products that are not kept in stock. This is due to the fact that such products do not require long-term planning in the same manner as stock-held products do, which can be related to such products being procurement goods. Another reason for this filtering is that products that are not kept in stock do not place capacity requirements on the warehouses, which in KåKå's case is their main operational activity. Therefore, these products do not need to be planned for and taken into consideration in demand planning.

ABC-XYZ analysis

Once the data regarding both sales value, shelf life and if the products are kept in stock was organized according to the description above, the ABC-XYZ analysis was performed. The ABC-categories were based on the sales value whilst the XYZ-categories were based on the shelf life. In order to decide upon the limits for each category, the discussions held during the focus group at KåKå were utilized. The desired output from the focus group was to receive an indication on what could be considered as a short, medium or long shelf life as well as low, medium or high sales values. The guidelines regarding the classification of products based on sales value provided by KåKå was that the Pareto-rule, presented by Stojanović & Regodić (2017) in Section 3.2.2, would create the most relevant category limitations. For the limitations of product shelf life, specific intervals were provided by KåKå since they had relevant insight on this area.

After the focus group, the Pareto-principle was applied to all of KåKå's products that are kept in stock and forecasted. To apply this principle, the guidance for category identification provided by Swamidass (2000) was utilized. The author presented that, when dividing products into three categories, intervals of category limits can be used. For A-category products Swamidass (2000) presented that this group is usually represented by 10-20% of the total products and 50-70% of total sales value. This was followed by 20% of the total products and approximately 20% of the total sales value for the B-category. Lastly, the C-category was stated to consist of 60-70% of the total products that account for 10-30% of the total sales value. These category guidelines were used as guidance when performing the categorization on KåKå's products. Firstly, the total annual sales value for all products was calculated followed by the calculation of each products percentual share of the total annual sales value. Thereafter, according to the Pareto-principle, the percentual shares were ordered from highest to lowest and summarized until a total share of 80% was achieved. The calculation then proceeded to summarize the remaining percentages until a total of 15% was achieved and lastly until a total of 5% was achieved. This resulted in 12,7% of KåKå's products accounting for 80% of the total sales value and therefore belonging to the A-category. The B-category consisted of 21,6% of KåKå's products and the remaining 65,7% of the products belonged to the C-category. The limit for A-category products was those products that obtained a yearly sales value of over SEK 437 211, B-category with between SEK 95 750-437 211 and C-category products with a sales value lower than SEK 95 750.

To categorize the products according to their shelf life, input from KåKå was utilized as described above. KåKå presented that a short shelf life was considered to be under 100 days since the shelf life provided in the Excel-file includes all involved parties contracted shelf life. This means that of those 100 days, only 33 days is contracted to KåKå as the supplier and customer are also contracted approximately a third of the total shelf life each. It was therefore motivated to not be reasonable to consider e.g. 30 days as a short shelf life since this would only mirror 10 days for KåKå. The X-category products are therefore those with a shelf life equal to or lower than 100 days. The limit for a medium shelf life was not as clearly motivated as the short shelf life, but since a shelf life of one year is too long to consider as a medium shelf life for KåKå's products, a guideline of approximately six months, i.e. 183 days, was given. When utilizing this limit for the analysis, it provided a reasonable number of products in each category and was therefore utilized for the Y-category limit. This implied that the Y-category consisted of products with a shelf life between 101-183 days. The final shelf life category, the Z-category, consisted of all products with a shelf life longer than 183 days. The limits for each product category are presented in Table 19 below along with the resulted number of products in each product category.

Table 19: The results from the ABC-XYZ analysis performed on KåKå's products

		Sales value (SV)		
		A (SV ≥ 437 211)	B (95 570 ≤ SV < 437 211)	C (SV < 95 570)
Shelf life (SL)	X (SL ≤ 100)	39	32	21
	Y (100 < SL ≤ 183)	46	47	44
	Z (SL > 183)	250	488	1666

As mentioned in Section 5.4, the main purpose of the ABC-XYZ analysis was to identify which product categories that are the most critical and therefore should receive most focus. Flores & Whybark (1986) discusses the two-dimensional analysis, ABC-XYZ, and what the purpose of the analysis is as well as how the results can be used. In the example presented by Flores & Whybark (1986), the ABC-XYZ analysis could be used to identify which products should be of subject to certain priorities and procedures. The example was based on dollar usage and lead times and resulted in that those products that had a high dollar usage and long lead time to customer should be of high priority to manage. Those products on the opposite side of the matrix are those that could be dealt with by implementing an inventory decision rule. Products that landed in the middle of the matrix are normally rather standard products that can follow standard procedures. This example was used to compare the results from the ABC-XYZ analysis performed on KåKå's products. As seen in Table 19, the products that should be of high priority are those that belong to category AX due to the large contribution to the total sales value and the short shelf life that the products posses. Moreover, due to the importance of the product characteristics, the categories BX, AY and BY were also considered to be of high priority. The shelf life of such products is still considered to be short enough that the products need to be discussed in demand planning. This, together with the high share of the total sales value, implies that these products should also be identified as high priority products. On the opposite side of the matrix, in the CZ-category, it is possible to identify a a clear majority of KåKå's active and stock-kept products. It is also possible to see that there is a rather high number of products in the the remaining two Z-categories, i.e. AZ and BZ. Such products that have a long shelf life should not be of focus during the demand planning process as, if they are subject to appropriate forecast methods, they should be manageable. Lastly, the products that belong to categories CX and CY are those with a short to medium shelf life but that account for a rather small share of the total sales volume. Due to this, these products are not identified to be of high priority and should instead also follow standard procedures.

Furthermore, as mentioned in Section 5.4, the product groups presented in Table 10 can be used in combination with the ABC-XYZ analysis. These groups were used as they have been identified as appropriate in order to conduct decisions on a product group level during the demand planning process. The product groups from Table 10 have been combined with the results from the ABC-XYZ analysis in Table 19. In Table 20 below, it is possible to identify the distribution of product groups in each category. From the table below, it was possible to identify that 52% of the products that belong to the AZ-, BZ- and CZ-cateogries are non-food products. With this in mind, this indicates that the result from Table 19 and the indication of an inventory decisions rule for such products as Flores & Whybark (1986) presented, aligns well with these products being a majority in these categories. On the other side of the matrix, the AX-, BX, AY- and BY-categories are identified to be of high priority due to the short shelf life and high sales value. This is further motivated by a large portion of the products in these categories belonging to the Sandwich food category. This category consists of food products such as prawns, cheeses, hams and other sandwich mixes that all have a very short shelf life and that account for a large portion of the total annual sales. It is therefore clear that such products should be of high priority and discussed during the demand planning process in order to ensure that these products are available in the right place and at the right time.

Table 20: Distribution per product group from the ABC-XYZ analysis

	AX	BX	CX	AY	BY	CY	AZ	BZ	CZ
Masses	2	0	0	1	3	0	12	8	0
Chocolate	0	0	0	0	0	0	15	31	81
Flour	0	0	0	1	1	4	24	15	23
Powder	0	0	0	5	4	4	26	58	28
Baking aid	0	0	1	1	0	1	7	12	5
Filling	4	3	1	4	5	7	2	1	8
Sugar/Syrup	0	0	0	1	1	1	15	10	18
Ice cream	0	0	0	0	0	0	7	35	89
Jam/Fruit/Berries	1	0	0	0	2	0	14	19	20
Yeast	2	1	0	0	0	0	1	0	1
Vanilla cream	1	0	0	2	0	0	0	0	0
Margarine	3	1	0	11	3	6	7	1	1
Dairy/Vegetable	4	2	0	2	0	2	1	1	4
Sandwich food	14	20	15	2	8	7	3	16	43
Beverage	0	3	2	1	2	5	0	22	49
Acquisition Martin	0	0	0	0	0	0	0	0	0
Separation oils	0	0	0	0	0	0	5	5	2
Import commodities	0	0	0	0	0	2	30	25	63
Bake-off	7	0	1	11	17	5	42	43	31
Non-food	0	2	1	0	0	0	34	179	1147
Other	1	0	0	4	1	0	5	7	53
Total	**39**	**32**	**21**	**46**	**47**	**44**	**250**	**488**	**1666**

5.4.2 Product planning management

As described in the empirics and in Section 5.1.2, KåKå has a broad product assortment where their products are currently categorized in an unstructured manner. This has caused employees to use different product categories depending on the purpose, which has thereafter led to an unnecessary number of product categories. Moreover, there are also multiple products of the same type which, as explained by the interviewees, causes the product assortment to become unnecessarily large. The first problem that KåKå faces with the unclear and unstructured product categories is managed by the product categorization for both forecasting and demand planning presented in Sections 5.3.1 and 5.4.1 above. The second problem, with the very large product assortment, must be addressed. As described in Section 5.1.2, the product phase out process at KåKå does not work as intended, which causes the assortment to increase. Due to this, it is identified that implementing a new, structured product phase out process is necessary. However, a new process will not be adequate on its own. To begin with, KåKå will need to initiate an extensive product review in order to identify new, substitute and old products. This will provide an indication on which products that must be phased out, which need to be introduced, and those that may need to advance in their life cycle. The review should also be used to thoroughly look at the whole product assortment to identify if there are products that are or could be made redundant. As described above, one main cause of the large assortment is that there are too many products that can be seen as substitutes to one another. This indicates that an extensive product review where KåKå goes through all products with similar characteristics in order to determine whether or not all are necessary to keep in the assortment should be performed. If not, then a product phase out should be initiated.

The product review process will also be necessary for the product grouping processes that have been developed in Sections 5.3.1 and 5.4.1. Firstly, new products will need to be provided an initial product category given assumptions regarding their demand patterns. Thereafter, it is important that the products are reviewed to analyze if the demand patterns have changed and if so, identify if they include a trend or seasonality. If the pattern has changed, the product might need to be transferred to another product group that is subject to another forecast model. Secondly, since products and their demand patterns may change throughout their life cycle, it is important to regularly review all products in order to identify if another product group is more appropriate than the current one. This can, for example, occur if a stable product starts to obtain a negative or positive trend, then it should be moved from Group 2 to Group 3 in Table 12. The same change for a product would also be reflected in a product's sales value which, if it decreases significantly enough, should be moved to a category more suitable considering sales value. Lastly, product trends will require a more frequent review process. This is due to the trend identification process being based on a historical period of 12 weeks which implies that e.g. a yearly review process would be inadequate for such products. During a whole year, multiple changes in a trend can occur, and it is therefore necessary to adjust the review process accordingly.

Apart from being beneficial for ensuring that the product groups for forecasting and demand planning are kept up to date, the product review is also beneficial for managing the products that were not identified to require forecasting groups, i.e. those that were found in the left quadrant in Figures 15 and 16. Such products were chosen to follow a make-to-order-policy in the study conducted by D' Alessandro & Baveja (2000). This choice was based on the fact that products in the left quadrants obtain a low average demand and high variability, which makes forecasting difficult and warehousing costly. In KåKå's case, such products need to be reviewed in order to identify a strategy regarding how they should be managed. The questions KåKå needs to discuss and answer are the following:

1. Should these products be forecasted at all?
2. Should these products be kept in stock, but on a rather small scale?
3. Should these products be procurement goods that are not kept in stock at all?

If a product has a very sporadic demand pattern then trying to apply an appropriate forecast method will be complex. In these cases, KåKå must identify if there is a strong need to keep these products in stock or if it is more beneficial to transition such products to procurement goods. By transitioning products to procurement goods, KåKå can inform their customers and make them aware of when they need to order to receive those products in time.

Another important aspect to consider is how distinguish the handling of stocked and non-stocked products. In demand planning and S&OP, the purpose, according to theory, is to create long-term plans for products that require operations capacity and assure that the supply plans align with demand plans. As discussed in Section 5.4.1, procurement goods do not require capacity from warehouse operations. Such products are typically not critical products since those purchasing the products are normally informed regarding as to when such products need to be ordered and the lead time for receiving the products. Therefore, this implies that procurement products do not require the same management as stock goods since these products do not put requirements on capacity or costs such as tied-up capital and discarded products. In relation to demand planning and S&OP, this implies that products that do not put requirements on capacity do not need to be included in the demand planning process. In KåKå's case, this is reflected on products that are not kept in stock, since warehouse operations are their main operational activity. Therefore, non-stocked products do not need to be included in their demand planning and S&OP process.

5.5 Sales and Operations Planning analysis

The perception obtained from the empirical study is that KåKå's current setup of the S&OP process deviates from the theory in several ways. The most obvious gaps between theory and practice that have been identified relate to the process structure, the information sharing across departments and the time horizon. These topics have also been identified as the main issues with KåKå's S&OP process design and a further discussion on these three issues will follow below.

5.5.1 Process structure

As presented in Section 5.1.4, KåKå currently conducts one single meeting in their monthly S&OP process which corresponds to the final executive meeting in the theoretical four step process. With this in mind, this single meeting must also capture all subjects that should have been conducted in the precedent steps according to theory. However, this is not the case in KåKå's process as the outputs that should follow from the demand planning phase and supply planning phase in theory are not obtained at all. The sales plan and resource requirements plan are not discussed individually since they rather establish a final plan for individual products immediately during the one meeting that is conducted. One of the main success factors of S&OP presented by Lapide (2004) is to conduct ongoing, routine S&OP meetings which means that the four meetings that represent the four steps need to occur on a routine basis. Since only one meeting is currently held at KåKå the current process needs to be restructured in order to be successful and to enable the company to experience the benefits that an efficient S&OP process offers. How the process can be restructured to achieve this is presented in the following paragraphs.

The S&OP process should consist of at least the four steps presented in Section 3.1.3. To begin with, it is necessary that KåKå develops an unconstrained baseline demand forecast that captures what the company could sell to their customers, i.e. solely based on customer demand and not warehouse constraints. The baseline demand forecast is identified by Lapide (2004) as one of the main success factors of S&OP since it forms the initial working draft that all following S&OP activities are based on. It is therefore important that it is unbiased, unconstrained and includes all known impacts on future demand (Lapide 2004). The baseline demand forecast is usually developed by using statistical forecasting methods which can be done through a meeting, which would resemble the first step in the S&OP process. During this step, it is important that those with relevant knowledge are involved, such as sales and marketing as well as KåKå's assortment manager. The reason for this, as Grimson & Pyke (2007) states, is that the demand forecast needs to take new product introductions and product obsolescence into consideration, and it has been understood that such knowledge is possessed by multiple departments at KåKå. It is also during this first step that the product review process described in Section 5.4.2 will be of great use since this will provide an updated picture of how products must be managed as well as how the demand patterns for certain products look. Once the demand forecast has been developed this step will consist of updating the demand forecast on a monthly basis for the monthly S&OP process.

To proceed to the second step in the S&OP process, the output from the first step is required as input. The demand forecast is typically used in this step to create a supply plan, which is designed to fulfill the demand forecast requirements (Grimson & Pyke 2007). It is also in this plan where both resource and capacity constraints are considered as stated by Olhager (2019). In theory, capacity often refers to the production capacity since most S&OP theory is based on manufacturing companies. Due to this and to the fact that KåKå is a non-manufacturing company, it is necessary to adapt this second step to fit the main operational activity of the company. As KåKå's main operational activity is warehousing, this step should rather regard the warehouse capacity instead of production capacity. However, it is not solely the warehouse capacity that determines if KåKå can supply customer demand but it is also the capacity of their suppliers. Therefore, this step should involve planning supply by considering both the warehouse- and supplier capacity constraints. This step should consist of a meeting that is held to discuss the constraints and develop the initial supply plan. Those that possess knowledge of the warehouse and supplier constraints, as well as customer demand, should be present and could be the Warehouse Manager and a Strategic Purchaser in KåKå's case. The Warehouse Manager should possess detailed knowledge regarding the warehouse capacity whilst the Strategic Purchaser should possess knowledge regarding the suppliers capacity constraints such as volumes and lead times.

Once the first two steps are completed, which also means that the demand- and supply plans are complete, the third step can be initiated. This step is, as presented by Olhager (2019), a pre-meeting that is used to perform a common review of the demand and supply plans. During this meeting, product groups are discussed and thus the demand planning groups presented in Table 20 should be utilized. The groups should be used as a basis for discussion regarding problems that may occur and to identify how they can be solved. By performing discussions on a product group level, the pre-meeting can be kept effective and ensure that other activities can be performed. It is also during this meeting that the agenda for the executive meeting is set. The meeting agenda is presented by Lapide (2004) to be one of the main success factors of S&OP. This is an important part of the process since the meetings are meant to be performed on a routine basis, and a structured agenda enables all parties to be aware of the expectations and purpose of each meeting. Even though it is during this meeting that the agenda is set for the final meeting, each of the pre-meetings that occur during the three first steps require a structured agenda for the same reasons. KåKå will therefore need to ensure that each of the new steps that they have not performed previously receive clear and structured agendas. An agenda can be structured in various ways and should also present the dedicated time frame for each point on the agenda. Lapide (2004) presents an example of a meeting agenda and motivates that the following should be raised: a review of the previous plans performance together with the root-causes if deviations have occurred, discussions that lead to aligned demand- and supply plans, and final closure in order to finalize the decisions that have been made during the meeting. Other points that are relevant to raise are the unsolved problems from the pre-meeting.

The fourth and final step of the S&OP process presented by Olhager (2019) is the executive meeting. The agenda from the pre-meeting is utilized and decisions are made regarding the product groups in Table 20. If the previous three steps are performed properly, an effective executive meeting is possible to obtain. The S&OP team attends this final meeting and Grimson & Pyke (2007) state that it is important that this is a cross-functional team consisting of representatives from sales and marketing, operations and finance. It is also important that senior executives participate in order to gain approval on the work presented from the previous steps as well as to grant the S&OP team authority to make decisions regarding planning implementation (Grimson & Pyke 2007). The empowerment of employees to enable decision making has also been identified by Lapide (2004) to be one of the main success factors for S&OP since decisions must be made throughout the whole process and not solely during the executive meeting. It is therefore important that employees obtain such decision making authority in order to make decisions based on knowledge and discussions with other employees. At KåKå, the current participants in the monthly S&OP process represent a cross-functional team. This cross-functional participation is, however, not enough to create an effective and successful S&OP process today. The attendance of representatives from multiple functions is not enough on its own. As Lapide (2004) explains, an active participation of all participants in combination with clear roles and responsibilities is required to be able to achieve an sufficient S&OP process. This has also been identified by the author as one of the main success factors for S&OP.

5.5.2 Information Sharing

Another key issue that was identified in Section 5.1.4 was information sharing across different functions and departments in KåKå's organization. When identifying information sharing as a key issue, two root-causes to the problem were also identified. The first root-cause was the lack of collaboration throughout the organization which is due to the old and traditional mindset that the organization obtains. Due to this old mindset, cross-functional collaboration is not highly prioritized or encouraged in order to achieve better process outcomes. Instead, the functional silos continue as usual and impede the performance of processes such as S&OP. Functional silos and the lack of collaboration has been identified in Section 3.1.4 as barriers to successful S&OP and are therefore important issues for KåKå to solve to be able to achieve a successful process. To be able to deconstruct function silos and the resulting silo mindset, Stone (2004) emphasizes the action of creating a culture for collaboration. By creating a collaboration culture, open communication in all channels, i.e. via e-mail, telephone and in-person, can become the new norm and increase information sharing between functions. However, to succeed with the implementation of a collaboration culture it is important that senior management models the collaborative behaviour that they desire to implement. This is of great importance since the desired behaviour of employees will only be achieved if top management leads the way (Ling & Goddard 1988). As functional silos are currently impeding the information sharing at KåKå, implementing a culture for collaboration is of great importance in the near future. This will require engagement from top management if the cultural change is to be performed adequately throughout the organization. The engagement of top management should not only include communicating the purpose of the cultural change but also modelling the behaviour expected from the employees in the new culture. In the cultural change to a more collaborative organization, Lapide (2014) has identified the need for an internal collaborative process as one of the main success factors for S&OP. This implies that a collaborative process should be designed in order to achieve consensus-based plans and accountability, which are two important factors in S&OP (Lapide 2014). Consensus-based plans are plans that all functional organizations have agreed upon and to achieve such a plan, the functional managers must commit to purpose and obtain accountability for doing so (Lapide 2014). Without accountability for different roles and responsibilities, the necessary activities for S&OP will be difficult to achieve.

Furthermore, the second root-cause to the lack of information sharing at KåKå was identified to be the lack of adequate theoretical understanding of both S&OP and demand planning. As Pedroso et al. (2016) explains, the lacking understanding could be caused by not providing relevant training and education within the area. At KåKå, it has been understood that no relevant S&OP training or education has been provided to the employees nor to those working with S&OP. It is therefore of importance to provide such training and education when restructuring the process according to Section 5.5.1 above. If the employees are well-educated within the area, an increased understanding of the purpose and benefits of S&OP can be obtained. Additionally, educating employees can enable the possibility to provide clarity regarding roles and responsibilities within the S&OP process as well as the consequences that can follow if employees do not obtain accountability for their responsibilities. Clarifying roles and responsibilities has also been identified by Stone (2004) to be an important action to conduct when deconstructing functional silos. By doing so, employees can also gain an understanding of others' responsibilities and how they effect each other. In addition to Stone (2004), Lapide (2014) has also identified the need of clearly defined functional roles at each meeting in the S&OP process as one of the main success factors for the process. Lapide (2014) states that the roles of each function must be clarified in order to leverage functional expertise that is needed in a sufficient S&OP process.

5.5.3 Time horizon

The final key issue that was identified with the current S&OP process at KåKå was the chosen time horizon of one month that was not identified to be adequate. The short planning horizon risks KåKå not considering longer supply-demand lead times as well as an inability to identify market changes fast enough to consider them in the planning process. S&OP is, as Olhager (2013) states, desired to provide supply- and operations plans for a longer horizon of between 15-18 months. Grimson & Pyke (2007) present that the planning horizon can range between six months to 3 years but the most reoccurring planning horizon has been identified to range between six to 18 months. Lapide (2014) has identified the planning horizon as one of the main success factors for S&OP and explains the importance of choosing a planning horizon that is long enough to cover the longest supply-demand lead time. The planning horizon must therefore cover the supply lead time of resources and materials as well as the demand lead time for sales and marketing activities (Lapide 2014). With this in mind, KåKå would need to consider their longest supply-demand lead time in order to decide upon a adequate planning horizon for S&OP. In KåKå's case, the longest supply-demand lead time identified in this study is 180 days, i.e. approximately six months. This, combined with theory from Lapide (2014) would indicate that a planning horizon of six months would be appropriate for KåKå's S&OP process. However, it is also important to acknowledge that the horizon can be affected by the type of industry, product seasonality as well as when the S&OP occurs (Grimson & Pyke 2007). If an industry has long production lead times or offers products with high seasonality, then the planning horizon is normally longer than for short production lead times and products with low seasonality. Since KåKå obtains a product assortment that is subject to many different seasonalities, this should also be considered in the planning horizon decision.

6 Final Recommendations

This chapter begins by concluding the results from the Findings and Analysis chapter and aims to provide tailored recommendations for KåKå given the results. Firstly, the recommendation regarding how products can be categorized to facilitate forecasting along with the most appropriate forecast method per forecast group is presented. Secondly, the recommendation for how products can be categorized to facilitate the demand planning is presented. Lastly, an additional recommendation for future actions to take in order to improve the S&OP process is provided before a concluding summary.

6.1 Main recommendations

The objective of this thesis was to focus on the demand planning phase of KåKå's S&OP process since multiple problems were identified within this area. With this in mind, the main recommendations in this section will regard the key identified issues in the areas: forecasting and demand planning. The recommendations are based on the results from the analyzes performed in Sections 5.3 and 5.4.

6.1.1 Forecasting

The first main recommendation to KåKå is to conduct a transformation of the current forecasting process. As presented in Section 5.1.1, the main issue with the current method is that one single forecast method, with inadequate parameter values, is applied for all products and this results in a poor forecast accuracy. The recommended solution to this problem includes two different parts, primarily to define product groups and thereafter to assign an appropriate forecast method for each group. All products that are subject to forecasting should be assigned to different groups according to the process presented in Section 5.3.1. This grouping is based on the demand model of each product and will facilitate KåKå's identification of which products to forecast and which forecast methods to apply. The grouping is conducted by reviewing the demand variability, trend and seasonality of each product. Thereafter, the authors recommend that KåKå applies the following forecast methods to the three product groups that should be subject to forecasting:

- *Constant group*: Single exponential smoothing, Alpha = 0,1
- *Trend group*: Simple linear regression
- *Seasonal group*: Seasonal linear regression

As presented in Section 5.3.2, this transformation could result in a decreased forecast error, measured in WMAPE, from 82% to 15% for the constant group. For the trend group, the corresponding change in forecast error could be improved from 62% to 23% and lastly, the forecast error of the seasonal group could decrease from 90% to 10%. With this in mind, the recommended forecast transformation would have a significant impact on the forecast accuracy overall and this will have a positive impact on several other aspects. Following an increased forecast accuracy, the employees' trust of the forecasts would increase and the amount of manual work would be reduced. For example, the Operational Purchasers would be able to use the forecasts as a basis for purchases without requiring manual changes to a greater extent than today. Another impact of improved forecast accuracy is that it will help ensure that the right amount of products are in stock at the right time, which in turn increases the service level to customers, reduces unnecessary rejections and decreases the amount of tied-up capital in the warehouses. An important aspect to acknowledge when implementing the recommendation above is to continuously evaluate the performance of the chosen methods and make adjustments if needed.

6.1.2 Demand Planning

The second main recommendation to KåKå is closely connected to the purpose of this thesis. In order to develop an improved demand planning process at KåKå, it is necessary to begin by identifying what needs to be planned. Since planning in S&OP, and therefore also demand planning, is normally performed on a product group level it is recommended that KåKå performs a product grouping process in line with the one performed in Section 5.4.1. By performing the demand planning product grouping process, which is done through an ABC-XYZ analysis, KåKå can create product groups that are based on important characteristics and thereby facilitate product management. Furthermore, the product grouping process also allows KåKå to identify the most critical products that should receive the most focus and resources. To perform the ABC-XYZ analysis, the authors recommend that the characteristics utilized should be product shelf life and sales value with the limitations presented in Section5.4.1. By identifying and focusing on products with a short shelf life and that account for a large share of the total yearly sales value, KåKå can ensure that focus during demand planning meetings is aimed in the right direction. By focusing on the critical product groups the meetings can become more efficient and lead to more decisions being made. These product groups are also recommended to be utilized throughout the entire S&OP process since they will help facilitate discussions and decision making during all process steps.

Another main recommendation connected to demand planning regards the first step that Olhager (2019) presented in the demand planning phase, which is reviewing the product portfolio. The authors recommend that KåKå should design and implement a continuous process for reviewing their product assortment as this is not performed to any extent as of today. The lack of such a process has caused problems such as an unnecessarily large product assortment and too many products being forecasted incorrectly. Since no product review exists in the demand planning phase today, it is recommended to initiate the process by performing an extensive product review in order to identify if products are redundant and if any products need to be phased-in or moved in their life cycle. The authors further recommend that the review process should include, at least, the Assortment Manager, Sales Manager and Supply and Demand Manager. Other participants that are identified as necessary can be included by KåKå. It is also recommended that roles and responsibilities are clarified for both the review process and the activities that must be performed after the review. Once the initial review has been performed, it is recommended that the review should occur at least once every half a year to begin with in order to ensure that a well-structured product assortment is created. Once the products are reviewed and the assortment is made manageable, the review can come to occur on a yearly basis to ensure that the product assortment is kept up to date regarding market knowledge and internal changes. As discussed in Section 5.4.2, trend products need a more frequent review process. It is therefore recommended that this review process should occur once every six weeks. Since the historical period used when calculating trends is set to 12 weeks, updating the trend analysis for the assortment every six weeks ensures that the historical and new trend period will be taken into account simultaneously. Performing a more frequent product review process in this manner will ensure that the trends are followed accurately and more trustworthy forecasts can be obtained. By implementing and performing the recommended product review processes, the second step of the demand planning phase, which is to update the product forecasts, can be performed more efficiently and with more accurate information regarding product introductions, trends, phase outs etc. By having access to more accurate product information, KåKå's forecast accuracy can be improved. This recommendation also enables KåKå to acquire better product knowledge and can enable more informed decision making regarding which products to keep on stock.

The third and final recommendation regarding demand planning is connected to the product review process. As identified in the forecast analysis performed in Section 5.3, 1336 products in Lomma and 1292 in Örebro should not be subject to forecasting due to their low weekly demand and high demand variation. The recommendation regarding these products is that KåKå should perform an extensive review and evaluation in order to decide upon the following questions:

1. Should these products be forecasted at all?
2. Should these products be kept in stock, but on a rather small scale?
3. Should these products be procurement goods that are not kept in stock at all?

By answering these questions, KåKå could improve in multiple areas. One possible improvement this recommendation can lead to is an increased forecast accuracy which could improve by removing products that should not be forecasted and therefore result in high forecast errors. Another improvement can be accomplished by deciding if such products should be kept on stock since this can help ensure that KåKå has the right products in stock and can therefore decrease unnecessary levels of tied-up capital. The authors therefore recommend that these products need an extensive product review that is performed in parallel with the one previously recommended.

6.2 Additional recommendations

An additional recommendation to the two presented above is connected to the remaining key issues that were identified in Section 5. Firstly, the authors recommend that KåKå needs to undergo an extensive restructuring of their current S&OP process as the current process is not adequate compared to theory. Therefore, it is recommended that the restructuring should include the designing and implementation of four S&OP steps in line with those presented by Olhager (2019). The first step of this recommendation is to implement the recommendations above regarding forecasting and demand planning, as these are the first activities to be performed in the S&OP process and composes the base for all following activities. As previously recommended, the Demand Planner, Sales Manager and Assortment Manager should participant in the first step, demand planning. Thereafter, the output from this step needs to be reviewed and adjusted according to constraints, and it is therefore recommended to conduct a meeting together with a Strategic Purchaser and the Warehouse Manager. The third step recommended to implement by the authors is a pre-meeting where all participants in the previous two steps together with the Supply and Demand Manager should participate. During these meetings it is recommended to focus on and discuss the supply- and demand plans for the critical products obtained from the demand planning product grouping process with the aim to come to a consensus. Finally, an executive meeting is recommended to be held with all of the previously mentioned S&OP participants as well as top management. The purpose of this meeting should be to discuss and decide upon unsolved issues and finalize the supply- and demand plans. The authors further recommend that these meetings and activities should be performed on a monthly basis in order to ensure that the processes are performed correctly without allowing to much time to pass. By implementing the recommended S&OP process, KåKå should be able to obtain the benefits of an sufficient S&OP process as theory describes.

To succeed with the implementation of the restructured S&OP process, KåKå must perform actions with the aim to deconstruct functional silos to be able to improve the information sharing and collaboration within the organization. To begin the transition to a more collaborative organizational culture, it will be of great importance that the top management is highly engaged in the transition as well as communicating and modelling the desired behaviour. Apart from top managements involvement, the understanding and knowledge of the purpose and implication of S&OP must be spread among the employees. This is recommended to be conducted through educational training within the S&OP area to create a common understanding of why KåKå is implementing the structured process and what benefits they can obtain from it. Furthermore, the educational training can also help break functional barriers and create a common understanding of the roles and responsibilities required to create a sufficient process. Lastly, the collaborative culture must be encouraged continuously, which can be done by creating incentives for collaboration and awarding collaborative behaviour. By combining these recommendations, information sharing and collaborative behavior can become the norm in the organization and help increase the success of the S&OP process.

The final additional recommendation regarding KåKå's S&OP process is in regards to the current time horizon that is utilized. From the findings in the empirical study and analysis of this thesis, the authors have identified that the current time horizon is not adequate in comparison to the theoretical recommended range and it is therefore recommended that KåKå performs necessary actions to extend the planning horizon. By implementing all of the above mentioned recommendations, KåKå should be able to create and implement a more sufficient S&OP process, which should also enable them to lift their currently short-term view and extend it to a longer horizon. Initially, the authors recommend KåKå to extend their time horizon to six months which allows them to consider their products with their longest supply-demand lead times as well as to identify and adapt to market changes a lot faster than today. However, since KåKå also offers products that are subject to seasonality, this time horizon may need to be extended in the future once KåKå can manage product planning on this time horizon. In the future, the planning horizon needs to include the planning for seasonal products and since KåKå's products mostly have yearly seasonality, a time horizon of approximately one year is to be recommended once six months has been implemented and is well-managed. By doing so, KåKå can include all necessary impacting factors in a time frame that considers all of their products in the assortment. Exact measures that can be taken to extend the time horizon have not been identified in theory and will therefore be discussed in Section 7.4. When extending the planning horizon, it is also necessary to evaluate if the item level for forecasting should be changed to a more aggregated level as suggested in Table 5.

6.3 Summary of the recommendations

As described above, multiple recommendations have been identified for KåKå within the main areas: forecasting and demand planning. Furthermore, additional S&OP recommendations were also identified and presented above. All of the identified and tailored recommendations are summarized and presented in Table 21 below.

Table 21: Summary of the recommendations for the identified problem areas

		Recommendations	
		What?	How?
Problem area	Forecast Method	Group products based on demand models	Evaluate each product's demand variability, trend and seasonality
		Apply forecast method to each product group	Choose the method resulting in lowest forecast error
	Product Management	Group products based on shelf life and sales value	Perform an ABC-XYZ analysis and divide into categories
		Create a manageable product assortment and keep the groups updated	Implement a product review process
	Information sharing	Establish a collaborative organizational culture	Top management leads by example
		Improve employees theoretical knowledge on S&OP	Provide training and education
	S&OP process design	Restructure the S&OP process	Implement the four theoretical steps
		Work more proactively	Extend the planning horizon

7 Conclusion

This chapter will present the concluding remarks of this thesis. In the first part, the purpose and the research questions of this thesis will be reviewed and answered. This is followed by a discussion of the limitations and generalizability of the thesis and lastly, some suggestions of future research will be presented.

7.1 Reviewing the purpose and research questions

The purpose of this thesis was *to improve the demand planning phase of KåKå's S&OP process to create better conditions for more efficient operations.* To reach this purpose, appropriate research methodology was chosen and followed by a profound theoretical review on the subject concerned. The next step was an empirical study of the current situation at KåKå and thereafter an in-depth analysis based on both qualitative and quantitative data was performed to fulfill the purpose. Lastly, some final recommendations to KåKå were presented to enable the fulfillment of the formulated purpose of the thesis. All of these parts have resulted in several tools and suggested solutions that KåKå can apply to improve their demand planning phase of the S&OP process. Furthermore, some suggestions of how KåKå can improve the S&OP process in general have been provided. However, the implementation of the suggested solutions has to be performed by KåKå themselves in accordance with the authors' recommendations to completely achieve the purpose. In addition to the purpose of the thesis, three different research questions have set the focus throughout this study and a final review of these will be presented in the following sections.

7.1.1 Research Question 1

The first research question of this thesis was about mapping the current situation at KåKå and this was necessary to analyze to be able to identify problem areas as well as gaps between KåKå's practice and theory, which was needed to fulfill the purpose. The research question is presented below, followed by the answer obtained throughout the thesis.

RQ1: How is the current demand planning process at KåKå designed and how does it perform?

As of today, KåKå has no clear and pronounced demand planning process but they perform activities that are defined as demand planning activities in theory. Most of the activities are performed by the Demand Planner at KåKå, whose main task is to manually adjust the statistical forecasts. The gathering of necessary data for this task is mostly conducted through the different information systems as well as internal Excel-files. Prior to the forecasting, the update of the product portfolio is an activity that should be conducted, according to theory. At KåKå, the forecasts are generated automatically in IBP on a daily basis while the update of the product portfolio occurs less often since this does not change on a daily basis. The update of the product portfolio follows a rather structured process for the phase in of new products, while the phase out process is more unstructured. Another aspect of demand planning is the information regarding market knowledge, which is currently obtained through specific files and temporary meetings where the Demand Planner receives necessary information that is used to adjust the forecasts accordingly. However, the number of customer changes that are actually reported is limited. All activities and discussions involved in the demand planning process are conducted on a product level and no product grouping is utilized. A more thorough description of KåKå's current demand planning process is presented in Section 4.5 in the empirical study.

The performance of KåKå's current demand planning process can be partly evaluated from the accuracy of the final forecasts. As of today, the forecast accuracy is poor and KåKå is far from reaching their target of 80% forecast accuracy. The low forecast accuracy is further displayed by the fact that the employees do not trust the forecasts. Two other aspects indicating that the current demand planning process is performing poorly are that the employees perceive the product assortment to be too large and that the phase out of products is essentially non-existent. Furthermore, the information sharing across departments, for instance in terms of customer changes, is inadequate. To summarize, there are several aspects indicating that KåKå's current demand planning process does not align with theory and does not perform as well as it could.

7.1.2 Research Question 2

Once the mapping of KåKå's current situation was complete, the thesis proceeded to perform an analysis in order to answer the remaining research questions. The second research question is presented below together with the answer to the question.

RQ2: How can bakery products be categorized, based on characteristics, to simplify the forecasting and demand planning process?

During the analysis of product groups it was found useful to obtain two separate groups for forecasting and demand planning as the purpose of these groups are of different nature. The purpose of forecasting product groups is to be able to allocate different forecast methods to the groups, while product groups in demand planning and S&OP are necessary to facilitate the decision making and prioritization of resources. For forecasting, bakery products can be categorized by evaluating each product's demand model in terms of demand variability, trend and seasonality. Demand variability can be assessed by calculating the CoV which is presented by D' Alessandro & Baveja (2000) in theory, while trend can be found by applying a Linear regression method such as the LSM used in this thesis. When identifying trends, it is important to evaluate if a trend is significant to know if it should be considered in the forecast model, which can be done by using Wald's test presented by Sundell (2012). A suggested way of evaluating the seasonality in an assortment is by utilizing employees expertise and knowledge in the area. Furthermore, the product grouping for demand planning can be conducted by using an ABC-XYZ analysis. The analysis should be based on two important product characteristics identified by the company and should fulfill the purpose of performing the analysis. Thereafter, category boundaries must be defined which can be done in collaboration with the company due to their large insight in the dimensions or by using theoretical rules, such as the Pareto-principle. Finally, it is possible to identify critical demand planning categories from the ABC-XYZ analysis. The critical categories may contain many products and can therefore be divided further into chosen product groups to help facilitate decision making by providing information on a higher level, i.e. a product group level.

7.1.3 Research Question 3

As mentioned above, the forecast product grouping process and the demand planning product grouping process were performed separately due to different purposes of the grouping. The forecast groups were based on demand models, for which appropriate forecast methods were identified. This relates to the third and final research question of this thesis, which is presented and answered below.

RQ3: How can forecast methods be selected to fit different demand patterns?

Forecasting methods can be selected by testing different types of methods for the same time series and applying the one resulting in the highest forecast accuracy when comparing to actual demand. In this thesis, it was found that one of the simple forecast method that can be applied for each demand model performed best in most measures. For bakery products with a constant demand model, the forecast method Single exponential smoothing, with a smoothing parameter value of 0,1, was found to be the method that should be selected to achieve the highest forecast accuracy on a monthly horizon. For trend products, Simple linear regression was found to be the most appropriate, while Seasonal linear regression was identified as the best method for seasonal products. This is one example of how forecast methods can be selected but the result of which method that performs best might differ from one assortment to another. However, one important aspect to keep in mind when selecting forecast methods is the risk of over-fitting when selecting complex methods. To avoid this and achieve more robust forecasts, the methods of the simpler type that are suitable for each type of demand model should be selected.

7.2 Limitations

Throughout this thesis, multiple limitations have been identified, where the first limitation is the time constraint. This thesis has been conducted during 20 weeks and did therefore not have enough time to perform a more comprehensive study than the one performed in this thesis. Due to the time limit, it was neither possible to perform an implementation of the recommendations provided for the case company. If more time had been available, performing an implementation of the recommendations and evaluating the performance would have provided the authors with more accurate results. Performing and evaluating the success rate of an implementation of the recommendations would allow the authors to conduct another iteration of the thesis and perform adjustments accordingly. A longer time frame would also have been beneficial in regards to demand planning and S&OP since it would allow the authors to follow the implementation of the new processes and evaluate the change in performance compared to KåKå's current situation.

Strongly connected to the first limitation is the second limitation of not conducting more extensive interviews due to the time constraint. During this thesis, multiple interviews were performed in form of both individual interviews and groups interviews. In total, individual interviews were held with six different employees and one focus group was held with all of the previously interviewed employees. If more time was available, several more interviews would have been beneficial to conduct. By interviewing more employees, an even more unbiased perspective could have been retrieved regarding the problems and more relevant perspectives could have been obtained. Other interviews would have been advantageous in order to interview multiple employees from the same functional department in order to analyze if there is a common perspective of the problems among a function. It would also have been valuable to interview other employees such as the Assortment Manager, since they work closely with the product assortment and have valuable insight in processes such product phase ins and phase outs, and the Warehouse Manager, since they work closely with the main operational activity at KåKå and are identified to obtain an important role in the recommended demand planning and S&OP processes.

The third identified limitation of this thesis is the fact that forecasts were only calculated and compared to actual sales in one single four-week period, which is also related to the time limit of the thesis. If more time would have been available, it would be possible to perform forecast calculations in multiple periods and thus obtain the forecast accuracy of several different months. By performing more forecast calculations, the reliability of the obtained result would increase as the impact of potential random factors occurring in the reviewed period would be reduced. Furthermore, with more time available, the analysis could have been extended to review the forecast accuracy on several different time horizons. This would make it possible to examine which forecast method performs best in the short- and long term, in addition to the monthly time horizon.

The final limitation identified is the limited amount of literature found on the topic of this thesis. In general, there is a lot of literature and studies regarding forecasting, demand planning and S&OP but there was very limited literature on these topics with regard to non-manufacturing companies and the bakery industry. Since the case company is a non-manufacturing company within the bakery industry, additional literature on this specific area would have enabled a more comprehensive literature review as well as more company-specific recommended improvements.

7.3 Thesis Generalizability

In this thesis, a single case study has been conducted and due to this, a large part of the forecasting analysis has been performed in the company's own system. It is also important to acknowledge that the sample used as a basis for analysis and the final recommendations is company specific data. Due to this, the generalizability of this thesis is limited. The lack of generalizability aligns with Höst et al. (2006) who stated that it is not common that case studies are possible to generalize. However, if a company with similar conditions to the case company were to apply the methods of this study, it is possible that the findings would be similar to those of this study or that it could be possible to imitate this thesis' findings (Höst et al. 2006). It is therefore important to acknowledge that applying the results from this case study to a different case company cannot assure that the same results and improvements will be obtained. Instead, the actions must be adapted to the specific situation, as Meredith (1998) stated.

7.4 Future research

During the execution of this thesis, multiple gaps were identified in the available theory that could be of interest for future research. The first gap identified was theory on S&OP in non-manufacturing companies. As of today, most research conducted on the topic of S&OP is focused on manufacturing companies where production is the main operation within the organization. However, as discussed throughout this thesis, this process is also of interest in non-manufacturing companies. With this in mind, it would be highly interesting with research examining more thoroughly how S&OP should be conducted in non-manufacturing companies and how this might differ to the available theory on S&OP in manufacturing companies. This guidance would be helpful for all companies whose value-adding activities are not related to production. Another identified gap in theory that is a potential subject for future research is how to extend the time horizon in an organization working with a short horizon. It would be of interest to investigate what approach should be applied when extending the time horizon to ensure that nothing gets overlooked. This includes the activities and processes required to manage this change as efficiently as possible and achieve the benefits of working with more foresight. Furthermore, the time aspect of how quickly you can and should increase the time horizon is an interesting subject for all organizations interested in shifting their focus to work more proactively.

7.5 Contribution to theory

This thesis' contribution to theory is the understanding of how forecasting, demand planning and to some extent S&OP can be handled appropriately in a non-manufacturing company within the bakery industry. The main contribution concerns the approach of how products can be grouped, for both forecasting and demand planning, to facilitate the work in a company within the bakery industry. There is available theory on general approaches for product grouping but limited information regarding how to practically implement these approaches. For example, theory presents groupings based on each product's demand model as appropriate in forecasting, but there is little information of how to, step by step, conduct this grouping process. In this thesis, a thorough approach of how the demand model of products can be identified is presented. This approach includes an evaluation of the demand variability, which was conducted by applying the matrix presented by D' Alessandro & Baveja (2000). In contrast to theory, this thesis present an additional example of where the boundaries between low and high demand variability can end up. This analysis was based on a significantly larger product assortment than other examples presented in theory, which brings an additional aspect to the subject. Furthermore, this study contributes with a presentation of specific forecast methods, including potential parameter values, that are found to be the most appropriate for four different demand models in the bakery industry.

7.6 Contribution to practice

As mentioned in Section 7.3, the fact that this thesis has been conducted as a single case study limits the generalizability of the results. The use of a single case study required several company-specific parameters and values to be used throughout the thesis. These parameters and values were developed to fit KåKå and might therefore differ in other companies. However, it is believed that the developed approach can be relevant for other companies experiencing similar problems. The processes for product categorization and forecast method identification follow a general approach. This implies that if the company-specific parameters and values are adapted, relevant results from applying the general approach in practice should be possible to obtain for other companies. Except for the suggested length of the time horizon, the recommendations regarding S&OP also follow theory that can be applied to other companies. Therefore, the findings from this thesis contribute to practice in addition to the contribution to KåKå and theory.

References

Axsäter, S. (2006). *Inventory control* (2nd ed.). International series in operations research & management science. Springer.

Bai, B. (2022). Acquiring supply chain agility through information technology capability: the role of demand forecasting in retail industry. *Kybernetes*. https://doi.org/10.1108/K-09-2021-0853

Calisir, F., Cevikcan, E., & Camgoz Akdag, H. (2019). *Industrial Engineering in the Big Data Era: Selected Papers from the Global Joint Conference on Industrial Engineering and Its Application Areas* (1st ed.). Springer International Publishing. https://doi.org/10.1007/978-3-030-03317-0

Chapman, S. N. (2006). *The fundamentals of production planning and control*. Pearson/Prentice Hall.

Chief Operations Officer (2023). *S&OP and Demand Planning*. Interview 21st Mar.

D' Alessandro, A. J. & Baveja, A. (2000). Divide and Conquer: Rohm and Haas' Response to a Changing Specialty Chemicals Market. *Interfaces*, 30(6), 1–16. https://doi.org/10.1287/inte.30.6.1.11627

Das, N., Robinson, D., & Mankala, V. (2020). *Measuring forecast model accuracy to optimize your business objectives with Amazon Forecast*. https://aws.amazon.com/blogs/machine-learning/measuring-forecast-model-accuracy-to-optimize-your-business-objectives-with-amazon-forecast/. Accessed 2023-05-15

Demand Planner (2023). *S&OP and Demand Planning*. Interview 23rd Jan.

Flores, B. E. & Whybark, C. D. (1986). Multiple Criteria ABC Analysis. *International Journal of Operations & Production Management*, 6(3), 38–46. https://doi.org/10.1108/eb054765

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

Huber, J., Gossmann, A., & Stuckenschmidt, H. (2017). Cluster-based hierarchical demand forecasting for perishable goods. *Expert Systems with Applications*, 76, 140–151. https://doi.org/10.1016/j.eswa.2017.01.022

Huber, J. & Stuckenschmidt, H. (2020). Daily retail demand forecasting using machine learning with emphasis on calendric special days. *International Journal of Forecasting*, 36(4), 1420–1438. https://doi.org/10.1016/j.ijforecast.2020.02.005

Hyndman, R. J. & Athanasopoulos, G. (2018). *Forecasting: principles and practice* (2nd ed.). Otexts, online, open-access textbook. https://otexts.com/fpp2/. Accessed 2023-03-02

Höst, M., Regnell, B., & Runeson, P. (2006). *Att genomföra examensarbete.* Studentlitteratur.

Jacobs, F. R., Berry, W., Whybark, D. C., & Vollman, T. (2011). *Manufacturing planning and control for supply chain management* (6th ed.). McGraw-Hill/Irwin.

Kampen, T. J., Akkerman, R., & van Donk, D. P. (2012). SKU classification: a literature review and conceptual framework. *International Journal of Operations & Production Management*, 32(7), 850–876. https://doi.org/10.1108/01443571211250112

Kotronoulas, G., Miguel, S., Dowling, M., Fernández-Ortega, P., Colomer-Lahiguera, S., Bağçivan, G., Pape, E., Drury, A., Semple, C., Dieperink, K. B., & Papadopoulou, C. (2023). An Overview of the Fundamentals of Data Management, Analysis, and Interpretation in Quantitative Research. *Seminars in Oncology Nursing*, 39(2), 151398. https://doi.org/10.1016/j.soncn.2023.151398

Kotzab, H., Seuring, S., Müller, M., & Reiner, G. (2005). *Research methodologies in supply chain management.* Physica-Verlag.

KåKå (n.d.). *Supplier of ingredients and accessories to bakeries, patisseries and the bakery industry.* https://www.kaka.se/en-us/about-us. Accessed 2023-02-13

Laguna, M., Laguna Coral, M., & Marklund, J. (2013). *Business process modeling, simulation, and design* (2nd ed.). CRC Press/Taylor & Francis Group.

Lapide, L. (2004). Sales and Operations Planning Part I: The Process. *The Journal of Business Forecasting Methods & Systems*, 23, 17.

Lapide, L. (2007). Sales and Operations Planning (S&OP) Mindsets. *The Journal of Business Forecasting, Spring*, 21–31.

Lapide, L. (2014). Sales and Operations Planning Process Pillars. *Supply Chain Management Review*, 18, 2.

Ling, R. C. & Goddard, W. E. (1988). *Orchestrating success: improve control of the business with sales & operations planning.* Wiley.

Makridakis, S. G., Wheelwright, S. C., & Hyndman, R. J. (1998). *Forecasting: methods and applications* (3rd ed.). John Wiley & Sons.

Meredith, J. (1998). Building operations management theory through case and field research. *Journal of Operations Management*, 16(4), 441–454.

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: a methods sourcebook* (3rd ed.). SAGE Publications, Inc.

Moon, M. A., Mentzer, J. T., Smith, C. D., & Garver, M. S. (1998). Seven keys to better forecasting. *Business Horizons*, 41(5), 44–52. https://doi.org/10.1016/S0007-6813(98)90077-5

Olhager, J. (2013). Evolution of operations planning and control: from production to supply chains. *International Journal of Production Research*, 51(23-24), 6836–6843. https://doi.org/10.1080/00207543.2012.761363

Olhager, J. (2019). *Supply Chain Management - Produktion och logistik i försörjningskedjor*. Studentlitteratur AB.

Olhager, J. (2023a). *Exjobb - Introkurs 2023 - Del 2 - Forskningsmetodik*. Presentation 16th Jan.

Olhager, J. (2023b). *Exjobb - Introkurs 2023 - Del 3 - Forskningsmetodik*. Presentation 17th Jan.

Olhager, J., Rudberg, M., & Wikner, J. (2001). Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics*, 69(2), 215–225. https://doi.org/10.1016/S0925-5273(99)00098-5

Oliva, R. & Watson, N. (2011). Cross-functional alignment in supply chain planning: A case study of sales and operations planning. *Journal of Operations Management*, 29(5), 434–448. https://doi.org/10.1016/j.jom.2010.11.012

Orkla (n.d.). *About us*. https://www.orkla.com/about-us/. Accessed 2023-02-13

Pedroso, C. B., da Silva, A. L., & Tate, W. L. (2016). Sales and Operations Planning (S&OP): Insights from a multi-case study of Brazilian Organizations. *International Journal of Production Economics*, 182, 213–229. https://doi.org/10.1016/j.ijpe.2016.08.035

Project Consultant (2023). *S&OP and Demand Planning (Reoccurring)*. Interview 16th Jan.

Riva, M. (2021). *Understanding Forecast Accuracy: MAPE, WAPE, WMAPE*. https://www.baeldung.com/cs/mape-vs-wape-vs-wmape. Accessed 2023-04-11

Rosengren, K. E. & Arvidson, P. (2002). *Sociologisk metodik* (5th ed.). Liber.

Sales Manager (2023). *S&OP and Demand Planning*. Interview 22nd Mar.

SAP (n.d.). *Forecasting Algorithms*. https://help.sap.com/docs/SAP_INTEGRATED_BUSINESS_PLANNING/feae3cea3cc549aaa9d9de7d363a83e6/e1751a550f343e6ae10000000a44176d.html. Accessed 2023-05-15

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2007). *Research methods for business students* (4th ed.). Financial Times/Prentice Hall.

Scholz-Reiter, B., Heger, J., Meinecke, C., & Bergmann, J. (2012). Integration of demand forecasts in ABC-XYZ analysis: practical investigation at an industrial company. *International Journal of Productivity and Performance Management*, 61(4), 445–451. https://doi.org/10.1108/17410401211212689

Seber, G. A. F. & Lee, A. J. (2003). *Linear Regression Analysis* (1 ed.). Wiley Series in Probability and Statistics. Wiley. https://doi.org/10.1002/9780471722199

Spens, K. M. & Kovács, G. (2006). A content analysis of research approaches in logistics research. *International Journal of Physical Distribution & Logistics Management*, 36(5), 374–390. https://doi.org/10.1108/09600030610676259

Stojanović, M. & Regodić, D. (2017). The Significance of the Integrated Multicriteria ABC-XYZ Method for the Inventory Management Process. *Acta Polytechnica Hungarica*, 14(5), 29–48. https://doi.org/10.12700/APH.14.5.2017.5.3

Stone, F. (2004). Deconstructing silos and supporting collaboration. *Employment Relations Today*, 31(1), 11–18. https://doi.org/10.1002/ert.20001

Sundell, K. (2012). *Att göra effektutvärderingar*. Gothia. OCLC: 830379362.

Supervisor at KåKå (2023a). *Introduction to KåKå SC*. Presentation 16th Jan.

Supervisor at KåKå (2023b). *Kassationer 2022*. E-mail 10th Feb.

Supervisor at KåKå (2023c). *This is OFI*. Presentation 16th Jan.

Supply and Demand Manger (2023). *S&OP and Demand Planning*. Interview 23rd Jan.

Swamidass, P. M., editor (2000). *ABC ANALYSIS OR ABC CLASSIFICATION in Encyclopedia of Production and Manufacturing Management*. Springer US. https://doi.org/10.1007/1-4020-0612-8_4

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

Team Leader Internal Sales (2023). *S&OP and Demand Planning*. Interview 22nd Mar.

Ulrich, M., Jahnke, H., Langrock, R., Pesch, R., & Senge, R. (2022). Classification-based model selection in retail demand forecasting. *International Journal of Forecasting*, 38(1), 209–223. https://doi.org/10.1016/j.ijforecast.2021.05.010

Veiga, C. P. d., Veiga, C. R. P. d., Puchalski, W., Coelho, L. d. S., & Tortato, U. (2016). Demand forecasting based on natural computing approaches applied to the foodstuff retail segment. *Journal of Retailing and Consumer Services*, 31, 174–181. https://doi.org/10.1016/j.jretconser.2016.03.008

Voss, C., Tsikriktsis, N., & Frohlich, M. (2002). Case research in operations management. *International Journal of Operations & Production Management*, 22(2), 195–219. https://doi.org/10.1108/01443570210414329

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

Wallace, T. F. & Stahl, R. A. (2008). *Sales & operations planning: the how-to handbook* (3rd ed.). T.F. Wallace & Co.

Wallace, T. F. & Stahl, R. A. (2014). *Sales & operations planning: the executive's guide*. T.F. Wallace & Co.

Yin, R. K. (2018). *Case study research and applications: design and methods* (6th ed.). SAGE.

Świerczek, A. (2019). The Effects of Demand Planning on the Negative Consequences of Operational Risk in Supply Chains. *Logforum*, 15(3), 315–329. https://doi.org/10.17270/J.LOG.2019.340

Appendix A - Interview Guide

Introduction

- What is your role in the company and what are your daily tasks?

S&OP

- Do you know what S&OP is?
- How is the S&OP process at KåKå configured in general?
- Is there a clear S&OP team who leads and guides the process?
- How are the meetings structured?
- What is the input to these meetings?
- What is the output of these meetings?
  - How is the output used at KåKå?
- Which meetings do you attend?
- What is your role in the S&OP process?
- Is there a need for you to prepare in advance of the meetings?
- Which time horizon is the process focused on?
- Are there any specific systems or tools used to facilitate the process?
- Are the meetings discussion meetings or decision meetings?
- Is the information discussed during the S&OP meetings shared with non-participants?
  - If so, how?
  - Is outside input encouraged?
- Has the S&OP resulted in any improvements?
- If so, what kind of improvements and to what extent have they affected KåKå's overall performance?
- Do you think that S&OP can help KåKå to perform better?
  - If so, in what way(s)?
- Are any KPIs used to assess the S&OP performance?
- What are the objectives with S&OP?
- Do you have any specific bottlenecks that affect the S&OP process?

Demand planning

- How is the demand planning process at KåKå configured in general?
- Who leads and guides the demand planning process?
- How often do the meetings/activities occur?
- How are the meetings/activities structured?
- What is the input to these meetings/activities?
- What is the output of the meetings or the demand planning activities?
  - How is the output used at KåKå? E.g. For budgeting? sales? purchasing? S&OP?
- Is there a need for preparation in advance?
- Are people prepared?
- Which time horizon is the process focused on?
- Are there any specific systems or tools used to facilitate the process?
- Who attends the meetings or takes part in the demand planning activities?
- How do you work with phase-ins of new products and phase-outs of old products?
- How do you work with market knowledge in regards to demand planning?
  - E.g. campaigns, price changes, current situation with competitors and economy in general?
- Are any KPIs used to assess the performance?
- Do you think that demand planning can help KåKå to perform better?
- What are the objectives of demand planning?

Forecasting

- How are forecasting activities at KåKå configured in general?
  - What does the process look like?
  - What system is used?
  - Which forecasting methods are used?
    - How are the parameters set?
  - How often is forecasting conducted?
  - Are the forecasts generated automatically?

- Which time horizon is used?

- Who leads and guides the process?
- Who is involved?
- For how long have you been working with forecasting?
- What is the input to the process?
- What is the output from the process?
  - How is the output used? E.g. For budgeting? sales? purchasing?
- How do you forecast phase ins and phase outs?
- How do you adjust forecasts according to campaigns, price changes, current situation with competitors and economy in general?
- Are any KPIs used to assess the performance?
  - How do you measure forecast accuracy?
- How accurate do you think the forecasting is today?
- Do you think that forecasting can help KåKå to perform better?
- What are the forecasting objectives?

Product categorization

- How many products are included in KåKå's assortment today?
- How often are new products introduced to the market?
- How do you categorize the products?
  - How are the categories created?
  - For what purpose?

Appendix B - Focus Group Guide

Purpose

The purpose of the focus group is to present and discuss product groups for demand planning. An additional aim of the focus group is to discuss seasonal and trend items in order to perform the necessary product categorization.

Discussion points

In order to conduct an efficient focus group, relevant discussion points were developed and utilized as a guideline for the meeting. The discussion points used are presented below.

Forecast groups

The first step in creating forecast groups is to distinguish which products are currently forecasted and stocked but have very low and irregular demand, and thus possibly should not be forecasted at all. It is also necessary to analyze demand variation and average demand, and would like to discuss the following:

- What is a reasonable limit to distinguish low average weekly demand from high average weekly demand?

Trends also have an impact on which forecasting method is suitable to apply to a product and will therefore affect the product groups. Connected to trends, we would therefore like to discuss the following:

- How large must an increase or decrease be to be considered as a trend?
- Do KåKå's employees have knowledge of products that are currently considered to be subject to either positive or negative trends?

Seasonality also affects the forecast grouping process. The file provided by KåKå was sent to the participating prior to the focus group in order to discuss the content:

- Does the file contain any products that are not considered to be subject to seasonality?
- Are there any products currently missing from the file that should be considered as seasonal products?

Demand Planning and S&OP roups

To perform the demand planning grouping process, products must be grouped based on their shelf life and sales value. The following must therefore be discussed:

- What is currently considered to be a short, medium and long shelf life?
- What is currently considered to be a low, medium and high sales value?

Appendix C - Chi-squared Distribution Table

The Chi-squared distribution table found in Table C1 below was utilized in Wald's significance tests performed in Section 5.3.1.

Table C1: Chi-Square Distribution Table from Laguna et al. (2013)

n	$c^2_{0.995}$	$c^2_{0.99}$	$c^2_{0.975}$	$c^2_{0.95}$	$c^2_{0.90}$
1	7.88	6.63	5.02	3.84	2.71
2	10.60	9.21	7.38	5.99	4.61
3	12.84	11.34	9.35	7.81	6.25
4	14.86	13.28	11.14	9.49	7.78
5	16.75	15.09	12.83	11.07	9.24
6	18.55	16.81	14.45	12.59	10.64
7	20.28	18.48	16.01	14.07	12.02
8	21.95	20.09	17.53	15.51	13.36
9	23.59	21.67	19.02	16.92	14.68
10	25.19	23.21	20.48	18.31	15.99
11	26.76	24.73	21.92	19.68	17.28
12	28.30	26.22	23.34	21.03	18.55
13	29.82	27.69	24.74	22.36	19.81
14	31.32	29.14	26.12	23.68	21.06
15	32.80	30.58	27.49	25.00	22.31
16	34.27	32.00	28.85	26.30	23.54
17	35.72	33.41	30.19	27.59	24.77
18	37.16	34.81	31.53	28.87	25.99
19	38.58	36.19	32.85	30.14	27.20
20	40.00	37.57	34.17	31.41	28.41
21	41.40	38.93	35.48	32.67	29.62
22	42.80	40.29	36.78	33.92	30.81
23	44.18	41.64	38.08	35.17	32.01
24	45.56	42.98	39.36	36.42	33.20
25	46.93	44.31	40.65	37.65	34.38
26	48.29	45.64	41.92	38.89	35.56
27	49.65	46.96	43.19	40.11	36.74
28	50.99	48.28	44.46	41.34	37.92
29	52.34	49.59	45.72	42.56	39.09
30	53.67	50.89	46.98	43.77	40.26
40	66.77	63.69	59.34	55.76	51.81
50	79.49	76.15	71.42	67.50	63.17
60	91.95	88.38	83.30	79.08	74.40
70	104.21	100.43	95.02	90.53	85.53
80	116.32	112.33	106.63	101.88	96.58
90	128.30	124.12	118.14	113.15	107.57
100	140.17	135.81	129.56	124.34	118.50