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Development of a Forecasting Model for Original Equipment Manufacturer (OEM) Components

A Design Science Study at Tetra Pak

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Abstract

Title: Development of a Forecasting Model for Original Equipment Manufacturer (OEM) Components. A Design Science Study at Tetra Pak.

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Background: The importance of accurate demand forecast is set due to the drivers of short lead-times, just-in-time-deliveries and cost effectiveness linked to demand. Two common methods for forecasting can be used in the context of manufacturing firms, qualitative and quantitative forecasting model. Inaccurate forecasts can result in disruptions of activities throughout the phase of planning, ordering and replenishing of products with high costs. Collaborative forecasting can improve overall supply chain performance, thus increasing overall responsiveness and product availability assurance while achieving optimized inventory. Forecasting plays therefore a vital role for an enterprise to achieve success on the market.

Purpose: Develop a forecasting model for Tetra Pak's OEM Components department based on historical sales data, installation project size and components category.

Research Questions: (1) *How should the solution be designed in order to fulfill the key properties?* (2*) What factors except from historical data and installation projects should be included?* (3) *How do we establish a more secure business environment with the help of the forecasting model?*

Methodology: The paper is based on a design science study contributing to theory and practice through purposeful design and evaluation. The study also aims to develop theoretical knowledge contributing to solving an improvement problem. Initial As-Is analysis was conducted in order to analyze the performance of the current forecasting model and to receive valuable information from stakeholders at Tetra Pak and Supplier X. The model was initially built using the information regarding the project opportunities pipeline. This first attempt did not deliver the required results but provided valuable analysis and data for the company. Finally, a model based the well-known forecasting method of exponential smoothing, was applied to develop the new forecasting model for Tetra Pak.

Conclusion: The new model represents a standardized and reliable method to forecast OEM Components. Improvements have been established when comparing the old model to the new one. Key properties such as Easy-To-Use, Scalable, Reliable and Flexible are represented in the new model. The model is not taking project opportunity pipelines into consideration, but instead is based on time series data. The study has also illustrated the importance of combining qualitative adjustment to the quantitative data obtained from the model such that external factors can be taken into consideration.

Keywords: Forecasting Model, OEM, Opportunity Pipeline, Forecasting Accuracy

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Stakeholders from both Tetra Pak and Supplier X have been included and collaborated with throughout the whole study. The authors would like to give their sincere gratitude to all the involved stakeholders for their essential cooperation. We also wish to gratitude our supervisors Nicole Uvenbeck and Jim Ahlgren Kvist from Tetra Pak for their continues support throughout the entire study. It has been a privilege to be part of such an amazing team and company who commits to making food safe and available everywhere by protecting what's good.

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Lund, May 2022

Faruk Kodzaga & Giacomo Daniele

Table of abbreviations

- OEM – Original Equipment Manufacturer
- MAD – Mean Absolute Deviation
- MSE – Mean Square Error
- MFE – Mean Forecast Error
- MAPE – Mean Absolute Percentage Error
- ROW – Rest Of the World
- DMAIC – Define Measure Analyze Improve Control

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1. Introduction

This section presents the background of the study with the aim of capturing the reader's attention and explaining the topic. The section also contains a detailed problem description. The first section ends with presenting the purpose of the study, several research questions, delimitations, and the general outline of the study.

1.1 Background

A forecast can be described as an estimate of a future level of some variable within various branches of science (Bozarth & Handfield 2013). The variable used is often demand, hence the name demand forecasting. The importance of accurate demand forecast is set due to the drivers of short lead-times, just-in-time-deliveries and cost effectiveness linked to demand. This makes therefore forecasts with high accuracy an integral part of a firm's general competitiveness since it has a direct impact on the profitability of the firm (Kaya & Demirel 2015).

Bozarth & Handfield (2013) describes that in the context of manufacturing firms, two common methods for forecasting can be used, qualitative and quantitative forecasting model. Quantitative models rely on historical data and have been popular since the 1970's due to their good performance (Laamanen 2015). The importance of having high accuracy in demand forecasts in enterprises has been increasing over the past decades. Herbig, Milewicz and Golden (1994) state however that the time horizon of the forecasts should be taken into consideration. The greater the time horizon of the forecasts, the greater the chance that established patterns and relationships will change, and thereby invalidating the forecast. According to Kaya and Demirel (2015), quantitative models are still popular nowadays and can be combined with a qualitative forecasting model to increase the overall performance. Qualitative forecasting models, also known as judgmental forecasting, rely on practitioners' expertise (Laamanen 2015). The challenge with using qualitative forecasting is its anticipation to indicate the change in demand clearly, hence the recommendation that it should be used in combination with a quantitative forecasting model (Bozarth & Handfield 2013).

Inaccurate forecasts can result in disruptions of activities throughout the phase of planning, ordering and replenishing of products with high costs (McCarthy & Golicic 2002). Forecasts do however allow managers within an enterprise to minimize the risk of uncertainty with changing demand (Kaya & Demirel 2015). A case study made from McCarthy and Golicic (2002) on enterprises engaging in interfirm collaborative forecasting resulted in improved supply chain performance. The achievements obtained from collaborative forecasting was increased responsiveness and product availability assurance while achieving optimized inventory and associated costs at the same time (McCarthy & Golicic 2002). The result from the study indicates that forecasting in general plays a vital role for an enterprise to achieve success on the market.

1.2 Company Description

Tetra Pak is part of the Tetra Laval Group, a private group started in Sweden which comprehends also DeLaval and Sidel. Tetra Laval group has his headquarters in Switzerland. AB Tetra Pak was founded in 1951 by Ruben Rausing in Lund, Sweden. It can now be considered as a world leading company in food processing and packaging solutions. Tetra Pak is globally developed and accounts for 89 sales offices, 31 market companies, 55 production plants, 10 product development centers. The company has over 25,000 employees globally and reaches customers every day in 160 countries. Tetra Pak offers processing, packaging, and service solutions. Processing solutions focus on machine equipment for cheese, dairy, ice cream, beverages, and prepared food. Packaging comprehends a wide range of carton packaging solutions. Service solutions at Tetra Pak focus on preventing and fixing breakdowns, and on protecting investments. Finally, the company offers end-to-end solutions to the customers with the aim of integrating processing, packaging, automation, and technical services (Tetra Pak, 2022). In this thesis we will focus on forecasting the demand of components from the processing and end-to-end solutions.

The vision of Tetra Pak consists in making food safe and available everywhere with the promise of "protects what's good" (Tetra Pak, 2022). This means for the company to protect food, people, and future. These are the three pillars of the sustainability story at Tetra Pak. Protecting food is translated in safety, quality, and availability of food through packaging and processing solutions. Protecting people can be seen as safeguarding and supporting employees, communities, and people who are influenced by Tetra Pak. Protect the future means working to achieve a full life cycle approach contributing to a circular economy and to develop innovative and smart solutions by understanding the customers' needs.

Original Equipment Manufacturer (OEM) Components is the department at Tetra Pak which will be the focus of this study. The mission of the OEM Components department is to "continuously improve the OEM Components portfolio ensuring competitiveness and supporting business strategies whilst complying to Tetra Pak standards and legal demands" (Nicole Uvenbeck, OEM Components Manager, January 2022). OEM Components can be defined as Global Standard Portfolio of commercial components from selected supplier for which the department offers global product management and support (Nicole Uvenbeck, OEM Components Manager, January 2022). The aim of the OEM Components department is to continuously improve the portfolio while at the same time ensure quality and compliance. The product groups in the OEM Components portfolio are valves, pumps, instrument and sensors, electrical and automation, mechanical drives and motion, chemicals, pneumatics, tank components, and other mechanical components. This design science study will initially focus on valves, pumps and tank equipment, which can be seen in Figure 1.

Figure 1. Valves, Pumps and Tank equipment

1.3 Problem Formulation

Tetra Pak's Original Equipment Manufacturer (OEM) Components department consists of product managers who are responsible for the OEM Components portfolio throughout its full life cycle. The product managers responsibility is to decide what to bring into their respective portfolio. The OEM Components are used in installation projects all around the world. The OEM Components team's current procedure for forecasting and planning the quantity that will be sourced from their suppliers is very basic. A non-scientific model is used today, which results either in over or under purchasing of components. When Tetra Pak is purchasing more than the forecast this can cause challenges for the suppliers to manufacture and deliver the components in time for the installation's projects. Purchasing less than what it was stated in the forecast can instead results in stock being built at the supplier. At the moment, the forecasting done by the OEM Components department is missing a clear and structured method.

Supplier X is a global company, and it is the main supplier of Tetra Pak for what it concerns the components purchased. There are currently four channels that drives the demand of components for Tetra Pak from the main Supplier X, see Figure 2.

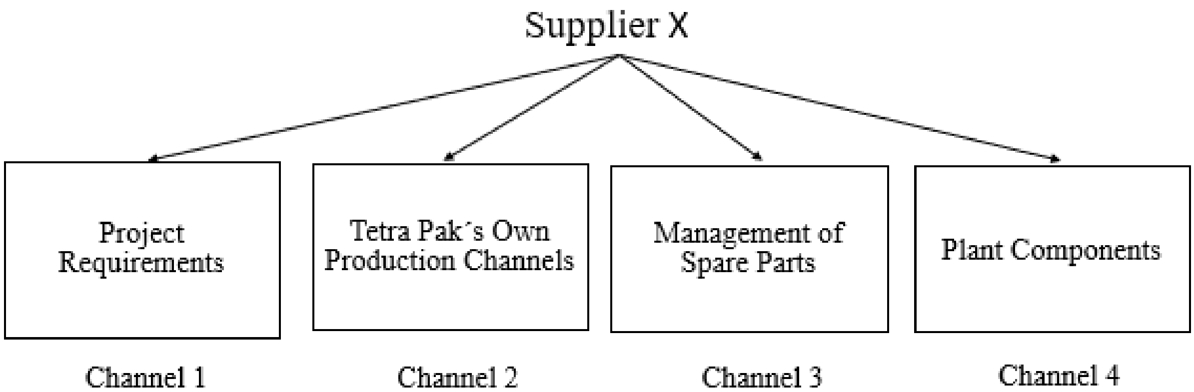

Figure 2. Tetra Pak's four demand channels

Projects requirements is characterized by existing as well as new customers reaching out to Tetra Pak in order to realize various projects. Tetra Pak can provide equipment for building new production plants of a specific product category or to start a project in an existing plant. Components bought from the Supplier X are in particular common in bigger projects, thus resulting in components being bought in bigger quantities. Fluctuating demand peaks occur due to variation of large projects in place over a specific time frame, which creates an overall challenge for establishing an accurate forecast. The challenge of establishing an accurate forecast increases therefore with their current non-scientific forecasting model.

The own production channel is characterized by Tetra Pak purchasing components from Supplier X that are assembled on Tetra Pak's own designed equipment of machines. An example can be a pressure transmitter which is integrated and becomes a part of a homogenizer. Management of spare parts is the third channel that drives the demand. Depending on the number of current projects as well as the number of sold machines, the demand for spare parts increases, thus increasing the need for accurate forecasts. Accurate forecasts need to be in place to reduce e.g., shortages and long lead-times for delivering spare parts to Tetra Pak's customers via Supplier X.

Plant components sales is the fourth channel. The channel is characterized by Tetra Pak having an after-market organization responsible for reaching out to customers to sell additional components such as pumps, valves, and tank equipment from their Supplier X. This channel can be described as stand-alone components in order to differentiate them from components utilized within the projects. Understanding the four channels and their characteristics is a challenge. The complexity varies depending on the channel, thus increases the importance to thoroughly understand them in order to establish as accurate forecasts as possible.

Since the company is missing a precise forecasting model, the objective with this thesis is to build a new forecasting model based on historical sales data, installation project size and components category. A project size can change from a very small to a very big deal, this influences the number of components that each project will need. Another factor influencing the number of components needed for each project is the components category such as pumps, valves, and tank equipment. Furthermore, each project can have a different process category focusing for example on processing cheese, dairy, beverage, or ice cream. It is important in order to build an accurate forecasting model to find pattern of consumption of the different components in correlation to the project size and the project category.

The forecasting model will be established on one of the key suppliers of Tetra Pak, Supplier X. Establishing a reliable forecast model will contribute to a more secure business environment for both the OEM Components team as well for the supplier. Following key properties has been established by the Tetra Pak's OEM Components department which the new forecasting model has to be based upon.

- **Flexibility:** The model should be applicable for shorter periods (2-3 months) as well as for longer time periods (1 year)

- **Scalability:** The model needs to be applicable no matter if sales are high or low.

- **Easy to use:** The model should be easy to understand and use without having a solid background knowledge within forecasting, logistics and other relevant areas.

- **Reliability:** The model should be based on logics and facts and give a trustable output that both Tetra Pak and their suppliers can rely on.

1.4 Purpose of the Study and Research Question

Purpose of the study is to develop a forecasting model for Tetra Pak's OEM Components department based on historical sales data, installation project size and components category. The forecasting model will in the future be used for establishing a more secure business environment for both their OEM Components department team as well for their suppliers. The thesis will answer and follow the following research questions:

1. *How should the solution be designed in order to fulfill the key properties?*

2. *What factors except from historical data and installation projects should be included?*

3. *How do we establish a more secure business environment with the help of the forecasting model?*

1.5 Delimitations

One of the requirements from Tetra Pak when creating the quantitative forecasting framework was that the model needed to be easy to understand and use for people without a solid background knowledge within forecasting. The model also needed to be scalable and flexible, meaning that the model should be applicable for both shorter (2-3 months) and longer periods (1 year) no matter if sales are high or low. Lastly, the model needs to be reliable in the sense that it provides a trustable output that both Tetra Pak and its suppliers can rely upon.

Tetra Pak has 9 product groups within the department of OEM Components. This study is limited to only create a forecasting model for their pumps, valves and tank equipment components. These components are related to a specific supplier which therefore also is a delimitation in this study. The design science study will primarily focus on the supply from Supplier X developed from the projects and the components sold as stand alone.

1.6 Thesis Outline

This section contains a comprehensive description of the thesis outline. Table 1 contains a summary of the content in each chapter.

Table 1. Overview of the thesis outline with a short description of each chapter.

1. Introduction	*This section presents the background of the study with the aim of capturing the reader's attention and explaining the subject. The section also contains a detailed problem description. The first section ends with presenting the purpose of the study, several research questions, delimitations and the general outline of the study.*
2. Material Collection	*This section presents the course of action as well as the method used to reach the purpose of the study and its related research questions. The section also contains a discussion regarding the research quality of the study.*
3. Theoretical Framework	*In this chapter, the theoretical framework is presented of this design science study that will be used as a base for the analysis and discussion throughout the study. This chapter initially focuses on qualitative and quantitative forecasting models. Different methods for measuring forecasting accuracy are presented. Theory regarding sales funnels, building the forecasting model and also the DMAIC approach are also presented in this section.*
4. Empirical Findings	*In this chapter, empirical findings of the current forecasting procedure will be presented. In addition, the forecasting procedure will be explained from the perspective of both Tetra Pak and Supplier X. Furthermore, the current demand has been studied in order to identify possible trends or patterns and to segment and differentiate the components.*
5. Development of The Model	*In this chapter, the approach for developing the model will be presented. In addition, the chapter contains the first attempt in building the forecast model based on project pipelines. This first attempt will lead to the consideration that it is not possible to find a strong correlation between the project opportunity pipeline and to the total demand forecast. The chapter will follow by presenting the Exponential Smoothing method utilized to determine the*

	forecast for the next quarter and the consideration for the other components. Lastly, the chapter will end with comparing the performance of the new forecast model with Tetra Pak's current forecast model.
6. Discussion	*The following chapter contains a discussion and reflection regarding both the new and the old forecasting model for Tetra Pak. The chapter begins with presenting the key findings of this design science study. The key findings section covers a discussion regarding the current forecasting model used at Tetra Pak. In addition, key findings are discussed regarding the new developed forecasting model, including a summary of its strengths and weaknesses. Furthermore, a discussion regarding the attempt of building a model based on the project opportunities pipeline is presented. The DMAIC approach applied to the development of the model is also discussed. The chapter is finalized by reviewing the research questions of this study.*
7. Conclusion	*This chapter contains a conclusion regarding the design science study. Areas of future research and recommendations for Tetra Pak are presented in this chapter.*

2. Methodology

This section presents the course of action as well as the method used to reach the purpose of the study and its related research questions. The section also contains a discussion regarding the research quality of the study and its ethical positions.

This paper is based on a design science study contributing to theory and practice through purposeful design and evaluation. Design science, also known as exploratory research, aims to develop theoretical knowledge contributing to solve improvement problems (Denyer, Tranfield & Van Aken 2008). “Artificial phenomena” must be created by the researcher in order to evaluate it in the later stages of the process. In addition, the artificial phenomena contribute to create, collect and analyze the right data required (Van Aken 2004).

Design science research is adopted to develop design propositions following the CIMO-logic approach. The logic of prescription for CIMO approach is that if you want to achieve outcome O in context C, then intervention type I should be used. Intervention type I contribute to invoke the generative mechanism M applied to deliver outcome O. Figure 3 illustrates the CIMO approach in detail (Denver, Tranfield & Van Aken 2008).

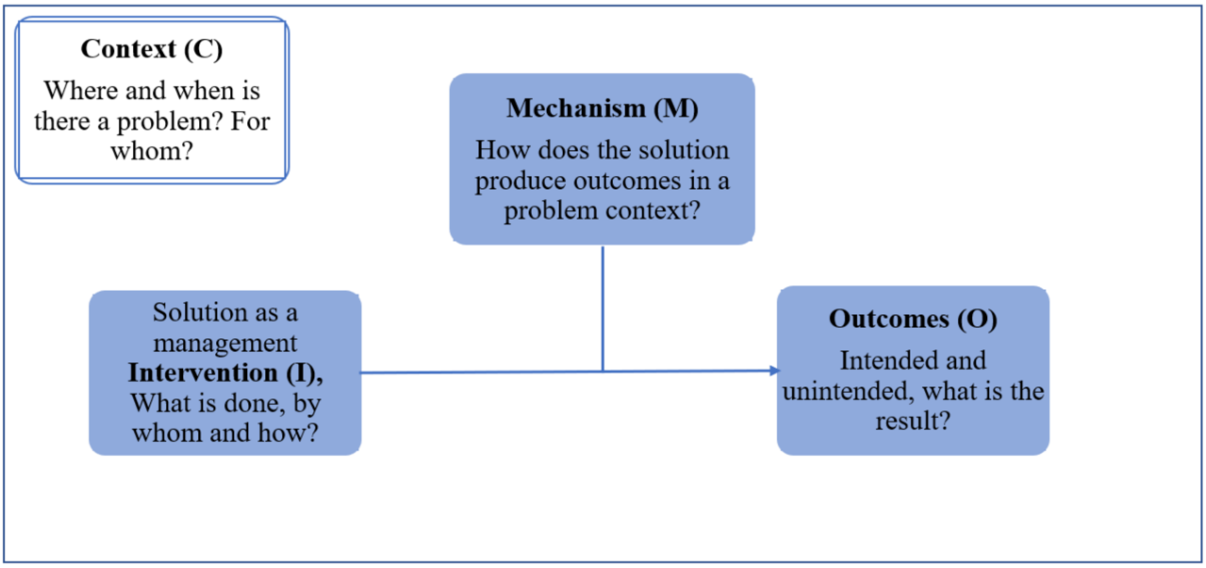

Figure 3. CIMO Approach

The proposition of the design science can be seen as an input to design the specific solution, hence its contribution to this study. The strength of design science study is its explicit focus on improving practice. The challenge lies however in the ability to lead to novel theoretical insights (Holmström & Ketokivi 2009). As mentioned earlier in this section, the study can be characterized as exploratory research. The research will be based on direct observations, interviews and historical data suitable in a design science study. In addition, the study will allow us to develop a customized model for Tetra Pak while also contributing to theory building regarding forecasting and OEM Components.

Figure 4 illustrates the general outline of the study. The first step in the general outline of the project is to have the thesis scope defined by the OEM Components department at Tetra Pak. The following step is to conduct a literature review on demand forecasting which will provide a theoretical framework that can be used as a base for the model building. Interviews to gather qualitative data from managers at Tetra Pak and Supplier X will be conducted simultaneously along with the literature review process. The forecasting model will thereafter be analyzed and tested hence resulting in further adjustments to be made. The general outline of the study will end with recommendations to the department of OEM Components at Tetra Pak containing analysis and further discussion on the finalized forecasting models for the firm.

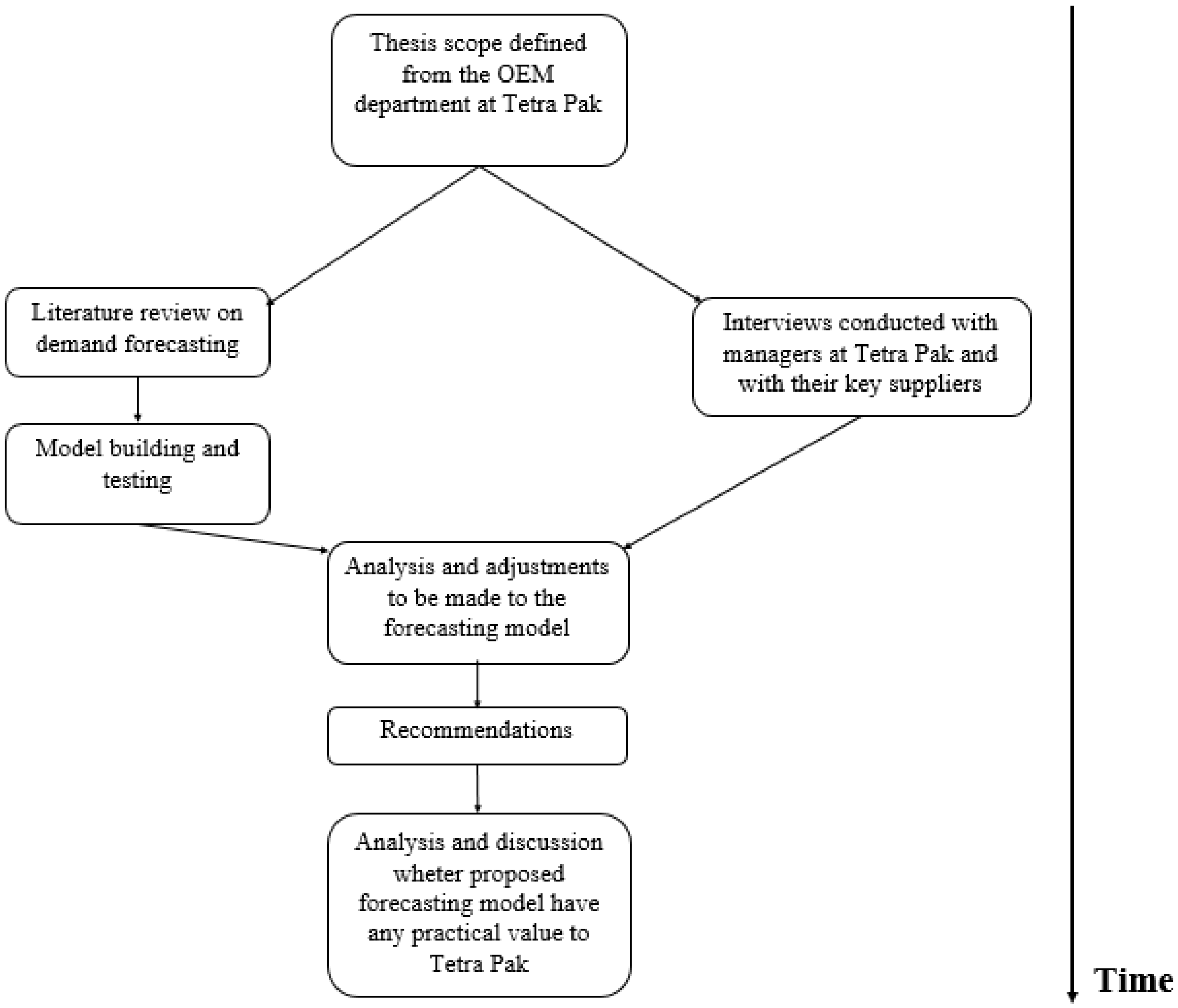

Figure 4. General outline of the work for this study

2.1 Material Collection

The material collection followed a structured literature review. The unit of analysis is the forecasting process within the OEM Components department at Tetra Pak. The literature review was mainly based on collecting information regarding how to create a forecasting model and the types of forecasting methods available. Furthermore, to determine the accuracy of the forecasting model, measures of errors of forecasting were investigated. Both textbooks and research papers were reviewed during the process of material collection. Textbooks were used to obtain a broader knowledge regarding demand forecasting and the different types of forecasting methods as well as errors appropriate for developing a forecasting model. Research papers were used with the aim of finding relevant case studies that could be used to understand the required steps and variables to be taken into consideration when developing the model. Elsevier, Emerald and Web of Science, known for their broad databases of scientific journals were used for finding appropriate research papers. Keywords such as 'Demand forecasts', 'Forecasting methods' and 'Demand forecast and models' were used to find appropriate research papers. Additional papers were thereafter identified with the 'Snowballing' approach based on using the reference list of selected papers to identity additional papers.

2.2 Data Collection

Both qualitative and quantitative data were collected in this study. Qualitative data are characterized as data retained through interviews, while quantitative data are characterized as data readily quantified and generated into numerical form (Stuart, McCutcheon, Handfield, McLachlin & Samson 2002).

2.2.1 Qualitative Data

Qualitative data were collected through interviews among various employees from both Tetra Pak and Supplier X. The aim of the interviews with Tetra Pak was to understand how the current forecasting model is used and to receive valuable information regarding the performance of the model. Furthermore, it was necessary to understand where data on historical sales data, project opportunities pipelines and product categories can be extracted from. Lastly, the interviews with Tetra Pak made possible to gain a broader understanding of the portfolio of pumps, valves, and tank equipment. The aim of conducting interviews with Supplier X was to understand their business environment, to understand how they work with the quarterly received forecast and to see from their point of view what are the advantages and disadvantages of the current model. Five semi-structured interviews were held in total throughout the study and Table 2 provides the main information concerning the conducted interviews.

Table 2. Descriptive information of the semi-structured interviews

Interview	Company	Areas of responsibility	Aim with the interview
1	Tetra Pak	Manager Project Management and Co-ordination Strategy Capabilities	• Gain broader understanding of the project opportunity pipelines at Tetra Pak. • Receive insights into Power BI and BO software.
2	Tetra Pak	Procurement Manager Paperboard	• Gather information from the respondent who tried to build a forecasting model earlier. Understand what went wrong at that time.

3	Tetra Pak	Senior Supplier Manager	• Understand the project opportunities, what pre-announcement means and how it is connected to a forecast. • Understand how the current forecasting model is used between Tetra Pak and Supplier X from their point of view
4	Tetra Pak	Technical Product Manager for pumps	• Receive a broader understanding of the portfolio of pumps.
5	Supplier X	Product Manager for pumps & Sales and Operations Planning Manager	• Gather general information regarding Supplier X as a company • Understand how they manage the forecast which they receive from Tetra Pak quarterly. See from their point of view what their thoughts are regarding the current process of forecasting

As mentioned previously, information were gathered through semi-structured interviews which generally lasted between 30-60 minutes. Every interview was carried out following a pre-established document containing topics and questions that needed to be covered for each interview. Every interview protocol was sent out in advance to the respective respondent in order for them to be well prepared in advance. Appendix 1 presents the structure of the interviews. The outline of the interview protocol starts with a general introduction of the respondents and their area of responsibilities within the company. The protocol focuses thereafter on targeted questions for the respondent which contribute to increase the overall knowledge regarding Tetra Pak´s current forecasting model. The protocol is finalized with an open question where the respondents have the opportunity to share any information which they believe can be of value for the study. Due to the Covid-19 restrictions at the time of the qualitative data collection, every interview was held online. The data from different interview were collected by recording the audio and taking notes.

2.2.2 Quantitative Data

Quantitative data were obtained in order to conduct an as-is analysis of the current situation for the forecasting. The data regard the historical forecast and the actual demand of 2020 and 2021. By analyzing these data, it was possible to evaluate the forecasting errors for the current model which will be possible to compare in the future with a new model. Furthermore, the demand for the OEM Components has been analyzed using the historical data in order to identify possible patterns and trends. The quantitative data regarding the forecast were obtained through the different demand forecasts sent out in 2020 and 2021. Furthermore, it was possible to obtain quantitative data on the demand and the spend analysis from SAP Power BO software. These data were summarized in a file can Master File data containing all the orders from Tetra Pak for Supplier X in 2020 and 2021.

2.3 Model Building and Testing

The model was initially built using the information regarding the project opportunities pipeline. In this case various data were used from the Master File in order to connect the components with the projects size and category and to segment the demand in the different channels. This first attempt did not deliver the required results but provided valuable analysis and data for the company. Thereafter another model was built using a different forecasting technique that will be showed later in this study. In this case there was the opportunity to apply this model to forecast the second quarter of 2022. After testing the model, it was necessary to modify and improve it in order to provide a final solution.

2.4 Research Quality

The quality of the research design can be judged trough certain logical tests. These tests can be applied to evaluate the quality of the research design (Stuart et al. 2002) (Malhotra & Grover 1998). The following four tests will be used in order to evaluate the research quality of the study:

- Construct validity
- Internal validity
- External validity
- Reliability

2.4.1 Construct Validity

Whether the design science is designed to be exploratory or explanatory, the study must demonstrate that its means of measuring are valid (Malhotra & Grover 1998). Construct validity can be seen as the primary concern for this design science study and is used to determine how well the measurements reflect upon the phenomena that is analyzed. A technique called *triangulation* can be applied to ensure construct validity. The technique of triangulation implies that multiple sources of evidence must be applied to every important element within the study (Van Aken 2004). The technique of triangulation has been valuable for this study during the data collection phase. The construct validity has been strengthened in the qualitative data collection phase by conducting several interviews. The qualitative data collection included interviews with different stakeholders within both Tetra Pak and Supplier X in order to receive their point of view regarding the performance of the current forecasting model. The construct validity of the data collection phase has been strengthened by using both Power BI and SAP BusinessObjects (BO) software provided by Tetra Pak.

2.4.2 Internal Validity

Internal validity for design science studies can be accomplished once the researchers have recorded evidence on why and how observed patterns occur in a specific way (Van Aken 2004). Malhotra and Grover (1998) state that without internal validity, a result cannot demonstrate a causal link between two variables and provide a reliable conclusion. In order to strengthen the internal validity in this design science study, different potential conclusions have been analyzed. Focus has also been on carefully choosing and analyzing the right data to create the forecasting model.

2.4.3 External Validity

External validity refers to the domain to which study's findings are applicable to similar studies than the active one (Stuart et al. 2002). The same authors state that external validity indicates that replicating the procedure of the study should result in the same or similar results. Well-known theory used in this study has been based on both master thesis papers focusing on demand forecasting and on textbooks written by famous researchers. A study replicated and illustrating similar results indicates that the implied theory within the study can be supported. This design science study will contribute to further research done towards the area of OEM Components and the establishment of demand forecast models. Studies conducted within similar research area will be able to use the following study as support to their external validity.

2.4.4 Reliability

Reliability refers to the capability of another party to repeat the study and obtain the same results (Stuart et al. 2002). The aim with reliability is to reduce the errors and biases in the study (Voss, Tsikriktsis & Frohlich 2002). In order to increase the reliability of this study, both a general outline of this design science study and also the general research process steps for a design science study has been presented. Reliability has also been strengthened throughout the study by conducing several interviews with employees with different position within the company of Tetra Pak, thus contributing to a broader perspective of insights. Some interviews for qualitative data gathering also included more than one respondent, which strengthens the overall reliability.

3. Theoretical Framework

In this chapter is presented the theoretical framework of this design science study that will be used as a base for the analysis and discussion throughout the design science study. This chapter initially focuses on qualitative and quantitative forecasting model in general, followed by the introduction of different measures that can be used to evaluate the accuracy of the forecast. Furthermore, more specific topics are discussed such as sales opportunities funnel, the procedure for building a forecasting model, and the DMAIC approach applied to forecasting.

Forecasting can be defined as "an estimate of the future level of some variable" (Bozarth & Handfield 2013, p.252). Different variables can be forecasted such as demand, supply, and price for example. As it will be explained further in this chapter, forecasts can be either qualitative, quantitative or a combination of the two. Two important aspects to be considered when developing a forecasting model are the trend and seasonality of the variable that is object of the forecast. According to Bozarth and Handfield (2013, p.258) we can define trends as long-term movements up or down in the level of a certain variable. Instead, seasonality is a repeated pattern of spikes or drops in the level of the studied variable, that can be identified in specific times of the year.

3.1 Qualitative Forecasting

Qualitative forecasting, also known as judgmental forecasting, refers to the use of human intuition or informed opinions to produce or adjust a forecast (Chatfield 2000, p.3). A study from Dalrymple (1987) on American companies, indicated that the majority of them used qualitative forecasting as the single most used forecasting method in the sample. A couple of decenniums later, qualitative forecasting is still being seen as the most used technique (Fildes, Goodwin, Lawrence & Nikolopoulos 2009). The simplicity of qualitative methods is one of the reasons why it is still popular among different companies (Bozarth & Handfield 2013, p.256).

Bozarth and Handfield (2013, p.256) state that qualitative forecasting is used in situations where the access to quantitative data is not available. There are several techniques that can be used. Bozarth and Handfield (2013, p.257) mention four common types of forecasting methods. Figure 5 illustrates the different methods of qualitative forecasting.

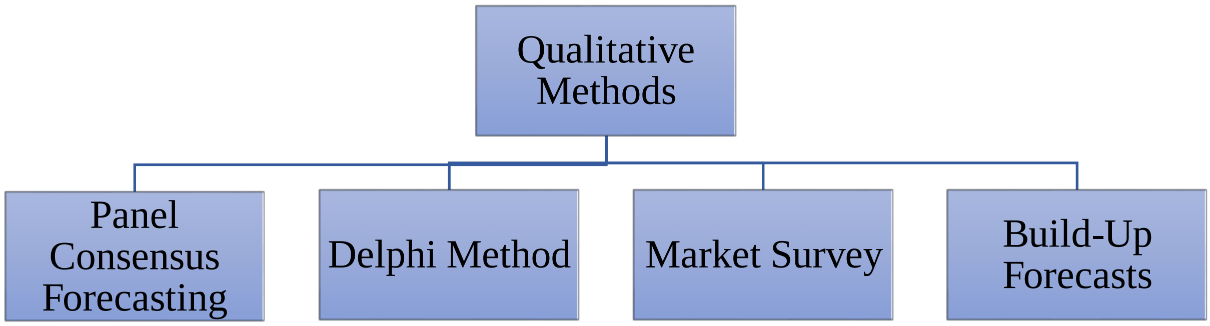

Figure 5. Common qualitative forecasting methods

Depending on the specific situation, resources and the competences within a firm, different methods can be utilized. According to Bozarth and Handfield (2013, p.257), the panel consensus forecasting refers to the usage of experts to establish a commonly agreed forecast. Delphi method is similar to the previous one. However, the same authors state that the method puts emphasis on experts individually developing forecasts which in a later stage are shared among the whole group. The purpose of the group meetings is to share knowledge regarding each other's forecasts in order to adjust them and in the end reach a common consensus (Olsen, Wolcott, Haines, Janke & McLaughlin 2021). Olsen et al. (2021) state however that these two methods are rather expensive due to the time requirements. However, if the procedure is followed correctly, then they tend to be quite accurate (Bozarth & Handfield 2013, p.256).

Market survey can be described as an approach that uses interviews and surveys to judge and assess demand (Bozarth & Handfield 2013, p.256). Market surveys can be applied in order to receive opinions regarding new product launches or even regarding current products on the market. Build-up forecast is characterized as the fourth qualitative forecasting method and one of the qualitative methods that will be used in this design science study study. The purpose with build-up forecast is to use individuals that are familiar to either a specific market segment or regarding a specific product category to create a forecast. The individual forecasts are then added up together in order to create an overall forecast (Bozarth & Handfield 2013, p.257).

Studies such as Fildes et al. (2009) and Laamanen (2015) indicate that qualitative forecasts tend to underperform in comparison to quantitative forecasting models due to bias. Laamanen (2015) defines the bias in forecasting as the "tendency to systematically overestimate or underestimate the forecasted variable". The question to ask is then: how do you ensure that you obtain optimal performance out of the qualitative forecast while minimizing the bias? First, it is important to ensure that the system forecast is performing well on its own. Once that is ensured, it is crucial that the people managing the forecast do understand how the baseline of it is produced (Laamanen 2015).

Qualitative forecasts are often combined with quantitative forecasts. Bozarth and Handfield (2013, p.257) state that combining these two methods reduces the overall time spent on analysis while it also contributes to understanding either a problem or a segment more in depth.

3.2 Quantitative Forecasting

Quantitative forecasting models are used when there are measurable and historical data that can be used to generate a forecast (Bozarth & Handfield 2013, p.255). Furthermore, a quantitative method for forecasting is appropriate when it is possible to identify a relationship between the variable of interest and other variables (Bozarth & Handfield 2013, p.255). There are various quantitative methods that can be divided into time series models, when a variable future level is seen as function of time, or causal models, when the variable is seen as function of something different from time (Bozarth & Handfield 2013, p.256). In this section three important quantitative forecasting methods will be described more in detailed, see Figure 6.

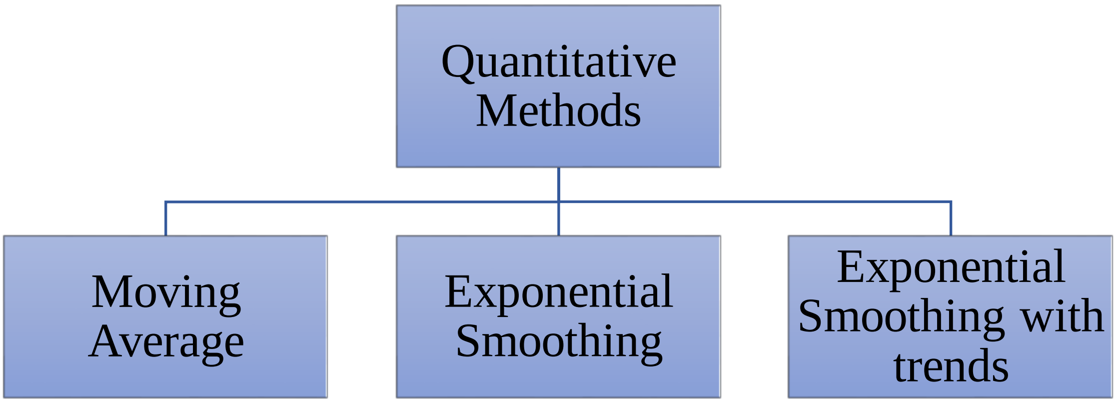

Figure 6. Common quantitative forecasting methods

3.2.1 Moving Average

The moving average model consists in forecasting the demand in a certain period t by using the average of the actual demand in previous periods. If we consider N time periods, then to forecast the demand in the next period t it is necessary to utilize the average actual demand from periods $t - 1 - N$ to $t - 1$ (Ching-Chin, Ieng, Ling-Ling & Ling-Chieh 2010). It is important to consider an appropriate number of periods N to base the forecast on. The higher the number of N periods considered is, the less responsive the model will be to recently observed actual demand (Ching-Chin et al. 2010). This type of forecast can be considered as a smoothing model, meaning that by basing the forecast on multiple values then it is less influenced by random fluctuations in the demand (Bozarth & Handfield 2013, p.259).

3.2.2 Exponential Smoothing

The exponential smoothing model is similar to the moving average, but the updating procedure is different. In this case the forecast for the next period is a weighted average of the actual demand of the current period and the forecast of the current period (Axsäter 2006, p.12). Bozarth and Handfield (2013, p.261) describe the exponential smoothing with the following notation:

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

where:

F_{t+1} = forecast for time period $t + 1$ (the new forecast)

F_t = forecast for time period t (the current forecast)

D_t = actual demand for time period t

α = smoothing constant ($0 \leq \alpha \leq 1$)

The value of the smoothing constant α determines the relative weight that is assigned to the actual demand and the forecasted demand of the current period (Bozarth & Handfield 2013, p.259). Choosing a high value of α means that the forecast is more responsive to the recent observations of the actual demand (Ching-Chin et al. 2010). The case limit would be $\alpha = 1$ resulting in the forecast of the next period being equal to the actual demand of the current period (Axsäter 2006, p.12). Instead, when the value of α is closer to zero then the forecast is more stable and a bigger focus is put on the past forecasts (Bozarth & Handfield 2013, p.262) and (Ching-Chin et al. 2010). In general, to determine an appropriate value of α we can follow the rule stated by Bozarth and Handfield (2013, p.262) "the greater the randomness in the time series data is, the lower α value should be".

3.2.3 Exponential Smoothing with Trends

Another model that can be useful for this design science study is the exponential smoothing with trends. This forecasting model can be used when there are systematic linear changes in the demand, also called trends (Axsäter 2006, p.17). The other models explained above in case of an upward or downward trend would lag behind the demand when forecasting it. In this case the idea is the same as the exponential smoothing, but with the addition of a trend adjustment factor (Bozarth & Handfield 2013, p.265) (Ching-Chin et al. 2010). The trend adjustment factor can be defined using the notation of Bozarth and Handfield (2013, p.265) as it follows:

$$T_{t+1} = \beta\,(F_{t+1} - F_t) + (1 - \beta)\,T_t$$

where:

T_{t+1} = trend factor for the next period

T_t = trend factor for the current period

F_{t+1} = forecast without the trend factor for the next period

F_t = forecast without the trend factor for the current period

β = smoothing constant for the trend adjustment factor

The trend factor for the next period is added to the unadjusted exponential smoothing forecast for the next period resulting in a forecasting model that keeps into consideration the trends (Bozarth & Handfield 2013, p.265) (Ching-Chin et al. 2010). For the exponential smoothing, higher values of α and β mean that the forecasting model will react faster to changes but this will also make the forecast more sensitive to deviations (Axsäter 2006, p.17).

3.3 Combining Qualitative and Quantitative Methods

As mentioned earlier, combining qualitative forecasts with quantitative methods is quite common today. Qualitative forecasts are the majority of the time used for adjusting an already existing quantitative forecast. These adjustments are often performed by either salespersons or managers due to their knowledge and information that can be used as an advantage for a firm to improve the forecast of future demand (Egnell & Hansson 2013).

One method commonly used in these circumstances is the procedure called *anchoring*. According to Egnell and Hansson (2013), *anchoring* can be an advantage when trying to capture information and management knowledge in order to adjust an already pre-existing quantitative forecasting model. The procedure of *anchoring* can be described as either adding or subtracting a percentage to the quantitative forecasting model depending on specific circumstance which has been evaluated by several key people. The percentage added or subtracted can be based on information that the quantitative model does not take into consideration. Taking notes and explaining every change and factor involved is therefore important in order to increase the validity of the final forecasting model (Egnell & Hansson 2013).

According to a study that Fildes et al. (2009), established on more than 60,000 quantitative forecasts indicated that 80 percent of them included a qualitative adjustment. The surprising result however was that three times out of 4, a more accurate forecast was established. This result highlights that the individual knowledge is important in order to improve a quantitative forecast by making final qualitative adjustments. The size of the qualitative adjustment applied to the existing forecasting model is a factor that has to be taken into consideration. In the same study developed by Fildes et al. (2009), the authors illustrate that large adjustments increase the overall accuracy while small adjustments can result in the opposite effect. The broad knowledge that a specific key person has can result in larger adjustments made to the quantitative model. People with less knowledge and experience tend to use the "gut-feeling" in order to make smaller adjustments which tend to result in lower overall forecast accuracy.

3.4 Measures of Forecasting Accuracy

Peter Drucker, former Austrian American consultant manager once said: "you can't manage what you can't measure" (Koutsandreas, Spiliotis, Petropoulos & Assimakopoulos 2021). What he meant was that you do not know whether you are successful or not unless you continuously measure it. By measuring the forecasting accuracy, the model can be ensured to be utilized correctly both within the organization and outside of the organization between other included stakeholders. Implementing forecasting accuracies in the forecast model enables support for both operations management, planning and decision making (Koutsandreas et al. 2021).

Each forecasting measure has its advantages and drawbacks. There are several challenges for selecting appropriate methods for measuring forecasting accuracy. According to Koutsandreas et al. (2021), different types of methods used may lead to different conclusions since each method displays its own properties. No matter which type of method of measurement that is used for determining the accuracy of the forecasts, it is a general prerequisite for supporting decision making between an organization and its stakeholders.

This chapter will therefore focus on defining several types of appropriate forecast measures that will be used throughout this study.

3.4.1 Mean Absolute Deviation

Mean Absolute deviation, also known as MAD, is commonly used for measuring the performance of the forecasting model. MAD tracks the average size of the errors, regardless of its direction (Bozarth & Handfield 2015, p.278). MAD can be defined using the notation of Bozarth and Handfield (2013, p.278) as it follows:

$$Mean\ Absolute\ Deviation\ (MAD) = \frac{\sum_{i=1}^{n}|FE_i|}{n}$$

Where:

n = number of observations

$\sum_{i=1}^{n} FE_i$ = sum of the forecast errors for periods 1 to n

3.4.2 Mean Squared Error

Mean squared error (MSE) eliminates the problem of positive errors outstanding negative errors by utilizing the square value of the forecasting error. This means that the MSE method always has a positive sign. Koutsandreas et al. (2021), state that the benefit with MSE is that large errors tend to be magnified, thus making easier to identify large deviations of errors within the forecast. The method is therefore recommended to be applied in situations where small forecast errors don’t cause too much of a problem, but large errors can be devastating. MSE can be defined using the notation of Koutsandreas et al. (2021) as it follows:

$$Mean\ Square\ Error\ (MSE) = \frac{\sum_{i=1}^{n} e_i^2}{n}$$

Where:

n = number of observations

e_i^2 = Forecast error for period i

3.4.3 Mean Forecast Error

Mean forecast error, also known as MFE measures the bias of a forecast model. The MFE measure can be also applied for determining if either a forecast is under or over performing (Bozarth & Handfield 2015, p.278). An unbiased forecast would have an MFE value of zero. A negative MFE value indicates that the model is over-forecasting while a positive MFE value indicates that the model is under-forecasting. It is important to examine the accumulation of errors over time since forecast error in one time does not provide much information. MFE can therefore be defined using the notation of Bozarth and Handfield (2013, p.278) as it follows:

$$Mean\ Forecast\ Error\ (MFE) = \frac{\sum_{i=1}^{n} FE_i}{n}$$

Where:

n = number of observations

$\sum_{i=1}^{n} FE_i$ = sum of the forecast errors for periods 1 to n

3.4.4 Mean Absolute Percent Error

Mean absolute percent error (MAPE) is similar to MAD since it considers the absolute value of the forecast error also. MAPE can be used for indicating the magnitude of the forecast errors. A problem with MAD is that the values depend on the magnitude of the variable forecasted. If the forecast is measured in high values of thousands or millions, then the MAD can be very large. To avoid this problem, MAPE can be used for evaluating how large the inaccuracy of the forecast was relative to its size of actual value (Koutsandreas et al. 2021). MAPE can be defined using the notation of Bozarth and Handfield (2013, p.278) as it follows:

$$Mean\ Absolute\ Percent\ Error\ (MAPE) = \frac{\sum_{i=1}^{n} 100\% \left|\frac{FE_i}{D_i}\right|}{n}$$

Where:

n = number of observations

$\sum_{i=1}^{n} FE_i$ = sum of the forecast errors for periods 1 to n

$D_i =$ Demand for time period i

3.4.5 Tracking Signal

Tracking signal can be defined as a method for indicating the performance of a forecasting model, which means that it either under-forecasts or over-forecasts (Bozarth & Handfield 2013, p.278). A well performing forecasting model has a tracking signal value between -4 and 4. Every value outside this previous mentioned range can be seen as a problem where usually the wrong fitting model has been used since the beginning. Tracking signal can be defined using the notation of Bozarth and Handfield (2013, p.278) as it follows:

$$Tracking\ Signal = \frac{\sum_{i=1}^{n} FE_i}{MAD}$$

Where:

n = number of observations

$\sum_{i=1}^{n} FE_i$ = sum of the forecast errors for periods 1 to n

3.5 Sales Funnels

According to Cova and Salle (2007) a project is defined as “a complex transaction concerning a package of products, services and works, designed specially to realize in a certain period of time a specific asset for a client”. The sales funnel or pipeline can be described as the process of acquiring new projects from customers through different steps or stages (Söhnchen & Albers 2010). Different authors describe various definitions of these steps, but in general the projects move through the pipeline from the initial contacts for a possible project to a final closed deal. According to Söhnchen and Albers (2010) the first stage consists in the “Qualification” in which possible prospects are identified and evaluated usually by salesperson. The “Approach” is the following step in which there is an initial contact between the buyer of the project and the company providing it. Next step is the “Product Presentation” by sales representatives with the aim of identify customers’ needs and present the benefits of the product offered. Söhnchen and Albers (2010) identify as the fourth step as the “Design of an Offer” in which an offer is formulated and submitted to the customer. The following stage consists of "Handling Objections" in which possible problems or resistance are addressed and possibly can be overcome. The last stage of the project acquisition is the "Closure" in which the deal is finalized and accepted by both parties.

It is particularly important in order to produce an accurate forecast to keep into consideration the projects opportunities contained in the pipeline. Every project can be associated with a certain stage in the pipeline and associated with a certain success probability. When a project is moving down in the pipeline the probability of being finalized increases and therefore should be included in the forecast for the next period (Söhnchen & Albers 2010). This concept is particularly relevant for Tetra Pak and an example on how to imagine the sales funnel is presented in Figure 7.

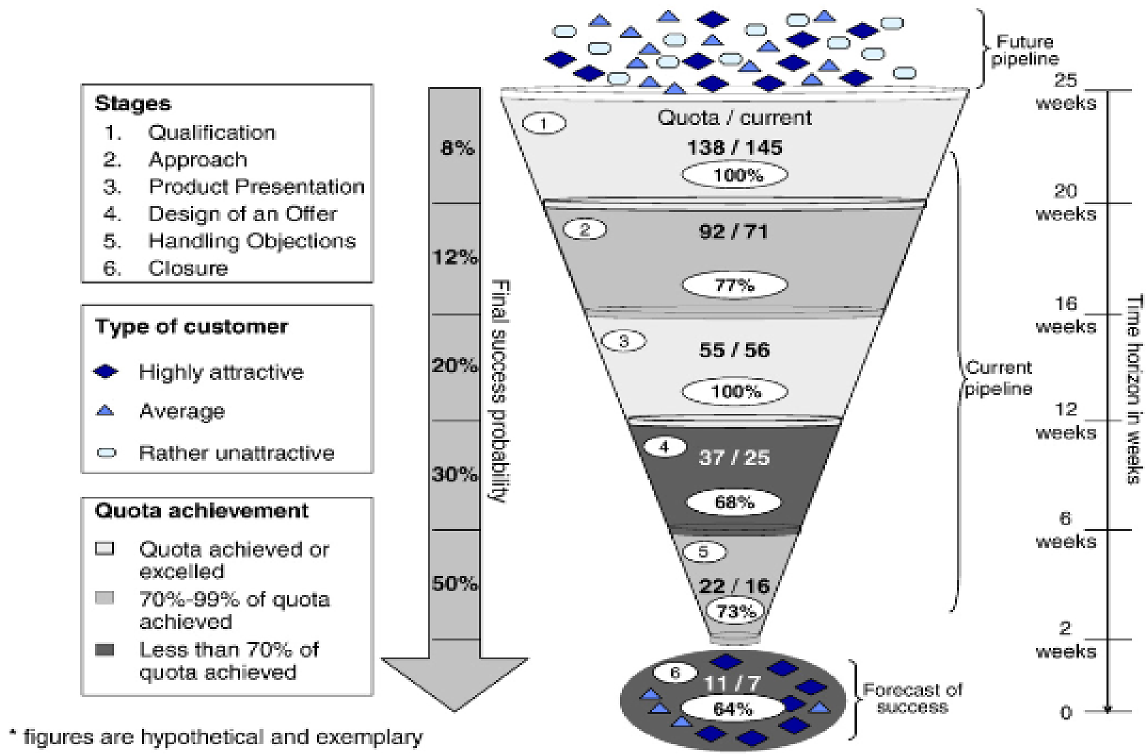

Figure 7. General example of a sales funnel.

At Tetra Pak the sales funnel concept is applied to the projects opportunities that the company is facing. When building a quarterly forecast the projects contained in the pipeline with a high probability of success must be considered for the next quarter. This idea is sustained by Kotler, Rackham, and Krishnaswamy (2006) who argue that the sales funnel can be a great strong tool in sales management and therefore in forecasting.

3.6 DMAIC Approach

DMAIC approach stands for Define, Measure, Analyze, Improve and Control and was originally designed for reducing variation in the context of quality control and Six Sigma process improvements (Chakravorty 2009). DMAIC has however, with the course of time, evolved into a generic problem-solving method with a wide range of applications (Pyzdek & Keller 2010). There are several benefits when using the DMAIC approach. One of the benefits is that DMAIC enables challenges to be solved in a precisely and structured form (De Mast &

Lokkerbol 2012). DMAIC is suitable for either structured or semi-structured problems and not for smaller, unstructured problems that are loosely defined (Egnell & Hansson 2013).

The DMAIC approach will in this design science study be adopted to improve the current forecasting model that Tetra Pak is using. Table 3 illustrates each phase included in the DMAIC approach and its proposed activities in a forecasting context (Pyzdek & Keller 2010).

Table 3. DMAIC approach in forecasting

DMAIC	Activity
Define	❖ Define the goals of the new forecasting model ❖ Identify stakeholders and interview them in order to obtain their perspective
Measure	❖ Establish an As-is analysis in order to see the performance of the current forecasting method ❖ Quantify the business impact of the current forecasting method used
Analyze	❖ Create an improved quantitative model in order to reduce the gap between current performance and the desired goal
Improve	❖ Establish all the requirements into the new forecasting model ❖ Improve continuously throughout the creation of the model
Control	❖ Ensure that every stakeholder is informed about the new model and that the model has managerial support ❖ Ensure that KPIs are applied in order to control the performance of the model

The breakdown structure of Table 3 will be used as a checklist for this design science study. Be aware that the DMAIC approach majority of the time may not provide a final solution but rather continuous monitoring and improvements for challenges that might arise during the project.

3.7 Theoretical Framework – Summary

The aim of this section was to introduce the main theoretical frameworks that will be used throughout this design science study. The focus was initially on describing different qualitative and quantitative forecasting methods in detail. Afterwards, different forecasting measures were introduced with the aim of identifying possible ways of measuring the forecasting accuracy. Lastly, the chapter introduced the concept of sales funnel which will be of great importance throughout the study, the approach to the model building, and the DMAIC approach.

It is now necessary to apply the knowledge acquired in the theoretical framework to a single design science study. The next section presents the as-is analysis of the current situation regarding the perspective of Tetra Pak and its main supplier on the forecasting process. The as-is analysis will be used later on as a comparison base for the final solution.

4. Empirical Findings

In this chapter, empirical findings of the current forecasting procedure will be presented. In addition, the forecasting procedure will be explained from the perspective of both Tetra Pak and Supplier X. Furthermore, the current demand has been studied in order to identify possible trends or patterns and to segment and differentiate the components.

4.1 Current Forecasting Situation

An analysis of the current forecasting process at Tetra Pak was conducted. This was accomplished in order to identify and compare relevant metrics with the results obtained from the new constructed model. The three component categories pumps, valves and tank equipment were analyzed based on data obtained from two different forecasting documents handed out by the OEM Components manager. The documents include information on both stand-alone components and components sold within a solution. The three components' categories can in addition be segmented into sub-categories, as explained in Table 4. All the components illustrated in Table 4 are included in the current forecasting model used by Tetra Pak and shared with Supplier X. The components included in the forecasting model vary depending on the geographical area which is forecasted.

Table 4. Component's description

Component	Product Category
1.LKB	Valves
2.ISSV	Valves
3.USSV	Valves
4.SMP-BC	Valves
5.Unique-Mixproof	Valves
6.Unique-Mixproof MB	Valves
7.Unique CP3/PMO	Valves
8.ICP2000	Pumps
9.LKH	Pumps
10.LKH Prime	Pumps
11.SRU	Pumps
14.Cleaning	Tank Equipment
15.Agitator	Tank Equipment

A pie chart has been created to understand the distribution of the supplied components corresponding to the total demand of 2021. The pie chart is illustrated in Figure 8 and displays that LKB components represent almost 50% of the total demand for OEM Components at Tetra Pak for year 2021. LKB components are used in the majority of projects that Tetra Pak carries out, hence the reason for its dominance in the pie chart. Observe that the reason behind Agitator and Cleaning components not being visible in Figure 8 is due to its low percentage in comparison to the other components.

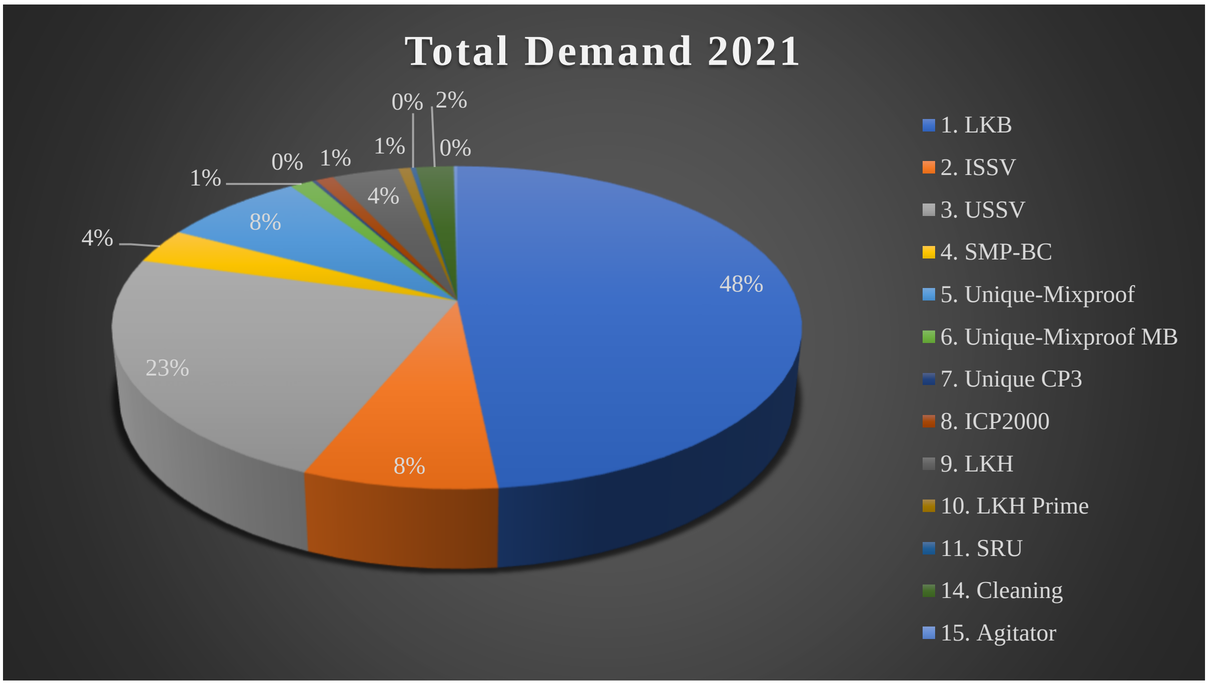

Figure 8. Total demand for OEM Components 2021

4.1.1 Perspective From Tetra Pak

In order to understand the current forecasting process between Tetra Pak and Supplier X, an interview was held with Nicole Uvenbeck, the manager of the OEM Components department. The current forecasting process is done on a quarterly basis. The forecast file which the manager of OEM Components sends to Supplier X contains the forecasted demand for the next five quarters. The estimated demand for each quarter is divided into four continents: Americas, China, Europe and the rest of the world (ROW). Each continent contains the codes representing the different types of components purchased from Supplier X for that region. The forecast for the next quarter is calculated as it follows:

$$\mathrm{Q}_{\mathrm{i+1}} = \left(\frac{D_i + D_{i-1}}{2}\right) * \left(1.012 + \left(\frac{Oppurtunity\ Pipeline}{Average\ Opportunity\ Pipeline}\right)\right)$$

Where:

$\mathrm{Q}_{\mathrm{i+1}}$ is the forecast for the next quarter $i+1$

D_i is the actual demand of the quarter i

The 1.012 is a coefficient that represents the stand-alone components, which are included in this forecast and have an increasing trend. Furthermore, the opportunity pipeline is the number of projects that are contained in the pipeline for the next quarter. It is possible by dividing the opportunity pipeline with the average of the opportunity pipeline of the last four quarters to obtain another coefficient. The coefficient obtained includes the expected projects of the new period in the forecast.

As explained in the document, there are also the forecasts for the following four quarters, but in this case, it was not possible to identify a common method to determine these numbers. Indeed, the forecast of the following quarters is based on a qualitative analysis and there is not a systematic methodology.

4.1.2 Perspective From Supplier X

An interview with the main Supplier X was conducted in order to gather valuable information about the current forecasting process. A Product manager and the Sales and Operation Planning manager at Supplier X were interviewed. The focus of the interview was to understand how the forecast provided by Tetra Pak is used by the supplier and to visualize possible improvements from their point of view.

As explained earlier the forecasting process takes place on a quarterly base. The supplier provides a set of historical data to Tetra Pak regarding the different components that are object of the forecast. These historical data sets are gathered and sent by a team of four Product Managers at the Supplier X. Once Tetra Pak has received the data and built the forecast, they send it back to Supplier X. This forecast provided by Tetra Pak is then used by the supplier as an input for a more complex internal forecasting process. Since Tetra Pak is not the only customer of Supplier X, the data received are utilized to build a broader forecast for the entire business at the supplier. Four Product Managers of different product groups are responsible for the forecasting process at the supplier. They utilize different tools to build the forecast and to manage the data received from Tetra Pak. The data received from Tetra Pak, which is the most important customer are considered as a fundamental input for building the forecast.

There are, in addition to this quarterly forecast, monthly pre-announcement meetings between Tetra Pak and Supplier X. The main goal of these meetings is to understand the projects in the pipeline of Tetra Pak and when they will be of interest for the forecast. It is fundamental for the supplier to understand when these projects will enter in their supply chain. It is necessary to plan ahead of the production and the supply of raw materials since the projects require different components, which is more difficult to forecast.

It was possible during the interview to understand that the supplier also is interested in improving the forecasting process. From their point pf view, it is necessary to increase the accuracy of the forecast that they receive from Tetra Pak. According to the interviewed managers, by building a better forecast it would be possible for the supplier to increase their planning capacity. This would enable Supplier X for example to reduce their production lead time and become in general a “better” supplier for Tetra Pak.

4.2 Current Forecast Accuracy

As mentioned earlier in this section, the forecast document contains the estimated demand for each quarter divided into four areas: Americas, China, Europe and the Rest of the World (ROW). Each of the four areas has been analyzed with the help of several forecasting measures. MAD, MSE, MFE, MAPE and Tracking Signal were the forecasting measures used in order to obtain an overview of the current forecasting process. Table 5 illustrates data computed for the five different forecasting measures on each of the 13 different components included in Tetra Pak's forecast document. Data were taken from two different documents sent out from the OEM Components department. Data regarding the first quarter were taken from a document sent during the first quarter of 2021 to Supplier X, while the rest of the data was taken from the forecast sent out during the second quarter of 2021. The data contained in Table 5 will be used as a benchmark in order to evaluate the new forecasting model.

Table 5. Measures of forecast accuracy Q1-Q4 of 2021 including all geographical areas

Component	MAD	MSE	MFE	MAPE (%)	Tracking Signal
1. LKB	5055,52	66415674	4230,03	16,34	3,35
2. ISSV	1882,78	5425389	49,22	45,95	0,10
3. USSV	3653,48	22567054	796,89	27,08	0,87
4. SMP-BC	534,26	337252	49,54	30,24	0,37
5. Unique-Mixproof	1008,81	1985912	329,51	21,85	1,31
6. Unique-Mixproof MB	247,95	92951	241,65	35,18	3,90
7. Unique CP3/PMO	113,15	17150	-12,71	207,50	-0,45
8. ICP2000	259,30	90636	8,11	113,72	0,13
9. LKH	253,69	128515	89,83	11,84	1,42
10. LKH Prime	86,80	9817	27,70	27,46	1,28
11. SRU	37,06	1688	0,76	28,54	0,08
14. Cleaning	121,77	21651	7,08	11,94	0,23
15. Agitator	26,62	944	22,62	23,69	3,40

Several conclusions can be drawn from analyzing Table 5. MAD tracks the average size of the errors, regardless of its negative or positive direction. A small difference between the forecasted demand and the actual demand will result in better MAD-value. A low value of the MAD indicates that the forecast is more accurate. As seen from Table 5, MAD differs in value for each of the 13 components. The LKB components have the highest MAD-value, therefore indicating that the forecast for these components is far from a good fit. The reason behind this can be found in the great supply volume of these components, meaning that in case of a forecasting error the result is a high MAD-value.

As mentioned earlier, Table 5 illustrates MSE-values computed for the different components. MSE determines the performance of an estimator. However, the results obtained cannot be taken into consideration by its own. It´s a comparative number, hence it will be used for comparing with the MSE obtained from the new forecast model later in this study.

MFE measures the bias of a forecast and indicates if a forecast is either over-forecasting or under-forecasting. An unbiased forecast would result in an MFE-value equal to zero. A negative MFE-value indicate that the model is over-forecasting, while the opposite applies to a positive

MFE-value. Table 5 illustrates that the components Unique CP3 are over-forecasting, while the other products are over-forecasting. SRU components have an MFE-value close to zero, which indicates that looking at the total numbers of 2021 the forecast is satisfying.

MAPE indicates the number of errors obtained from the forecast. MAPE can be applied for evaluating how large the inaccuracy of the forecast was relative to the size of the actual value. Table 5 illustrates that majority of the components have a MAPE-value between 10-50%. MAPE-value between 10-50% indicates that the average difference between forecasted value and actual demand are low. This is however not applied to the Unique CP3/PMO and ICP2000 component since a significantly greater MAPE-value has been obtained.

Tracking signal notifies when there is unexpected outcome departure from the forecast. Data computed and illustrated in Table 5 illustrates that the tracking signal is acceptable for all the components and within the recommended limit. The recommended limit for a well performing forecast is between value -4 and 4.

In addition, each quarter has been studied in order to gather more precise data regarding the forecast accuracy. Figure 9 illustrates the comparison between the forecast and the actual demand for each of the components analyzed. The data regards the total sum of the world for the first quarter of 2021. The Absolute Forecast Error line highlights the absolute difference between the forecast and the demand for the quarter. As we can see, the main problems regard the components with a higher supply volume. The forecasting error of the ISSV components is over 3800 units and represents the least accurate forecasting measure.

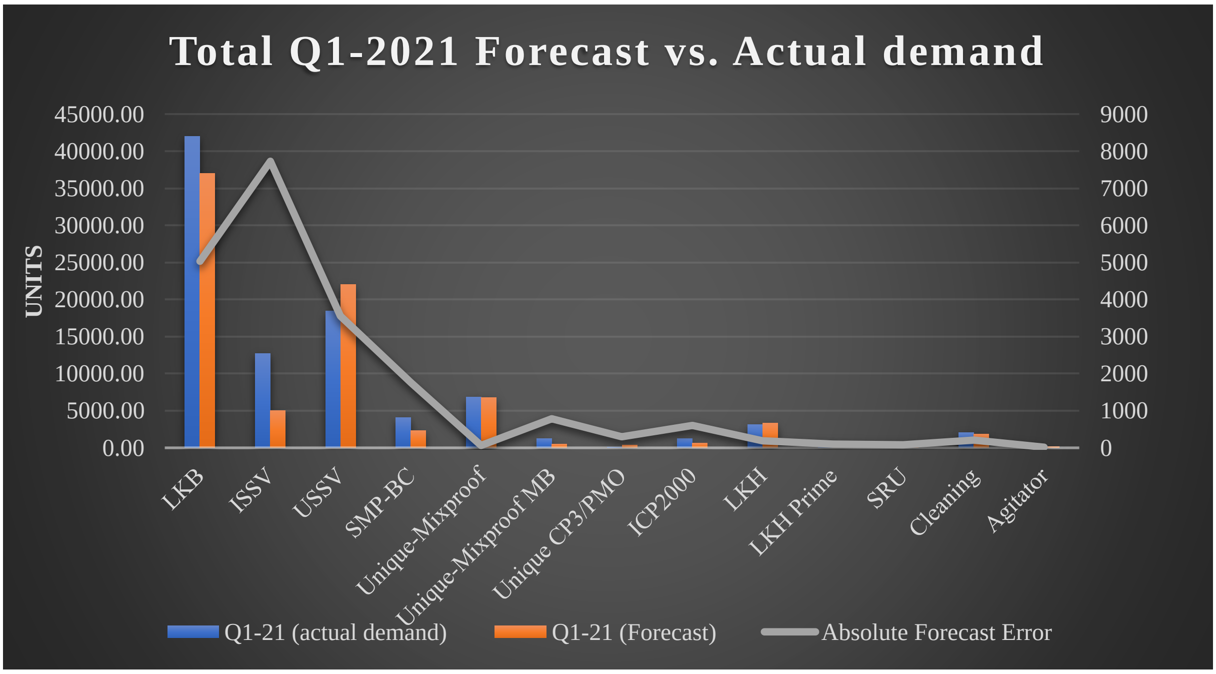

Figure 9. Total Q1-2021 Forecast vs. Actual Demand and Absolute Forecast Error

Furthermore, the absolute percentage error has been utilised in order to study the relative error of the forecast as shown in Figure 10. In this case, the results show that the different components have reasonably low percentage of the error apart from the Unique CP3/PMO. This is due to a wrong forecast in the first quarter of 2021 for these components. It was not possible to see this issue in Figure 9 with the absolute forecast error since the supply volume in this case is very low. It is important to note that no components present high value in both the absolute forecast error and the absolute percentage error, which would have been a problematic situation.

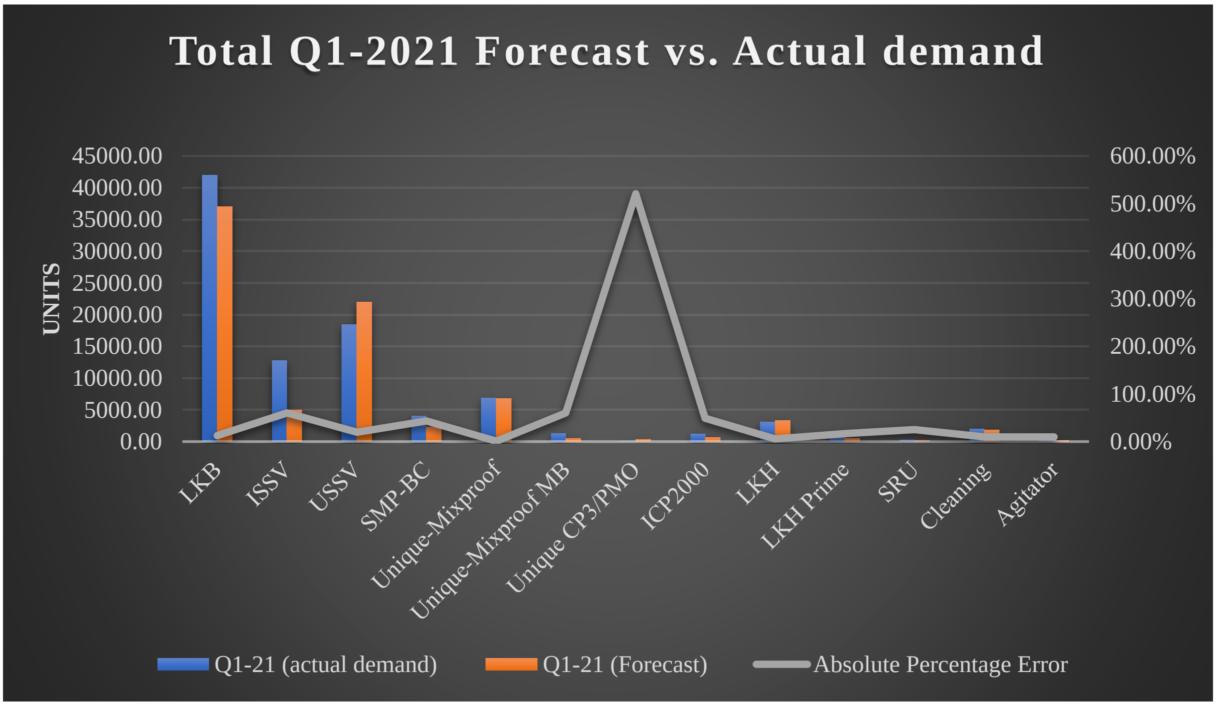

Figure 10. Total Q1-2021 Forecast vs. Actual Demand and Absolute Percentage Error

Figure 11 illustrates the comparison between the forecast and the actual demand for each of the components analyzed. The data regards the total sum of the world for the second quarter of 2021. The Absolute Forecast Error line highlights the absolute difference between the forecast and the demand for the quarter.

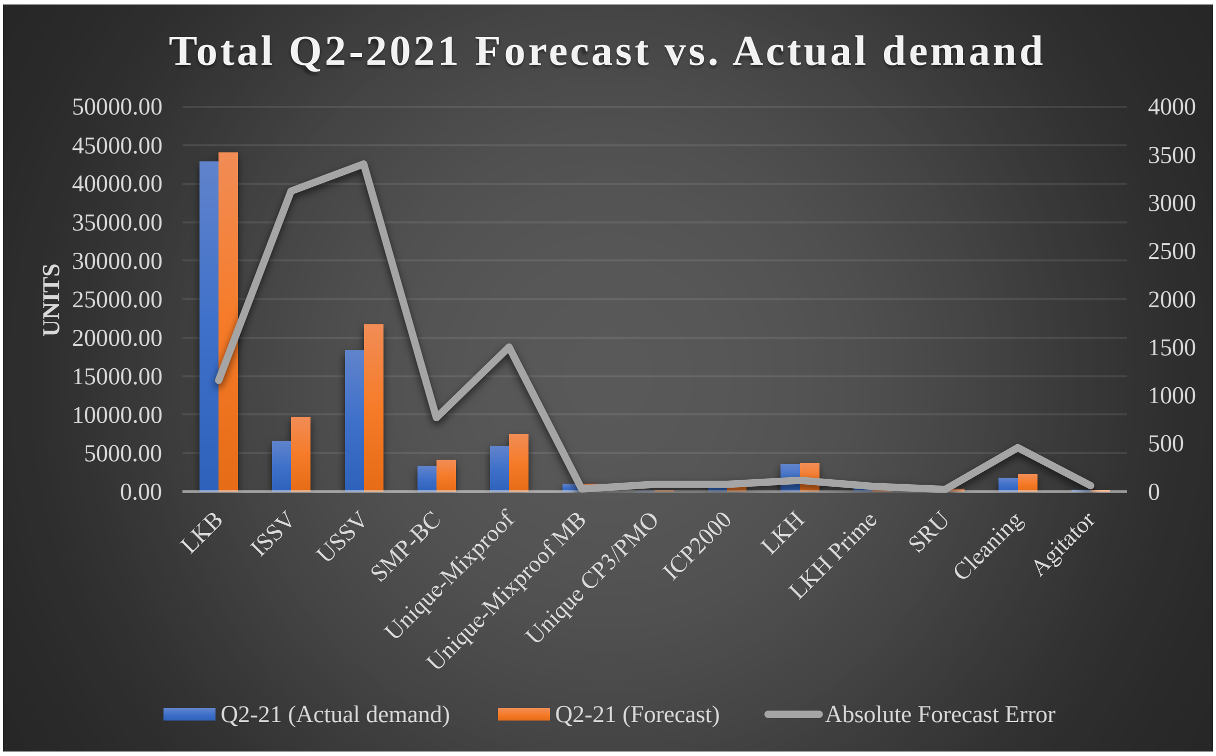

Figure 11. Total Q2-2021 Forecast vs. Actual Demand

As seen from Figure 11, the main problems regard the components with a higher supply volume. These components indicates that the difference between actual demand and forecast are high. In addition, the forecasting error of the ISSV, USSV, SMP-BC, Unique-Mixproof and Cleaning components are high and represents the least accurate forecasting measure.

In addition, the absolute percentage error has also been utilized in order to study the relative error of the forecast. Figure 12 is showing that the Unique CP3/PMO components present the same issue as the first quarter with a very high absolute percentage error due to a forecasting error. In this case compared to the first quarter the forecast presents higher absolute percentage error due to the higher inaccuracy of the forecast. The ISSV components have an absolute percentage error of around 50% and also an absolute forecast error of around 1500 units. In this case both of the errors present relatively high value indicating that for these components the current forecast model is not working properly.

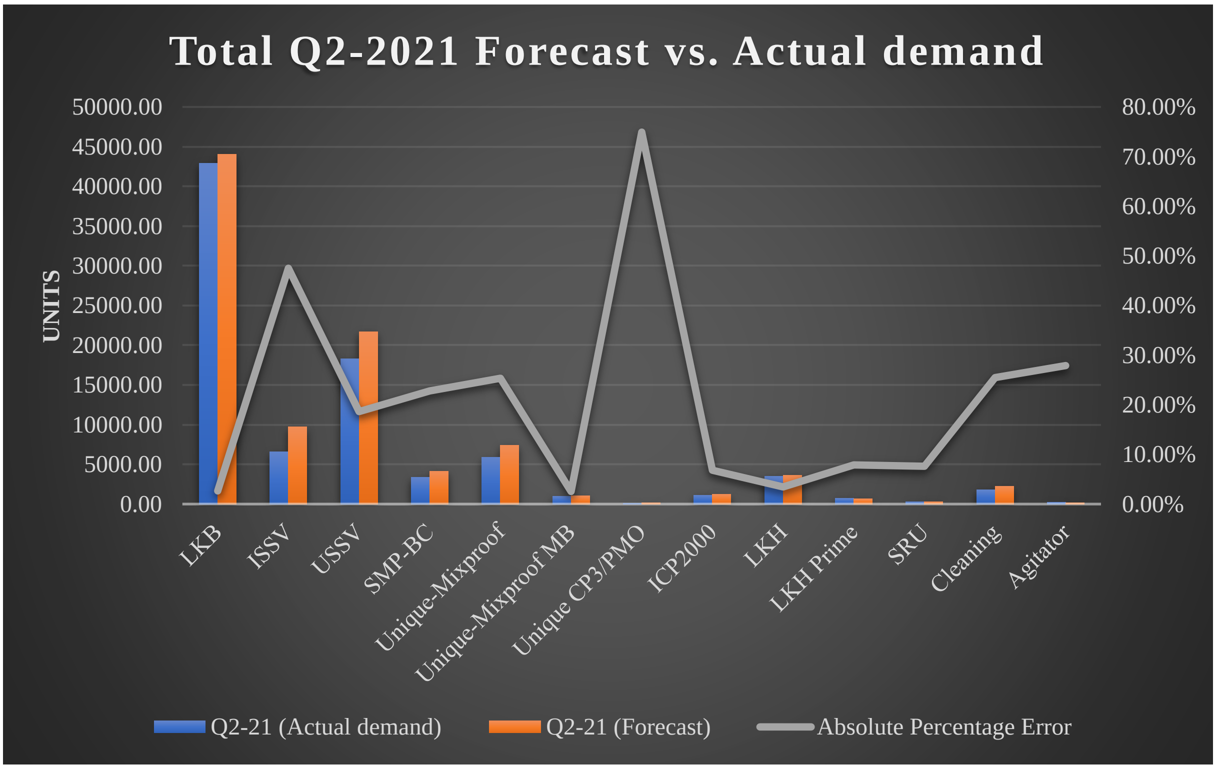

Figure 12. Total Q2-2021 Forecast vs. Actual Demand and Absolute Percentage Error

See Appendix 2 regarding the sum of the world for the third and fourth quarter of 2021 containing the comparison between the forecast and the actual demand. The specific geographical areas have been studied as well and resulted in similar patterns as the total numbers.

4.2.1 Analysis of Demand 2020

An analysis of the total demand, including all the geographical areas has been conducted for both year 2020 and 2021. This was done in order to identify any specific patterns that might have occurred throughout the two years for each of the three product categories. Figure 13 illustrates the total demand for pumps year 2020. Figure 13 indicates that LKH pumps had the highest demand throughout all four quarters during 2020. LKB pumps corresponds to a value of approximately 3000 units for each quarter. LKH pumps can be seen as the most used components used in nearly every project that Tetra Pak carries out.

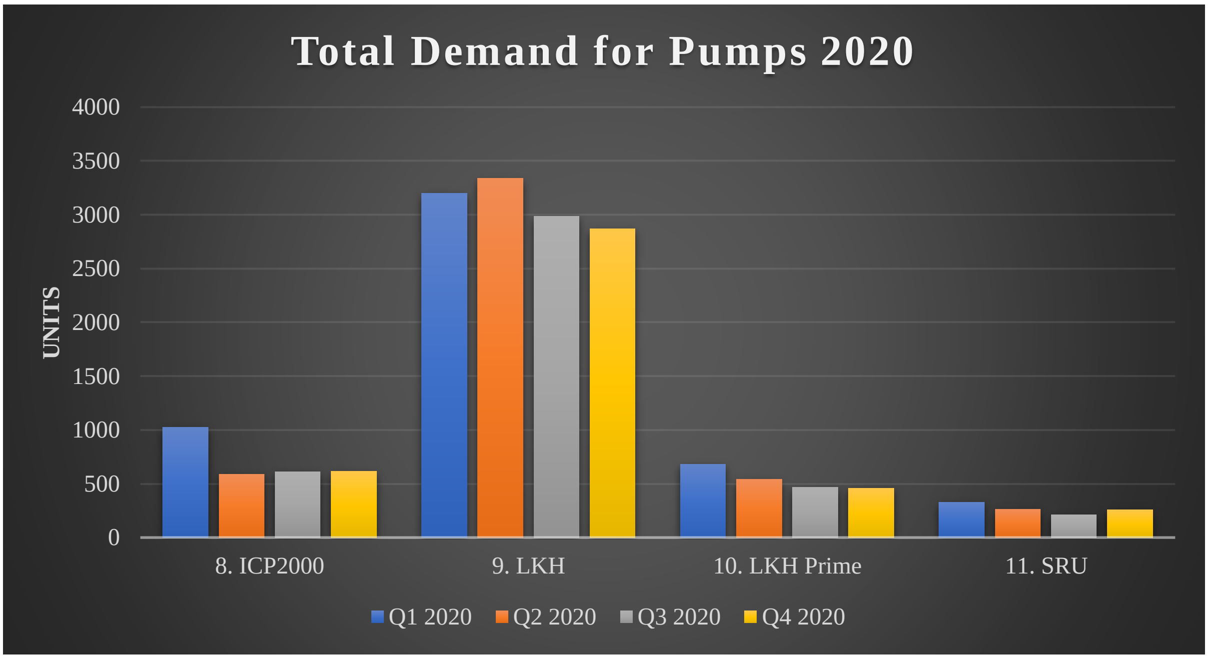

Figure 13. Total demand for pumps 2020

Figure 14 illustrates the total demand for valves during 2020. The figure indicates that LKB during 2020 was the most used component within the category of valves. USSV was the second most used component within the category of valves. Both LKB and USSV are two commonly used valves components within Tetra Pak's projects.

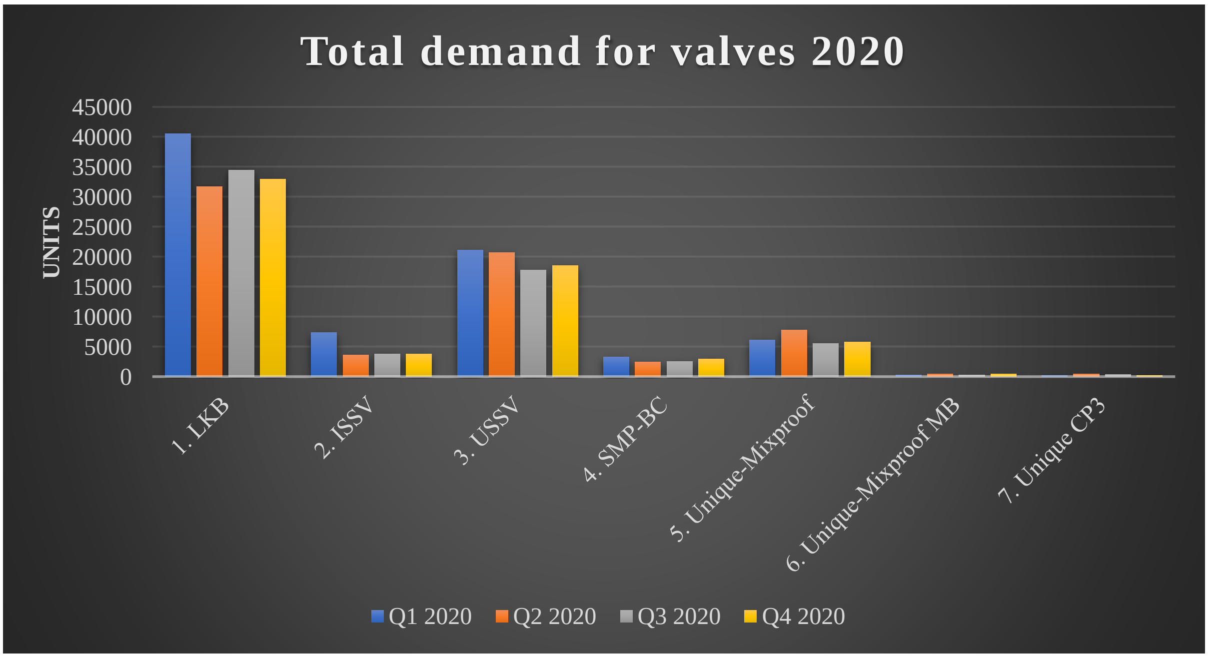

Figure 14. Total demand for valves 2020

Figure 15 illustrates the total demand for tank equipment during 2020. Figure 15 clearly indicates that cleaning equipment in comparison to agitators are mostly used within the category of tank equipment during 2020. In addition, Figure 15 illustrates that the demand for cleaning and agitators for each quarter is almost constant.

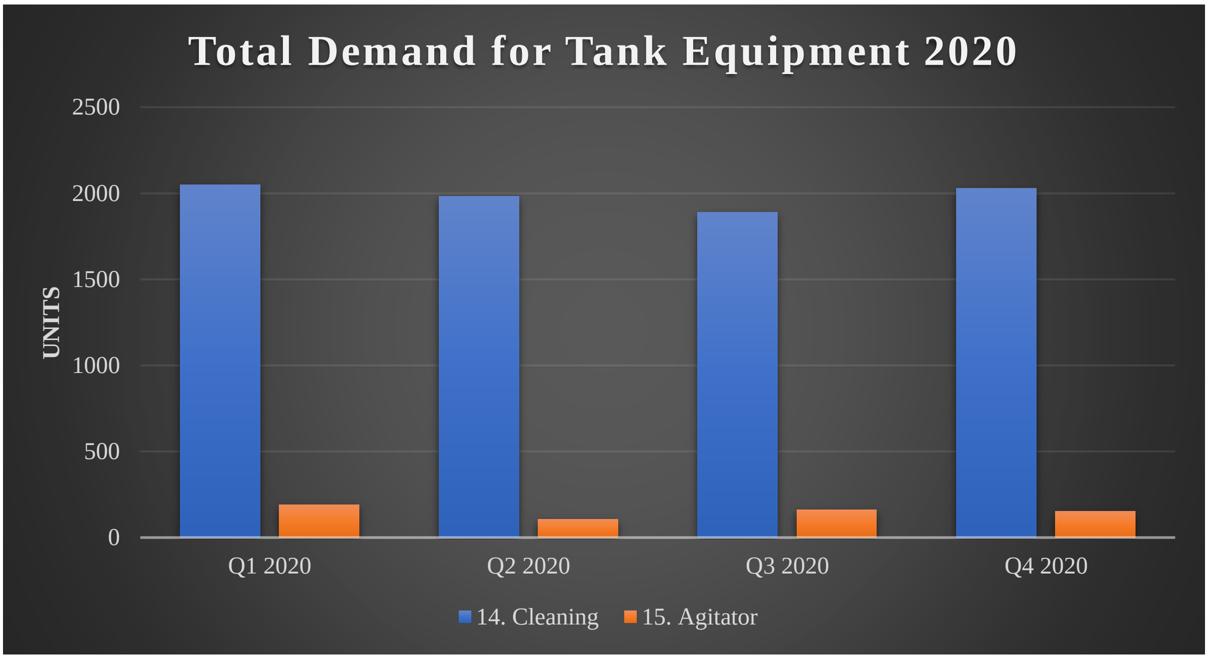

Figure 15. Total demand for tank equipment 2020

4.2.2 Analysis of Demand 2021

As mentioned earlier, analysis of the total demand for pump during 2021 was conducted, see Figure 16. From analyzing Figure 16, LKH pumps still has the highest demand within the category of pumps. The demand for pumps during 2020 and 2021 is similar. There is however a peak for LKH components during the fourth quarter. According to the OEM Components manager, the order intake increased during the fourth quarter of 2021. This was due to a change in the price policy of Tetra Pak expected in the first quarter of 2022, which pushed the customers to order in advance.

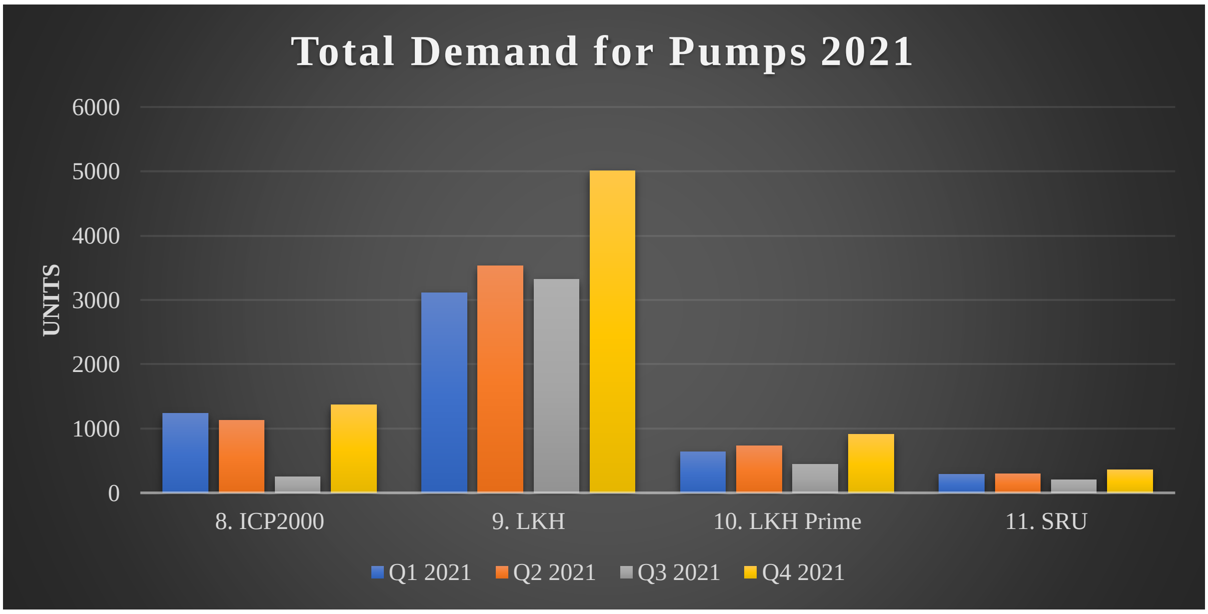

Figure 16. Total demand for pumps 2021

Figure 17 illustrates the total demand for valves during 2021. As seen in figure below, the demand increases for all categories of valves during the fourth quarter. Same reason behind this peak can be applied as for the demand of pumps during 2021. LKB continues throughout 2021 to be the most used component within the category of valves.

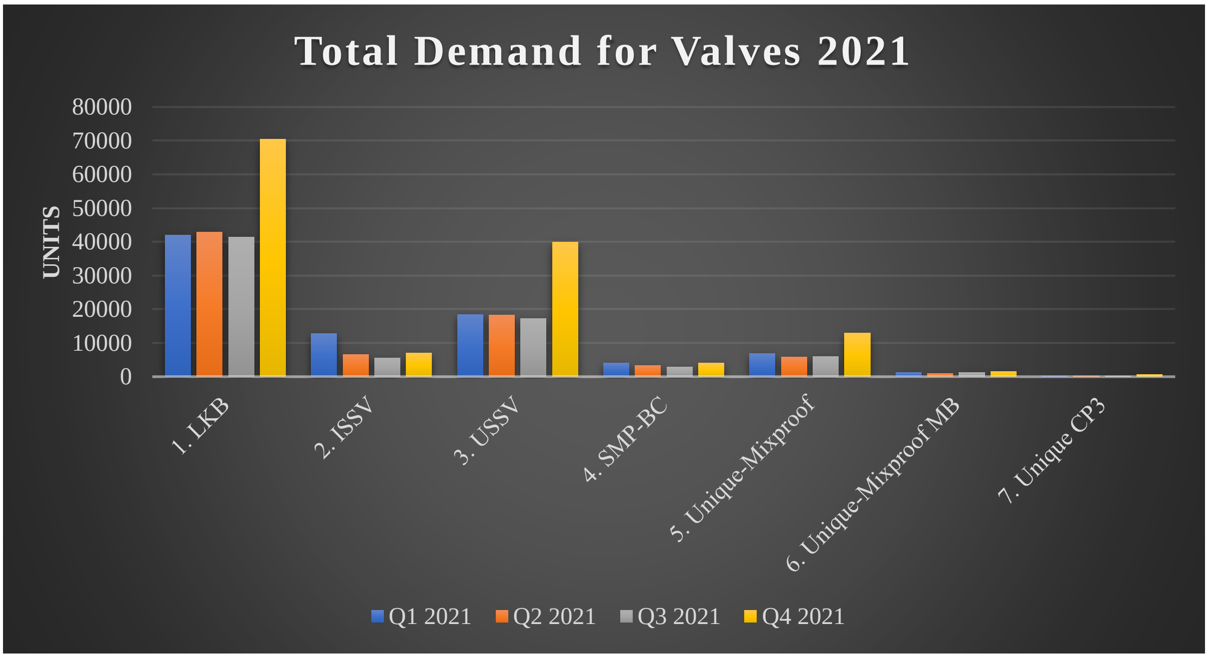

Figure 17. Total demand for valves 2021

Figure 18 illustrates the total demand for tank equipment during 2021. Figure 18 indicates that the demand for agitators decreased and conversely for cleaning equipment during the fourth quarter. Despite this small change, we still see similar demand patterns when comparing the total demand for tank equipment during 2020 and 2021.

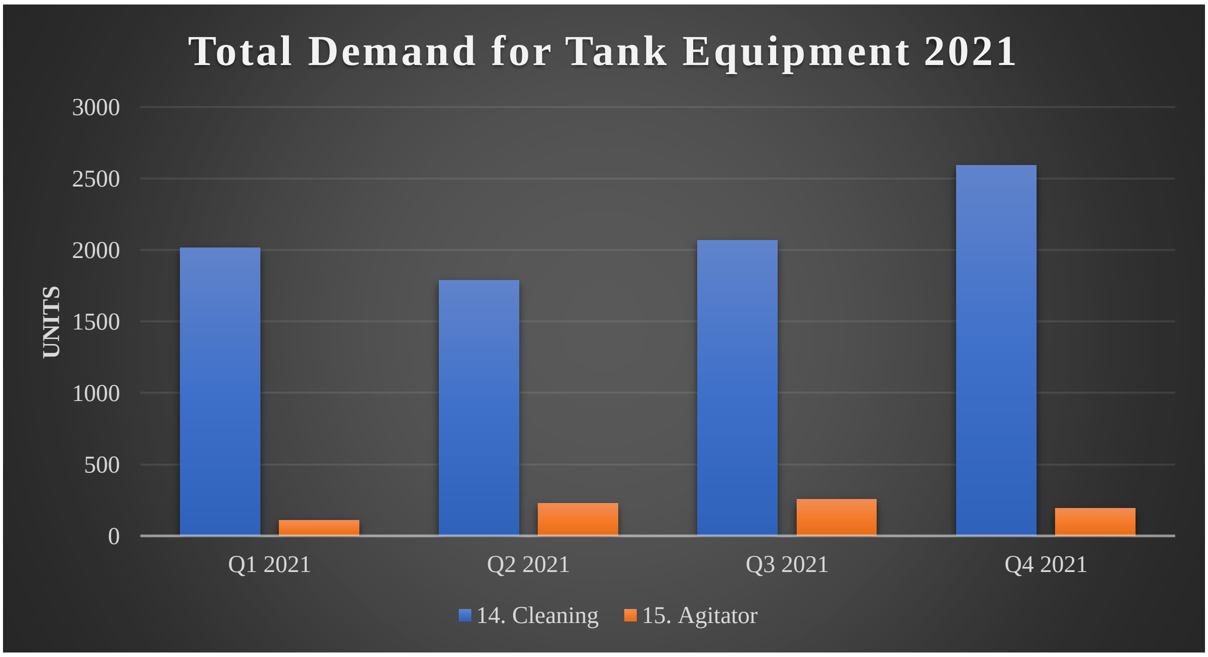

Figure 18. Total demand for tank equipment 2021

4.3 Empirical Findings – Summary

As we can see from the data above, the current forecasting procedure does not perfectly fit the demand. This results in an inaccurate forecast for the different quarters, which is impacting negatively both Tetra Pak and their supplier. Main reason behind this is the lack of a scientific and defined model that could help to build a more accurate forecast. The formula utilized at the moment provides a low accuracy. Low accuracy occurs at the level of each quarter, while performing when considering the sum of the entire year. It is necessary to build a scientific model that can improve the identified low accuracy currently occurring in the forecasting process. It was possible during the interview with Supplier X to understand from their point of view that it is necessary to improve the current forecasting process. A more accurate model could benefit the supplier for the planning operations and therefore reduce the production lead time. This benefit would have a positive impact on Tetra Pak, while increasing the overall reliability between the two stakeholders.

The components studied have very different demand patterns. The current formula applied to all of them results in high forecasting errors. In the following chapter, demand of the different components will be studied in relation to size and type of projects in order to identify specific trends. It is possible to note that the tank equipment components already have a relatively steady demand, especially during the year 2020. Common forecasting models such as Moving Average can therefore be applied in order to increase the accuracy of the forecast. This is however not applicable for valves and pumps since the demand is very dependent on the number, type and size of projects that are in the pipeline for each quarter. This aspect will be further investigated in the next chapter when building a new forecasting model. It has to be highlighted that the fourth quarter of 2021 has had an exceptional demand, which results in a lower accuracy of the forecasting model compared to the usual. As explained, this is due to a change in the price policy of Tetra Pak expected in the first quarter of 2022, which pushed the customers to order in advance. This aspect has to be taken in consideration for future forecasts since it does not represent a typical demand expected by Tetra Pak during a quarter.

Now that the as-is analysis of the current situation is concluded, it is possible to proceed to the next chapter regarding the development and testing of a new forecasting model for Tetra Pak.

5. Development of The Model

In this chapter, the approach for developing the model will be presented. In addition, the chapter contains the first attempt in building the forecast model based on project pipelines. This first attempt will lead to the consideration that it is not possible to find a strong correlation between the project opportunity pipeline and to the total demand forecast. The chapter will follow by presenting the Exponential Smoothing method utilized to determine the forecast for the next quarter and the consideration for the other components. Lastly, the chapter will end with comparing the performance of the new forecast model with Tetra Pak's current forecast model.

5.1 Model Based on The Project Opportunities Pipeline

As mentioned earlier in the Problem Formulation chapter, the objective with this thesis is to build a forecasting model based on historical sales data, installation project size and components category. This new forecast model should mainly focus on the following three product groups: pumps, valves and tank equipment's. Data from 2020 to 2022 were extracted from a software program called SAP Power BO. This software program and the data extracted from it were used in order to understand if it was possible to develop a forecast model based on installation project sizes and categories. These installation project sizes are connected to both components and project categories.

The extracted data file, also known as the Master Data file, was required to be cleansed before doing the actual analysis. Once the data were cleansed, analysis were conducted to understand the amount of a specific component connected to both a specific project size as well as to a specific project category. Beverage, Cheese, Dairy, Ice-Cream, Powder and Prepared Food are included in the possible project categories. As example, Table 6 illustrates the average amount of LKB components connected to a beverage category project and divided into the five different project sizes in year 2021. In addition, Table 6 also illustrates the amount of beverage projects that are connected to a specific project size.

Table 6. LKB components in beverage projects for 2021

2021	Beverage (Projects)	Beverage (LKB)	Average (LKB/Project)
L0	16	154	20
L1	106	2734	52
L2	54	4594	170
L3	42	1106	52
L3+	20	928	92

Table 6 illustrates e.g., that an average of 10 LKB components were utilized for the L0 projects connected to a beverage category during year 2021. The average amount of LKB components per project should in point of fact increase the higher the size of the project is. The reason behind this is precisely because larger projects require more components. Table 6 illustrates however that the average amount of LKB components per beverage project decreases during year 2021 for a project size of L3. The previously mentioned statement contradicts the point of fact and indicates an uncertainty of the data in the Master file. These uncertainties in the Master Data file needs to be taken into account when developing the forecast model.

Table 7 illustrates the average amount of LKB components connected to a beverage category and to the five different project sizes in year 2020. In addition, Table 7 displays the amount of beverage projects connected to specific project sizes.

Table 7. LKB components in beverage projects for 2020

2020	Beverage (Projects)	Beverage (LKB)	Average (LKB/Project)
L0	20	32	4
L1	118	1406	24
L2	66	1468	44
L3	34	2166	128
L3+	6	410	136

As illustrated in Table 7, the average amount of LKB components per beverage project during 2020 increases in relation to the project size. Seen from Table 7, a beverage project of size L3+ utilizes in average 34 times more LKB components in comparison to a L0 beverage project. Table 8 illustrates the average amount of LKB components connected to both a beverage category and to the five different project sizes during year 2020-2021. There are in total 482 beverage projects when adding up the total amount of beverage projects for year 2020 and 2021. Beverage project of L1 size corresponds for approximately 50 percent of the total amount of beverage projects during 2020-2021.

Table 8. LKB components in beverage projects for 2020-2021

2020-2021	Beverage (Projects)	Beverage (LKB)	Average (LKB/Project)
L0	36	186	10
L1	224	4140	36
L2	120	6062	102
L3	76	3272	86
L3+	26	1338	102

As mentioned earlier in this section, the average amount of LKB components per project should in point of fact increase the higher the size of the project is. Table 8 does not present this relation since the average amount of LKB components for a beverage project of size L3 is smaller in comparison to a project size of L2. The same procedure explained for beverage products was applied to all the different project categories.

Table 9 presents a summary of the average amount of LKB components per project corresponding to a certain size and project category. The same procedure was applied to different components contained in the Master File in order to obtain the same summary table.

Table 9. Average LKB component per project size for six different product categories

Average LKB/Project	Beverage	Cheese	Dairy	Ice Cream	Powder	Prepared Food
L0	10	2	12	0,48	2	20
L1	36	14	24	64	22	26
L2	102	104	108	202	46	98
L3	86	28	294	120	96	42
L3+	102	12	674	0	210	0

According to Table 9, Cheese, Dairy, Ice Cream, Powder and Prepared food have been taken into consideration when finding the average LKB per project. Table 9 indicates once again that there might be uncertainty with the data in the Master file, which must be taken into consideration when developing the new model. The purpose with Table 9 was to then multiply the average number of components per project with the projects pipeline of the next quarter. Appendix 3 presents the summary tables for the other components with the average numbers for project size and category. The following components were included in the analysis:

- *USSV*
- *SMP-BC*
- *Unique-Mixproof,*
- *LKH*
- *LKH Prime*
- *Cleaning*
- *Agitator*

5.1.1 Project Opportunity Pipeline

One of Tetra Pak's objective was to develop a forecast model by connecting the opportunity pipelines for the upcoming quarter to both a project size and category. Software system called Smart Sales CRM was used for extracting data regarding the opportunity pipeline of Q2-2022. Projects having a go and a get rate above 70% within the sales funnel between the date 2022-04-01 and 2022-06-30 were selected in order to find the projects to be won by Tetra Pak during the current quarter of 2022. Table 10 presents the number of projects within the opportunity pipeline of Q2-2022 connected both to a certain project size and geographical area.

Table 10. Projects in the opportunity pipeline for Q2-2022 segmented into geographical areas and project sizes

Q2-2022	L0	L1	L2	L3	L3+	Total
Number of projects	280	278	84	36	2	680
Europe	94	84	26	12	0	216
Americas	78	72	18	6	0	174
China	22	48	20	12	2	104
ROW	86	74	20	6	0	186

It is possible to see from Table 10 that there in total was 680 projects within the opportunity pipeline for Q2-2022 containing a go and a get rate above 70%. In addition, Europe stands for approximately 32% of the total amount of projects within the opportunity pipeline for the same quarter. It was possible with the Smart Sales CRM program to do further in-depth analysis by categorising and understanding the number of projects within the opportunity pipeline connected to a specific project category and project size. Table 11 illustrates the number of projects within the opportunity pipeline for Q2-2022 segmented into geographical areas, project categories and project sizes.

Table 11. Projects in the opportunity pipeline for Q2-2022 segmented into geographical areas, project category and project sizes

Summary Q2-2022	Beverage	Cheese	Dairy	Ice Cream	Powder	Prepared Food
Rest of the world (ROW)						
L0	10	4	40	16	8	8
L1	10	4	46	2	8	4
L2	4	0	10	0	2	4
L3	0	2	2	2	0	0
L3+	0	0	0	0	0	0
Europe						
L0	10	22	38	14	4	6
L1	18	6	24	6	0	30
L2	4	6	10	4	0	2
L3	0	4	0	2	2	4
L3+	0	0	0	0	0	0
China						
L0	8	0	10	2	0	2
L1	8	0	22	18	0	0
L2	0	0	8	12	0	0
L3	2	0	8	2	0	0
L3+	0	0	2	0	0	0
Americas						
L0	10	4	36	14	6	8
L1	10	4	44	2	8	4
L2	4	0	8	0	2	4
L3	0	2	2	2	0	0
L3+	0	0	0	0	0	0

Table 11 illustrates that dairy in comparison to the other project categories contains the largest amount of projects within the opportunity pipeline of Q2-2022. The product category of powder corresponds for the smallest number of projects within the opportunity pipeline of Q2-2022. By knowing the number of projects of e.g., a L0 project connected to a dairy project, it would be possible to determine the amount of a specific OEM Component it corresponds to. Since we have data on the average amount of e.g., LKB components corresponding to both a specific project size and product category, as explained in chapter 5.1, it is possible to determine the total amount of components for the upcoming quarter. This can be done by combining it with the results obtained in Table 11 showing the projects expected within the next quarter. At this point it would be possible to obtain the total number of components needed for the projects in the next quarter. It has to be noted that the total demand consists of four different channels, so it is necessary to translate the project requirements demand into a total demand. At this point, the uncertainties related to the approximations and average numbers considered made the numbers not completely reliable. It would be required to segment the total demand and try to apply this method in order to demonstrate that this method would have low accuracy.

5.1.2 Segmentation of The Total Demand

Further analyses were conducted using the data extracted from the Master Data file. In this case, the analysis was done to understand the percentage of the demand of OEM Components for year 2020 and 2021 connected to each of Tetra Pak's four demands channels. The objective in this case was to segment the demand and find the percentage that each channel is accountable for in the total demand. The idea was that, assuming to be able to forecast the demand for the Project Requirements channel, there was then a need to translate that into a total demand for all the channels. By knowing the forecast of the components connected to the projects and at the same time knowing the percentage they represent in the total demand, it is possible with a proportion to forecast the total demand. This method represents an approximation since the percentage can change from year to year and from quarter to quarter. Table 12 presents the four different demand channels which drive the demand between Tetra Pak and Supplier X for year 2020. The fifth channel called "Random" represents small purchases from Tetra Pak to Supplier X that are not categorized in the four main categories and can therefore be neglected due to the very low percentage that they represent.

Table 12. Total demand of 2020 divided in percentage into the different demand channels

2020	% Project Requirements	% Spare Parts	% Production	% Plant Components	% Random
1. LKB	34,3	7,5	6,4	51,2	0,3
3. USSV	36,5	2,7	22,8	37,6	0,4
4. SMP-BC	54,8	0,9	0,0	43,2	1,1
5. Unique-Mixproof	45,7	2,3	4,5	46,4	1,1
9. LKH	39,1	4,0	19,2	37,2	0,6
10. LKH Prime	60,6	3,4	0,9	34,2	0,9
14. Cleaning	15,4	22,0	18,5	44,1	0,0
15. Agitator	35,4	1,6	0,8	62,2	0,0

The analysis in Table 12 have been conducted for eight of Tetra Pak's OEM Components. Three out of these eight OEM Components are segmented within the product category of valves, while two out of the eight OEM Components are segmented within the product category of pumps. Finally, the Cleaning and Agitator are segmented within the product category of tank equipment. Since some components were not found in the Master Data file only eight out of 13 OEM Components were analyzed. As can be seen from Table 12, the percentage value for every demand channel varies depending on the OEM Component being analyzed. For example, LKB Component during 2020 had its largest demand from the demand channel named Plant Components, while LKH Prime components had their largest demand from the Project Requirements.

Table 13 presents the four different demand channels which drives the demand between Tetra Pak and Supplier X for year 2021.

Table 13. Total demand of 2021 divided in percentage into the different demand channels

2021	% Project Requirements	% Spare Parts	% Production	% Plant Components	% Random
1. LKB	36,1	4,9	5,5	52,9	0,01
3. USSV	36,5	3,0	20,2	40,4	0,01
4. SMP-BC	59,1	0,7	0,00	40,2	0,02
5. Unique-Mixproof	50,0	1,4	3,9	44,6	0,00
9. LKH	85,2	1,2	4,3	9,2	0,02
10. LKH Prime	48,4	3,2	0,6	47,9	0,00
14. Cleaning	14,7	22,7	19,7	42,9	0,00
15. Agitator	34,8	0,00	3,7	61,5	0,00

According to Table 13, similar behavior can be seen between some of the OEM Components when comparing year 2020 to 2021. For example, LKH components also had during 2021their largest demand from the demand channel of Plant Components. As mentioned earlier, the objective with conducting this analysis was to understand if any patterns could be found regarding how much each demand channel corresponded in percentage to a certain OEM Component. When analyzing the two tables and especially year 2020 and 2021, some OEM Components did have a similar pattern while others unfortunately did not have. For example, the LKH component do not have a pattern when analyzing the Project Requirements channel for year 2020 and 2021. The demand during 2020 for LKH and the Project Requirement category channel corresponded to approximately 40% of the components total demand. When analyzing LKH during 2021, the demand for the same channel increased by 100%, thus indicating that no patterns can be found for these components. In this case the problem is that it is not possible to identify an accurate and steady percentage in the total demand of the project requirements. Same results could be seen for other OEM Components obtaining similar results. The inaccuracy of these data adds further approximations in the model and therefore decrease the reliability and the accuracy. At this point the steps of the model are completed but the data do not present the hoped results. There are various approximations in this method and the number obtained cannot be considered as reliable. Furthermore, this method can be only applied to few components for which it was possible to find data and approximate patterns. The method can be already considered as inaccurate and unreliable and not applicable to the components. It was performed anyway an example in order to check the various steps on certain components. Other reasons for considering this method as inappropriate are presented in the Discussion chapter.

An example for the geographical area of Americas will be presented in order to illustrate that this approach for developing a forecasting model is inappropriate. Data for Q4-2021 have been utilized in order to conduct the analysis. The first step is to find the projects within the opportunity pipeline of Q4-2021 for Americas, which is presented in Table 14. Smart Sales CRM and a snapshot from 2021-09-30 have been used in order to extract the projects within the specific pipeline. The projects selected within the pipeline have a go and get rate above 70%.

Table 14. Project opportunities pipeline for Americas Q4-2021

Americas (Q4-2021)	Beverage	Cheese	Dairy	Ice Cream	Powder	Prepared Food
L0	2	12	4	4	14	20
L1	8	0	4	12	22	2
L2	2	0	0	2	6	4
L3	4	0	0	2	0	2
L3+	2	0	0	0	0	0
Total	18	12	8	20	42	28

Table 14 presents the total amount of projects within the opportunity pipeline for Beverage, Cheese, Dairy, Ice Cream, Powder and Prepared Food. Powder corresponds to the product category containing the largest number of projects within the pipeline of Q4-2021. In addition, Table 15 presents the average amount of LKB Components per project size corresponding to a certain project category.

Table 15. Average LKB Component per project size for six different project categories

Average LKB/Project	Beverage	Cheese	Dairy	Ice Cream	Powder	Prepared Food
L0	10	2	12	0,48	2	20
L1	36	14	24	64	22	26
L2	102	104	108	202	46	98
L3	86	28	294	120	96	42
L3+	102	12	674	0	210	0

By multiplying Table 14 and 15, the total amount of LKB Components can be found within the opportunity pipeline for Q4-2021 in Americas. There are 14 Powder projects of size L0 in the opportunity pipeline for Q4-2021. Since one LKB component in average for a L0 Powder project is utilized, the total amount of LKB's for a Powder project of L0 size within the pipeline in Americas will be 14. Table 16 illustrates the total amount of LKB Components within the opportunity pipeline for Q4-2021 in Americas.

Table 16. Total LKB Components forecasted for projects Q4-2021 in Americas

Americas, LKB (Q4-2021)	Beverage	Cheese	Dairy	Ice Cream	Powder	Prepared Food
L0	10	60	24	0,96	14	200
L1	144	0	48	384	242	26
L2	102	0	0	202	138	196
L3	172	0	0	120	0	42
L3+	102	0	0	0	0	0
Total	530	60	72	708	394	464

Table 16 illustrates that 2228 LKB components in total is within the opportunity pipeline for Q4-2021 in Americas. These 2228 LKB valves represent the project requirements for the next quarter, but they are not the total demand of the next quarter. It is possible to determine the total demand of LKB's in Americas with a proportion method. We know in addition from Table 12 and 13 that the channel called Project Requirements corresponds in average to 35% of the total demand for LKB components. We assume that the percentage of the project requirements will remain the same as in 2020 and 2021. The total demand can therefore be computed with the following equation:

$$\boldsymbol{Total\ LKB's\ forecasted\ (Q4-2021)} = \frac{2228 * 100\%}{35\%} = 6366\ LKB\ Components$$

The previous calculation indicates that 6366 LKB valves in total can be forecasted for Q4-2021. Actual demand of Q4-2021 are used in order to understand the performance of the previously forecasted demand. The actual demand for LKB valves in Americas during Q4-2021 was 4556, thus indicating a large difference between the actual and forecasted demand. Same method was applied to all other OEM Components analyzed in this study. Table 17 illustrates the forecasted demand in comparison with the actual demand for Q4-2021 in Americas by applying the same method as with the LKB Valves.

Table 17. Forecasted demand versus actual demand for Q4-2021 in Americas

OEM Components	Forecasted Demand	Actual Demand	Forecasting Error	Forecating Error (%)
1.LKB	6366	4556	1810	33%
3.USSV	4118	10124	6006	59%
4.SMP-BC	186	108	78	72%
5.Unique-Mixproof	1544	972	572	59%
9.LKH	2008	648	1360	210%
10.LKH Prime	48	102	54	53%
14.Cleaning	294	264	30	11%
15.Agitator	24	6	18	300%

The results obtained from Table 17 indicates that majority of the components have a very large forecasting error and relative percentage error. The Agitator and LKH prime components have a MAPE value above 200% which can be seen as too high. This approach, as tested in this section and the results obtained have a lot of uncertainties. The forecasting errors obtained are high and the method in general is not reliable due to its several approximations applied throughout the method. The following section will therefore focus on developing a forecasting model based on a method called Exponential smoothing.

5.2 Final Model Developed

Since the model based on the opportunities pipeline did not provide appropriate results, it was necessary to provide an alternative forecasting method. Exponential smoothing was found as the most appropriate method to use in order to provide a forecast for the demand in the next quarter. This is due to the nature of the demand that has been analyzed in the previous chapter and does not present any relevant seasonality or trend. Furthermore, this is a standard method widely used in companies and deeply studied in the literature (Billah, King, Snyder & Koehler 2006). A comparison was conducted with the moving average technique, in order to establish which method could deliver the best results. Different past quarters were forecasted and analyzed using the two forecasting methods. The exponential smoothing provided more reliable results in terms of accuracy, and it was therefore chosen as the appropriate forecasting method. The forecasting model was developed using Excel in order to apply the exponential smoothing technique in an effective and flexible way.

The final solution for the forecast consists in an Excel file, which can provide as a result the forecast for the next quarter. A snapshot of the model can be seen in Figure 19. The model's inputs are the historical data of the demand in the last eight quarters. As can be seen from Figure 19, the historical data can be inserted in the model up to a maximum of 25 components at the same time. This means that the historical data of one geographical area at the time can be inserted in the model and then forecasted. The output is the forecast of the next quarter for each component that has been added to the model, which can be seen in Figure 19 and highlighted in green.

			2020			2021				2022	
Alfa	1- Alfa	Components/ Quarter	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2
0.17	0.83	1. LKB	3258	2490	2144	4210	1630	2128	2776	4556	3080
0.02	0.98	3. USSV	3634	2898	3362	4060	3144	3616	2502	10124	3710
0.66	0.34	4. SMP-BC	234	70	70	12	186	108	174	108	124
0.00	1.00	5. Unique-Mixproof	640	336	380	602	804	916	642	972	640
0.00	1.00	7. Unique CP3	190	406	352	186	58	94	72	558	190
0.61	0.39	8. ICP2000	0	0	36	22	56	80	28	44	43
1.96	-0.96	9. LKH	486	530	412	258	314	368	384	648	887
0.00	1.00	10. LKH Prime	72	162	42	28	42	128	62	102	72
0.35	0.65	11. SRU	28	52	46	18	50	60	46	48	47
0.00	1.00	11A. Duracirc	0	0	0	0	0	2	0	0	0
0.03	0.97	12. Automation	4646	2266	2592	4504	4044	5072	3928	6444	4553
0.69	0.31	13. Indi Top	550	132	262	200	138	200	154	100	120
0.50	0.50	14. Cleaning	140	260	220	208	186	200	296	264	256
0.65	0.35	14A. RSH SB	112	20	52	0	4	46	44	22	28
0.90	0.10	15. Agitator	34	14	16	14	4	8	12	6	7
0.14	0.86	16. Bends	13960	8088	16162	11494	9788	12770	10746	27882	14671
0.45	0.55	19. Tees	3560	1204	2550	1362	1224	1648	2230	8728	4990
0.00	1.00	17. Connections	26392	15278	34034	26328	24608	30268	33222	37608	26392
0.09	0.91	18. Reducers	3148	1522	3000	1552	1800	1808	2950	2982	2733
0.00	1.00										0
0.00	1.00										0
0.00	1.00										0
0.00	1.00										0
0.00	1.00										0
0.00	1.00										0

Forecast

Zero Alfa

Clean Historical Data

Figure 19. Snapshot of the model applying Exponential Smoothing

The model can find the optimal alfa values to apply the exponential smoothing method. The optimal value of alfa is found as the one that minimizes the value of the MAD in the last eight quarters. The optimal value is found by using the Solver function in Excel. It was necessary to set as the objective to minimize the cell containing the calculated MAD of the last eight quarters. It is possible by running the Solver to find the optimal value of alfa that minimizes the objective cell. This procedure had to be repeated for all the components contained in the forecast. It was possible using a loop function in Virtual Basic for Applications of Excel to create a Macro that automatized this process. This Macro is automatically finding the optimal alfa values of the different components at the same time using the Excel Solver. The model includes a button called "Forecast", connected to the Macro code, that can be pressed after the historical data have been inserted. Once the optimal values of alfa are defined, the model applies the Exponential Smoothing method to the components and display the forecast for the next period. The alfa values in the forecast model must be between zero and one. The accepted values of alfa are between 0 and 1, but the recommended values have a maximum of 0.5 at most. Since the Solver calculates at the same time for all the components, it was not possible to insert the constraint of alfa between 0 and 1 for each component. The alfa values displaying a value above one will automatically be highlighted in red. Exponential smoothing technique is not applicable for the components having an alfa value above one, meaning that manual and qualitative adjustments must be done for those components. Furthermore, as suggested in the Theoretical Framework the value of alfa should be lower the greater the randomness is. Values of alfa are recommended to be lower than 0.5, those values higher than 0.5 but lower than 1 are highlighted in yellow in this case. The advice for all the components highlighted in red and yellow is to manually set the alfa value at 0.5 and then perform a qualitative check and adjustment. Most of the components will present alfa values higher than 0.5 and therefore be highlighted in yellow or red. This is due to the increased demand in quarter 4 of 2021 and first quarter of 2022. Since this increase is due to the change in price policy it cannot be considered as a trend that necessarily will continue in the next quarters. The model will however have to be adjusted by including a trend variable in case this trend continues within the next quarters.

The forecast model consists of two additional tables apart from the one presented in Figure 19. The cells of these tables are connected to the main table and used in order to perform the calculations for the Exponential Smoothing. The tables are shown in Figure 20 and 21. The first table, in Figure 20, is used for storing the forecast of the previous quarters, which is useful for the exponential smoothing technique. As we can see in this case, the starting point of the forecast in Q3-2020 was set equal to the actual demand of the previous quarter. The following quarters are calculated using the exponential smoothing technique.

Forecast	*2020*			*2021*				*2022*	
Forecast	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**
1. LKB		3258	3127	2959	3173	2909	2776	2776	3080
3. USSV		3634	3621	3617	3624	3616	3616	3597	3710
4. SMP-BC		234	125	89	38	136	117	155	124
5. Unique-Mixproof		640	640	640	640	640	640	640	640
7. Unique CP3		190	190	190	190	190	190	190	190
8. ICP2000		0	0	22	22	43	66	43	43
9. LKH		486	572	258	258	368	368	399	887
10. LKH Prime		72	72	72	72	72	72	72	72
11. SRU		28	36	40	32	38	46	46	47
11A. Duracirc		0	0	0	0	0	0	0	0
12. Automation		4646	4568	4504	4504	4489	4508	4489	4553
13. Indi Top		550	262	262	219	163	189	165	120
14. Cleaning		140	200	210	209	198	199	247	256
14A. RSH SB		112	52	52	18	9	33	40	28
15. Agitator		34	16	16	14	5	8	12	7
16. Bends		13960	13126	13557	13264	12770	12770	12482	14671
19. Tees		3560	2496	2520	1997	1648	1648	1911	4990
17. Connections		26392	26392	26392	26392	26392	26392	26392	26392
18. Reducers		3148	3000	3000	2868	2771	2683	2708	2733
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0

Figure 20. Forecast table of the model

The second table, in Figure 21, is used in order to calculate the MAD of each component. For each component is calculated the absolute forecast error of every past quarter. The MAD is then calculated as the average of the absolute forecast error of the last seven quarters. Figure 21 is useful for setting the objective that has to be minimized in the Excel Solver, which can be seen as the green column in the figure.

	2020			2021				2022	
Absolute Forecast Error	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*MAD*
1. LKB		768	3127	1251	1543	781	0	1780	1321
3. USSV		736	259	443	480	0	1114	6527	1366
4. SMP-BC		164	55	77	148	28	57	47	82
5. Unique-Mixproof		304	260	38	164	276	2	332	197
7. Unique CP3		216	162	4	132	96	118	368	157
8. ICP2000		0	36	0	34	37	38	1	21
9. LKH		44	160	0	56	0	16	249	75
10. LKH Prime		90	30	44	30	56	10	30	41
11. SRU		24	10	22	18	22	0	2	14
11A. Duracirc		0	0	0	0	2	0	0	0
12. Automation		2380	1976	0	460	583	580	1955	1133
13. Indi Top		418	0	62	81	37	35	65	100
14. Cleaning		120	20	2	23	3	97	17	40
14A. RSH SB		92	0	52	14	37	11	18	32
15. Agitator		20	0	2	10	3	4	6	6
16. Bends		5872	3036	2063	3476	0	2024	15400	4553
19. Tees		2356	54	1158	773	0	582	6817	1677
17. Connections		11114	7642	64	1784	3876	6830	11216	6075
18. Reducers		1626	0	1448	1068	963	267	274	807
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0
0		0	0	0	0	0	0	0	0

Figure 21. MAD calculation table

The Exponential Smoothing technique applied in this model provides the forecast only for the next quarter. It is not possible to forecast quarters further away in time since there are not data regarding the actual demand of the previous quarter, which are necessary when applying the Exponential Smoothing formula. In this case, the following quarters are assumed having the same forecast as the quarter that can be forecasted. Each of these quarters will have to be adjusted qualitatively with information regarding the possible increase or decrease of demand in the upcoming quarters. It is particularly important to provide an indication regarding the increase or decrease of demand for the components during the next year. Supplier X is interested in this data which is contained in the forecast since it supports their long-term planning of the needed capacity to fulfill the demand.

5.2.1 Comparison With the Old Method Applied to Q1-2021

The forecasting errors have been calculated and analyzed in order to understand the performance of the model and its accuracy. It was necessary to compare the new model with the old technique used for the forecast of the next quarter. The forecast for the first quarter of 2021 was suitable for a comparison since the data regarding the old forecast were available and also the historical data necessary for the new model. It was possible to compute the forecasting errors since the actual data of the demand of a past quarter are available. The first step was to utilize the model in order to get a new forecast. In this case, the components with an alfa value highlighted in red or yellow, meaning above one, were manually changed to a value of 0.5. Table 18 presents the results using the new model.

Table 18. Forecasting errors of the new model for Q1-2021 compared to the old method.

Component	MAD	MSE	MFE	MAPE (%)	Tracking signal
1. LKB	1523	5036753	983	42%	2.58
3. USSV	288	99103	-179	18%	-2.49
4. SMP-BC	219	154371	208	37%	3.80
5. Unique-Mixproof	271	88463	22	34%	0.32
9. LKH	49	3355	3	23%	0.25
10. LKH Prime	24	1362	20	23%	3.27
12. Automation	5125	70516674	5125	32%	4.00
14. Cleaning	42	2521	10	18%	0.96
14A. RSH SB	21	557	-20	366%	-3.68
15. Agitator	7	88	-5	85%	-2.82

The green cells in Table 18, represent an improvement for a certain dimension of a component, while the red cells indicate a negative impact of the new method. The average forecasting errors were calculated by using the data of the different geographical areas. Only the components that were found as common to all the geographical areas were suitable for computing the average forecasting errors. Table 19 presents the forecasting errors of the results applying the old method for the same quarter.

Table 19. Forecasting errors applying the old method for Q1-2021.

Component	MAD	MSE	MFE	MAPE (%)	Tracking signal
1. LKB	1216	3283664	628	35%	2.07
3. USSV	444	247359	-444	32%	-4.00
4. SMP-BC	232	184225	220	33%	3.79
5. Unique-Mixproof	220	67060	7	24%	0.13
9. LKH	70	5098	-26	28%	-1.51
10. LKH Prime	27	1194	13	39%	1.94
12. Automation	5766	77864727	5766	47%	4.00
14. Cleaning	35	1862	24	15%	2.79
14A. RSH SB	22	577	1	341%	0.09
15. Agitator	8	69	-8	132%	-4.00

In most of the components we can see an improvement in the accuracy of the model, even though the trend is opposite for some components. It has to be noted that, the numbers of the forecast were taken from the new model without any qualitative adjustments. It is necessary when using the model to take into consideration possible qualitative adjustment made by the manager that further will increase the accuracy of the new model. A qualitative adjustment of the number provided by the new model would increase the accuracy of the forecast and deliver even better results. An example of the need of a qualitative adjustment can be seen in the LKB component, for which the model is not performing optimally. The MAD in Table 18 is calculated as an average of the absolute forecast errors of the different geographical areas. Specifically, there was an increase of three time in the components purchased in Q1-2021 compared to the previous quarter when analyzing the numbers of China. These sudden types of increases from one quarter to the next are difficult to forecast exclusively with quantitative forecasts. It is important, especially for a component like LKB, to gather information regarding a possible increase or decrease in the demand. Information regarding a decrease or increase in demand would increase the performance of the qualitative adjustment before sending the entire forecast to Supplier X. We can from Table 18 in addition see that the values of the tracking signal are acceptable since they all are within the recommended boundaries of -4 and 4.

5.2.2 Comparison with the Old Method Applied to Year 2021

Comparison was thereafter performed between the same results as obtained above from the new model and the forecasting errors calculated for the old method. The accuracy of the old forecasting method was analyzed in section 4.2, corresponding to Table 4. Table 20 presents the new results of Q1-2021 in comparison to the accuracy in the total demand of 2021. The numbers are the same of Table 18 but compared in this to the forecasting errors calculated in section 4.2.

Table 20. Forecasting errors of the new model in Q1-2021 compared to the accuracy of the old method

Component	MAD	MSE	MFE	MAPE (%)	Tracking signal
1. LKB	1523	5036753	983	42%	2.58
3. USSV	288	99103	-179	18%	-2.49
4. SMP-BC	219	154371	208	37%	3.80
5. Unique-Mixproof	271	88463	22	34%	0.32
9. LKH	49	3355	3	23%	0.25
10. LKH Prime	24	1362	20	23%	3.27
14. Cleaning	42	2521	10	18%	0.96
15. Agitator	7	88	-5	85%	-2.82

Green cells in Table 20 represent an improvement in the forecast accuracy for that dimension, compared to the accuracy of the old model calculated in section 4.2. The red cells highlight a decrease in the accuracy of a certain dimension compared to the old method. Table 21 illustrates the results obtained during the as-is analysis regarding the accuracy of the old method. Table 21 has been utilized as a comparison in order to understand the improvements of the new model as highlighted above.

Table 21. Forecasting errors calculated for the entire year 2021.

Component	MAD	MSE	MFE	MAPE (%)	Tracking signal
1. LKB	5056	66415674	4230	16	3.35
3. USSV	3653	22567054	797	27	0.87
4. SMP-BC	534	337252	50	30	0.37
5. Unique-Mixproof	1009	1985912	330	22	1.31
9. LKH	254	128515	90	12	1.42
10. LKH Prime	87	9817	28	27	1.28
14. Cleaning	122	21651	7	12	0.23
15. Agitator	27	944	23	24	3.40

In this case, as we can see from Table 21, the results show a clear improvement in the forecasting accuracy, especially when analyzing the MAD-values obtained. This is due to the fact that the new model applied to forecast the demand has the objective of minimizing the

MAD. The MAPE instead shows a negative trend for most of the components compared to the accuracy of the total demand of 2021. The numbers in Table 21 illustrates the average result of an entire year. As explained earlier, the old method is providing good forecast for the total results of an entire year. Since the values in Table 19 refers to a single quarter but different geographical areas could be the reason for obtaining the negative values regarding MAPE.

6. Discussion

The following chapter contains a discussion and reflection regarding both the new and the old forecasting model for Tetra Pak. The chapter begins with presenting the key findings of this design science study. The key findings section covers a discussion regarding the current forecasting model used at Tetra Pak. In addition, key findings are discussed regarding the new developed forecasting model, including a summary of its strengths and weaknesses. Furthermore, a discussion regarding the attempt of building a model based on the project opportunities pipeline is presented. The DMAIC approach applied to the development of the model is also discussed. The chapter is finalized by reviewing the research questions of this study.

6.1 Key findings

The key findings are discussed in this section both regarding the old method, the project opportunities pipeline attempt and the new model.

6.1.1 Current Forecasting Model

The design science study started with an As-is analysis regarding Tetra Pak´s current forecasting procedure. The forecasting process of the demand for Supplier X is done by the OEM Components department. Once it was possible to get access to the forecasting model, we understood that the current forecasting process is established on a quarterly basis. The estimated demand is computed by combining an average of the actual demand of the previous two quarters with a coefficient representing the stand-alone components increasing trend. The calculation of the estimated demand includes a coefficient of expected projects to be in the opportunity pipeline during the new period. Once the As-is analysis was finished, it was noticeable that Tetra Pak’s current forecasting procedure is not based on a scientific model. This aspect made the model not reliable especially for the demand of each quarter. In addition, interviews were conducted with other stakeholders connected to the forecasting process. It was possible with the support from the interviews to understand the importance of having a good forecasting procedure and its contributing benefits. A more accurate model could benefit the supplier for the planning operations and thus reduce the production lead time. By having support from Supplier X, it was possible to also understand that the model should take forecasting errors into consideration. Forecasting errors were therefore studied to primarily analyze the performance of the current forecasting model. Findings from the model were that the forecasting errors were relatively high in respect to MAD, MSE, MFE and MAPE. The tracking signal of every OEM Component indicated however a positive result since the values were within the recommended values. It was recognizable in addition that the demand pattern deeply varied depending on the different OEM Components, such as pumps, valves, and tank equipment. Some components indicated a relatively steady demand pattern, while other components indicated a more volatile demand pattern. It was therefore important to apply different forecasting methods such as exponential smoothing, moving average or exponential smoothing with trend in order to determine which of them was more suitable to the demand of the OEM Components. What we in addition could see from the As-is analysis was that the current forecasting procedure did not perfectly fit the demand. Low accuracy occurs at the level of each quarter, while instead the performances were better when considering the sum of the entire year.

6.1.2 New Developed Forecasting Model

According to Tetra Pak's desire, the forecasting model should be developed and based on project opportunities pipelines. A software program called SAP Power Bo was used in order to perform a spend analysis of Tetra Pak for year 2020-2021. The objective was to understand more in detail the demand between Tetra Pak and Supplier X. It was possible with the spend analysis to categorize and understand the amount of a component that is connected to both a specific project size as well as to a specific project category. This was established for both year 2020 and 2021 in order to see if any patterns or similarities could be observed. Significative patterns were unfortunately not found for both year 2020 and 2021. The results indicated that the average amount of e.g., LKB components per beverage project decreases during year 2021 while the opposite for year 2020. Similar studies made with the other product categories such as Cheese, Dairy, Ice-Cream, Powder and Prepared Food indicated similar results as explained for the Beverage category. These previously mentioned results indicate that no correlations can be found between the two analyzed years in the Master Data file. In addition, uncertainties within the data of the Master File might be one of the major reasons behind not finding any correlations between year 2020 and 2021. Furthermore, there was no clear match between the number of 2020 and 2021 for what it regards the average of components needed for a certain project size and category. This means that when calculating the average of the two years the risk is to obtain an approximated number that does not represent the reality.

At same time as part of the model, the objective was to connect the results obtained from the analysis of the components needed for each type and size of project to the opportunity pipeline of the quarter to forecast. The opportunity pipeline was in this case obtained from Smart Sales CRM system for the second quarter of 2022. By knowing the amount of a specific category project within the opportunity pipeline for Q2-2022, it would be possible in theory to determine the quantity of a specific OEM Component connected to it. In order to do this, it was necessary to multiply the average of components needed per project with the projects in the pipeline for the next quarter. With this procedure it was possible to obtain the number of components needed in the next quarter for the project requirements. It was necessary as the last step of the model to understand how to translate the demand only for the projects into a total demand for all the four channels in the next quarter. Using the Master Data file, it was possible to segment the demand of year 2020 and 2021 in the different channels. Correlation and similarities were found for some components such as LKB. For other components as shown in section 5.1.2 unfortunately the percentage were very different in 2020 and 2021. The idea was to find the average of the projects requirement percentage in order to determine the total demand.

As presented in section 5.1.2, this method was applied to some components for which it was possible to gather the necessary data. As seen, the results were not appropriate when compared to the actual demand for the period. The reasons behind this can be found in the numerous approximations that was necessary to perform in order to obtain the final forecast. First of all, the number of components per each type and size of project is obtained as an average of the data in 2020 and 2021. By looking at the Master Data file more in detail it is possible to note that each of the size and type of project of the same type can have very different numbers of components needed. By taking an average of all of these projects the number we obtain cannot be considered as reliable. Furthermore, there are significative differences between the numbers of 2020 and 2021 which means that is not possible to find an average that reflects in an appropriate way the reality. Another factor that contributes to the low level of reliability of this model is the discussion around the project pipeline. It is not clear how long it takes between the moment that a project deal is closed and the moment when the components are ordered from

Supplier X. This aspect adds insecurity to which ones are the projects within the pipeline that should be included in the next period of opportunities. The assumptions here is to consider those projects that have a go and get-rate above 70%. This assumption does not assure that the components related to these projects will be ordered in the next quarter. Furthermore, another aspect that can provide errors and insecurity is the segmentation of the demand in the different channels. Some of the components showed a steady percentage of the demand represented by the projects both in 2020 and 2021. This means that we for the next quarter can assume that the project requirements will represent the same percentage of the total demand. The percentages in 2020 and 2021 for other components were very different and therefore very difficult to identify the total demand in a reliable way. Further analysis was conducted in order to strengthen the statement of not recommending a forecast model to be based on opportunity pipelines. It was possible by extracting projects within the opportunity pipeline and multiplying with the average quantity that a specific OEM component corresponds with to find the total quantity that e.g., five beverage projects of a L0 within the opportunity pipeline in Q4-2021 stands for. The results obtained indicated that there was a large difference in comparison to the actual demand of Q4-2021.

Thereafter, exponential smoothing was found as the most appropriate method to use when developing the forecast model for Tetra Pak. The reason for selecting Exponential smoothing over forecasting methods such as Moving average or Exponential smoothing with trend was due to the behavior of the demand. No trends were found during the analysis of the demand, thus excluding the method called Exponential smoothing with trend. A comparison was thereafter conducted between Exponential smoothing and Moving average. It was in this occasion important to find out which of these two forecasting methods suited the fluctuating demand best. Exponential smoothing provided in the end more reliable results in terms of accuracy, thus it was chosen as the appropriate forecasting method for the new model. The new model was developed in Excel due to its easiness to handle. Furthermore, the model provides result for the next quarter, while historical data from the last eight previous quarters are used as inputs. The final model can be applied to a maximum of 25 components, which can be seen as acceptable since new components continuously are introduced while other becomes obsolete. One geographical area can be inserted to the model and forecasted at the time. Forecasting one geographical area at the time can be seen as a disadvantage. There are in total four geographical areas, thus indicating that the model in total must be simulated four times.

In addition, the model consists of several functions available in Excel, thus increasing the model’s actual procedure. Excel Solver in combination with applying Virtual Basic for Application in Excel enables the model to be applied quicker, even though it must be repeated four times. The model enables the optimal alfa value to be found and applied efficiently to the exponential smoothing method. Additional functions have been applied for the employees at the OEM Components department to understand the models provided output. The additional function displays the alfa values above one to automatically be highlighted in red. Further instructions and recommendations are included on how the OEM department should proceed with components receiving a high alfa value. Improvement on the accuracy was seen on several components when comparing the new forecasting model with the old one. Some components illustrated however the opposite result and especially when analyzing some specific forecasting errors. When applying old data from the first quarter of 2021, tracking signals for all components were acceptable and within the recommended limits. Table 22 illustrated the strengths and weaknesses that were discussed with the final model.

Table 22. Strengths and weaknesses with the new forecasting model.

Strengths	Weaknesses
Highly automated procedure. Low run time for simulating the model.	One geographical area can be applied at the time. Requires the same procedure to be repeated four times.
Flexible and scalable. Can be applied up to a maximum of 25 components	Can only forecast one quarter ahead. Qualitative adjustments have to be applied for quarters further away.
User friendly. Easy to use, understand, and general guidelines of the model are included.	Qualitative adjustments required to be taken into consideration in order to include trends or occasions which the model cannot predict.
Forecast model based on a standardized procedure	
Forecasting errors taken into consideration in the model	

The DMAIC approach and respective activities have been followed throughout the design science study. The goals of the new forecasting model were defined in the beginning of the study. The goals have continuously been updated throughout the study due to limitations with data extracted from Power BO. Stakeholders from both Tetra Pak and Supplier X have been identified and interviewed continuously throughout the study in order to receive additional support with developing the most appropriate model. Measure is the seconds step in the DMAIC approach. Measure has been established by both conducting an As-is analysis on the current forecasting model and on the new model. Performance of the currently used model indicated results of low accuracy. Low accuracy occurs at the level of each quarter, while better performances were identified when considering the sum of the entire year. Additional measures were conducted once the new forecasting model was established. The objective with the measures was to illustrate an improved performance of the new forecasting model for most of the OEM Components analyzed.

As explained earlier, different approaches for developing a forecasting model were conducted. The final model is based on using a time-series forecasting method called exponential smoothing. Exponential smoothing in combination with applying the key properties and also including forecasting errors improved the performance of the new model. The model has throughout the study been improved to increase its performance. The exponential smoothing together with a temporary solution of the model was tested during Q2-2022. The forecasted values obtained were later sent to Supplier X. The fifth and last step within the DMAIC approach is Control. Control puts emphasis on ensuring that every stakeholder is well informed about the new forecasting model and its properties. The forecasting model has been demonstrated several times to the supervisors of this study. The objective with demonstrating the model is to receive continuous feedback and possible improvements that could be made to it. The model includes several guidelines to make it more user friendly. Several KPI´s have been applied to the model in order to track its performance. The model focuses on minimizing the MAD value while at the same time analyzing the alfa-values. OEM Components forecasted and resulting in an alfa-value equal or above one will automatically be highlighted with red. Color red indicates that qualitative adjustments have to be applied in order to estimate the forecasted demand. The DMAIC approach have been used continuously throughout the design science study as a support to develop the final model.

6.2 Reviewing the Research Questions

The three research questions that have been used throughout the design science study are listed below:

1. *How should the solution be designed in order to fulfill the key properties?*

2. *What factors except from historical data and installation projects should be included?*

3. *How do we establish a more secure business environment with the help of the forecasting model?*

The research questions were defined in the beginning of the study and has been taken into consideration in order to guide us throughout the entire design science study.

For what it concerns the first question, it helped us especially when developing the new model. It is important to remember that the key properties required by Tetra Pak are ***Flexibility***, ***Scalability***, ***Easy to Use***, and ***Reliability***. In order to fulfill them and answer the research question, the model was designed using Excel and with an easy layout to understand. The fact that the model is built in an Excel file makes it easy to use since it is a very well know software and most of the workers know how to handle it. Flexibility was achieved by making possible to forecast multiple components at the same time. Furthermore, the geographical areas have a different number of components to forecast but this is not an issue since the number of the components forecasted is not fixed. The model can forecast up to 25 components at the same time, but it can be easily adapted to forecast more in case the number of components in the future increases. This can therefore be seen as fulfilling the scalability requirement. For what it concerns the scalability, the model contains eight quarters as the historical data. The model can in case of needs easily be increased or decreased. Reliability of the model is assured using a well-known forecasting method called Exponential smoothing. Exponential smoothing is used by numerous companies and largely studied in the literature. The model automatically highlights components for which the alfa values are not appropriate and therefore the exponential smoothing might not be appropriate.

The second research question was fundamental during the attempt to develop a forecasting model based on the opportunity pipeline. This research question enabled us to e.g., develop a study on the percentage of the different channels contributing to the total demand. The main answer to what other factors should be included regards the importance of the qualitative adjustment in a forecasting model. It was possible throughout the entire study to understand how important it is to add qualitative information to the quantitative analysis. The exponential smoothing forecast is not able to predict a sudden increase in the demand due to political, social, or other reasons and especially if there are not trends in the past quarters. It is extremely important to be informed about relevant change of the demand in the different channels when filling the forecast. An example is the change in the cost policy at Tetra Pak that happened at the end of the last quarter of 2020. In this case many customers ordered a higher number of components in order to avoid the price increase in the next period. This sudden increase cannot be identified by the model based only on quantitative analysis. It has to be taken in consideration by a qualitative adjustment based on the assumption that the demand will increase due to the price change in the next quarter.

It was necessary in order to ensure a more secure business environment to develop a reliable forecasting model with an increased accuracy. To achieve this, it was necessary to understand problems and requirements from the different stakeholders towards this project. This understanding was achieved with the interviews performed at the beginning of the study both to Tetra Pak and Supplier X. It was fundamental to deeply understand the requirements and challenges for the forecast model in order to develop a new solution. A more secured business environment can be achieved by controlling and evaluating the performance of the forecast model. It is necessary to regularly check and calculate the accuracy of the forecast model when the actual demand data are available. It is possible with this follow-up operation to check the real performance of the model and adjust aspects that might be identified as critical.

7. Conclusion

The following chapter contains a conclusion regarding this design science study. Areas of future research, recommendations and the studies contribution to theory are presented in this chapter.

The objective of this Master Thesis project was to develop a forecasting model using the information contained in the project opportunities pipeline. This idea has demonstrated its complexity throughout the design science study and did not provide the desired results. Indeed, it was not possible to develop a forecasting model based on the project opportunities pipeline. As discussed above in Chapter 6, this was due to many layers of approximation and missing correlations and patterns between different years and quarters. The complexity of extracting data also made this project more challenging. It can be argued from another perspective, that not finding this correlation is a result itself. The idea of developing a forecast model looking at the projects in the quarters is in theory valuable. Not finding the necessary data and correlation made this idea not possible to realize. The tables containing the correlation of each project category and size for different years can still be considered relevant as a result of this study. These data can be useful for the OEM Components Department to have a better vision over the different projects and how the components such as valves, pumps, and tank equipment's are used. This study shows that the correlation between the projects in the pipeline and the total forecast of the demand is not immediate. There are various factors to be taken into consideration as discussed and analyzed. First of all, there are many channels contributing to the total demand and the risk by only looking at the Project's Requirement is to underestimate the changes in other channels. It was necessary to make approximations and assumptions in order to obtain the necessary data for computing the forecast. These approximations contributed to less reliable results when we obtained the correlations between the size and type of project and the number of components needed.

The new model that is developed represents a standard and reliable method to forecast the next quarter by looking at the numbers of actual demands in the past quarters. The new method represents an improvement compared to the old non-scientific method utilized in the past. It can be considered as easy-to-use, scalable, reliable, and flexible. This method is not taking into consideration information regarding the project opportunities pipeline, but instead based on time series data. On the other hand, this study also showed the importance of having qualitative adjustments related to forecasting in real life occasions. There are external factors that influence the increase or decrease of the demand which cannot be identified by a quantitative forecasting method. These factors should be considered, and qualitative adjustments should be made in order to obtain a better forecast.

7.1 Areas Of Future Research and Recommendations

The quarterly data made it difficult to identify an increase or a decrease in the demand from one quarter to the other. The 3 months periods within a quarter can be difficult to forecast and consequently resulting in larger forecasting errors. Monthly data is recommended to extract in order to handle better unexpected increases and decreases in the demand. Monthly data used by Tetra Pak can benefit them to monitor in detail the demand patterns and better understand possible trends for the future. We believe by analyzing monthly instead of quarterly periods that it is possible to handle and understand the demand better, especially in those occasions that contains unexpected demand.

The time that it takes for a project to enter and exit from the opportunity pipeline is another interesting aspect to further analyze in the future. This can be very useful for a future attempt to develop a new forecasting model by looking at the projects pipeline. This information is fundamental in order to understand which projects contained in the pipeline will have an impact in the next quarters. This proposed recommendation also emphasizes on understanding the time that elapses from when a contract with a customer is finalized to when an order for the components is placed to Supplier X. This aspect was unfortunately not analyzed due to the study's limited timespan.

There are four main channels as we could understand that contributes to the total demand from Supplier X. The focus in this study was regarding the channel driven by Project Requirements. Further research can be carried out on the remaining three demand channels. These channels might be more stable, with less variables and therefore easier to forecast. It can be useful correlated to this point to improve the communication with e.g., the departments responsible for plant components and spare parts. Improving the communication can produce more information and awareness regarding the next quarter, which will result in a more accurate forecast.

7.2 Contribution to Theory

The design science study is a contribution to theory and practice through purposeful design and evaluation. This study can be characterized as an exploratory research based on direct observations, interviews and historical data. The design science study has allowed us to develop a customized model with the purpose to forecast OEM Components between Tetra Pak and Supplier X. Developing a model based on opportunity pipelines requires reliable and accurate data without several approximations applied. The previously mentioned statement can be valuable for other enterprises operating in a similar environment as Tetra Pak and interested in developing a forecast model based on it. The final forecasting model was based on Exponential smoothing, which could be applied to a broader portfolio of OEM Components. Exponential smoothing is one of the most utilized time series methods within forecasting. This study can therefore support the statement of Exponential smoothing being appropriate when forecasting OEM Components, which therefore can be implemented to enterprises operating in a similar environment as Tetra Pak. This study has finally emphasized the importance of including a qualitative forecasting method to adapt to trends or changes in the demand, which would increase the performance of the forecast.

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Interviewees:

Nicole Uvenbeck, OEM Components Manager, January 2022

Appendix

Appendix 1 – Semi-Structured Interview Protocol

Semi-structured interviews applied throughout all the interviews conducted with both Tetra Pak and Supplier X employees. The objective with the semi-structured interviews is to motivate the discussion on the topic in question.

Appendix 1.1

Participants: Faruk Kodzaga, Giacomo Daniele and employees from Supplier X
Equipment used: Notebook & tape recorder
Place: Microsoft Teams
Date: 11th of February
Aim with the interview: Gather general information regarding Supplier X as a company, information regarding their pumps and to understand how they manage the forecast that they receive from Tetra Pak. See from their point of view what they think about the current process of forecasting.

General Introduction

What is your role at Supplier X and what are your main responsibilities?

Could you explain what Supplier X is mainly working with?

What types of components are you working with and how many types?

Are you working in B2B environment? If a customer of Tetra Pak orders pumps as stand alone, do you drop ship it directly to the customer or do the pumps go via Tetra Pak?

Targeted Questions Regarding the Forecasting Model

Are the pumps, valves & tank equipment custom designed for only Tetra Pak?

What is the lead time for producing the pumps, valves, and the tank equipment?

What is the lead time for delivering the pumps, valves, and the tank equipment to Tetra Pak?

How do you use the forecast model after you receive it from Tetra Pak? What information are included in the forecast that you receive quarterly? What do you believe are the pros and cons with the current forecasting model?

As we understood, you have monthly meetings with Tetra Pak regarding the pre-announcement process. How do you use this information about the pre-announcements? Is this influencing the forecast that you previously received?

Conclusion

Are you satisfied with the forecasting model that you receive? What improvements do you believe can be made?

Appendix 1.2

Participants: Faruk Kodzaga, Giacomo Daniele & Manager Project Management and Coordination Strategy Capabilities.
Equipment used: Notebook & tape recorder
Place: Microsoft Teams
Date: 4th of February 2022
Aim with the interview: Gain broader understanding of the project opportunity pipelines at Tetra Pak. Aim is also to receive insights into Power BI & SAP BusinessObjects (BO) software.

Introduction

What is your role within Tetra Pak, what are your main responsibilities?

What types of components are you working with in the projects and how many?

Targeted Questions Regarding the Forecasting Model

How would you define the different opportunities for Tetra Pak? How is that correlated to the projects?

Are you providing the project opportunity pipeline to the forecast? How do you develop the project opportunity pipeline? What are the most relevant data when developing a project opportunity pipeline?

What is the lead time from when the project is signed with a customer and when the order is placed to Supplier X?

As we have understood, Power BI and BO software can be relevant for our master thesis. Do you agree and in what way do you think it is appropriate for us? Could you illustrate shortly how the software works?

Conclusion

What improvements do you believe can be made regarding the creation of a forecasting model?

Appendix 1.3

Participants: Faruk Kodzaga, Giacomo Daniele & Procurement Manager Paperboard
Equipment used: Notebook & tape recorder
Place: Microsoft Teams
Date: 9th of February 2022
Aim with the interview: The respondent tried a couple of years ago to create a forecasting model. The aim is to obtain information on what went wrong during the time when he tried to create the model and receive valuable information for succeeding in our project.

Introduction

What is your role within Tetra Pak, what are your main responsibilities?

Targeted Questions Regarding the Forecasting Model

What was the reason behind creating a forecasting model in the first place? Any specific needs?

How did it go when you tried to create the forecasting model? What challenges did you face throughout the project?

Do you have any recommendations or valuable information that you believe can be useful in our project? (We can explain our task and objective more in detail to get some input).

Would you recommend us to use any specific software system during our project and any specific analysis that you recommend us to do?

I see that you have shared a research paper regarding how to improve demand forecasting and two additional power points. Is there anything specific from the research paper that you believe are important for us in particular?

Conclusion

Is there any other relevant information or insight that you would like to share with us?

Appendix 1.4

Participants: Faruk Kodzaga, Giacomo Daniele & Senior Supplier Manager
Equipment used: Notebook & tape recorder
Place: Microsoft Teams
Date: 9th of February 2022
Aim with the interview: Understanding the perspective of the supplier. Supplier X, on the project's opportunities. Obtaining a clear picture about the need of better forecasting model. Finally, to understand what pre-announcement means and how it is connected to a forecast.

Introduction

What is your role within Tetra Pak, what are your main responsibilities?

How long have you been responsible for Supplier X from supply management?

Targeted Questions regarding Supplier X and Supply Management

Why do you believe that Tetra Pak needs a better forecasting model?

Could you elaborate a little bit on supply management and its perspective to Supplier X? How is supply management connected to forecasting?

As we have understood, you also work with opportunities and pre-announcement from the perspective of supply management. What does this mean regarding Supplier X and how can opportunities and pre-announcement be connected to the forecasting?

Which do you think are the main requirements for a good forecasting from the point of view of Supplier X?

Conclusion

Is there any other relevant information or insight that we missed and that you would like to share with us?

Appendix 1.5

Participants: Faruk Kodzaga, Giacomo Daniele & Technical Product Manager for Pumps
Equipment used: Notebook & tape recorder
Place: Microsoft Teams
Date: 14th of February 2022
Aim with the interview: Receive a broader understanding of the portfolio of pumps. Interviewing Anders who is the product manager for pumps will be of our advantage before starting with the actual forecasting model

Introduction

What is your role within Tetra Pak, what are your main responsibilities?

Targeted Questions Regarding Pumps and the Current Forecasting Model

How many different types of pumps are there in the portfolio? How many of these pumps are purchased from Supplier X?

Are there any relevant data that you believe is worth sharing to us that might be useful for us when trying to develop the forecast model for the pumps of Supplier X?

What do you believe are the pros and cos with the current forecast model for Supplier X?

Are you included in the monthly meetings with Supplier X regarding opportunities?

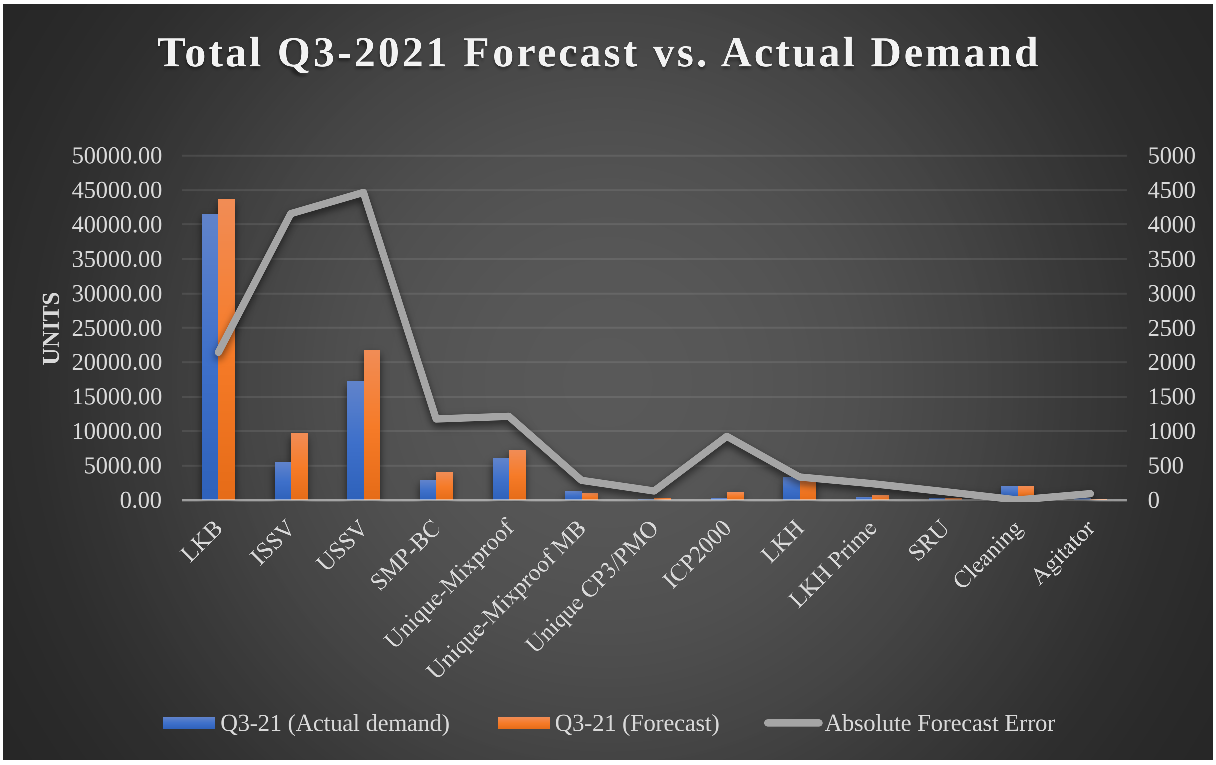
Conclusion

Is there any other relevant information or insight that we missed and that you would like to share with us?

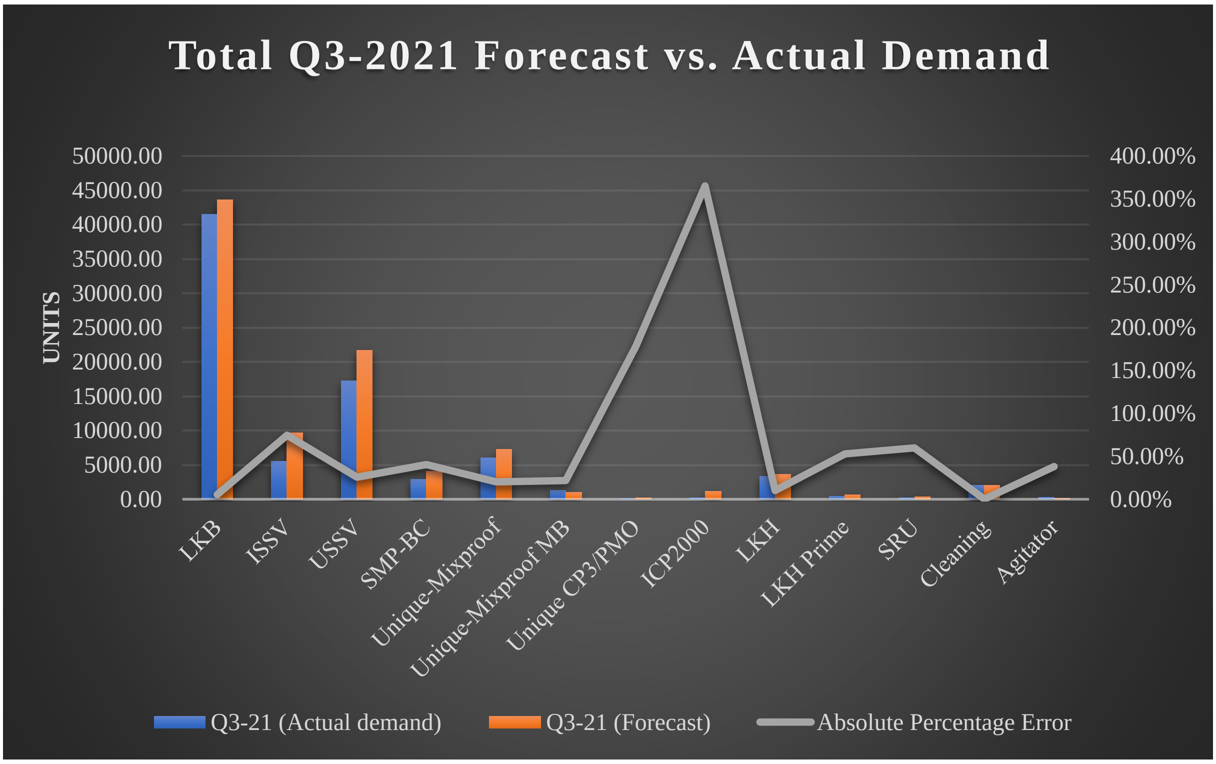
Appendix 2 – Forecast accuracy

Following appendix illustrates the comparison between the forecast and the actual demand for each of the components analyzed regarding the total numbers of the third and fourth quarter of 2021.

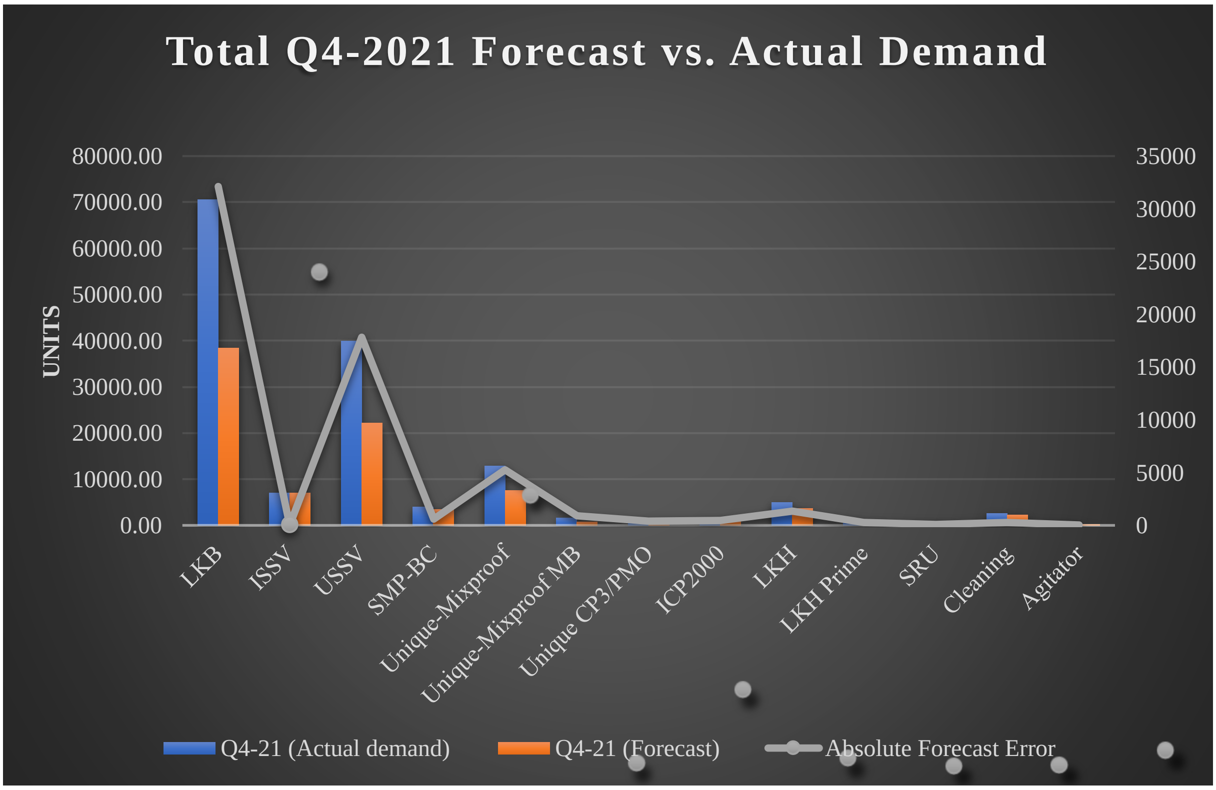
Illustrates the comparison between the forecast and the actual demand for each of the components analyzed including an Absolute Forecast Error. The data regards the total sum of the world for the third quarter of 2021



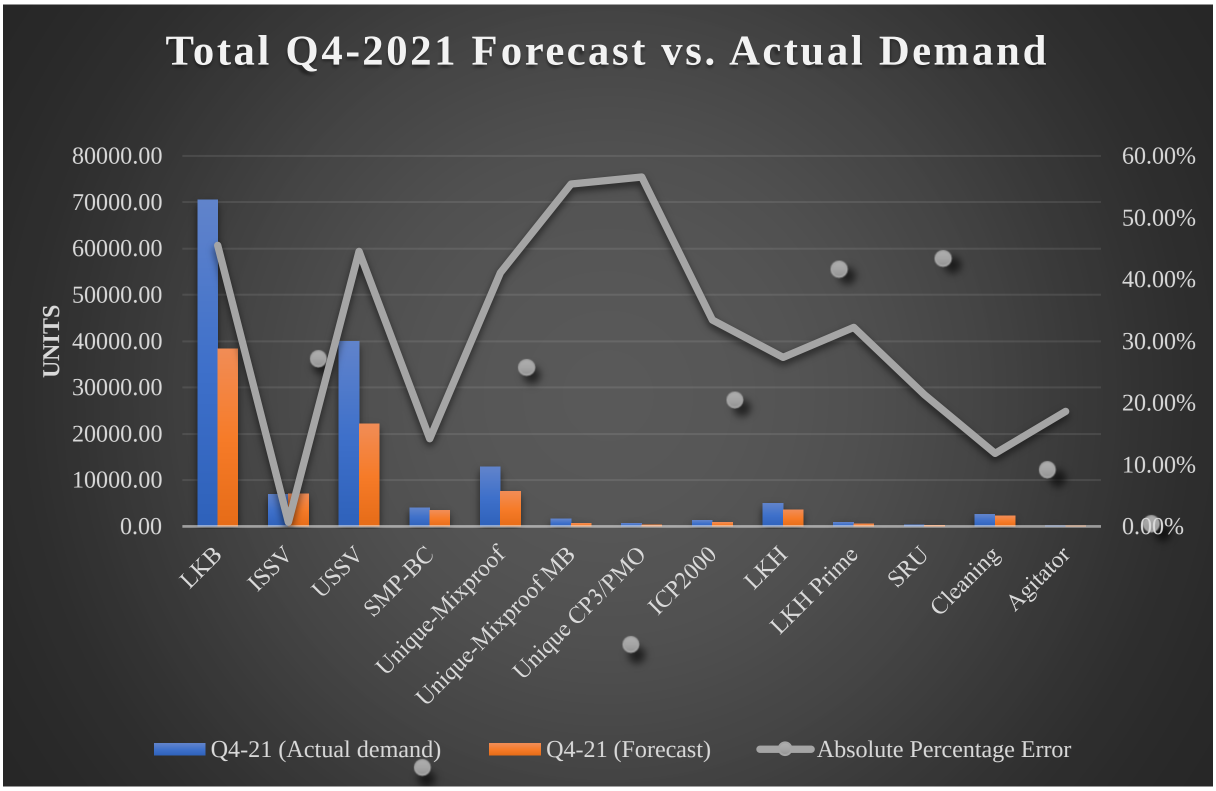
Illustrates the comparison between forecast and actual demand for all components analyzed including an Absolute Percentage Error. The data regards the total sum of the world for quarter three 2021.



Illustrates the comparison between the forecast and the actual demand for each of the components analyzed including an Absolute Forecast Error. The data regards the total sum of the world for the fourth quarter of 2021



Illustrates the comparison between the forecast and the actual demand for each of the components analyzed including an Absolute Percentage Error. The data regards the total sum of the world for the fourth quarter of 2021



Appendix 3 – Components and Projects Correlation

Following appendix illustrates the average amount of required components for a beverage product category depending on its project size. This is presented for year 2020, 2021 and for the accumulated value 2020-2021. The components analyzed are USSV, SMP-BC, Unique-Mixproof, LKH, LKH Prime, Cleaning and Agitators.

USSV

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice Cream	Powder	Prepared Food
L0	10	2	6	0	0	6
L1	16	16	20	26	15	24
L2	44	62	48	76	42	66
L3	68	32	82	92	60	52
L3+	280	70	80	0	178	0

SMP-BC

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice cream	Powder	Prepared Food
L0	0,78	0	1	0	0	0
L1	1	0	2	6	2	2
L2	4	0	12	6	0,28	0,64
L3	8	0	80	0,32	1	2
L3+	16	0	146	0	14	0

Unique-Mixproof

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice cream	Powder	Prepared Food
L0	0,66	0	0,6	0	0	30
L1	6	0	8	6	4	12
L2	12	0	14	34	10	10
L3	20	0	42	96	14	8
L3+	76	0	62	0	32	0

LKH

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice cream	Powder	Prepared Food
L0	2	0,94	2	0,72	0	2
L1	2	4	2	2	2	2
L2	4	8	4	10	6	4
L3	4	2	4	12	2	4
L3+	1088	4	2	0	22	0

LKH Prime

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice cream	Powder	Prepared Food
L0	0,54	0,48	0	0	0	0
L1	0,3	0,24	0,30	0	0,24	0
L2	2	2	2	2	0,80	0
L3	2	0,60	8	2	2	0
L3+	4	0	8	0	4	0

Cleaning

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice cream	Powder	Prepared Food
L0	0,1	0	0,24	0	0	0,5
L1	2	0,12	0,2	0,80	0,08	0,4
L2	6	2	2,68	0,12	0,08	1,1
L3	4	0,2	2	0	2	10
L3+	0,16	0	32	0	2	0

Agitator

Avg. 2020-2021	Beverage	Cheese	Dairy	Ice cream	Powder	Prepared Food
L0	0	0	0	0	0	0
L1	0,32	0,02	0,1	0,06	0	0,02
L2	2	0	0,2	0	0	0,08
L3	0	0	2	0	0	1,3
L3+	2	0	0	0	0	0