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On the Service Level Disparities between Spare Parts Segments

A Case Study at Tetra Pak Technical Service

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June 2023

Acknowledgements

We would like to express our sincere appreciation to Tetra Pak for this opportunity along with their cooperation and support throughout our investigation. We extend our gratitude to Markus Persson, our company supervisor, Jan Olhager, our University supervisor, and Erik Birath, for their valuable guidance and assistance throughout this thesis. We are grateful to all the interview subjects who generously shared their time and valuable knowledge. We also thank Henrik Lönn for initiating the project and giving us reassurance along the way. Finally, we are grateful to Överklagandenämnden for granting an exemption that was essential for one of the authors.

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Abstract

Title: *On the Service Level Disparities between Spare Parts Segments - A Case Study at Tetra Pak Technical Service*

Problem Description: Tetra Pack Technical Services provides spare parts for Packaging and Processing product segments. Despite similar inventory management, the processing segment consistently has a lower spare parts service level. Understanding the reasons behind this disparity is crucial, especially with the anticipated increased growth of the Processing segment in the future.

Purpose: The purpose of this thesis is twofold: firstly, to investigate and understand the factors and root causes behind the difference in service levels for spare parts; and secondly, to propose and evaluate potential implementations aimed at increasing the service level for processing materials, from an impact-effort standpoint.

Research Questions:

- **RQ1 -** Why is the Service Level higher for Packaging Spare Parts compared to Processing and what factors and root causes are responsible?
- **RQ2 -** How can these factors and root causes be counteracted?

Methodology: An exploratory case study is performed using documentation, archival records and interviews. With the data collected both qualitative and quantitative analysis is performed in order to determine the root causes.

Conclusion:

- Processing spare parts have lower target service levels due to lower sales volumes.
- Processing Suppliers exhibit higher lead time variability which is not accounted for.
- The Processing Customer base is less likely to communicate demand planning in advance for maintenance.
- Processing spare parts contain less detailed information that accommodate the planning process due to a more decentralized organization.

Recommendations include accounting for lead time variability, differentiation between Packaging and Processing item segmentation methods, revising Target Service Level criteria, increasing Planned Ratio for Processing, and understanding supplier behavior differences.

Keywords: *Spare Parts Management*, *Spare Parts Inventory Management*, *Service Level Disparities*, *Inventory Control*

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Acronyms

CV Coefficient of Variation

EOQ Economical Order Quantity

ERP Enterprise Resource Planning

FIFO First In, First Out

M&A Mergers and Acquisitions

NS Not Stocked

OFR Order Fill Rate

PO Procure to Order

RI Replenishment Indicator

SKU Stock Keeping Unit

SL Service Level

SP Spare Part

SPIM Spare Parts Inventory Management

SPP Service Parts Planning

SS Safety Stock

SSN Services Supply Network

ST Stocked

TPMS Tetra Pak Maintenance System

TPTS Tetra Pak Technical Services

TSL Target Service Level

VAU Value Annual Usage

1 Introduction

This section will provide some context and background to the studied phenomenon as well as a general description of the case company and its relevant business units. After this, a general problem description is provided along with purpose, focus and delimitation and a report outline.

1.1 Background

In virtually all producing industries, minimizing equipment downtime is a key success factor. Consequently, efficient and timely maintenance is paramount, which in turn relies on a well-developed spare parts management system.

As formulated by Hu et al. (2018), the management of spare parts is often considered to be a special case of general inventory management with some peculiar characteristics, which makes it especially difficult.

In recent years a movement called "right to repair" has been gaining traction, which concerns the legal right of end costumers to be able to gain information regarding parts, tools and blueprints from the producers so that they can perform repair and maintenance either themselves or through other channels (Zhang et al., 2021).

While this might seem to affect mostly consumer electronics at the moment, Zhang et al. (2021) stipulate that this trend is part of a larger movement towards creating more sustainable supply chains. This would be achieved by moving away from the current culture some manufactures have of *"planned obsolescence"*, where products are designed to be short lived in order to promote new products, and adopting a more customer service minded after-sales culture where companies offer services that help make sure that the producer-customer relationship thrives

With the aforementioned in mind, one of the most important performance indicators of spare parts management becomes the extent to which customers are served on time. A large part of this is measured in terms of Service Level (SL).

The complexity of spare parts management, its rising importance, and its connection to service level demonstrates the relevancy of understanding how spare parts management decisions impact service levels.

1.2 The Company

The main themes of this thesis is spare parts management and service levels. These themes will be investigated within the Services Supply Network (SSN) division at Tetra Pak. In Figure 1, the placement of SSN is displayed.

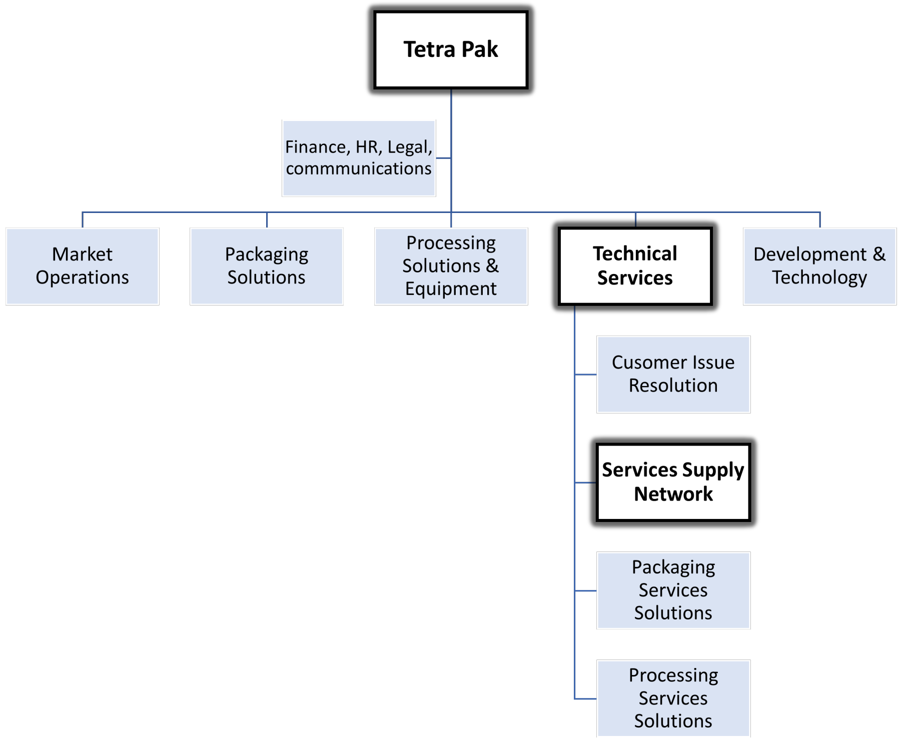


Figure 1: Tetra Pak Organizational chart. The placement of Services Supply Network is highlighted.

Tetra Pak is a global food packaging and processing company founded by Ruben Rausing in 1949. The company prides itself in providing safe, innovative and environmentally sound products to customers in more than 170 countries. Tetra Pak is itself owned by Tetra Laval. The company's product portfolio is divided into two main businesses: Processing and Packaging solutions, referring to the purpose of the product. Currently, 8870 Packaging machines and 104726 Processing machines are in operation. In 2022, the net sales of Tetra Pak reached over €11 billion ("Tetra Pak in figures", 2022), and Tetra Pak Technical Services (TPTS) accounted for an undisclosed, yet significant portion of these.

TPTS plays a crucial role in the operations of Tetra Pak, as its main responsibility is the after-sales services, including machine maintenance, spare parts and repairs. Within TPTS, SSN is responsible for executing and realizing the strategic goals of the spare parts supply chain. These goals strive towards maximizing machine uptime for customers while minimizing risk and cost. In their operations, this goal translates into balancing service levels and inventory costs for spare parts, which is an extremely complex task in a global supply chain. A simplified illustration of the Tetra Pak Supply Chain Structure can be seen in Figure 2, where the dotted line indicates the scope of this thesis.

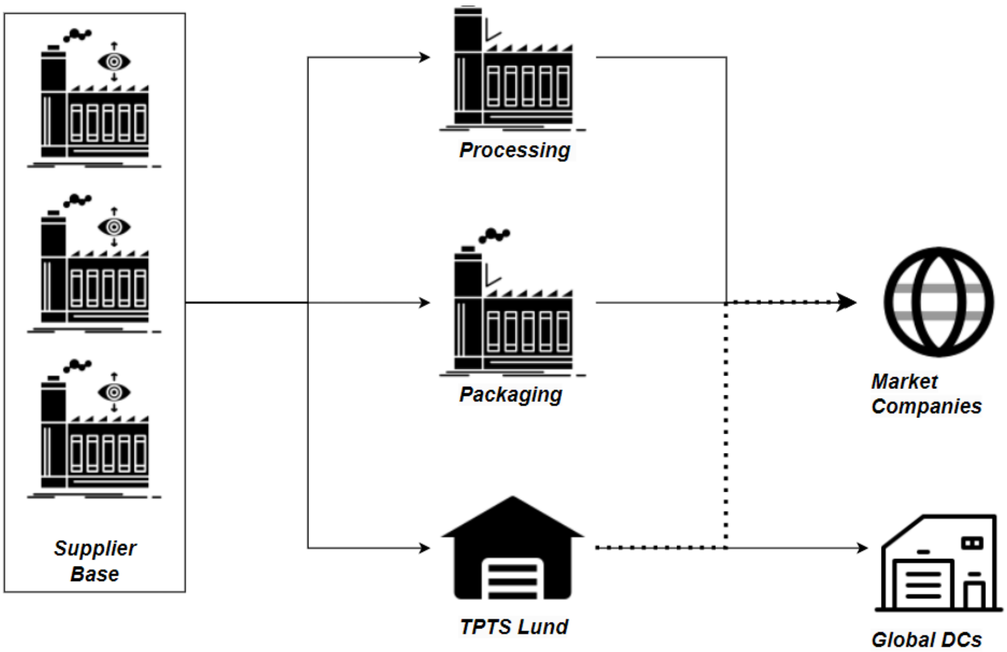


Figure 2: Simplified illustration of TPTS's role in the Tetra Pak Supply Chain

1.3 Product Characteristics

1.3.1 Packaging Solutions

The Packaging solutions offered by Tetra Pak can be divided into two main categories: filling machines and downstream equipment. Downstream equipment include accumulators, conveyors, cap or straw applicators etc.

Generally, filling machines and downstream equipment setups are very similar across the customer base. This is mainly due to the standardized nature of carton packages offered to retail customers.

From a spare parts perspective, Tetra Pak has a good knowledge of their installed base of Packaging machines and the what components each machine is comprised of.

1.3.2 Processing Solutions

The Processing solutions offered by Tetra Pak include a wide range of machines with different applications such as separators, homogenizers, filtering solutions etc.

Generally, processing equipment has to be customized to the customer to a much higher extent that for packaging solutions. Even small differences in recipe can greatly impact the design of a machine.

From a spare parts perspective, Tetra Pak does have a good knowledge of how many Processing machines have been produced historically. However, they do not have a good knowledge of how many of these are still active, their locations and in what system configuration they exists. They also lack specific knowledge of what components historical Processing machines is comprised off compared to Packaging machines.

1.3.3 Comparison

In Table 1, a comparison of some key figures between the Packaging and Processing businesses is displayed.

	Processing	Packaging
Installed bases	104726	8870
Achieved Spare Part Service Level	90.1%	94.1%
No. of Spare Part Order Lines	228000	786000
Number of Equipment categories	34	4

Table 1: Comparison of some key figures between the Processing and Packaging business as of 2022. Numbers are scrambled due to confidentiality.

1.4 Problem description

TPTS currently shows a significant difference in service level between their two main segments: Packaging and Processing parts. These segments refer to spare parts for Tetra Pak's packaging and food processing machines, respectively. The service level for the Processing segment has been consistently lower than that of the Packaging segment. Figure 3 displays the achieved service level over the years 2019-2022.

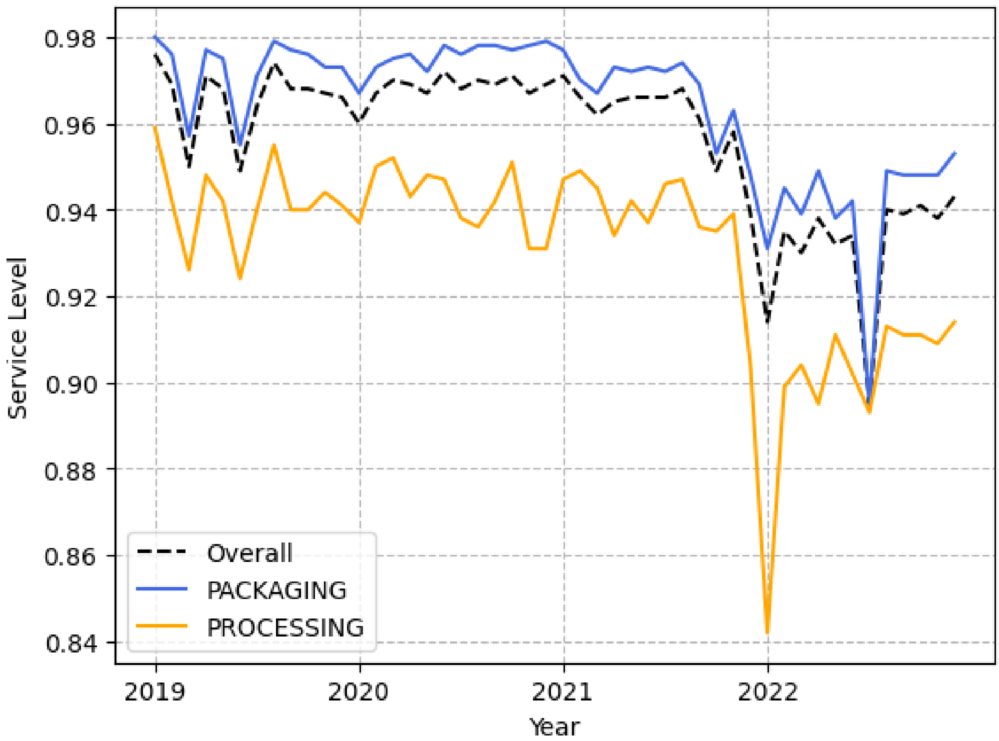


Figure 3: Achieved service level overall, and for Packaging and Processing respectively for the years 2019-2022.

2022 was a particularly challenging year for TPTS, due to many global supply chain disruptions. Most notably, semiconductor shortages and Covid-19 lockdowns in China. However, these disruptions seem to have affected both segments somewhat similarly.

1.5 Purpose

The purpose of this thesis is twofold: firstly, to investigate and understand the factors and root causes behind the difference in service levels for spare parts; and secondly, to propose and evaluate potential implementations aimed at increasing the service level for processing materials, from an impact-effort stand- point.

From this, the following research questions were constructed:

- ***RQ1* - *Why is the Service Level higher for Packaging Spare Parts compared to Processing and what factors and root-causes are responsible?***
- ***RQ2* - *How can these factors and root causes be counteracted?***

1.6 Focus and Delimitations

The following factors were not addressed, as they were deemed out of scope of this thesis:

- **Seasonality**
- **The impact of lost sales**
- **The multi-echelon effects of the TPTS supply chain.**

For all numbers and figures, if not else stated, the data is delimited in the following way:

- Only the Lund warehouse (denoted TS01) is considered.
- In all sales related data, only end customers who are in the TS01 Bill of Distribution are considered.
- Only the year 2022 is considered.
- Some assortment groups are excluded:
    1. Maintenance units,
    2. All types of kits, i.e. products comprised of several spare parts,
    3. 3rd party equipment.
- Some markets are excluded due to legal reasons. These are not disclosed due to confidentiality.

The goal was to identify a dataset that maximized the Internal validity, as described by Yin (2018), meaning the results should be as applicable as possible to all TPTS sites and points in time. The delimitations were chosen based on interviews with key personnel, and the interview guide for this is found in Appendix B. Initially, the year 2019 was chosen. However, as there was a lack of historic data, this was changed to 2022.

1.7 Report Outline

Introduction

This section will provide some context and background to the studied phenomenon as well as a general description of the case company and its relevant business units. After this a general problem description is provided along with purpose, focus and delimitation and a report outline.

Methodology

The methodology section will detail the methodology of this master thesis. This includes detailing the general research approach, choice of methodology, literature reviews and information about the data gathering process. The steps taken to achieve a certain level of research quality is also discussed.

Theory

The theory section will provide a summary of the findings from the literature review with the two main parts being theory regarding Spare Parts Inventory Management and general Inventory Control policies and definitions. Included is also a short section about different item segmentation methods that might be applicable to spare parts. All of this is then used to evaluate the current processes at TPTS.

Empirical Findings

In this section, the collected data is presented. Firstly, relevant supply chain processes are described in the Supply Chain Processes section. Then, the process connected to inventory planning system, the SPP Planning Process, is described in detail. The Current Situation subsection then provides an overview of the present state of the problem. Finally, a short summary of the empirical findings connected to research question 1 is presented.

Analysis

In this section, qualitative and quantitative analysis is performed on the empirical findings. This starts off with analyzing both Stocked Spare Parts and Non-Stocked Spare parts, before concluding with a root cause analysis that summarizes the identified issues.

Recommendations

This section deals with answering RQ2 by discussing possible recommendation identified. These recommendation have been categorized into four main areas and are of different degrees of difficulty when it comes to implementation as well as project size and time-horizons. Firstly, the recommendations are elaborated and discussed. Then, their respective impacts and efforts are estimated and compared.

Conclusion

This section contains summarized conclusions for the research questions, followed by a discussion of the limitations of the thesis with regards to the data and general applicability. Finally, some areas of future research based on the recomendations are discussed.

2 Methodology

This section will detail the methodology of this master thesis. This includes detailing the general research approach, choice of methodology, literature reviews and information about the data gathering process. The steps taken to achieve a certain level of research quality is also discussed.

2.1 Approach

Yin (2018) outlines a six-step framework for the case study process. It consists of the following phases: *plan*, *design*, *prepare*, *collect*, *analyze*, and *share*. A visualisation of this process can be seen in Figure 4. Inspiration from this framework was taken in this case study while trying to find the initial approach to constructing it.

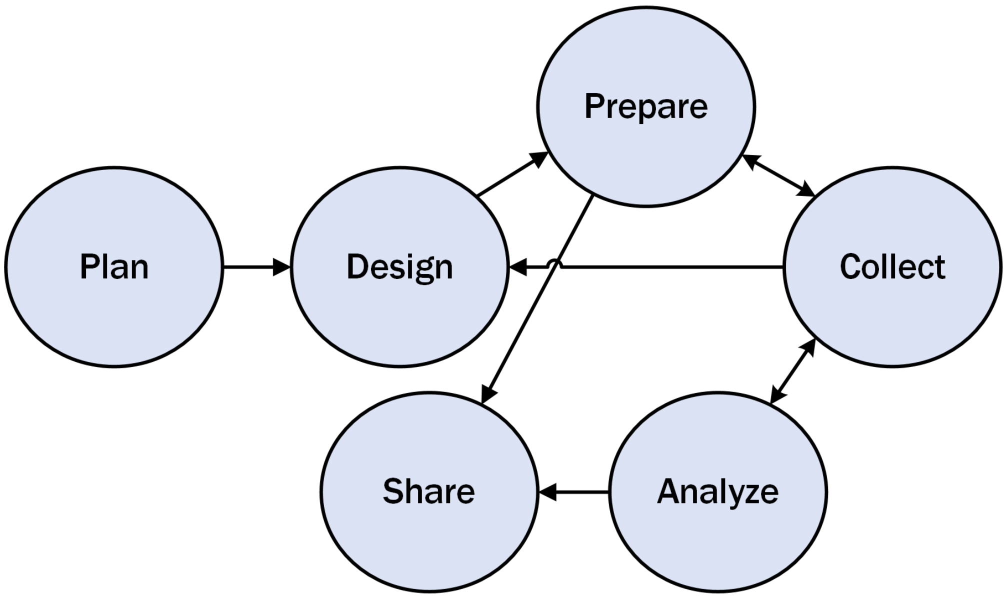


Figure 4: Case Study Process Framework(Yin, 2018).

Yin (2018) mentions four main research methods and the fact that the applicability of a method is based on three conditions: *Form of Research Question*, *The Requirement of Control over Behavioural Events*, and if the focus is on *Contemporary Events*. A framework for this can seen in Table 2.

Table 2: Research Methods mentioned by Yin (2018)

Method	Form of Research Question	Requires Control Over Behavioral Events?	Focuses on Contemporary Events?
Experiment	*how, why?*	*yes*	*yes*
Survey	*who, what, where, how many, how much?*	*no*	*yes*
Archival Analysis	*who, what, where, how many, how much?*	*no*	*yes/no*
History	*how, why?*	*no*	*no*
Case Study	*how, why?*	*no*	*yes*

As the phenomenon being studied was service levels at TPTS, the research questions were constructed to be of a *"how, why?"* nature. The two research questions seen in section 1.5 were then constructed.

As there is no control over behavioral events and there is a focus on contemporary events, it was concluded that an exploratory case study is the most applicable research method for this case study.

In the *Design* step of the framework constructed by Yin (2018), the main goals are in defining the case(s) that are to be studied as well as identifying the case study design. As TPTS came to the authors with a desired problem to be investigated, it was only natural that they would be the case and unit of analysis. And while a multiple case study might lead to higher level of generalizability and the evidence can be considered to be more compelling, Yin (2018) states it also requires additional resources and time compared to a single-case study. Moreover, as the problem description is so specific to TPTS the depth afforded by a single case study was considered sufficient.

The framework provided by Yin (2018) was compared to one constructed by Voss et al. (2002). The latter outlines the following five research steps when performing a case study in the field of operations: research framework and questions, choosing cases, review against literature, data collection, and analysis. These steps as presented by Voss et al. (2002) are illustrated in Figure 5.

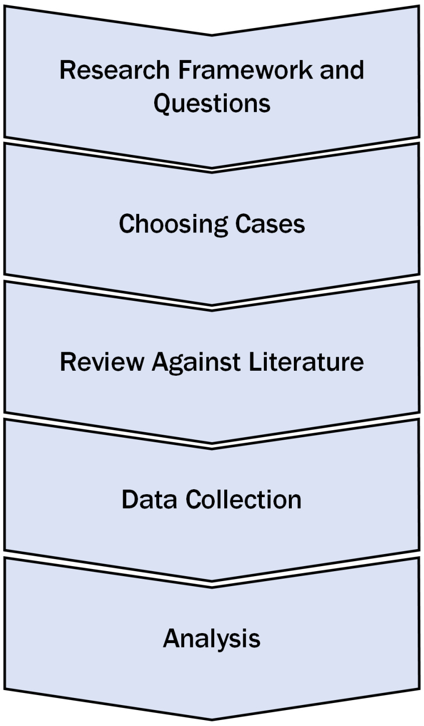


Figure 5: Research Steps for a case study as outlined by Voss et al. (2002)

These steps correspond well to the research approach that was used in this master thesis, with the slight modification that the Research Framework and Questions were constructed based on prompts from the case company as they had a current phenomenon they wanted studied.

2.2 Data Collection

2.2.1 Literature Review

The first step in the data collection process was to conduct a literature review to get a sense of what current existing research has been done on matters relating to the phenomenon. This literature review was then used to construct a theoretical framework which is used to compare the as-is situation to corresponding literature when possible.

Rowley and Slack (2004) discuss the four following search strategies while performing a literature review with a web source:

- **Citation Pearl Growing** - Performed by using a term from one or a few starting documents in order to find other documents with similar themes. Usually easy to perform for newcomers.

- **Briefsearch** - Retrieves few documents crudely and quickly. Generally good starting point.
- **Building Blocks** - Uses synonyms and related terms on already searched concepts in order to expand the material found. Thorough but may be time consuming.
- **Successive Fractions** - Used in order to reduce the size of a large set of documents by searching within the set.

Rowley and Slack (2004) also mention the process of *Concept Mapping* as a useful tool in visualizing relationships between concepts and finding additional search terms through this. In this case study, a combination of *Citation Pearl Growing*, *Building Blocks* and *Concept Mapping* was used while performing the literature review for this case study. A rough sketch of the concept map that was yielded can be found in Appendix D.

2.2.2 General Data Gathering

Yin (2018) mentions six primary sources of evidence that can be used in a case study, the main three that will be used in this case study are the following:

- **Documentation** - Includes but is not limited to Administrative documents, emails, calenders and meeting minutes and reports.
- **Archival Records** - Data files and records that can include statistical data, organizational and personnel records and service records.
- **Interviews** - Interviews of varying structure with key personnel.

The ***Documentation*** that was used for this case study was mainly in-house documents and presentation that have been used to explain the different processes and organizational structures in meetings. The main ***Archival Records*** were the vast data TPTS has collected concerning their inventory management of spare parts. Finally, different ***Interviews*** with key personnel were performed in order to both help limit what data should be looked at and also attain further information of different factors that could impact service level performance, but also to help verify and see if the findings and analyses were reasonable.

Triangulation, as shown in Figure 6, as well as trying to establish a *Chain of Evidence* as can be seen in Figure 7 was used to achieve *Convergence of Evidence*, so that multiple measures were provided of the phenomenon in order to strengthen the research quality of the case (Yin, 2018). This will be further discussed in the ***Research Quality*** section.

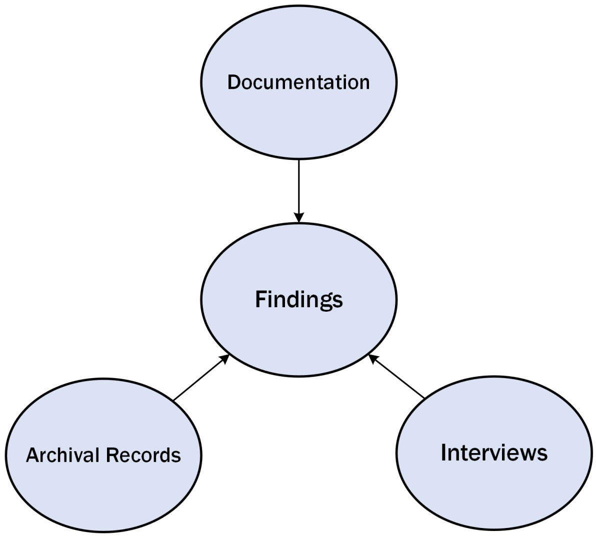


Figure 6: Illustrated Diagram of the proposed Triangulation method in order to achieve Convergence of Evidence as proposed by Yin (2018)

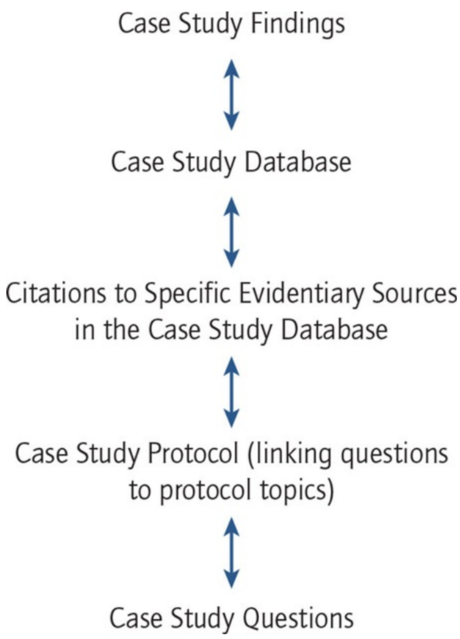


Figure 7: Illustrated framework for maintaining Chain of Evidence by Yin (2018)

The importance of maintaining a Case Study Protocol and Database is mentioned by Yin (2018) as being a key principle of data collection for case studies. How this was maintained for this case study will be specified in the *Research Quality* section.

In combination with trying to achieve *convergence of evidence* with the help of multiple source of evidence, maintaining a chain of evidence according to Figure 7 was also attempted. Here, constructing a Case Study Database with the help of Power BI and documentation was used to gather all relevant data and findings, then specific findings from the case study database were presented in an unstructured type setting to a *focus group*, consisting of key personnel. The key focus here was to make sure that *"...no original evidence should have been lost, through carelessness or bias, and therefore fail to receive appropriate attention in considering the findings in a case study."*(Yin, 2018, p.180). An illustrated framework for this can be found in Figure 8.

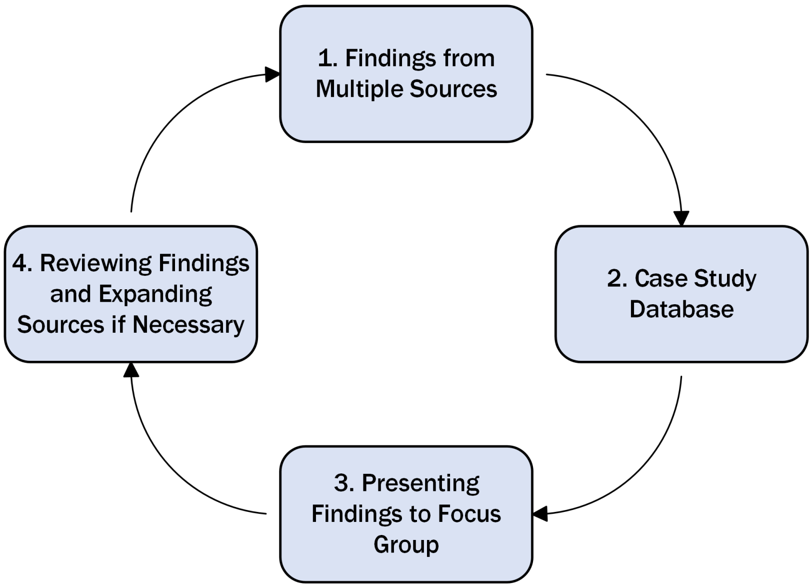


Figure 8: Framework for Chain of Evidence based on similar framework proposed by Yin (2018).

2.2.3 Interviews

As previously mentioned, interviews are used not only used to collect field data, but also to validate findings while constructing the chain of evidence. An important part of the case study was the weekly meetings with the company supervisor, which were used to both present the findings and data collected in order to discuss its validity, while also addressing new questions that had arisen since last time. Sometimes these meetings would be joined by more key personnel and turned into a sort of *ad hoc* focus group that greatly helped in validating the data while also opening up new areas of discussion.

Olhager (2021) discusses the following three main different styles of interviews:

- **Structured interview** - Where all the questions are determined in advanced and asked in a specific order.
- **Semi-Structured interview** - General areas of discussion is determined beforehand and questions are raised depending on responses from the subject of interview.
- **Unstructured interview** - Interview is more akin to an open dialogue where the questions arise depending on responses.

The styles that were used for this case study was mostly ***Unstructured*** as it was deemed to be prudent to prepare the topic of discussion and what information was needed while still allowing for flexibility. A few interviews were ***Semi-Structured***, such as the focus groups interviews, along with the Data Collection TPMS interviews seen in Appendix B and C.

Voss et al. (2002) list the following sets of skills that are important while conducting interviews in a case study setting:

- *To be able to ask good questions and interpret the answers.*
- *To be a good listener and not be trapped by preconceptions.*
- *To be adaptable and flexible.*
- *To have a firm grasp of the issue being studied.*
- *To be unbiased by pre-conceived notions and thus receptive and sensitive to contradictory evidence.*

As these are mostly soft skills that are hard to quantify, it was deemed important to always have these in mind when constructing, performing and reviewing an interview. Another important note is that as both case study authors have worked at TPTS in the past, prior bias from both personal experience and knowledge had to be combated. This was addressed by always having the mentality of trying to examine a topic of discussion from the ground up without relying on prior knowledge.

Table 13 shows all of the interview subject alongside the motivation for interviewing the subject while appendix A shows the date of each interview with the interview form and the topic of discussion. It should be noted that there were many short informal inquiries to the interview subjects in the hallways and such, but the interviews listed were the ones that were considered to be long-form interviews or focus groups sessions.

Table 3: List of Interview Subjects

Interview Subject	Motivation
Manager Planning & Inventory Optimization	*Has a holistic view of the Inventory Management policies for TPTS*
Global Planning Expert A	*Regularly analyzes the SC performance, is a supervisor.*
Global Planning Expert B	*Regularly analyzes the SC performance.*
Global Supply Chain Optimization Manager	*Good holistic view of issues facing TPTS.*
Supply Network Expert	*Good holistic view of issues facing TPTS.*
Global Planning Expert C	*Regularly analyzes the SC performance.*
Manager CoE Maintenance Processing	*Works with expanding TPMS for Processing.*
Planning & Quality Director	*Director for the entire Planning & Quality Division.*

2.3 Analysis

According to Yin (2018) it is important to have a well thought out analytical strategy while performing a case study, which is complicated by the fact that there are no few fixed formulas or recipes that are accepted as standard. Instead, Yin (2018) states that the analytic strategy largerly depends on the case research own empirical thinking and how the evidence is presented and interpreted. Furhermore, Yin (2018) formulates four general strategies that can help guide a case study analysis:

- **Relying on Theoretical Propositions -** Use the propositions that constructed the original objectives and case study design in order to find analytical priorities.
- **Working your data from the "ground up" -** Pour through the data collected in order to find suggested analytical paths.

- **Developing a case description -** Organize the analytical path according to a descriptive framework, can be useful in case the two first strategies are not applicable.
- **Examining plausible rival explanations -** Used by trying to test plausible rival explanations in order to test if the outcome of the analysis was based on an outside influence.

The main strategy used in this case study by the authors was the **Working your data from the "ground up"** variant, this was achieved with the help of the *case study database* developed using Power BI which housed all of the data collected and made for easy data visualization in order to better understand what data had been collected and what analysis could be possible.

Next, Yin (2018) descibes five analytic techniques that are useful for case study analysis, these are:

- **Pattern Matching -** a desirable technique for case study analysis that compares an empirically based pattern with a predicted one made before data collection, helping to strengthen internal validity and draw conclusions about the "how's" and "why's" of a case study.
- **Explanation Building -** a type of pattern matching used to analyze case study data in a narrative form, where a set of causal sequences about a phenomenon is stipulated in order to understand "how" or "why" some outcome has occurred, and the final explanation is likely to result from a series of iterations that involve revising tentative theoretical statements or explanatory propositions and comparing the data against them.
- **Time-Series Analysis -** a tool for case studies because it can trace changes over time, although it can be complicated to identify the appropriate starting or ending points for the analysis, and it can be used to compare different time patterns in a single-case or multiple-case study, and statistical tests can be used to analyze the data.
- **Logic models -** a technique used in case study evaluations and theories of change, which operationalize a complex chain of events over time to show how a program is implemented, and these models have the potential to explain how an intervention produces the ultimate outcome.
- **Cross-Case Synthesis -** particularly useful in multiple-case studies and involves a case-based approach to synthesize any within-case patterns across cases to compare or retain the integrity of the entire case, and contrasts with the data aggregation approaches in conventional

research syntheses that aim to reach conclusions about the variables but not necessarily about the cases.

From these four, a time-series analysis method mixed with a pattern matching technique is best used to describe the analysis method for this case study. As the authors looked over a unit of time to find patterns that affect the service level at TPTS and performed some statistical tests to verify the data. A simplified framework for the analysis method can be seen below in Figure 9, this shows that the collected data was then processed or reduced in order to get a better overview of what had been collected. After this, the data was visualized in order to further see relationships and possible cause-and-effect relationships from which conclusions were drawn. Finally, verification of these conclusions were attempted when possible. It is also shown in this framework that if something was found lacking or a new avenue of analysis emerged in the visualization state, the authors went back to the well of data in order to collect more. The same thought was put when drawing conclusion, if new avenues opened up in this state or question marks remained the authors went back to the data visualisation state in order to enhance the understanding of the data collected and processed.

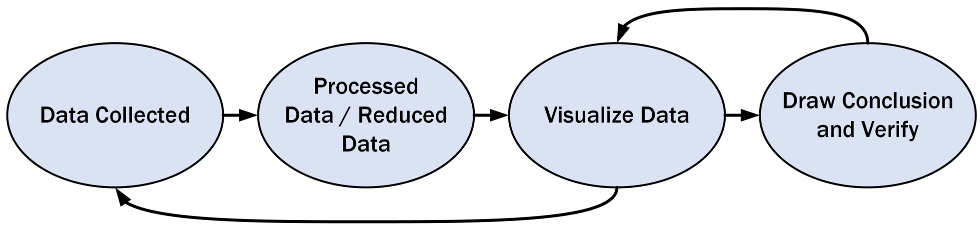


Figure 9: Framework to describe the data analysis method used in this case study.

2.4 Research Quality

To further help assess the research process, another important aspect mentioned by Yin (2018) is the quality of the research being performed, being the four design criteria used in order to judge the quality of the research designs, was consulted. These include the following:

- **Construct validity** - Identifying correct operational measures for the concepts being studied.
- **Internal validity** - Seeking to establish a causal relationship, whereby certain conditions are believed to lead to other conditions, as distinguished from spurious relationships.
- **External validity** - Showing whether and how a case study's findings can be generalized.

- **Reliability** - Demonstrating that the operations of a study—such as its data collection procedures—can be repeated, with the same results.

2.4.1 Construct Validty

Increasing the *Construct Validty* can be done by three tactics as detailed by Yin (2018). These include using *multiple sources of evidence*, establishing a *chain of evidence* and finally having the draft case study report reviewed by key informants in the case. As mentioned previously, maintaining a *multiple sources of evidence* and a *chain of evidence* was done in this case study.

2.4.2 Internal Validty

Internal Validty is especially important in exploratory case studies such as this, where the question is to answer *"how?"* and *"why?"* regarding events and relationships (Yin, 2018).

Specific tactics in achieving *Internal Validity* used by this methodology is *pattern matching* and *Time Series Analyis.* As well as constantly checking the data collected and analysed in order check its validty to the results.

2.4.3 External Validty

External Validty is directly connected to the *generalizability* of a case study, Yin (2018) states that the initial research questions have a profound impact on the *External Validity.* Yin (2018) therefore proposes that it is important that the research questions have been properly designed to reflect *"how?"* and *"why?"* during the research design phase in order augment the analytic generalization of a study.

2.4.4 Reliability

As Yin (2018) states, *Reliability* should always be a main goal during a case study, however, the opportunity to repeat a case study rarely occurs. This is why it is important for the research procedure to be well documented and that it is as explicit as possible and allowed. A way this case study has striven for *Reliability* is by having a *Case Study Database* as well as documenting the research steps as much as possible in this thesis.

3 Theory

The theory section will provide a summary of the findings from the literature review with the two main parts being theory regarding Spare Parts Inventory Management and general Inventory Control policies and definitions. Included is also a short section about different item segmentation methods that might be applicable to spare parts. All of this was then be used to try and evaluate the current processes at TPTS.

3.1 Spare Parts Inventory Management

Spare Parts Inventory Management (SPIM) involves managing and making stocking decisions for spare parts. This case study focuses on the sale of spare parts to end customers as an after-sales service, not the management of companies spare parts at their own production facility.

As the demand pattern of spare parts can be quite different from regular products (Kennedy, W.J. et al., 2002) combined with the importance of production up-time and after-sales services and the above factors, there has been an increased attention towards SPIM (Zhang et al., 2021).

3.1.1 Differences compared to normal inventory management

As stated by both Kennedy, W.J. et al. (2002) and Zhang et al. (2021), the demand pattern for spare parts can be quite erratic and different compared to other products. The product life cycle for spare parts compared to their corresponding sales of new products is illustrated in Figure 10 by Zhang et al. (2021).

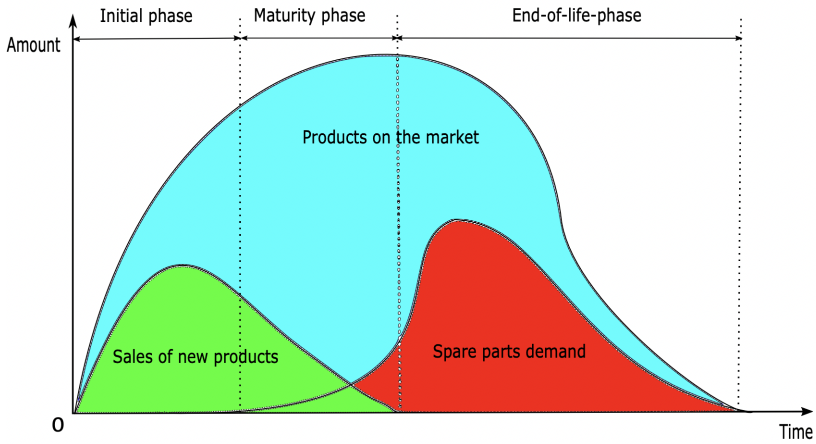


Figure 10: Product Life Cycle of new products compared to spare parts (Zhang et al., 2021).

Furthermore, Hu et al. (2018) stipulate that there are four characteristics that gives SPIM a peculiarity compared to normal inventory management:

- *Intermittent demand patterns are common among spare parts contributing to difficulties with regards to the forecasting process.*
- *The number and variety of spare parts are usually very large which, can make it difficult to identify and apply a stock control strategy for each part.*
- *Due to the risk of spare parts' obsolescence when normal products go into their End Of Life stage, it can be extra important to try and reduce inventory so as not to incur extra costs.*
- *The factor of a spare parts criticality with regards to its importance in maintenance and to make sure production up-time is kept adds another dimension of difficulty in managing spare parts.*

Huiskonen (2001) also defines four defining characteristics of spare parts and corresponds each to an element of a logistic systems. This can be seen in Figure 11.

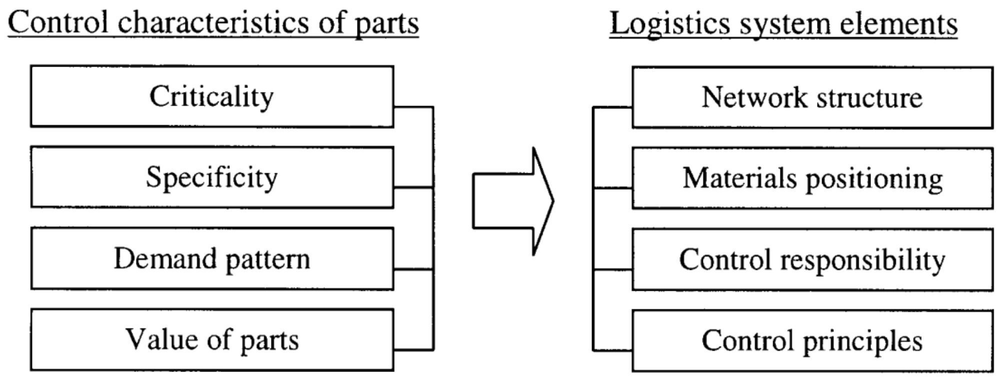


Figure 11: Four Characteristics and their corresponding element in a logistic system (Huiskonen, 2001)

3.1.2 Item Segmentation Methods

A popular method for Item and product segmentation is the ABC-XYZ method, the method is built on the ABC-analysis which has its roots in the pareto principle (*"80-20 rule"*) and has added the XYZ dimension which takes into account demand variability (Stojanović, Milan & Regodić, 2017). Demand variability is commonly quantified as the average number of picks of an item (Olhager, 2019). A framework of the model can be seen in Figure 12.

	X	Y	Z
A	*High Value* *High Predicatbility* *Continous Demand*	*High Value* *Medium Predicatbility* *Fluctuating Demand*	*High Value* *Low Predicatbility* *Irregular Demand*
B	*Medium Value* *High Predicatbility* *Continous Demand*	*Medium Value* *Medium Predicatbility* *Fluctuating Demand*	*Medium Value* *Low Predicatbility* *Irregular Demand*
C	*Low Value* *High Predicatbility* *Continous Demand*	*Low Value* *Medium Predicatbility* *Fluctuating Demand*	*Low Value* *Low Predicatbility* *Irregular Demand*

Figure 12: ABC-XYZ analysis framework (Stojanović, Milan & Regodić, 2017)

Another method for item segmentation proposed by D'Alessandro and Baveja (2000) can be seen in Figure 13. The stated benefit to this method as opposed to the classic ABC-XYZ analysis is measures demand variability through the *Coefficient of Variation* of the demand. Therefore it supposedly creates an more accurate portrait of the relationship between the weekly demand and its relative variability. Quadrant 1 contains high volume and low variability products, quadrant 2 contains high volume and high variability products, quadrant 3 contains low volume and high variability products, and quadrant 4 contains low volume and low variability products. D'Alessandro and Baveja (2000) set the distinction point between the quadrants accordingly: On the x-axis, the mean average demand is used. On the y-axis, a Coefficient of variation of 0.5 is used.

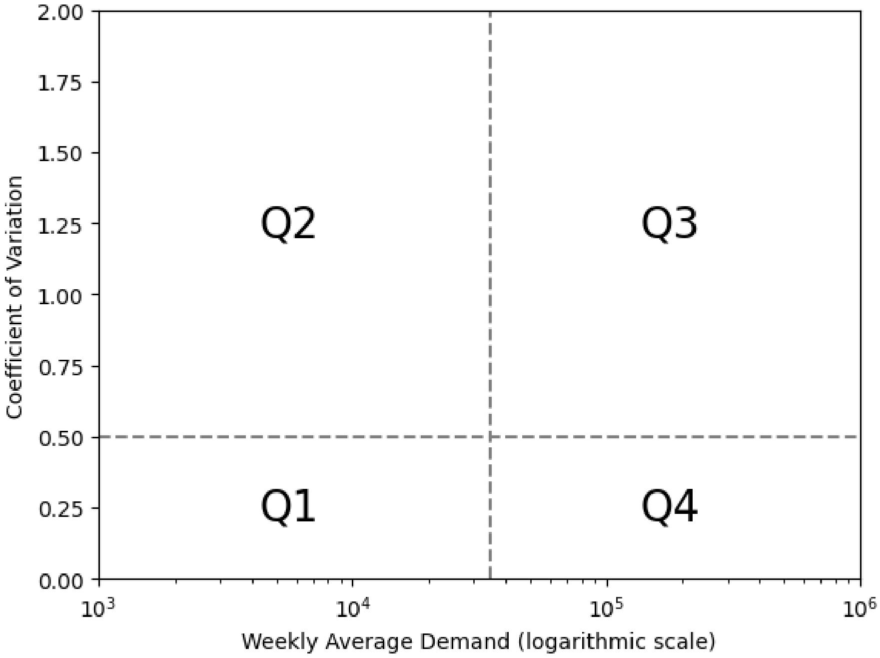


Figure 13: Item Segmentation Method with regards to the Coefficient of Variation and Average weekly demand (D'Alessandro & Baveja, 2000).

A qualitative classification method called VED-analysis is also used sometimes and based on the functional importance of inventory and categorised stock into three categories: Vital, Essential, and Desirable (Roda et al., 2014).

- **Vital** - Inventory that is necessary for production, if not on hand production may stop.
- **Essential** - Inventory that is next closest to being vital, might lead to temporary production stop but the part might be repairable.
- **Desired** - The least important, unavailability may result in only minor stoppages.

Item segmentation aids in creating an understanding of where effort should be put most effectively. In any multi-criteria analysis, most common is to use 3 categories for each criteria. Silver et al. (1998) argue that the number of categories appropriate for a particular company depends on its circumstances and the degree to which it wishes to differentiate its policies. Meanwhile, Vollman et al. (2005) argue for the importance of having the number of policies to a number with which people can cope.

3.2 Inventory Control

3.2.1 Definitions of Service Level

One of the most important performance measurements of an inventory control system is *service level*. It is supposed to measure the extent to which customers are served on time, which can be done in numerous ways. As such, several definitions exist, three of which are described by Axsäter (2006):

1. Probability of no stockout per order cycle.
2. *Fill rate* - fraction of demand that can be satisfied immediately from stock on hand.
3. *Ready rate* - fraction of time with positive stock on hand.

Fill rate, sometimes called volume fill rate or item fill rate, is one of the most common ways to measure service level in practice (Guijarro et al., 2012). This is in part due to the fact that the achieved fill rate during a given time period T can, in a real setting be measured according to (1).

$$FR = \frac{\text{Number of items immediately satisfied from stock on hand during } T}{\text{Total number of ordered items during } T} \tag{1}$$

Larsen and Thorstenson (2014) differentiate between fill rate as described above, and Order Fill Rate (OFR). The OFR service measure is specified as the probability that an arbitrary customer order can be satisfied completely from inventory without delay, i.e. all that all ingoing order lines of a customer order are satisfied instantly and completely. In a real setting, this can be measured for a given time period T using (2).

$$OFR = \frac{\text{Number of orders immediately satisfied from stock on hand during } T}{\text{Total number of orders during } T} \tag{2}$$

3.2.2 Demand Models

Below follows the two most common ways of modeling stochastic demand, as described by Axsäter (2006):

A ***constant model*** assumes that demands in different periods are observations of independent random deviations from an average. It uses the following notation:

x_t - Demand observed in period t,
a - Average demand per period,
ϵ_t - independent random deviation with mean zero.

The demand in period t can then be represented using (3):

$$x_t = a + \epsilon_t. \tag{3}$$

A ***trend model*** assumes demand is going to systematically increase or decrease. The same notation as the constant model is used, with one extension:

b - The systematic increase or decrease per period.

The demand in period t can then be represented using (4):

$$x_t = a + bt + \epsilon_t. \tag{4}$$

3.2.3 Forecasting Techniques

Several methods exists for predicting future demand. Below follows a brief description of some common techniques.

First Order Exponential Smoothing assumes a constant demand model and uses the following notation (Axsäter, 2006):

$\hat{a}_t$ - The forecast for the period $t+1$,
α - The smoothing constant $(0 < \alpha < 1)$,
x_t - The demand for period t.

$\hat{a}_t$ is calculated using (5).

$$\hat{a}_t = (1-\alpha)\hat{a}_{t-1} + \alpha x_t \tag{5}$$

Second Order Exponential Smoothing assumes a trend demand model and uses the same notation as the first order exponential smoothing, with some extensions (Holt, 2004):

$\hat{a}_t$ - The demand forecast for the period $t+1$,
$\hat{b}_t$ - The trend forecast for the period $t+1$,
α - Smoothing constant $(0 < \alpha < 1)$,
β - Smoothing constant $(0 < \beta < 1)$,
x_t - The demand for period t.

Estimates of a and b are successively updated according to (6) and (7).

$$\hat{a}_t = (1-\alpha)(\hat{a}_{t-1} + \hat{b}_{t-1}) + \alpha x_t \tag{6}$$

$$\hat{b}_t = (1-\beta)(\hat{b}_{t-1} + \beta(\hat{b}_t)\hat{a}_{t-1} \tag{7}$$

The forecast for a future period, $t+k$, is then calculated using

$$\hat{x}_{t,t+k} = \hat{a}_t + k \cdot \hat{b}_t \tag{8}$$

The ***Croston Model***, as suggested by Croston (1972), is used to predict sporadic demand patterns. The forecast is only updated in periods with positive demand, otherwise it is kept constant. The following notation is used:

k_t - The stochastic number of periods since the preceeding positive demand,
$\hat{k}_t$ - Estimated average of the number of periods between two positive demands at the end of period t,
$\hat{d}_t$ - Estimated average of the size of a positive demand at the end of period t,
$\hat{a}_t$ - Estimated average demand per period at the end of period t,
x_t - The demand for period t.

$\hat{k}_t$ and $\hat{d}_t$ are updated using first order exponential smoothing, according to (9) and (10):

$$\hat{k}_t = \begin{cases} \hat{k}_{t-1} & \text{if } x_t = 0, \\ (1-\alpha)\hat{k}_{t-1} + \alpha k_t & \text{if } x_t > 0. \end{cases} \tag{9}$$

$$\hat{d}_t = \begin{cases} \hat{d}_{t-1} & \text{if } x_t = 0, \\ (1-\beta)\hat{k}_{t-1} + \beta k_t & \text{if } x_t > 0. \end{cases} \quad (10)$$

Where $0 < \alpha, \beta < 1$ are smoothing parameters.

$\hat{a}_t$ is then calculated using (11):

$$\hat{a}_t = \frac{\hat{d}_t}{\hat{k}_t}. \quad (11)$$

3.2.4 Ordering Policies

To manage the inventory of a Stock Keeping Unit (SKU), an ordering policy must be employed. Below follows a description of the ones most commonly used, as described by Axsäter (2006).

1. The (R, Q) policy: when the inventory position declines to or below the reorder point R, a batch of size Q items is ordered.
2. The $(S-1, S)$ policy: often referred to as the base stock policy. When the inventory position drops below S, an order for one item is placed. This policy can be seen as a variant of the (R, Q) policy with $R = S-1$ and $Q = 1$.

A special case of the base stock policy is the Procure to Order (PO) policy. Here, no internal stock is kept and orders are only placed when there exists backorders on the item. This results in an $(S-1, S)$ policy where $S = 1$.

3.2.5 The Classical EOQ Formula

Derived by Harris (1913), The classical Economical Order Quantity (EOQ) formula is still widely used as a base for inventory control related decisions. The formula makes the following assumptions:

1. Demand is constant and continuous.
2. Ordering and holding costs are constant.
3. No partial deliveries occur.
4. No shortages are allowed.

The following notation is used:

$$\begin{aligned}
h &\text{ - Holding cost per unit and time unit,}\\
A &\text{ - Ordering or setup cost,}\\
d &\text{ - Demand per time unit,}\\
L &\text{ - Lead time,}\\
C &\text{ - Costs per time unit,}\\
Q &\text{ - Order quantity,}\\
EOQ &\text{ - Economic order quantity.}
\end{aligned}$$

The relevant costs C associated with keeping an item on stock, is obtained as

$$C = \frac{Q}{2}h + \frac{d}{Q}A. \tag{12}$$

As (12) is convex in Q, the optimal Q is obtained by the first order condition:

$$\frac{dC}{dQ} = \frac{h}{2} - \frac{d}{Q^2}A = 0 \tag{13}$$

Solving for Q in (13) obtains the EOQ:

$$EOQ = \sqrt{\frac{2Ad}{h}}. \tag{14}$$

If an (R, Q) policy is used, $Q = EOQ$. With the given assumptions, R should be dL to cover the demand during the lead time.

3.2.6 Considering Stochastic Demand

In many cases, (14) is used to determine the order quantity when employing an (R, Q) policy, while the calculation of R is based on other assumptions. A common approach is described by Olhager (2019), Silver et al. (1998) among others, which assumes a normally distributed demand model. Then, R can be implicitly derived from the Safety Stock (SS), which uses the following notation:

SS - The safety stock of the spare part,
SL - The target service level,
L - The supplier lead time,
σ - The standard deviation of the forecast error during the demand period,
σ_L - The standard deviation of the forecast error during the lead time,
k - The safety factor,
γ - A constant.

σ_L is calculated using (15):

$$\sigma_L = \sigma L^{\gamma} \tag{15}$$

γ depends on the correlation between the forecast errors between periods. If no correlation exists, $\gamma = 0.5$. If that is the case, the safety stock SS can be attained using (16):

$$SS = k\sigma_L \tag{16}$$

Where the safety factor k is a tabulated value which depends on the target service level SL. Finally, R is attained from SS using (17)

$$R = SS - \theta, \tag{17}$$

where θ is the expected demand during the lead time.

3.2.7 Considering Stochastic Lead Times

If uncertainty in lead times exist, the safety stock can be extended to assume lead time as a stochastic variable (Olhager, 2019). Assuming demand is normally distributed, and the distribution of demand and lead times are independent, (16) can be modified.

$$SS = k(SL)\sqrt{L\sigma^2 + D^2[\sigma(L)]^2} \tag{18}$$

where D is the demand per time period and $\sigma(L)$ is the standard deviation of the lead time.

If the lead time variation is small, this adjustment only contributes to a small increase in safety stock, and can be ignored. If it is large however, its impact must be evaluated. If $D^2[\sigma(L)]^2$ is the dominating term in the safety stock calculation, a more efficient approach might be to employ safety lead times instead. With a safety lead time, orders are planned to be ready some time before the underlying demand lies. Introducing safety lead times extends the total lead time across the supply chain, and can therefore lead to an extended planning horizon.

4 Empirical Findings

In this section, the collected data is presented. Firstly, relevant supply chain processes are described in the Supply Chain Processes section. Then, the process connected to inventory planning system, the SPP Planning Process, is described in detail. The Current Situation subsection then provides an overview of the present state of the problem. Finally, a short summary of the empirical findings connected to research question 1 is presented.

4.1 Organizational differences between Processing and Packaging

From the interviews conducted several differences between the way Processing and Packaging operate emerged. What follows is key takeaways and points that is believed to have an overall influence on the difference in Spare Part (SP) service level.

- **Packaging has been a more centralized Business Unit** - Processing has compared to Packaging been more decentralized as it has grown more from the outside in compared to expanding from inside of the organization. For example, Processing started as a part of Alfa Laval that was bought out by Tetra Pak when they sold of their majority stake. Since then, a factor in its growth has been acquiring other Processing-type companies. This meant that from an organizational standpoint, Processing has been decentralized compared to Packaging.
- **Packaging has had more resources poured into its after-sales service** - A large part of Tetra Paks goal for Packaging has been that the machines should never experience a standstill situation as their profitability has been directly connected to the paper that goes into the filling machines. This has not been a historical focus for Processing, as uptime has not been as directly linked to profitability. For Packaging, resources such as on-site Engineers have then been provided to the customers that can help plan the maintenance for the machines. A lot of the Maintenance connected services have also been introduced first within Packaging, and later been adopted by Processing. An example of this is Tetra Pak Maintenance System (TPMS). From interviews, it was also noted that Processing has felt that there has not been enough resources, clear justification, and help provided by TPTS when it comes to evolving their Service & Maintenance platform.
- **Packaging has had a more unified production development** - When developing new a product, Packaging uses a catalogue of parts

already used in existing machines, in order to maximize standardization. Processing has not had anything similar largely due to its decentralized nature.

4.2 Supply Chain Processes

This section covers supply chain processes relevant to the phenomenon studied. From interviews with key personnel, relevant processes where identified, and then described using in-house documentation.

4.2.1 Order Logic

Customer orders are served according to a First In, First Out (FIFO) logic. Three types of orders can be placed to TPTS:

- *Planned* orders have a 3-6 week lead time. In return for this long lead time, customers are discounted a percentage of the cost.
- *Priority* orders are shipped the same or next day.
- *Express* orders are only to be used in emergency cases. TPTS attempts to supply the customer as quickly as possible by any means available. An express order is associated with an Express fee.

4.2.2 Tetra Pak Maintenance System

Tetra Pak Maintenance System (TPMS) is a system aimed at providing optimal maintenance recommendations for TPTS SPs. These recommendations are generated through a cyclic process consisting of six steps, described below. In Figure 14, a map of the process can be seen.

1. **Create maintenance recommendations.** Based on component specification and application, the amount of running hours for the part is generated.
2. **Schedule maintenance event.** Based on estimated running hours of ingoing components in a machine, maintenance is scheduled.
3. **Perform maintenance event.** The actual tasks are performed either by Tetra Pak staff, the customer staff, or both.
4. **Capture feedback.** Following the maintenance event, the details of the tasks performed and other findings are captured.
5. **Analyze feedback.** Information generated from the previous step is analyzed from a local and global perspective.
6. **Drive continuous improvements.** The findings of the feedback analysis is used to update and improve maintenance recommendations.

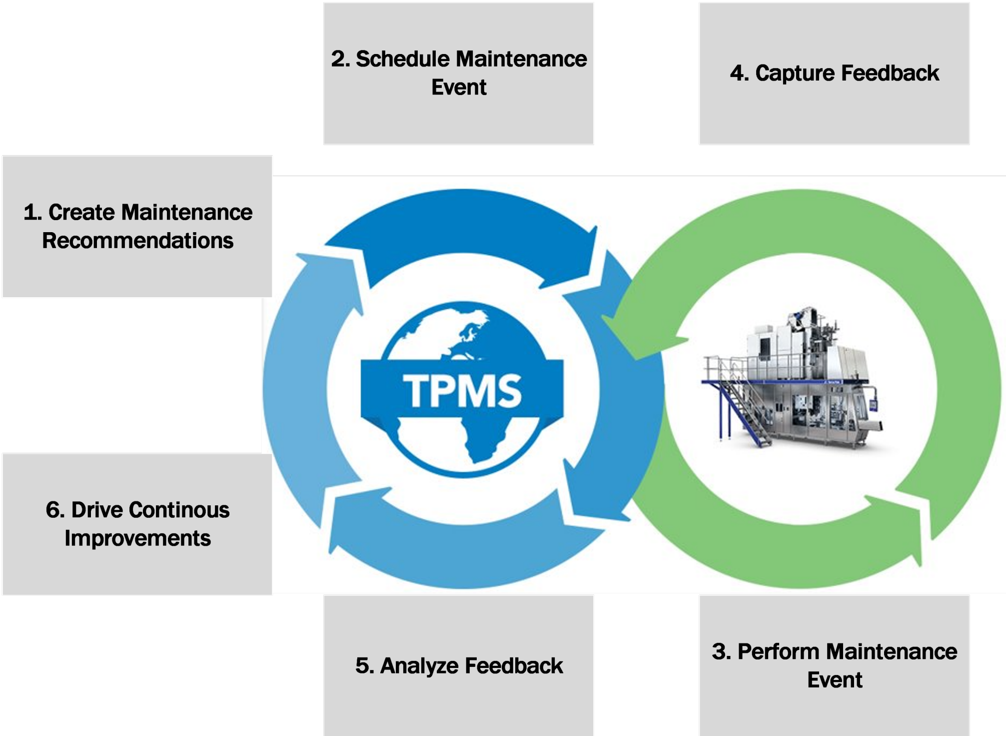


Figure 14: The TPMS process (Tetra Pak, 2022).

Currently, TPMS exists for both Packaging and Processing. However, Packaging has implemented it to a much further extent compared to Processing as seen in Table 4, which shows that Packaging has maintenance recommendation for almost half of their installed compared to only 14% for Processing. Also, a larger portion of the Packaging installed base with TPMS is initialized, meaning the TPMS reccomendations are actually used to schedule maintenance for that specific machine.

Table 4: Comparison of total Installed Bases with TMPS and total Installed Bases with TPMS initialized for Packaging and Processing

	Processing	Packaging
Installed Base with TPMS	**14%**	**54%**
Installed Base with TPMS Initialised	**7%**	**42%**

4.3 SPP Planning Process

Inventory control is managed by an module within the company Enterprise Resource Planning (ERP) called Service Parts Planning (SPP). This process was mapped with help from in house documentation and interviews from key personnel, and will be described in this chapter. Firstly, The overall process, consisting of several sub-processes, will be described. Thereafter, the ingoing sub-processes will be explained.

4.3.1 Overall Process

The Process Map in its entirety is presented in Figure 15. Firstly, the stocking decision sub-process is performed, which will be explained in detail later. From this, the SP attains a Replenishment Indicator (RI). Two RIs exist: Stocked (ST) and Not Stocked (NS). Secondly, the min SS sub-process is performed. Here, some SPs are assigned a minimum safety stock which overrides any safety stock assigned by SPP. Regardless of RI, a SP can be assigned a min SS. For example, SSN might wish to assign min SS to parts with high criticality despite low or non-existent sales volumes. Thus, parts with RI=NS can, despite the name, be kept on stock. The rules for assigning min SS varies for Processing and Packaging parts. This is because Packaging SPs contain more detailed information on things as expected life time, criticality, and installed base. The result of the stocking and min SS decision is a *Stocking Status* for the SP. Based on the stocking status, different ordering policies will be employed. SPs with RI=ST are ordered using an (R, Q) policy where R and Q are determined in the Forecasting, EOQ & Safety Stock sub-process. SPs with RI=NS are ordered using an $(S-1, S)$ policy, where S is determined according to (19).

$$S = \begin{cases} 0 & \text{if stocking status is } NS, \\ \mathit{min\ SS} & \text{if stocking status is } \mathit{NS\ min\ SS}. \end{cases} \tag{19}$$

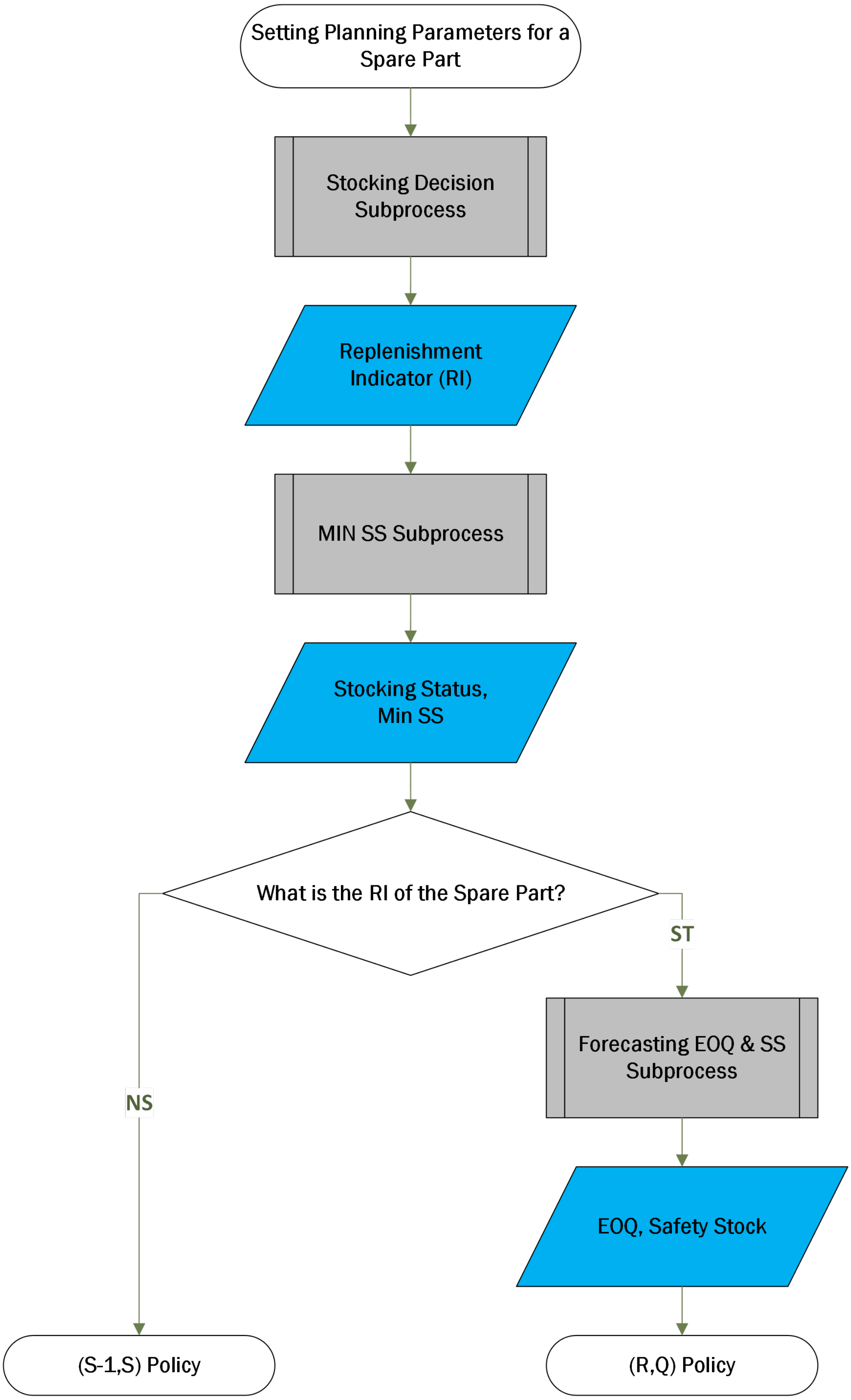


Figure 15: The Overall SPP Process.

4.3.2 Stocking Decision Sub-process

A map of this sub-process is displayed in Figure 16. If thirteen months of historical sales data exists, the SP will be put in the stocking decision table. Here, an RI is assigned based on Pick Class and Cost Group of the SP. Cost groups are based on the procurement cost of the SP while Pick Classes are based on how many times the SP was picked in the thirteen month historical period. The stocking decision table is outlined in Figure 17. As can be seen, a part is assigned RI=ST if the number of picks and procurement cost is sufficiently high.

For several reasons, some parts should never be stocked. For example, SPs containing batteries must be kept in a separate hazardous goods warehouse which is managed in a separate process. Therefore, an exclusion table exists which overrides the stocking decision to set RI=ST, and sets the RI=NS for the part. Similarly, some parts should always be stocked. Therefore, an inclusion table exists which overrides the stocking decision to set RI=NS and sets the RI=ST for the part. A common example of an inclusion override is SPs which are replacing existing parts with RI=ST. Since no historical sales data exists for the replacing part, it is not placed in the stocking decision table. However, it is highly likely that it will behave similarly to the replaced part and should thus be stocked.

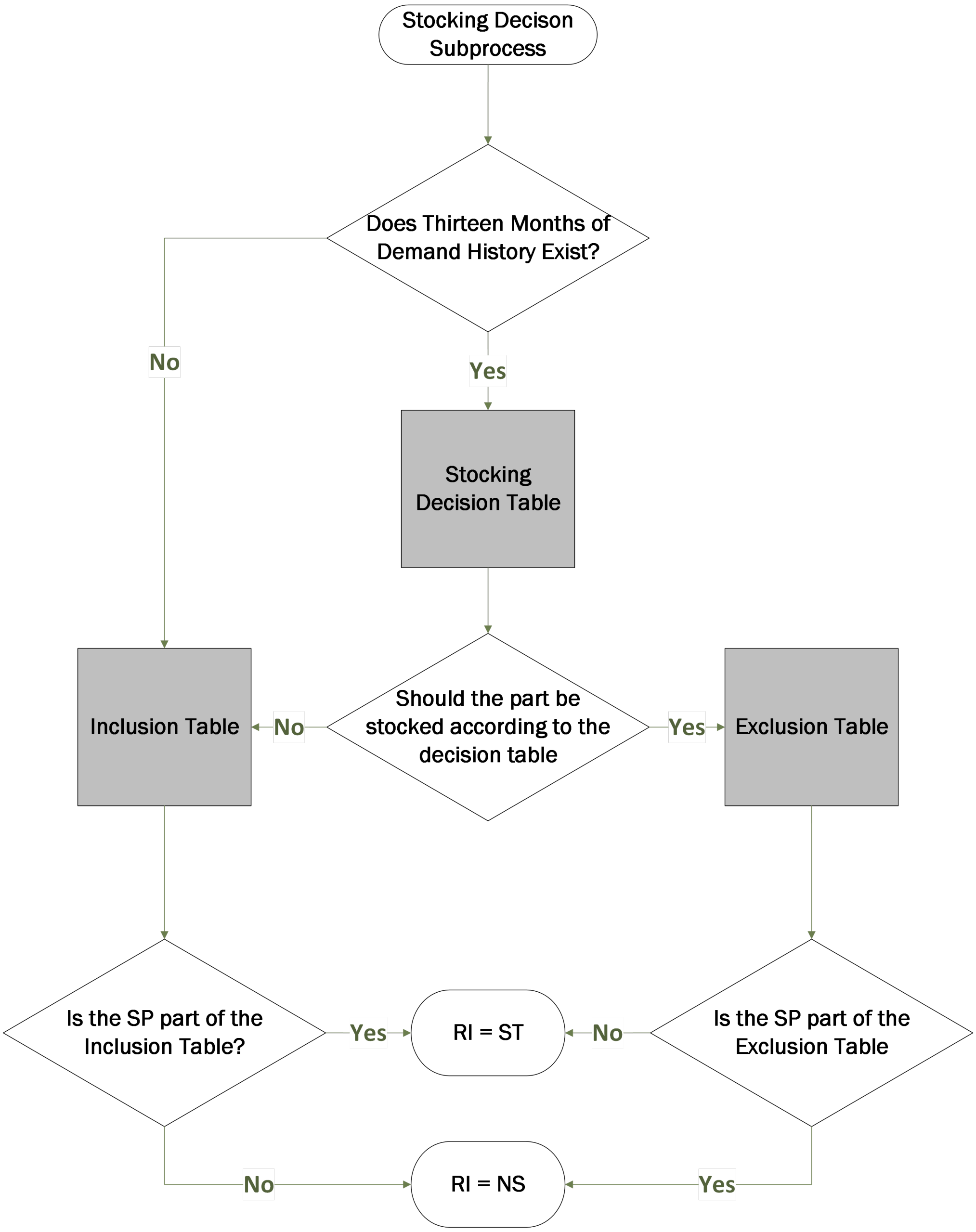


Figure 16: The Stocking Decision Sub-process.

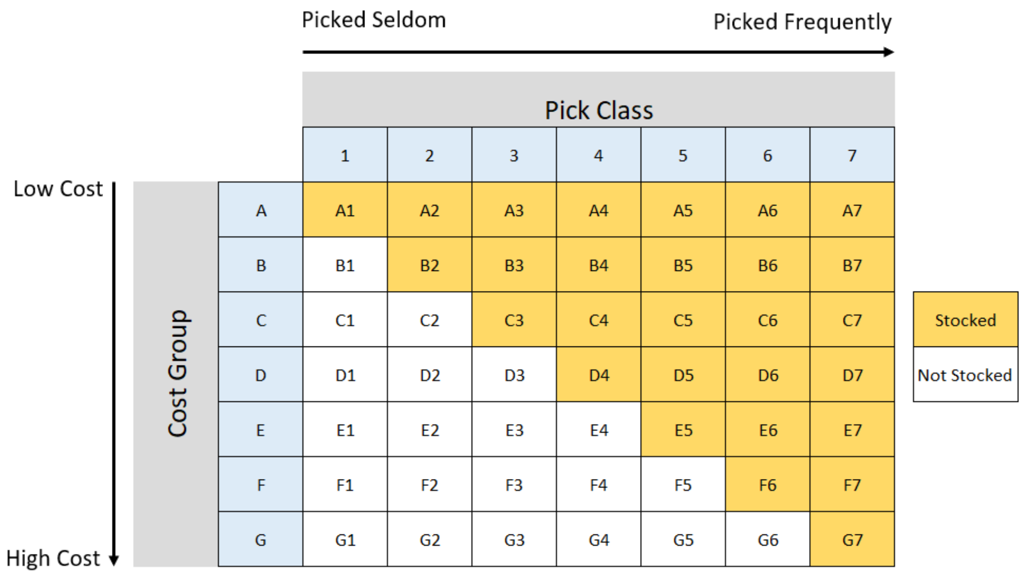


Figure 17: The Stocking Decision Table. All numbers are undisclosed due to confidenciality.

4.3.3 Forecasting, EOQ & Safety Stock Sub-process

A map of this sub-process is displayed in Figure 18. The first step of this sub-process is to manage demand history, where the systems corrects for outliers and disqualifies demand which is considered not relevant. 13 months of historical data is considered. Non-relevant demand could include internal orders for R&D projects and the like. A customer order is considered an outlier if the order quantity exceeds a threshold. This threshold corresponds to a multiple of the standard deviation of the average order quantity. If an outlier is observed, the order quantity is truncated down to the threshold. N.b. that only orders exceeding the upper threshold are corrected and not orders that fall short of the lower one. This procedure is visualized in Figure 19.

Then, a forecast strategy is selected. Based on the nature of the demand history, the system selects one of the following models:

- *A1* - First order exponential smoothing. Used for stable demand patterns.
- *D1* - Second order exponential smoothing. Used for demand patterns with simple trend behaviours.
- *B1* - Linear regression. Used for demand patterns with sophisticated trend behaviours.
- *G1* - The Croston Model. Used for intermittent demand patterns.

When a forecast strategy has been selected, the parameters related to the model are calculated by the system. The forecasting strategy and its selected parameters are called a *Forecasting Profile*.

The system also categorizes the SP in Value Annual Usage (VAU) classes and Pick Classes. VAU classes group SPs based on the procurement cost times the forecasted number of pieces, while Pick Classes are based on the number of annual picks. VAU classes are constructed so that a certain percentage of the sold value are in each class, while pick classes are based on the actual number of picks. In Table 5, the criteria for the pick classes are listed, and in Table 6, the critera for the VAU classes are listed.

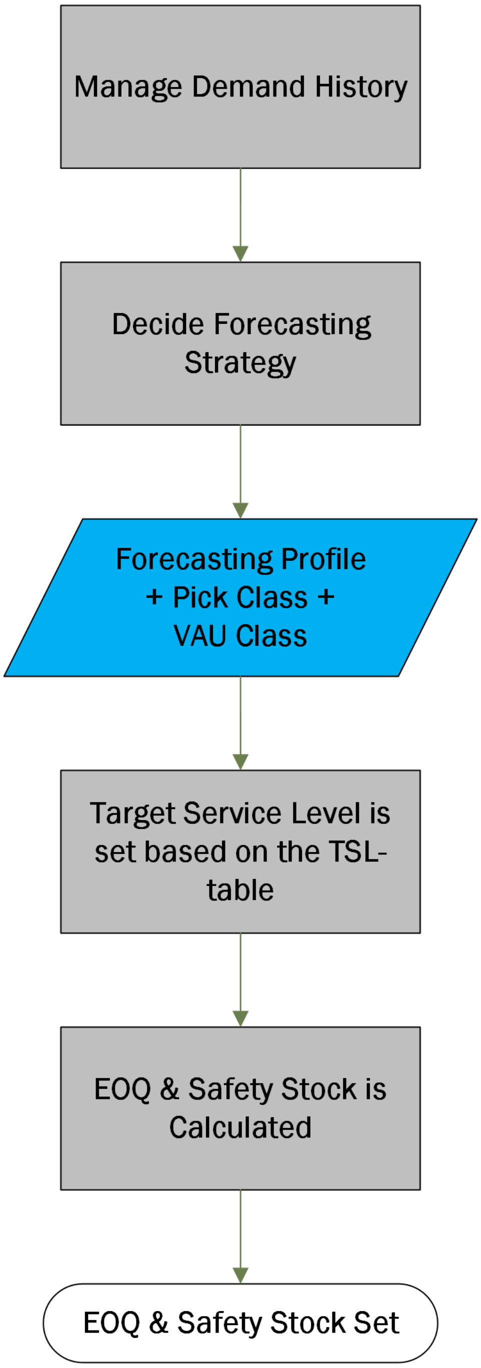


Figure 18: The Forecasting, EOQ & Safety Stock sub-process.

Table 5: The criteria for the pick classes used at TPTS. Numbers are scrambled due to confidentiality.

Number of yearly picks	Pick Class
0-5	0
6-10	1
11-15	2
16-20	3
21-25	4
26-50	5
51-75	6
76-300	7
>300	8

Table 6: The VAU classes used at TPTS. Numbers are scrambled due to confidentiality.

VAU class	Percent of value	Cumulative sum
A	36%	100%
B	16%	64%
C	13%	48%
D	10%	35%
E	8%	25%
F	7%	17%
G	6%	10%
H	3%	4%
I	1%	1%

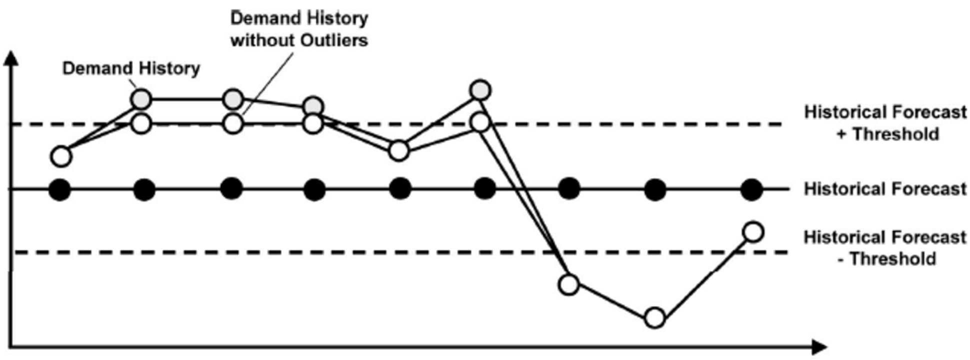


Figure 19: Visualization of the outlier correction performed by SPP.

Based on the Pick and VAU Classes, the SP is categorized into one of 81 Target Service Level (TSL) groups. The matrix can be seen in Figure 20.

Based on the Target service level, the system calculates a reorder point R and an order quantity Q for the part. If the forecasted demand exceeds a certain threshold, demand is considered to be normally distributed, and Q is calculated using (14), and then rounded to the nearest batch quantity defined by the supplier. R is implicitly calculated using the safety stock, which is calculated using (16). If the forecasted demand does not exceed this threshold, demand is considered to be Poisson distributed and Q and R are calculated another way. For stocked parts this is a very rare occurence, and will not be covered in this thesis.

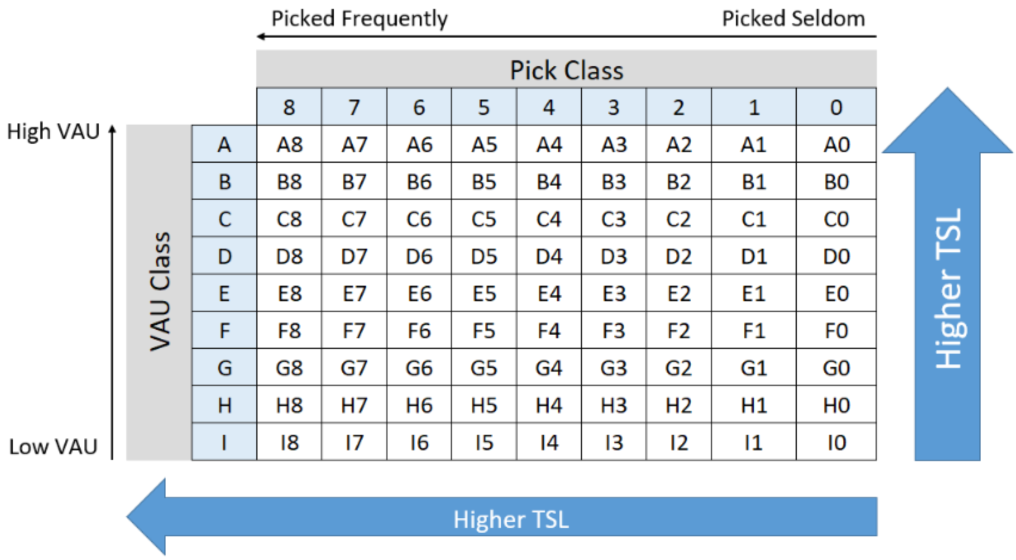


Figure 20: The TSL matrix used by SPP.

4.4 Current Situation

4.4.1 Portfolio

To understand how the Packaging and Processing portfolio differs, the stocking status distribution of *active* SPs were investigated. In this context, an SP is considered *active* if it has ever had a historical sale.

The majority of active SPs in TS01 are Packaging parts, as can be seen in Figure 21. The stocking status distribution for both respective businesses are seen in Figure 22. A larger proportion of Packaging SPs have RI=ST. Also, Packaging SPs are to a greater extent assigned minimum safety stocks.

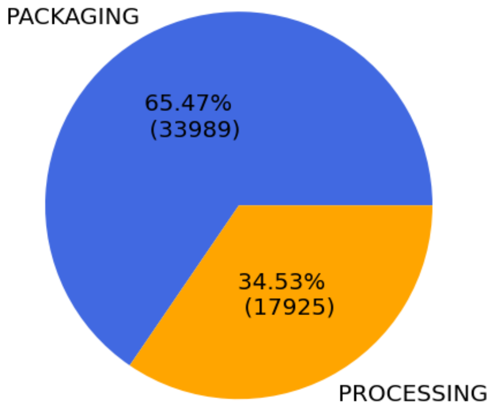


Figure 21: Overall distribution of Active SPs per business.

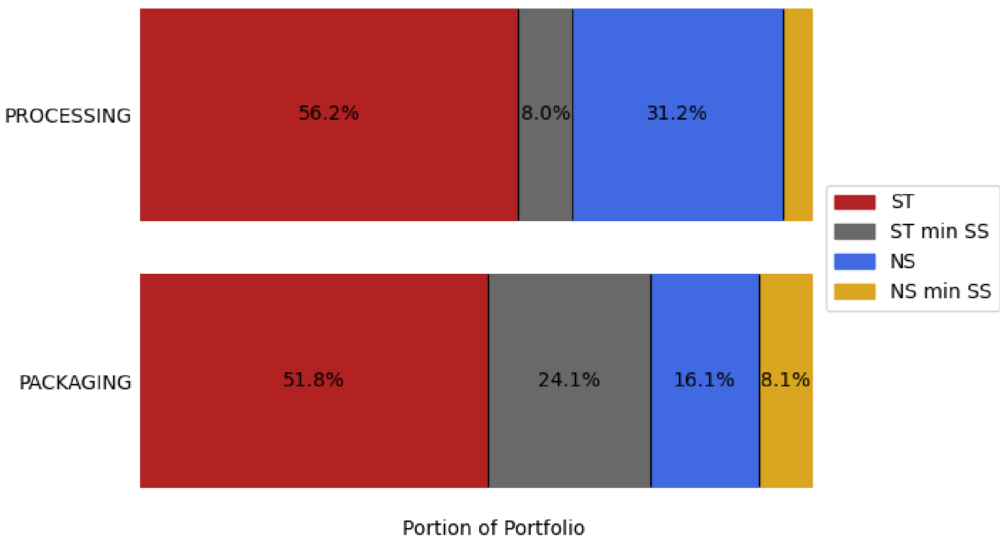


Figure 22: Stocking status distribution and share of total portfolio for Processing and Packaging, respectively. Numbers are scrambled due to confidentiality.

4.4.2 Orders and Customer behaviour

In Figure 23, the distribution of order lines between per business is displayed. A comparison can be made between this distribution and the one displayed in Figure 21: Processing accounts for approximately 35% of the active SPs, but only 26% of the total number of order lines. Figure 24 displays how order types are distributed in each business. Here, it can be seen that Packaging materials are to a greater extent placed on planned orders. Also, Processing exhibits a somewhat larger portion of express orders.

Figure 25 displays the distribution of missed order lines per business. Here, two notable differences can be observed. Firstly, the portion of ST min SS is for much greater for Packaging. Secondly, The portion of NS is much greater for Processing.

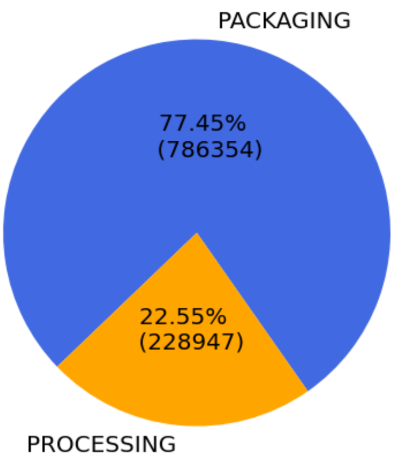


Figure 23: Order Line distribution per Business. Numbers are scrambled due to confidentiality.

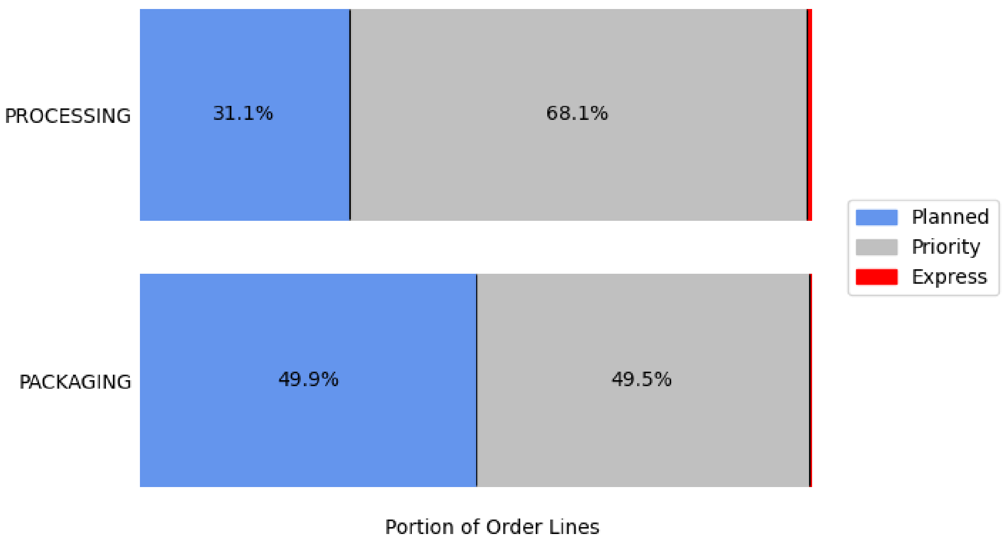


Figure 24: Order Line distribution by delivery type per Business, and overall Order line distribution. Numbers are scrambled due to confidentiality.

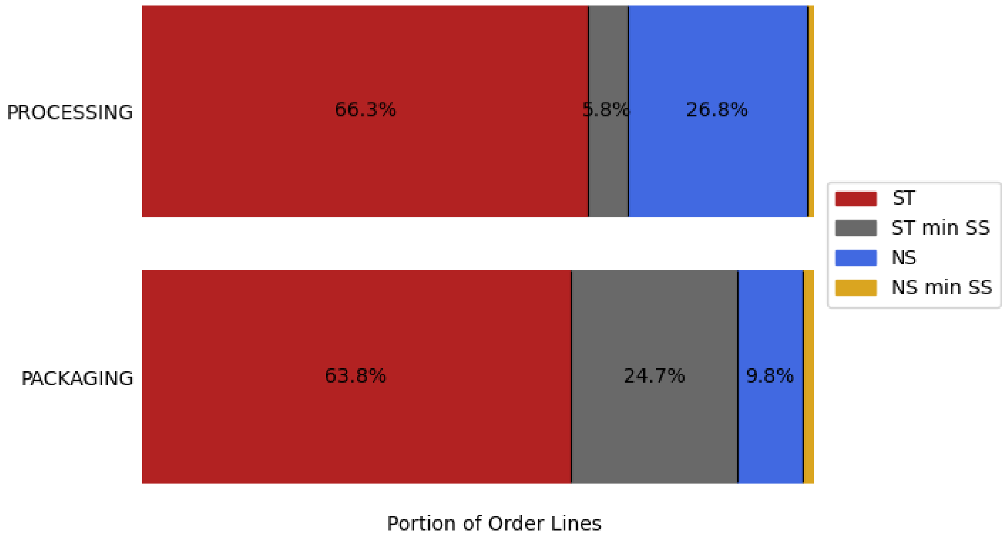


Figure 25: Distribution of missed order lines per business. Numbers are scrambled due to confidentiality.

4.4.3 Service Levels

In Figure 26, the total number of order lines per stocking status are plotted versus difference in service level between Packaging and Processing. The difference in service level was defined as the Processing service level subtracted by the Packaging service level. Consequently, a positive number correlates to a higher service level for Packaging SPs. As SPP sets the stocking status of an SP based on the number of picks, it is no surprise the vast majority of orders are placed on stocked SPs. Worth noting is also 12.07% difference in service level for parts with stocking status NS.

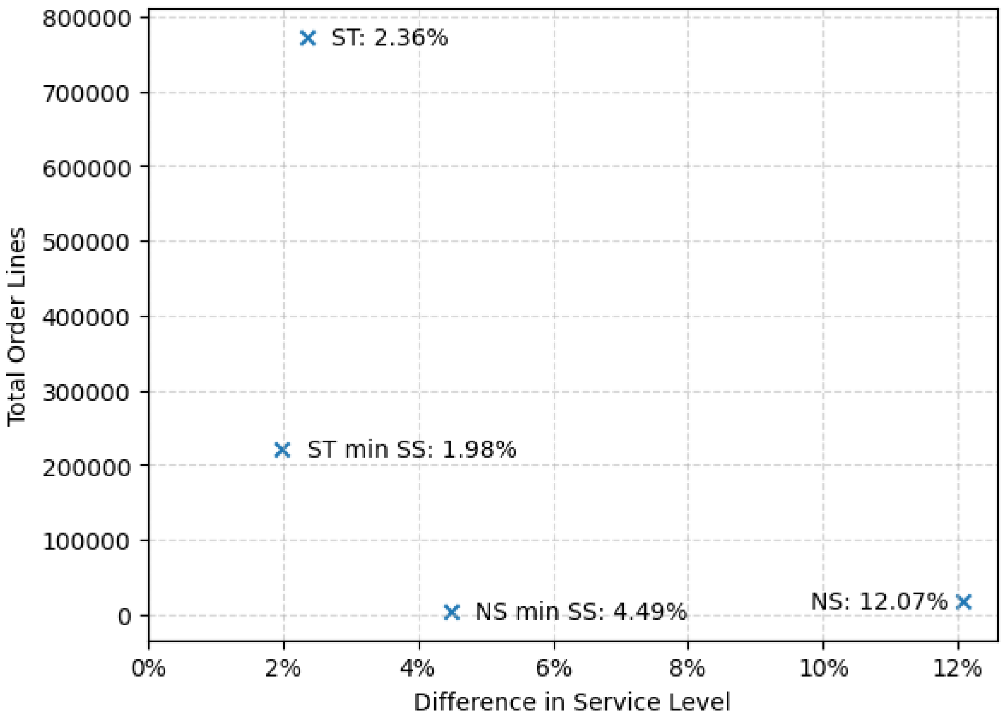


Figure 26: Number of order lines and difference in Service Level per stocking status and business. A positive number correlates to a higher service level for Packaging SPs.

4.4.4 Target Service Levels

All numbers and figures in the following section are for SPs with stocking status ST. To capture the impact of the SPP system without manual interference, materials with stocking status ST min SS have been excluded. Figure 27 displays how the TSL and achieved SL differs for Packaging and Processing, respectively. As can be seen, Processing has a lower overall TSL. This partially explains the lower overall service level of Processing SPs. However, as the difference between achieved service level and TSL generally is higher for Processing, this does not explain the difference in its entirety.

Then, the distribution of SPs within the TSL matrix was investigated. For simplicity, the 81 cells of the TSL matrix used by SPP (as displayed in Figure 20) were grouped into 9 categories. A detailed Figure on how this was performed is provided in Appendix E. Figure 28 displays how all SPs are distributed within the TSL matrix, and Figure 29 displays how this distribution differs between Packaging and Processing SPs. Here, it can be seen that Processing SPs are more skewed towards a lower pick class (category Z).

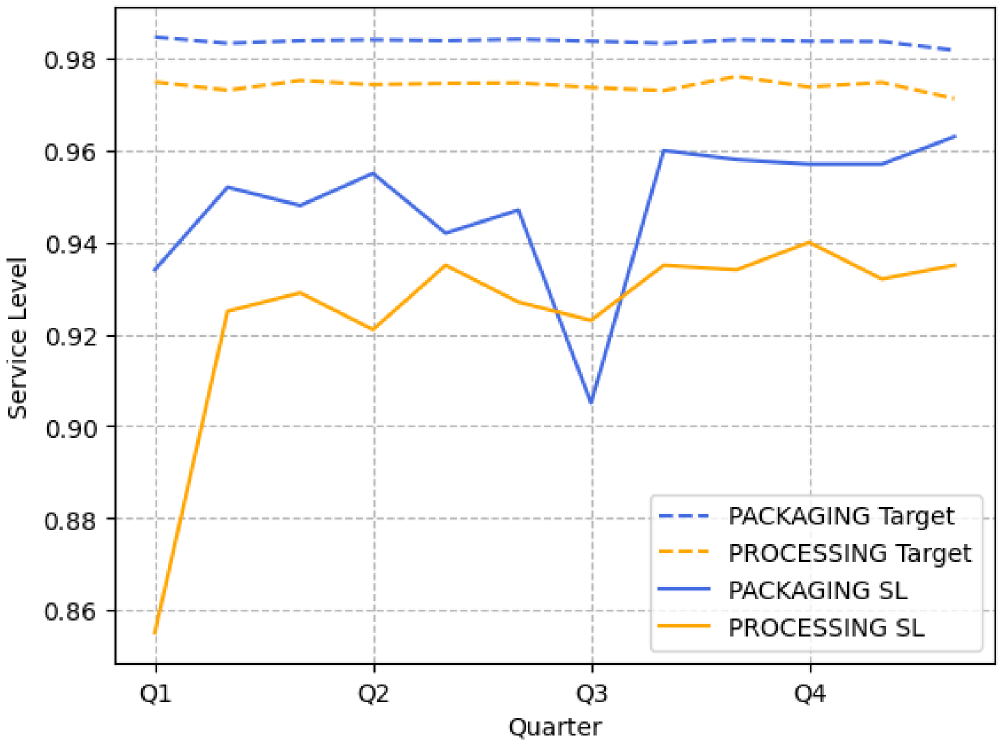


Figure 27: Target and achieved service level for Packaging and Processing SPs.

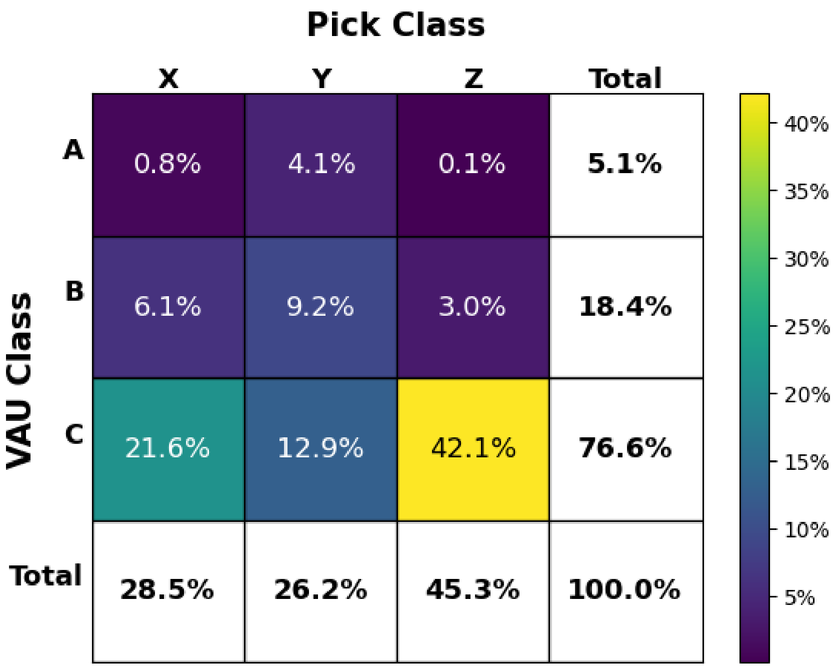
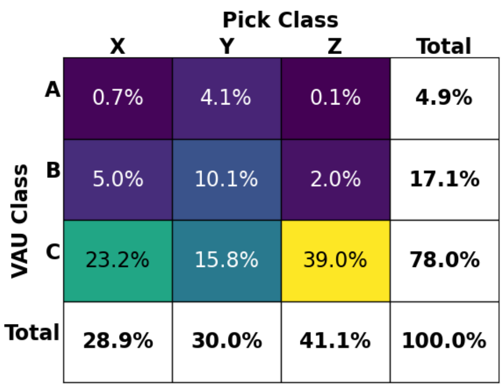
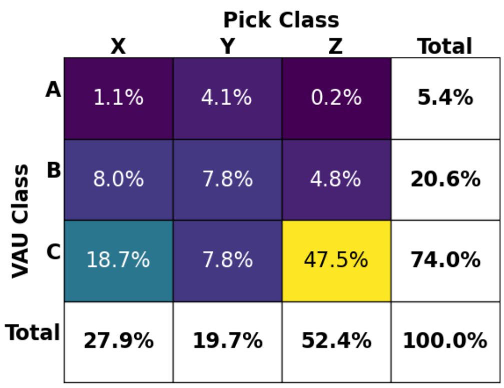


Figure 28: Overall distribution of SP within the TSL matrix. Cells are colored based on their respective concentration.



(a) For Packaging



(b) For Processing

Figure 29: Distribution of SPs within the TSL matrix. Cells are colored based on their respective concentration.

4.4.5 Demand and Forecasts

All numbers and figures in this section are, as in the previous, for materials with stocking status ST. To investigate how the different characteristics of the Packaging and Processing portfolios affect the Forecasting, the *Forecast ratio* was calculated for each SP. It was defined according to (20).

$$\text{Forecast ratio of month } n = \frac{\text{Forecasted demand during month } n}{\text{Sales during month } n} \tag{20}$$

Then, the average Forecast ratio was calculated for each pick class and business. For this comparison, the pick classes were not grouped as before, in order to get a more detailed overview. in Figure 30, This comparison is displayed. Although the two businesses exhibit slight differences, none of these were deemed significant based on the figure. Up until pick class 3, SPP is on average under-forecasting for both businesses. Also, the forecast ratio increases up until pick class 6, and then declines.

At first glance it looks like SPP is heavily over-forecasting for higher pick classes. However, the authors are hesitant to draw conclusions regarding this for several reasons. First of all, the forecast ratio is the quotient of the sales and the forecast, and does not account for lost sales. This is especially relevant in 2022, where Tetra Pak experienced many global supply disruptions. Secondly, TS01 is the global distribution center for the entire Tetra Pak supply chain, while the forecast data in question is only for the end customers of TS01. The forecast data is known to generate inconsistencies when it aggregates demand along the bill of distribution. For the purposes of this thesis however, the behaviour is the same for Packaging and Processing SPs, and a thourough explanation for why the forecast ratio is so high for higher pick classes were deemed out of scope.

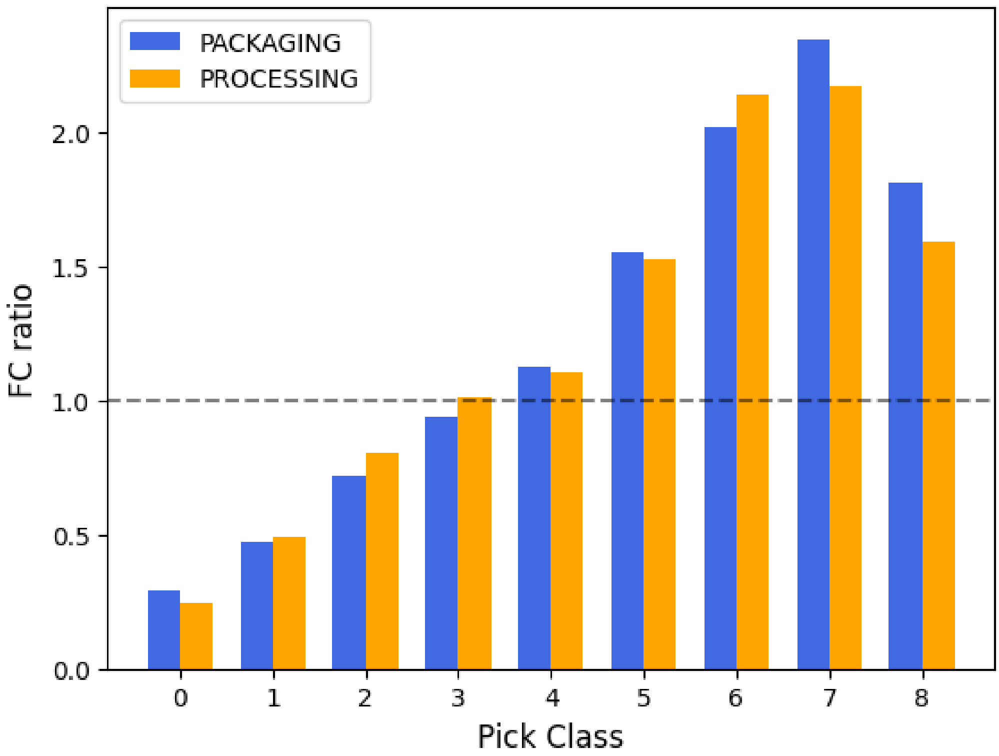


Figure 30: Average Forecast ratio per pick class and Business. A number greater than 1 corresponds to a forecast higher than sales.

In an effort to estimate the "lumpiness" of demand, the *relative order quantity*, denoted OQ_R was calculated for each SP. It was defined according to (4.4.5).

$$OQ_R = \frac{\text{Quantity requested of an SP in one order}}{\text{Monthly forecast of an SP}}$$

Then, the average relative order quantity, $\overline{OQ}_R$, was calculated for each cell in the TSL matrix, respectively for Processing and Packaging. Figures 31 and 32 display $\overline{OQ}_R$ for all cells within the TSL matrix for packaging and processing SPs, respectively. Overall, OQ_R is similar for both business, apart from cell I0 where a vast difference can be observed. In the lower right corner of the TSL matrix, many cells display a value well above one, meaning order quantities are on average larger than the forecast. This is because SPs here generally have forecasts far below 1.

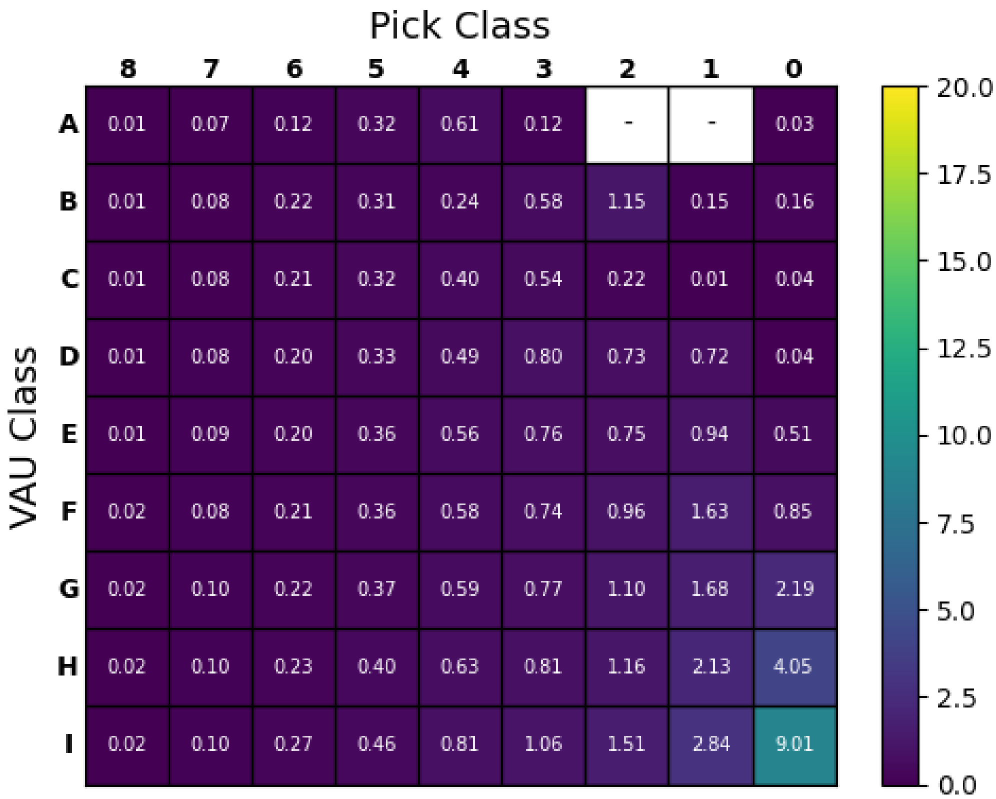


Figure 31: Relative order quantity for Packaging SPs. Cells are color coded based on their relative value. White cells contain no observations.

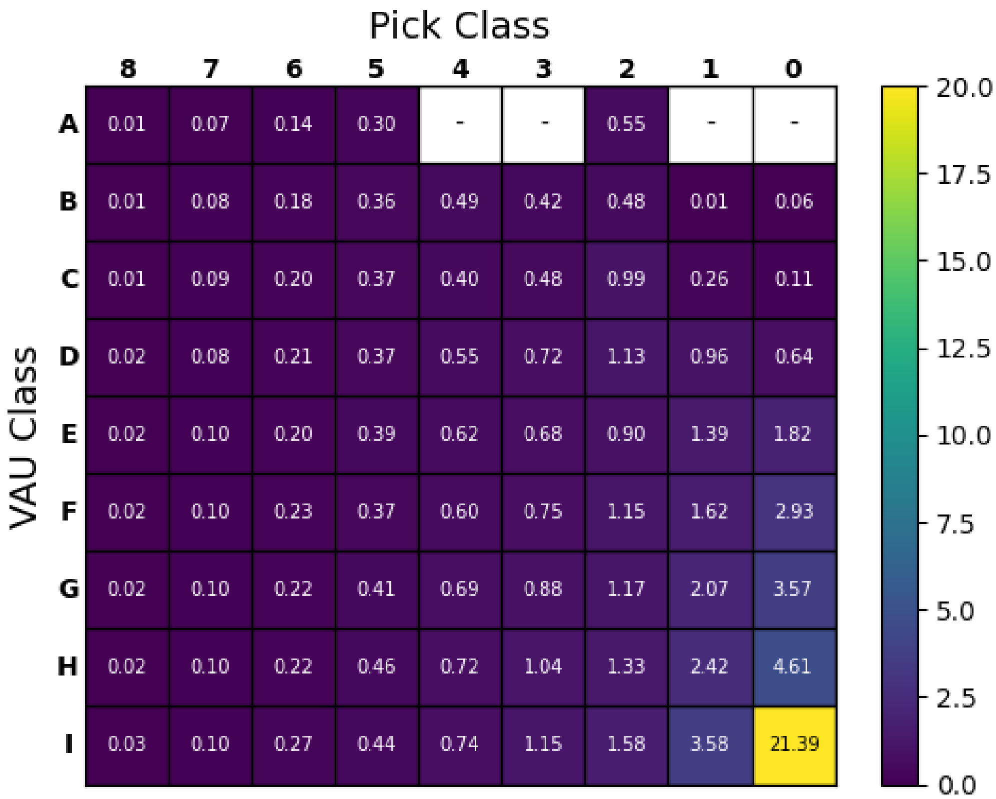


Figure 32: Relative order quantity for Processing SPs. Cells are color coded based on their relative value. White cells contain no observations.

4.4.6 Supplier Lead Times

To investigate the differences between the Packaging and Processing supplier performance, the average lead time and sample standard deviation per month was calculated for each SP. Then, the quotient between these two, i.e. Coefficient of Variation (CV), was calculated for each SP. As the sample standard deviation is undefined for singleton sets, SPs with only single orders in the data set were excluded. From this, the following measurements where calculated for Packaging and Processing, respectively:

$$\overline{\overline{L}} \text{ - mean average lead time,}$$
$$\overline{CV}_{\overline{L}} \text{ - average lead Coefficient of Variation.}$$

In Figure 33, $\overline{\overline{L}}$ is plotted. For all stocking statuses, Processing SPs have a lower average lead time for all stocking statuses. However, Processing SPs also have a significantly higher coefficient of variation, as shown in Figure 34.

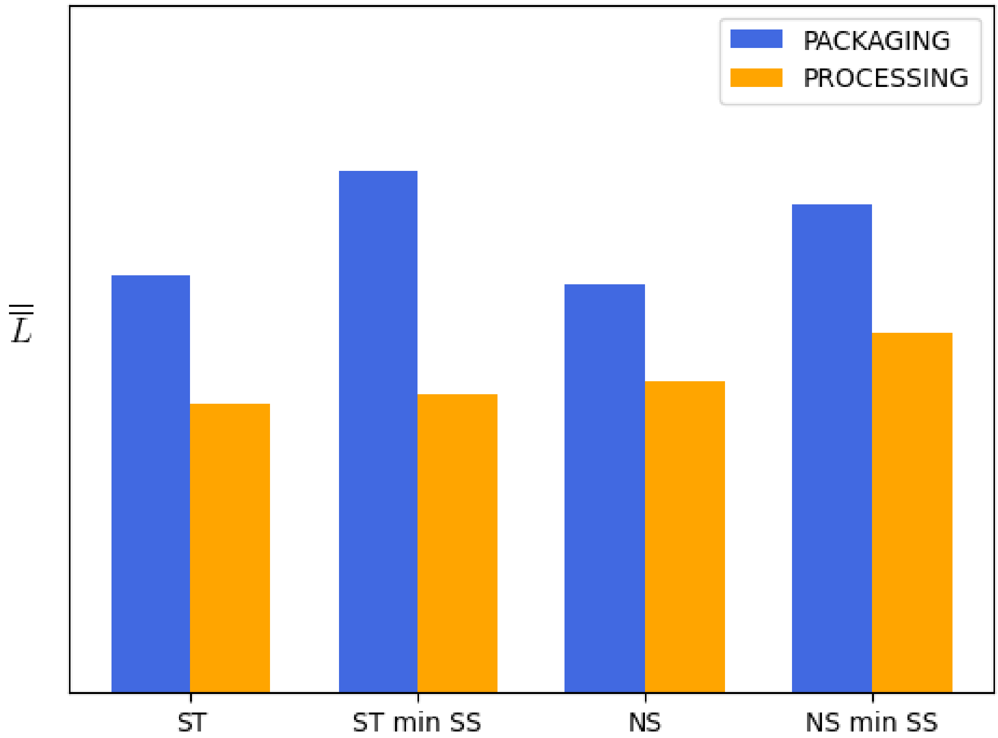


Figure 33: Mean average supplier lead time per stocking status and Business. Numbers are undisclosed due to confidentiality.

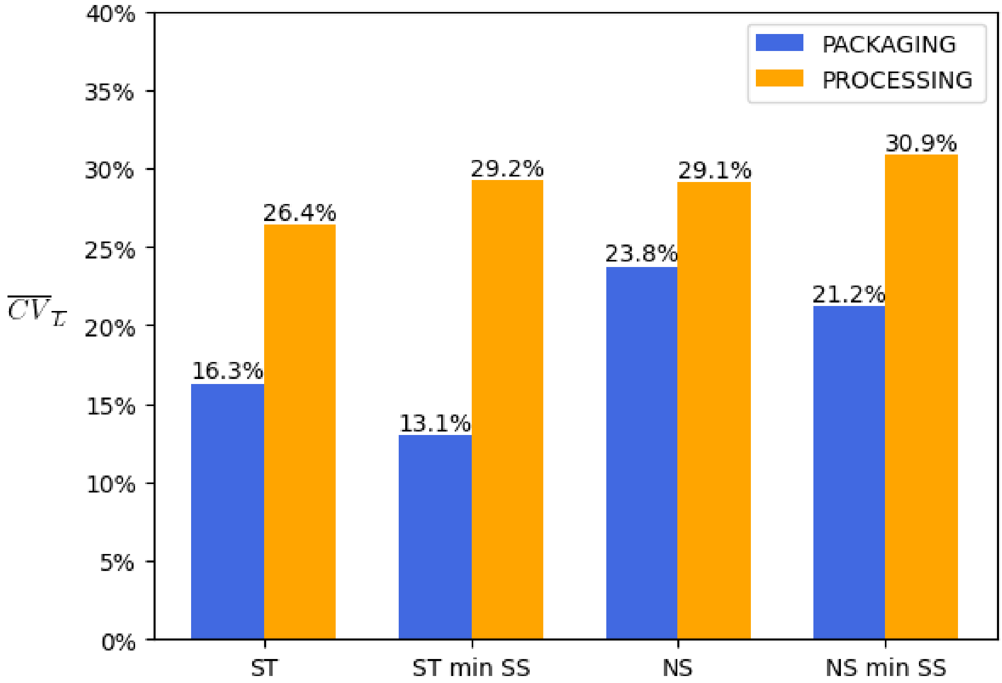


Figure 34: Average Coefficient of variation of supplier lead time per stocking status and Business.

4.4.7 Minimum Safety Stocks

In this section, the impact on availability of manual safety stocks is investigated. Only SPs with stocking status NS min SS were considered, and SPs with stocking status ST min SS were excluded. This was done to exclude other factors identified to the greatest extent possible. For each SP, the *safety stock ratio*, denoted SS_D, was calculated as the quotient between the safety stock of an SP and sold quantity within a month. Here, the sold quantity considered was the total sales from TS01 (not only TS01 designated customers), as the minimum safety stocks are accounting for this demand as well. Figure 35 displays, on the primary y-axis, the average safety stock ratio, denoted as $\overline{SS}_D$, for both businesses. On the secondary y-axis, the achieved service level is displayed. This achieved service level is, as for SS_D, considering all sales from TS01. As can be seen, the $\overline{SS}_F$ is somewhat greater for Processing SPs. Meanwhile, Packaging achieves a higher service level.

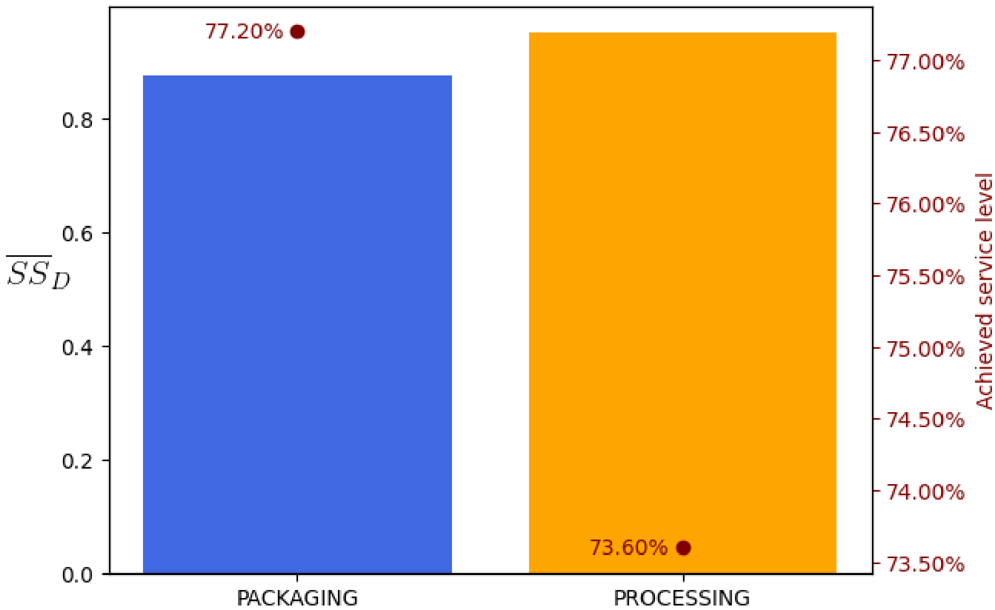


Figure 35: Average safety stock ratio for parts with minimum safety stocks, for Packaging and Processing, respectively.

4.5 Summary of Empirical Findings

Below follows a brief summary of the empirical findings:

- There is a difference in the Packaging and Processing portfolio. Lower sales volumes within processing causes SPP to assign lower target service levels. Also, the lower sales volumes imply more relative demand variance.
- Packaging SPs have a higher ratio of planned orders. Because of the longer lead times, planned orders make managing inventory easier.
- SPP is forecasting similarly for both businesses. However, lower pick classes have a lower forecast ratio, which the authors argue is logical, when considering the fact that the demand for these parts are more prone to outlier correction. Since Processing has a larger portion of SPs within these classes, this affects Processing more.
- Packaging SPs have lower relative lead time variation. Since SPP does not account for stochastic lead times, this impacts Processing more.
- Packaging SPs have more manual safety stocks, and achieves a higher service level for parts with stocking status NS min SS. Because of the more detailed information available on criticality and installed base, SSN is able to more accurately assign minimum safety stocks for Packaging SPs.

5 Analysis

In this section, qualitative and quantitative analysis is performed on the empirical findings. This starts off with analyzing both Stocked Spare Parts and Non-Stocked Spare parts, before concluding with a root-cause analysis that summarizes the suspected issues.

5.1 Stocked Spare Parts

As concluded in section 4.4.4, Processing SPs have a larger gap to their target service level. However, it remains to be proven that this gap is statistically significant. If it is not, the entire service level difference can be explained by the design of SPP. To investigate this, the following measurements were defined:

S^i - Achieved service level for an SP in month i,

Δ_S^i - Difference between target and achieved service level for an SP in month i,

$\overline{\Delta}_S$ - Average difference between monthly target and achieved service level for an SP.

$$\overline{\overline{\Delta}}_{\mathbb{P}} = \frac{1}{n}\sum_{i=1}^{n} \overline{\Delta}_{S_n}, S_n \in \mathbb{P} \text{ where } \mathbb{P} \text{ is a set of SPs.}$$

Firstly, $\overline{\overline{\Delta}}_{\mathbb{P}}$ was calculated for all Packaging and Processing SPs, separately. The difference in $\overline{\overline{\Delta}}_{\mathbb{P}}$ between the two businesses was not tested for statistical significance, as the different order line distributions are not the same for Packaging and Processing. These calculations are displayed in Table 7.

Table 7: $\overline{\overline{\Delta}}_{\mathbb{P}}$ (percentage points) for all parts with stocking status ST, calculated for Packaging and Processing respectively.

	Packaging	Processing	Difference
$\overline{\overline{\Delta}}_{\mathbb{P}}$	-2.11	-2.75	-0.64

Then, The difference in $\overline{\overline{\Delta}}_{\mathbb{P}}$ between Packaging and Processing was calculated for each cell in the TSL matrix, and Welch's test was performed on a 95% significance level for each cell to verify statistical significance. A minimum requirement of 50 observations for each calculation of $\overline{\overline{\Delta}}_{\mathbb{P}}$ was set, to ensure that the central limit theorem could be applied. In Figure 36, the difference in $\overline{\overline{\Delta}}_{\mathbb{P}}$ between Packaging and Processing is displayed. Seven cells display a significant difference between Packaging and Processing. In three cells, Processing is outperforming Packaging, and in the remaining four, the opposite is true. Important to note is that the impact on the overall service level depends on the number of order lines within each cell. In Table 8, the cells displaying a statistically significant difference are listed together with their respective portion of total order lines.

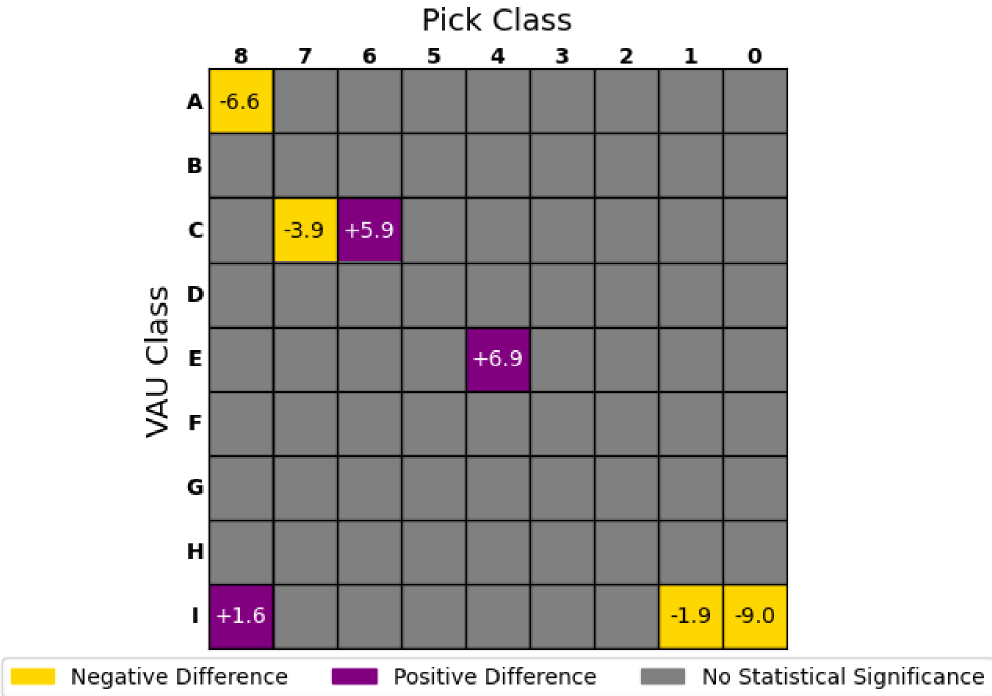


Figure 36: Difference in $\overline{\overline{\Delta}}_{\mathbb{P}}$, expressed in percentage points, between Packaging and Processing.

Table 8: Difference in $\overline{\overline{\Delta}}_{\mathbb{P}}$, expressed in percentage points, and portion of total order lines placed to TPTS, for cells displaying a statistically significant difference.

Cell	Difference in $\overline{\overline{\Delta}}_{\mathbb{P}}$	portion of Total OLs
A8	-6.6	11,05%
I8	+1.6	2,61%
C7	-3.9	1,35%
I0	-9.0	0,96%
I1	-1.9	0,92%
C6	+5.9	0,15%
E4	+6.9	0,07%

The difference in cell **A8** is believed to be a consequence of the way the TSL matrix is designed. SPs in pick class 8 have 300 or more yearly order lines, and because of larger sales volumes and because of the larger sales volumes of Packaging SPs, it is possible that the factors impacting $\overline{\overline{\Delta}}_{\mathbb{P}}$ are magnified by the difference in sales volume. Figure 37 displays the average monthly sales volume per VAU class and business, for SPs in pick class 8. Here, the difference between the two businesses is much greater for VAU class A than for any other. The authors argue that comparing $\overline{\overline{\Delta}}_{\mathbb{P}}$ in this cell is an unfair comparison because of this large difference.

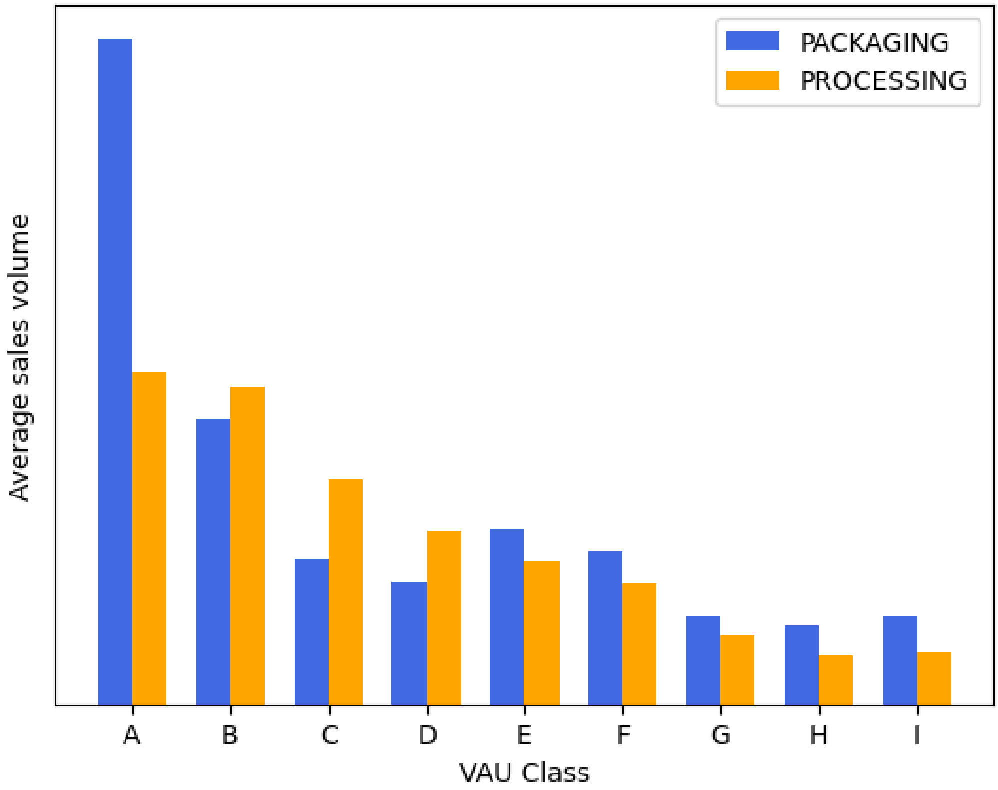


Figure 37: Average monthly sales volume per VAU class, for SPs in pick class 8, for Packaging and Processing. Numbers are hidden due to confidentiality.

The difference in cell **I0** is believed to be the consequence of customer behaviour. As Figures 31 and 32 show, Processing exhibits a much larger lumpiness in demand here. For the remaining cells, the authors have not been able to find one outstanding factor that could explain the difference. Instead, the reason is believed to be caused my a combination of the factors hitherto discussed.

5.1.1 Impact of Planned Ratio

As one identified factor was the degree to which customers place planned orders, it was investigated how well an SP meets its target service level based on its *planned ratio*. For each SP, the *planned ratio* was calculated, as the average ratio of total order lines placed on planned orders. $\overline{\overline{\Delta}}_{\mathbb{P}}$ was then plotted against the planned ratio, which was divided into bins of size 0.05. Then, least-squares linear regression was performed to fit a line describing $\overline{\overline{\Delta}}_{\mathbb{P}}$ as a function of planned ratio for Packaging and Processing respectively. The data points and regression lines are plotted in Figure 38. Evidently, the planned ratio is correlated to the degree to which an SP meets its target service level. However, SPs with a planned ratio equal to zero seem to not be following the overall trend. The reason for this remains unknown to the authors. Moreover, Processing seems to be more affected by the planned ratio, which is believed to be due to the shorter average lead times in Processing SPs.

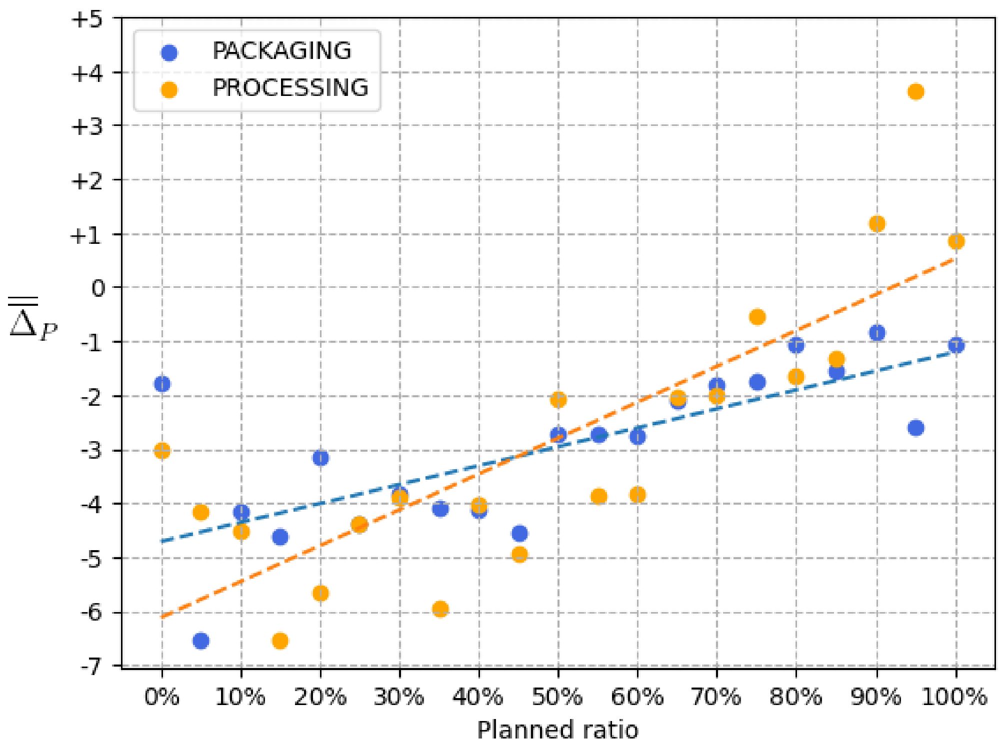


Figure 38: $\overline{\overline{\Delta}}_{\mathbb{P}}$, expressed in percentage points, as a function of average planned ratio. Lines are fitted for Packaging and Processing, respectively.

5.2 Non-Stocked Spare Parts

A plausible explanation for the large difference in service level for parts with stocking status NS was hypothesized to be due to the difference in planned ratio. Therefore, the achieved service level of non stocked parts was calculated for all non-planned orders, and then for only planned orders. In Table 9, these calculations are displayed. The difference is much smaller for planned orders, which again highlights the impact of planned ratio.

Table 9: Achieved service level and difference in percentage points between Packaging and Processing for SPs with stocking status NS.

	Packaging	Processing	Difference
Non-Planned orders	45.9%	29.4%	16.4%
Only Planned orders	57.4%	48.9%	8.5%

5.3 Impact of Minimum Safety Stocks

As previously discussed, Packaging SPs with stocking status NS min SS on average have lower safety stock ratios, while simultaneously achieving a higher service level. This implies that minimum safety stocks increase the expected service level more for Packaging SPs. It is possible that this can be explained in its entirety by the factors already discussed, such as higher planned ratio. However, the authors believe part of the explanation to be what is discussed in section 4.3.1: there exists more, and better, information on Packaging SPs, which is the basis for min SS decisions.

5.4 Inventory Classification Methods

Comparing the TSL matrix to the theoretical classification methods mentioned in section 3.1.2 it can be summarised that it resembles an **ABC-XYZ** classification method, where the pick classes somewhat measure the demand variability, usually labeled as **XYZ**, and the **VAU** classes corresponding to the quantity shown in the **ABC** axis. To evaluate the accuracy of number of yearly picks as a measurement of demand variability, the coefficient of variation of demand was calculated for each SP, and then the average coefficient of variation for each number was calculated. In Figure 39 these calculations are plotted, and evidently the coefficient of variation declines with an increasing number of picks. Thus, a correlation can be assumed, but the degree of this correlation will not be established here. The authors argue however, that approximating demand variability through pick classes is a computationally effective, although imprecise, way.

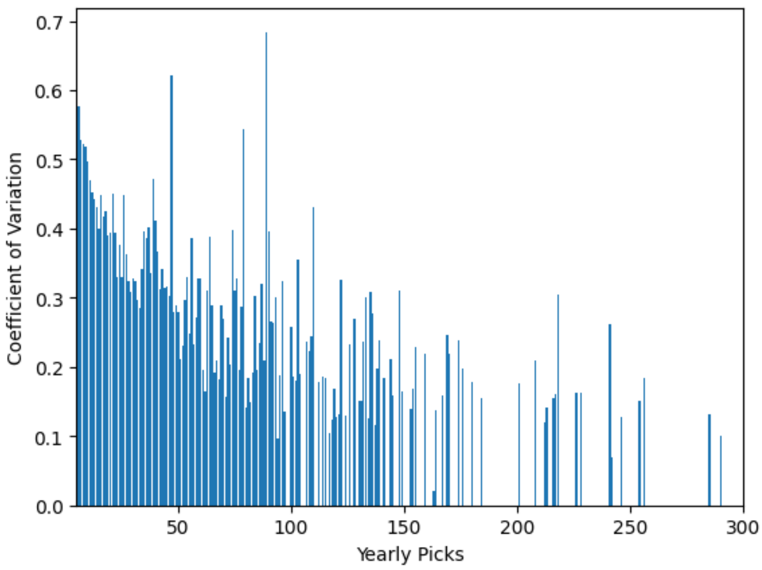


Figure 39: Average demand Coefficient of Variation per number of yearly picks.

One major difference between the TSL-table and the classic **ABC-XYZ** segmentation is that it contains $9 \cdot 9 = 81$ total categories as opposed to the standard $3 \cdot 3 = 9$. This level of detail is discouraged by Vollman et al. (2005).

The way SSN currently assigns minimum safety stocks based on information such as recommended service time or expected time to failure can be compared to the **VED** classification also shown in section 3.1.2.

5.5 Factors and Root Causes

Taking inspiration from the Cause-and-effect analysis described by Gangidi (2019), a root-cause analysis along with a diagram was constructed in order to help identify which factors and root causes might be responsible for the lower availability for Processing Spare Parts. The factors were identified based on the previously mentioned Empirical Findings and crosschecked with interviews and focus groups, this subsection will explain how the analyis was done for this and how the diagram was constructed root-by-root. The entire final diagram can be seen in appendix F along with a color key that displays if the factor or root cause is influence by **Customer Behavior**, **SPP System**, **Supplier Performance** or overall **Organizational Differences**.

The Root Cause analysis was divided into the following three categories:

- **System-wide** - Pertain to workflows such as SPP that have a clear system definition.
- **Occurrence Specific** - Includes more general Organizational Factors that do not pertain to any specific inventory management process regarding SPs
- **Human Factors** - Factors that have a direct human involvement that affects the service level. It can be noted here that no such factor or root cause was identified as having an impact on the service levels.

5.5.1 System-Wide Factors and Root Causes

The system category analysis can be seen in Figure 40. Two main strands were identified to start with, these and what empirics were used to identify them will follow below.

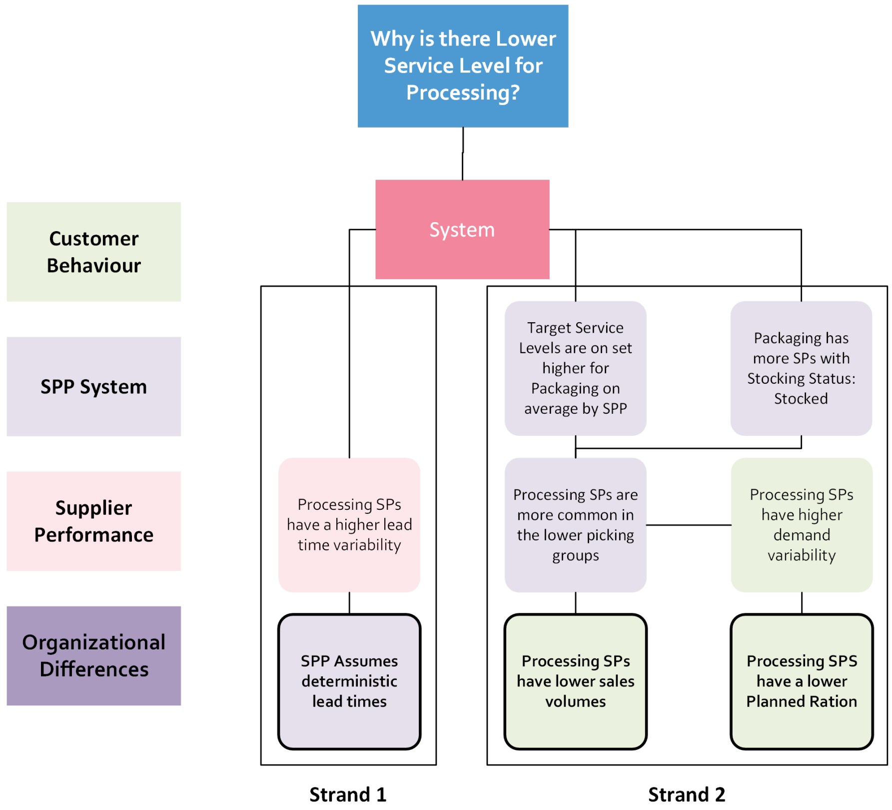


Figure 40: Root Cause and factors for the lower service level in processing identified in the System-wide category with a color legend to identify which type of factor or root cause.

Continuing on with **Strand 1**, the factor ***Processing SPs have a higher***

relative lead time variability was identified by looking at the Supplier lead times for Processing and Packaging seen in Figures 33 and 34. From this, along with the formula from SPP used to set the Safety Stock seen in equation 16, a possible root cause being that ***SPPs assumed deterministic lead times*** was identified.

Two main starting factors were identified for **Strand 2** as shown in Figure 40; these being that the ***Target Service Levels are on average set higher for Packaging by SPP*** and that ***Packaging has more SPs with Stocking Status: Stocked***. This was identified respectively from Figure 27 which shows that the overall TSL is higher for Packaging and Figre 22 which shows the Stocking Status distribution for Packaging and Processing. The reason for both of these factors was identified from Figure 29 which shows that ***Processing SPs are more common in the lower pick groups*** in the TSL-table. From this, one root factor was identified, being ***Processing SPs have lower sales volume*** compared to Packaging, as was seen in the order line distribution in Figure 23. Another reason for Processing SPs being more common in the lower pick groups is the factor that ***Processing SPs have a higher demand variability***. This reasoning stems from the definition of the pick groups and can be seen in Figure 29 which shows a that around 50% of Processing SPs are located in Pick Class Z compared to around 41% for Packaging. The root cause identified for this higher demand variability is that ***Processing SPs have a lower Planned Ratio*** compared to Packaging, this can be seen in Figure 24 which shows that while Packaging has an almost even split of Planned vs. Priority orders lines, Processing only has a third of the total order lines in the Planned category. It is believed that this ratio between Planned vs. Priority shows that the customer segment for Processing is less likely to communicate their demand planning in advance for maintenance compared to packaging, thus increasing the uncertainty. The impact that the planned ratio has on the service level was also shown in Figure 38 and table 9, where a correlation between higher planned ration to increased availability was found.

5.5.2 Occurrence-Specific Factors and Root Causes

The Occurrence-Specific analysis can be seen Figure 41, the first factor identified in **Strand 3** was the current differences in TPMS for Processing and Packaging discussed in 4.2.2. This along with the Organizational Differences paints a picture that Processing has not implemented services such as TPMS to the same extent as Packaging, which the authors claim leads into the second factor: ***Processing Customer Base not as Developed***. For different reasons, Processing has a far less amount of installed bases with maintenance recommendations through TPMS, and they do not have such services such as on-site engineers which leads to there not being the same opportunity to plan their maintenance and spare parts order compared to Packaging. The factor that influences this is believed to be that ***Processing has generally not had a centralized after sales process compared to Packaging***, due to them having a larger product portfolio compared to Packaging. The final root cause for the occurrence specific analysis is then believed to be ***Processing has largely had a decentralized organisation due to Mergers and Acquisitions (M&A) compared to Packaging***, this was discussed in 4.1 and is deemed to be the root cause which has caused the there not being as detailed information for maintenance need for Processing compared to Packaging.

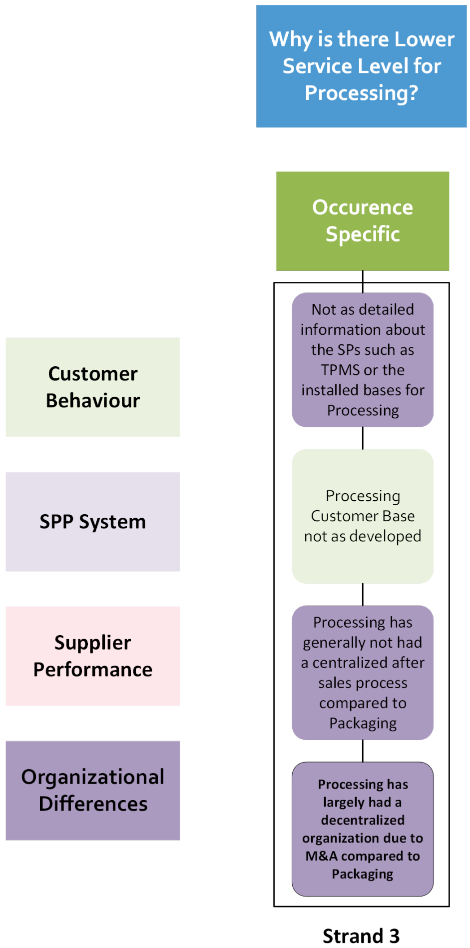


Figure 41: Root Cause and factors for the lower service level in processing identified in the Occurrence-Specific category with a color legend to identify which type of factor or root cause.

6 Recommendations

This section deals with answering RQ2 by discussing possible recommendation identified. These recommendation have been categorized into four main areas and are of different degrees of difficulty when it comes to implementation as well as project size and time-horizons. Firstly, the recommendations are elaborated and discussed. Then, their respective impacts and efforts are estimated and compared.

6.1 Account for Lead Time Variability

Tetra Pak could modify their safety stock calculation to account for lead time uncertainties. To investigate the impact of this, a set of SPs were identified where lead time variability was relevant. For all SPs with stocking status ST, and a normal demand model, order quantity and safety stock was calculated using the method currently used by SPP, but with (18) as the formula for calculating safety stocks. Then, the expected stock cost was calculated for each SP using (12). In Table 10, the relative increase in expected stock cost is displayed for the average SP, and as a total for Packaging and Processing. As expected, the expected cost of Processing parts increase more because of more lead time variability, but both businesses increase extremely. Evidently, this modification is not realistic. It is possible however, that this implementation is in fact suitable and beneficial for a subset of the Tetra Pak portfolio, but this has not been investigated further. Moreover, (18) uses the standard deviation of the lead time as a measurement of variability. For the absolute majority of SPs, deliveries are so infrequent that the estimate of the lead time standard deviation should be regarded with scepticism.

Table 10: Increase in expected stock cost, for an average SP, and in total, for Packaging and Processing.

	SP Average	Total
Packaging	176%	701%
Processing	188%	794%

A safety lead time is more suitable for most, if not all SPs with a high lead time variance in the TPTS portfolio. Such an implementation would, as Olhager, 2019 mentions, extend the planning horizon for these parts. With the current order logic employed by TPTS, this would be most easily be facilitated through an increase in planned order ratio.

6.2 Changing Classification systems

6.2.1 Differentiate Between Packaging and Processing

As one identified root cause was the difference in sales volume, an argument can be made that the TPTS SPIM policy is unfair from a customer perspective. Packaging customers enjoy higher service levels simply because there are more of them. To remedy this, the following actions can be taken.

First of all, TPTS could **reconfigure the stocking decision table**. As Figure 25 shows, a missed order line is much more probable to be for an SP with stocking status NS within Processing. This is mainly due to Processing having a larger portion of SPs with this stocking status, which in turn is a direct consequence of the logic in the stocking decision table. A stocking decision is based on cost and pick class of an SP, and since Processing has lower sales volumes, the average pick class is lower for these SPs.

Secondly, TPTS could **reconfigure the TSL matrix**. As Figure 36 shows, Processing SPs have lower target service level, which is mainly due to lower sales volume.

These changes could be performed in such a way that Processing and Packaging have an equal ratio of NS parts, and similar target service levels, which would result in customers receiving a much more equal level of service. At the same time, inventory costs would increase for processing SPs to a great extent. However, as the processing business is expected to grow within the near future, these costs need not be permanent. If these actions are pursued, it would be possible to gradually adjust the stocking decision table and TSL matrix as Processing sales volumes increase.

6.2.2 Change Criteria for Target Service Level

The TSL matrix currently used by TPTS contains room for improvement. One alternative classification method is the one proposed by D'Alessandro and Baveja (2000), to better handle demand variability.

Of course, implementing such a change is a great commitment which requires thorough investigation, the bulk of which is outside the scope of this thesis. However, as an initial comparison, the active SPs of Tetra Pak were classified according to this system in order to gain an overview of how differently SPs would be classified. For each SP, average demand and the coefficient of variation of the demand was calculated. Even though D'Alessandro and Baveja (2000) Recommend calculating these measures on weekly observations, they were calculated on the 12 months in 2022, as there does not exist accurate historical data on a weekly basis. As the coefficient of variation is calculated using the sample standard deviation, a minimum of two observations is required for a defined output. Therefore, SPs with less than two observations were excluded. in Figures 42 and 43, the classification is plotted for Packaging and Processing SPs respectively. A general color gradient can be observed along the x-axis for both businesses, which indicates there is correlation between the two systems. At the same time, it is evident that there are vast differences in them as well. For example, the darkest data points, corresponding to SPs with the lowest target service level, are scattered seemingly randomly. In Figure 44, all SPs are plotted, and color coded by their respective business. As a consequence of their lower sales volumes, processing SPs are more skewed to the left. This means, should this classification be implemented as presented here, Processing SPs would on average be assigned lower target service levels. Differentiation is however possible and quite simple if desired. For example, the x-axis cutoff point is here calculated as the mean average demand of all SPs, but could be separately calculated for the two businesses instead.

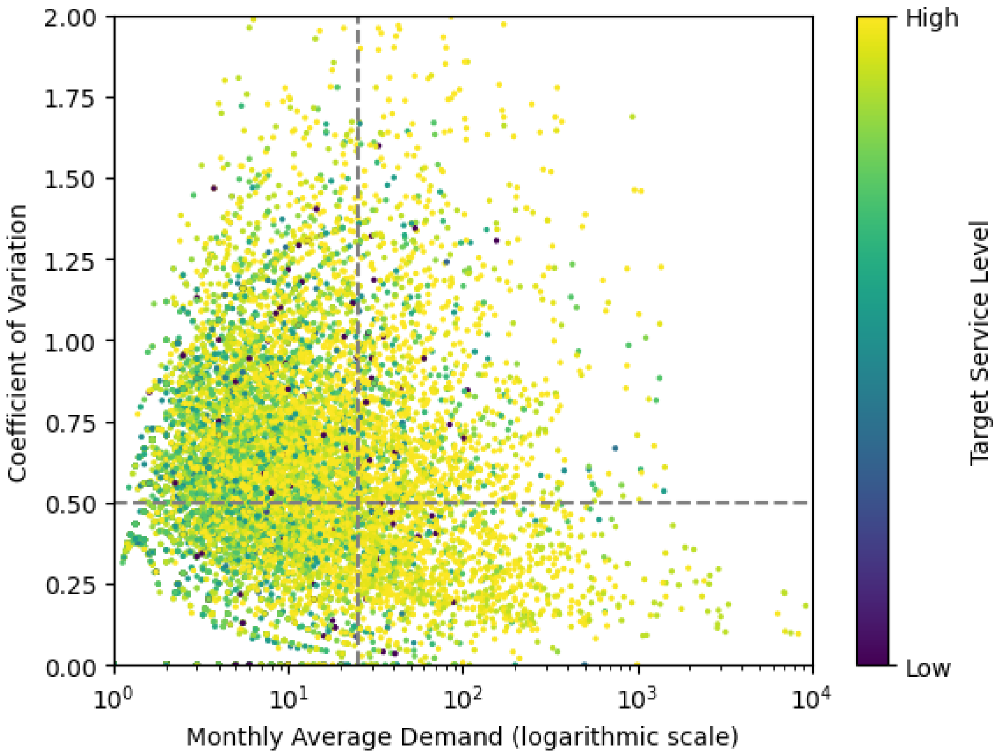


Figure 42: Packaging SPs classified according to the system described by D'Alessandro and Baveja (2000). Data points are color coded according to their current target service level.

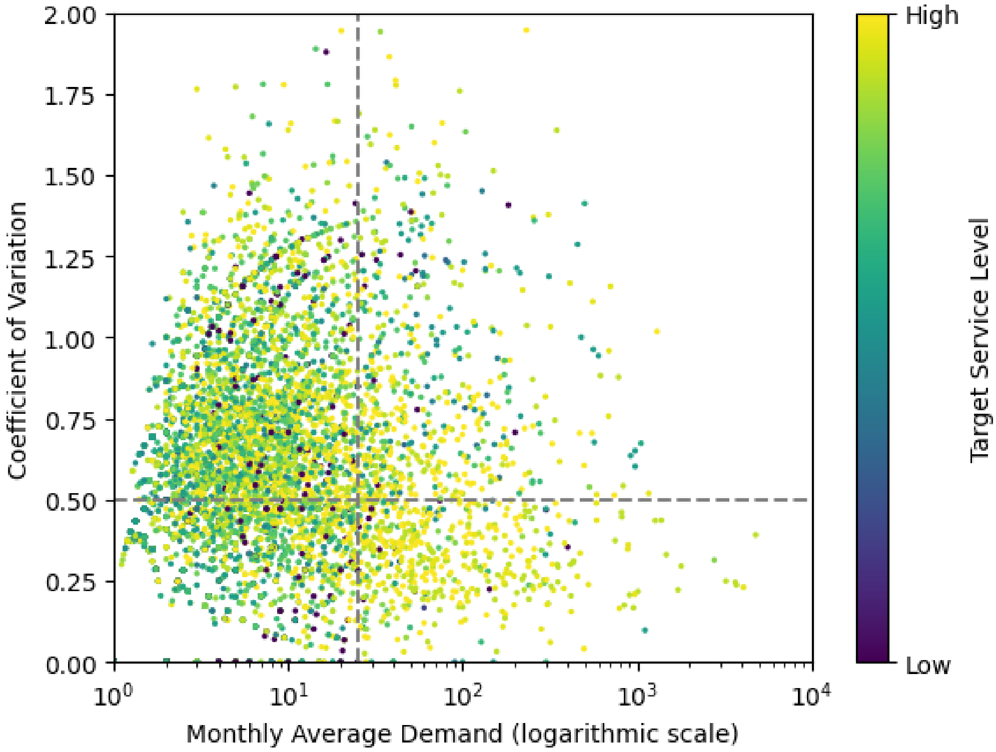


Figure 43: Processing SPs classified according to the system described by D'Alessandro and Baveja (2000). Data points are color coded according to their current target service level.

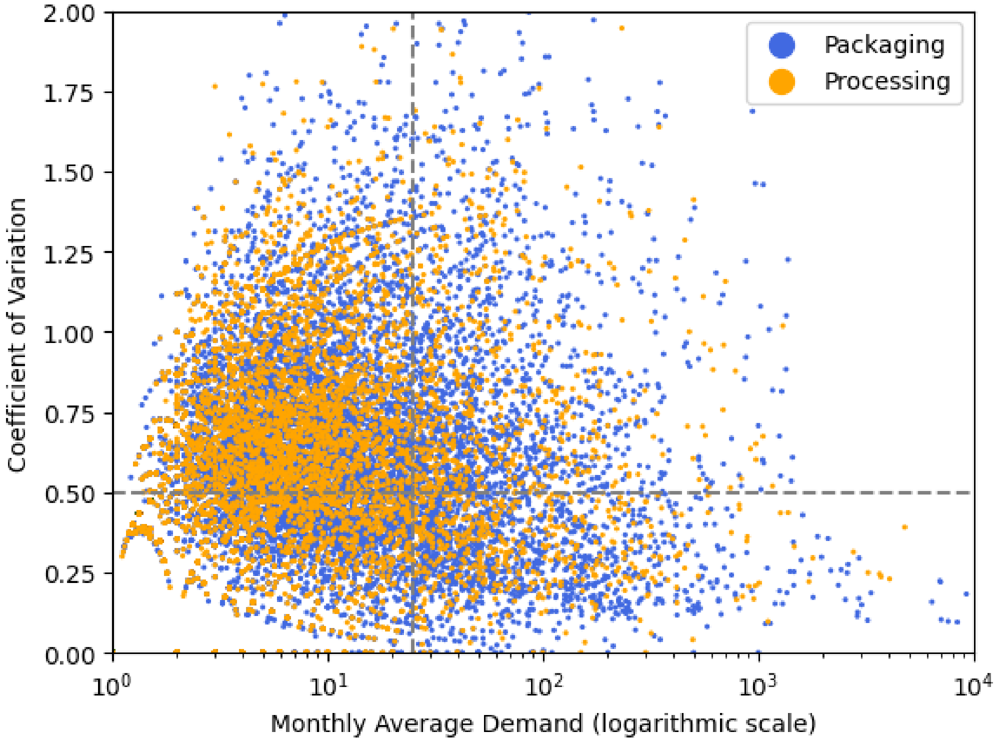


Figure 44: Processing SPs classified according to the system described by D'Alessandro and Baveja (2000). Data points are color coded based on their respective business.

The application of this classification system on TPTSs portfolio poses an immediate problem: SPs with less than two historical orders are undefined, and even for SPs with more observations than that, the accuracy of the coefficient of variation can be put into question when the sample size is small. However, it theoretically captures demand variability better, which both Zhang et al. (2021) and Huiskonen (2001) point to as a major characteristic to consider when working with SPIM.

6.2.3 Increase Planned Ratio

From the analysis performed it seems to show that the higher planned ratio has a direct influence on the higher average service level for Packaging SPs. Therefore, it is the authors belief that if work is done to increase the planned ratio for Processing an increase in service level will follow. Main ways of doing this can include the following two points:

- **Work with continuous development and understanding of the customer base -** Continuous work in understanding and developing the processing customer base with the help of market companies will facilitate a comprehensive understanding of customer behavior and order patterns, ultimately enhancing customer knowledge. This increased customer knowledge can be leveraged to improve the planning of processing spare parts orders. By closely analyzing customer preferences, demand patterns, and historical data, it becomes possible to anticipate and proactively address customer needs, resulting in more accurate and informed planned orders for processing spare parts. Also, continuous communication regarding the benefit of planned orders to the Market Companies and from them to the end customer is thought to be beneficial in trying to achieve this.

- **Expand Processings' TPMS catalogue -** Increasing the TPMS catalogue for processing spare parts is thought to likely impact the possibility for the customer to plan their maintenance and therefore their spare part orders better. While outside of the scope of TPTS, the authors thought this was a salient point to include as there is already an ongoing project to achieve this and it would be wise of TPTS to monitor this situation and keep open communication with Processing regarding the importance of each others goals.

Increasing the planned ratio of processing customers can be a monumental task for TPTS due to the inherent different product characteristics compared to Packaging. However, it is the authors belief that the two point discussed here is an adequate first start into investigating the customer behaviour which from the root cause analysis seems to be a large part in the service level differences. Figure 38 suggests that the planned ratio of an SP is directly correlated to its ability to meet its target service level. While this might be true, there might be many underlying correlations at play here. Thus, SSN needs to understand what underlying factors impact the planned ratio of an SP.

6.2.4 Understand the Supplier Behaviour Differences

Investigating the supplier behavior differences between packaging and processing spare parts is of crucial importance due to the observed disparities in lead times and lead time variability. Although processing spare parts exhibit lower average lead times compared to packaging spare parts, their higher lead time variability introduces a level of uncertainty and potential disruptions in the supply chain. While TPTS at the moment reguraly evaluates suppliers, understanding and addressing supplier behavior differences between the product categories is essential for several reasons:

- **Risk mitigation -** By investigating the supplier behavior differences, organizations can identify the root causes of higher lead time variability in processing spare parts. This knowledge enables them to develop proactive strategies to mitigate risks associated with potential delays or disruptions in the supply chain. It allows for the implementation of contingency plans, such as alternative sourcing options or buffer inventory, to ensure a consistent and reliable supply of spare parts for processing operations.

- **Enhanced planning and scheduling -** Supplier behavior differences, particularly in terms of lead time variability, necessitate adjustments in planning and scheduling activities. Through a comprehensive investigation, organizations can gain insights into the factors contributing to the variability and tailor their planning processes accordingly. This may involve setting more conservative lead time estimates, incorporating buffer times, or implementing dynamic scheduling techniques that account for the inherent uncertainty in processing spare parts supply.
- **Improved customer satisfaction: -** Understanding supplier behavior differences and effectively managing lead time variability can positively impact customer satisfaction. By minimizing disruptions in the supply chain and consistently meeting customer expectations, organizations can enhance their reputation for reliability and responsiveness. This, in turn, strengthens customer relationships, fosters loyalty, and may lead to increased customer retention and market share.
- **Cost optimization -** Investigating supplier behavior differences enables organizations to optimize costs associated with spare parts procurement and inventory management. By accurately assessing lead time variability, organizations can avoid unnecessary inventory holding costs while ensuring an adequate level of safety stock to buffer against potential supply disruptions. This optimization helps strike a balance between minimizing inventory carrying costs and avoiding costly production delays due to stockouts.

Understanding the supplier behavior differences between Packaging and Processing spare parts is essential for managing risks, improving planning processes, enhancing customer satisfaction, and optimizing costs. By gaining a deep understanding of these differences, TPTS can develop effective strategies to address lead time variability and maintain a robust and efficient supply chain for spare parts procurement and delivery as well as closing the gap in the service level differences.

6.3 Impact-Effort Estimation

The discussed actions were classified according to their perceived impact and effort. Impact pertains to the extent to which an action lessens the service level disparity between Processing and Packaging. Effort pertains to the required resource intensity and time horizon of an action. Figure 45 displays the actions placed in an impact-effort matrix. Actions 1 and 2 address the difference in lead time variability. These were considered to require the least amount of effort, as they would "only" require a change in the SPP logic. Meanwhile, as the reasonable scope of SPs for these are estimated to be quite small, a small impact is implied. Actions 3 and 4 are the ones deemed to have the highest impact to effort ratio, since differentiating between Packaging and Processing would be an efficient way to reduce the differences in service level. Having said that, the authors do not believe these actions to be very beneficial as they would incur a substantial increase in stock holding costs for Processing SPs. Action 5, which is to change the criteria of which the TSL table is based, is though to have a small impact relative to its effort. Despite this, the authors believe this is an action SSN should consider. Compared to the other recommendations, it does not address the difference in service level between Packaging and Processing as explicitly, but it is believed that this classification is beneficial for the overall SP portfolio. Action 6, which is to increase the planned ratio of Processing SPs, is believed to be what can remedy the disparities the most. As such, it is resource intensive and more importantly, has a long time horizon. Finally, the recommendation discussed in section 6.2.4, which addresses the differences in supplier behaviour, has not been put into the matrix. This is because understanding the difference in supplier behaviour does not itself remedy the service level disparities. Instead, this action would be a first step in formulating actions that would help Processing suppliers in achieving the same performance as Packaging.

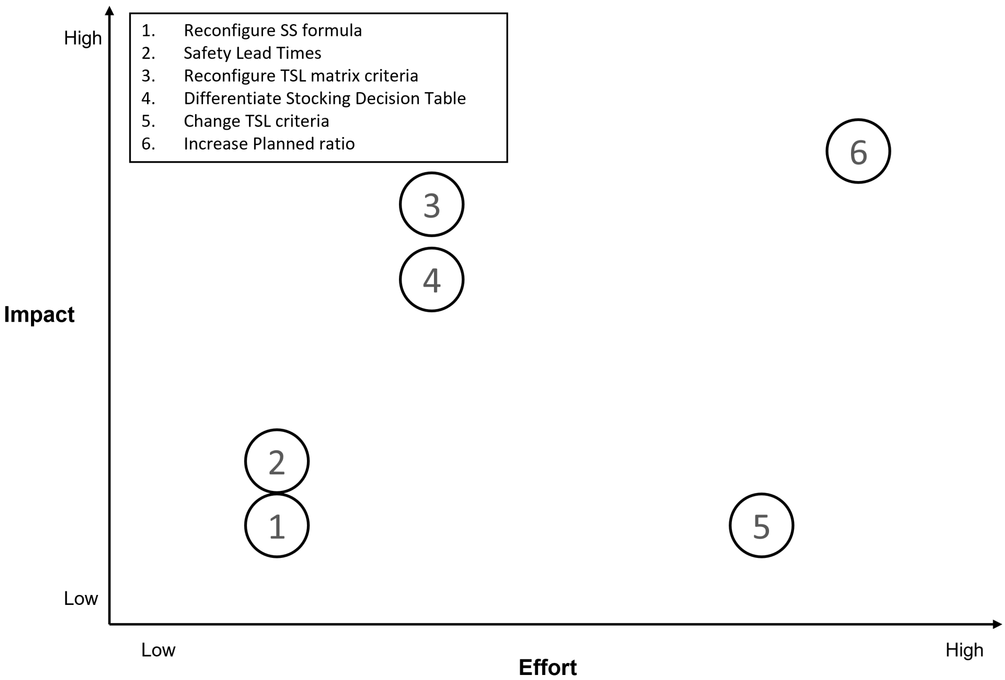


Figure 45: The discussed actions classified by impact and effort.

7 Conclusion

This section contains summarized conclusions for the research questions. Followed by a discussion of the limitations of the thesis with regards to the data and general applicability. Finally some areas of future research based on the recomendations are discussed.

7.1 Research Question 1

After conducting the root-cause analysis seen in section 5.5 and appendix F, it was found that several factors contribute to the lower service level of Processing Spare Parts compared to Packaging Spare Parts. The analysis identified factors and root causes falling under two major categories: System-wide and Occurrence-specific.

Under the System-wide category, it was identified that Processing SPs have a higher relative lead time variability, which is not accounted for by SPP. Additionally, the Target Service Levels are on average set higher for Packaging by SPP. This is because Processing SPs have lower sales volume and higher demand variability, due to a lower Planned Ratio compared to Packaging. It is believed that the customer segment for Processing is less likely to communicate their demand planning in advance for maintenance compared to Packaging, thus increasing uncertainty.

The Occurrence-specific analysis identified several factors, including the differences in TPMS for Processing and Packaging, Processing Customer Base not being as developed, and Processing having a largely decentralized organization due to M&A. These factors have led to Processing not having the same opportunities to plan their maintenance and spare parts orders compared to Packaging, resulting in lower service level for Processing SPs.

In conclusion:

- Processing SPs have lower target service levels due to lower sales volumes.
- Processing Suppliers exhibit higher lead time variability which is not accounted for.
- The Processing Customer base is less likely to communicate demand planning in advance for maintenance.
- Processing SPs contain less detailed information that accommodate the planning process due to a more decentralized organization.

7.2 Research Question 2

The authors have identified several factors and root causes that contribute to the lower average service level for processing spare parts compared to packaging. These include lead time variability, differences in sales volume, classification systems, target service levels, and planned ratio. To counteract these factors and root causes, the following strategies and actions can be implemented:

- **Account for Lead Time Variability -** Tetra Pak can modify their safety stock calculation to account lead time uncertainties. Implementing a safety lead time can help extend the planning horizon for SPs with high lead time variance, thereby reducing the risk of stock-outs and improving service levels.
- **Differentiate Between Packaging and Processing -** Reconfigure the stocking decision table and target service level matrix to ensure a more equal ratio of NS parts and similar service levels for both packaging and processing SPs. This will provide customers with a more equitable level of service while gradually adjusting the system as processing sales volumes increase.
- **Change Criteria for Target Service Level -** Explore alternative classification methods to better handle demand variability. By accurately capturing demand patterns, the target service levels can be tailored to each SP's specific characteristics, leading to improved service levels.
- **Increase Planned Ratio for Processing -** Focus on understanding and developing the processing customer base to enhance customer knowledge and improve the planning of spare parts orders. Continuously analyze customer preferences, demand patterns, and historical data to anticipate and address customer needs, resulting in more accurate planned orders. Expand the TPMS catalogue for processing spare parts to allow customers to plan their maintenance and spare part orders more effectively.
- **Understanding the Supplier Behavior Differences -** Conduct a thorough investigation of supplier behavior differences between packaging and processing spare parts. This will help identify the root causes of lead time variability and develop proactive strategies to mitigate risks. Adjust planning and scheduling processes to account for lead time uncertainties and ensure a consistent and reliable supply of spare parts. This will ultimately enhance customer satisfaction and optimize costs.

By implementing these strategies, Tetra Pak can address the factors and root causes responsible for the lower average service level for processing spare parts. This will lead to improved service levels, increased customer satisfaction, and a more efficient supply chain for spare parts procurement and delivery.

7.3 Limitations

7.3.1 Data

While all the steps mentioned in sections 2.2.2 and 2.4 were taken in order to ensure objective data gathering and analysis, the dataset used in this thesis contains error sources. Below, the main error sources are listed and discussed.

- **Data Quality.** Instances of inaccurate historical records were encountered during the writing of this thesis. For example, the forecast data discussed in section 4.4.5 is known to contain inconsistencies. Some data may be inaccurate without the knowledge of the authors, which risks harming the reliability of the study.
- **Timeframe.** Because of lack of older historical data, the year 2022 was chosen, which was extraordinary in many aspects. Global supply disruptions and other anomalies harm the study's internal validity, external validity, and reliability.
- **Multi-Echelon Effects.** The TPTS supply chain contains several echelons. The investigated warehouse, TS01, supplies all downstream installations and thus handles volumes far greater than the demand of its designated customers. In regards to this aspect, the authors are mainly concerned about the internal validity of the conclusions of this thesis.

Moreover, while precautions mentioned in section 2.2.3 were taken in order to have an objective interview process as possible, there is still inherent biases in the people interviewed that can be missed and undetected. Therefore, all the interviews cannot be said to be inherently objective.

7.3.2 Literature

While the present study tried to employed a rigorous literature review discussed in section 2.2.1, relying solely on peer-reviewed sources, it is important to acknowledge that even with these stringent criteria, limitations may exist in the literature collection. Firstly, the scope of any literature review is constrained by the available resources and time constraints, potentially resulting in the exclusion of certain relevant studies. Secondly, the subjective nature of the review process introduces the possibility of overlooking significant works due to human error or bias. Moreover, the ever-evolving nature of research means that new studies may have been published subsequent to the completion of the literature review, further potentially missing out on the most up-to-date findings. Therefore, it is essential to recognize that while efforts were made to ensure a comprehensive review, the overall completeness and perfection of the literature review may be affected by these inherent limitations.

One notable possible problem that occurred while performing the literature review was that the terms *"Spare Parts Management"* and *"Spare Parts Inventory Management"* could also refer to a production facility's management of spare parts, and not a spare part warehouse such as TPTS. Therefore, care was needed to be taken to ensure that the term used in literature was applicable to TPTS.

7.3.3 General Applicability

The general applicability of the findings in this study should be considered in light of certain factors. Firstly, the data collected for this research may present challenges in terms of reproducibility due to the specific context, sample size, and availability of resources. However, it is important to note that the methodology employed in this study was designed with a rigorous approach, aiming to ensure reliability and validity. By documenting the procedures and techniques used in data collection, analysis, and interpretation, future researchers can potentially replicate the study with similar rigor. Although contextual variations may exist, it is expected that adherence to the outlined methodology will yield comparable results and facilitate the validation of the conclusions drawn from this research. Nonetheless, it is crucial to acknowledge that the generalizability of the findings may also be influenced by unique characteristics of the study population or specific contextual factors, necessitating caution when extrapolating the results to broader populations or diverse settings.

7.4 Future Research

Building on the recommendations mentioned in section 6.3 the following avenues for future research have been uncovered:

- **Lead Time Variability Analysis:** Conduct a comprehensive analysis of lead time variability to identify its root causes and impacts on service levels. Explore statistical models or simulation techniques to quantify the effects of lead time uncertainties on stockouts and service levels. This research could provide valuable insights into developing more accurate safety stock calculations and lead time management strategies.

- **Service Level Differentiation:** Investigate the impact of different target service levels for packaging and processing spare parts. Analyze customer preferences and demand patterns to determine the appropriate service level ratios and stocking decision tables for each category. Conduct surveys or interviews with customers to assess their satisfaction levels with the proposed service level differentiations and gather feedback for further improvements.

- **Advanced Classification Methods:** Evaluate alternative classification methods that better handle demand variability. Compare the effectiveness of these methods in accurately capturing demand patterns for different spare parts. Analyze the implications of using alternative classification approaches on target service levels and customer satisfaction.

- **Customer Base Analysis:** Conduct a detailed analysis of the Processing customer base to gain a deeper understanding of their specific needs and requirements. Explore customer segmentation techniques to identify distinct customer groups with varying demand characteristics. This research can aid in tailoring spare parts planning and ordering processes, resulting in more accurate forecasts and improved service levels.

- **Supplier Behavior Investigation:** Investigate the differences in supplier behavior between Packaging and Processing spare parts. Analyze the root causes of lead time variability and develop proactive strategies to mitigate risks. Explore approaches such as supplier collaboration, improved planning processes, and contract renegotiation to ensure a consistent and reliable supply of spare parts.

- **Forecasting profile Investigation:** Understand how the different forecasting profiles used by SPP affect the service level performance of an SP. This was initially an ambition the authors had, however due to lack of historical data it could not be pursued.

By addressing these research possibilities, further insights can be gained into the factors affecting service levels for Processing spare parts. This knowledge can inform the development and implementation of targeted strategies, leading to improved service levels, increased customer satisfaction, and a more efficient spare parts supply chain for Tetra Pak.

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A List of Interviews

Table 11: List of interviews performed during the Case Study

Date	**Interview Subject(s)**	**Interview Form**	**Topic of Discussion**
2022-12-08	Manager Planning & Inventory Optimization, Global Planning Expert A, Global SCO Manager	Unstructured	Topic Introduction and Brainstorming
2023-01-12	Global Planning Expert A	Unstructured	General Introduction and Discussion
2023-01-19	Global Planning Expert A	Unstructured	Spare Part Planning Process
2023-01-26	Global Planning Expert A	Unstructured	Spare Part Planning Process
2023-02-02	Global Planning Expert A	Unstructured	Spare Part Planning Process
2023-02-09	Global Planning Expert A	Unstructured	General Problems
2023-02-16	Global Planning Expert A, Global Planning Expert B	Semi-Structured	Data Collection
2023-02-22	Manager Planning & Inventory Optimization	Semi-Structured	Data Collection
2023-03-01	Manager Planning & Inventory Optimization	Unstructured	Supplier Performance
2023-03-02	Global Planning Expert A, Planning & Quality Director, Supply Network Specialist A, Supply Network Specialist B, Manager Planning & Inventory Optimization	Semi-Structured	Focus Group Session
2023-03-09	Global Planning Expert A	Unstructured	Project Status and General issues
2023-03-16	Global Planning Expert A	Unstructured	Project Status and General issues
2023-03-23	Global Planning Expert A	Unstructured	Project Status and General issues
2023-03-30	Global Planning Expert A, Planning & Quality Director, Supply Network Specialist C, Manager Planning & Inventory Optimization	Semi-Structured	Focus Group Session
2023-04-06	Global Planning Expert A	Unstructured	Project Status and General issues
2023-04-20	Global Planning Expert A	Unstructured	Project Status and General issues
2023-05-04	Global Planning Expert A, Planning & Quality Director, Global Planning Expert C, Manager Planning & Inventory Optimization	Semi-Structured	Focus Group Session
2023-05-11	Global Planning Expert A	Unstructured	Project Status and General issues

B Choice of Dataset - Interview Plan

Background

To evaluate the spare parts management system currently employed by TPTS, we need to quantify the root causes of difference in service level between Packaging and Processing parts. This requires a choice of dataset to analyze. We need to understand the implications of our choice.

Problem Formulation

The complex nature of the supply chain provides that there are almost an infinite number of impacting factors on the SC performance. The goal is to evaluate the system when everything is working as intended, I.e. no "outliers" should be included. For example, the impact of the semiconductor crisis should be excluded.

Purpose

To decide on what dataset to base our evaluation of the spare parts management system.

Method

Perform a semi-structured interview.

Start by reading the following:

We want to understand why Processing parts have a lower service level. To do this, we need to limit our dataset to something that represents how the SC is expected to normally perform.

Questions:

- *What time frame do you think best describes "normal" SC performance?*
- *What past/present anomalies should we exclude from our dataset with regards to the entire portfolio?*
  - *How can we exclude these?*
- *What past/present anomalies should we exclude from our dataset with regards to packaging?*
  - *How can we exclude these?*
- *What past/present anomalies should we exclude from our dataset with regards to processing?*

- *How can we exclude these?*

Interview Subjects

Table 12: List of Interview Subjects for the Choice of Dataset

Position	Motivation
Global Planning Expert A	*Regularly analyzes the SC performance, is the supervisor*
Global Planning Expert B	*Regularly analyzes the SC performance*
Manager Planning & Inventory Optimization	*Has a holistic view of the issues facing TPTS*

C Processing TPMS Situation - Interview Plan

Background

TPTS has a team that is devoted to increasing the amount of Proccessing modules that have a TPMS. As this thesis has hopefully shown, TPMS is an important factor for both Packaging and Processing in increaseing the Service Level to TPTS customers. Therefore it was deemed prudent to have a conversation with the manager of this team in order to get their view on the current situation.

Purpose

To get general ideas of what the differences exist in establishing TPMS procesuders for Processing compared to Packaging and get a sense of what the current status is.

Method

Perform a semi-structured interview.

Start by reading the following:

We want to understand why Processing parts have a lower service level compared to Packaging Spare Parts. In order fully understand the scope of this we would like to ask you some questions about your view on this.

Questions:

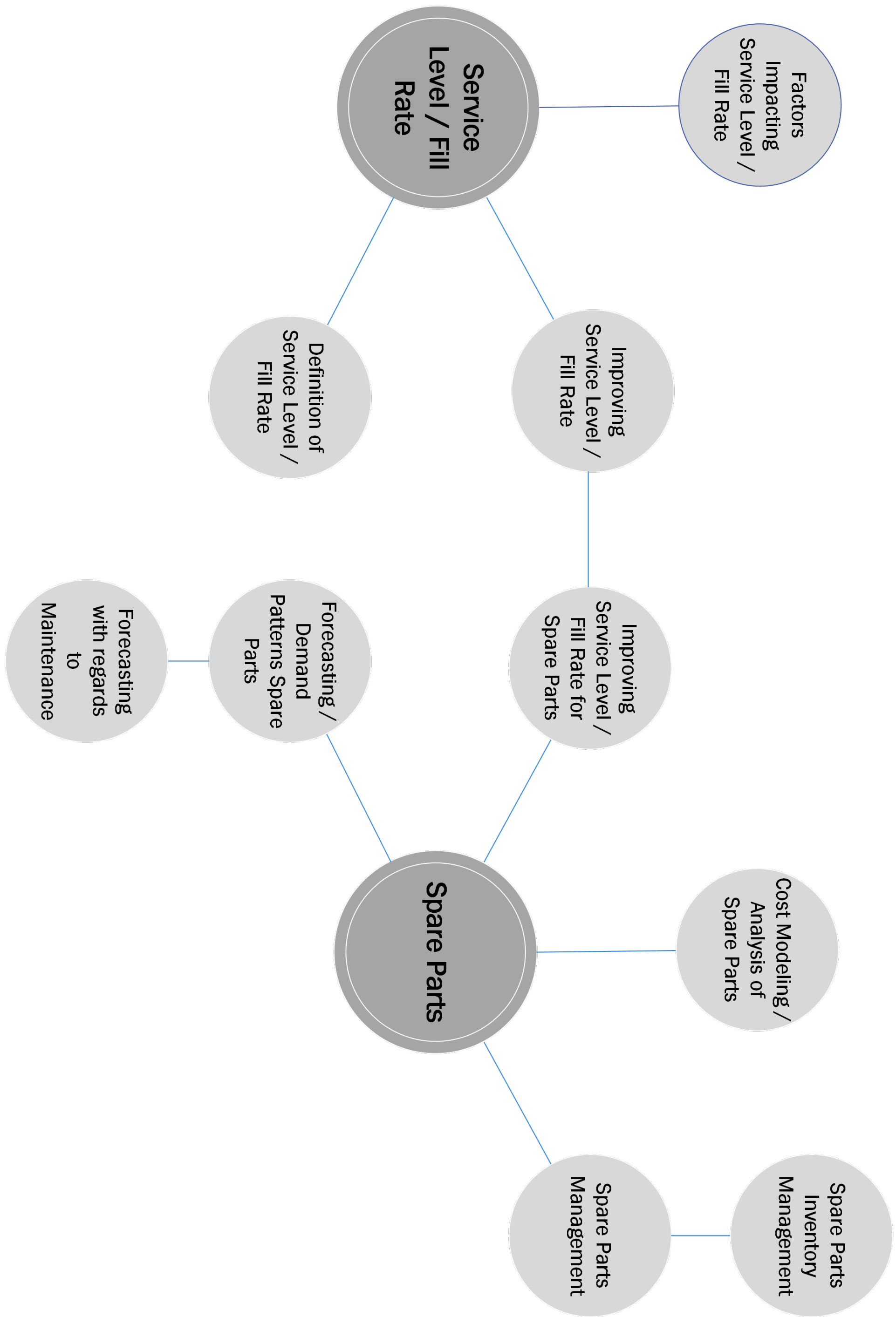
- *What is your sense of the differences between Packaging and Processings spare parts flow?*
  - *Do you perceive any general differences in such tasks as Sourcing and supplier development?*
  - *Do you perceive any general differences in working with customer development?*
- *Have you had any experience or past projects in trying to up the Service Level for SPs?*
- *What current projects are you working on related to this?*
- *What projects would you like to see in the future? If you can think of any necessary?*

Interview Subjects

Table 13: List of Interview Subjects for Processing TPMS Situation

Position	Motivation
Manager CoE Maintenance Processing	*Works with expanding TPMS for Processing*

D Concept Map for Literature Review



E TSL Matrix Transformation

VAU Class	Pick Class	X			Y			Z		
		8	7	6	5	4	3	2	1	0
A	A	A8	A7	A6	A5	A4	A3	A2	A1	A0
	B	B8	B7	B6	B5	B4	B3	B2	B1	B0
	C	C8	C7	C6	C5	C4	C3	C2	C1	C0
B	D	D8	D7	D6	D5	D4	D3	D2	D1	D0
	E	E8	E7	E6	E5	E4	E3	E2	E1	E0
	F	F8	F7	F6	F5	F4	F3	F2	F1	F0
C	G	G8	G7	G6	G5	G4	G3	G2	G1	G0
	H	H8	H7	H6	H5	H4	H3	H2	H1	H0
	I	I8	I7	I6	I5	I4	I3	I2	I1	I0

Pick Class / VAU Class	X	Y	Z
A	AX	AY	AZ
B	BX	BY	BZ
C	CX	CY	CZ

F Root Cause Diagram