Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Mechanical and Industrial Engineering

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Data Visualization for the Evaluation of Safety Stock Method Performance in Manufacturing Inventory Management

Master's thesis in Engineering and ICT
Supervisor: Anita Romsdal
June 2023

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Preface

This master’s thesis was conducted during the spring semester of 2023 at the Department of Mechanical and Industrial Engineering of the Norwegian University Of Science and Technology (NTNU). The thesis marks both the conclusion of my degree and the end of seven years in Trondheim.

I would like to thank my supervisor Anita Romsdal for her helpful guidance and suggestions over the course of the project. Further, I want to thank Brynild for its contributions to the case study. Lastly, I want to thank my partner, friends, and family.

Erlend Lavrans Haugen Skau

Trondeim, December 2022

Abstract

This master's thesis was conducted in conjunction with the DigiMat innovation project at the Norwegian School of Science and Technology (NTNU) during the spring semester of 2023. The ambition of the thesis was to investigate how manufacturers can use data visualization to evaluate safety stock method performance. Its methodology consisted of a literature study, a proposed concept, and a case study. Furthermore, the project was divided into four objectives, the findings of which made up the research results. Roughly reflecting the methodology, the objectives comprised mapping existing literature, developing the concept, examining a real-world case, and attempting to validate the concept in the context of a real manufacturer.

The literature study first examined inventory fundamentals, normal distributions, and safety stock calculation. Then, the challenges of Big Data were briefly investigated. Furthermore, data visualization and visual dashboard design was studied. Lastly, research on the food supply chain was briefly examined. The purpose of the literature study was to uncover existing research and provide a solid theoretical foundation for the rest of the project. These outputs are relayed in the theoretical background chapter.

The discoveries of the literature study were used to design a concept for a software solution for the visual evaluation of safety stock method performance. The concept was then adapted after interviewing a potential end-user. Moreover, the main aspects of the concept were developed as a web-based prototype intended to validate the concept in the case study. The case study further investigated the safety stock and inventory data visualization practice for the case company, where suggestions were provided for uncovered weaknesses.

For the concept validation, it was arranged that the case company would supply several predetermined data sets. Regrettably, these were never delivered due to unforeseen data extraction challenges on the side of the case company. By the time this was revealed, there was only enough time to generate simplified mock-up data as a substitute. Besides this significant limitation, the findings somewhat suggested that drill-down operations, dynamic queries, and tooltips combined with simple plots effectively made viewing inventory data manageable. Subsequently, comparing inventory levels to orders over time seemed to be a good indicator of safety stock method performance. Other findings suggested that even if widely employed, using a set period of average expected demand as safety stock is a suboptimal method. Moreover, it was discovered that the case company seldom evaluated its safety stock levels, rarely visualized its inventory data, and struggled to extract its inventory data.

Sammendrag

Denne masteroppgaven ble gjennomført i sammenheng med innovasjonsprosjektet DigiMat ved Norges Teknisk-Naturvitenskapelige Universitet (NTNU) gjennom vårsemesteret 2023. Oppgavens ambisjon var å undersøke hvordan produsenter kan bruke datavisualisering for å evaluere prestasjon av sikkerhetslagermetode. Metodologien bestod av en litteraturstudie, et foreslått konsept og en case-studie. Oppgaven var videre delt i fire gjøremål, hvor funnene utgjorde oppgavens resultater. Gjøremålene reflekterte i stor grad metodologien og bestod av å granske eksisterende litteratur, designe konseptet, undersøke en eksiterende case, og forsøke å validere konseptet i konteksten av en ekte produsent.

Litteraturstudiet tok først for seg grunnleggende lagerteori, normalfordelinger, og beregning av sikkerhetslager. Deretter ble datavisualisering og design av visuelle dashbord undersøkt. Til slutt ble forsyningskjeden for matprodukter raskt studert. Formålet med litteraturstudiet var å avdekke eksisterende litteratur og bygge et solid teoretisk grunnlag for resten av prosjektet. Utbytte av litteraturstudent er å finne i kapittelet "Theoretical Background."

Funnene fra litteraturstudiet ble videre benyttet i å designe et konsept for en programvare for visuell evaluering av prestasjon for sikkerhetslagermetode. Dette konseptet ble videre tilpasset etter et intervju med en potensiell sluttbruker. Videre ble den sentrale funksjonaliteten av konseptet utviklet som en web-basert prototype med hensikt å kunne validere konseptet som en del av case-studie. Case-studiet undersøkte også eksisterende praksis av sikkerhetslager og visualisering av lagerdata hos case-selskapet, hvor forslag ble gitt til avdekkede svakheter.

For valideringen av konseptet ble det avtalt at case-selskapet skulle forsyne flere avtalte datasett. Dessverre ble disse aldri sendt på grunn av tilsynelatende uforutsette utfordringer med datauthenting hos case-selskapet. Innen dette ble tydelig var det såpass lite tid igjen at forfatteren ble nødt til å bruke data generert under forenklede antagelser som erstatning. Til tross for denne betydelige hindringen så prototypen ut til å peke på "drill-down operations," "dynamic queries," og "tooltips" kombinert med enkle "plots" som effektive i å gjøre vising av lagerdata håndterbart. Samtidig virket det som at å sammenligne lagernivå og bestillinger over tid ga en god indikator på prestasjonen til en sikkerhetslagermetode. Andre funn understøttet at å bruke en satt periode med gjennomsnittlig forventet behov som sikkerhetslager ikke var en optimal metode, til tross for dens popularitet. Videre ble det avdekket at case-selskapet sjeldent evaluerte satte sikkerhetslagertall, sjeldent visualiserte dens lagerdata, og slet med uthenting av lagerdata.

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1 Introduction

For transactions of goods between actors in a supply chain to be possible, the actors must manage facilities for temporary storage at the contact points of the supply chain (Yerpude & Singhal, 2018). These goods are among what is called inventory, which typically comprises 20 to 60% of a manufacturer's total assets (Chapman et al., 2017). As a business's inventory levels significantly affect its provided customer service and plant operation costs, effective inventory management is critical for its success (Chapman et al., 2017). A key area of inventory management consists of setting safety stock levels (Chapman et al., 2017). Manufacturers use safety stock, also called fluctuation inventory, to guard against potential stockouts resulting from unexpected demand or lead times (Chapman et al., 2017). According to Schmidt et al. (2012), several methods exist for calculating safety stock, where the performance of a given method depends mainly on the variation of replenishment lead time and customer demand. The former factor is particularly present for Norwegian food manufacturers because of the difficult terrain, uneven population distribution, and harsh climate of the country (Romsdal, 2014).

Zhong et al. (2016) concluded that businesses require tools to fully utilize the increasing amount of data they collect from their supply chain management activities. Khakpour et al. (2021) further stated that visual analytics function as a key component in such tools. "Visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision making on the basis of very large and complex data sets" (Keim et al., 2008, p. 157). Keim et al. (2008) explained traditional visualization work as related to visual analytics but different in that it does not require the incorporation of data analysis algorithms and is not necessarily used for data analysis tasks.

Card et al. (1999, p. 7) defined visualization as "the use of computer-based, interactive visual representations of data to amplify cognition." Card et al. (1999) further described how visualization manifests as raw data mapped to visual form through a series of user-adjustable transformations. The visualization designer's job is to determine the types of mappings and interaction techniques that best match the visualization's overall intention. The holy grail of information visualization is to provide the end user with "unexpected discoveries, a deepened understanding, or a new way of thinking about their data" (Chen, 2010, p. 388). The project's purpose was to examine how such benefits can be used to evaluate the performance of a manufacturer's safety stock practice.

The project was built upon a specialization project on a similar topic conducted during the autumn semester of 2022. One key discovery from the specialization project was that there is very little existing literature on visualization in inventory management. The project also concluded that developing and testing a prototype for a visualization tool in collaboration with a real-world manufacturer could yield valuable results. The motivation for this thesis was to explore these benefits further by designing and validating a concept for a software solution applying data visualization to safety stock method evaluation.

1.1 Problem Statement

This section explains the research scope and question, which together define the project's problem.

1.1.1 Research Scope

Although there is a clear relation between data visualization and visual analytics, these terms are not interchangeable (Keim et al., 2008). This project was limited to data visualization as it examined knowledge formation resulting from graphically representing data without incorporating data analysis algorithms. Even so, the results of this project might still be helpful for further works on visual analytics. Moreover, the project was limited to inventory management of finished goods stored at a single location. This excludes work-in-progress inventory and other supply chain management activities. This decision was made based on the data perceived as available from the case company Brynild. Also, the project only focused on businesses of a certain size. The findings of this project are likely most relevant for businesses within or just outside the small-medium enterprise classification, as this was the case for the studied manufacturer. These decisions were meant to concretize the research and to make the most out of the collaboration with Brynild.

1.1.2 Research Question and Objectives

For this project, it was decided to examine one broad research question accompanied by four more specific objectives.

Research Question: *How can data visualization facilitate the evaluation of safety stock method performance for manufacturers?*

Objectives:

1. Map and analyze literature on inventory management, Big Data, and data visualization.
2. Design a concept visualization tool for evaluation of safety stock method performance

and develop a prototype web application realizing the most critical functionality.

3. Analyze the safety stock and visualization practice of a real-world manufacturer and suggest potential improvements.

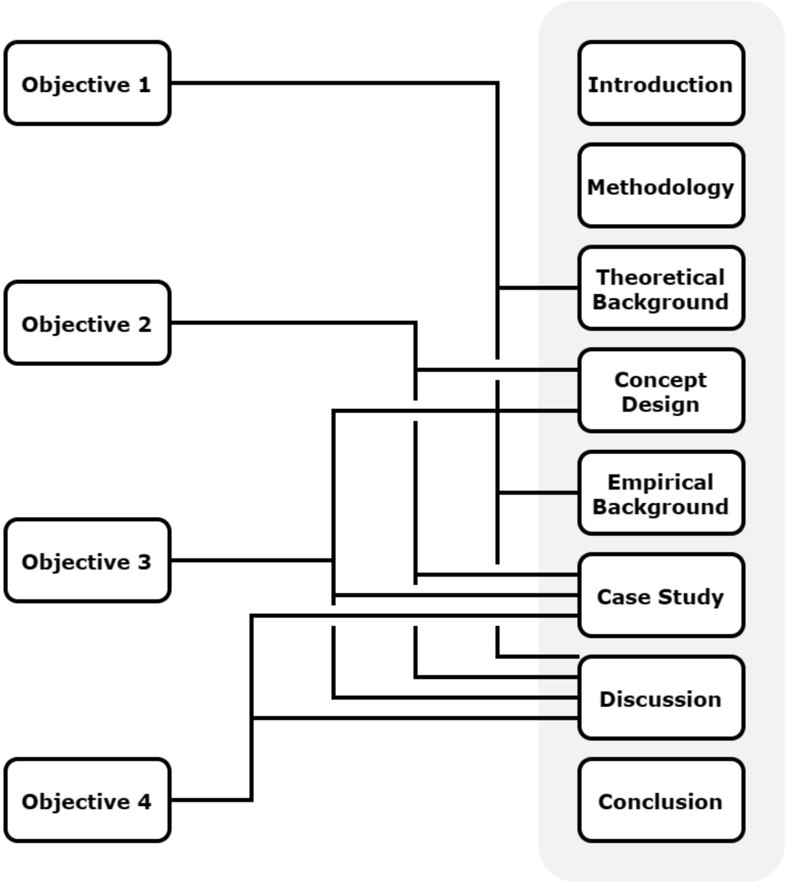
4. Validate the concept by using the prototype to examine a real-world case.

1.2 Report Structure

Figure 1 shows how the results of the objectives are documented in the different chapters of the report.

Figure 1

Objectives and report structure



2 | Methodology

This chapter describes the project's methodology by justifying the choice of methods and explaining how they approached the problem stated in the introduction. The methodology consists of a literature study, a concept design, and a case study.

2.1 Literature Study

The purpose of the literature study was to build a sufficient theoretical foundation and identify the state-of-the-art concepts within the relevant research areas. This master's thesis was built on a project thesis conducted during the autumn semester of 2022. Although the project thesis was differently scoped, examining information visualization for inventory management decision support (Skau, 2022), much of the theory relevant to this thesis overlapped. For this reason, most of the articles included in the literature study for the project thesis were immediately included in the literature study for the master's thesis. This fact may have led to some accidental likeness in the text, even if everything in this report has been written from the ground up. It is important to note that the overall structure of the theoretical background section in the two reports is similar for the same reason.

During the project thesis, it was agreed with the supervisor that textbooks would serve as a suitable source for theory on inventory management fundamentals (Skau, 2022). Chapman et al. (2017) was chosen for this purpose because of the author's acquaintance with the textbook (Skau, 2022). The research scope was subject to much change over the course of the project. Most notable were the shifts from examining inventory management as a whole to safety stock method evaluation specifically and from information visualization to the more general topic of data visualization. After these developments, the final topics for the literature study comprised inventory fundamentals, normal distribution, safety stock calculation, Big Data, data visualization, visual dashboard design, and the food supply chain.

Initially, a predetermined list of search terms was constructed for the literature study. Unfortunately, this list was not sufficiently updated throughout the project and eventually became irrelevant. Figure 1 contains a table of search terms more reflective of the report's content, constructed largely from memory. The relevance of an article was determined by first reading the title and abstract and then quickly scanning through the rest of the article. In addition to published articles, the final selection of sources included textbooks, book chapters, websites, a doctoral thesis, conference proceedings, and technical reports.

If several works on the same topic were identified, the relevance was decided on either publication date or citations. Many additions were also found by searching the reference list of already included works.

Table 1

Literature study search terms

Main search term	Additional search terms
Inventory management	Fundamentals
Safety stock	Calculation Methods
Normal distribution	Z-scores
Big Data	Challenges
Visualization	Data Scientific Information Interaction
Dashboard	Visual Design
Food industry	Norway Supply chain Supply chain management Characteristic Information systems

2.2 Concept Design

The concept was primarily built by considering the literary findings regarding inventory management and data visualization. After becoming aware of the concept of visual dashboards, it was decided to follow the design procedure presented by Pappas and Whitman (2011). Also stated by Pappas and Whitman (2011) was that visual dashboard design should incorporate end-user involvement to ensure the relevance of the final product. It was determined that the production manager of Brynild would be prioritized as an end-user, which made certain parts of the concept design and case study overlap. This was furthered by the fact that the case study included an attempt at validating the concept. The overlap is also present in this report. After an initial description and an accompanying wireframe had been constructed, a meeting was held with the production manager to gather feedback, which was considered when developing the concept further.

In order to be able to validate the concept, it was decided that the main aspects of the concept would be realized through a web application prototype. It was determined that the prototype should be developed with current technologies to be most relevant for further work. Additionally, an attempt was made to choose technologies well suited for the thought-out features. With these factors in mind, together with the author's preferences, technologies were selected, with Vite, React, and D3 being the most prominent. The report explains these choices and how they were used in further detail in the concept design chapter.

2.3 Case Study

This master's project was a part of DigiMat, an innovation project financed by various participating businesses and The Research Council of Norway (NTNU, n.d.). The inclusion of a case study on Brynild was determined in advance as they are also a part of DigiMat. The purpose of the case study was to explore the research topic up close, evaluate theories from the literature study, and validate the proposed concept. Table 2a and 2b show the case study protocol, conveying how the main parts, topics, questions, and sources of data collection relate to each other.

As the protocol shows, three parts were planned for the case study. The first part consisted of examining and analyzing Brynild and its current safety stock and inventory data visualization approaches. The primary data sources for the general examination of Brynild were previous guest lectures held at NTNU and presentations given at a Digimat workshop hosted by Brynild at their main facility in Fredrikstad. The guest lectures also came in handy for the current inventory data visualization approach. The data regarding the present safety stock practice was gathered from a digital meeting with Brynild's production planner, as well as from the guest lectures. Table 3 includes the interview questions for this interview. Note, as it became clear that the manufacturer did not evaluate safety stock levels to a notable extent and that the interviewed individual did not really use data visualization in other areas of their job, some of these questions (marked with *) became obsolete. The second part consisted of presenting and gathering feedback on the concept. A central objective for the concept was to account for both previous research and potential flaws uncovered from the analysis of Brynild's current approach. Data for this stage was collected through a digital interview with Brynild's production planner as well as an informal physical meeting with its supply manager in conjunction with the visit to Fredrikstad.

For the final part, it was initially planned to validate the concept by two means. One of these consisted of forming several statements concerning Brynild's safety stock approach based on the findings from the previous parts of the case study. These issues were then supposed to be explored using the prototype fed a subset of Bryrild's actual inventory data. It was then intended that the procedure's perceived convenience would be judged against attempting to attain the same results only by looking through the raw data tables. This would partially be done by documenting both the time and clicks necessary to attain the desired results in the appropriate context. The second mean entailed presenting the prototype to the potential end user to gather further feedback and assess whether they tought concept succeeded in its purpose.

Unfortunately, these plans could not be realized. During a meeting with a representative of Brynild on Apr 25, it was agreed that several data sets of inventory data for three products with different demand patterns could be expected to be received by the end of the week. This did not occur, and after a follow-up email the week after, it was revealed that the reason for this was unforeseen challenges related to data quality. It was, however, communicated that the data would be sent over by the end of that week. This pattern continued for several weeks until it eventually became clear that even if the consultants delivered the agreed-upon data sets, the deadline would be too close to adapt it to work with the prototype. With little time left, it was determined to construct fictional values based on data made available by Brynild in context with the project thesis the semester before. An attempt was made to verify a general statement about Brynild's safety stock practice, but without real data, the related findings were severely limited. Subsequently, when reaching out to the production manager asking for a second interview, no response was received.

Table 2a

Case study protocol

Case part	Topic	Question(s)	Source(s)
Examination of and suggestions for the current practice	Case foundation	What characterizes Brynild as a manufacturer? What characterizes Brynild's supply chain? How many articles of finished goods does Brynild sell?	2022 guest lecture by supply chain manager
	Safety stock management	What are the procedures for safety stock calculation? How is the adequacy of safety stock levels/calculation methods determined?	Digimat workshop Mar 1 - 2, 2023 Digital meeting with Brynild production manager Apr 13, 2023
	Use of visualization	What are the current procedures/preferences for data visualization?	Digimat workshop Mar 1 - 2, 2023 Digital meeting with Brynild production manager Apr 12, 2023
Concept feedback	Needed views and specifications	How should the data be represented graphically?	Digital meeting with Brynild production manager Apr 12, 2023

Continues on next page

Table 2b

Case study protocol continued

Case part	**Topic**	**Question(s)**	**Source(s)**
Concept validation	Data construction	What is a Brynild product with low demand variability?	Data folder shared by Brynild in 2022 Unpublished project thesis
	Statement examination	How many D-Paks comprise a pallet of the given product? Under what conditions does the warehouse owner charge Brynild?	Data folder shared by Brynild in 2022 Unpublished project thesis

Table 3

Pre-development interview guide

Topic	Questions
Safety stock management	What calculation methods do you use for safety stock levels? Do you calculate safety stock levels for aggregate groups, individual items, or both? What software do you use for safety stock calculation? By what criteria do you evaluate the adequacy of safety stock levels/calculation methods? *What software do you use to evaluate the adequacy of safety stock levels/calculation methods? With what service levels do you operate?
Use of visualization	For what other decisions do you use data visualization? *How do you typically represent data graphically? *To what degree is interactivity present in typical plots? *What software(s) do you employ for data visualization?
Needed views and specifications	What data should be included in a visual dashboard for safety stock evaluation? How does the data rank in terms of importance? How should the data be represented visually? How should the user be able to interact with the dashboard? Is there suspected available information you find difficult to interpret?

3 | Theoretical Background

This chapter contains the outputs from the literature study. The section aims to establish a theoretical foundation on the subjects relevant to the research problem. First, fundamental inventory management theory is presented, together with ABC inventory management and safety stock calculation. Second, a description of Big Data and related challenges are relayed. Lastly, the section presents the subject of visualization, covering the visualization pipeline, plot types suited for the relevant data types, visual dashboard design, and interaction techniques.

3.1 Inventory Fundamentals

For a typical manufacturer, there is a need for temporary storage in between the different stages of its production process (Chapman et al., 2017). Likewise, they also need dedicated storage for incoming and outgoing goods (Chapman et al., 2017). These goods are called *inventory* and form between 20 and 60% of a company's total assets (Chapman et al., 2017). Inventory affects the manufacturer's profits (Chapman et al., 2017). Keeping it reduces stock-out risks, thus preventing the loss of potential income, yet redundant quantities lead to unnecessarily high operating costs (Chapman et al., 2017). *Inventory management* is defined as maintaining this balance, ensuring sufficient supply while preventing oversupply (Singh & Verma, 2018).

3.1.1 Types of Inventory Management

Chapman et al. (2017) distinguished between managing aggregations of inventory and individual items. In *aggregated inventory management*, inventory is controlled based on common characteristics shared by multiple items (Chapman et al., 2017). Usually, items are aggregated based on their function, that is, whether they are raw materials to be used as input for the production process, work-in-process items stored in-between operations, or finished goods ready for sale (Chapman et al., 2017). With aggregate inventory management, it might be more efficient (and sufficient) to control all raw materials using a single set of conditions (Chapman et al., 2017). In *item inventory management*, managers establish policies based on the characteristics of individual items (Chapman et al., 2017). For example, a type of good necessary for the production of a great number of finished products might be purchased under different conditions than other raw materials.

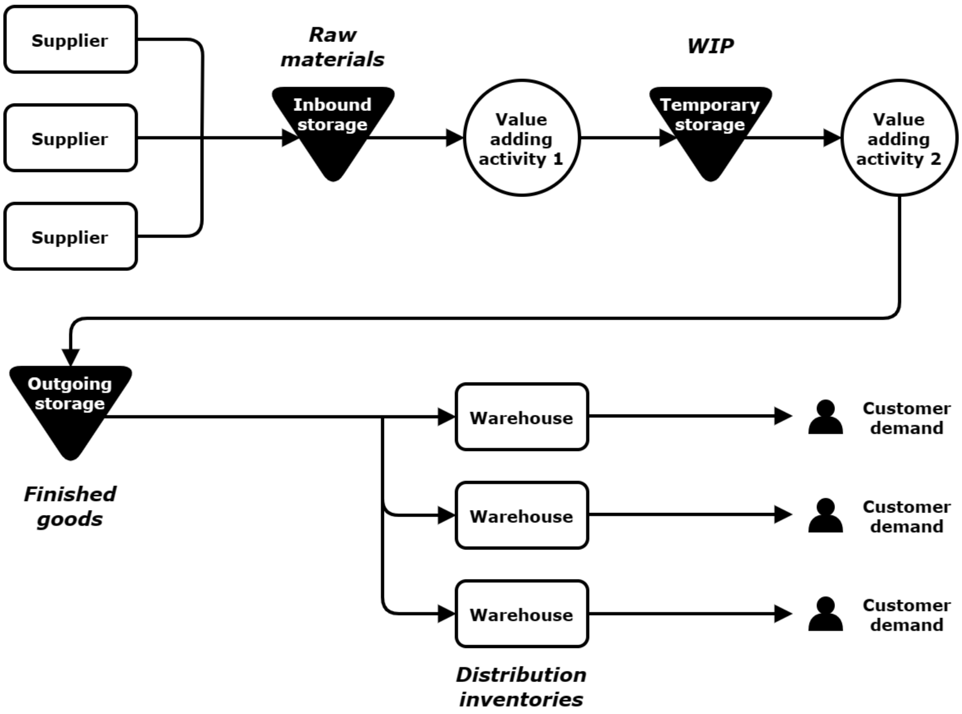
3.1.2 Flows and Functions of Inventory

Figure 2 shows the typical flow of material throughout a manufacturing facility (Chapman et al., 2017). Chapman et al. (2017) classified inventory based on its position in the flow of material and explained the categories as follows:

- *Raw materials* serve as input for the production process. These goods are used in value-adding activities and include components, sub/assemblies, and other purchased materials.
- *Work-in-process* (WIP) materials are stored in between value-adding activities. These goods are waiting to have more work performed on them.
- *Finished goods* have been through the production process and are ready for sale. These goods are stored either at the manufacturing facility or at other dedicated storage facilities.
- *Distribution inventories* belong to a sub-category of finished goods that are being distributed.

Figure 2

Inventory types related to flow of material



Note. Adapted from Chapman et al. (2017).

For most products, customer demand is characterized by uncertainty to some degree, and to avoid being unable to fulfill orders, manufacturers produce them in lots or batches

(Chapman et al., 2017). The nature of this system leads to a natural buildup of inventory in the contact points between the various actors and activities in the flow of material (Chapman et al., 2017). Chapman et al. (2017) distinguished between six types of such buildup according to function:

- *Anticipation inventory* is built up in anticipation of a highly suspected fluctuation in demand or capacity. Examples of the causes of such fluctuations are peak selling seasons, sales campaigns, or a worker strike.
- *Safety stock* (fluctuation inventory) is kept to protect against potential stockouts caused by unpredictable increases from forecasted demand or lead time disruptions. As manufacturers don't know when these events might occur, they try to keep a constant level of safety stock.
- *Lot-size inventory* (cycle stock) occurs when goods are ordered or produced in greater quantities to take advantage of benefits like quantity discounts, lower setup costs, and reduced shipping costs. Lot-size inventory is cyclically depleted and replenished.
- *Transportation inventory* is a term used to describe goods that are under transport from one point in the flow of material to another.
- *Hedge inventory* are products that fluctuate in keeping with global supply and demand held by manufacturers who wish to benefit from these fluctuations.
- *Maintenance, Repair, and Operating Supplies* (MRO) don't become a part of the final product but rather support its manufacturing process. Examples of these items are machine parts and cleaning supplies.

3.1.3 Inventory-related Costs

Chapman et al. (2017) stated that a manufacturer would at least have maximum customer service, low-cost plant operation, and minimum inventory investment as objectives for their inventory management. These objectives relate to five types of inventory costs listed and explained by Chapman et al. (2017):

- *Item costs* is the amount paid for acquiring individual items. For purchased items, this includes the item's price as well as potential indirect costs such as shipping and customs. The term is also used concerning in-house-produced goods. In this case, the cost includes direct materials and labor used in manufacturing the item, as well as the cost of running the manufacturing facility.
- *Carrying costs* encompasses all costs resulting from holding inventory. Carrying costs

are divided into three sub-categories. *Storage costs* refer to the cost of renting and utilizing the storage space, *capital costs* result from lost investment opportunities, and *risk costs* refers to potential loss in revenue from factors affecting the manufacturer's ability to sell the product at the intended price. Risk costs may be incurred from deterioration, and for manufacturers of perishable goods, these may equal as much as the product's total value.

- *Ordering costs* include several costs that are incurred once every time an order is placed, either from a supplier or with the manufacturing facility. Ordering costs are independent of order quantity. Examples include the costs of production control and machine setup costs.
- *Stockout costs* occur when actual demand is higher than forecasted demand. In addition to lost sales, stockouts can result in deterioration in customer relationships and, in the worst case, complete loss of customers. To protect against stockouts, manufacturers carry safety stock.
- *Capacity associated costs* result from measures taken to handle insufficient capacity. *Capacity*, in this case, refers to the amount of work the manufacturer can perform over a specific interval. Examples capacity associated costs are paying for overtime or increasing/decreasing the workforce.

3.1.4 SKUs and ABC Inventory Control

As explained above, manufacturers must handle many different types of goods. Even those of a smaller size may handle thousands of stock-keeping units (Ng, 2007). A *stock-keeping unit* (SKU) is a good that is unique in its combination of purpose, dimension, looks, and typically location (Silver et al., 1998). Different SKUs possess different characteristics that affect what inventory policies best suit them (Van Kampen et al., 2012). When the number of SKUs becomes large, tailoring inventory control to each of them becomes difficult (Van Kampen et al., 2012). One option for countering this issue is for manufacturers to establish standard policies for SKU classifications based on common characteristics (Van Kampen et al., 2012).

ABC inventory control is an example of this type of classification and groups items with demand profile as its criteria (Van Kampen et al., 2012). *ABC inventory control* is based on the *Pareto principle*, which states that a small number of participants account for a large portion of the result (Chapman et al., 2017). Ng (2007) suggested identifying three groups of SKUs in relation to how much they make up of total revenue and total inventory. The groups were labeled and described as follows:

- Group A makes up 70% of total revenue and 10% of total inventory.

- Group B makes up 20% of total revenue and 20% of total inventory.
- Group C, as follows, makes up 10% of total revenue and 70% of total inventory.

Group A items are those most valuable to the manufacturer and should be prioritized to a higher degree than items from groups B and C (Ng, 2007).

3.1.5 Normal Distribution and Safety Stock Calculation

Holickȳ (2013) stated that many naturally occurring phenomena within engineering correspond to probability distributions for continuous random variables. Out of these distributions, the most important one is called the *normal distribution* (Holickȳ, 2013). According to Chapman et al. (2017), most demand patterns are normally distributed. A normally distributed random variable X defined on an interval from $-\infty$ to ∞ is dependent on its mean μ and its standard deviation σ (Holickȳ, 2013). As stated by Holickȳ (2013), the distribution of X is commonly written as N(μ, σ) with its probability density function equalling:

$$\phi(x) = \frac{1}{\sigma_x\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu_x}{\sigma_x}\right)^2\right], \quad -\infty < x < \infty \tag{1}$$

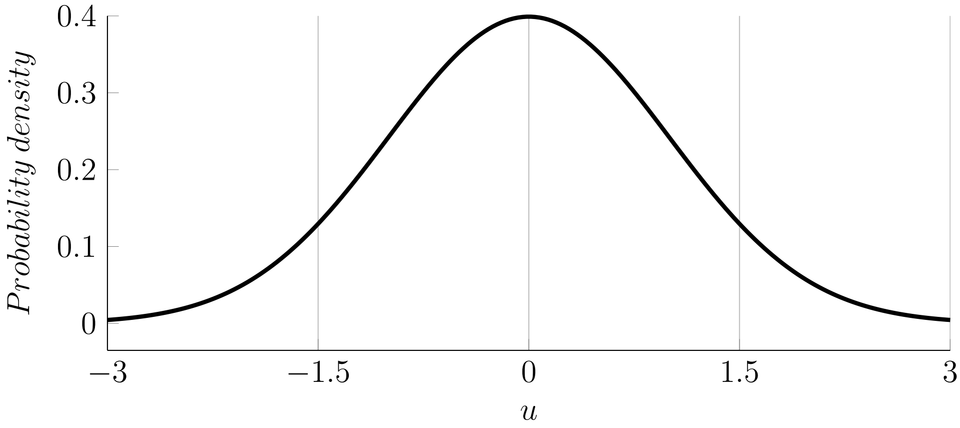
The cumulative distribution function for a random variable equals the integral of the probability density function from the minimum value of the desired range to the maximum (Holickȳ, 2013). As these expressions cannot be written in a convenient analytical form, Holickȳ (2013) suggested using numerical tables of already computed values (often called standard scores) available in the literature and on the web. These tables almost always correspond to the standard normal distribution denoted N(0, 1), and to utilize them, it is necessary to transform the observations of the respective variable to observations of the standardized variable U (Holickȳ, 2013). Holickȳ (2013) presented the transformation of a normal random variable X to the standardized variable U as:

$$U = \frac{X - \mu_x}{\sigma_x} \tag{2}$$

Figure 3 shows a plot of the probability density function for the standard normal distribution with $\mu = 0$, which and $\sigma = 1$. Like many frequently used probability density functions, the curve takes the shape of a bell (Holickȳ, 2013). The function is plotted from -3 to 3, covering an occurrence of probability up to 0.9973 (Holickȳ, 2013). A noteworthy property of this curve is that it is symmetrical about $u = 0$ (Holickȳ, 2013).

Figure 3

Plot of standard normal distribution



Note. Adapted from Holický (2013)

As stated by Chapman et al. (2017), there are two types of uncertainty within supply and demand. *Quantity uncertainty* arises when the actual demand/supply differs from what is forecasted, and *timing uncertainty* happens if the time of receipt of supply/demand changes unexpectedly (Chapman et al., 2017). The most common way to protect against these uncertainties is by using safety stock (Chapman et al., 2017). According to Chapman et al. (2017), determining safety stock levels depend on the following factors:

- Lead time and demand fluctuation lead to a need for higher safety stock levels.
- Reorder frequency affects how easy it is to detect demand variations. A higher frequency decreases the amount of needed safety stock.
- Desired service level affects how many stockouts the manufacturer permits itself. A higher service level means an increased need for safety stock.
- Length of replenishment lead time determines when a stockout is possible. Longer lead times lead to a higher probability of a stockout occurring and, therefore, a need for more safety stock

To determine safety stock levels Chapman et al. (2017) explained the following procedure based on the assumption that demand is normally distributed. The first step is estimating the standard deviation for an assumed normally distributed random variable X representing demand (Chapman et al., 2017). Chapman et al. (2017) suggested a variation of the sample standard deviation based on n samples using the formula below:

$$s_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(F_i - A_i)^2} \tag{3}$$

Where F_i is the forecasted demand for the period i, and A_i is the respective actual demand.

The next step of the procedure proposed by Chapman et al. (2017) is to determine a service level. A service level is a target for the percentage of lead time where no stockouts occur (Chapman et al., 2017). Following this step, use the previously mentioned standard score tables to find the standard score corresponding to the determined service level (Chapman et al., 2017). With a service level of 98%, the manufacturer's total stock would have to be enough to cover the actual demand 98% of the time, equivalent to the probability $P(x \leq 0.98)$. From the tables, the corresponding standard score is shown to be about 2.1.

After having found the standard score, the next step entails reversing the transformation above to obtain the total amount of needed stock (Chapman et al., 2017):

$$X = U\sigma_x + \mu_x \tag{4}$$

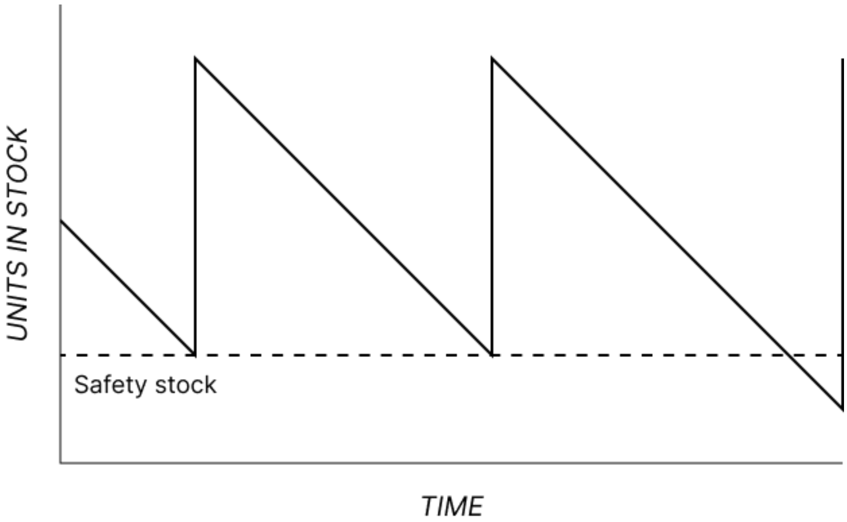
The final step is to derive the needed amount of safety stock, subtracting the expected demand μ_x (Chapman et al., 2017):

$$SS_x = X - \mu_x = U\sigma_x \tag{5}$$

Several other methods for calculating safety stock exist, which will not be explored further in this study. Schmidt et al. (2012) compared several such methods and stated that the optimal choice depends on lead time and demand variability for the given products. Figure 4 shows how Chapman et al. (2017) illustrated safety stock in relation to inventory levels graphically.

Figure 4

Typical illustration of safety stock



Note. Adapted from Chapman et al. (2017).

3.2 Big Data Challenges

Big Data refers to a more recent phenomenon of significant data sets possessing characteristics making them difficult for conventional systems to manage (Nasser & Tariq, 2015). The presence of this phenomenon was established due to the prompt introduction of technologies like data-capturing instrumentation (Nasser & Tariq, 2015). Even with businesses capturing great quantities of data, they struggle to extract valuable information without the proper analytical methods (Nasser & Tariq, 2015). If utilized efficiently, Big Data can provide businesses with valuable insights for decision-making (Nasser & Tariq, 2015). Preventing these benefits, however, are certain potential challenges (Nasser & Tariq, 2015). Nasser and Tariq (2015) attempted to classify these challenges into three main categories: data, process, and management challenges. This section will explain a sub-set of the challenges listed by Nasser and Tariq (2015) perceived as relevant to the thesis, mainly from the data and process categories.

Challenges in the data category stemmed from the raw data attributes (Nasser & Tariq, 2015). What follows are the included challenges as explained by (Nasser & Tariq, 2015):

- *Volume challenges* arise from a current system being unable to process the data because of its sheer size.
- *Veracity challenges* refers to situations when the data does not reflect the truth it measures. Examples of such challenges are incorrect or missing measurements.
- *Quality challenges* should not be mistaken for veracity challenges and refers to the data's usefulness in decision-making. Good quality data is accurate, timely, available, and complete.

Several challenges also occur from the means by which data is processed (Nasser & Tariq, 2015). The following challenges belong to the process category proposed by Nasser and Tariq (2015), which explained them as follows:

- *Data acquisition and recording challenges* stem from the means by which the data is captured. Challenges included in this category are, for example, regularly defective equipment.
- *Information extraction and cleaning challenges* relates to the process of taking the initial data, which may not be useful in its raw state, and producing structured data suitable for further study. The actual challenges stem from ensuring and upholding the quality of such procedures.

3.3 Visualization and Knowledge Formation

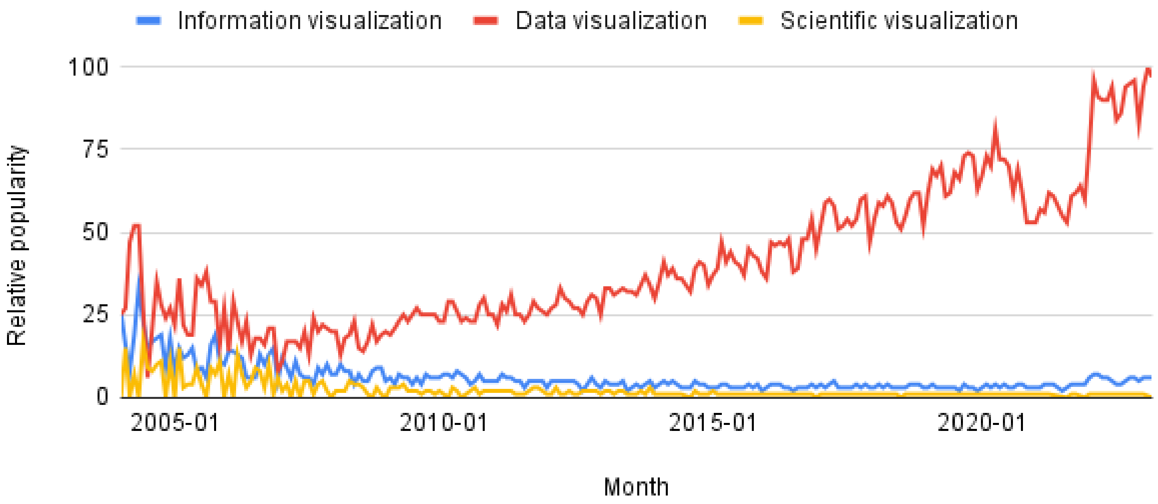
Gershon et al. (1998, p. 9) defined *visualization* as "the process of transforming data, information, and knowledge into visual form making use of the humans' natural visual capabilities." Visualization makes visible relationships and properties inherent in the data, in doing so, letting the user identify otherwise hidden characteristics (Shiravi et al., 2012). Visualization is made up of the subfields of information visualization and scientific visualization (Keim et al., 2008). *Information visualization*, often referred to as Infoviz (Gelman & Unwin, 2013), is "the use of interactive visual representations of abstract, nonphysically based data to amplify cognition" (Card et al., 1999, p. 7). According to Fekete et al. (2008), this definition by Card and Shneiderman is most accepted by the Infoviz research community. *Scientific visualization* differs in that it deals with physical data, often of scientific nature (Card et al., 1999). Nagel (2006) stated that while scientific visualization aims to convey the real world precisely, information visualization seeks to provide the user with a mental model of an abstract data set for characterization prediction and decision-making. Information visualization usually relates to exploratory analysis, while scientific visualization tends to handle confirmatory analysis (Nagel, 2006).

Two other visualization-related terms discovered in the literature study were data visualization and visual analytics. In the modern industry landscape, supply chain activities, and thereby inventory management, generate data in vast quantities (Chae & Olson, 2013). Visual analytics is a critical tool for making these data useful for decision-making (Khakpour et al., 2021). Keim et al. (2008, p. 157) defined *visual analytics* as the combination "of automated analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision making on the basis of very large and complex data sets." Contrary to the belief of some, visual analytics is not the same as information visualization (Keim et al., 2008). It does, however, build to the topic as well as scientific visualization, data management, data analysis, and cognition research (Keim et al., 2008).

For data visualization, contrary definitions were identified. Li (2020) used the term interchangeably with visualization, referring to a definition by Card et al. (1999, p. 7) reading the "use of computer-supported, interactive, visual representations of data to amplify cognition." While (Li, 2020) viewed data visualization as a supercategory of information visualization, Keim et al. (2008) suggested that the two terms label distinct research fields that have evolved together. (Chen, 2010) distinguished between the two fields according to the characteristics of the conveyed data, where data visualization, similarly to scientific visualization, regards data already in quantitative form. Figure 5 shows the Google search trends for the terms mentioned above. As shown, data visualization has become, by far, the most popular term over the years. Table 4 contains an overview of the mentioned terms.

Figure 5

Visualization-related search terms according to relative popularity



Note. Data source: Google Trends (https://www.google.com/trends).

Table 4

Definitions of visualization-related terms

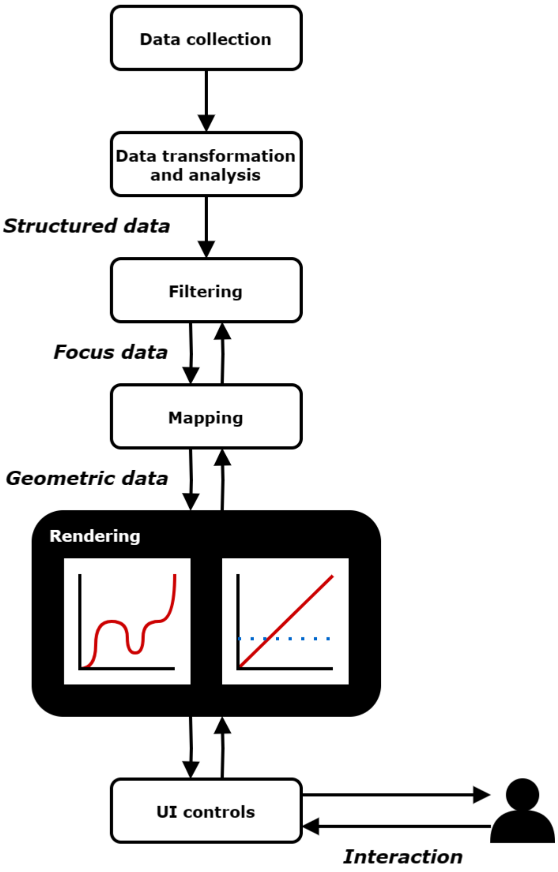
Term	Definition
Information visualization	The "use of interactive visual representations of abstract, nonphysically based data to amplify cognition" (Card et al., 1999, p. 7)
Scientific visualization	The "use of interactive visual representations of scientific data, typically physically based, to amplify cognition" (Card et al., 1999, p. 7)
Data visualization	The "use of computer-based, interactive visual representations of data to amplify cognition" (Card et al., 1999, p. 7) *Note.* Used interchangeably with visualization by Li (2020)
Visual analytics	The combination of "automated analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision making on the basis of very large and complex data sets" (Keim et al., 2008, p. 157) *Note.* Incorporates data analysis algorithms and is restricted to analysis tasks (Keim et al., 2008)

3.3.1 The Visualization Pipeline

To facilitate the discussion and comparison of visualization systems, Card et al. (1999) presented a visualization reference model based on the process of transforming raw data into interactive views presented to the user. This *visualization pipeline* depicted the process's various data mappings linked by their respective transformations (Card et al., 1999). For this project, a similar but more current reference model by Liu et al. (2014) was chosen. The model served as a frame of reference for both the concept design and discussion parts of this project. Additionally, the model proved useful when conducting the case study.

Figure 6

Illustration of the visualization pipeline



Note. Adapted from Liu et al. (2014).

The visualization pipeline, depicted in figure 6, is made up of five modules termed: data transformation and analysis, filtering, mapping, rendering, and UI controls (Liu et al., 2014). The process takes in a data set that can be in either structured or unstructured form (Liu et al., 2014). In this case, the term *structured* means "organized in a highly regular way, such as in tables and relations, where the regularities apply to all the data in a particular data set" (Losee, 2006, p. 441). The first module is the *data transformation and analysis module*. The module receives the input data and passes on a prepared set of structured data (Liu et al., 2014). With unstructured input data, it first uses data mining techniques to construct a basis for visualization in the form of a new structured data set (Liu et al., 2014). Other tasks of the module include reducing data, correcting and interpolating values, and applying a smoothing filter (Liu et al., 2014). The next module is the *filtering module*. This module takes in the structured data from which it forms a subset either automatically or with help from the user (Liu et al., 2014). Such a subset is called *focus data* and comprises a manageable portion of the original data to be visualized simultaneously (Liu et al., 2014). The following module is the *mapping module*. This module, explained in greater detail below, constructs a data set of geometric primitives along with attributes based on the focus data (Liu et al., 2014). Next, the *rendering module* takes the geometric data from the mapping module and constructs respective image data for the device screen

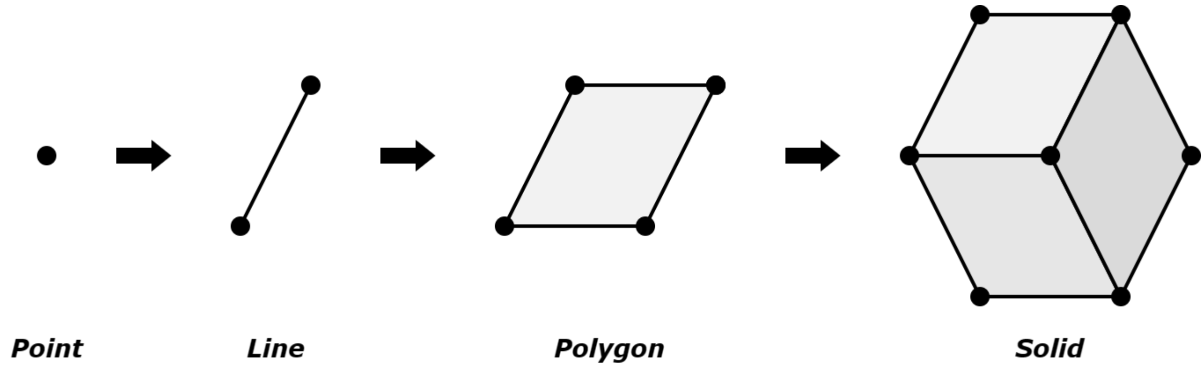
(Liu et al., 2014). The last module is the *UI control module* which facilitates altering the image by adjusting the various transformations of the pipeline through a user interface (Liu et al., 2014).

3.3.2 Visualizing Different Data Types

As mentioned above, it is the responsibility of the mapping module to build actual geometry from the data (Liu et al., 2014). According to Liu et al. (2014), it does this by constructing geometric primitives to which it also assigns attributes. A *geometric primitive* is "a curve or surface which can be described by an equation with a number of free parameters" (Roth & Levine, 1993, p. 1), and *geometric data* is "an unordered list of points in two- or three-dimensional cartesian space" (Roth & Levine, 1993, p. 1). Xia et al. (2020, p. 686) provided a different definition, reading, "the basic geometric unit is the point, with groups of points forming geometric primitives." Xia et al. (2020) further divided geometric primitives into shape primitives and structure primitives. With shape primitives, a great number of points make up entire lines, surfaces, and volumetric shapes (Xia et al., 2020). In the case of structure primitives, points make up skeletons, 2D outlines, and 3D edges (Xia et al., 2020). Figure 7 shows basic geometric primitives suggested by Ford (2004). Geometric primitive attributes include other factors determining the look of a graphical element, including size, position, and color (Liu et al., 2014). To summarize, it is the mapping module that decides how the data is represented graphically.

Figure 7

Different geometric primitives

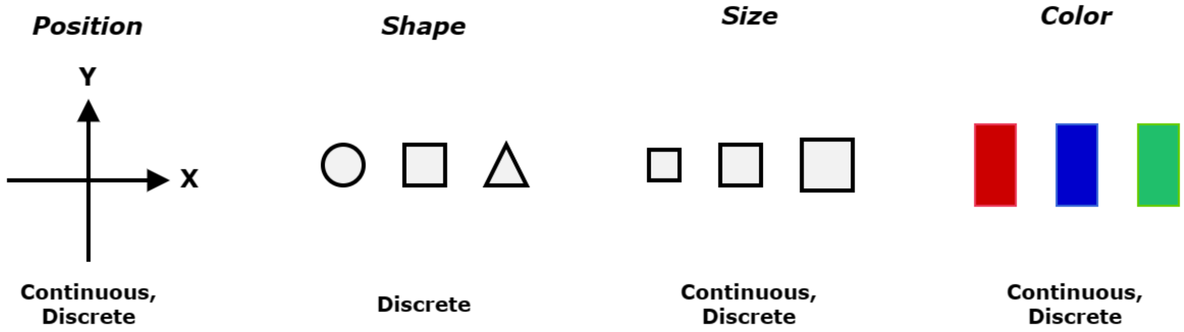


Note. Adapted from Ford (2004).

Wilke (2019) stated that data visualizations result from transforming data values into graphical elements in a systematic and logical fashion. The outputs of this procedure may amount to, for example, scatterplots, pie charts, or heat maps (Wilke, 2019). Wilke (2019) further stated that although these examples differ considerably, their features and relationship to the original data can be expressed in a shared language. Wilke (2019) introduced *aesthetics* as a key term of this language, referring to the quantifiable aspects of a graphical element. Shape, size, color, and position are aesthetics that must be specified for all graphical elements (Wilke, 2019). Wilke (2019) remarked that aesthetics describe either continuous or discrete data. With continuous data, any given pair of values denote an arbitrarily sized subinterval of additional legal values (Wilke, 2019). For discrete data, no valid intermediates exist between neighboring values (Wilke, 2019). Figure 8 illustrates the basic aesthetics along with what type of data they usually represent.

Figure 8

Basic graphic element aesthetics



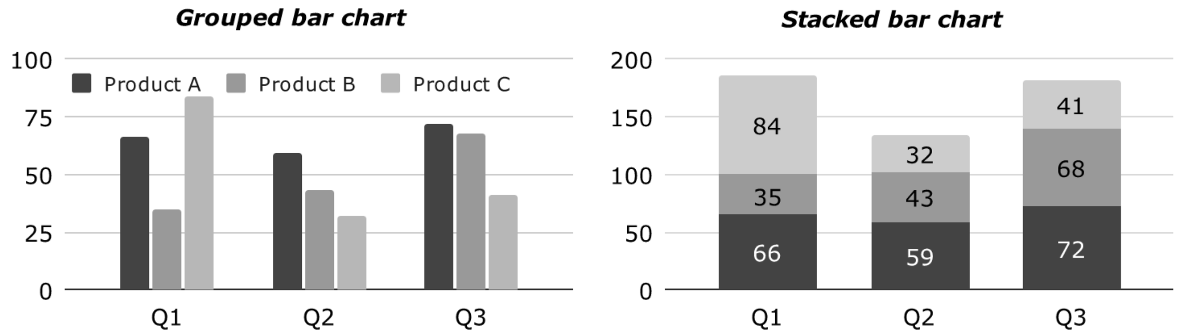
Note. Adapted from Wilke (2019).

Building visualizations representative of data requires an established relationship between the domain of data and the range of aesthetics (Wilke, 2019). This task is accomplished through the use of scales (Wilke, 2019). Wilke (2019, p. 17) defined a *scale* as a "unique mapping between data and aesthetics." An example of a scale is a function taking in data values for monthly sales and returning pixel values for corresponding bar chart heights. Wilke (2019) further emphasized the importance of scales being one-to-one. Scales of the types one-to-many or many-to-one will lead to visualizations with low interpretability (Wilke, 2019).

Wilke (2019) proposed a collection of commonly used visualizations grouped by the nature of the data they convey. Cases where the data consist of groups, each with a single corresponding quantitative value, are referred to as visualizing amounts (Wilke, 2019). The bar chart is the typical plot for communicating relationships of this type, but heatmaps and dot plots are other viable options (Wilke, 2019). Wilke (2019) further explained two variations of the classic bar chart for when two sets of categories are of interest. With grouped bar charts, bars are clustered and positioned according to one variable and colored according to the other (Wilke, 2019). With stacked bar charts, bars are divided into segments representing one variable and positioned based on the other (Wilke, 2019). Stacked bar charts should not be used unless the sums of the segment values are also significant (Wilke, 2019). Figure 9 conveys these chart types.

Figure 9

Subcategories of bar charts

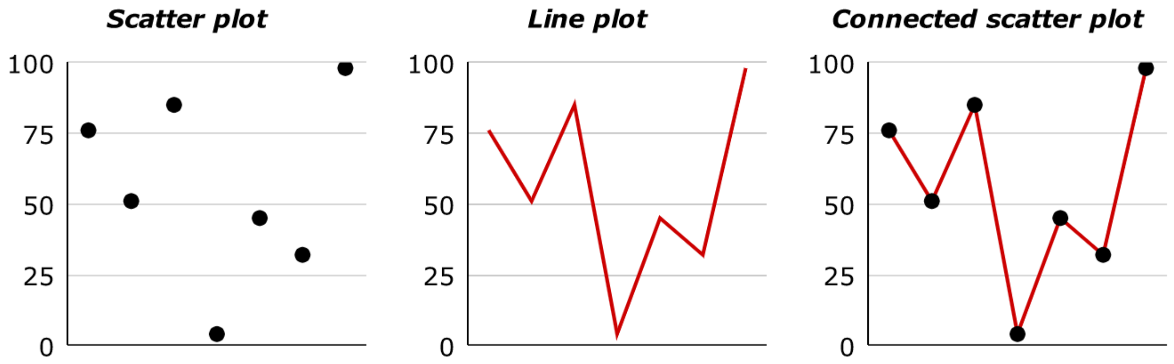


Note. Adapted from Wilke (2019).

Esling and Agon (2012, p. 12) defined a *time series* as "a collection of values obtained from sequential measurements over time." Typically, time-series data sets are frequently updated, of considerable size, and high in dimensionality (Fu, 2011). Such data sets are often found in fields like science and finance, where examples include electrocardiograms, daily stock prices, and weekly product sales (Fu, 2011). Wilke (2019) declared that time series data introduces a distinct instance of plotting two variables against each other. With one of these variables being time, values exist in an inherent sequence (Wilke, 2019). This attribute makes line charts the typical plot of choice (Wilke, 2019). In line charts, neighboring values are joined by line segments (Wilke, 2019). If the values themselves are included as points, the graphic is called a connected scatter plot (Wilke, 2019). Although the line segments do not correspond to the actual data, their presence helps the user perceive how it evolves (Wilke, 2019). Figure 10 illustrates the covered time series plots.

Figure 10

Different types of time series plots



Note. Adapted from Wilke (2019).

3.3.3 Visual Dashboards

As a consequence of the rapid developments in information technology, businesses have access to magnitudes of data regarding their activities (Pappas & Whitman, 2011). For these data to be advantageous in decision-making, they must be partitioned and presented in an apprehensive manner so as not to overwhelm the decision-maker (Pappas & Whitman, 2011). One way to tackle this challenge is by the use of dashboards (Pappas & Whitman, 2011). The purpose of traditional dashboards, typically found in automobile and aircraft design, is to communicate a collection of recent measurements (Pappas & Whitman, 2011). Dashboards intended for decision-making are further required to provide context, such as previous measurements for comparison (Pappas & Whitman, 2011). Moreover, the use of interactivity increases a dashboard's effectiveness considerably (Pappas & Whitman, 2011).

The scope of a dashboard depends on the activity and end-user it intends to support (Pappas & Whitman, 2011). Pappas and Whitman (2011) relayed three categories of dashboards from Few (2006):

- *Strategic dashboards* quickly convey how the business performs concerning specific objectives. These dashboards typically have long time frames, moderate data update frequencies, and low degrees of interactivity.
- *Operational dashboards* provide real or near real-time data for monitoring activities. Short time frames, limited data scopes, and low degrees of interactivity are further attributes typical for such dashboards.
- *Analytical dashboards* combine characteristics from both of the above categories. Compared to strategic dashboards, analytical dashboards put a higher emphasis on data exploration, which necessitates a greater degree of interactivity. Other defining attributes are long time frames and low update frequencies.

When designing a dashboard, the first step is establishing its end user and purpose (Pappas & Whitman, 2011). The next step entails mapping out and prioritizing the available data (Pappas & Whitman, 2011). Involving the end user through interviews is vital to ensure that the outcome of this phase is valid (Pappas & Whitman, 2011). The subsequent step is selecting the visualizations and interaction techniques for conveying the designated data (Pappas & Whitman, 2011). Documenting the end user's present procedures for viewing data and what visual representations they currently employ will facilitate this part of the process (Pappas & Whitman, 2011). The final step is organizing the interactive visuals in a combined view, where the highest priority information is at once perceptible and detailed information is accessible through interaction if necessary (Pappas & Whitman, 2011).

3.3.4 Interaction Techniques

Card et al. (1999) stated that the purpose of interaction in information visualization is to let users select data subsets to locate or analyze data or alter the transformations of the visualization pipeline. Figueiras (2015) stated that the purpose of interaction techniques varies and that making data more manageable and engaging is the most typical. Yi et al. (2007) claimed that establishing taxonomies for interaction techniques is demanding as new developments quickly make them outdated, and Figueiras (2015) asserted that no commonly recognized taxonomy exists. Figueiras (2015) further presented a taxonomy of 11 categories accounting for recent developments. The remainder of this section highlights the categories, with respective examples, considered particularly relevant for the thesis.

Filtering techniques let users shrink or grow the presented data set by establishing specific conditions through a user interface (Figueiras, 2015). Their goal is to support cognition by presenting only pertinent portions of the available data (Figueiras, 2015). *Dynamic queries* are an example of a filtering technique where the graphics immediately reflect user-made changes (Yi et al., 2007). Dynamic queries can be implemented through several types of UI controls, for example, checkboxes (Yi et al., 2007). In order to realize the potential of this technique, the system must provide the appropriate response without significant delay (Figueiras, 2015).

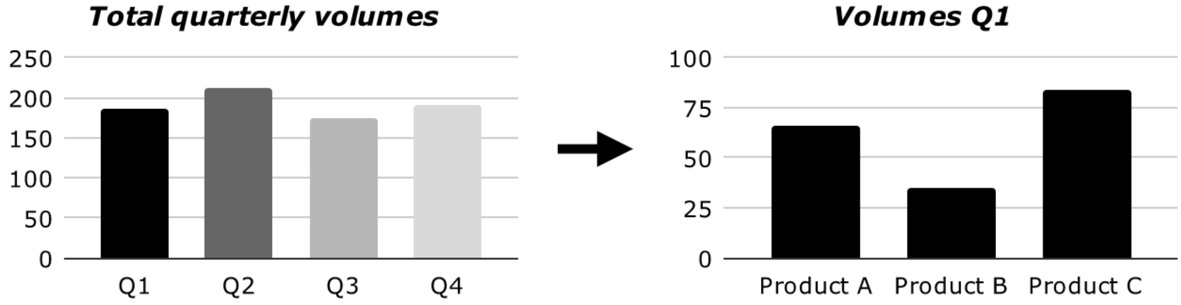
Abstract/elaborate techniques let users regulate the presented level of detail (Yi et al., 2007). An example of an interaction type from this category is details-on-demand (Figueiras, 2015). *Details-on-demand* techniques provide further data as the user interacts with one or more graphical elements (Figueiras, 2015). These techniques come in forms like *drill-down operations*, where the visualization adapts to a data subtree as users click on an element, and *tooltips*, where textboxes appear with supplementary data when users hover over an element with the cursor (Figueiras, 2015; Yi et al., 2007). Figure 11 provides an example of a drill-down operation where a bar chart showing monthly total production volumes possesses clickable bars providing bar charts detailing the volumes for different products produced that month.

Shneiderman (1996, p. 337) introduced the *visual information-seeking mantra* "overview first, zoom and filter, then details on demand," describing a chain of tasks for effective visual data exploration directed by the user. The overview category corresponds to the first part of this mantra which involves initially presenting the user with a representation of the entire data set (Craft & Cairns, 2005). According to Craft and Cairns (2005), it is from the overview that themes and patterns are most visible. From here, abstract/elaborate techniques can be implemented to facilitate further investigation (Figueiras, 2015). Additionally, there is the explore category which regulates the amount of data on screen without altering the focus data (Yi et al., 2007). An example from this category is *panning*, which means moving the image itself to reveal previously cut-off content (Yi et al., 2007).

According to Shneiderman (1996), user interaction sometimes leads to unwanted results. *History* techniques allow users to backtrack in the exploration process and enable progressive refinement (Shneiderman, 1996). Undo and redo buttons are examples of an implemented history technique (Craft & Cairns, 2005). As stated by Figueiras (2015), the importance of history techniques is continually unrecognized. Lastly, it is worth mentioning the extraction category, which refers to exporting aspects of the visualization for external uses (Figueiras, 2015).

Figure 11

Drill-down operations example



Note. Adapted from Figueiras (2015)

4 | Concept Design

This chapter contains descriptions of the concept, its design process, and the accompanying prototype's development. The initial plan was for the project to rely much more on the prototype to illustrate the concept, and the following concept description was originally planned only to convey the planning process for the prototype. As it gradually became clear that the prototype could not be developed as far as planned, the purpose of the prototype changed primarily to validate the main aspects of the concept. The mentioned time restraints left little time to expand the concept description, leaving it less detailed than what would have been ideal. Looking at Figure 21 and 22, which depict the prototype, might help the reader better understand the concept description.

4.1 Description

According to Pappas and Whitman (2011), the first step in dashboard design is establishing the dashboard's end user and purpose. For the prototype, the prioritized end-user was the production manager of the case company, as this is the employee responsible for setting safety stock levels. This decision was also made because of the limited number of potential candidates. Moreover, it was determined that the proposed software solution would be an analytical dashboard for evaluating both the efficiency of individual products' safety stock levels and the manufacturer's safety stock method as a whole. Pappas and Whitman (2011) further stated that end-user involvement is critical when prioritizing data in dashboard design. As the master's project only ran for a semester and the case company contributed in parallel with their regular activities, an initial suggestion was drafted and then discussed with the production manager. The initial draft was then reworked accordingly. The rest of this section details the chosen data and its respective graphical representations in accordance with the design process conveyed by Pappas and Whitman (2011).

4.1.1 Selected Data

As expressed in the theoretical background section, the purpose of safety stock is to protect against stockouts. Therefore, the solution was decided to convey Brynild's historic service levels. Too much safety stock, on the other hand, will inherently lead to excessive holding costs. To discover these cases, one can compare customer orders to respective inventory levels. The solution was also decided to contain such a feature. Moreover, it was decided that the solution was to illustrate the developments of inventory levels compared to safety stock levels. As Brynild possesses no convenient way to extract historic safety stock levels, these would have to be calculated by the solution using Brynild's historical forecasts. It was agreed that to fully realize its purpose, the solution would have to display the discussed information on several aggregated levels. Specifically, it was decided that the solution should support viewing the data as both yearly and monthly averages. Based on these requirements, the selection for needed data comprised:

- Historic service levels per product.
- Orders from the finished goods warehouse per product.
- Inventory levels at the finished goods warehouse per product.
- All transactions in/out of the finished goods warehouse per product.
- Forecasts per product.

4.1.2 Selected Visual Representations

Figure 13 contains a rough wireframe for the application used to present the idea to Brynild's production manager. This figure only reflects the initial concept and deviates somewhat from the prototype. Moreover, the presented charts were simplified, which is why for instance, the connected scatter plots do not include points. These simplifications resulted from time constraints and were elaborated on during the meeting with the production manager. The wireframe is since been left unchanged except for fixing a few alignment issues and renaming the chart titles to be consistent with the report. At the time, it was deemed sufficient only to include View 1 in the wireframe, as View 2 was already under development and could be presented in its then state. For the selection of graphical representations, it was decided that simple conventional plot types were sufficient. Additional dimensions would instead be illustrated through interaction techniques, like tooltips, when needed. It was further acknowledged that straightforward plots are likely more recognizable, making them a better starting point for Brynild, which scarcely visualizes its inventory data at present. The identified plots listed in the case study section were also taken into consideration. The final list of selected visual representations consisted of:

- A variation of the connected scatter plot, called stairstep plot by Mathworks (n.d.), for daily inventory levels (Chart 5).
- Connected scatter plots for other time-series data (charts 1 and 2).
- A bar chart for comparing service levels for different customers (Chart 3).

- A scatter plot for comparing the ratio of inventory and orders on a product basis (Chart 4).

4.1.3 Dashboard Composition

The rest of this section describes the solution as it should be perceived by the user. It is vital to reiterate that this description was initially intended to convey the planning phase's output roughly and not to explain every aspect of the concept. An attempt has been made to change this; however, the prototype description should also be read to gain a complete understanding.

To efficiently convey the prioritized data, it was determined that the solution should contain two views labeled View 1 and View 2 in the wireframe. By default, View 1 is selected when opening the application, which in addition to a generic header, consists of three sections. The left section contains UI controls for specifying the data set to examine. The top portion of this section, titled "Data Selection," displays a list of Brynild's products. The user can choose which products to include from this list by clicking on the individual list items. Additionally, the list includes an option for conveniently selecting all products. The bottom portion of the left section is titled "Range Selection" and contains two buttons for selecting the time frame for the data points to include through conventional date pickers. Furthermore, it lets users set whether to aggregate values by year or month. When the application is opened, "All products" and "By year" are selected by default, while the time frame ranges from the date of the first available measurement up to the present. Data should be updated with dynamic queries, meaning that if the user interacts with the UI controls, the charts should reflect these changes immediately. Note that in the prototype, the titles of the sidebar subsections were renamed to "Select Product" and "Select Interval."

The section to the right of the UI controls contains the charts themselves. It is important to note that this report, from here on out, distinguishes between the terms "chart" and "plot," where "chart" is used loosely to describe isolated visualizations that make sense on their own. In contrast, "plot" is used to describe certain graphical elements, for instance, the connected scatter plots. Chart 1 includes a connected scatter plot where each point corresponds to the average service level of the selected products for all customers over one selected aggregation interval (either month or year). Additionally, the chart includes a line for the target service level. Chart 2 presents connected scatter plots for both inventory levels and orders. These plots work the same as the connected scatter plot in Chart 1, except their points amount to average inventory levels and orders, respectively. Chart 3 comprises a bar chart where each bar equates to the service level of the selected products for a single customer over the entire selected time frame. Chart 4 is a scatter plot where each point corresponds to the ratio of average inventory levels and orders for a single product for the selected time frame. In addition to the charts, the wireframe also depicts a text box for supplemental information like key numbers. This text box should at least contain the total number of stockouts occurring over the selected period. Above the charts section are tab-like buttons for switching to View 2 and showing that View 1 is currently selected.

As mentioned, View 2 lacks a wireframe depiction. View 2 is similar to View 1, except with different content in the charts section and somewhat restricted UI controls on the left-hand side. View 2 provides monthly reports for single products, which the UI reflects by letting users select only a single product and month. The chart section contains Chart 5, which incorporates a plot similar to a connected scatter plot where horizontal and vertical line segments connect the points in stairstep-like shapes. Mathworks (n.d.) conveyed a comparable plot type (without points) called a "stairstep plot." This report adheres to this naming convention. Chart 5 also contains a straight line for the target safety stock level. The elements of the stairstep plot that lie below this line stand out by being colored differently. Every chart described for both views has tooltip functionality displaying at least the values from the respective axes for a graphical element. For example, hovering over a point in Chart 1 displays the date and value of the relevant measurement.

4.1.4 Drill Down Example

The application's analytical functionality is realized using drill-down and linking interaction techniques which occur when users click certain graphical elements. These instances, explained in greater detail, are as follows:

- In View 1, if users have selected the "By year" option, clicking a point on the connected scatter plots will alter the focus data to comprise observations for that year only and change the aggregation interval to "By month."
- If users have selected the "By month" option instead, the connected scatter plot points in View 1 will lead them to View 2, adapted to reflect the relevant month.
- Clicking on a point in Chart 4 alters the focus data to reflect only that product.
- If users click an individual point in Chart 5, the application displays a table depicting all flows of materials that occurred on that day for the selected product.

The intent behind the interaction features is to facilitate the user discovering anomalies from a general overview of an extensive data set and to visually navigate to a detailed visualization of a smaller subset to discover their cause. An example of how this process can occur follows. Say the user is looking at the default overview and discovers an outlier in Chart 4. The user then clicks the mentioned point, which changes the focus data accordingly. Next up, the user discovers from Chart 1 that the service level for the product has been below the target level for the past year. The user now clicks any point corresponding to this year, which, as explained, alters the focus data further.

Again from Chart 1, the user discovers several months with frequent stockouts. Lastly, the user clicks on a single one of these months to investigate the circumstances of each stockout. Figure 12 depicts a UML activity diagram corresponding to the described example.

Note that the purpose of Figure 12 was to communicate how the interaction techniques work in practice. Additionally, the example itself is likely not the most realistic. For instance, with the initial data selection comprising observations from the entire time that the manufacturer has collected data, it is unlikely that a single product would be the only outlier. In real-life usage, the user would likely specify a much shorter time frame from the start.

Figure 12

Activity diagram for the data exploration example

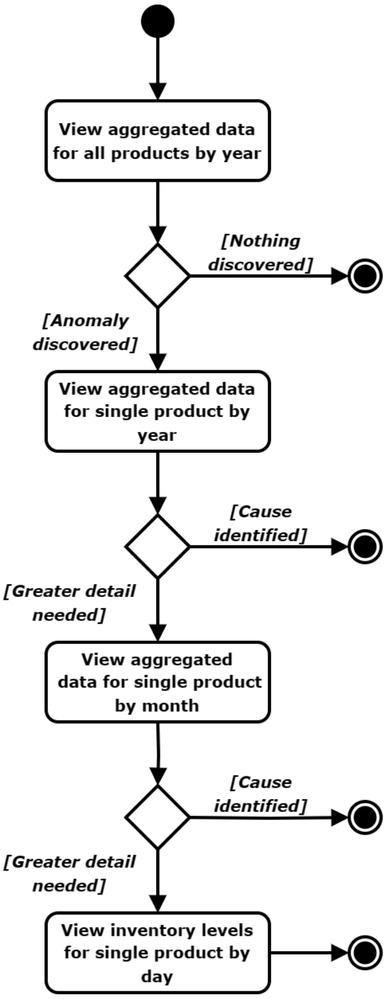
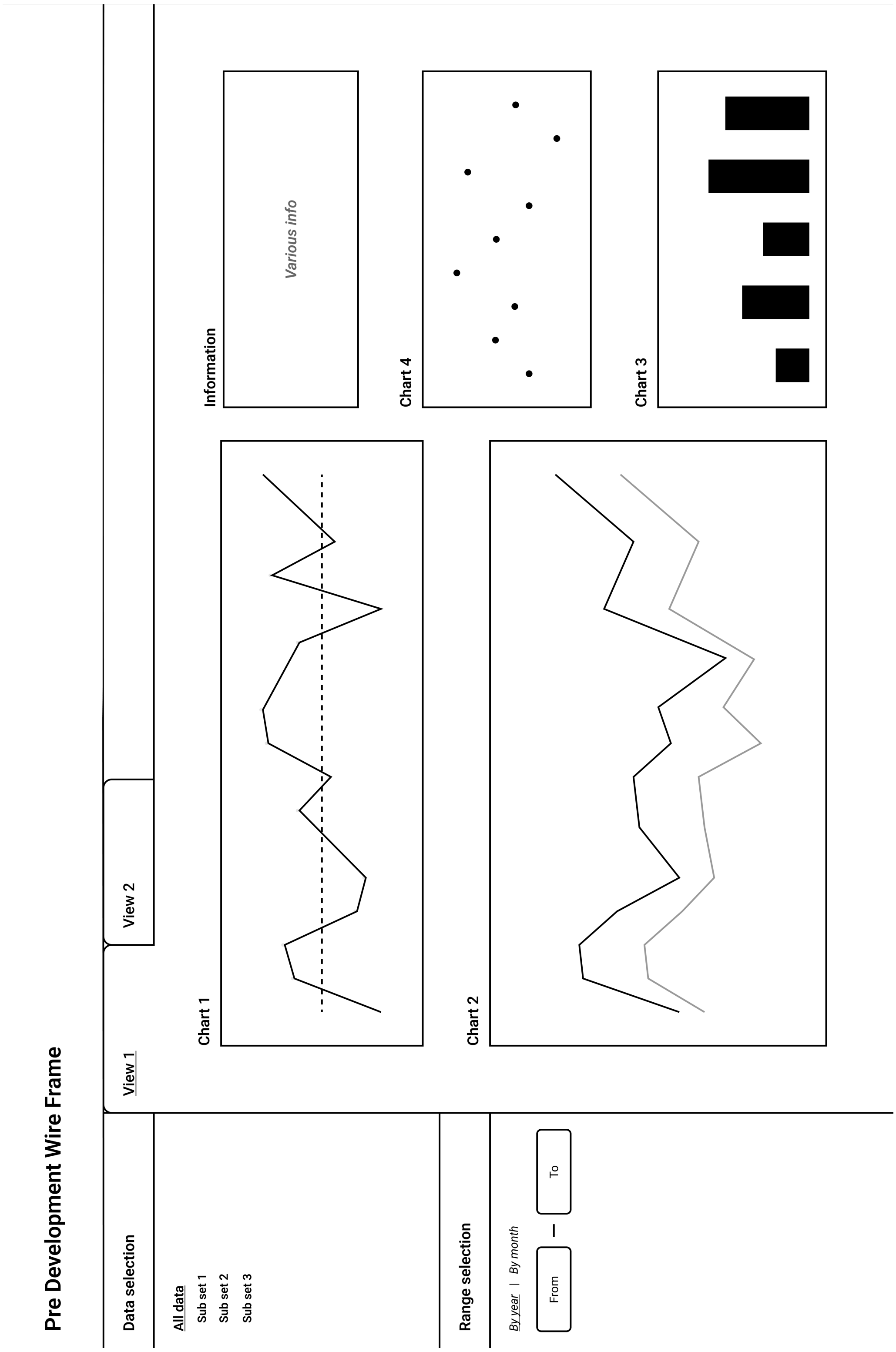


Figure 13

Pre development wire frame



Note. Has been somewhat altered since its initial use

4.2 Prototype Development

The section is concerned with the development of the prototype. First, a brief introduction to the chosen technologies is given, followed by a general explanation of how the charts were constructed. Then, each chart is described in further detail, along with the required data format for the given chart. Finally, the composition and usage of the dashboard are presented, as well as how the UI controls were implemented. An attempt has been made to explain the prototype in the context of the visualization literature to remain consistent with the scope of the project. In practice, this means that technical web development terms are omitted unless when perceived as strictly necessary. Note that there was not enough time to complete the functionality of the "Select Products" list, charts 3 and 4, and the text box illustrated in the wireframe. All these are, however, included as mostly static components, except the text box, which was omitted entirely. A public color palette found on Flat UI Co (n.d.) was used for a significant portion of the prototype. This section directly references the application code attached to this report in a zip file. The zip file contains folders for every discussed React component with high-resolution JSX and CSS file images.

4.2.1 Choice of Technologies

As stated in the methodology chapter, the purpose of the concept was to examine the effect of data visualization principles applied to safety stock method evaluation. It was quickly realized that fully implementing some of these principles would require tools offering a great deal of control. Additionally, it was recognized that Brynild already employs a tailor-made web application for the visualization of their factory system. It was decided to implement the prototype as a web application, as these technologies both offered the needed flexibility and conformed with what Brynild uses for their factory system visualization. Another heavily weighted factor was that the author had experience with front-end web development from previous projects.

The most notable of the chosen technologies were Vite, React, and D3. To understand why these technologies were opted for, it helps to know what JavaScript is. JavaScript is the programming language run by all web browsers, including Microsoft Edge, Google Chrome, and Mozilla Firefox (MDN Web Docs, 2023b). Initially, JavaScript was only used for small tasks on simple websites (MDN Web Docs, 2023a). Now, however, heavily JavaScript-dependent, large-scale applications are hosted in browsers (MDN Web Docs, 2023a). This evolution introduced a need for JavaScript modules, which are isolated pieces of JavaScript that developers can export and import as building blocks for their applications (MDN Web Docs, 2023a). In the past, browsers did not support modular JavaScript natively, requiring tools like Webpack to bundle source code into browser-compatible files (Vite, n.d.). As applications continued to include more modules, bundling became a bottleneck in web development (Vite, n.d.). Vite is a build tool that combats this problem, providing a fast development server taking advantage of browsers now supporting ES modules (Vite, n.d.).

React is a JavaScript library for UI implementation (MDN Web Docs, 2023c). React allows for decomposing a UI into modules called components (MDN Web Docs, 2023c). Components are reusable and typically serve a distinct purpose (MDN Web Docs, 2023c). For example, all the charts in the prototype are contained in single components. Applications made in React can consist of a hierarchy of many components (MDN Web Docs, 2023c). Furthermore, React utilizes an extension of JavaScript's syntax called JSX to create and manipulate HTML elements alongside regular JavaScript in a convenient fashion (MDN Web Docs, 2023c). JSX is made to resemble HTML and must be converted into regular JavaScript to be interpretable by browsers (MDN Web Docs, 2023c). Vite also handled this task for the prototype.

The most noteworthy technology choice for this thesis is that of the JavaScript library D3. The name D3 is derived from "data data-driven documents," referring to its core functionality of binding data to the document object model (DOM) (D3, n.d.), which is a representation of the web document as a tree structure (MDN Web Docs, 2023d). D3 is low-level, highly flexible, and fast (D3, n.d.). A key feature of the library is what it calls selections (D3, n.d.). Selections are arrays of DOM nodes and are straightforward to manipulate with D3-provided functions (D3, n.d.). Most notably, D3 allows for appointing a selection's properties, like attributes and styles, as functions of bound data (D3, n.d.). For example, D3 makes it possible to create a selection of scalable vector graphics (SVG) rectangles from an array of values and then set the height of each rectangle based on the corresponding value. This procedure results in a typical bar chart. The library also provides a magnitude of other features helpful in data visualization, like functions for creating scales and axes (Bostock, 2021). D3 was used to create all the charts for the prototype.

4.2.2 Chart Components

All the charts from the planning phase were implemented as React components in JSX files, which can be found in the attached zip file of this report. A chart component returned a top-level parent container which, at the very least, contained a title, a container with a tooltip and an SVG, and a legend. A separate component was made for the legends, as these function the same for every chart. Figure 14 shows the return statement for the component corresponding to Chart 1 from the case design section. The figure also details technical aspects such as styling and component properties.

D3 was used to construct vector graphics from input inventory data. The SVG element found in the return statement of Figure 14 functions as a root element for D3 to append to and manipulate. For this to work, the D3 functions need direct access to the root SVG DOM node, which is achieved using an aspect of React called useRef. According to React (n.d.-a), *useRef* is part of a set of React functions called *hooks*, which allows one to access React features from within a component. All of the hooks used in the prototype implementation can be found in React (n.d.-a).

Furthermore, all D3 functions for a chart were placed inside another type of hook called useEffect. According to React (n.d.-b), a *useEffect* hook takes in a setup function and an array of dependency variables as parameters. The setup function runs when the component renders and is rerun every time a dependency changes (React, n.d.-b). In the case of the chart components, the setup function consisted of all the D3 functions, while the dependency array comprised the relevant inventory data and the SVGs' height and width. In practice, this allowed the charts to update accordingly whenever their input data (or specified dimensions) changed. In order to remain within the confines of the project's scope, the use of these React hooks will not be explained in further detail. However, their exact uses can be found in the code provided in the zip file.

Even though the included chart components differed from each other to varying degrees, they all shared a common procedure for how D3 was used to construct the content of their SVGs. First off, the root SVG node was defined as a D3 selection titled simply "svg." Then, a group titled "elements," meant to contain all other SVG elements, was appended to this selection. The group's dimensions were further specified so that no graphical elements added later would be cut off. This step took inspiration from Soma (n.d.).

D3 provides functions for defining various types of scales for mapping abstract data to graphical data (Bostock, 2023). For every chart, scales for the x and y dimensions were defined, named "xScale" and "yScale," respectively. The type of scale function used depended on the purpose of the chart and the format of the input data. D3 also supplies functions for generating axes based on defined scales (Bostock, 2023). For every chart, either one or two axes were appended to the mentioned group container using such axis generators. The axis generators were named either "xAxisGenerator" or "yAxisGenerator," depending on the type of scale they were built from. The axes themselves were similarly named either "xAxis" or "yAxis."

The rest of the graphical elements were constructed using the defined scales and various other D3 functions, the more consequential of which will be explained in greater detail where relevant. Additionally, D3 provided several valuable functions for implementing

Figure 14

Minimal chart return statement

```
return (
  <div
    style={{
      display: "flex",
      flexDirection: "column",
      background: "white",
      padding: "1rem",
      gap: "1rem",
    }}
  >
    <h3
      style={{
        fontFamily: "Roboto, sans-serif",
        fontSize: "0.9rem",
        margin: "0",
        color: "#2c3e50",
        fontWeight: "500",
      }}
    >
      Monthly Service Levels
    </h3>
    <div style={{ display: "flex" }}>
      <div ref={tooltipRef}></div>
      <svg ref={svgRef}></svg>
    </div>
    <ChartLegend
      legendMappings={[
        { title: "Service Levels", color: serviceLevelsColor },
        { title: "Target Service Level", color: targetLevelColor },
      ]}
    />
  </div>
);
```

the interaction techniques. These included functions for adding event listeners to specific elements and attaining the cursor's pixel coordinates in relation to the SVG. Such functionality was implemented through appropriately named functions specified to run on certain events. For example, the tooltip was realized through the functions "handlePointMouseEnter," "handlePointMouseLeave," and "handlePointMouseMove," which updated the position, content, and appearance of the tooltip div when the cursor entered, left, or moved within a graphical point, respectively. When creating the tooltips, inspiration was taken from Vardhan (n.d.). The drill-down interactions were implemented much the same way and are further explained later in this section.

Figure 15 shows the "ServiceLevelsChart.jsx" component, which corresponds to Chart 1 in the wireframe from the concept description. The component took in inventory data as an array of JavaScript objects where every object possessed a "date" and a "value" property. In addition to the discussed elements common to all the implemented charts, the chart included a connected scatterplot corresponding to either yearly or monthly average service levels for the selected time frame and a dashed line depicting the target service level. The connected scatter plot was implemented as a group titled "serviceLevelsPlot," which comprised an SVG path, a sub-group of SVG circles named "points," and a sub-group of text elements named "valueLabels." D3 provides a generator function that constructs line plots from data (Bostock, 2023). The SVG path element was built using such a line generator simply titled "lineGenerator." The generator was further specified to transform x and y values employing the defined scales. The points were created by binding the input data to circle elements and specifying their position by mapping these values to geometric data using scales. Event listeners and handling functions were also defined so that clicking on a given point adjusted the viewed data to reflect the relative interval. The labels above the points were made in a similar way using SVG text elements. The procedure explained above serves as a good example of how the graphical contents of the charts were constructed and named.

Figure 15

Chart containing the monthly averages of weekly service levels

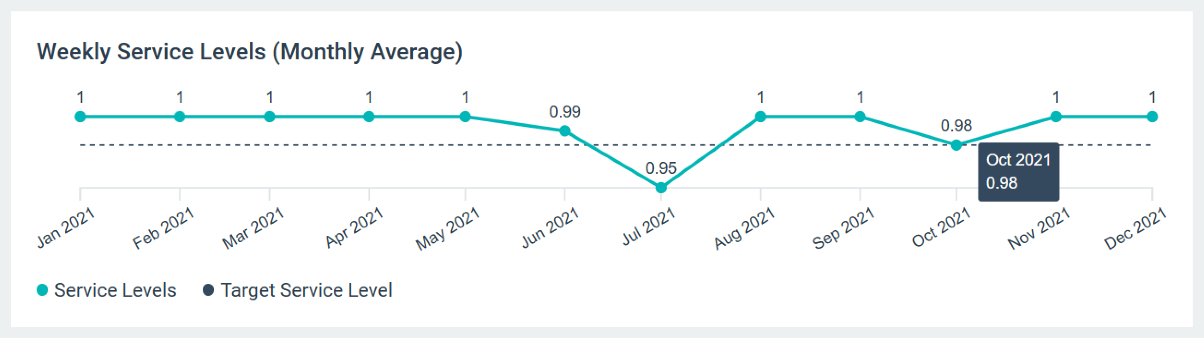


Figure 16 contains the "InventoryAndOrdersChart.jsx" component, corresponding to

Chart 2 from the wireframe. As in the concept description, this chart was similar to the service levels chart, the key difference being that it contained two plots, one depicting the average inventory levels for an aggregation interval while the other showed average orders. The component took in two data sets in the same form as the previously explained chart. As there was a risk of the plots overlapping, a feature was implemented where only one plot was active at a given time. The active plot existed as a connected scatter plot with tooltip functionality like the plot in the service levels chart. In contrast, the inactive plot existed as a simple line plot with lowered opacity so as not to damage the active plot's interpretability. The inactive plot also had no tooltip functionality. Clicking the inactive plot changed its status to active, making it appear as such. Subsequently, the plot previously considered active changed status along with its appearance accordingly. By default, the inventory levels chart possessed the active status.

Figure 16

Chart containing monthly averages of weekly inventory levels and orders

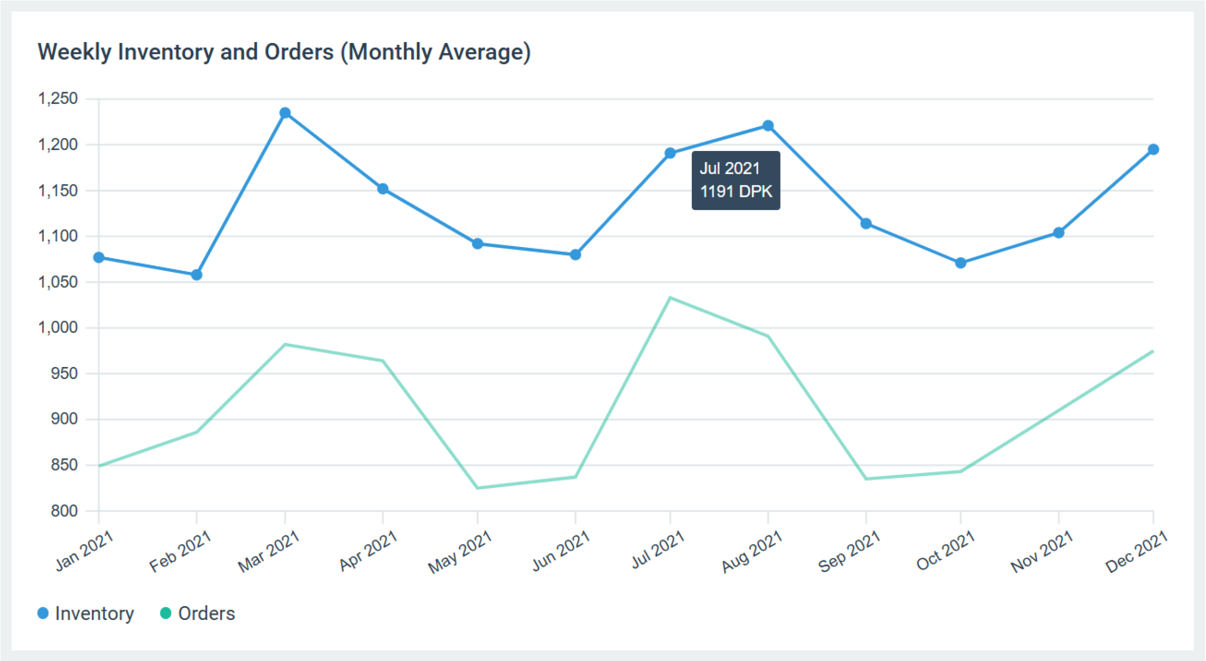
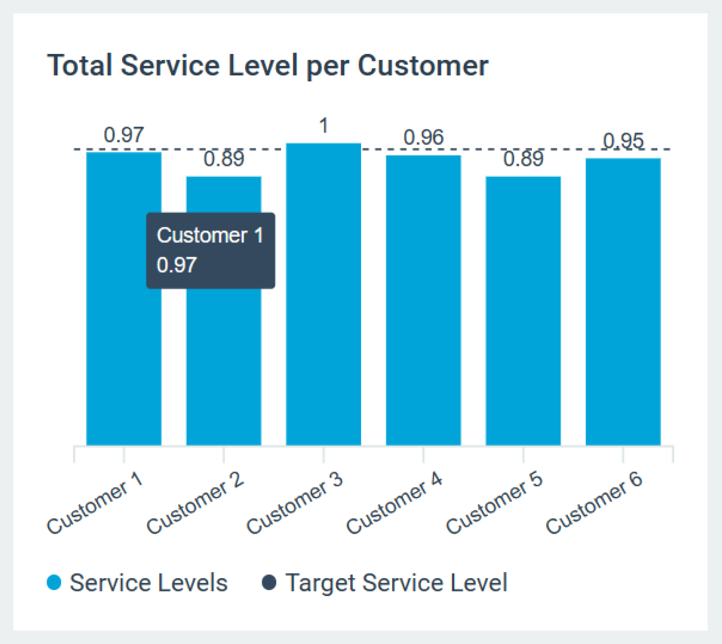


Figure 17 shows the chart corresponding to Chart 3 from the concept description. The component is titled "SerivceLevelPerCustomerChart.jsx" and comprises a bar chart intended to show the total service level for each customer for the entire selected period. The component took in data as an array of JavaScript objects with properties "actor" and "value." Moreover, the chart contained a dashed line reflecting the target service level and value labels above each bar. Like the previously mentioned charts, this chart possessed a tooltip, which appeared as the cursor overlapped with an individual bar. As mentioned, the implementation of this chart was not completed in that its displayed data was not altered by user interaction.

Figure 17

Chart depicting total service levels per customer



The chart in Figure 18 corresponds to Chart 4 from the content description's wireframe and was partially realized in the component "InventoryOverOrdersChart.jsx." This component took an array of objects with properties "item" and "value." It depicted a scatter plot where each point was supposed to represent the average kept inventory divided by the average amount of orders for a single product over the selected time frame. Clicking on a point was supposed to adjust the data selection to reflect only the respective product for the same time frame as what was already specified. As mentioned, this feature was not completed. If the initial product selection was large, for example, if the "All products" option was selected, many points would likely overlap. For the chart to be as readable as possible in such situations, the opacity of the points was set to 80%, making them slightly see-through. This measure was deemed sufficient as it was thought that particularly interesting points would exist as outliers. Another measure to ensure the chart's interpretability was omitting an x-axis entirely. Identifying the product names was instead provided by the tooltip along with the exact value.

Figure 18

Chart showing the ratio between inventory levels and orders per product

Figure 19 depicts the chart component located in the detailed view. The component was named "InventoryChart.jsx," and its main element was a stairstep plot representing daily inventory levels for a selected month. In agreement with the concept described in the previous section, every sub-element of the stairstep plot below the target safety stock level was of a contrasting color so as to stand out to the user. This was achieved by using a linear gradient taking inspiration from Strebe (2016). Additionally, the chart contained a dashed line, along with a corresponding label, marking the target safety stock level. The component accepted data in the same format as the service levels chart.

The chart set itself apart from the others in that the tooltip was implemented somewhat differently. First, a separate group was appended to the group for all graphical elements mentioned earlier. This new group was named "interactables" and was intended only for elements that should trigger the tooltip. These included the stairstep plot, dashed target line, and a transparent rectangle spanning the dimensions of the initial group. In practice, this ensured that the tooltip always showed as long as the cursor was placed within the confines of the chart. This measure was taken because, in contrast to the other connected scatter plots, the line segments between the points in the stairstep plot also represented real-world data. To quickly indicate which part of the stairstep plot the tooltip corresponded to, a rectangle with the width of a single day was made to update its position according to which day on the x-axis was closest to the cursor. This rectangle was named "focusRect" and was appended before the "interactables" group in order not to obstruct the other elements. If the user clicked a point, a table showing the transactions on the respective was planned to appear. This feature was, however, also not realized. As a substitute, transactional data was also conveyed by the tooltip.

Figure 19

Chart showing daily inventory levels and transactions for a given month

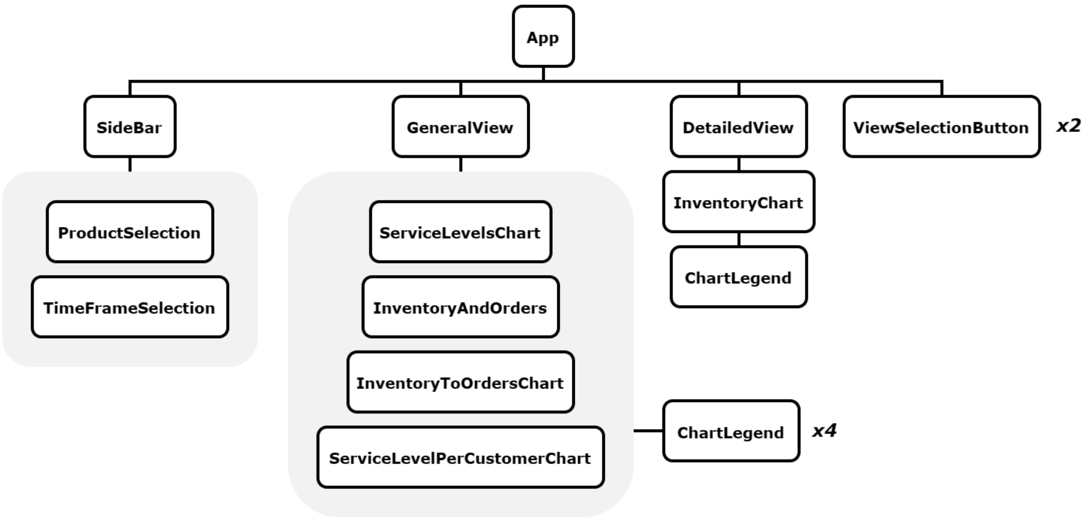
4.2.3 Application

Figure 21 and 22 show the prototype version of the general and detailed view, respectively. The first step in creating the dashboard was using Vite's feature to automatically set up a functioning application. This project scaffold included a React component named "App.jsx," which functioned as a root in the component hierarchy. The component comprised a "header" element, containing a generic logo and a page title, and a "main" element denoting the page's main content. The latter further comprised a sidebar component and components corresponding to the general view and the detailed view mentioned in the concept description. Depending on the user's preferences, the application would only render one of the view components at a given time. All components not constituting charts had accompanying style sheets with the same name as the component but with a ".css" file extension. For example, the styling for the "App.jsx" component was written in the "App.css" file.

The two view components were appropriately titled "GeneralView.jsx" and "DetailedView.jsx." These each returned compositions of the explained charts that reflected the wireframe in the concept description. The general view included "ServiceLevelsChart.jsx", "InventoryAndOrdersChart.jsx", "ServiceLevelPerCustomerChart.jsx", and "InventoryOverOrdersChart.jsx". The detailed view contained "InventoryChart.jsx." Additionally, the view components passed input data to their children and possessed functions for extracting the user-specified data subsets. The sidebar component comprised "ProductSelection.jsx", including the inactive list intended for limiting the data set to specific products, and "IntervalSelection.jsx", which included generic HTML month picker elements for limiting the data set to be visualized to a start date and an end date. Figure 20 conveys the component hierarchy.

Figure 20

Hierarchy of React components



Note. The context provider and less important HTML elements are excluded.

For implementing the feature for selecting data subsets, the *useState* React hook was utilized. This hook allows for defining variables within components that cause the component to re-render when updated (React, n.d.-c). The useState hook takes in a value and defines a new state variable, set to equal the provided value, and a function for updating it (React, n.d.-c). The "App.jsx" component possessed five state variables. The first of these was defined as "selectedView," which contained a string representing which view component to render with "General" as its initial value. The next one was defined as "selectedProducts," which contained a list of strings corresponding to the names of the products selected from the list in "ProductSelection.jsx" and was not used any further. "selectedTimeFrame" possessed an array of two string on the format "YYYY-MM," representing the start and end month of the data entries to be included in the general view. The default value was set to the months of the first and last entry in the available data. The next state variable was defined as "selectedMonth," which contained a string representing the selected month for the detailed view. The last was defined as "selectedAggregation," which contained a string representing the selected aggregation level.

In order to make the state variables available to the children of the "App" component, a React feature called Context was used. This feature was less relevant to the visualization aspect of the prototype and will not be explained further in this report.

Figure 21

The general view of the prototype

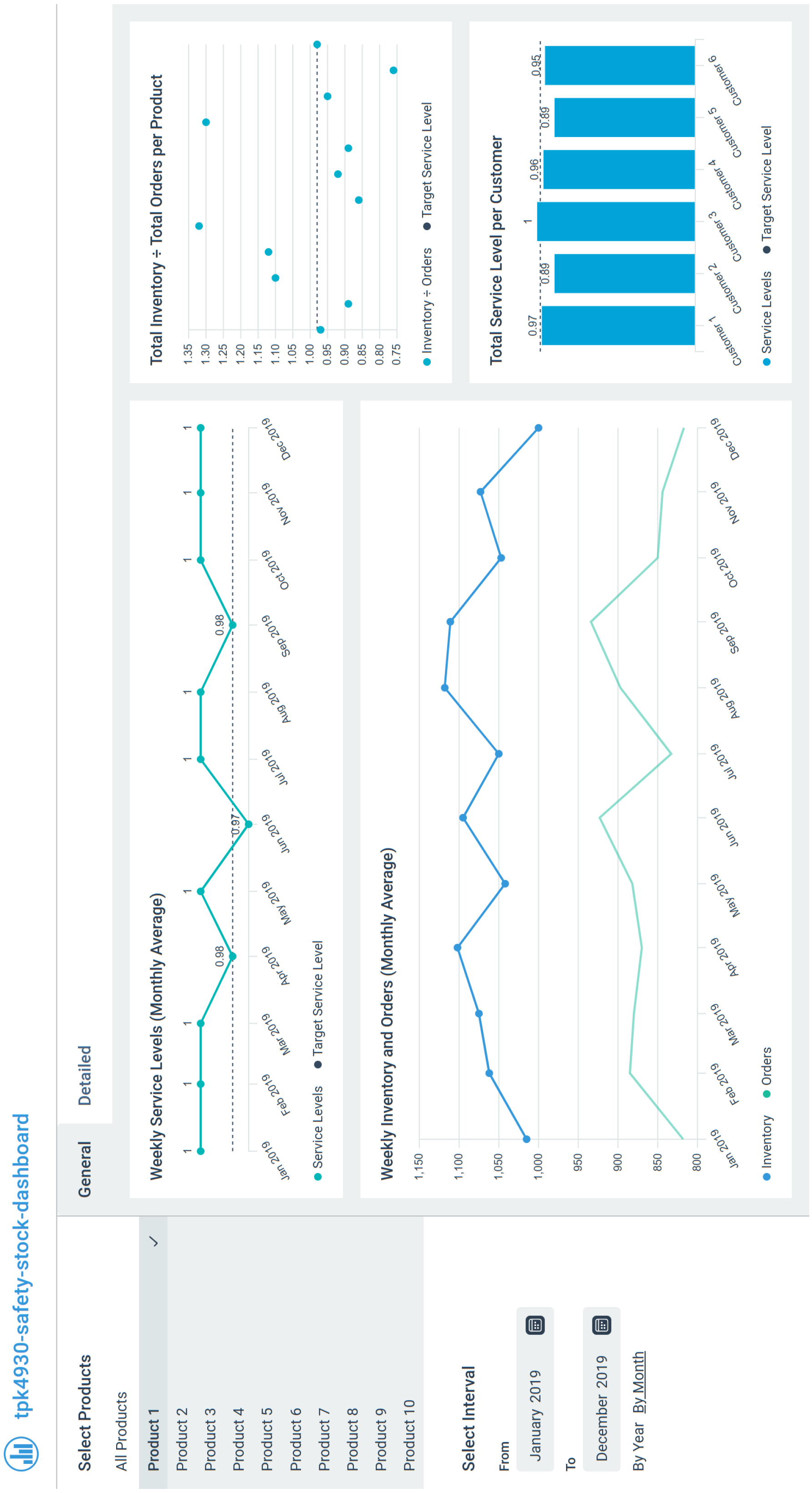
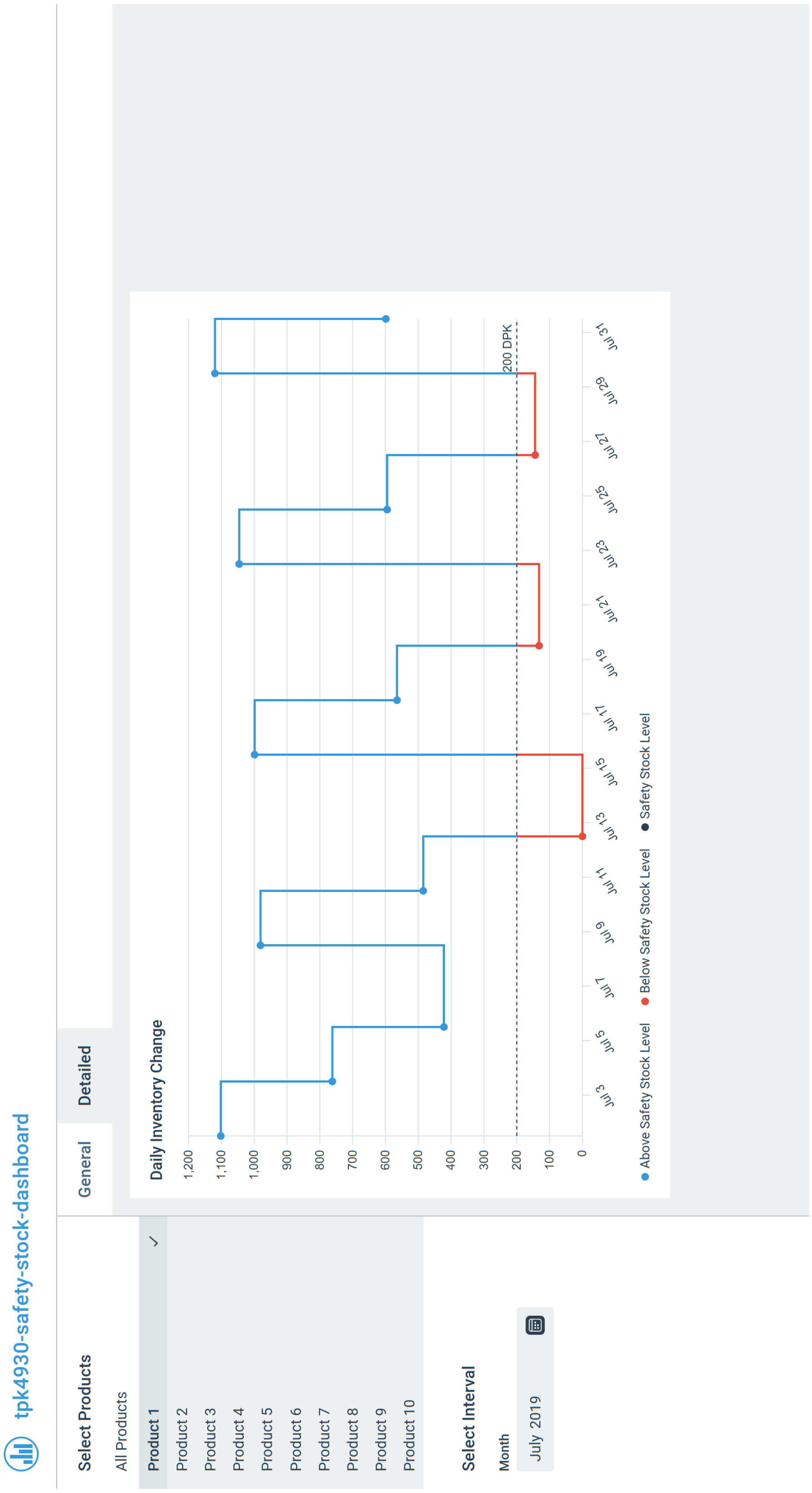


Figure 22

The detailed view of the prototype



Month
July 2019

5 | Empirical Background

5.1 The Food Supply Chain

A *supply chain* comprises a series of at least two businesses interlinked by flows of material, currency, or information (Stadtler, 2015). Examples of supply chain actors include manufacturers of finished products, suppliers of raw materials or components, third-party logistics providers, and the end customer (Stadtler, 2015). In reality, supply chains are rarely linear, forming networks with multiple parallel flows (Stadtler, 2015). Stadtler (2015) claimed that the competitiveness of a single actor is affected by the entire supply chain. As a result, competition has gradually shifted from the business level to the supply chain level (Stadtler, 2015). Stadtler (2015) further stated that improving supply chain competitiveness encompasses either improving customer service level or minimizing costs while an agreed-upon customer service level is maintained. The task of competitiveness-oriented integration and coordination of supply chain actors is known as *supply chain management* (Stadtler, 2015).

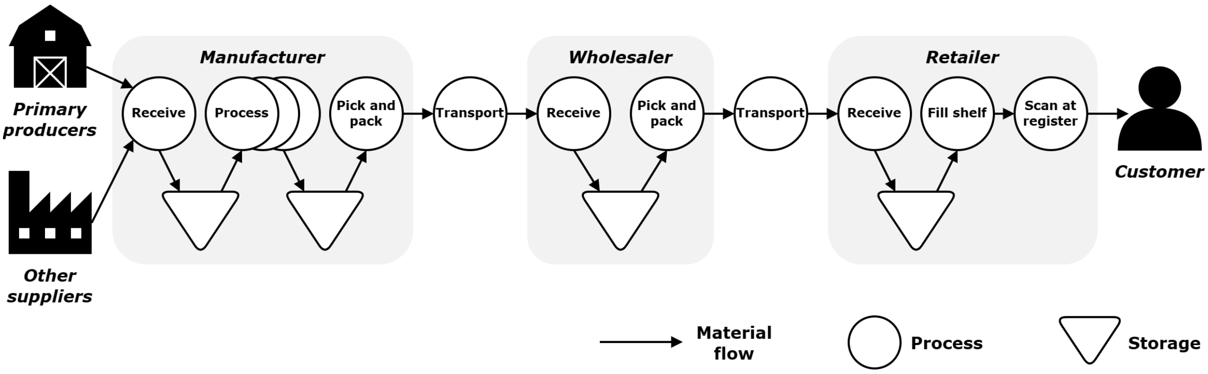
5.2 Supply Chain Structure

Romsdal (2014) stated that most food products result from significantly developed supply chains. Figure 23, adapted from Romsdal (2014), depicts a food supply chain comprising the flow of material from its raw state to a finished product in the hands of the customer. As illustrated, the manufacturer receives raw materials from primary sector producers in addition to premade components from other suppliers (Romsdal, 2014). The wholesaler then receives the manufactured goods before further distributing them to retailers, where they are made available for purchase (Romsdal, 2014). Besides wholesalers, food manufacturers may sell directly to institutions and hotel, restaurant, and catering (HORECA) clients (Romsdal, 2014). Furthermore, third-party companies may take care of transportation between supply chain contact points (Romsdal, 2014).

The last decades have introduced substantial industrial developments affecting the structure of Norwegian food supply chains (Romsdal, 2014). One such development is the increased focus on optimizing capacity utilization and achieving economies of scale (Romsdal, 2014). (Baumers et al., 2016, p. 199) defined economies of scale as "situations in which businesses are able to decrease the average unit cost by increasing total output." Reduced item cost resulting from larger batch sizes is an example of economies of scale in food supply chains beneficial for both the manufacturer and wholesalers (Romsdal, 2014). The shift in strategy has led Norwegian food manufacturers to employ centrally positioned high-tech facilities that produce in large quantities (Romsdal, 2014).

Figure 23

The food supply chain



Note. Adapted from Romsdal (2014).

Another noteworthy structural change comes from the increased presence of consolidation (Romsdal, 2014). Vertical integration occurs when a business owns and controls production processes where the output of one serves as input for the other (Maddigan, 1981). Romsdal (2014) stated that examples of vertical integration exist for all the typical food supply chain actors. Most notable is the merger of wholesalers and retailers, where four umbrella chains comprise nearly the entire Norwegian retail and distribution market (Romsdal, 2014). Table 5 shows this distribution based on a report from NielsenIQ (2021).

Table 5

Umbrella chain market shares (2019 and 2020)

Actor	2019	2020	Change
NorgesGruppen	43.73%	44.09%	+0.36pp
COOP	29.47%	29.33%	-0.14pp
Rema 1000	23.21%	23.17%	-0.04pp
Bunnpris	3.60%	3.42%	-0.18pp

Note. Adapted from NielsenIQ (2021)

5.3 Product Characteristics

Fast-moving consumer goods are characterized by being purchased by customers frequently and spontaneously in their daily lives (Niedermeier et al., 2021). The FMCG market is divided into food and non-food products (Niedermeier et al., 2021) and mainly constitute personal care products, packaged food and beverages, household care products, spirits, and tobacco (Bala & Kumar, 2011). Food products, in particular, are characterized by high perishability, meaning that they will degrade quickly, especially if they are not handled and stored adequately (Romsdal, 2014). The threat of degradation is present for raw materials, WIP, and finished goods alike and implies challenges for all stages of production (Van der Vorst et al., 2007). Other characteristics of food products include a high product variety, wide variety in packaging, and strict quality demands from customers (Bolseth & Alfnes, 2001; Van der Vorst et al., 2007).

5.4 Market Characteristics

Romsdal (2014) asserted that the food market stands out regarding delivery lead time, demand uncertainty, and inventory management. Van Donselaar et al. (2006) discovered that perishables have higher average weekly sales per product and potential delivery frequency compared to non-perishables. In addition, downstream actors in the food supply chain typically demand short delivery lead times (Bolseth & Alfnes, 2001). Regarding Norway specifically, the distinct geography makes it challenging for food manufacturers to meet these demands (Romsdal, 2014). Difficult terrain, uneven population distribution, and harsh climate lead to longer minimum delivery lead times and introduce greater delivery lead time variability (Romsdal, 2014).

The food supply chain is subject to increased consumer demand uncertainty (Van der Vorst et al., 2005). Van Donselaar et al. (2006) found that weekly sales vary slightly less for perishables than non-perishables. Taylor and Fearne (2006) explained that these variations, first and foremost, occur due to promotional campaigns. Also worth mentioning is the bullwhip effect, which is frequently present in food supply chains (Romsdal, 2014). The bullwhip effect signifies when demand gets gradually more distorted upstream from the customer (Lee et al., 1997).

When stockouts occur, customers purchase substitute products from the competition (Bolseth & Alfnes, 2001). To avoid such scenarios, manufacturers and retailers seek to keep their products available (Bolseth & Alfnes, 2001; Romsdal, 2014). However, the perishable nature of food products restricts how much safety stock an actor can hold (Van der Vorst et al., 2005). NielsenIQ (2022) found that American retail stores in Texas, Oklahoma, Louisiana, and Arkansas experienced stockout rates of 10% during the third and fourth wave of the COVID-19 pandemic.

5.5 IT Systems for Food Supply Chain Management

IT systems serve as a critical component in food supply chain management (Zhong et al., 2017). Zhong et al. (2017) distinguished between traceability systems and decision-making systems. Traceability systems map the product's physical trail through its separate phases (Smith et al., 2005). As for decision-making systems, Zhong et al. (2017) noted fleet management, planning, collaboration, and warehouse management systems (WMS) as widespread in food supply chain management. Furthermore, Zhong et al. (2017) found that the use of decision-making systems is more prominent in European countries.

6 | Case Study

This chapter contains the case study of the project. The chapter consists of three sections. The first section provides a general introduction to the case company Brynild and a factual description of the company's current safety stock and visualization practice. The second section conveys suggestions for potential improvements regarding these same areas. The third section contains the procedure and conditions for the mock-up data set construction, as well as an attempt to validate the concept by investigating a statement regarding Brynild's safety stock method.

6.1 Case Introduction

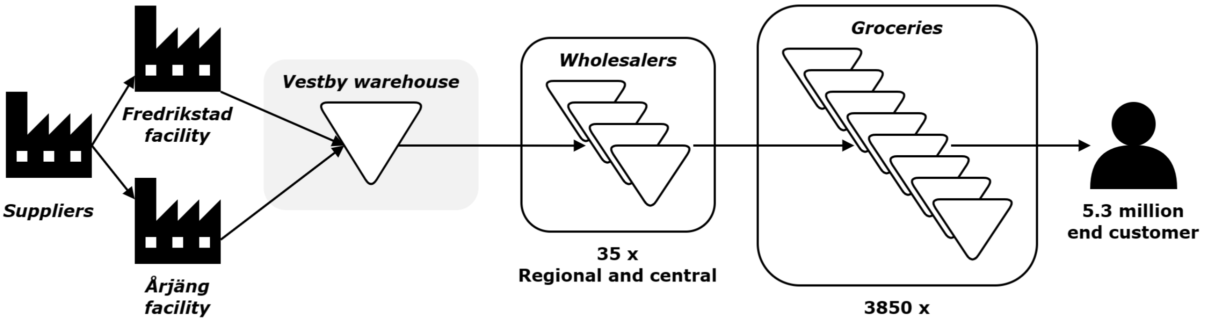
The information regarding Brynild's current approach to visualization and the management of safety stock was collected through two visits to Brynild's facilities in Fredrikstad, several digital meetings with Brynild personnel, and an introductory presentation given by Brynild's supply manager to students at NTNU.

Bryild Gruppen is a Norwegian snacks and confectionery manufacturer with facilities in Frerdikstad (Norway) and Årjäng (Sweden). In addition to Norway, Brynild delivers to Sweden, Finland, and Denmark. The Brynildsen family founded the business in 1895 and has owned it ever since. From 2006 to 2010, significant changes occurred to the structure of the organization, with one major manufacturing facility in Fredrikstad replacing three smaller distributed facilities. Another substantial development occurred in 2021 with Brynild's acquisition of a sugar confectionery manufacturing facility in Sweden. Minde Sjokolade, Den Lille Nøttefabrikken, Dent, Brynild, and St. Michael are examples of Brynild-owned brands.

Figure 24 shows Brynild's supply chain. As depicted, Brynild's facilities, as well as external suppliers, deliver to a finished goods warehouse located in Vestby (Norway) operated by the 3PL provider Leman. From here, goods are further distributed to regional and central wholesaler warehouses by wholesalers/retailers. Next, goods are transported to grocery stores before being purchased by the final customers. Brynild's potential Norwegian customer base makes up 5.3 million people, and its product turnover at retailers amounts to 1.7 billion NOK, excluding VAT. Within the Norwegian market, Brynild's market share comprises approximately 28% of nuts sales, 13% of sugary confectionery sales, 10% of pastilles sales, and 3% of chocolate sales as of 2021. Brynild's supply chain roughly matches the typical food supply chain from Romsdal (2014) reiterated in the empirical background section.

Figure 24

Brynild's supply chain



Note. Adapted from 2022 introductory lecture at NTNU.

Brynild recognizes three distinguished types of customer demand patterns:

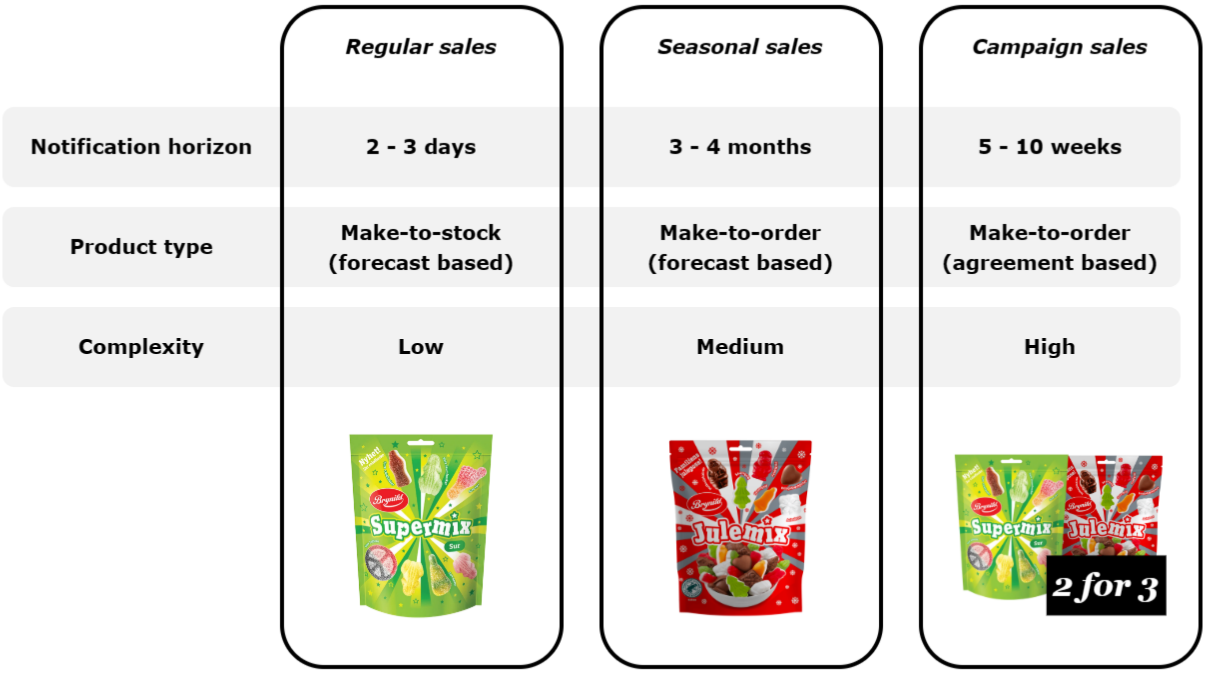
- *Regular demand* comprises the typical demand for regular on-shelf products.
- *Campaign demand* consists of additional demand caused by agreed-upon promotions.
- *Seasonal demand* is additional demand resulting from seasonal factors, e.g., higher sales of candy during Christmas.

Brynild utilizes the ERP system SAP with its SAP APO module to forecast future demand. The module computes one value for each product approximating its monthly demand. The forecasting process covers several upcoming months. Brynild practices distinct planning strategies for each type of customer demand. To meet regular demand, the manufacturer plans according to the SAP forecasts. For campaign demand, it produces pre-determined quantities agreed upon with the retailer. Seasonal demand is planned for four months ahead of the respective season based on separate forecasts. Brynild initiates these preparations long in advance as the magnitude of the seasonal demand spikes far surpasses their short-term production capacity. Figure 25 shows characteristics regarding the different types of orders.

Brynild distinguishes four types of articles in its value chain: raw materials/packaging, intermediates, finished goods, and sales solutions/displays. Table 6 shows approximately how many articles belong to each group. As illustrated, Brynild manages roughly 200 articles considered finished goods. Pallets of finished goods consist of distribution packages (NO.: distribusjonsforpakning) shortened D-pak, either of a single or mixed type. A D-Pak unit further consists of consumer packages (NO.: forbrukerforpakning), shortened F-pak, which is what is typically purchased by the final customer. Brynild delivers F-Paks for single articles in various sizes, as well as additional packages intended for special sales solutions. In total, Brynild supplies approximately 450 SKUs to the Nordic market.

Figure 25

Different types of orders



	Regular sales	Seasonal sales	Campaign sales
Notification horizon	2 - 3 days	3 - 4 months	5 - 10 weeks
Product type	Make-to-stock (forecast based)	Make-to-order (forecast based)	Make-to-order (agreement based)
Complexity	Low	Medium	High

Note. Adapted from 2022 introductory lecture at NTNU.
Image source: Brynild (https://www.brynild.no/brynild/produkter/supermix-sur/112848)
Image source: Brynild (https://www.brynild.no/brynild/produkter/brynild-julemix-280-g/112612)

Table 6

Rough numbers of different articles

Type	Nuts	Sugar	Chocolate	Sum
Raw material/packaging	200	500	100	800
Intermediates	70	90	40	200
Finished Goods	70	100	30	200
Sales solutions/displays	20	10	10	40

Note. Adapted from 2022 introductory lecture at NTNU.

6.2 Current Practise

6.2.1 Safety Stock Calculation and Evaluation

The case study provided several meaningful insights into how Brynild handles the topic of safety stock. One such discovery is that Brynild manually sets safety stock levels for each product. Additionally, it utilizes no software for the computations, calculating each level manually using a standard calculator and adjusting it based on experience if thought necessary. The computed levels are then entered into SAP, where they are taken into account in other areas of planning. Brynild's way of calculating safety stock matches the following formula explained by Jonsson and Mattsson (2019):

$$Safety\ Stock = Number\ of\ Days * Average\ Daily\ Demand \tag{6}$$

Where $Number\ of\ Days$ is a margin intended to cover replenishment lead time (Jonsson & Mattsson, 2019). In the case of Brynild, this factor is based on experience and typically corresponds to two weeks. To decide $Average\,Daily\,Demand$, the manufacturer uses their forecasts for regular demand. Specifically, it computes an average of forecasted values for the given product, usually for the upcoming three months. Brynild calculates safety stock in units of D-pak.

Brynild themselves describe their safety stock practice as "set it and forget it." In other words, they seldom reevaluate established safety stock levels, with an exception being for newly introduced products. Naturally, Brynild possesses no historical data for a new product, which likely diminishes the accuracy of its respective forecasts. As the employed safety stock calculation method depends entirely on the regular demand forecast for a product, Brynild monitors actual demand closely for a brief period after its introduction making adjustments to its safety stock level if necessary. Previously employed safety stock levels that have since been changed can be derived from a product's materials master record. However, Brynild finds that SAP R3 (its currently employed version) does not provide functionality for viewing these changes in a generated report.

Brynild operates with a service level requirement of 98% set by the retailers it supplies. Historic service levels are essential indicators of Brynild's performance and apply to several cases. For example, when evaluating the manufacturer's overall relationship with a customer, the service level for all products to the individual customer is important to consider. On the other hand, when assessing a product's safety stock level, the service level for the single product to all customers is more interesting. Overall, Brynild deems service levels for individual customers as more influential in their decision-making.

6.2.2 Visualization of Inventory Data

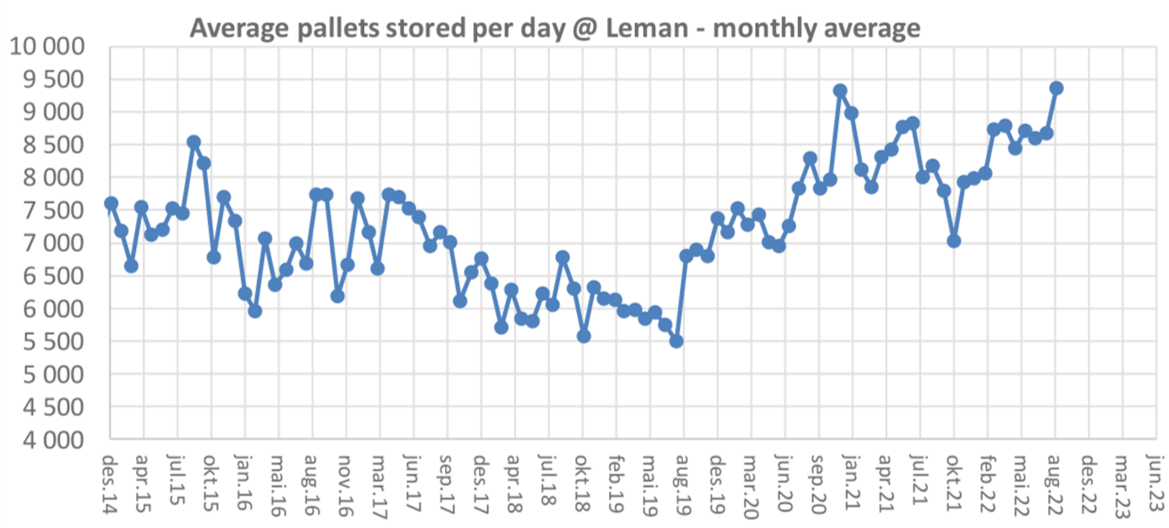
As discussed above, Brynild does not currently employ visualization to evaluate its safety stock levels or method. However, the case study did identify circumstances where it used visualization to monitor key performance indicators (KPI) regarding inventory management. The findings consisted of several scatterplots and connected scatterplots conveying transactional data from the finished goods warehouse in Vestby. Figure 26 depicts one of these plots. The discovered plots comprised monthly averages from December 2014 to August 2022 for the following areas:

- Average pallets stored per day
- Inbound pallets per month
- Outbound full pallets per month
- Picked cartons per month

The study also recognized respective plots showing accumulated 12-month averages for the same areas. Even if meant for different use cases, these plots are explicit examples of Brynild visualizing its inventory data for finished goods. Therefore, the process by which they were created is considered highly relevant to this thesis. Note that the measurements in the identified plots also included some raw materials and packaging.

Figure 26

Typical plot used for inventory management KIP monitoring



Note. Taken from 2022 introductory lecture at NTNU.

The identified plots visualized inventory data supplied by Leman's WMS. It was, however, discovered that Brynild can extract the same information from SAP transactional data.

As this case study is scoped to Brynild, it is concerned with the procedure of it visualizing its inventory data without it having to be externally requested. The process for how this would be done follows:

1. Brynild's available inventory data consists of transactions registered in SAP. However, it finds that SAP does not provide satisfactory visualization features and employs additional software to compensate. To accommodate this, Brynild first exports the desired data from SAP as comma-separated values files (CSV).
2. Once it has exported the data, Brynild imports it into Microsoft Excel, a spreadsheet software providing calculation and visualization features.
3. SAP tracks transactions in/out of the finished goods warehouse. Brynild uses the Excel workspace to adapt the transactional data into the values they wish to visualize. For example, in creating a connected scatterplot like in Figure 26, Brynild would first calculate the total quantity stored daily by accounting for every transaction since a known starting point and then computing monthly averages.
4. Brynild then chooses one of Excel's plot types to create a static visualization of the newly prepared data set. Lastly, it customizes the plot, for example, by choosing colors, adding legends, or rotating labels.

6.3 Suggestions

As stated by Directorate-General for Internal Market, Industry, Entrepreneurship, and SMEs (2020), a business is categorized as a small-medium enterprise (SME) if it possesses no more than 250 employees and has no more than 50 million EUR in annual turnover or an annual balance sheet total not exceeding 43 million EUR. According to Proff (n.d.), Brynild had roughly 200 employees and an annual balance sheet total of 45 million EUR as of 2021. In comparison, its annual balance sheet total equaled about 42 million EUR in 2020, while its annual turnover exceeded 50 million EUR in both years (Proff, n.d.). From these observations, one can conduct that Brynild has recently outgrown the SME classification. As a large manufacturer, Brynild might cut holding costs significantly by improving how it handles safety stock.

6.3.1 Safety Stock Calculation and Evaluation

The first discussion-worthy aspect of Brynild's present-day approach is its use of a calculator in setting safety stock levels. A calculator might provide sufficient aid for performing the calculations as they are relatively simple but depends on much unnecessary involvement from the employee. This might increase the risk of human errors and, by extension, inefficient safety stock levels. Furthermore, manually calculating the safety stock level for individual products is likely time-consuming and tedious work. Brynild could make this procedure more convenient by either writing a program to automate it or even replacing the calculator with a more feature-rich alternative like Microsoft Excel. This suggestion assumes that Brynild can access the required data in an appropriate format.

It is also worth commenting on the number-of-days safety stock method itself. Silver et al. (2016) stated that a big international consulting firm identified this approach as utilized by 80 - 90% of its clients. Despite the method's large user base, Silver et al. (2016, p. 247) labeled it "seriously in error" as not accounting for forecast uncertainty. Moreover, Silver et al. (2016) described a real-world case where it neither attained satisfactory service levels for products with high demand variability nor minimized holding costs. Detailing different safety stock calculation methods was beyond this project's scope. Even so, it is recognized that Brynild possesses the necessary data to adapt the statistical method described in the theoretical background section, and investigating this further is suggested.

As discussed in the theoretical background chapter, inefficient safety stock levels will likely have significant negative implications for the manufacturer. It is, therefore, substantial that Brynild does not evaluate its safety stock levels to a greater extent. Even if Brynild explained its safety stock approach as "set it and forget it," it does apparently monitor its service levels which are heavily related. This observation implies that the present safety stock practice does not cause considerable stockouts, as this would likely have induced alarm. However, Brynild cannot deduct whether the safety stock levels are too high from service levels alone. It is, therefore, advisable for Brynild to invest in software for this purpose. Such a solution would not necessarily have to depend on data visualization, but given its mentioned benefits, considering it is advised.

6.3.2 Visualization of Inventory Data

Another noteworthy finding is the small extent to which Brynild utilizes data visualization of its inventory data. Furthermore, the case study identified no instances of the manufacturer applying data visualization to safety stock calculation or evaluation. With the current number of use cases being so few, it is natural that Brynild has not invested much in its approach to the topic. However, if it wishes to take advantage of the benefits noted in the theoretical background section, a few suggestions regarding today's process are worth discussing. For one, the process requires a significant amount of data wrangling. Much of Brynild's available inventory data consists of SAP-registered transactions. As it currently stands, employees must derive other data from these themselves. There is also no guarantee that they will save the wrangled data or make it available to others. This characteristic introduces a risk of either them or other employees having to redo the task later. One way to counter this issue would be to implement a software solution that fetches the raw data, computes the desired values, and stores them in a shared database.

It is noticeable how the identified plots seemingly had few or no implemented interaction techniques, restricting the plots' potential to convey information and rendering data exploration impossible. Additionally, the plots only showed one variable in relation to time. These observations seemingly indicate that much of the potential in interactive data visualization is yet to be utilized by Brynild. If attempting to improve on this matter, the manufacturer's use of Microsoft Excel will likely restrict it. While the spreadsheet software allows for implementing UI controls, briefly looking through its online documentation suggests that it does not support directly interacting with individual graphical elements. The software does provide some practical benefits, perhaps the most notable being that it, in the experience of the author, requires little prior knowledge to learn. Other benefits include how it comes with many built-in plot types and features for easily sharing and collaborating on files (Microsoft, n.d.). Even so, Brynild is advised to acquire a more advanced data visualization software solution.

6.4 Concept Validation

This section presents the attempts made to validate the concept. As mentioned in the methodology chapter, the original intention was to feed the prototype real-world data supplied by Brynild and then employ it to examine a statement regarding its safety stock method formulated based on the case study. Also mentioned was the fact that Brynild could not supply the promised data in time, which made it necessary to construct dummy data so that, at least, the central functionality of the concept could be realized. This section primarily details the process and assumptions made for creating these data sets. Additionally, it presents the statement intended to be examined and describes how the prototype would be used for such a purpose.

6.4.1 Data Construction

Because of the mentioned time constraints, it was determined only to construct data sets for a single product. Additionally, it was determined that four years of observations would be sufficient to illustrate the features implemented in the prototype. Based on these factors, the construction of at least nine data sets was necessary: inbound transactions, outbound transactions, daily inventory, average inventory (monthly), average orders (monthly), average service levels (monthly), average inventory (yearly), average orders (yearly), and average service levels (yearly). Additionally, the product's target safety stock and service level were needed. An attempt was made for these entries to have some basis in reality by assuming that the demand for the product followed a normal distribution and estimating the mean and standard deviation based on data made available by Brynild for a different thesis in 2022. Assuming normally distributed demand was considered in line with Chapman et al. (2017). The target service level was set to equal 98%, as was uncovered from the interview.

The data used to estimate the parameters for the normal distribution consisted of monthly sales of the product "SM Chip Nuts Paprika 110g 10stk" through 2021 in units of D-Pak. These data were found in several Excel sheets intended to report forecast accuracy. It was assumed that the sales values that were lower than their respective forecasted value were representative of the demand for that week. Sales for months January to June met these conditions and were written down on paper. Subsequently, an array named "demand" containing the same values was defined. With the observed sales as input, JavaScript was used to calculate the sample mean and standard deviation with the following formulas extracted from Holický (2013):

$$m_x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{7}$$

$$\hat{s}_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - m_x)^2} \tag{8}$$

Where m_x is the sample mean, and s_x is the sample standard deviation for a population sample of observations $x_1, x_2, x_3, ..., x_n$. The values were assigned to respective variables named "sampleMean" and "sampleStandardDeviation."

The data for inbound transactions, outbound transactions, and daily inventory were generated through a for loop iterating 209 times, one iteration for each week from the first week of 2018 to the last week of 2021. D3 provides a function to define a number generator capable of generating normally distributed samples (Bostock, 2023). Before the loop, a generator function named "sampleGenerator" was defined to adhere to the computed sample mean and sample standard deviation. A variable for the target safety stock, named "safetyStockLevel," was then defined as equalling the average of twelve generated samples times two weeks. This procedure roughly followed Brynild's calculation method for safety stock calculation, except in terms of weeks instead of days. Five empty arrays were then defined named "inboundTransactions," "outboundTransactions," "dailyInventory," "weeklyOrders," and "weeklyInventory." Several other variables were also defined to support pushing generated entries to these arrays. All arrays had objects on the form "date" and "value" pushed to them. The explanation for the creation of each of these sets of data follows.

For simplicity's sake, it was decided that a finished product delivery arrives at the warehouse once every Monday. The arriving quantity was decided to equal the sum of the average of the orders for the past three weeks and the target safety stock minus the inventory already on hand. In other words, just enough stock was supplied to equal the expected orders for that week plus safety stock. This approach was decided as logical as using only a fixed order quantity would lead to gradual inventory buildup. At the start of every iteration, an object with the date corresponding to the Monday of that week and a value assigned to the computed inbound quantity was pushed to the array for inbound transactions. A similar entry, except with the value equalling the sum of the inbound quantity and the value of the previous daily inventory entry, was then pushed to the weekly and daily inventory arrays.

It was decided that inventory was transported from the warehouse every Wednesday and Friday. A variable for the combined orders, named "WeeklyOrder," for that week was assigned to a newly generated sample. Subsequently, a variable named "wednesdayOrder" was assigned the combined order divided by two (rounded when necessary), and a variable named "fridayOrder" was assigned the combined order subtracted by the Wednesday order. If the Wednesday order was greater than the value of the last daily inventory entry, a variable named "wednesdayOutbound" was set to equal this inventory value. Otherwise, this variable was simply assigned the value of the Wednesday order. An entry with the date of that week's Wednesday and the value of the Wednesday outbound quantity was then pushed to the outbound transactions array. A similar entry was pushed to the daily inventory array but with the value set to the value of the past entry minus the outbound quantity. The same procedure was then performed for the Friday orders, pushing further entries to the outbound transactions and daily inventory arrays. The final step of the loop iteration was to assign the sum of the outbound transactions for the week to a variable "sumOutbound" and push an entry to the weekly service levels array where the value comprised the summed outbound transactions divided by the weekly order. The dates of these entries were set to the Monday of the relevant week.

Two functions called "getMonthlyAverage" and "getYearlyAverage" were defined for constructing the remaining data sets. As the names suggest, these functions took in a data set in the same form as the ones constructed through the loop and returned a new one with values either comprising monthly or yearly averages. The functions worked similarly by defining an empty array named "result," iterating through every entry of the input array, and pushing an entry to the result whenever the date of the current element differed in a specific way from the previous one. More precisely, the monthly average function would push an entry when entering a new month, while the yearly average function would push when entering a new year. The functions kept running sums of weekly values and how many iterations had occurred in computing the next entry. When an entry was pushed, the value comprised the rounded average of weekly values, and the date represented the relevant month or year, depending on the function. The functions took in a number, representing how many decimals to include in the rounding.

With all the needed data sets constructed, an object named "ProductData" was defined. The object had the following attributes:

- "safetyStockLevel"
- "inboundTransactions"
- "outboundTransactions"
- "dailyInventory"
- "monthlyInventory"
- "monthlyOrders"
- "monthlyServiceLevels"
- "yearlyInventory"
- "yearlyOrders"
- "yearlyServiceLevels"

6.4.2 Hypothesis Testing

As mentioned, Silver et al. (2016) deemed that the number-of-days method for setting safety stock failed both to minimize holding costs and prevent stockouts for products with high demand variability. Based on this literature finding, it was hypothesized that these patterns would be visible in Brynild's inventory data. Furthermore, it was planned to validate the proposed concept by examining these hypotheses' using the developed prototype. As the needed data was eventually shown to be unattainable, it was only possible to mimic parts of the planned experiment using the dummy data.

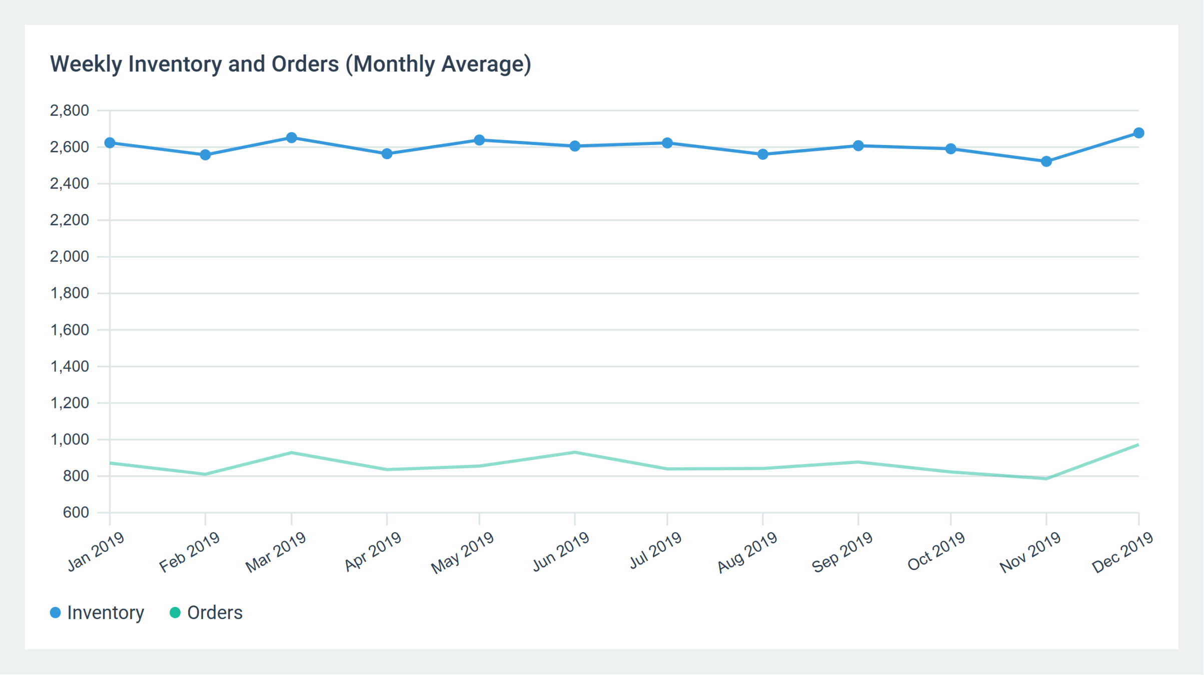
Figure 27 shows the chart for monthly average inventory levels and orders for the generated data. At least in this case, it does appear that two weeks of demand is far too much safety stock for a product with relatively stable demand. The daily inventory reports confirm this and show that stockouts are nowhere near occurring. From the figure, one gathers that weekly inventory typically exceeds weekly orders by around 1700 units of D-Pak. Rosshaug (2018) stated that Leman charges a fixed cost of 2 NOK per pallet for keeping inventory at its warehouse in Vestby. The data folder containing the Excel sheets reporting forecast errors also contained a dataset with various information regarding the products Brynild produces. From this data, it was discovered that a pallet with "SM Chip Nuts Paprika 110g 10stk" comprised 108 units of D-Pak. Note that the sales of these products were used to define the normal distribution for the data construction. Assuming that Leman also charges for weekends and holidays, the yearly cost of holding the redundant inventory for a year with 52 weeks can be computed as follows:

$$Yearly\ Holding\ Cost = \frac{1700}{108} * 2 * 7 * 52 \approx 11459 \text{ NOK} \tag{9}$$

Suppose Brynild's real-world difference in weekly inventory and orders for products with stable demand is similar to that of the dummy data. In that case, the computed number indicates that Brynild has much to gain in reducing its safety stock for these products. If a similar observation was to be made from examining Brynild's actual data, this should strengthen its incentive to implement more advanced methods of safety stock calculation.

Figure 27

Inventory and orders chart with generated data



7 | Discussion

This chapter discusses the findings of the study. The chapter attempts to answer the research question and is structured according to the objectives presented in the problem statement. Specifically, the research question was attempted to be answered by examing findings from existing literature and current practices and the design and validation of a concept. Implications and weaknesses related to each finding are also examined. Furthermore, the consequences of the unfortunate circumstances regarding data for the prototype are further discussed. To reiterate, the research question reads as follows:

"How can data visualization facilitate the evaluation of safety stock method performance for manufacturers?"

7.1 Objective 1

"Map and analyze literature on inventory management, Big Data, and data visualization."

This objective aimed to build a theoretical foundation for supporting the rest of the objectives. As it mainly consisted of examining previous research and other academic literature, it thus yielded few original findings of its own. One interesting discovery, however, was the apparent contrary definitions of data visualization, where Li (2020) viewed the term interchangeably with visualization. In contrast, Keim et al. (2008) defined it as a research field separate from information visualization. Contradictions like this may lead to further inconsistencies in future research, implying that the visualization field would likely benefit from an updated taxonomy defining its sub-fields. The literature study was somewhat limited in that it did not study inventory systems more closely, which would have enabled setting more accurate conditions for the data generation. However, by the time this necessity arose, there was not enough time left to extend the search.

7.2 Objective 2

"Design a concept visualization tool for evaluation of safety stock method performance and develop a prototype web application realizing the most critical functionality."

Objective 2 was the study's most extensive objective, taking insights from both the visualization literature and the inventory management literature to develop a concept for a software solution for safety stock analysis. The objective further consisted of making a prototype realizing the most consequential functionality of the concept in the form of a web application. As recommended by the literature, an attempt was made to involve a potential end user in development to make more informed decisions. For the case company, the production planner was responsible for safety stock and, therefore, a convenient choice for this role. A limitation of the project was that this individual could have been much more involved. It is possible, however, that this would have proved difficult as the individual likely had little time available besides their regular tasks.

From this objective, it seemed that service levels over time, in combination with inventory levels compared to orders over time, were suitable indicators for safety stock method performance. Additionally, the value of the drill-down techniques was affirmed. Clicking on graphical elements to gradually reveal more detailed information seemed an efficient way to divide the inventory data into interpretable portions and to navigate between these intuitively. This finding conformed with the description of the abstract/elaborate advantages by Figueiras (2015). Likewise, tooltips seemed useful for providing additional information when altering the visualized data sub-set was not needed. As the theory also suggested, dynamic filtering seemed to work well for quickly observing how changing parameters adjusted the data selection. In hindsight, it would have been useful to let the user choose the unit of the displayed values (i.e., D-pak, F-pak, or pallets). As stated by Shneiderman (1996), history features help enable an iterative exploration process through progressive refinement. The concept could also have benefited from such features.

Note that the effectiveness of these techniques was based on the author's subjective and biased impressions. As previously stated, the original intent was to feed the prototype actual inventory data and examine at least one statement regarding the case company's safety stock practice. Under these circumstances, the plan was to quantify the effectiveness of the concept by measuring how many clicks were necessary to achieve the desired insights and compare with the results of attempting the same task by looking through raw data files. When it eventually became necessary to substitute the real data with dummy data, it was decided to omit this procedure. As the sizes of the generated data sets were assumed to be much smaller than real-world equivalents, the results presumably would not be reflective of the real world. This fact, combined with the dummy data being generated under significantly simplified conditions, made it very difficult to judge the concept as a whole, which was a considerable weakness of the project.

Developing a prototype to validate the designed concept was decided early on in the project. As the author had experience in web development, it was further decided that developing the prototype as a web application was the most convenient. This process also provided noteworthy findings. The D3 library was chosen due to its low-level nature, which was expected to not introduce any restrictions in realizing the charts and interaction functionality of the concept. This assumption was affirmed in the development process, proving D3 a suitable choice for the task of mapping inventory data to graphical elements.

Subsequently, it was the author's experience that it took substantial time to both become familiar with and develop in D3. This might not have been the case with a higher-level library, which should be considered in further development.

The other used technologies also seemed to introduce no unforeseen restrictions. React, with its Context functionality and useState hook, worked particularly well for illustrating the drill-down functionality and the dynamic queries. It is worth reiterating that for the purpose of demonstrating the concept, it was deemed sufficient to place the data file in the application front end and to omit a backend entirely. The prototype thus only mimics dynamic queries, which should be noted if the code for this project is to be developed further. Another case for the chosen technologies is the apparent popularity of JavaScript, with GitHub (n.d.) proclaiming it as the most popular programming language for GitHub projects.

7.3 Objective 3

"Analyze the safety stock and visualization practice of a real-world manufacturer and suggest potential improvements."

This objective partially comprised analyzing the practice for setting and evaluating safety stock for a real-world case and mapping potential weaknesses. The first central finding regarding this objective was the lack of any evaluation of the performance of an employed safety stock calculation method for the case company. As can be gathered from Chapman et al. (2017), an inappropriate safety stock practice leads to either lost sales and damaged customer relationships, unnecessarily high inventory holding costs, or both. From Schmidt et al. (2012), it can be further deduced that the most suitable choice of safety stock calculation method depends on the variability of both the demand and lead time. A manufacturer that never monitors the appropriateness of set safety stock risks letting serious errors go unnoticed and will be unable to optimize this part of its inventory management.

The decision to employ the "set it and forget it" approach may stem from a lack of knowledge of the subject or an unwillingness to change. It may also stem from the manufacturer not capturing the necessary data or possessing a system to utilize it. The latter seemed to be the deciding factor for the case studied in this report. A weakness of this finding was that the degree to which Brynild was representative of manufacturers in general regarding this area could not be verified. A study mapping the degree of safety stock evaluation in different categories of manufacturers would provide valuable insights for further research.

The following important finding was that the case company utilized a safety stock calculation method where safety stock was set to cover a certain period of average expected demand. This finding coincided with that of Silver et al. (2016), which stated that 80 - 90% of the clients of a global consulting firm used this approach. Silver et al. (2016) further stated that when studied in a real-world case, the method did far from optimizing holding costs. This finding implies that such manufacturers should invest in researching more advanced methods of safety stock calculation. As the optimal choice of calculation method differs from product to product, it may be inferred that manufacturers benefit from employing different methods simultaneously.

The case study of this project somewhat conformed with this finding. First, data sets were generated from a normal distribution defined from actual Brynild sales data where the demand pattern was seemingly stable. The safety stock was then computed as two weeks of average demand. When fed the generated data, the prototype showed a consistent excess of stock, equalling a yearly value of about 11 459 NOK. Considering that this value was computed for one product only and that Brynild supplies roughly 450 SKUs to the Nordic market, there is at least some implication that the manufacturer can save considerable costs in reducing its safety stock.

The weight of the former finding was greatly reduced as little actual inventory data could be collected from the case company. As this became clear very late in the project's run, there was little time left to create substitute dummy data. This restriction made it necessary to prioritize efficiency over accuracy and to introduce significantly simplified conditions for the data generation process. Perhaps the largest of these was the exclusion of lead time disruptions, which would have decreased the difference in orders and inventory. Another flaw was that the study did not investigate the demand patterns of Brynild's products to a greater extent. The chosen product had relatively stable demand, lessening the need for safety stock. Moreover, the utilized delivery and pick-up frequencies were decided based on convenience, as no information was collected from the case study regarding this. It is, however, worth reiterating that literary findings supported the assumption of normally distributed demand and that the utilized mean and standard deviation were estimated from real measurements.

When investigating the visualization practice at the case company, a central finding was that it did not utilize visualization for examing safety stock. In fact, there were very few instances of the company visualizing its inventory data at all. Additionally, the production planner recognized that the company possessed much inventory data that could provide valuable insights. As for the few instances identified, these relied on a time-consuming process with much necessary involvement from the employee. This assumably made the process time-consuming and tedious, which likely made employees want to avoid it entirely. These findings imply that there is a current restriction in inventory management where a lack of dedicated tools prevents companies from utilizing their available data for decision-making.

7.4 Objective 4

"Validate the concept by using the prototype to examine a real-world case."

Several findings related to this objective have been mentioned already, as they provided clear implications regarding other findings. As mentioned, the objective also had to be altered significantly over the course of the project as the case company could not provide the agreed-upon inventory data. All tough unfortunate for the overall value of the project, this factor yielded an interesting implication. It appears that even though manufacturers capture large quantities of inventory-related data, they face significant difficulties extracting it in such a form that it can be utilized for inventory management decision-making. There can be several causes of this issue, some of which were identified in the case study.

One such challenge consisted of incorrect measurements in the raw data files. The personnel responsible for delivering the relevant data expressed this as one of the reasons for the delays, as the process of correcting these values was time-consuming. This data issue can be classified as belonging to the veracity category proposed by Nasser and Tariq (2015). The cause of the incorrect measurements was not identified, although it presumably stems from the means by which the data was captured. This issue should be investigated if the concept presented in this thesis was to be implemented in an actual manufacturer. Errors stemming from faulty data-capturing devices could be avoided by introducing spare equipment to take over when other equipment has failed.

Another reason for the mentioned delays was that the manufacturer did not possess some of the agreed-upon data sets in the correct form. An example of this can be recognized in the process of inventory data visualization explained in the case study. Here, the data set for average pallets stored at Leman per day had to be built from SAP-registered transactions. This was also the case for the data sets of inventory levels requested for the concept validation part of the case study. It was gathered from email correspondence with the mentioned party that this process had proved more difficult than first assumed. Precisely why the process was challenging was not uncovered. The great magnitude of the raw data might be a possible cause and which would be in line with the data challenges presented by Nasser and Tariq (2015). Nasser and Tariq (2015) listed maintaining the data cleaning and extractions process as a challenge of Big Data which this finding also conforms to.

When the project was initially planned, there was no intention of examining these types of challenges. The findings discussed above were all gathered for continuous communication with the external consultants tasked by the case company to provide the data. The relevance of the findings was only realized at the very end of the project, which restrained the degree to which they could be investigated further. This constraint is a noteworthy limitation of the project, as present Big Data challenges such as those discussed likely affect a manufacturer's ability to realize the proposed concept significantly. It would likely also have benefitted the project if Big Data and Industry 4.0 had been examined to a greater degree in the literature study. A more thorough mapping of the challenges manifested in the case company might also have provided valuable insight into the development of the concept itself.

8 Conclusion

This section summarizes and attempts to generalize the findings, comments on the perceived success of the objectives, and presents suggestions for further research.

8.1 Summary and Generalisability of Findings

The first objective suggested that a standardized taxonomy on visualization-related terms could benefit further research. This finding is entirely specific to the research field of visualization and has little relevance outside this topic. Findings from the second objective suggested that the interaction techniques drill-down operations, tooltips, and dynamic queries combined with simple plot types effectively enabled the user to view and navigate its inventory data. While these findings were largely subjective, they possess high generalisability as they are not specific to manufacturing. In this case, the process of gradually revealing more detailed data is interesting, not the nature of the data itself. The objective further suggested that the chosen technologies were suitable for realizing the concept, which likewise is relevant outside the project's scope.

Regarding objective 3, both the concept validation and supplemental discovered literature suggested that the number of days safety stock method was not a good choice, especially for products with stable demand. As what was discovered in the literature did not adhere to this project's scope, it is reasonable to assume that this applies to other types of inventory besides finished goods and for industries other than the food industry. It was also discovered that the case company seldom evaluates its safety stock levels or overall safety stock method performance. Moreover, it was discovered that it rarely visualizes its inventory data. The last two findings were harder to generalize due to it being difficult to assess whether or not Brynild is a typical example of a manufacturer.

Findings from objective 4 suggested that the case company struggled to utilize its data due to problems with the data veracity and its information extraction and cleaning procedure. These findings further suggested that data volume and quality, as well as the data capturing procedure, might also cause hindrances for the manufacturer. These findings were also specific to the case study and, therefore, hard to generalize. Their implicated drawbacks, however, would be equally as present for manufacturers in other industries, as well as for other areas of management. The same goes for the findings regarding the limited evaluation of safety stock method performance and visualization of inventory data from objective 3.

8.2 Suggestions for Further Research

Many of the discussed limitations subsequently highlighted potential areas for future research. An unexpected finding of the case study was how difficult it was for the case company to extract its captured inventory data. Such challenges likely have significant implications for a concept like the one proposed by this thesis. If this concept is to be developed further, it would be beneficial to map these challenges to a greater extent, both in literature and from real-world cases. Moreover, the contradicting definitions of the term visualization suggest, as mentioned, that there is a need for a study with the goal of establishing a taxonomy for visualization-related terms.

The most significant limitation of the study stemmed from the fact that the case company could not supply the agreed-upon inventory data. These circumstances largely prevented the planned concept validation and greatly impacted the value of the study. Subsequently, it implies much potential in a study that further examines the effectiveness of the suggested concept. This should at least include applying the concept to real data, as was initially planned for this thesis. Such a study would benefit further from incorporating the other suggestions of this section. It is also likely that the selected data in the concept description is relevant for other decision areas. This observation implies that it is worth considering expanding the purpose of the concept to include these as well.

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