An inventory problem at the Ålesund hospital, a case study about inventory in a healthcare environment

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Acknowledgements

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In front of you lies my master's thesis. With this thesis, I conclude my student time and with that, my time at the University of Twente. The past few years have been an amazing journey, which I got to share with great people whom I will know for the rest of my life. Without these people, the past five years would have been a lot more boring.

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My student time was indeed the best time of my life. Onward to new adventures!

David Evers

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Acronyms

Economic Order Quantity (EOQ) Method to determine the optimal order quantity.

Enterprise Resource System (ERP) Computersystem that facilitates all, or some, business processes within a company.

Inventory Turnover Ratio (ITR) A KPI for how many times the inventory is sold in a period of time.

Key Performance Indicator (KPI) Indicator that, together with other indicators, indicates how well a model or process operates.

Net Stock (NS) The on hand stock minus back orders.

On Hand Inventory (OHI) Amount of items on the shelf.

Operating Room (OR) Rooms in the hospital where people receive surgery.

Point-Of-Use (POU) The ward in the hospital where the goods are used.

Proof of Principle (PoP) Realization of a certain method or idea in order to demonstrate its feasibility, or a demonstration in principle with the aim of verifying that some concept or theory has practical potential.

Ready Rate (RR) Percentage of the time the net stock is positive.

Stock Keeping Unit (SKU) A unique code for a specific item or product kept in inventory.

User Experience (UX) UX is the gap between a user's expectations and their real outcomes.

User Interface (UI) How an application looks like and how the user navigates trough the application

Management summary

Research goal and context

The Helse Møre og Romsdal hospital in Ålesund is a hospital from the 1970s. In the coming years, Helse Møre is planning renovations for the hospital. Recently, the inpatient surgery department was renovated, and in 2024/2025 the outpatient surgery department will be renovated. The outpatient surgery department executes surgeries after which the patients needs to stay in the hospital for at least one night. These surgeries require various specialized items, not always supplied by the central warehouse of the hospital. Therefore the hospital orders these items directly at the manufacturer, these are external ordered items. In the past years more external ordered items were added to the assortment for various reasons, without validating the need and use for that item. As a consequence roughly 40% of the external ordered items are non moving and the department is suffering from an overstocking problem. On the department itself are various signs of overstocking. A surgery room is used as inventory space and the evacuation hallway is full of inventory too. The plans of the renovation of the department shows that less inventory space would be available in the future, which creates a need to reduce the assortment.

Research showed that surgeries in the hospital are not standardized and demand for items per week is therefore unknown. Staff is passively risk averse, meaning that staff chooses the easiest solution for reducing the risk of coming short on items. In the case of the hospital passively reducing risk means buying more items "just to be sure". Further we conclude that incentive programs, benchmarks and lack of trust in the supply chain are other reasons for overstocking.

Methods

A framework is developed to resolve overstocking and to move to a sustainable situation where risk is actively managed by planning demand for items. The approach within the framework consists of three steps: 1) sorting 2) standardizing and 3) constructing an inventory plan. The first step involves input from staff to label each item in the assortment to importance. The second step involves linking items to surgeries. The third step is executed on a regular basis, for example weekly. Within the third step staff links the surgery planning to the current inventory and the approach will help staff by creating an advice on which items to order and for what reason, taking constraints such as a order restrictions and the total available capacity on the department into account.

A Proof of Principle (PoP) was made to demonstrate the principles and potential of the approach. A selection of items from the urology and gynecology category was taken as input for the PoP. A fictive standardisation list was made to demonstrate the idea of standardising items to surgeries. The construction of the inventory plan was done in an Excel tool, which was extended to a simulation. The simulation is meant to simulate scenarios and so provide insights in how inventory reacts to various changes in variables, such as demand and lead time. We provided an extensive analysis on scenarios where lead time, demand or capacity changes. The main takeaway from the simulation study are areas of further research and possible actions on certain events.

Conclusion and discussion

The research presents a first version of the framework to reduce overstocking issues in a healthcare setting. The framework is a first step for healthcare organisations to move to a sustainable situation in where inventory is balanced between having enough on stock and the available capacity. The approach helps staff to become more actively risk averse instead of passively risk averse, because the approach creates insights in demand and so in needed inventory. The three step approach is very flexible and has several parameters staff can adjust to the circumstances in the hospital. With the provided simulation staff is able to simulate scenarios and anticipate on the expected changes in lead time or demand. Further research is needed on parameter estimation and exact implementation of the tool.

Contents

1 Introduction

In the context of completing the masters of Industrial Engineering and Management, this thesis. The Helse Møre og Romsdal hospital in Ålesund suffers from a lockup of capital in unused inventory of items that are ordered outside the normal process, also external ordered items. The hospital did not succeed in changing their inventory approach to match the On Hand Inventory (OHI) with future demand. The research in this paper aims to demonstrate the improvement potential in inventory performance by introducing standardisation and modelling.

This chapter introduces the problem context and research goals. Section 1.1 provides a concise description of the Helse Møre og Romsdal hospital in Ålesund and the problem context, Section 1.2 provides a more in depth analysis on overstocking, 1.3 provides an insight in the capacity requirements after the renovations and the research questions are presented in section 1.4.

1.1 Context

The group Helse Møre og Romsdal serves about 265000 people in the region and does that with four hospitals. The hospitals are located in Ålesund, Volda, Molde and Kristiansund. The group has approximately 6400 employees and a budget of 6 billion NOK. Helse Møre og Romsdal itself is part of the regional health authority Helse Midt-Norge, which is controlled by the Norwegian state.

The hospital has two departments that execute surgeries. The outpatient surgery department, also called daycare or day surgery department, and the inpatient surgery department. The outpatient surgery department executes relatively easy surgeries, after which the patient can go home. The inpatient surgery department executes the complex surgeries after which the patient needs to stay in the hospital for one or more nights.

1.1.1 Problem description

Helse Møre og Romsdal has plans to renovate the inpatient surgery department in 2024/2025. The renovation plans show that less inventory space will be available, something that staff is worried about. Because of the wide range of surgeries the department offers, the department has a lot of various items in inventory. From those items, three categories categories can be distinguished: 1) Consignment items, 2) Usable Items and 3) Re-usable items. Consignment items are items that are still in possession of the vendor, but are stored at the hospital. Only when the item is used, the hospital pays for the item. Usable items are all items that can only be used one time. Reusable items are items that are cleaned and could be reused. The cleaning of reusable items is done by the cleaning department, steril central.

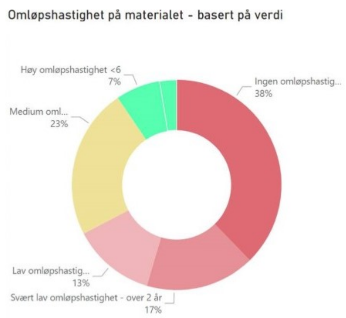


Figure 1: Overview of the turnover rate of the total stock in the inpatient OR, updated August 2021

Usable items can be subdivided to internally ordered items and externally ordered items. Internally ordered items are supplied by the logistic department of Helse Møre og Romsdal and do not provide extra work for staff. External ordered items are ordered outside the system and are not supplied by the logistic department, but rather directly from the supplier. This cause extra work for nurses, who must take the order and supply the selves. If an item needs to be ordered internally or externally is addressed by the color of the label corresponding to the item at the shelf. An item can be ordered at one of the following suppliers:

- Externally ordered: Items bought in bulk and where the purchasing department has contracts with the suppliers. These items are bought for a fixed, lower, price. These items are ordered from the central warehouse in the hospital. In 2025 these items are supplied by the central warehouse of the group of hospitals in Trondheim (blue label).

- Internally ordered: Item that are not bought in bulk by the purchasing department. The hospital can have agreements with the supplier, but does not need to be the case. Item is directly ordered at the manufacturer and can therefore have a longer lead time or a minimum order quantity (yellow label).
- Reusable items: that are ordered from the sterile central department (White label).

At the department there are over a 1000 external ordered items. Figure 1 shows the extent of the problem, by showing that at least 38% of these items are not used for over two years.

Signs of too much inventory on hand can be observed at the department. Appendix A.1.1 shows an impression of the current situation in terms of storage. A surgery room is rebuild to provide more storage room. The hallway behind the surgery rooms is an evacuation route, but is blocked with closets full of storage. The plans for the renovation shows that the surgery rooms will grow and the hallway behind the surgery rooms will disappear. This decreases the space for storing inventory.

1.2 Reasons for overstocking

Staff has various reasons for overstocking. Three main categories are distinguished and described in this section.

1.2.1 The ERP system

The hospital implemented a central system from where everything related to hospital supplies is handled. This relates to the ordering of items, keeping track of stock and manage mutations of stock. Staff experiences problems with this ERP system for various reasons. Staff thinks the system is complex. They are unsure how to execute certain tasks. One of these tasks is for example the ordering of items. Internally ordered items need to be ordered somewhere else than external ordered items. Because of this complexity, staff prefers to order more items at a time so that they do not have to worry about the item for a longer period of time.

Other often heard issues with the ERP system are:

- The search function within the ERP system works illogical. For example, post its are called notebooks with glue.
- Order something that is not in the system needs to be done by filling out a form. This is not clear to everybody.
- Nurses can not track their order. Therefore nurses have to trust the system and that the order has been taken care of. Also no confirmation email is sent. Therefore it is unclear if and when an order arrives.

1.2.2 Malfunctioning supply chain

Staff has stated that lead times are unreliable and long. For the past years the hospital experienced supply chain problems and stock outs often occurred because of this. Data about lead times proved this too, various items were found with a median lead time of longer than 30 days. This is another reason why staff wants to have a large inventory on hand, so they can overcome these longer lead times.

In addition, there are other reasons for staff not to trust the supply chain as well. For example, between the purchasing and inpatient surgery department there exists an issue of communication. Staff indicated that often the purchasing department stopped buying items, without informing the responsible nurse. Therefore staff decided to keep more on stock for these unexpected events. Furthermore, it can also happen that a manufacturer stops producing the item. There is little time after that to find a suitable alternative, so staff decided to overstock.

1.2.3 Unknown demand

Staff does not know the demand for an item in advance. This can have several reasons. First, only when a patient is "open" the doctors can decide what size of implant is needed. The hospital needs to have all sizes on hand so they can use them during surgery. Not having the right implant on stock is not done. Second, tools needed per surgery are not standardised. Therefore it is not known for staff what tools are needed in a surgery. When the surgery planning for the next two weeks is final, staff can not plan inventory for the coming weeks. The easiest solution for staff is to make sure more than enough items are on hand. The last reason why demand is hard to predict, is due to the various preferences of the doctors. Various doctors can use various tools for the same surgery. Therefore the hospital needs to have multiple different tools on hand, to execute the same surgery. What tool belongs to which doctor is not known. On the question why staff do not change this, the answer is that they have always done it this way.

1.3 Storage available after renovations

This section outlines the extend of cubic meters available post-renovation. Appendix A.1.6 shows the drawing of the new department including the storage space indicated with pink ink. An estimation is made based on the available m^3 in the architectural drawings.

In this stage of the process the plans are not final and storage space could be added or deleted. The drawing gives a good idea about the situation and the amount of storage space. The hospital is currently planning on 127,15 m^2 bare storage space. Within the storage rooms are cabinets of about 70cm depth, 100cm width and 200cm high. In total we find 73 of these cabinets present in the drawing. Next to that the hospital plans on 24 cabinets which can accessed from the operating rooms as well as the storage rooms. These cabinets are smaller, About 70cm depth, 100cm width and 100cm high. In table 1 the data is summarized.

	Amount	**Width (cm)**	**Depth (cm)**	**Height (cm)**	**Total** m^3
Normal cabinets	73	100	70	200	102,2
Access from two rooms cabinets	24	100	70	100	16,8
Total	96				119

Table 1: Summarized storage space in m^3 in the new situation.

1.4 Research questions

Based on the problem statement the following main research question is defined:

"What inventory approach should the Ålesund hospital adopt for external ordered items to resolve overstocking while at the same time maintaining the service level and complying to the capacity?"

In order to answer the main research question in a structured and systematic manner, a series of sub-questions have been formulated. The first two of these sub-questions aim to identify and comprehend the environment and theory that are pertinent to the research. The remaining sub-questions are centered around the design and evaluation of the approach proposed in this study. Collectively, the answers to these sub-questions will provide a comprehensive response to the overarching research question.

1. *"What is the current situation regarding the restocking process?"*

To obtain better insights in the current situation, we research the current restocking process and measure performance of the current inventory.

2. *"What adjunct literature is available about similar cases like the Ålesund hospital?"*

We establish a theoretical framework that can provides adjunct literature. The database used for this literature review is Scopus, in which articles were selected based on relevant search term. The goal of the literature review is to present a literature overview of possible other root causes and solutions in adjunct cases.

3. *"What should the new inventory approach for externally ordered items look like?"*

This question is answered in Chapter 4 and presents the solution for the hospitals overstocking problem. The chapter takes the requirements from chapter 1, 2 and 3 and explains the new approach, which is simulated in Chapter 5.

4. *"How does the designed inventory approach performs in terms of service level and cost under various simulated scenarios?"*

In this phase we test the model designed in chapter 4. The model is tested on service level and OHI value. Several scenarios are worked out to observe the behaviour in various circumstances.

2 Background on the inventory processes

The goal of this chapter is to answer the first research question: "What is the current situation regarding the restocking process?". External ordered items are part of the restocking process. Therefore the differences in the various restocking processes are researched in Section 2.1. We calculate KPIs found in the literature in Section 2.2. These calculations show whether there are signs of overstocking proven by data.

2.1 Workflow diagram

The inpatient operating department conducts both complex and emergency surgeries, which require a sufficient inventory of various surgical tools to ensure a high level of service to patients. However, excessive inventory levels can lead to negative consequences, such as capital freezing and capacity restriction violations. As shown in Figure 1, the hospital has experienced capital freezing due to overstocking. Chapter 1 highlights indicators of overstocking. Staff that is concerned with inventory management are the department's nurses, in consultation with the department leader. They determine the necessary inventory levels, including item storage locations and quantities. Surgeons also provide input on their preferred items and quantities. The director of the surgery department oversees the budget, aiming to spend it as efficiently as possible. The director has ultimate responsibility for inventory spending, and must approve any item orders exceeding 50,000 NOK requested by doctors or nurses. The logistical staff assists the inpatient operating department by regularly restocking inventory, and provides advice on appropriate inventory levels, although they do not have decision-making authority over inventory management.

The difference in internally and externally ordered items can be described by the restocking process which is split up in two processes: 1) Restocking of items ordered internally and the 2) restocking of items ordered externally. Appendix A.1.2 shows the flowchart we made of the restocking process. We first describe the ordering process of the internal ordered items. In general the following steps must be followed:

1. Count the items left at the department and order up to the order up to level.
2. Collect the items in the central warehouse.
3. Go back to the department and resupply the shelves.

The logistical staff works according to a schedule and supplies the inpatient surgery department on a weekly basis. Figure 2 is an example of such a schedule. Under the days of the week, we find rows containing the names of departments that need to be resupplied that day of the week. We also observe a * behind the names of some departments. A * means that step one is executed by the logistical staff. Departments without a * do the count them self and the logistical staff is only responsible for executing step 2. The items the logistical staff supplies, internal ordered items, are marked as used in SAP. Keeping track of this inventory is therefore not necessary.

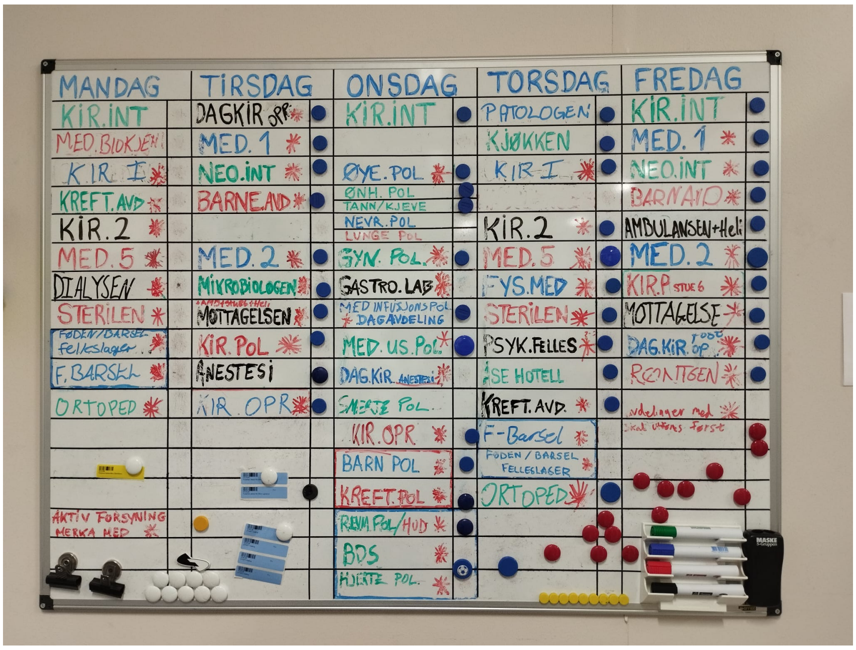


Figure 2: Resupply schedule, photo taken November, 2021.

For the items ordered externally, and so where logistical staff is not involved, the process is different. The inpatient operating department is registered as a warehouse in SAP. The registration of a warehouse means that the operating department has stored inventory. Inventory levels of external ordered items are therefore monitored in SAP and must be scanned in and out to keep track of the inventory levels. By scanning out an item when used, the inventory level got adjusted down. It can happen that scanning out items if forgotten by staff, this causes inaccurate data. Therefore nurses count the external ordered items on a daily basis to make sure that the numbers in SAP are correct. Nurses manually orders replenishment stock. Once delivered to the department, the nurses restock the items. Nurses are by definition not supposed to do these kind of jobs. The more because nurses are a scarce resource in the hospital. In earlier research on improving nurse productivity, Heesterman and Stroop (2022) identified this activity as a non nurse related task.

The logistical department is not part of the restocking process for external ordered items, which is a problem. The logistical department should be in charge of this, to relieve workload from nurses. We have found four reasons why this is not the case:

1. It has always been like this.
2. In the past the logistical staff was not allowed to resupply all items (this has changed now.)
3. The logistical department does not have an overview of external ordered items.
4. The logistical department does not have the resources to also supply items ordered outside the normal process.

2.2 Evaluation of current inventory performance

This section present an evaluation of the inventory approach used by the hospital in 2021 and 2022. The dataset used for this analysis contains 1301 different SKUs held in inventory over both years. To assess the performance of the inventory approach, three KPIs are identified in the literature: the total OHI value, the Ready Rate (RR) and the Inventory Turnover Ratio (ITR). These KPIs are computed based on data from 2021 and 2022 (up to November). A detailed description of the available data sets is provided in Appendix A.1.5, and the results of our analysis are presented in this chapter.

Total OHI value

The KPI total OHI value reflects the total amount of value stuck in inventory at time t. If calculated for multiple time periods, the KPI can be plotted in a graph. The plot says something about the growth or decline in inventory value over time. This information is usefull to validate if the efforts from staff to reduce overstocking are indeed reflected by data. The KPI is also usefull to compare against outcomes of simulation studies, and so to conclude whether the simulated approach yield better results. Figure 3 presents such a plot for the inventory of external ordered items at the inpatient surgery department. The graphs reflects the efforts to reduce OHI value in 2021 and 2022.

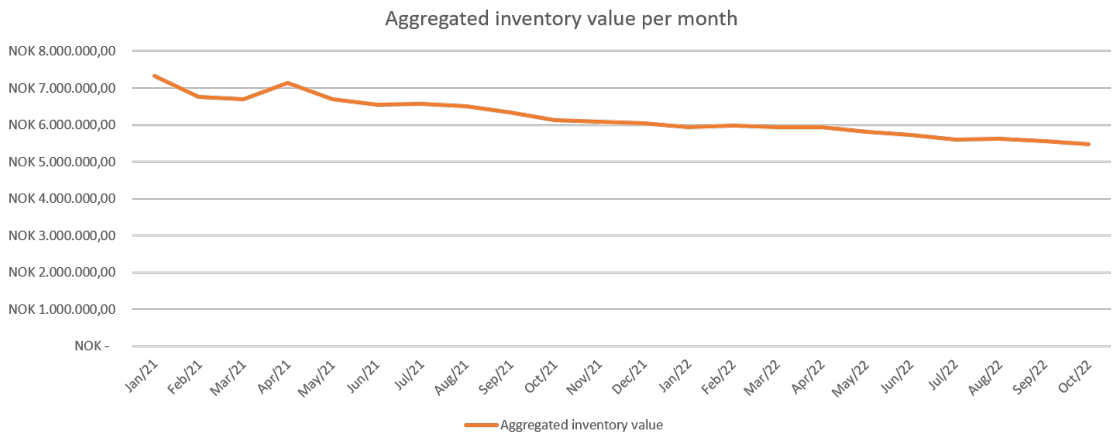


Figure 3: Total inventory value of blue label items from 04/01/2021 till 01/11/2022 based on SAP data. N=1301.

Read Rate

The KPI RR is defined as the percentage of the time the OHI is positive. The RR is used in situations where items are used for emergency purposes (Silver, Pyke, & Thomas, 2016). A high average RR can be an indication for overstocking, since it is clear that not all items needs to be on hand all the time. The average RR of external ordered items equals 98,7%. Figure 4 shows the RR for all external ordered items. The RR of these items considered high, since almost all items are available all time. This observation is also a confirmation that the hospital does not suffer from understocking. If the hospital is understocked, the average RR would much lower.

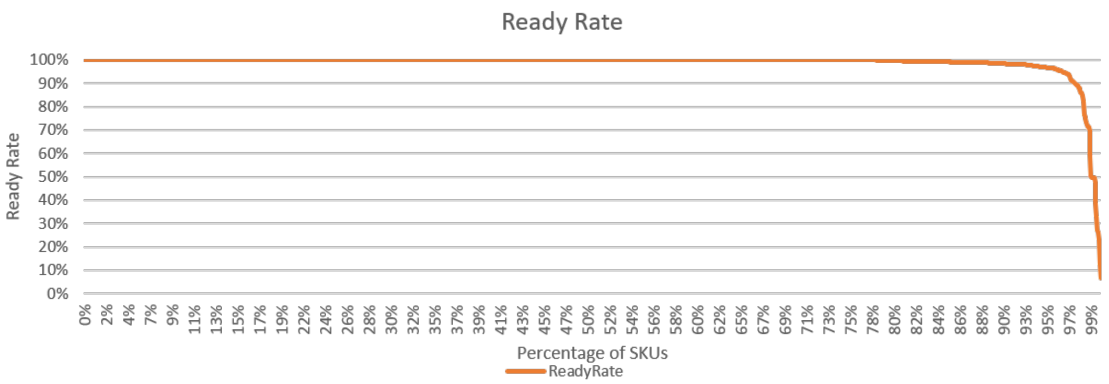


Figure 4: Ready Rate per SKU, N=1301, from 04/01/2021 to 09/11/2022. Based on SAP data

Inventory Turnover Ratio

The ITR is a measure of the number of times inventory is sold or used in a time period such as a year. An ITR of > 1 means that inventory is used in less than a year. An ITR of 1 < means that the total inventory is used in more than a year. A low ITR could be a sign of overstocking, a high ITR could be a sign of understocking (Silver et al., 2016). The ITR is a well known measure, meaning that we could compare the ITR of the hospital to the industry average to compare performance.

Table 2 presents a summary of the findings derived from the analysis. The results show an average inventory turnover ratio of 0.92 in 2021 and 0.74 in 2022. By contrast, the industry average is 1.16 (macrotrends, 2022), indicating a turnover on the average of 314 days. The time to sell out all inventory at the inpatient surgery department is on the average 130 days longer than the industry average. While this is not a direct indication that the hospital suffers from overstocking, there could be various reasons why inventory moves more slowly in this hospital. However, it is a strong indication that there is significant potential for optimization.

Year	**ITR**	**Days**	**Number of different items**
2021	0,92	397	1259
2022	0,74	492	1270

Table 2: Overview of the average Inventory Turnover Ratio in 2021 and 2022 (till November 9, 2022). Based on SAP data.

Figure 5 shows graphical representation of the ITR for up to 97% of the SKUs. The last three percent of the SKUs not displayed, was not on hand in either 2021 or 2022.

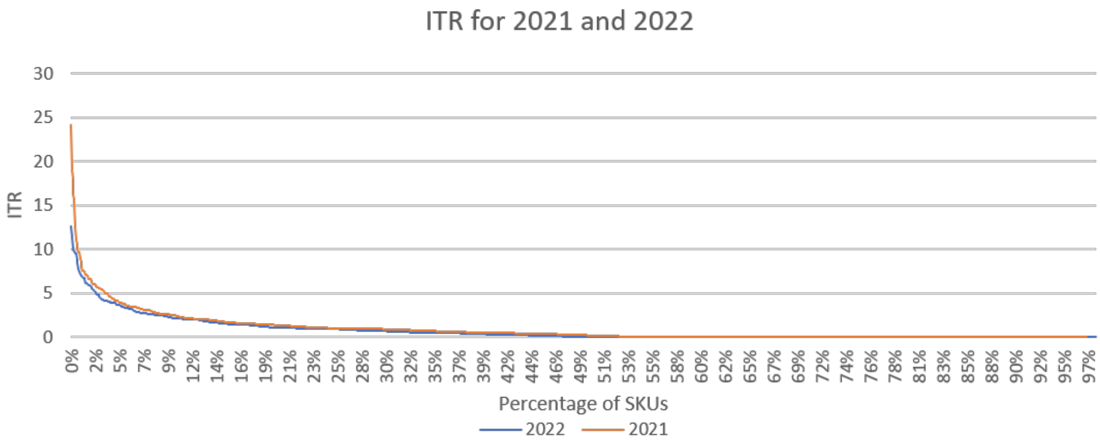


Figure 5: Graphical representation of the ITR of SKUs in 2021 and 2022 (till November 9). $N_{2021} = 1259$, $N_{2022} = 1270$. Based on SAP data.

2.3 Conclusion

In this chapter, the focus has been on providing a background of the restocking process and inventory performance at the inpatient surgery department. It was found that external ordered items are handled differently than internal ordered items, and that nurses are responsible for restocking external items rather than logistical staff. Additionally, the handling of external ordered items creates further issues such as inaccurate data and increased workload for the nurses. Four reasons were identified for why external ordered items are treated differently:

1. It has always been like this.
2. In the past the logistical staff was not allowed to resupply all items (this has changed now.)
3. The logistical department does not have an overview of external ordered items.
4. The logistical department does not have the resources to also supply items ordered outside the normal process.

Thee three various KPIs stated that over the past 1,5 years inventory value decreases, but the overstocking issue is not resolved. The ITR indicated that the department has enough inventory to survive for more than a year, where the industry average is lower. The ready rate showed that almost all items are always available, where that is not necessary. From those three KPIs we could conclude that the hospital has too much inventory of various items that could be worth looking at.

3 Theory on classification, overstocking and inventory policies

This section presents a literature review executed by the framework of Webster and Watson (2002). Adjacent literature shows that classifications, behaviour and POU inventory control models are often used to solve similar problems (Bijvank & Vis, 2012; Cavalieri, Garetti, MacChi, & Pinto, 2008; Chang et al., 2012; van Kampen, Akkerman, & van Donk, 2012). Therefore we summarise the available literature to classification techniques, behaviour leading to overstocking in healthcare and best practice POU inventory control systems.

3.1 Classification of SKUs

Inventory in the hospital consists of many items with differences in importance and cost. Based on those characteristics items can be categorised. Classification helps with applying various inventory strategies to the various items. Also literature about spare parts is considered, because medical equipment shares similar characteristics with spare parts. Both can be expensive, but important to have on stock. This section aims to identify various classification techniques used in the literature and conclude what classification techniques would best suit the hospital case. The first part of this literature review is to review an already existing framework of classification, after that various existing classification methods are discussed.

van Kampen et al. (2012) performed a literature review on all the available literature on SKU classification. They find among all papers four factors that are used in every classification scheme:

- Aim of the classification. Ex: Inventory management, forecasting or production strategy.
- Characteristics: what characteristics to use from the SKU? Ex: Customer information, volume, importance, etc.
- Techniques used: judgemental or statistical techniques. Judgemental characteristics are characteristics not available in the data. Statistical techniques are based on data.
- Context: in what context the SKUs are labeled? Ex: Hospitals, mining industry or lighting industries, etc.

Figure 6 shows the conceptual framework made by van Kampen et al. (2012). The framework provides an uncluttered overview of how to create new classification methods. An example of a method for assessing the importance of SKUs is the VED method, which is discussed in Section 3.1.1.

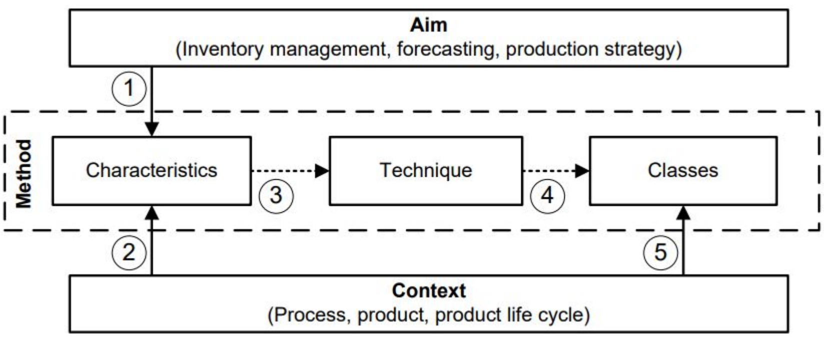


Figure 6: Conceptual framework for SKU classification, (van Kampen et al., 2012)

3.1.1 VED method

The Vital, Essential, Desirable (VED) method is a judgemental method to classify SKUs. The method relies on priory knowledge or expertise. Staff must judge the critically of each item, which cannot be read from data (Bialas, Revanoglou, & Manthou, 2020). The SKUs are characterized by the following definitions:

- Vital: the item is crucial to the operation, without it the operation must be canceled.
- Essential: the item is desirable, but a replacement is acceptable.

- Desirable: low critical value. Nice to have.

Bialas et al. (2020) combines the VED method with the ABC method. Cavalieri et al. (2008) extend the VED method to AHP and combines that with the demand variability. The ABC method labels SKUs based on their demand * revenue history (Shank & Govindarajan, 1988). The ABC method is often combined with the XYZ method. The XYZ method measures the uncertainty of demand (Dhoka & Choudary, 2013). van Kampen et al. (2012) makes the argument that the ABC method does not work for all situations, because money is not always the most important consideration, such as in healthcare. The VED method does take importance into account by the judgement of staff.

3.1.2 Other classification techniques

Cirillo (1999) uses in his thesis about spare parts, a combination of the VED-BRIC method. The BRIC method is a score of 1 (highest importance) to 5 (lowest importance). The letters BRIC represent the following: Breakdown effects, Running (according production shifts), Importance, Conditions of aging. By multiplying the four scores, a score would come out that defines the level of criticality of the equipment. The model assumes that the most critical items get a low score. The lowest scores are defined vital.

Al-Qatawneh and Hafeez (2011) came up with a different variant of the VED, the HML method:

1. High-critical: essential for the work carried out and no alternative available.
2. Medium-critical: important for the work but may have acceptable alternatives.
3. Low-critical: unlikely to affect the well being of a patient other than causing minor inconveniences.

Al-Qatawneh and Hafeez (2011) combined this labeling technique with the ABC method. All high-critical items must have service level of a 100%, the lowest service level is 80% for low-critical items in the A and B category.

3.2 Risk-avoidance behaviour

This subsection presents possible causes for overstocking according to literature. Adjacent literature shows performance programs and risk avoidance of staff causes all kind of side affects. We link those reasons to overstocking.

Section one describes that one of the causes for overstocking at the hospital is the fear of not having enough items. The staff wants to ensure that all items are there in case of an emergency or before the start of a surgery. Overstocking is a way to ensure no stock outs, but at high cost. B.J. Muller (2021) performed research to emergency orders the at the Isala hospital in the Netherlands. An emergency order is an order for an item that is not on stock but needed with urgency. The problem in this case was that staff placed too much emergency orders. Due to various reasons the hospital was understocked constantly. B.J. Muller (2021) found that staff was risk averse and made unnecessary high cost to avoid not having items on the day of the surgery. Staff did not realise how much an emergency order cost and so did not consider alternatives, such as a regular order. Within the Ålesund hospital, staff do not place emergency orders for external ordered items but they overstock these so they rarely run out of these. A main found cause for overstocking is the unnecessary avoidance of risk of hospital staff in cases where risk could also be reduced in other ways.

Chang et al. (2012) points bench marking programs and comparative effectiveness research as one of the reasons for risk-avoidance behavior. Due to these programs, staff lacks the confidence in risk adjustment, in an effort to improve their ranking. Examples of benchmarking programs are: turnover, mortality rates, number of medical specialists, etc. This data is published in order to compare hospitals with each other. These benchmarking programs put pressure on the staff to perform and therefore staff rather has too much inventory than too little. On questions regarding the necessity of certain items, the staff often answer that they are keeping them "just in case", particularly with orthopedic items. When asked if they can order items as needed, staff often ask "what if it is needed in an emergency situation or the doctor prefers to use it?". Sometimes, there are alternative items available, but they may be more expensive or not preferred by the doctor. For example, the hospital stocks an item that connects tubes with each other. The item is a backup item, in case something happened to the main, and more expensive, item that has the tubes already connected. That something happens to the main item is rarely the case. But this is a good example of risk-averse behavior and an attempt to reduce costs by adding inventory, thus building up inventory value.

Huber, Huber, and Bär (2014) defines the difference between passive and active risk avoidance. Passive risk avoidance is choosing a less risky alternative. Active risk avoidance is avoiding risk by introducing a tool that helps avoiding or reducing the risk. B.J. Muller (2021) gives the example of surgeons choosing to only use tools they are completely used to, without considering the alternative such as learning to use all tools. This choice results in multiple items being kept in stock for the same purpose within the hospital. B.J. Muller (2021) suggest that surgeons should learn to use all tools, as such the total assortment could be reduced. And less items in the assortment leads to an easier to manage inventory and less needed capacity. An example of passive risk at the Ålesund hospital is overstocking, keeping excessive amount of items that are only used in planned surgeries and have a short lead time. An alternative could be that staff actively link the item to a surgery and only order items in advance when necessary.

Another way of reducing uncertainty is by standardizing. Ribes-Iborra et al. (2022) improves surgical sets for trauma surgeries and uses the 4S approach. The paper revealed that in this case study only 13-22% of the surgical items per tray was used, concluding that over 3/4 of the items got resterilized again without being used. They took the 4S approach to redesign the contents of the trays. The 4S procedure includes: standardized trays, sterile portfolio, safety certification, service and advanced planning. With the 4S procedure the study showed that they improved the utilization and that all tools were used during surgery. The Ålesund case differs from the described case study in the category of items. Nevertheless, one could expect that standardizing usable items per surgery helps in making the needed inventory more predictable and therefore less is needed.

3.3 POU models in the literature

Within this chapter we summarize the available literature on POU inventory management systems. There is little literature available describing such a policy in a hospital setting, even less studies that take capacity into account.

Most hospitals use a (R, s, Q) inventory policy, in where every R time units staff checks the inventory level. If the inventory level is below s, they order Q items (Bijvank & Vis, 2012). Another often used inventory policy is the min-max method for all items (Kelle, Woosley, & Schneider, 2012). Perhaps the most serious disadvantage of these methods is that they do not take the common characteristics of a hospital supply chain into account. The key characteristics of a hospital supply chain can be listed as follows: lost sales, short lead times, limited storage capacity and periodic reviews. Therefore improvement in inventory management within hospitals could often be obtained by setting parameters better and take the characteristics into account (Kelle et al., 2012).

Hafnika, Farmaciawaty, Adhiutama, and Basri (2016) use the Economic Order Quantity (EOQ) to reduce overstock with 56,93%. The difficulty with using the EOQ method, is the calculation in exact ordering cost, holding cost and demand. Therefore Basri, Farmaciawaty, Adhiutama, Widjaja, and Rachmania (2018) do a sensitivity analysis on the EOQ, based on a case study. They find that an 100% increase or decrease in ordering cost will only affect the inventory status with 2-4%. Change in holding cost with a 100%, will lead to 7% change in number of overstock and understock. The research concludes that the misestimation of EOQ parameters does not lead to a significant different inventory status.

Bijvank and Vis (2012) develops two models. A model for a single-item inventory model and later add a multi level inventory model. The single-item inventory model is a LP model that can be used to maximize the service level, with capacity as a constraint. Or to minimize the occupied capacity with service level as a constraint. They propose a knapsack approach where the algorithm makes a trade-off between adding service level and decrease capacity to design a multi item inventory system.

Next to the single-item and multi-item algorithms, Bijvank and Vis (2012) also introduce an easy to understand inventory rule for (R, s, Q) replenishment systems to decides upon the reorder level and order size. The simplicity of this rule is that it can be implemented using a spreadsheet program. Therefore it is appealing to many hospitals to use this rule.

Lapierre and Ruiz (2007) point out three reasons why working with only the reorder point would not work. 1) the model does not account for the limited human resources, 2) it does not account for physical storage capacities particularly the one at the POU, 3) the decisions are only based on costs and not on cost control. Instead of taking only inventory control into account, Lapierre and Ruiz (2007) takes the whole supply chain into account and develops a multi-item inventory replenishment problem with storage and manpower capacity restrictions. In there model they assume deterministic and known demand. They use tabu search to solve a non-linear mixed-integer problem.

Different papers take capacity into account in a different way. Bijvank and Vis (2012) describe that inventory management at hospitals can be described as multiple bins that have a capacity of C(i) units of item i. This method is very precise, but requires much effort from staff to find out and to establish these parameters. A different way of taking capacity into account is by estimating the total available m^3 and the m^3 of the items.

3.4 Conclusion

This literature review answers the question *"What adjunct literature is available about similar cases like the Ålesund hospital?"*. Adjunct literature shows that three topics are important in solving inventory problems: label items, behaviour of staff and a clear policy for POU inventory. This better understanding of inventory solutions should help to find the correct labeling technique of items for the Ålesund hospital. Literature also gives a better understanding on the perspective of staff on inventory management and on the choices staff makes. The solution must tackle the root causes of the behaviour of staff and help them to move to being actively risk averse.

4 Solution design

This chapter outlines a general approach for resolving overstocking and achieving a stable situation, based on the OR planning and statistical data. Our approach combines quantitative and qualitative analysis, and relies on input from hospital staff. To illustrate the method, we link it to the Ålesund hospital case and build a PoP. A full detailed solution for the Ålesund hospital case would require more time than available for the project and a substantial amount of detailed work which does not contribute to a better approach. We therefore use a sample of externally ordered items from the "Urologi og Gynekologi" category to demonstrate the working.

4.1 General outline of the approach

This section outlines the general steps of the approach and provides background information for all the three steps. Figure 7 provides an outline of the approach. The approach consists of three steps: 1) Sorting, 2) Standardizing, and 3) Constructing an inventory plan. For the Ålesund case, the hospital deals with various items, some of which could be marked as dead stock. Section 2 describes the need for a reduction in OHI. Because staff has specific knowledge about the use and need of all items, they need to be involved in the sorting process. The sorting system developed in this thesis (Section 4.2) helps staff classifying items and let them have a discussion on what they really need. The second step in the approach is standardizing the needed items per surgery. In that case, the inventory can be planned in advance and there is no need to hold items in stock that are only needed for planned surgeries. The last step is constructing an inventory plan. The constructed plan must convince staff to change from being passively risk-averse to actively risk-averse. The plan is linked to the importance of an item and the standardization of an item. The more important the item, the higher the safety level to guarantee the availability of stock. If the item is linked to a surgery, the plan takes that into account. The approach generates the following outputs:

- An assortment that is critically reviewed by staff and contains only the most important items.
- Items linked to surgeries.
- A tool capable of constructing an inventory plan based on the OR schedule.

The outputs address the problem by: 1) dead and unnecessary stock is removed from the assortment, which reduces the needed space for items. 2) Items are linked to a surgery so that inventory can be planned and linked to the OR schedule. Overstocking is no longer necessary, since it is known in advance how much stock is needed over a period of time. For items not linked to surgeries, historical data is used to estimate their expected usage.

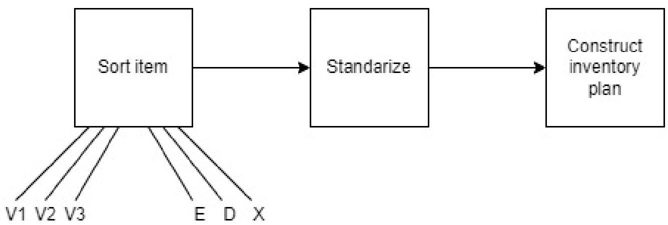


Figure 7: Schematic outline of the approach.

4.2 Step 1: Sort Items

Different classes dedicated to the hospital case are designed. The design principles for new labeling techniques from van Kampen et al. (2012) are used during this process. The goal of the classification is to identify differences in the importance of items and to identify stock that could be removed from the assortment for various reasons. A second reason is that items that are used in plannable surgeries are identified, as well as the criticality of each item. These characteristics of an item are used in the construction of the inventory plan later. To label the item by importance, we use judgemental techniques and have staff classify the item on the basis of objective criteria. The labeling method helps staff to discuss the importance of an item, its use, and possible alternatives. A major advantage of the VED method is that it has already proven to be effective in literature. To fit the overstocking case, the VED method is extended from 3 to 6 classes. Each class represents a different level of importance and criteria. We made the following classification: Vital 1 (V_1), Vital 2 (V_2), Vital 3 (V_3), Essential (E), Desirable (D), Unnecessary (X):

- $Vital_1$ V_1: If the item is not on hand it can cost lives.
- $Vital_2$ V_2: Unknown in advance if the item is needed during a surgery or not. If the item is not available the surgery cannot be finished and must be rescheduled.
- $Vital_3$ V_3: Known in advance if the item is needed during surgery (plannable). If the item is not on stock when the surgery is planned, the surgery must be postponed.
- $Essential$ E: Without the item a surgery can start as planned, with only a small delay, different surgery technique or a different item. If the item is needed during the surgery, it causes no significant problems if not available.
- $Desireable$ D: Without the item the surgery can start as planned.
- $Unnecessary$ X: The item is no longer available at the supplier, the item is unused for a long time period and does not serve a purpose anymore and/or is not required by law to have on hand or an alternative is on agreement.

4.2.1 Implementation of the labeling scheme in the Ålesund hospital case study

For the PoP we made an example of a list with extra parameters that could help the staff decide on the criticality of each item. Figure 8 shows an example of the labeling sheet. The sheet presents every item that is stored at the department including helpful information. For this PoP we focused on the Urologi og Genekologi items. To help the staff classify an item, we included additional information such as: available since, times requested, lead time, and the value of an item.

SAP code	Description	Productgr	Productgroep	Available since	On Stock (9/11/2022)	Times requested	Value/item (NOK)	Label after revisit (V1, V2, V3, E, D, X)	Lead time (days)	Comment
4047254	335626 Supergl. JJ-tumorstent ch7 26 cm	100310	Urologi og gynekologi	04/01/2021<	4	7	[redacted]	V3	54	
4047255	335628 Supergl. JJ-tumorstent ch7 28cm	100310	Urologi og gynekologi	04/01/2021<	3	2	[redacted]	V3	21	
4050115	Re-Usable Sterile 200um Surgical Optical	100310	Urologi og gynekologi	04/01/2021<	4	18	[redacted]	V2	13,5	USAble 10 times,
4048405	561016 Suprapubisk kateter ch16	100310	Urologi og gynekologi	19/03/2021	4	7	[redacted]	X	13,5	
4050106	Conestent 6.0-9.5 Fr	100310	Urologi og gynekologi	04/01/2021<	1	0	[redacted]	V3	69	
4050141	Conestent 7.0-14.0 Fr	100310	Urologi og gynekologi	04/01/2021<	1	0	[redacted]	V3	45,5	
4015464	Guidewire PCNL stiv 0,035 145cm	100310	Urologi og gynekologi	04/01/2021<	6	13	[redacted]	V2	4	
4022872	Biopsitang til URS 3Fr fleksibel	100310	Urologi og gynekologi	04/01/2021<	2	4	[redacted]	D	3	
4024598	Lone Star elastic stays 5mm	100310	Urologi og gynekologi	04/01/2021<	3	4	[redacted]	X		
4041175	Hylse tilgang ureter URS 10/12Fr 46cm	100310	Urologi og gynekologi	04/01/2021<	8	11	[redacted]	V2	3	
4046041	BPS-Y Biopsi Port Seal Y-adapter	100310	Urologi og gynekologi	04/01/2021<	3	5	[redacted]	D	34	
4046315	KIT-UT-01 Promedon Splentis	100310	Urologi og gynekologi	04/01/2021<	2	5	[redacted]	V3	7	
4047251	223602-000030 Ureterkat. Nr.3 sidehull	100310	Urologi og gynekologi	04/01/2021<	12	2	[redacted]	V2	6	
4047336	41708370 SecuFix uterusmanipulator Set	100310	Urologi og gynekologi	04/01/2021<	8	65	[redacted]	V3	5	
4047722	M006 3903100 Microv StoneCone 3fr 7mm	100310	Urologi og gynekologi	04/01/2021<	4	0	[redacted]	X		
4047844	Hylse tilgang ureter URS 10/12Fr 24cm	100310	Urologi og gynekologi	04/01/2021<	7	36	[redacted]	V2	5	
4047845	EG61038BX Access sheat uretral 38cm	100310	Urologi og gynekologi	04/01/2021<	6	42	[redacted]	V2	5	
4047893	AQ-022610 Ureterkat flexi-tip	100310	Urologi og gynekologi	04/01/2021<	5	10	[redacted]	V2	7	
4047966	GS35153M Terumo wire 0.89mm x150cm 5stk	100310	Urologi og gynekologi	04/01/2021<	1,2	109	[redacted]	V2	4,5	
4047996	M006 740101 Microv Conect tube 7-10fr	100310	Urologi og gynekologi	04/01/2021<	5	6	[redacted]	V2	2	

Figure 8: Example of labeling sheet (exact price of product is left out for confidentiality).

4.3 Step 2: Standardization

In order to reduce uncertainty in demand and make more accurate predictions about the items that will be needed in the future, we standardize items per surgery. This is done in the second step because we have already filtered out items for which an alternative is available. Standardizing items without first reducing the assortment list would result in unnecessary work, as we would need to standardize items that will eventually be removed from the assortment. When items are not standardized, statistical data can be used to estimate the number of items needed.

4.3.1 Standardizing in the Ålesund hospital case study

The surgery department of the Ålesund hospital has no standardization in place. To demonstrate the potential of this approach, an example standardization list was generated in Excel for the purpose of the PoP. Figure 9 shows this list. The items on the list are from the urologi og gynekologi category and assigned to V_3 in the labeling classification. For each surgery code, the necessary items are listed, along with their SAP number and a short description.

SAP number	Description	Quantity	Preparationlist/surgery code
4009120	Gyncare TVT Abbrevo	1	UQ
4050141	Conestent 7.0-14.0 Fr	1	UQ
4050141	Conestent 7.0-14.0 Fr	2	UG
4050106	Conestent 6.0-9.5 Fr	1	UG
4009120	Gyncare TVT Abbrevo	1	UG
4050106	Conestent 6.0-9.5 Fr	2	UI
4050106	Conestent 6.0-9.5 Fr	1	UD
4009120	Gyncare TVT Abbrevo	1	UD
4046315	KIT-UT-01 Promedon Splentis	1	UD
4047336	41708370 SecuFix uterusmanipulator Set	1	UD
4047254	335626 Supergl. JJ-tumorstent ch7 26 cm	1	UY
4047254	335626 Supergl. JJ-tumorstent ch7 26 cm	2	UW
4009120	Gyncare TVT Abbrevo	2	UW
4009120	Gyncare TVT Abbrevo	1	UR
4047255	335628 Supergl. JJ-tumorstent ch7 28cm	1	UR
4046315	KIT-UT-01 Promedon Splentis	1	UC
4009120	Gyncare TVT Abbrevo	2	UC

Figure 9: Example of standardization list.

4.4 Step 3: Constructing inventory plan

The final step in the process is to construct an inventory plan. The plan combines the labeled items, standardization, and most recent OR planning. Because the OR planning changes on a weekly basis and is, in case of the Ålesund hospital, known 2 weeks in advance, this step can be executed every week. The fundamental idea of the algorithm is to determine demand of standardised items over the plannings horizon. For items that are not standardized, we use historic averages and standard deviations to make an estimate of their expected need. Because the current inventory stock of externally ordered items is known, we subtract that from the current advice. If the advice is still positive, it is up to the nurses to make the decision to order the item or not. Because items are ordered externally, there might be a minimum order size.

The plan is constructed in the following way: the algorithm first checks for each item if it is standardized and categorized. If the item is standardized, the algorithm searches the OR plan for related surgeries. If the item is not standardized, the algorithm checks the classification of the item, average demand, standard deviation and current inventory level. If the expected use of the item is greater than the amount of items on stock, the algorithm will recommend ordering up to the expected use + a safety factor, or the minimum order quantity. Equation 1 shows the equation for the advice. $\widehat{X}$ is here the average demand during review and lead time, k the safety factor and σ the standard deviation of demand during review and lead time.

$$Order\ Advice\ =\ \widehat{X}_{L+R} + k\widehat{\sigma}_{L+R} - On\ hand\ stock - On\ Order \tag{1}$$

It is important to realize how the data is built up. In the case of the Ålesund hospital, the data validity could not be taken for granted. Due to errors in scanning in and out items, demand per day might be wrong. For the recommended order quantity, the algorithm uses the lead time, standard deviation of historic demand, and importance of classification. The importance of classification is used here to determine the safety factor. If the item is important, the algorithm will automatically have more on hand of the item than for less important items. Appendix A.2 presents the pseudocode for the algorithm.

4.4.1 Ensuring capacity restriction

To ensure that the available capacity is not exceeded, the algorithm uses a knapsack algorithm that maximizes the importance-to-volume ratio and takes total capacity as a restriction to adjusts the recommended order quantity. Capacity means all capacity available on the department. A violation occurs when OHI volume and expected future capacity use is more than the total available capacity. Expected future capacity consists of the on order list and the order advice. If the constructed advice violates the capacity restriction, the algorithm needs to adjust the amount of items to be ordered such that capacity is not violated. The knapsack algorithm is used that maximizes the $\frac{importance}{volume}$ with total capacity as a restriction. For the PoP the V_1 item is given 10 important points. A V_2 item is 5 important points, V_3 4 important points, E 2 points and D 1 point. An X item gets 0 points. Appendix A.3 presents the knapsack model.

4.4.2 Safety factors

For all items other than V_3 items with a short lead time, there need to be a certain amount of safety stock on hand. The safety stock covers the amount of demand that is higher than the average demand. The safety stock also guarantees a certain service level. Table 3 shows target service levels as applied in the PoP. V_3 items are plannable items and therefore the service level is left blank. The exact safety factor is hard to determine, because of the lack of data in this case study. Therefore we performed a Monte Carlo simulation to determine the correct parameters for the various classes.

Label	Service Level
V_1	99,9%
V_2	98%
V_3	-
E	80%
D	75%
X	0%

Table 3: Target service levels for the different categories of items as agreed on with staff

4.4.3 Case study subjected parameters

We obtained the parameters for the model used in the case study in the following way:

- Lead time is measured and saved in SAP for all the items ordered. We use the median lead time to compensate for outliers. If a lead time was not measured before, we took the lead time agreed upon in the contract. If the lead time in the contract is also not available, we assumed a lead time of 14 days (2 weeks).
- The total capacity of the new situation is estimated in Section 1.3. We measured all items in used in the PoP and used that as an input for the model.
- To demonstrate the working of the approach, we used real data from the the Ålesund hospital. We made use of the data of items from the "urologi og gynekologi" category. The dataset consists of 32 items. In total, we found 1 V_1, 14 V_2, 8 V_3, 2 E, 2 D, and 5 X items.
- Within the OR plan dataset of the hospital, we can distinguish three types of emergency surgeries. Type 1, 2, or 3. Type 1 emergency operations need to take place within 6 hours, type 2 emergency operations within 48 hours, and type 3 emergency operations within 6 days. For two reasons we decided to keep a small amount of stock of V3 items with a median lead time longer than 5 days. The first reason is that the items can than be used in emergency surgeries and secondly items with a long lead time may not arrive in time for a planned surgery.

4.5 Implementation of the approach in the PoP

This section explains how the PoP is implemented for the research. The implementation of step 1 and 2 of the approach are described in Section 4.2.1 and 4.3.1 respectively. This section is about the experimental execution of Section 4.4 within the PoP. This Section describes the design, implementation and working of the tool.

4.5.1 Design of the PoP tool

Figure 10 shows the dashboard of the tool after an advice is made. At the bottom are multiple tabs in where different data is stored. The "Advice" sheet has a green color and placed at the left part of the screen, so the user intuitively knows where to start. The following aspects are observed in the advice sheet: 1) a list with items that are advised to be ordered, 2) a settings panel, 3) two buttons. The advice list contains the following elements: item number, descriptions of the item, Quantity to order, Comments and total value of the advised order. If the tool finds a solution that fits capacity, all rows are blank. If the first solution does not fit capacity, the tool uses the knapsack algorithm to find a suitable solution. Items removed from the initial solution are presented with a red fill. The user can see immediately what is not selected for the advice. In the comment section the tool describes why a certain quantity is advised. The log makes it clear for the user why a quantity is needed and can so build trust in the tool by validating the outcome. For budget reasons the total value of the order is presented. The second aspect, the settings panel, present KPIs and settings that be changed and inform the user. After the advice the user can check here how much capacity is taken by current stock, ordered items and how much is left. Last the total value of the advised order is presented here.

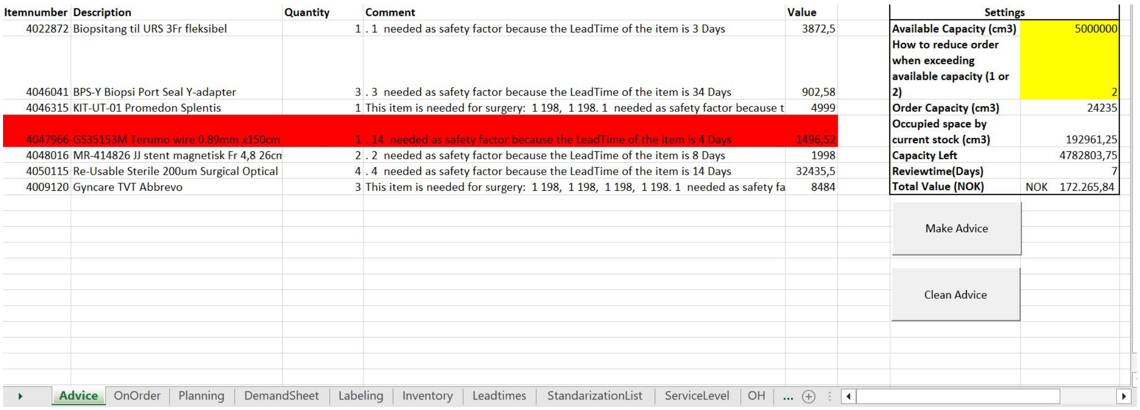


Figure 10: Screenshot of the dashboard of the PoP

4.5.2 Working of the PoP tool

The data that is needed the construct the plan is put into multiple sheets and collected from various sources. This makes it easy to update and refer to the data. The demand sheet summarises the demand per week. Weekly demand is considered instead of daily demand, because we assumed that an order for external items is placed once a week after the renovations. The second sheet is the labeling sheet, shown in Figure 8. The algorithm loops over all items on this sheet and only takes action if an item is labeled. If the label is missing, the user receives an error message on the advice sheet after the execution. According to the label a certain path in the algorithm is taken, as described in Section 4.4. The OR planning is simulated and given as an input in the sheet "Planning". The algorithm loops over all surgery codes and advises on the amount of standardised items needed until the end of the OR planning. Because the planning is certain two weeks in advance and the review time is 7 days, V3 items with a lead time longer than 5 days are kept on storage.

5 Validation of the proposed solution

Within this chapter we answer the question: *"How does the designed inventory approach performs in terms of service level and cost under various simulated scenarios?"*. The goal of the simulation study is show the behaviour of the approach under different circumstances. The simulation study evaluates the approach on various KPIs. First the safety factors are initialised to set them right for the observed average demand and lead time, so for normal circumstances. In the remaining sections the approach is evaluated on several extreme scenarios to study the behaviour of the approach.

5.1 Simulation description

For a successful implementation of the approach, it is important to discover how the approach behaves over time and what actions can change that behaviour. Real life barriers, such as time and resources prevent the approach of being tested in real life. The best alternative is to create a simulation on the computer to simulate the approach over time. The simulation can also be used by hospital staff to study various scenarios, which can help staff by designing the new inpatient OR department. The hospital can also study the course of OHI value in stress full situation as for example the COVID-19 situation where lead times increases even as demand. The simulation makes use of real demand and lead time data obtained from the hospital. The most relevant variables in the simulation study that are taken into account, are demand and lead time and the influence between the two.

The input of the simulation is the list of items to simulate including the importance per item, demand data, lead times, eventual standardisation and the OR planning is the input for the simulation study. The OR planning is necessary to calculate the expected use of plannable items related to surgeries. The output is the service level and OHI value. The service level is a number, the OHI value is given per simulated unit of time. In general the simulation works as follows. An OR schedule is generated after which incoming orders from the previous simulation rounds are updated and inventory is updated. The tool of the PoP is executed from where an advice follows. After the execution, the advice is ordered and inventory is updated by distracting the simulated use of items. KPIs are updated and the simulation should move on to the next round. Figure 11 describes our implantation of the generalised approach.

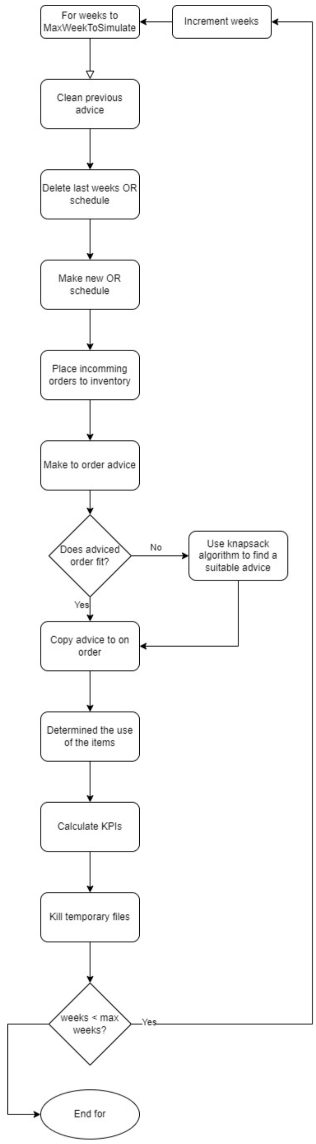


Figure 11: Implementation of the generals description of the simulation.

5.2 Grounding simulation in practice

5.2.1 Integrating the OR planning into the simulation

The OR planning is important in case of standardised items linked to surgeries. If the list of items do not contain "V3" or standardised items, the OR planning is not necessary for the simulation. In this case study, standardisation data and surgery codes were not available. Therefore a simplified version of the OR planning was simulated. The average amount of urology surgeries per week was obtained from the real OR planning, even as the total amount of surgeries. A hypothetical standardisation was created, as described in 4.3.1. Equation 2 is used to estimate the probability of the occurrence of a standardised surgery. It is important to have an accurate probability of occurrence when working with real data and simulated standardisation lists. If a surgery occurs more often than reflected in the data, chances are that safety stock would be insufficient.

$$P(Surgery) = \frac{\sum_{i=1}^{items\ surgery} P(item_i)}{Total\ items\ used\ in\ surgery} \tag{2}$$

5.2.2 Distribution of item demand

To determine if the approach is able to satisfy demand, we simulate the usage of items per week. It is important that the simulated usage per week is accurate enough, otherwise the determined historical average demand and standard deviation is incorrect which has consequences for the calculation of the safety stock, and so for the service level. Statistical tests proofed that theoretical distributions do not fit the item demand of items per week, therefore an empirical distribution was used in the simulation. The empirical demand distribution makes use of all historical observations. A disadvantage of the distribution is that outliers that could occur in a theoretical distributing, would not occur in the empirical distribution. Therefore extreme situation would not occur.

5.3 Settings and KPIs for grounded simulation

5.3.1 Initialize safety factors

Equation 1 shows the safety factor k. The safety factor k is used to determine the amount of standard deviations in demand added to the average demand during review and lead time. Enough safety stock on hand leads to obtaining the target service level. For the purpose of the initialisation of the simulation of this case study, several runs are performed with various settings. The best setting per category was chosen at the end of all the runs. A setting is right if it achieves the target service level with a suitable level of confidence . The results are shown in Appendix A.4.1.

5.3.2 Key performance indicators

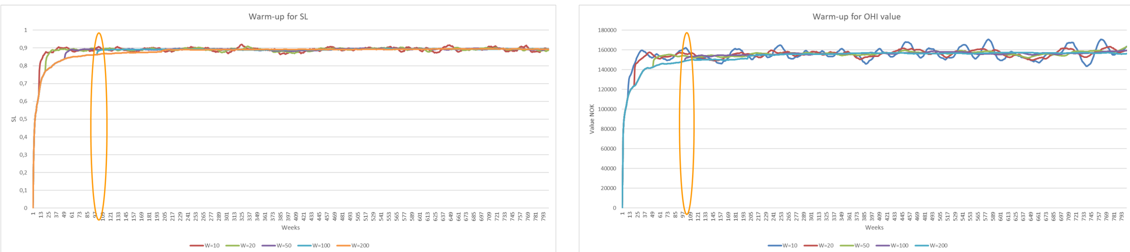
The simulation evaluates the developed approach with help of KPIs. The following KPIs are used to judge the simulation on and to compare simulation outcomes among each other:

- The service level, indicates what percentage of demand is met. This KPI indicates the performance of the approach. A high service level indicates that the approach works and demand is met.
- The OHI value, indicates the worth of all inventory, prefers to have as low as possible while remain having a high service level.

5.3.3 Warm-up period

The simulation starts with an empty system. In the first iterations the algorithm starts to order inventory and the system fills itself with items. Therefore, the first few weeks do not reflect an accurate representation of the working of the approach and are therefore not relevant for the results. For this reason a warm-up period is implemented.

We use Welch's method to determine the length of the warm-up period (Martijn R, 2021). We run 10 independent runs of 800 weeks, so that the average OHI value and service level can be determined. Figure 12 shows the smoothed results of the graph. The graph shows that the lines stabilise after approximately 100 weeks. Therefore the warm-up period for these simulations have been set to a 100 weeks.



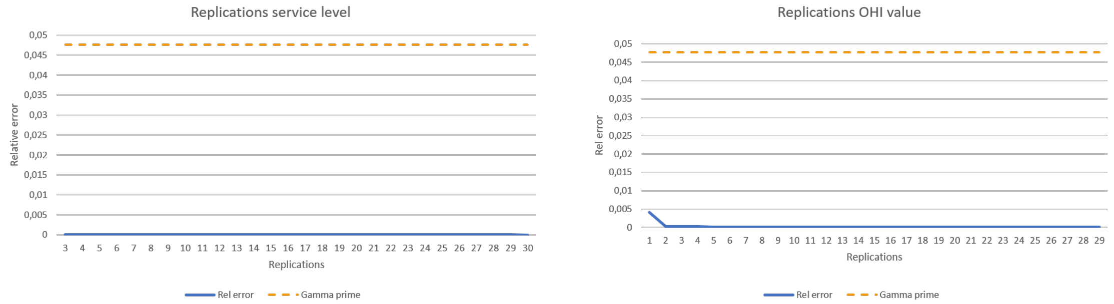
(a) Warm-up period according to Welch for the service level

(b) Warm-up period according to Welch for the OHI value

Figure 12: Welch's graphical procedure for windows 10, 20, 50, 100 and 200 for OHI value and service level (n = 800 weeks)

5.3.4 Replications

The number of weeks to simulate in a run is dependent on the warm-up period and the number of replications Martijn R (2021). The general rule is to simulate at least ten times the warm-up period. However, the number of replications is the key factor. A way to determine the number of replications needed per experiment is the relative errors measure of precision. When aiming for a relative error of 0.05, the actual error is 0.048. We ran 20 test runs and each run contained a 1000 weeks. We found that with a 1000 weeks only one replication was already enough. Next we tested the relative error using a subset of 300 weeks. The results are shown in Figure 13. We observe that one replication is enough to be under the thresh-hold. According to Martijn R (2021) the minimum number of replications should be five. Therefore we set the number of replications to 5 in our simulation and the run length to 400 weeks (including a 100 week warm-up period).



(a) Relative error for number of replications of the service level

(b) Relative error for number of replications of OHI value

Figure 13: Results of the relative error test

5.4 Testing various scenarios

The first experiment establishes a baseline, by running the model according to the settings from Section 5.1. The other experiments add variation in demand, in lead time and last add variation in both lead time and demand. All outcomes are compared against the baseline.

5.4.1 Baseline experiment

The first experiment is without an increase or decrease in demand or lead time. Figure 14 shows the OHI value and Table 4 shows the results per category of items in terms of service level. What stands out in Table 4 is the surprisingly low service level of V3 items. High lead times in combination with a review period of a week cause that the total lead time + review time is too long to anticipate on. A solution could be to increase the safety factors for V3 items, which we set to zero for these simulations. Another solution is to reduce the lead times and/or review period, but that is out of the scope of this research.

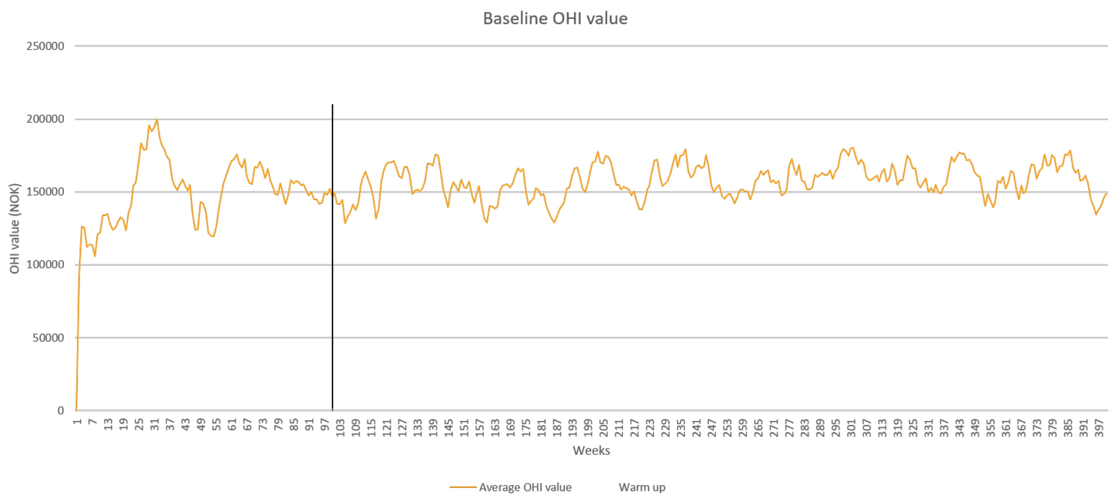


Figure 14: OHI baseline, based on 400 weeks simulation and five replications.

	R1	R2	R3	R4	R5	AVG
V1	1,000	1,000	1,000	0,979	1,000	0,996
V2	0,964	0,977	0,970	0,972	0,978	0,972
V3	0,824	0,797	0,803	0,800	0,815	0,808
D	0,747	0,795	0,854	0,911	0,766	0,815

Table 4: Results for the service level baseline, based on 400 weeks simulation data and five replications

5.4.2 Scenario: Variation in demand

Rapid shifts in demand can result in inadequate safety measures and consequently reduce service levels. In light of this, the current study investigates the impact of demand fluctuations and seeks to determine the optimal approach to mitigating such fluctuations. To simulate an increase in demand, the simulation employs a random factor between 4 and 5 to multiply the empirical distribution. In a separate scenario, a decline in demand is simulated by multiplying the empirical distribution by a factor between 0 and 0.5. The various experimental settings utilized are presented in Appendix A.4.2.

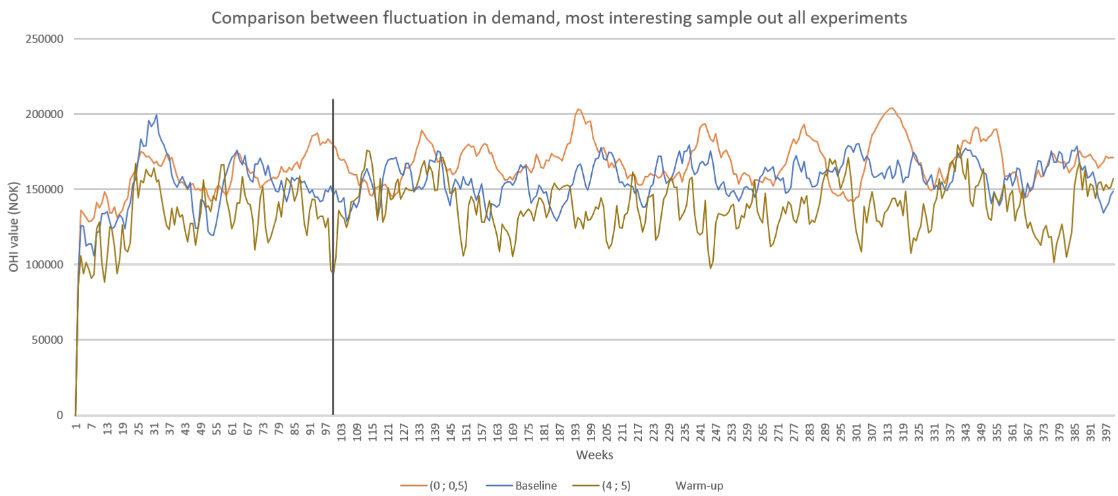


Figure 15: OHI value of most of various experiments fluctuating demand.

Figure 16: Results in terms of service level for the sample of experiments

Figure 15 displays a sample of two distinct experiments conducted to analyze the impact of demand fluctuations. The baseline is compared with demand levels that are 0 to 0,5 times the random demand generated from the empirical distribution, as well as with demand levels that are 4 to 5 times the demand derived from the same distribution. Our observations indicate that minimal or no demand results in higher OHI values, whereas elevated demand levels lead to lower OHI values. A statistical t-test conducted on the means verifies the significance of the difference. Figure 16 presents the outcomes in terms of service level, revealing that lower demand coupled with identical safety factors produces better service levels, while higher demand associated with the same safety factors generates inferior service levels. Consequently, we conclude that regular updates to safety factors and parameters are crucial to synchronize with fluctuating demand. It is essential to keep in mind that an incongruity between safety factors and demand could result in under- or overstocking.

5.4.3 Scenario: Variation in lead time

The surgery department is at risk due to changing lead times as longer lead times without appropriate anticipation can have a significant impact on the quality of care provided. Fluctuations in lead times can result in safety stock becoming insufficient, thereby increasing the risk of overstocking or understocking. In order to mitigate this risk, a simulation was conducted to investigate the impact of lead time variations on the OHI value. The results are presented in Figure 17, and various experiment settings are shown in Table A.4.2. The figure illustrates that shorter lead times lead to lower OHI value, with OHI value remaining stable as the lead time approaches zero. The statistical t-test indicates that there is a significant positive correlation between lead time and OHI value. This relationship follows from the way in which safety stock is calculated, where lead time and review time are taken into account. Consequently, higher lead times require more safety stock, leading to higher OHI value. This trend is most evident in scenarios with very high lead times, such as scenario (4 ; 5). To reduce the OHI value when dealing with uncertain lead times, safety factors could be adjusted. However, reducing safety factors may have an impact on the service level provided.

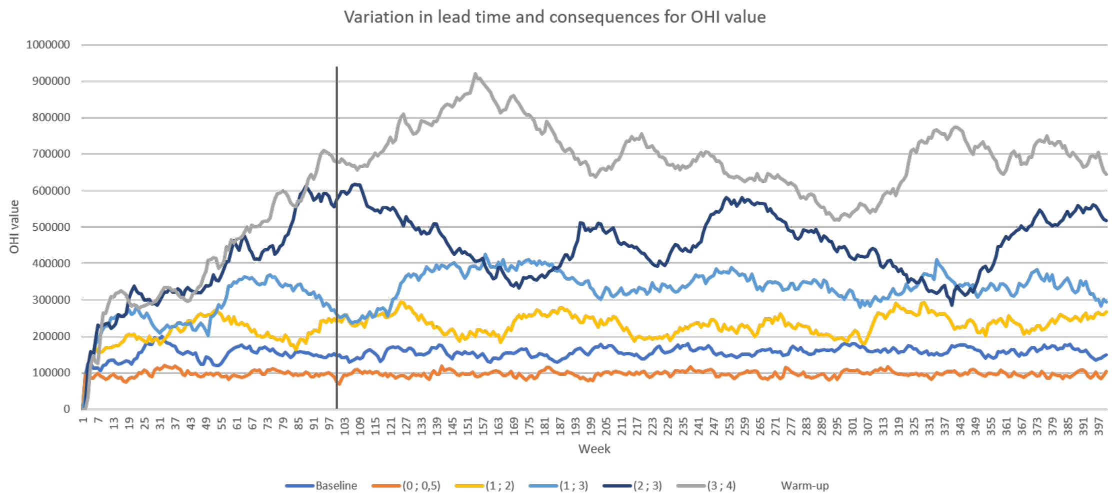


Figure 17: OHI values over time, based on a 400 week simulation with various lead time settings

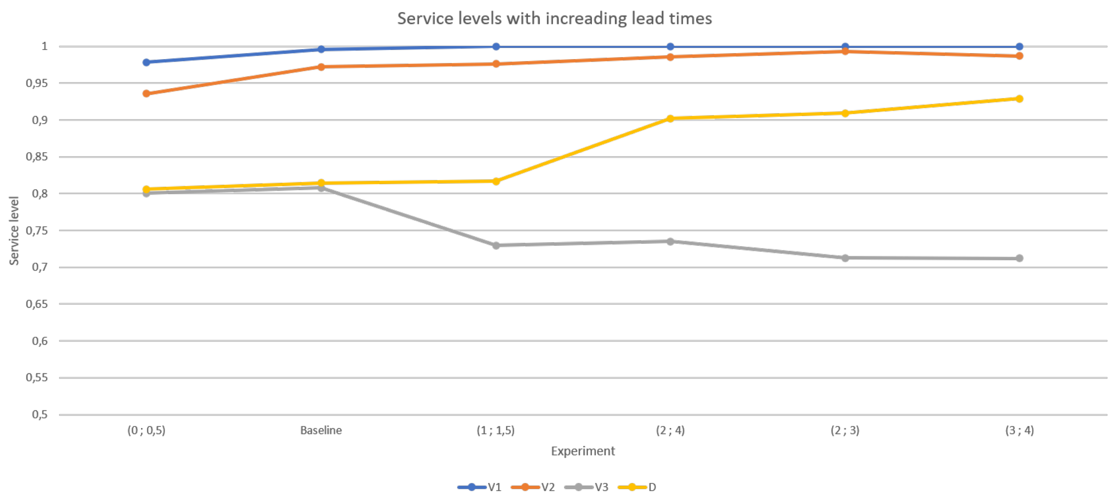


Figure 18: Service level over time, based on a 400 week simulation with various lead time settings

The presented figure, Figure 18, illustrates the results of the simulation in terms of service levels for different item groups when subjected to varying lead times. A statistical t-test was conducted on the means between the average service levels of (0,1 ; 0,5) and (1 ; 1,5) with a 95% confidence level to confirm that longer lead times lead to higher service levels. The observed trend indicates that the service level improves as the lead time increases, under the assumption that demand remains constant. This finding emphasizes the importance of anticipating changes in lead time, as it could have a significant impact on service levels.

5.4.4 Scenario: variation in both, lead time and demand

In this scenario, both lead time and demand exhibit a high level of uncertainty and can fluctuate substantially. Such circumstances can arise, for example, during periods of limited material availability amid a disease outbreak. The success of the simulation hinges on the identification of plausible causes and solutions to effectively manage these complex scenarios. Figure 19 portrays the evolution of the OHI value for the various experiments in which both lead time and demand are varied. Meanwhile, Figure 20 illustrates the corresponding service levels for each experiment.

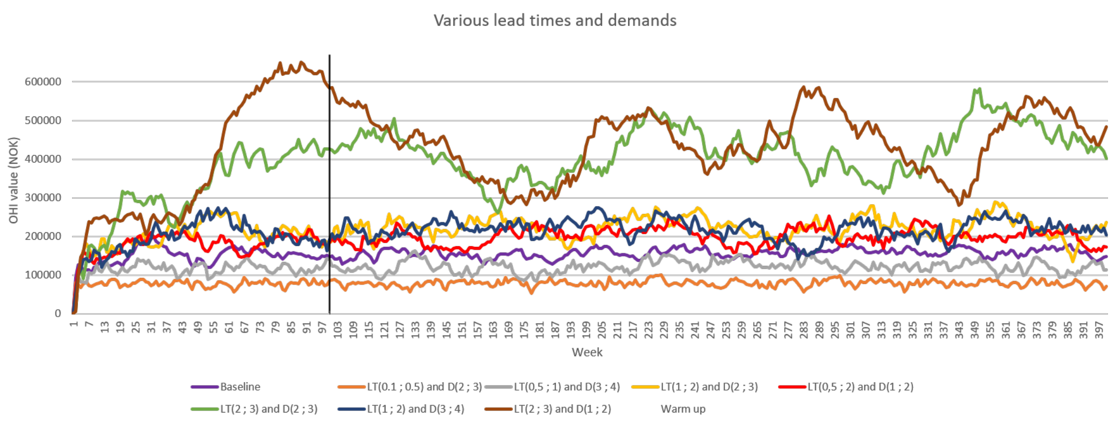


Figure 19: Results for both, various lead times and demand.

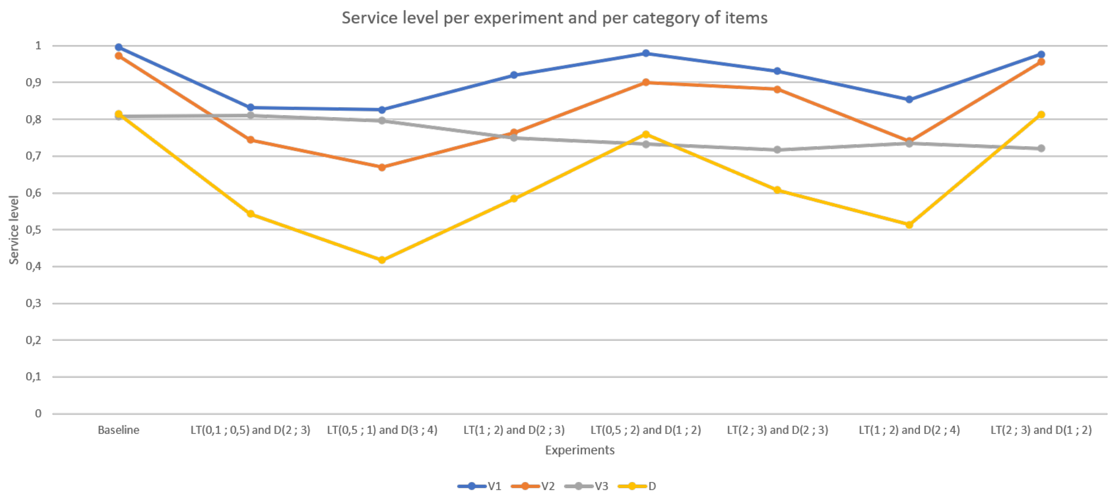


Figure 20: Service level for various experiments where both lead time and demand are fluctuated. Based on experiments of each 400 weeks and 5 replications

Figure 19 and Figure 20 illustrate the OHI value and service levels respectively for different experiments. It is observed that when there is an increase of 100% to 200% in lead time, there is an average increase of roughly 2,5 times more OHI value, which is not compensated by the increase in demand.

Moreover, Figure 20 shows that an increase in lead time, resulting in more safety stock, leads to better service levels compared to a decrease in lead time and an increase in demand. This highlights the importance of managing lead times, as they have a significant impact on both inventory and service levels in the face of uncertain demand. These findings suggest that mitigating the impact of uncertain lead times on the system should be a priority for ensuring better service levels and efficient inventory management.

It may seem counter intuitive that shorter lead times result in lower service levels, as shorter lead times should make the inventory more flexible and allow for easier demand fulfillment. However, it is important to note that the simulation does not automatically adjust its parameters, such as the average demand or safety factors. As a result, the simulation may generate lower service levels due to insufficient safety stocks, which is caused by the failure to update the safety factors to compensate for the shorter lead time.

5.4.5 Scenario Variation in capacity

Capacity is a crucial factor in POU locations in hospitals, and the approach has the capability to select the most important items when little capacity is available. In this subsection, the behavior of the approach is investigated when capacity is restricted. The capacity is calculated by adding the occupied capacity of the stock and the future orders. If the total of both is less than the total available capacity, the algorithm determines whether all recommended items can be ordered or if a selection must be made to avoid violating the capacity constraint. The selection process is performed using the knapsack algorithm as described in Section 4.4.1. Figure 21 illustrates the OHI value over time with various capacity caps. A decrease in the maximum OHI value is observed when dealing with less capacity.

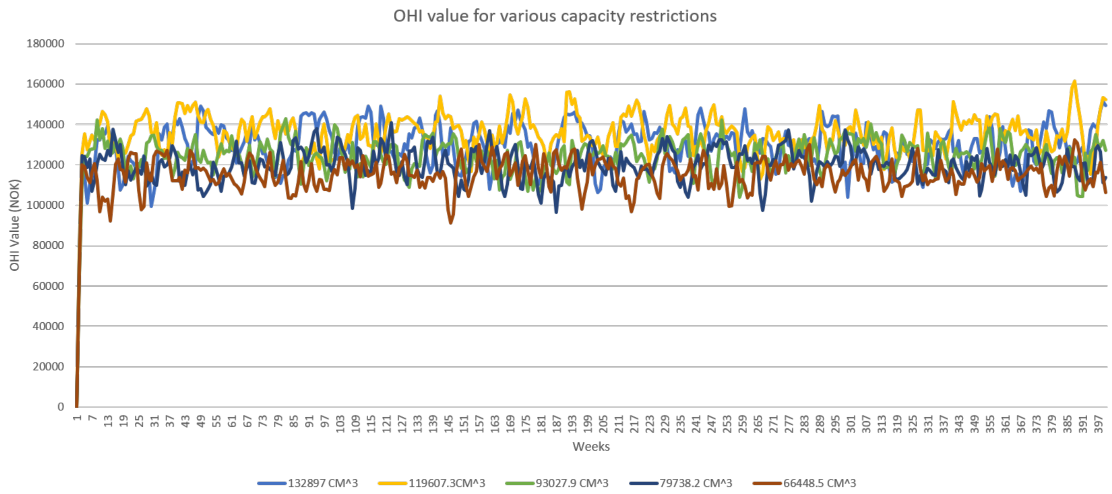


Figure 21: OHI value with decreasing capacity, settings as described in thesis.

Figure 22 illustrates the service level for each category group. The observed results deviate from what would typically be expected, as a decrease in all service levels is expected as capacity decreases. However, the opposite effect is observed, with the service level of planned items, or "V3" items, decreasing, while other service levels either remain the same or show a slight improvement. This unexpected result can be attributed to the parameter choices made in the study. Specifically, in Section 4.4.1, importance labels were translated to numerical values, with "V3" items assigned a score of four. Analysis of the dataset revealed that "V3" items are the largest items, resulting in a lower $\frac{Importance}{Volume}$ score. Consequently, the knapsack algorithm prioritizes smaller, less important items for safety stock, rather than "V3" items. The knapsack algorithm does have a lower bound for "V3" items, set at the amount of items required for surgery in the short term. However, due to the longer lead time for "V3" items, they do not arrive in time, resulting in a lower service level. Assigning a higher score to "V3" items would lead to an increase in service level.

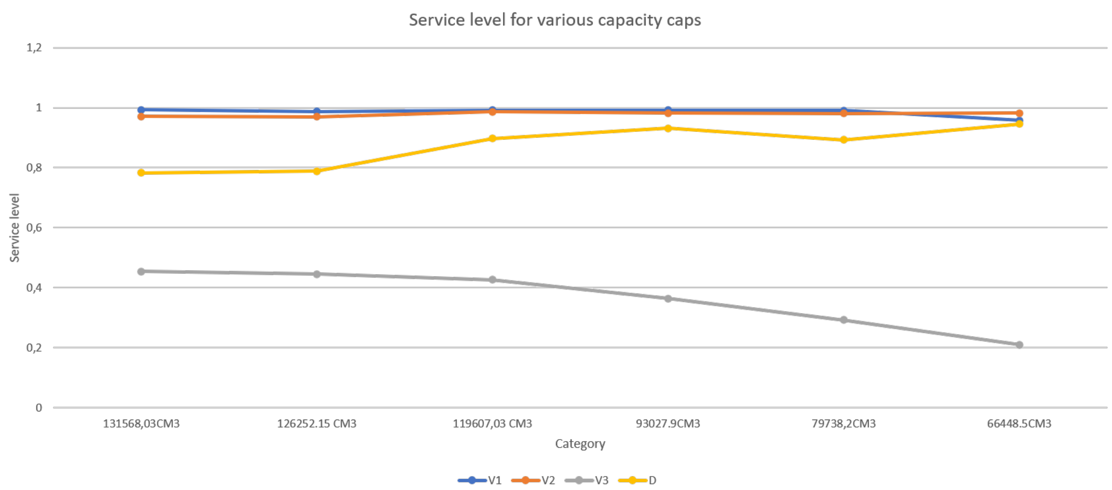


Figure 22: Service level for decreasing capacity setting.

After modifying the importance score for "V1" and "V3" items to 300 and 200 respectively, more experiments were conducted to observe whether a difference in service level would occur. The results of these experiments are presented in Figure 23 and Figure 24, which display the OHI value and service levels, respectively, for the various capacity caps. Notably, we observe that the service levels for "V1" and "V3" items are higher, making them the preferred items over "V2" and "D" items. These results demonstrate that changing importance parameters can have a significant impact on the approach's ability to select which items to order when faced with capacity restrictions.

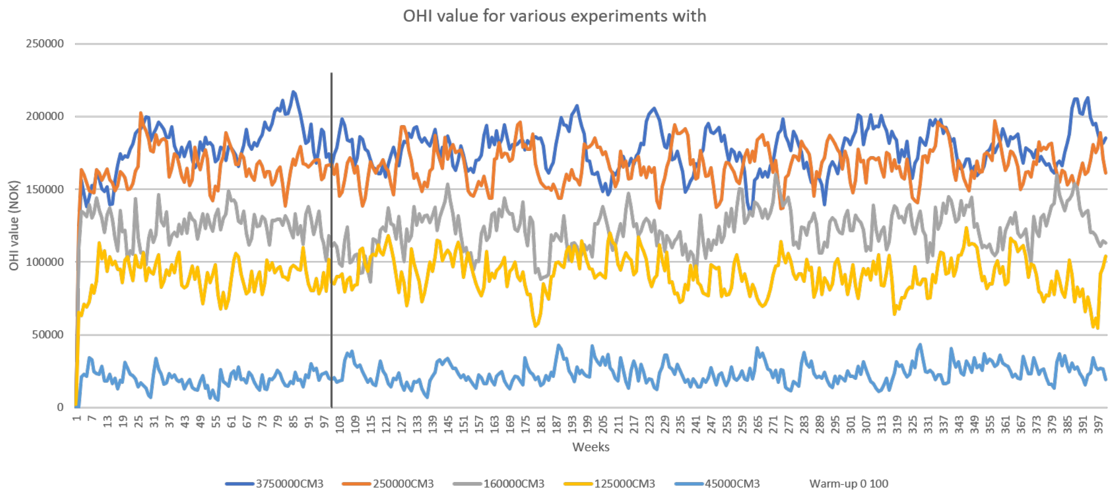


Figure 23: OHI value for various capacity caps with increased importance parameters for "V1" and "V3" items.

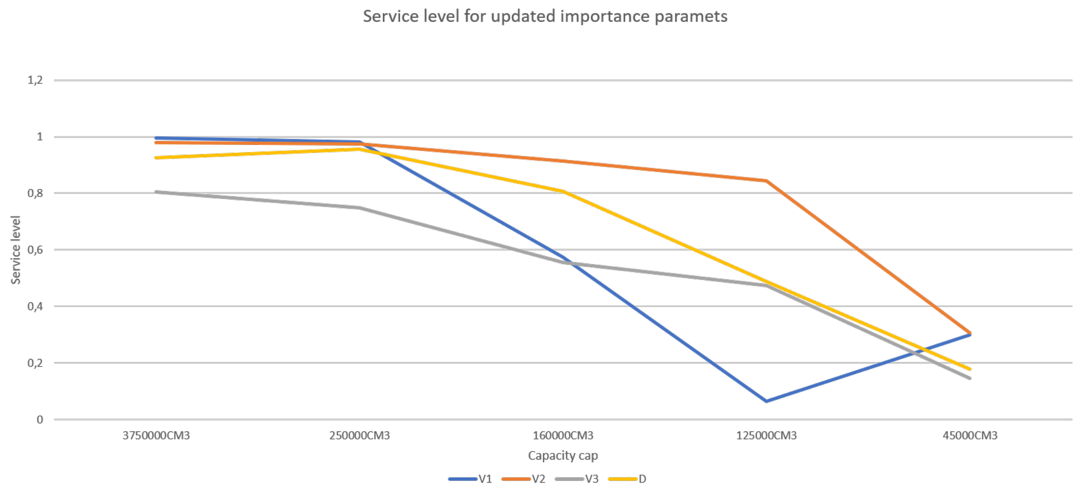


Figure 24: Service level for various capacity caps with increased importance parameters for "V1" and "V3" items.

5.5 Conclusion

In this chapter, we conclude both experiments and answer the research question "*How does the designed inventory approach performs in terms of service level and cost under various simulated scenarios?*". We continue with making a conclusion per subsection.

Conclusion fluctuation in demand and lead time

As expected, variations in demand and lead time cause disruptions in the working of the approach. When not updating the relevant parameters when change in demand or lead time happens, overstocking or under stocking could occur. We conclude the following:

- An uptrend in demand cause under stocking if the safety factors and average use parameters are not updated. The approach fails to have a high enough service level. For V1 items it is therefore important to choose the safety factor on the safe side, to have enough OHI if demand rises. For a downtrend of demand, overstocking could occur.

- For fluctuations in lead time only, the system overstocks when lead time increases and under stocks when lead time decreases. If the lead time increases by more than 200%, large fluctuations in stock are observed, which can cause logistical challenges for staff. Closely measuring and anticipating on matching expected demand with lead time is therefore key.
- When fluctuating both, lead time and demand, we observe that an increase in lead time of a 100% to 200% cause on the average 2,5 times more OHI value. Despite the increase of demand. If demand increases strongly and lead time increases too, safety stocks needs to reconsidered too, since they could not cover for the strong increase in demand. If lead time increases stronger than demand safety stock is enough to cover, but there exist a risk of overstocking. If both lead time and demand increase by approximately the same percentage, the safety stock would not be enough to cover the demand. In all cases an update on the parameters and/or update on the safety factors ensures that inventory management can continue without problems.

Conclusion capacity restriction

The capacity analysis leads to the conclusion that the available capacity plays a crucial role in determining the maximum OHI value and the corresponding service level. In situations where capacity is restricted, adjusting the importance parameters can help in achieving the highest possible service level for a particular group of items. Significant changes in the importance parameter tend to result in a preference for the approach that prioritizes the most important items, but it is important to note that the total size of the items also plays a vital role. In some cases, different settings may result in the approach choosing smaller, less important items over larger, more critical items. It is difficult to assess the system's performance in terms of capacity restriction, and further research is needed to precisely determine the parameters of the various importance groups. Ultimately, the decision will be made by the management.

6 Conclusion and discussion

6.1 Conclusion

The aim of this thesis was to provide insights into how to manage overstocking at the Ålesund hospital. The impetus for the study arose from an internal analysis that revealed approximately 40% of externally ordered items were non moving. Another driving factor was the upcoming renovation of the inpatient surgery rooms in 2024/2025, which would result in reduced space for inventory. To address these concerns, the following primary research question was formulated: "*What inventory approach should the Ålesund hospital adopt for external ordered items to resolve overstocking while at the same time maintaining the service level and complying to the capacity?*". The investigation revealed that the hospital had separate processes for replenishing inventory: one for items supplied internally and another for items ordered externally. However, the external process required a significant amount of staff participation, which detracted from other essential tasks. Additionally, the study identified several reasons contributing to the overstocking issue, including a resistance to change due to past practices, various doctor preferences, and a lack of trust in the system, leading to a preference for a conservative approach. The literature provided further insight into potential reasons, including the need for the hospital to perform well in benchmarking programs and passive risk aversion among staff.

Our study proposes a three-step approach to reduce overstocking, consisting of sorting, standardising, and inventory planning. During sorting, staff critically evaluate items and remove unnecessary ones according to predefined standards. Standardising items by surgery provides insights into future demand and takes away uncertainty, which can help staff to become more actively risk averse. In the third step, staff create an inventory plan that orders necessary stock for plannable items and calculates safety stock based on expected demand for unstandardized items. A simulation model was developed to simulate various scenarios, allowing staff to anticipate orders on changes in demand and lead time. Together, approach and the simulation model, provided a framework to improve inventory management.

A PoP was build for a small category of items and to demonstrate the principle of the approach. We labeled a small category of items and came up with a standardisation. These were inputs for the simulation model. The PoP was extended to a simulation study simulating multiple weeks and kept track of OHI value and service level. The OHI value is an indication for how much stock is on hand and how much budget will be needed, the service level indicates how well the approach works. We observed in the simulation study that an increase in lead time results in more OHI value, which results in a better service level. An increase in demand on the other hand, without updating the safety factors or average demand parameters, ensures lower service levels and lower OHI value. When both variables fluctuates at the same time, we saw that a strong increase in lead time has more consequences than a strong increase in demand. We concluded that relevant parameters in the model should be updated frequently. We further concluded that a short review time and a short lead time makes the model more flexible.

In addition to evaluating the approach on the ability to handle changes in lead times and demand fluctuations, the approach was also assessed its capacity to handle decreases in capacity. The approach utilizes a knapsack algorithm that considers the importance and size of each item when making decisions about which items to include in the inventory. The experiments revealed that varying the parameter settings can lead to different results. In the first experiment, we observed that the initial settings caused a decrease in service level for "V3" items, which is not desirable. Subsequently, in the second experiment, we changed the parameters, leading to a different outcome. In this scenario, the service level for "V1" and "V2" items increased and was deemed more desirable. These findings highlight the importance of carefully selecting and adjusting parameter settings to achieve optimal outcomes when utilizing the knapsack algorithm in the inventory planning process.

The PoP of the research provides quantitative data on the improvement potential of inventory performance by introducing sorting and standardisation. The hospital tried for years to get rid of overstocking, and this approach can be the first system that helps staff reducing stock in a smart and standardised way. Further, this approach provide staff the resources to actively avoid risk, instead of passively and so let the surgery department run more smoothly.

6.1.1 Discussion and validity of the research

In this part of the discussion, we reflect on the validity and reliability of the model. When validating a simulation model or any other type of model, there are two different processes: verification and validation (Pegden, Sadowski, & Shannon, 1995). Verification is the process of assessing that a model operates as intended, while validation is the process of ensuring that the model accurately represents the real world. Verification can be done by debugging the model and checking if the results are as expected, but it is only a necessary, small part of validating.

Internal validity concerns the extent to which a study is conducted with rigor and accuracy. One of the key determinants of internal validity is the input of the model. The data obtained from the hospital regarding item demand is unreliable and therefore invalid. The data reflects reality, but we know that the data contains errors. This affects the empirical distribution used in the simulation study, as well as the expected demand and standard deviation, resulting in a percentage of error compared to actual demand, and thus impacting the accuracy of the simulation. We assumed that the historical surgery planning obtained is reliable and valid, since it reflects all surgeries that happened. For the simulation model we needed information such as which plannable items are used in what surgeries and how is the amount of surgeries per day distributed. The surgery planning was not detailed enough for this. We made an assumption that all "urology og gynecology" items are used in surgeries from the urology department. Staff addressed that that is not necessarily true, but could not provide a full list connecting items with surgeries or departments abbreviations. These assumptions were necessary to generate the OR planning as described in Section 5.2.1. We also assumed that the amount of surgeries per day is normally distributed, while that is in fact not true. The distribution of the amount of surgeries per day has little to no influence on the result of the simulation planning, as long as it is in line with the standard deviation and average. These assumptions have an influence on the internal validity and cause the model to deviate from reality. Content validity deals with how complete the model is and how the variables are correctly related to each other to form strategic and environmental constructs (Carmines & Zeller, 2012; Wenzel & Babbie, 1994). The model is complete in terms of items and could be extended to other items as well. In terms of the simulation study, we used an empirical distribution. A shortcoming of the empirical distribution is that only observed demand values, and everything in between, is used in the simulation study. Extreme outliers which might be possible, are not observed. For plannable items this is not a problem, since the model orders the amount necessary. Another shortcoming of the model in terms of content validity, is the lead time. When unknown, we assumed a lead time of 14 days, while this might not be accurate. For some items we only observed the lead time once or twice, so we can't say for certain that the lead time is accurate. Because, for some items, the lead time is very long ($\geq$ 14 days), this can have consequences on the results. The last concern for the simulation study in terms of content validity, is the standardisation of items. We made an assumption here, as well as the probability of a standardised surgery happening. The combination of items in standardized surgeries might not be accurate and whole other combinations might be possible. However, for demonstrating the working of the approach this was sufficient.

Representational validity in terms of external validity can be described as the concern whether a model behaves in ways that are similar to the real world. Although the simulation in the PoP is not meant to copy the real world, we tried to come as close as possible with reasonable effort. By making substantiated assumptions in areas where they were needed, we could come close to modelling the real world. The tool itself, without the simulation model, is generally applicable. The math behind the algorithm provides an estimation on future use of not plannable items based on 1,5 years of historical data. Setting the correct safety factors should assure the target service level. For plannable items with a short lead time the tool would work if nothing unforeseen would happen in the supply chain causing higher lead times. The simulation should provide staff with insight into how to deal with inventory and what the benefits of standardization and planning are. The tool helps staff by generating an order list on a weekly basis for schedules that are fixed two weeks in advance. Showing staff the PoP gained positive feedback, but it is up to a final version to validate how staff trusts and uses the tool and so to establish the educational external validity.

6.2 Further research

This research presents a first version of an approach that helps the hospital reduce overstocking. During the research, we noticed several aspects that needs further research. The approach works with safety factors. For the PoP we initialised these per importance category. Further research can lead to an answer whether this is the best way to do it and what the exact safety factors must be. The target service level was set to some value to show the principle and to show that there must be a hierarchy, but further research is needed to determine the exact value of the service levels. We further set a value per importance category. But as the simulation study showed it is crucial to set these right. Further research is needed to the exact distribution of the numeration of importance categories. Further research is also necessary on how to handle items that are indicated as important by staff, but have an average demand of zero according to historical data.

This study primarily aimed to transform the risk-averse behavior of staff from a passive state to an active one, specifically concerning stock management. However, the observation that doctors use various tools for the same surgical procedure has not been incorporated further into this thesis. Further research is required to determine effective approaches for motivating doctors to adopt an active risk averse mindset, as opposed to a passive one.

At Ålesund Hospital, we only researched the external ordered items, as internal ordered items did not appear to be problematic. However, it would be beneficial to evaluate internal ordered items as well and to develop an approach for integrating the restocking processes of both internal and external items.

6.3 Design aspects for use of the tool

In order for staff to use and trust the tool, it must perform as expected and meet the desired requirements of the hospital staff. If the tool is developed as a separate program, rather than being integrated into SAP, it would be advisable to conduct further research to identify the key factors that are important for successful adoption. We have already conducted some preliminary work in this area, which we believe will be useful for guiding further research. Specifically, we have developed guidelines for designing the tool, which take into account general principles of User Interface (UI) and User Experience (UX) design that are relevant to the hospital context and are supported by the literature.

The approach is developed for the healthcare sector and therefore aspects related to this field must be taken into account. Bardram (2004) wrote a paper about context-aware working in a hospital setting. The paper explains the importance of privacy and security even as the need for innovation. As the hospital grows and innovates, the tool on which the approach is executed must grow with the hospital. A correct program that supports these circumstances is therefore crucial. A spreadsheet program, such as Excel, supports these needs and provides the flexibility of programming for specific functions that are difficult to implement within a cell only. All staff know Excel and it is therefore recommended to make the tool user-friendly for the end user.

We summarize general design principles found in literature that help in designing an appealing and easy-to-use UI and motivate staff to use the tool and avoid errors.

- Avoid overwhelming the user (Hadi, Tawfeeq, & Gh Saeed, 2014). Create a clean dashboard and hide advanced settings and detailed KPIs in other menus. This way, the user is not overwhelmed with options that may not be necessary every time the model is run.
- Be consistent in language, colors and design. Use, for example, red for errors, yellow for advice, and green for positive notifications Marcus (1995). To make the user feel more connected to the tool, use the company style format, for example. Be consistent with language and colors and make it identical to other systems that staff uses, so that staff does not have to interpret the meaning of a color or word, but can use a fast perceptual judgement.
- Be concise in wording when giving instructions. For example, "To [accomplish the stated goal], [do this]". This prevents errors associated with acting in response to a prompt before reading the consequence of an action. (Horsky et al., 2012, p. 1206)
- Integrate a convenient, straightforward, workflow in the tool. According to Bates et al. (2003), a primary concern of many clinicians is the speed of completing tasks. They need to rapidly receive advice and take appropriate action. The difficulty of interaction is directly related to the amount of clicks needed to obtain a result. Therefore, integrate a convenient workflow that minimizes the amount of clicks to obtain an advice. Make it clear where to start, what to import, and how the tool ends.
- Present the advice in a way that generates trust over time. Staff must be convinced that advice is accurate. Therefore explain to staff why a decision was made. This helps by avoiding the impression of being a black box and helps staff to trust and understands the system. A log for example with calculations could also help by understanding why an advice was generated.

- Don't let the system provide commands, but rather assessments, suggestions and recommendations. According to Walter and Lopez (2008), clinicians may perceive computer-generated, overly prescriptive advice infringing on their sense of professional autonomy. Therefore systems should formulate advisory messages and highlight potential and actual problems that require attention and suggest actions rather than dictate them.

- Have appropriate and representational formats of data and distinctive entry screens. The representation of the ordering advice is important for supporting quick perceptual judgements and accurate decisions (Zhang & Walji, 2011). Screens, modules and dialogs for ordering or advice for ordering should be clearly visually distinguishable by layout, color or shape.

A Appendix

A.1 Appendix chapter 2

A.1.1 Impression of the current situation

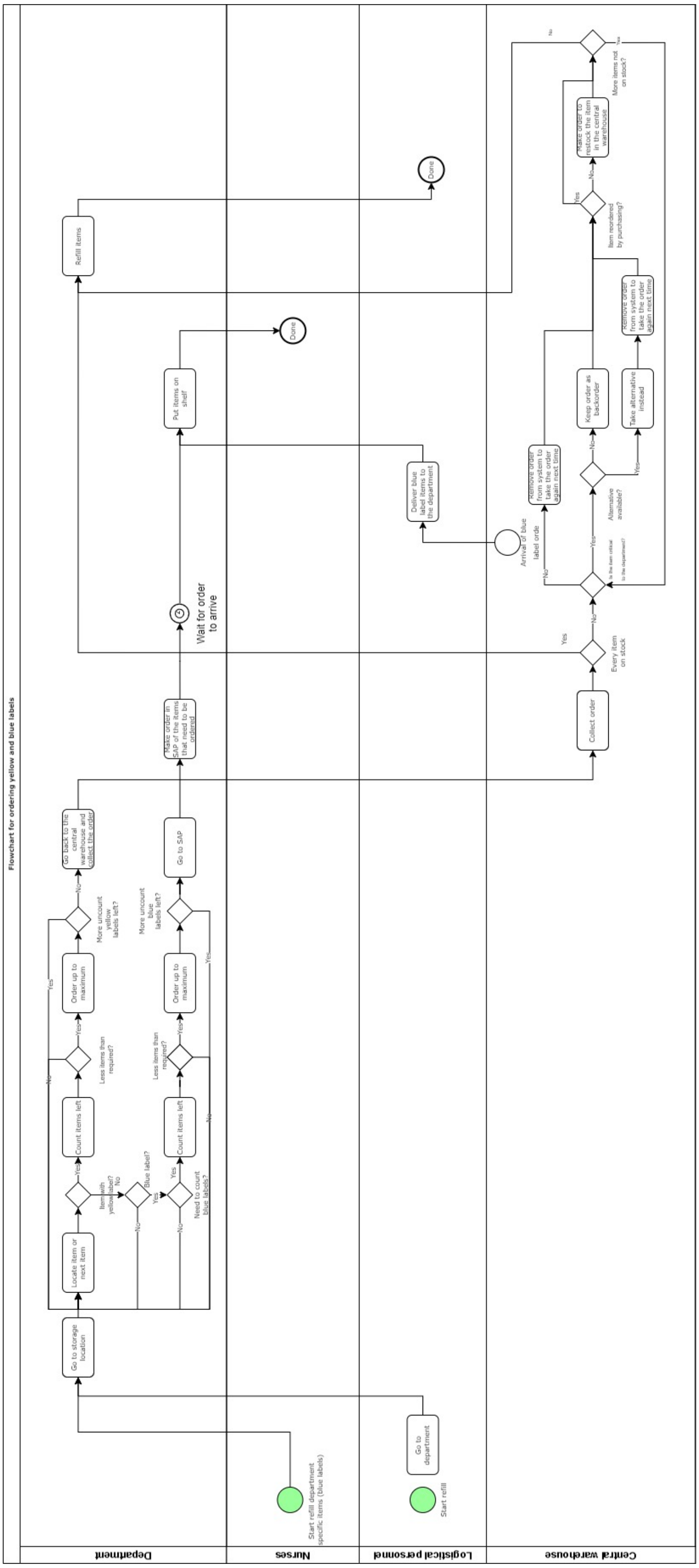
(a) Situation of a full storage locker. Date: 3 November 2022

(b) Full and unorganized parcel receiving room. Date: 3 November 2022

(c) The sacrificed OR for storage. Date 3 November 2022

(d) Evacuation hallway, behind the ORs, full with storage. Date: 3 November 2022

A.1.2 Current ordering process flowchart



A.1.3 Example of barcode

Figure 26 shows an example of a yellow label. This label contains the following information:

1. Barcode.

2. Item number.
3. Name of the good.
4. A handwritten number.

The barcode is used for taking the order and refers to the item in SAP. Under the barcode we find the item number. Further the name and a handwritten number. This handwritten number is the order up to level. The order up to number is not present on blue labels. Since these articles are ordered directly from the manufacturer, it is only possible to order a full box.

Figure 26: Example of a yellow label containing information about the SKU

A.1.4 Codes of the demand and supply datasheet

Code	**Definition**
101	Book stock in, resupply
102	Book in reserved stock
201	Book stock out for use
202	Book stock back in when taken the wrong item for example
301	From Central warehouse to A200
309	From department to A200
311	From A200 to another department
501	Book in consignment stock without making a purchase
502	Book consignment stock out without making a purchase
551	Used when items are expired or damaged and need to be thrown away
701	Stock adjusted up after counting items, correct number of items
702	Stock adjusted down after counting items, correct number of items

Table 5: Table: definition for codes in Demand and Supply sheet

A.1.5 Data preparation

In this Appendix can be read what data we obtained and how we prepared the data for further analysis.

We got four sources of data, namely:

1. All items that are on stock in the A200 storage. A200 refers to department (avdeling) 200, which is the inpatient OR.
2. A datasheet containing minimum amounts of stock and maximum amounts of stock for a certain SKU.
3. Demand and supply data for 2021 and 2022 for the consignment articles and for blue label items.
4. Billing data for items supplied by the central warehouse (yellow labels) to the inpatient OR or to Steril Central.

To come back at point 4. Steril Central cannot order items by them self, this has grown so over time. Therefore the inpatient OR department pays for their reusable items. According to hearsay statements this is not a big part, however we could not quantify this.

For the data set containing consignment SKUs and blue label SKUs, we find in total 2887 different item. 1283 items are consignment SKUs, 1604 items are blue label SKUs, or bought consignment stock. From the 1604 blue label SKUs, we have 303 SKUs that have zero items on hand or should be removed from the SAP system (indicated with a X). We remove these 303 items from the data set, since they are not relevant for the research. 1301 blue label SKUs remain. For the consignment articles, we find 205 items that have an on hand inventory of 0 or have an X. We remove these items from the data set too, since they are not relevant for the analysis. We remain having 1078 lines of consignment SKUs with inventory on hand.

The demand and supply data sheet is a collection of actions that happened to the consignment and blue label stock over the last two years. The starting point of this data set is 04/01/2021 and the end date is 09/11/2022, containing 21642 actions. The actions are indicated by codes, these codes and meaning of the codes could be seen in Appendix A.1.4. The change in inventory level per day can be calculated with equation 3. Note that the numbers present in equation 3 referring to the codes in Appendix A.1.4

$$Change\ inventory\ Level_{dayt} = 101-102+201-202+301+309-311+501-502-551+701-702 \quad (3)$$

Inventory Value To calculate the inventory value per month. We created a datasheet in Excel where all blue label items were in column A and all dates in between the lowest and highest date in the data set in row 1. In calculated the on hand stock per day. If the On Hand stock was negative, we set the value back to 0, because on hand stock can not be negative. Later we aggregated the on hand inventory per day to months. We multiplied the average stock per month with the value of the stock (assuming the value did not change over time) and summed that all together. The result can be seen in 3.

Ready Rate To calculate the RR, we took the same format as for Inventory Value. Only here we did not set the negative values back to zero. From here we used a VBA script in excel. The script first checked if the first cell was not zero. If the cell was not zero, we used a count if function to count all cells that had an inventory higher than 0 and divided that by all cells containing the Net Stock (NS). If the firs cell was zero, the script searched the first cell that was not zero and than performed the calculation for the RR.

Inventory Turnover Rate For the inventory turnover rate we need the cost of goods sold per time period, year in this case. Therefore we create another data sheet, this time only with the demand. We will sum the demand per year and monetize that with the corresponding value. That we divide by the average OHI in NOK. For some items the value is set to zero. That means that some of the items from the OHI do not count for the analysis, since dividing by zero is not possible.

The demand is addressed with the following code in the data, namely: 201. However from hearsay it could also be that used stock is addressed with 102. Code 551, which is for expired products, is sometimes mixed up with code 201. Therefore we can not completely rely on code 201, but we can also not compensate for this.

Dead and excessive stock Dead stock refers to outdated stock still hold in inventory. Excessive stock refers to stock that is in stock in large quantities and can take long before the stock is depleted again.

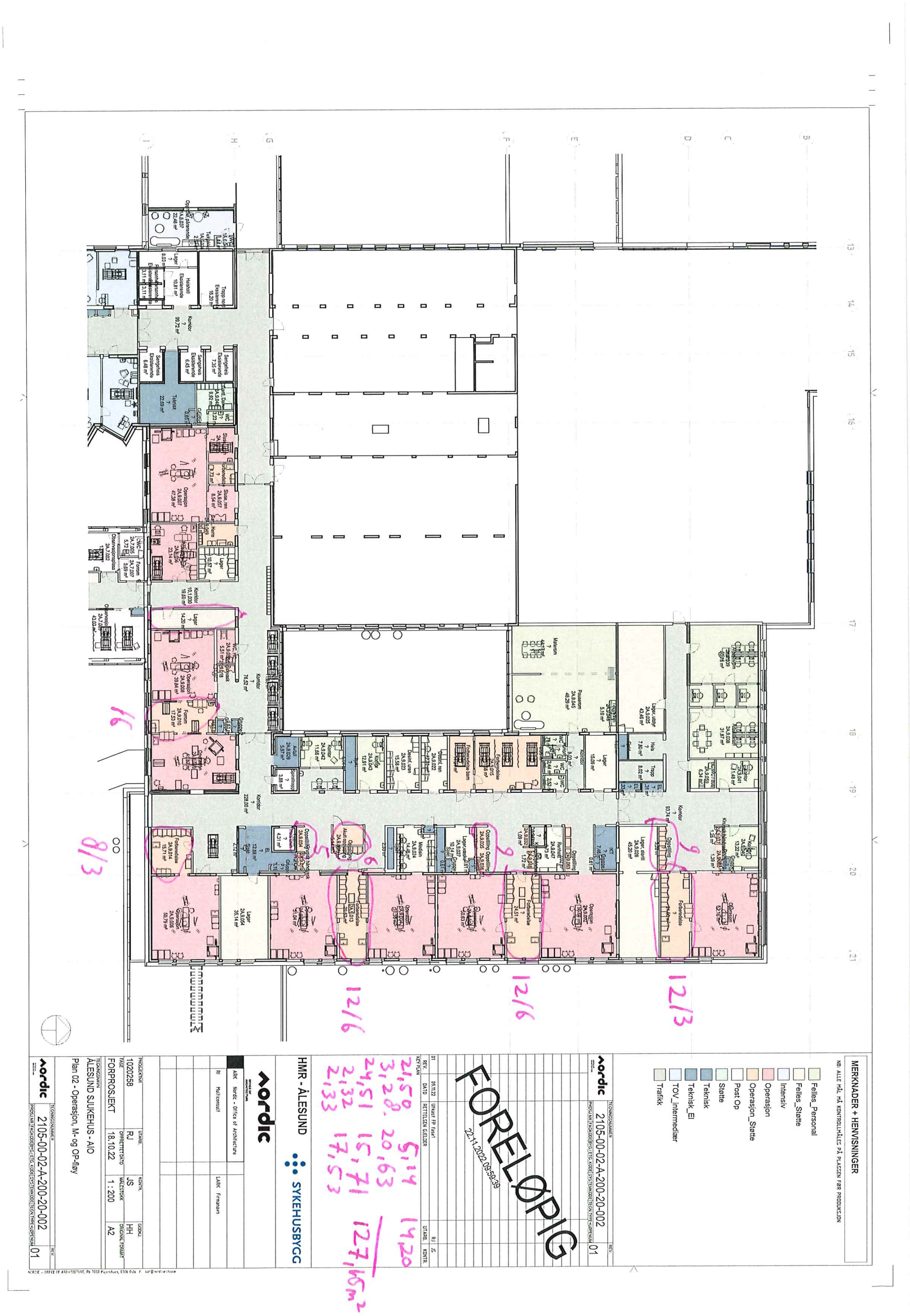
A way to determine what items are dead or excessive stock, is to use equation 4. Equation five is very much similar to ITR equation. The difference is that with the ITR we can determine how often we sell our inventory. With equation 4 we can determine how long the hospital has stock on average, before the stock is depleted.

We use the same data as we did for the ITR calculation, but now only over 2021, since 2022 is not complete yet. We are aware that therefore we miss certain SKUs, that were not in inventory in 2021, but are in 2022. However, since 2022 is not over yet, we do not have sufficient data on those items to make a reliable estimate. Further, this analysis is to get an idea about the current state.

We calculate the average OHI for 2021 and we sum the demand of 2021. The sum of demand will be our best estimate of the average demand per year, since we only have one year of data. We divide those according to Equation 4.

$$Time\ till\ item_i\ in\ inventory\ is\ depleted = \frac{Avg\ OHI\ of\ SKU_i}{Avg\ demand\ of\ SKU_i} \tag{4}$$

A.1.6 Map of the renovated OR department



A.2 Pseudo code for inventory plan construction algorithm

```

’pseudo code for making the inventory plan
for ’loop over all items
  if categorization not empty ’check importance
    ’check lead time, current stock, average use, standard deviation.
    if ’item is standarized
    ’check lead time, current stock, average use, standard deviation.
    ’check schedule
      ’if surgery is planned where they need this item.
        ’predict the amount of items needed for surgery
        ’if item is not V3
          ’check how much items will be used besides the planned items
        ’end if
        ’if leadtime >=14 and item is V3 days.
          ’check if after prediction enough is still in stock
          ’if not, advice to order enough for inventory
        ’end if
        ’check how much is already on order
        ’compare to current inventory level
        ’give advice on how much to order, if any

      ’else: no surgery planned where they need this item
        ’check importance
        ’do prediction on how much will most likely be used over the comming planning horizon
        ’if leadtime >=14 and item is V3 days.
          ’check if after prediction enough is still in stock
          ’if not, advice to order enough for inventory
        ’end if
        ’compare to current inventory level
        ’check how much is on order
        ’compare to current inventory level
        ’give advice on how much to order, if any

    else ’not standarized

    end if

  else ’if item is not categorized give warning
  ’Place on warning tap warning

  end if
next

’test on capacity
’if capacity is voilated
  ’change solution
’else
  ’Present solution
’end If
```

Listing 1: Pseudo code for construction algorithm

A.3 Knapsack LP model

Index

i: item $i \in Items\ \{1, .., Number\ of\ items\}$

Variables

X_i: Amount of item i to order

Parameters

C: Total capacity

I_i: Importance of item i $\frac{Importance}{size\ in\ volume}$

S_i: Space of item i in volume

A_i: Advised amount to order of item i

P_I: Amount of items planned in OR planning of item i.

objective function

$\max \sum_{i=1}^{Items} X_i * I_i$

S.T.

$$\begin{array}{ll} \sum_i X_i * S_i \leq C & \\ X_i \leq A_i & \forall i \\ X_i \geq P_i & \forall i \\ X : Integer & \end{array}$$

A.4 Result simulations

A.4.1 Calculation safety factors

This section in the appendix summarizes the results per safety factor. For each different safety factor we simulated 2500 weeks in a simplified Python simulation. The table below shows the average service level per safety factor (header) per importance label. A colored cell means that the corresponding safety factor is chosen as the safety factor for further simulations. We observe a DIV/0! error for the importance category "E". This is due to the lack of data for E items. The data set contains one E item. This item had zero demand and so the demand distribution is unknown. Therefore a service level could not be obtained.

Safety Factor \ Importance	**0**	**0,25**	**0,5**	**0,75**	**1**
V1	0,7963277	0,75493827	0,947203	0,946767	0,952201
V2	0,9054042	0,90704157	0,927574	0,943227	0,95266
E	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
D	0,9544818	0,9608512	0,979813	1	0,981132
	1,25	**1,5**	**1,75**	**2**	**2,25**
V1	0,9364802	0,97502714	0,972433	0,983631	0,966785
V2	0,9669903	0,96749628	0,986988	0,991433	0,991741
E	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
D	0,9680851	0,95646946	1	0,983607	0,994845
	2,5	**2,75**	**3**	**3,25**	**3,5**
V1	0,9990494	0,99651568	0,99639	0,998783	1
V2	0,9916922	0,98922984	0,989429	0,99652	0,995354
E	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
D	0,9860734	1	1	1	1

Table 6: Result of simulating 2500 weeks with different safety factors

A.4.2 Executed experiment settings

Experiment settings for various demand fluctuations

Exp	**Settings demand fluctuations (LB ; UB)**
1	(0 ; 0,5)
2	(0,1 ; 3)
3	(1 ; 1,5)
4	(1 ; 2)
5	(1 ; 2,5)
6	(1 ; 3)
7	(2 ; 4)
8	(3 ; 4)
9	(4 ; 5)

Table 7: Experiment settings for various demand fluctuations.

Experiment settings for various lead times

Exp	**Settings lead time**
1	(0 ; 0,5)
2	(0,1 ; 0,5)
3	(0,1 ; 3)
4	(1 ; 1,5)
5	(1 ; 2)
6	(1 ; 2,5)
7	(1 ; 3)
8	(2 ; 3)
9	(2 ; 4)
10	(3 ; 4)

Table 8: Experiment settings for various lead times.

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