Master's thesis

NTNU
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Inventory Classification Approaches for Ordering Policy Selection in Non-pharmaceutical Hospital Warehouses

Master's thesis in Mechanical Engineering
Supervisor: Fabio Sgarbossa
June 2023

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UNIVERSITETSSYKEHUSET I TRONDHEIM

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Preface

This report is a result of my master’s thesis with a specialization in production management at the Department of Mechanical and Industrial Engineering at NTNU. The research was carried out between January and June of 2023 in the final semester of the 5-year master’s program in Mechanical Engineering.

I am grateful to my supervisor Professor Fabio Sgarbossa for valuable advice and guidance throughout the semester. I would like to thank him for useful brainstorming sessions and thought-provoking questions. I would also like to thank Aili Biriita Bertnum and Mathias Farstad from Logistikksenter Helse Midt-Norge for taking the time to provide the necessary information and data to complete this thesis.

Furthermore, I would like to thank my parents for always supporting me, and particularly for their constructive feedback and suggestions regarding this thesis. Last, but not least, I am grateful to my fellow students in room 225 for their uplifting presence, encouragement, and meaningful conversations. This year would not have been the same without all of you.

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Trondheim
June 8th, 2023

Summary

With an aging and increasingly diverse population, there is an imminent need to improve the resilience of healthcare supply chains. Inventory management has been proposed as an improvement area allowing cost reductions and increased efficiency in healthcare supply chains, without sacrificing the quality of patient care in hospital wards. A key component of inventory management is the question of how much to order and when, which is answered through the implementation of ordering policies. Inventory classification can be used to simplify several inventory management practices such as the selection of ordering policies. There is a research gap in ordering policies for non-pharmaceutical hospital goods. This thesis investigates the use of inventory classification for the selection of ordering policies in non-pharmaceutical hospital warehouses.

The research is structured according to the following research questions; 1) How can inventory classification aid in selecting ordering policies in non-pharmaceutical hospital warehouses? 2) To what extent does the definition of inventory classification criteria levels affect ordering policy selection in non-pharmaceutical hospital warehouses? 3) To what extent do the results of this research point to a set of inventory classification criteria levels that could be used for ordering policy selection in non-pharmaceutical hospital warehouses?

The research design combines a literature study with a case study at the Helse Midt-Norge Logistics Center to create an inventory management framework for non-pharmaceutical hospital warehouses, which is tested through a simulation study. The defining characteristics of non-pharmaceutical hospital goods were used to create classification criteria, which led to ordering policy selection criteria for use in the framework. The two main steps to applying the developed inventory management framework are definition of the inventory classification criteria levels and selection of ordering policy based on these definitions.

Inventory classification criteria level definition will depend on the warehouse in question and the resources available. The testing of the framework showed how classification criteria level definition has a significant impact on ordering policy selection, regardless of the criterion. Results from the simulation study show that classification criteria levels based on information from the case warehouse are only in partial agreement with framework suggestions. Therefore, classification criteria level definition should be investigated further in future research on the topic.

The major contribution is synthesis of existing research on inventory classification and hospital inventory management, increased understanding of criteria level definition for classification of non-pharmaceutical hospital goods and its impact on ordering policy selection. The output of this study provides groundwork for future research to increase the knowledge in the aforementioned areas.

Sammendrag

Med en aldrende og stadig mer mangfoldig befolkning, er det et overhengende behov for å øke robustheten til verdikjeder innenfor helsetjenesten. Lagerstyring har blitt foreslått som et område hvor kostnader kan reduseres og effektiviteten økes i helsevesenet uten at det går utover kvaliteten i pasientbehandling ved sykehusavdelingene. Et sentralt spørsmål i lagerstyring er hvor mye som skal bestilles og når, og det besvares gjennom implementering av bestillingspolicyer. Vareklassifisering kan brukes for å forenkle flere lagerstyringspraksiser, for eksempel valg av bestillingspolicy. Det er en mangel på forskning på bestillingspolicy for ikke-farmasøytiske sykehusvarer. Denne oppgaven undersøker bruken av vareklassifisering som grunnlag for valg av bestillingspolicy for ikke-farmasøytiske sykehuslagre.

Studien er bygd opp etter følgende forskningsspørsmål; 1) Hvordan kan vareklassifisering bidra til valg av bestillingspolicy for ikke-farmasøytiske sykehuslagre? 2) I hvilken grad påvirker definisjonen av kriterienivå for vareklassifisering, valg av bestillingspolicy for ikke-farmasøytiske sykehuslagre? 3) I hvilken grad peker resultet av denne forskningen på et sett med kriterienivå for vareklassifisering som kan benyttes i forbindelse med valg av bestillingspolicy for ikke-farmasøytiske sykehuslagre?

Denne oppgaven kombinerer en litteraturstudie med en casestudie ved Logistikksenter Helse Midt-Norge (HMN) for å utforme et rammeverk for lagerstyring av ikke-farmasøytiske sykehusvarer, som testes gjennom en simuleringsstudie. De definerte egenskapene til ikke-farmasøytiske sykehusvarer ble brukt til å lage klassifiseringskriterier, som deretter ble basis for kriterier for valg av bestillingspolicy for bruk i rammeverket. To hovedtrinn er identifisert som nødvendige for bruk av rammeverket i praksis; definisjon av nivåene for klassifiseringskriteriene og valg av bestillingspolicy basert på disse definisjonene.

Definisjonen av klassifiseringskriterier vil avhenge av det aktuelle lageret og tilgjengelige ressurser. Testing av rammeverket viste hvordan definisjon av nivå for klassifiseringskriterier har en betydelig innvirkning på valg av bestillingspolicy for alle kriteriene. Resultat fra simuleringseksperimentene viser at nivåene for klassifiseringskriteriene basert på informasjon fra Logistikksenter HMN ikke er helt sammenfallende med anbefalingene basert på rammeverket. Definering av nivåer til klassifiseringskriterier er derfor et område det bør forskes videre på.

Hovedbidraget fra denne studien er syntese av eksisterende forskning på vareklassifisering og lagerstyring av sykehuslagre, økt forståelse av definisjon av kriterienivå for klassifisering av ikke-farmasøytiske sykehusvarer, og dens innvirkning på valg av bestillingspolicy. Resultatet av denne studien gir grunnlag for fremtidig forskning for å øke kunnskapen innenfor de nevnte områdene.

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List of abbreviations

AHP: Analytical hierarchy process

ANP: Analytical network process

EOQ: Economic order quantity

ERP: Enterprise resource planning

FOI: Fixed order interval

FTL: Full truckload

HMN: Helse Midt-Norge

LTL: Less than truckload

MCDM: Multi-criteria decision-making

OP: Ordering policy

POQ: Period order quantity

POU: Point of use

RFID: Radio frequency identification

ROP: Re-order point

SCM: Supply chain management

SD: Standard deviation

SKU: Stock keeping unit

SS: Safety stock

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1 Introduction

The introduction delves into the background and motivation of this thesis, rooting in the inventory management of non-pharmaceutical hospital warehouses. The research questions and objectives are presented based on the background and motivation. Before the research development and thesis structure are presented in relation to the research questions and objectives, the scope of the study is described.

1.1 Background and motivation

Inventory is a store or stock of goods and can be supplies or materials carried on-hand for sale or for further production of finished goods. Inventory management is a core operations management and logistics activity which includes managing the inventory a firm has on-hand, but also ordering frequencies and quantities (Chapman *et al.*, 2017, p. 24). In inventory management, an individual item in stock is referred to as a stock keeping unit (SKU). An SKU is unique in terms of size, brand, color, price and type of customer (Stevenson, 2021). The goal of keeping inventory of finished goods is to protect against variation in supply and demand. Some of the challenges related to inventory management are the volumes of goods to keep in stock, which materials should be in stock, and which are to be delivered. Ordering policies are used to determine how much should be ordered and when of each SKU.

Inventory management in hospital warehouses is a critical aspect of healthcare operations that involves controlling the flow of medical supplies and equipment (Parsa *et al.*, 2011). Hospitals rely on a well-functioning supply chain to ensure that they have the right products available when they are needed. To achieve this, hospital warehouses must manage their inventory levels carefully to avoid overstocking or running out of supplies. This requires a combination of forecasting demand, setting ordering policies, and monitoring inventory levels in real time.

The key in hospital inventory management is balancing the tradeoff between costs and quality of patient treatment, where the quality of treatment is seen as the most important factor (Fragapane *et al.*, 2019). This differs from most traditional manufacturing settings since the consequences of a stockout can lead to disease, sickness and even fatalities. A representation of the hospital inventory supply chain is presented in Figure 1: Standard hospital supply chain.

Figure 1: Standard hospital supply chain

The material suppliers provide inventory items to the healthcare logistics HUB, which can also be referred to as the central store warehouse, where inventory is kept until it is distributed to the hospitals. The hospitals then distribute the items required to the specific ward. In the healthcare supply chain there is an internal and an external chain which manages both medical and surgical supplies, as well as pharmaceutical products (Landry and Beaulieu, 2013). Non-pharmaceutical hospital goods are any items stocked at a hospital warehouse that are not considered pharmaceutical, medicinal, or biologically derived. These items are usually managed by a materials management department, which has the responsibility of receiving goods at a central store warehouse, storing the inventory, and deliveries to the points-of-use (POU) at a hospital (Landry and Beaulieu, 2013). Goods in this product group include both products that directly support the delivery of care, such as medical supplies, but also indirectly, such as stationery and cleaning products. Products in the healthcare sector are generally very customized, with a lower quantity requirement per item and there is often a need for a combination of different items for treatment of each individual patient (Battini *et al.*, 2014).

Classifying SKUs in inventory based on their defining characteristics is a crucial tool in simplifying the inventory management in warehouses containing many different types of products. There are several ways of classifying inventory. Some common techniques are classification based on annual dollar usage, pricing, expiration, criticality, demand, availability, and turnover rate (van Kampen, Akkerman and Pieter van Donk, 2012).

Lately, there has been a trend in increasing shortages of nurses, doctors and supporting staff, while the demand in hospitals has increased (Fragapane *et al.*, 2019). Additionally, patients expect treatment of a higher quality than earlier. The varying patient mix in hospitals creates large varieties in the demand, and the susceptibility to disruptions such as pandemics, war and natural disasters makes both the demand and supply unpredictable. Recently, inventory management in healthcare has been recognized as an important driver for increasing efficiency, as well as reducing costs and waste, whilst ensuring high quality patient care (Volland *et al.*, 2017).

Some important factors influencing the financial resources spent on healthcare are the population number, proportion of elderly people and the average income per person (Battini *et al.*, 2020). Public health spending could increase between 40-60% by 2050 for the EU countries, as projected by major international institutions. According to the statistical office of the European Communities (*More than a fifth of the EU population are aged 65 or over - Produit Actualité Eurostat - Eurostat*, 2021) 20.6% of the EU population was aged 65 years or older, which was 3 percentage points higher than the corresponding share from a decade earlier. Additionally, it is estimated that one third of the European population will be over 65 by 2060 (*European Commission issues 2021 Ageing Report | www.europeactive.eu*, 2021). A report by the United Nations on the aging world population (United Nations, 2018) shows how in various European countries healthcare expenses tend to increase exponentially as the population grows older. Furthermore, it is appropriate to assume this trend will continue as the population continues to age.

A report by the Norwegian Nurses Organization (NSF) highlights how the current health sector is nowhere near being able to meet the future demand for healthcare services and how this should be considered one of the most significant issues of our time (Døhlsmo *et al.*, 2021). Numerous areas of the healthcare sector in Norway are overloaded. The main causes of increased future demand for healthcare stem from a growing and aging population, as well as a steady increase in chronic illnesses. According to the Norwegian statistics bureau (SSB) it is expected that the staffing requirement in the Norwegian healthcare system will double by 2060 (Hjemås, 2019). In the case that the demographic and epidemiological circumstances diverge more than expected, the requirements may be even higher. Figure 2 shows the indexed development in the aged population between 2000-2020 and the expected increase in the years until 2040.

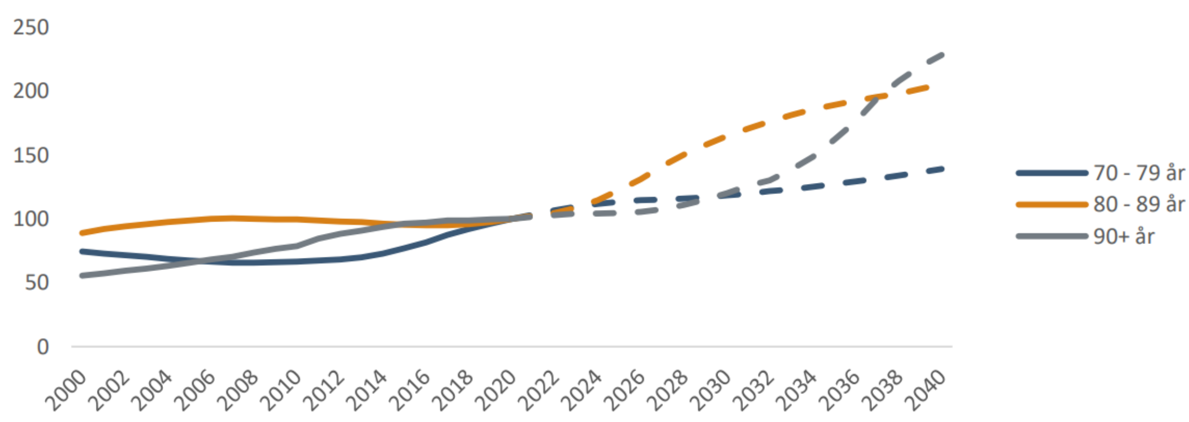


Figure 2: Aging population development 2000-2020 and until 2040 (Døhlsmo et al., 2021)

The Covid-19 pandemic greatly impacted several global sectors, including healthcare. Not only did the pandemic create a spike in demand for healthcare supplies due to the sudden increase in hospital patients and sickness in the general population, but supply was also significantly affected. Ripple effects from the pandemic have shown that the global healthcare supply chain needs to increase its resilience to unpredicted disruptions (Golan, Jernegan and Linkov, 2020).

Another example of a disruption in the healthcare supply chain, both unprecedented and unpredicted, was the blockage of the Suez Canal in March 2021 (Ramos *et al.*, 2021). The unanticipated shutdown of this crucial trading passageway caused a global shortage of many essential items, including surgical and medical supplies. The crisis was exacerbated, because many parts of the world were still greatly affected by the Covid-19 pandemic. This incident further highlights the need for the global healthcare supply chain to increase its resilience.

One study on inventory solutions for hospitals (Kelle, Woosley and Schneider, 2012) finds that inventory costs make up around 10-18% of hospitals' net revenues. Logistics and materials management have not traditionally been prioritized in hospital management due to the hospital's main goal of effective patient treatment, as well as the complexity of healthcare supply chains (Battini *et al.*, 2020). It has also been pointed out that organizations in the healthcare sector should stop thinking like hospitals and add elements from manufacturing companies in order to become more efficient and lower costs (*March 23, 2005 - Rattling the Supply Chain: The Opportunity for Supply Chain Management in Healthcare - Smarter Health Seminars 2004 - 05: Emerging Solutions - The infraNET Project*, 2005). Inefficient and redundant processes have been shown in several studies to be the cause of excess waste and costs in healthcare supply chains (Battini *et al.*, 2020). Following the publication of the Global Sustainable Development Report by the United Nations in 2019 there has been a heightened pressure for organizations in all sectors to contribute to sustainable development and reduced waste (United Nations, 2019).

In 2022 the Central Norwegian Regional Health Authority, Helse Midt-Norge (HMN), initiated a centralization and modernization process in their warehouses. This opened an opportunity for evaluation and optimization of their current inventory management practices towards the impending challenges of the near future. The new requirements for the healthcare sector regarding increased demand, as well as the possibility of significant disruptions in the global supply chain motivate the need for more efficient and resilient delivery of healthcare supplies. The advancement of inventory management methods has been recognized as a way of optimizing the healthcare supply chain without negatively impacting the end patient at hospital wards. As ordering policies contribute to answering the main questions in inventory management of how and when to order, they are a natural starting point for research aimed at improvement. This thesis will combine theory on inventory classification, ordering policies, and healthcare supply chains with a case study at a local hospital warehouse to develop and test a framework for ordering policy selection of non-pharmaceutical hospital goods through a simulation study.

1.2 Research questions and objective

Based on the theoretical and practical motivation presented in the preceding chapter, the research questions and objective of the study are presented. The main objective of the study is to investigate how inventory classification can be used as a tool in decision-making for the selection of ordering policies in non-pharmaceutical hospital warehouses.

The research questions are as follows:

1. *How can inventory classification aid in selecting ordering policies in non-pharmaceutical hospital warehouses?*

The first research question is necessary to map the current literature on the theory of inventory classification with regard to ordering policy development in general, as well as within the healthcare sector. A framework for inventory management of non-pharmaceutical hospital goods is developed based on results from a case study warehouse, in addition to background theory and a literature study on inventory classification, non-pharmaceutical hospital inventory items and ordering policies. There are two steps to applying the resulting inventory management framework; definition of classification criteria levels and selection of ordering policy based on the defined criteria levels. This is the baseline for the subsequent research questions.

2. *To what extent does the definition of inventory classification criteria levels affect ordering policy selection in non-pharmaceutical hospital warehouses?*

The second research question is necessary to tie the developed framework from the first research question into practice and to show how the application of the developed framework can be carried out in existing non-pharmaceutical hospital warehouses. It links the two steps of framework application together and investigates the correlation between classification criteria level definition and ordering policy selection. This is done through a simulation study together with a sensitivity analysis, based on data and information from the case study warehouse. The simulation experiment results are compared by examining two key performance metrics: service level and available inventory. Service level in inventory management is defined numerically as the number of times an item is provided on demand divided by the actual demand of the item (Vaz *et al.*, 2020).

3. *To what extent do the results of this research point to a set of inventory classification criteria levels that could be used for ordering policy selection in non-pharmaceutical hospital warehouses?*

The last research question focuses on the first step of the framework application and investigates the possibility of defining a set of classification criteria levels using results from the case study and the simulation study. Simulation results based on classification criteria levels chosen using data from the case study warehouse are compared to results from the sensitivity analysis by examining to what degree they correlate with the suggestions from the developed framework. This is meant to give an indication of the validity of the proposed criteria levels.

1.3 Research scope

The research scope outlines the boundaries and limitations of this study, including the research questions, literature study, case study and simulation study. The scope of this thesis encompasses several key aspects that are critical to ensuring effective and efficient delivery of medical supplies to hospitals. A supply chain is defined as *a sequence of organizations, their facilities, functions, and activities, that are involved in producing and delivering a product or service* (Stevenson, 2021, p.656). This research takes a supply chain management perspective, where the central objective is to ensure a match between supply and demand across all members of the supply chain, as opposed to solely prioritizing process optimization for singular corporations. Therefore, the focus will not be on the management of inventory, material flow or information flow within a warehouse, but more directed towards the inbound and outbound flow of materials and what the effects are towards the end patients at the POU. As the focus is hospital warehouses, the scope is limited to organizations with a more service-level oriented target, and with less of an interest in profit and economic gain. This research will, however, not include drug inventories or logistics of human blood sample inventories. The study will be limited to non-pharmaceutical products distributed from a central warehouse to POU locations, as pharmaceutical products such as medicines and vaccines are traditionally managed by a pharmacy. As shown in Figure 3, the focus area of this research does not include the warehouse suppliers, the hospitals, or the wards, but the information flow in and out of the warehouse from other actors in the supply chain is necessary to consider.

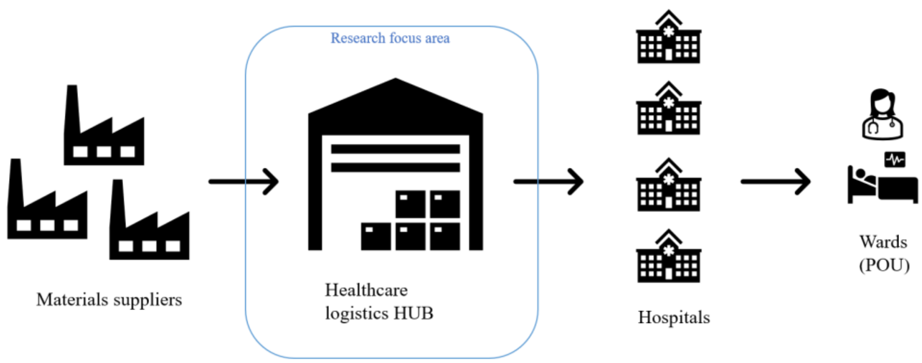


Figure 3: Research scope relating to the hospital supply chain.

There currently exists extensive research covering the inventory management of medicines, and blood samples have distinctive defining characteristics which present other requirements to inventory management, further creating a scope too wide for this study. Regarding the case study there is limited information available regarding suppliers, so this will be left out of the focus area of the research. Regarding the simulation study, many simplifications and assumptions are made to generalize the research and cater to certain constraints of the study, regarding time and information provided from the case warehouse. For these reasons, many details are left out of the scope of this study.

The research does not cover all important aspects of the topic, but an attempt has been made to address the areas which are significant for meeting the main objective and answering the research questions.

1.4 Research development and outline

The research development and thesis outline are presented in Figure 4. This thesis is a continuation of the research executed in the unpublished report resulting from the TPK4530 specialization project *"An inventory management framework for non-pharmaceutical hospital warehouses"* by the same author in the fall of 2022. The resulting theoretical framework from the specialization project, together with the background and motivation described in Section 1.1 provided the groundwork for definition of the research questions as presented in Section 1.2. Chapter 3 delves into the state-of-the-art background on ordering policies, inventory classification and healthcare supply chain management through a literature study. Simultaneously, a case study presented in Chapter 4 was performed at the Helse Midt-Norge Logistics center. The case warehouse was studied regarding its inbound and outbound material flow, together with an analysis of the non-pharmaceutical hospital goods at the warehouse. Information and data considering demand from the hospital to the warehouse was retrieved and analyzed. In Chapter 5 the findings from Chapter 3 and Chapter 4 created the baseline for framework development and a discussion of inventory classification criteria level definition.

Chapter 6 presents the testing of the framework and the classification criteria levels impact on the ordering policy selection through simulation experiments, using data and information from the case warehouse in Chapter 4. The suggested definition of classification criteria levels from Chapter 5 is also tested through the simulation study in Chapter 6. Chapter 7 is a discussion of each research question in light of the findings in Chapter 5 and Chapter 6. The developed inventory management framework from Chapter 5 is compared with the framework testing in Chapter 6 in order to validate the framework, investigate the criteria levels' impact on the ordering policy selection and assess the proposed classification criteria level definition. Chapter 8 concludes the thesis by stating the answers to the research questions based on the discussion in Chapter 7, followed by the research contribution of this study and the limitations. Lastly, further research is suggested based on the concluding remarks and limitations.

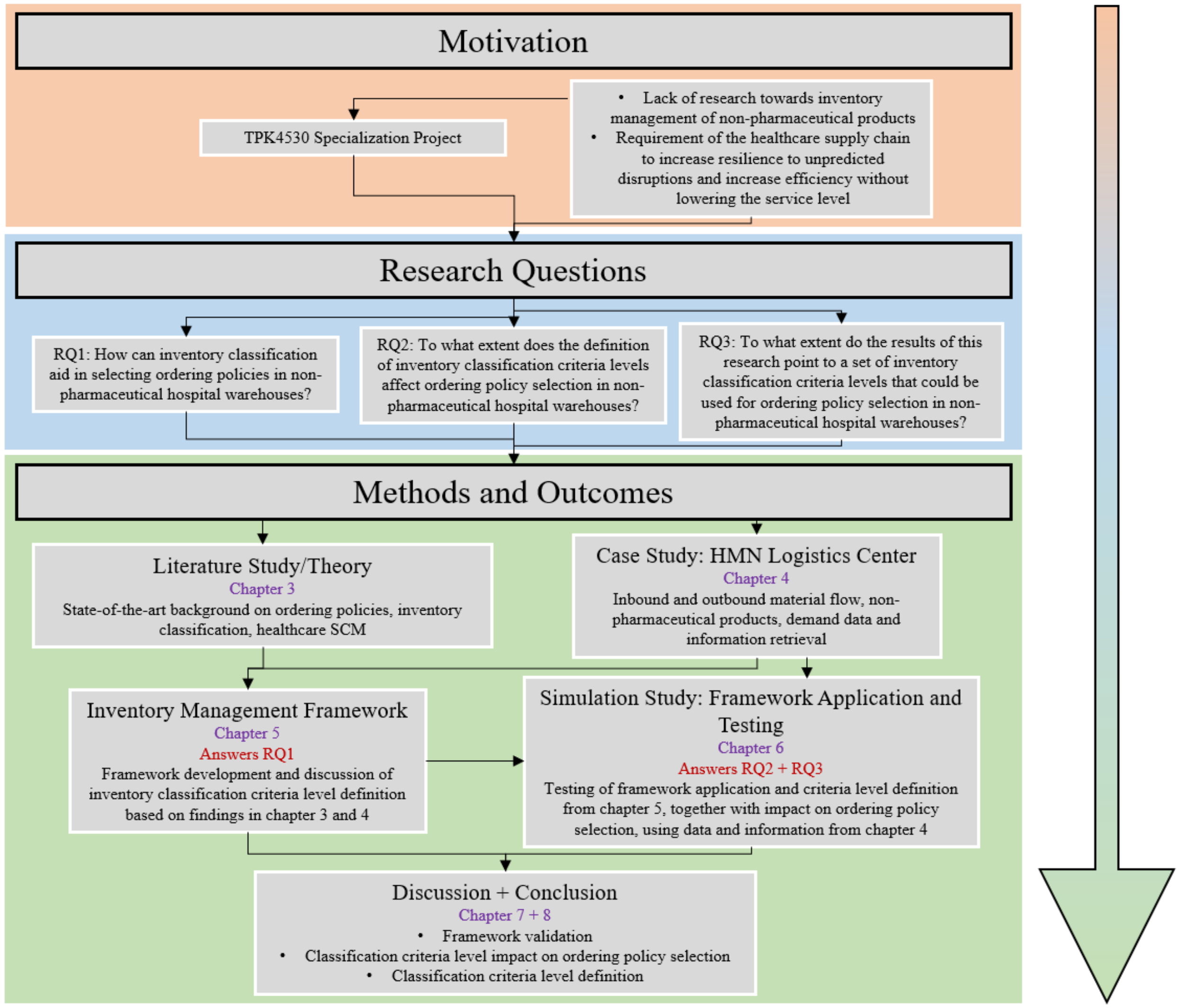


Figure 4: Research development and thesis outline

2 Methodology

This chapter is a detailed description of the research design and methods used to address the research problem. The purpose of this chapter is to give the reader a clear understanding of how the research was conducted and how the results were obtained. It establishes the validity and reliability of the research, as it provides a transparent account of the procedures used to collect and analyze the data. Additionally, the methodology chapter allows for assessment of the suitability of the methods used to address the research problem and to determine whether the results can be trusted. The approach used in this thesis is a combination of quantitative and qualitative methods. A literature study was carried out to provide the theoretical baseline for the study; the case study was conducted to familiarize the problem situation and collect data towards simulation; and the simulation study was performed using results from both the literature study and the case study in testing a developed framework for inventory management of non-pharmaceutical hospital goods.

2.1 Literature study

To understand the objective of a study and to contribute new research, a review of existing literature is necessary (Karlsson, 2016). Existing literature can be used for motivation, positioning and creating a framework for the study. It can also be used for borrowing existing constructs and concepts, explaining and interpreting findings, and discussions in relation to findings. For this reason, it is necessary to continue reviewing literature throughout the study, as the scope changes direction or is narrowed down, and new findings reveal aspects which are poorly understood.

When using literature for research, it is important to not only describe, but also critically analyze it (Karlsson, 2016). The choice of literature should be justified regarding how it is used to support the research. Another essential factor to consider is the possibility of misusing literature by introducing too many and possibly incompatible theories.

The literature study process for this research encompassed utilizing the search words from keyword set 1 in Table 1 by themselves and in conjunction with each other using the “OR” operator to broaden the search pool, as well as in conjunction with the search words from key word set 2 using the “AND” operator. Several excluding keywords were used with the “NOT” operator to limit the scope of the literature search to the scope of this study, such as “drug”, “vaccine”, “blood”, “pharmacy”, “medicine”, “medical”. Keyword set 1 represents a broader search pool, with more fundamental theory and concepts, whereas keyword set 2 was introduced to narrow down the scope of the study.

Table 1: Literature study search keywords

Keyword set 1	Keyword set 2
Inventory management Inventory control Ordering policy Inventory policy Replenishment policy	Hospital Healthcare Medical consumables Non-pharmaceutical Hospital warehouse Choice
Inventory classification SKU classification	MCDM AHP ANP

The literature searches were mainly conducted with the search engine Scopus, but Google Scholar and NTNU Oria were also used to a lesser degree. Additional literature suggested by the specialization project supervisor, for instance relating to inventory management of medical devices, was also added. Textbooks from courses in topics of operations management were reviewed and utilized for relevant background theory on inventory management. The citation program Zotero was used for in-text referencing, as well as the reference list at the end of the document.

2.2 Case study

Case research is a commonly used method of qualitative research in operations management and is especially widespread in the development of new theory (Voss, Tsikriktsis and Frohlich, 2002). Some of the benefits of case studies are that they can lead to creative, new theories, and often have a high validity. This research method allows for the study of situations in their natural setting and observations of actual practice, with a greater understanding of their complexity. It can be particularly beneficial for areas of research which lack significant understanding, to build on earlier studies, and where the definition of certain theoretical ideas is uncertain. Some of the challenges of case studies are that they can be time consuming compared to other research forms; they require skilled interviewers; as well as the need for drawing generalizable conclusions from a limited set of sources. With case-research being an iterative process, it is not uncommon for research questions, objectives, and scope to change throughout the study, leading to further enhancement of knowledge.

The case research for this thesis is based on a single case study. This is the most common approach for longitudinal research (Voss, Tsikriktsis and Frohlich, 2002). Longitudinal research is observational research conducted using information spanning over a certain period of time (*Longitudinal studies - PMC*, 2022). It is stated that decreasing the number of case studies for a given set of available resources will increase the opportunity for depth of observation. The potential limitations of using single-case studies can be the constraints to generalizability of the theory, models or conclusions developed, since not all potential problems or solutions may be included in the one case. Additionally, there lies a risk of exaggerating data that are easily available.

Yin (2003) presents five main circumstances and five rationales where a single case study design is an appropriate method: The critical case to test a well-formulated theory, the extreme or unique case, the representative or typical case, the revelatory case when the investigator has the opportunity to observe and analyze a phenomenon previously inaccessible to scientific investigation even if the phenomenon under scrutiny is common, or the case carried out over a long period specifying how certain conditions change over time.

The chosen case for this study was a local regional hospital warehouse in Norway. The warehouse is an accurate representation of government-owned health facilities in Northern Europe. In researching case-based data it is important to have a contact person who is senior enough and has the required authority to gather the necessary data, support the research, and know who to interview and conduct meetings with (Karlsson, 2016). The case study in this research was done through one-on-one informal discussions with contact persons at the case warehouse, as well as a focus group meeting with purchasing managers, tours at the warehouse and data collection.

The data for this research were collected from the case warehouse through exportations from their integrated Enterprise Resource Planning (ERP) system, SAP. Specifications as to what data were required were determined through discussions with the case warehouse contact person and an approved cloud service was used to transfer the raw data. The quantitative data used for the study were mainly in the form of large CSV files and the processing was done using Microsoft Excel software.

2.3 Simulation study

This section presents the methodology of the simulation study, including the conceptual model development preceding the simulation experiments.

2.3.1 Simulation

Simulation is a form of model-based quantitative research. In such research development, analysis or testing of the relationship between certain control variables and performance is carried out. Utilization rate or inventory position are examples of physical control variables, whereas revenue, profit and costs are examples of economic control variables. According to Karlsson (2016) quantitative model based research in operations management is *based on a set of variables that vary over a specific domain, while quantitative and causal relationships have been defined between these variables.*

Simulation modeling is a research method that involves creating a virtual model of a real-world system to understand its behavior and make predictions about its future performance. This approach allows researchers to test and analyze complex systems in a controlled environment. By constructing a simulation, researchers can manipulate variables and observe the effects on the system, thereby gaining insight into the relationships between variables and their causality. With causal variables it is meant that the change of a value “t” of one variable leads to a quantitative change in the “f(t)” of another variable (Karlsson, 2016). Simulation modeling also allows for the exploration of scenarios that might be too dangerous, expensive, or unethical to test in real-world conditions. The results of simulation studies can provide valuable information to decision makers and inform the development of new policies, products, or systems.

Simulation-based methods have previously been used in healthcare settings to optimize logistics problems regarding activity scheduling, job sequencing and patient paths inside hospitals (Battini *et al.*, 2020). The theory and modeling of system dynamics are highly suitable for tackling the dynamic complexity that is often associated with public health issues.

AnyLogistix is the software chosen for simulation modeling in this thesis. The software allows for testing of different supply chain scenarios and evaluation of the impact of various decisions on key performance indicators, such as inventory levels, transportation costs, and delivery times. AnyLogistix uses dynamic simulation, which utilizes the rules a system operates by and interdependencies between components, together with a description of the system, to see how the system behaves over time ('Supply Chain Optimization and Simulation: Technology Overview', 2023). The software allows for simulation considering the complexity of the supply chain, which can be caused by random, interacting and time-dependent effects, for instance lead time variability, demand fluctuations, or various inventory policies (Heckmann, 2016).

Some limits of using dynamic simulation include the laborious task of creating a model from scratch, in addition to the choice of level of abstraction of the model ('Supply Chain Optimization and Simulation: Technology Overview', 2023). The processing time of the simulation might increase unnecessarily if too many extra details are added to the model. Lastly, optimization is not directly added to dynamic simulation. It is only possible to test out different scenarios to see what happens, and the researcher will need to decide which one is optimal. Therefore, such a simulation model must be run several times to achieve optimization goals, which is often a time-consuming process. AnyLogistix does, however, include some optimization tools in the software, together with dynamic simulation, so it is possible to compare various scenarios more efficiently.

Computer simulation generally leads to a lower scientific quality of results than research using mathematical analysis, so justifying the choice of research with computer simulations requires proof that it is not possible to solve the problem in an analytical way (Karlsson, 2016). However, the scientific relevance of the problem studied might be much higher than the quality of the results. Therein lies the tradeoff which needs to be considered. In this research, simulating the supply chain is a much more efficient way of testing a framework for inventory management, as a real-world implementation would require large amounts of resources and could potentially harm patients at the POU if the warehouse is not able to provide the necessary hospital goods. In this research it is evident that the benefits outweigh the risks of using computer simulations.

Some critical steps in conducting research through simulation include conceptual modeling, justification of research methods, justification of hypothesis or heuristics, development of the scientific model, setup of the experimental design, analysis of the results, and interpretation of the results (Karlsson, 2016).

2.3.2 Conceptual modeling

Conceptual modeling is regarded as the most important aspect of a simulation project and the possibility of success in such research is significantly enhanced by a well-designed conceptual model (Robinson, 2008a). Conceptual modeling encompasses the abstraction of a model from a proposed or real system, where the issue is to make appropriate simplifications of reality for the purpose of simulation. It is an iterative process that is refined and repeated several times during the simulation study. Conceptual models aid in defining what is to be represented and how it is to be represented in the simulation. It is also important to note that conceptual models can be made independently of the simulation code or software. The conceptual model should include a description of the objectives, inputs, outputs, content, assumptions, and simplifications of the model. The four main requirements for conceptual models are credibility, validity, utility, and feasibility.

A framework for conceptual modeling is suggested in a study by Robinson (2008b) which includes the following steps:

1. *Understanding the problem situation*: This step is not formally part of the conceptual model, but still a vital part of development of the model. The need to improve a problem situation should always be the driver for a simulation study. Accurate research questions and discussions with the right people are both significant points in this step.
2. *Determining the modeling and general project objectives*: What can be achieved through both the development and the use of the model should be the baseline for expression of the objectives. The first component to a modeling objective is the achievement, which encompasses what is hoped to be achieved by the study, such as improved customer service or faster throughput in a system. The second component is performance, which encompasses the desired measure of performance, for instance a reduction in costs by 5%. The last component is constraints, which encompasses the constraints which the model must be made in, for instance available space. The nature of the model is also necessary to regard in terms of flexibility, run-speed, visual display, ease-of-use and model or component reuse.
3. *Identifying the model outputs:* The model responses or outputs have the purpose of identifying whether the modeling objectives have been achieved and in cases where they have not been achieved, to suggest reasons for this. The responses can be reported through numerical data, such as mean or standard deviations, or graphical reports, such as bar charts, line charts, or time-series.

4. *Identifying the model inputs:* The model inputs include the experimental factors which can be changed to achieve the modeling objectives. These can be in terms of either quantitative or qualitative data. The means by which the modeling objectives will be achieved are represented by the experimental factors. A range over which the experimental factors can be varied is often useful to define and these can be subject to change throughout the simulation study.
5. *Determining the model content:* This step encompasses determining the scope and the level of detail in the model. The scope regards the boundaries of the model and what is included in terms of entities, activities, queues, and resources. A justification should be made regarding which components should be included or not. Deciding how much detail to include for each component determines the level of detail of the model. These decisions can be made referencing the judgment of the modeler, past experiences, data analyses or prototyping and testing of the model.
6. *Identifying assumptions and simplifications:* This step should be made in conjunction with determining the model content. When there are uncertainties about the real world being modeled, it is necessary to make assumptions. Simplifications, however, are made to increase the speed of model development and use. Both assumptions and simplifications should be explicitly stated and explained. It may also be useful to assess their level of impact on the model responses and the confidence that can be placed in them. Some examples of simplification methods include replacing components with random variables and excluding events which seldom occur.
7. *Identifying data requirements:* Data requirements include contextual data which aids in understanding the problem situation, data for model realization and data for validation, such as past performance statistics. Estimations of data can be made if there is a lack of data, and sensitivity analyses can be made to understand the effects of these inaccuracies. It is also possible to change the conceptual model design to fit the data which are available.
8. *Model assessment:* This step should be performed in parallel with the preceding steps and encompasses making sure the conceptual model meets the requirements for credibility, validity, utility, and feasibility. To aid this assessment, a diagrammatic representation of the conceptual model is recommended, for instance through a process flow diagram or an event graph, which can be shared and expressed to all parties involved in the study.

3 Literature study/Theory

This chapter provides the theoretical groundwork and conceptual underpinning for the study. First, preliminary elements of inventory management are introduced, together with warehouse specific theory and key performance metrics. Thereafter, demand and forecasting are explored, to increase the understanding of their effect on inventory management. Demand modeling is also addressed in relation to simulation model development. Inventory classification methods are then presented, before relevant theory on ordering policies and ordering policy choice. Thereafter, a section on healthcare specific inventory management examines literature and research regarding non-pharmaceutical hospital goods, hospital warehouse ordering policies, and supply and demand characteristics specific to the healthcare industry. A summary of relevant findings towards framework development concludes this chapter.

Certain elements of this chapter are taken from the literature study chapter of the unpublished report from the TPK4530 specialization project *"An inventory management framework for non-pharmaceutical hospital warehouses"* by the same author in the fall of 2022.

3.1 Inventory management

The management of inventory is a core operations management activity, as it is critical for successful operations of a business (Stevenson, 2021, p. 503). Optimal inventory management supports a smooth flow of products and satisfied customers, whereas poor inventory management can have a significant negative impact on the business by slowing down operations and increasing costs.

Inventory can be grouped into either cycle stock or safety stock (Stevenson, 2021, p. 525). Cycle stock is known as the amount of inventory needed to satisfy demand. This is the inventory in warehouses that experiences a significant turnover. Safety stock is the extra inventory carried to reduce the risk of stockouts due to variability in demand or lead times. A stockout is a situation where there is no availability of a certain item for sale or further distribution in inventory (*STOCKOUT | English meaning - Cambridge Dictionary*, 2022). In a hospital setting, a stockout would therefore be a situation where there are no goods available of a certain type at the central warehouse to be delivered to the POU at the hospital. Lead time is defined as the time interval between ordering and receiving the order (Stevenson, 2021, p. 509). The level of safety stock is determined by the desired level of product availability, the uncertainty of supply, the uncertainty of demand and the chosen inventory ordering policies (Chopra, 2019).

The main purposes of having inventory for a business are usually to meet expected customer demand, to serve as buffers between operations, reducing the risk of stockouts, to support against sudden price increases and to take advantage of quantity discounts (Stevenson, 2021). The main objective of inventory management is maintaining reasonable inventory costs while providing satisfactory customer service. The two underlying issues to be addressed in inventory management are when to order products and how much to order.

The elemental requirements for effective inventory management are as follows (Stevenson, 2021, p. 507):

- A system keeping track of inventory on hand and on order.
- A reliable forecast of demand, including predicted forecast error.
- Information on lead times and lead time variability.
- Estimates of costs related to inventory management.
- A classification system of inventory items.

One way of distinguishing the management of on-hand inventory, which can impact the ordering policies, are periodic or continuous review approaches (Stevenson, 2021). In a periodic review approach the inventory is counted at recurring, fixed intervals, for example weekly or monthly. Based on the result of the count, an order is made to fulfill the demand for the next period. A continuous review system continually keeps track of the on-hand inventory and therefore can at any point in time have information regarding the current inventory level. An advanced approach to continuous review can utilize bar-codes or RFID (Radio-Frequency Identification) to keep track of on-hand inventory.

3.1.1 Warehousing

Warehouses are used to store different types of goods, ranging from raw materials, work in progress and finished goods (Chapman *et al.*, 2017). They are a cost-adding function of the supply chain, as they represent an interruption in the flow of goods. Therefore, warehouses should only be used if there is an obvious benefit overriding these costs. Factory warehouses, regional warehouses and local warehouses are all different types of warehouses. Suppliers or wholesalers can own and operate warehouses, or they can be publicly owned. Warehouses can be classified as a general warehouse or distribution warehouse. General warehouses have the purpose of storing goods until they are required for use. This type of warehouse is often used in anticipation of an increase in demand due to seasonal variations, and there is typically minimal movement and handling of goods. Distribution warehouses have the purpose of mixing and moving goods. Usually, a warehouse receives goods in large volumes and divides these into smaller and mixed packages for further distribution (Chapman *et al.*, 2017).

One logistics practice which avoids warehouse handling and storage costs is cross-docking, where inbound trucks with goods arriving from suppliers are directly loaded onto outbound trucks for further delivery (Stevenson, 2021) (p. 538). This is particularly useful for emergency orders, or if exact demand is known.

Truckloads between a warehouse and other actors in the supply chain are commonly based on one of two rate structures, either full-truckload (FTL) or less than truckload (LTL) (Chapman *et al.*, 2017). With a FTL structure, the truckload will only be sent if it is full. If the shipment is LTL, it can be delivered when necessary; it is not a requirement to wait until the truckload is full.

3.1.2 Performance metrics

Several performance metrics can be used to assess the inventory management performance of actors in a supply chain, and to detect whether or not there are problems which need to be addressed (Stevenson, 2021). Financial performance metrics include profits, costs, return on assets and cash flow. Order fulfillment performance metrics include order accuracy, percentage of incomplete orders shipped, backorders, time to fill orders, and percentage of orders delivered on time. In addition to the service level, specific performance metrics related to the physical inventory are average value, available inventory, turnover, and weeks of supply.

The four main costs related to inventory management are purchase costs, holding costs, ordering costs, and shortage costs (Stevenson, 2021). Purchase costs are usually the largest types of inventory costs and pertain to the costs related to purchasing the inventory from the supplier or vendor. These can include shipping costs. Holding costs are the costs of keeping inventory in storage. These include insurance, interest, taxes, depreciation, obsolescence, deterioration, spoilage, breakage, tracking, item picking, as well as warehousing costs such as rent, workers, equipment, heat, and security costs. Additionally, holding costs include the opportunity costs spent on keeping inventory, which could be used elsewhere. The variable costs within this category should be considered the most relevant. Holding costs are generally based on the dollar value of the item, but this can vary based on the type of product. These costs are usually stated in terms of percentage of unit price, or as a set NOK (currency) amount per unit. Annual holding costs tend to lie in the range between 20-40% of the item's value.

Ordering costs are costs that occur with the placement of an order, of ordering and receiving inventory (Stevenson, 2021). Included in these costs are costs in deciding how much is needed in the order, preparation of invoices, received goods quality and quantity inspections, and movement of inventory to temporary storage locations. Ordering costs are typically expressed in terms of a set price per order and are independent of the order size. Setup costs can be considered as the equivalent to ordering costs for manufacturing businesses that produce their own goods instead of ordering from suppliers. These costs include fixed value costs related to preparing machines for production, regardless of the production batch size. Lastly, if the demand for products exceeds the inventory available at the warehouse, shortage costs will occur. These include loss of customer goodwill, late charges, backorder costs, and opportunity costs of not making a sale. Shortage costs can be very high but are often difficult to estimate.

3.2 Demand

This section presents the characteristics of demand and principles of forecasting, as well as techniques for forecasting. Lastly, modeling demand is described in preparation for the development of conceptual modeling and simulation.

3.2.1 Characteristics

To understand the way demand can influence inventory management decisions it is vital to explain the characteristics of demand and how they can impact forecasting. The four main reasons for variation in demand are trend, seasonality, random variation and cycle (Chapman *et al.*, 2017). If there is a trend pattern, there is a steady pattern of demand from year to year. Some possible patterns include a linear trend, exponential trend, or geometric trend. The trend can rise or fall, but there is no change from period to period, the trend is considered level. Seasonality describes demand fluctuations throughout the year, which are dependent on the weather, holiday seasons or other events which take place seasonally. Seasonality can occur daily, weekly, monthly, or yearly. Random variation in demand is when factors affect the demand which occur on a random basis.

These can be large random variations, or smaller variations so that the demand pattern can still be understood. Lastly, there can be cycle characteristics of demand. These regard wavelike increases and decreases in the economy which can influence the demand over a span of several years.

The demand patterns of certain products or services exhibit variability over time, whereas others remain constant (Chapman *et al.*, 2017). The former is referred to as dynamic demand, whereas the latter is termed stable demand. Dynamic changes can induce alterations in the trend, seasonality, or randomness of actual demand. A greater level of stability reduces the complexity in forecasting demand.

In the context of demand, independence refers to a state in which the demand for a particular product or service is not contingent upon the demand for any other product or service, nor is it linked to the internal activities of the firm (Chapman *et al.*, 2017). Conversely, dependent demand pertains to instances in which the demand for an item is derived from that of a second item. Forecasts need not be generated for dependent demand items; rather they are calculated based on the demand of the independent demand item. It is only the independent demand items that necessitate forecasting, which typically include finished goods or end items, as well as service parts and items supplied to other plants within the same company.

There are various forms of uncertainty in every supply chain, where the uncertainty of customer demand is often regarded as the most fundamental uncertainty. It is also important to note that there is a distinction between demand variation and demand uncertainty. Demand variation pertains to the evolution of demand from period to period, whereas demand uncertainty relates to when demand becomes known (Johansen, 1999). Moving upwards in the supply chain from retailer to manufacturer it is known that demand variations often increase (Derbel *et al.*, 2013).

3.2.2 Forecasting

Demand forecasting is an essential component in inventory management, as it plays a part in answering the question of how much to order and when to order. Forecasting is defined by the Council of Supply Chain Management Professionals as predictions of how much of a product will be purchased by customers, and relies upon both qualitative and quantitative methods (*SCM Definitions and Glossary of Terms*, 2022). Some major factors impacting demand are competitive factors, general business and economic conditions, market trends, and a corporation’s plans for advertising, pricing and product changes (Chapman *et al.*, 2017, p. 202). More effective use of forecasts is aided by understanding the four major principles of forecasting:

- Forecasts are usually wrong.
- Forecasts should include an estimate of error.
- Forecasts are more accurate for groups of products.
- Forecasts are more accurate for the near future.

It is also important to remember that forecasts can only be as good as the data on which they are based. There are both qualitative and quantitative forecasting techniques. Qualitative techniques are usually based on intuition, judgment, and informed opinions. Qualitative techniques can be used for new products, through market research and historical analogy. Another qualitative technique is the Delphi method, where a panel of experts present their predictions. Quantitative forecasting techniques are based on numerical or historical data. Some examples of quantitative forecasting techniques are moving averages, which use the average demand for a given period, or the exponential smoothing technique, where old calculated forecast data are used together with new data to make predictions (Chapman *et al.*, 2017). Seasonal variations in demand can also be considered by adding a seasonal index to the forecast.

Forecast error is defined as the difference between actual demand and forecast demand (Chapman *et al.*, 2017, p. 216). The element of forecast error is essential to consider when making inventory management decisions. The most common approaches to calculating forecasting errors in demand forecasting are the mean absolute deviation (MAD) or the mean absolute percentage error (MAPE) (Tiacci and Saetta, 2009). Forecasted demand data are often the basis for the values of stock control parameters in ordering policies in many real cases. Inventory management is further complicated by the introduction of uncertainty in the demand pattern. Parameters for certain ordering policies should be updated over time since the demand rate for most products will likely change over time.

One study (Nyoman Pujawan, 2004) has shown how the choice of ordering rules in a supply chain echelon has an impact on the ordering patterns of echelons upstream in the supply chain. Therefore, it is important to consider the forecast of ordering patterns from the customer or the demand, when creating ordering policies for upstream echelons such as warehouses from suppliers.

3.2.3 Demand modeling

If the demand for inventory is known, it is said to be deterministic (Benkő, no date). However, in many cases it is more appropriate to model the demand as stochastic. In stochastic modeling, the demand is modeled as a random variable having a known probability distribution. Stochastic modeling is useful when assumptions and simplifications are required.

Demand distribution of items can roughly be considered to be singular, continuous, or lumpy (Hautaniemi and Pirttilä, 1999). If an item has singular demand, it is usually ordered in batches of one item and the ordering frequency is only now and then. For such items it is considered appropriate to model the demand as Poisson distributed. Lumpy demand items are also ordered only now and then, but have more variable batch sizes, and can be ordered in larger batch sizes.

Incomplete information regarding the distribution of demand during lead time is a common problem in inventory management, where the probability of demand is an important input (Ramaekers and Janssens, 2012). This is especially true for products which have been recently introduced to the market, or with slow-moving products that have a small turnover rate. In these cases, there is often not sufficient historical data available to model the demand distribution. For fast-moving items, it has been shown in practice that a Normal probability distribution is appropriate. Another option considered should be a Gamma distribution because of its feasibility to be used with fixed lead times and can be extended to probabilistic lead times. For items with a lower demand, Laplace or Poisson demand should be considered. If the demand is only a few items per year, it has been found that a Poisson demand can be appropriate.

3.3 Inventory classification

Each SKU in inventory can have differences in predictability of demand, product value, annual sales volume, or storage requirements. These are examples of characteristics which can influence inventory management of the given SKU (van Kampen, Akkerman and Pieter van Donk, 2012). To create an inventory classification scheme, it is necessary to figure out how many classes to use, as well as identify the boundaries between classes. Using similarities between products based on different attributes to systematically classify products is the main objective of SKU classification. These classifications can further be used to support decision-making in inventory management.

3.3.1 Classification criteria

Characteristics for SKU classification can be categorized into volume, product, customer, or timing (van Kampen, Akkerman and Pieter van Donk, 2012). The volume category includes sales volume, order size and variability. The product category includes relation to other products, profit margin, storage and handling requirements, services with delivery, substitutability, perishability, criticality, and duration of life cycle. The customer category includes heterogeneity of customers, number of customers, and interrelationship between customers behavior. The time category includes time window, speed and frequency of deliveries and order placing. The product category includes characteristics which are most used for inventory management decisions.

The characteristics of a product affecting the decisions related to inventory management can be translated into the criteria in a decision-making process (Partovi and Burton, 1993). Often there are several criteria that should be considered when categorizing inventory (Chen, Li and Liu, 2008). Some of the main criteria considered for inventory classification are price, obsolescence, repairability, criticality, lead times, demand, and substitutability (Partovi and Burton, 1993). The identification of the appropriate criteria is the most crucial step in classification of SKUs. Table 2 defines the most common product characteristics used as criteria found in literature regarding inventory classification.

Table 2: Definitions of common classification criteria

Criteria	Definition
Unit cost	The price paid for the purchased item in the warehouse (Chapman *et al.*, 2017, p.239).
Lead time	The time between an order is placed and the order arrives (Partovi and Burton, 1993).
Criticality	The consequence of not having an item available when it is required (Partovi and Burton, 1993).
Demand	Market or customer requests (Chapman *et al.*, 2017, p.204). Notice the difference between demand and sales. If demand cannot be satisfied, then actual orders or sales will be less than demand. Demand characteristics can be related to demand patterns, demand uncertainty and predictability of demand.
Turnover rate	Indicates how many times per time period the item is sold (Stevenson, 2021).
Supply characteristics	Includes characteristics such as availability of raw materials, supplier uncertainty, and scarcity. Product scarcity is when the product demand is greater than the availability in the market (*Scarcity | National Geographic Society*, 2022).
Obsolescence	To what degree the product has reached the end of its lifecycle and therefore very difficult or impossible to sell or use (*Obsolete inventory - definition and example - Market Business News*, 2022).
Substitutability	To what degree a product can be used in replacement of a similar product (*PRODUCT SUBSTITUTION - Cambridge English Dictionary*, 2022).

3.3.2 Methods for inventory classification

Inventory management on an SKU-level is not considered economically feasible (Chen, Li and Liu, 2008). Therefore, several classification techniques can be used to sort SKUs into manageable product groups. Classification in this manner should reduce the number of SKUs requiring considerable attention.

The ABC-approach is a commonly used inventory classification system, which categorizes products into three groups according to their usage and cost (Chapman *et al.*, 2017). It is based on Pareto's law which states that a small percentage of causes stand for a large percentage of the effects. For inventories, this can be transferred to a small percentage of items representing a large percentage of dollar usage, material scarcity or cost, depending on what criteria are more significant for the inventory management situation. Total dollar usage is the unit cost of the item multiplied by the unit usage of the item. This tool can be used to detect which products are the most important, and thus how different product groups should be managed in terms of ordering policies.

Group A is considered the most important group (Chapman *et al.*, 2017). It includes around 20% of items and stands for 80% of total dollar usage. Group B is the second most important, as it includes around 30% of items and stands for 15% of dollar usage. Group C is the least important group, as it includes about 50% of the items and accounts for 5% of the dollar usage. The percentages are not exact as they are simplified into a generalized model.

There are two main rules to follow when using the ABC-approach in inventory management:

- Keep high inventory levels of low-value items (group C). This means high levels of safety stock, larger order quantities, and less frequent review of inventory on-hand. Lower-valued items become important if there is a stockout, but they are inexpensive to keep on-hand.
- Reduce inventory of high-value items (group A). These items should be frequently reviewed and controlled tightly.

Group B items should be managed somewhere in between the policies for groups A and C.

One study (Gupta *et al.*, 2007) presents a model for inventory management of hospital goods derived from the traditional ABC-approach. Figure 5 presents the ABC-VED matrix, which accounts for both the cost and usage of products in the ABC component and introduces the criticality factor of the products in the VED component. The “V” represents vital components, which are products the hospital requires in order to function. The “E” represents essential items, which are not required for the hospital to function, but that still have the potential to affect the quality of patient care significantly. The “D” stands for desirable products, which are not essential for the hospital to function and that will not impact the quality of patient care significantly. Each category of items requires a specific inventory management model regarding ordering and safety stock.

CLASS	V	E	D	Categories
A	AV	AE	AD	Category 1
B	BV	BE	BD	Category 2
C	CV	CE	CD	Category 3

Figure 5: ABC-VED inventory classification matrix

Another classification scheme is the SDE scheme, which is based on the availability of raw materials (Ketkar and Vaidya, 2014). The “S” stands for scarce, which means the material or product is very uncommon, needs to be imported, or has a long lead time. “D” stands for difficult, which in this sense means that the material still has moderate lead times but is less prone to stockouts and is generally available. The last category, “E” for easy, represents goods that have a short lead time and are easily available.

The FSN classification scheme classifies inventory based on the quantity and frequency related to replenishment of the goods from a consumption perspective (Ketkar and Vaidya, 2014). The “F” stands for fast moving, which means that the product is consumed at a fast pace, for example within a week. The “S” stands for slow moving, which means the product is consumed at a moderate pace, for example a few weeks to a few months. The “N” stands for non-moving and refers to products that stay in inventory for an even longer period of time. The XYZ classification scheme is similar to FSN, but focuses on variability in demand (van Kampen, Akkerman and Pieter van Donk, 2012).

Multi-criteria decision-making

When classifying inventory, the use of only one characteristic might lead to impactful financial loss (Keshavarz Ghorabaee *et al.*, 2015). It might not be enough to consider even a combination of two methods or characteristics, as it could leave out some significant aspects. Furthermore, it is suggested that considering 4-5 characteristics for classification will give a more appropriate result (Ketkar and Vaidya, 2014). Another study finds that using three main criteria for classification of inventory is satisfactory to keep the classification process easy to understand and simple (Hautaniemi and Pirttilä, 1999).

Multi-Criteria Decision-Making (MCDM) methods have long been applied in various areas of manufacturing to support effective decision-making where there are several and possibly conflicting criteria (Sbai, Benabbou and Berrado, 2020). It is important to choose a fitting MCDM method related to the nature of the decisions and the type of problem. Some different types of MCDM methods which have been used in inventory management earlier include ELECTRE, PROMETHEE, AHP, TOP-SIS (Sbai, Benabbou and Berrado, 2020) and EDAS (Keshavarz Ghorabaee *et al.*, 2015). A study (Sbai, Benabbou and Berrado, 2020) on comparison of MCDM methods in inventory management states that the Analytic Hierarchy Process (AHP) method is theoretically not complex, is easily adaptable to different decision problem situations, can take criteria weights into account, and can provide ranking and selection of alternatives. The AHP method was developed by Thomas L. Saaty in 1984 and is defined as a *multiobjective, multicriterion decision-making approach which employs a pairwise comparison procedure to arrive at a scale of preferences among sets of alternatives* (Saaty, 1984, p. 286). In AHP a hierarchical structure is built from the decision problem and the criteria are given unequal weighting (Partovi and Burton, 1993). A major benefit of AHP is that inconsistencies in preferences are considered. In AHP, the criteria are mutually exclusive and independent of elements below in the hierarchy.

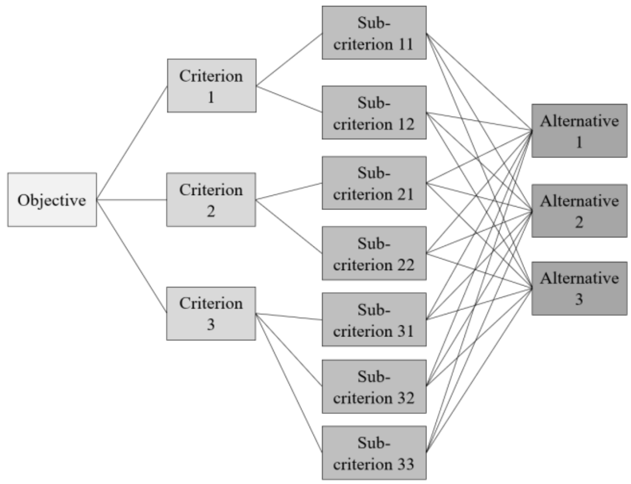


Figure 6: Standard of a hierarchical structure. Adapted from Russo and Camanho (2015)

Figure 6 shows the standard of a hierarchical structure, as used in AHP. The objective is the goal of the problem. The criteria and sub-criteria represent the decision-making criteria for the alternative choices. The Analytical Network Process (ANP), which was later developed by Saaty, generalizes the AHP method, so that it takes interaction and dependence between the elements of the hierarchy into account (Saaty, 2006). Furthermore, ANP can be used in problems where there is a dependence among alternatives and/or criteria. In decision-making, one must define the problem, the goal of the decision, the criteria and sub criteria affecting the decision, the alternative actions to take, and who will ultimately be affected by the decision (Russo and Camanho, 2015). It is also essential to define preferences and assess alternatives for each criterion in all decision problems (Sbai, Benabbou and Berrado, 2020). It has been proven that choosing a maximum of seven criteria when using AHP will keep both redundancy and consistency in the method (Russo and Camanho, 2015). According to a literature review on criteria in AHP by Russo and Camanho (2015), the average number of criteria used is between 4 and 5, and the mode is 3. Once the criteria are defined, the decision makers can use descriptive preferences to give different weights to each criterion. This is usually done by answering the question of how important one criteria is in relation to another, for example equally important or slightly more important (Partovi and Burton, 1993).

3.4 Ordering policies

This section presents an overview of the most common ordering policies in inventory management together with findings from the literature regarding the choice of ordering policies. Several different ordering policies exist for aiding purchasing managers in decisions about how much inventory to order and when. Some policies can be used concurrently. For example, one policy stating how much to order may be utilized together with an ordering policy stating when to order, or the ordering frequency.

EOQ

The Economic Order Quantity (EOQ) model identifies the order quantity that provides the lowest total annual inventory costs, which include costs varying with order quantity and frequency (Stevenson, 2021, p. 514). The EOQ produces an answer to the question of how much to order in inventory management, not necessarily when. Figure 3 shows how the total annual costs, including holding and ordering costs, vary with respect to the ordering quantity and where the EOQ is placed in relation to minimizing these costs.

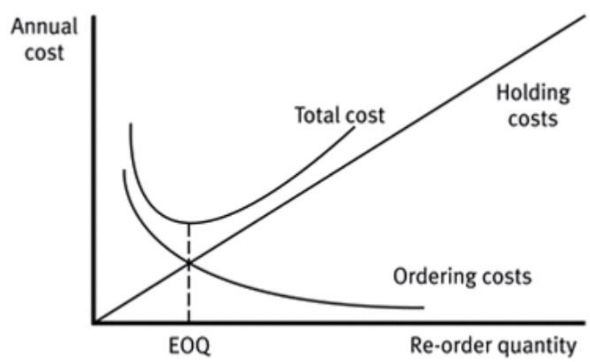


Figure 7: EOQ and total cost with respect to order quantity (PSQ Newsletter, 2022)

To utilize the EOQ model, certain assumptions must be made:

- One product is involved.
- Demand is known.
- The demand rate is constant.
- Lead time is known and constant.
- Each order is received in a single delivery.
- No quantity discounts.

Components needed in the EOQ are demand, usually in units per year, ordering cost per order and holding costs per unit, usually annual. In the following formula we find the quantity (Q) using the demand (D), order cost (S) and holding cost (H) (Stevenson, 2021, p. 516):

$$Q = \sqrt{\frac{2DS}{H}} \tag{1}$$

A notable point in using EOQ is that total holding and ordering costs remain relatively stable around the EOQ (Chopra, 2019, p. 286). It can therefore often be more suitable for a company to use a lot size close to the EOQ instead of the precise EOQ.

One noteworthy variation of the EOQ formula takes quantity discounts into account (Stevenson, 2021, p. 520). Quantity discounts are when suppliers reduce the price of larger orders, to persuade customers into buying larger quantities or quantities that are more economical for the manufacturer. When quantity discounts are available, storage space, product obsolescence or deterioration and financial resources should be considered. If the decision is to take advantage of the quantity discount, it is necessary to find the order quantity which will minimize the total cost. The total cost is the sum of carrying costs, ordering costs, and purchasing costs. In the following formula for total cost using the EOQ with quantity discounts a new variable is defined for unit price (P) (Stevenson, 2021, p. 521):

$$TC = \left(\frac{Q}{2}\right)H + \left(\frac{D}{Q}\right)S + PD \tag{2}$$

Other variations of the EOQ formula include Economic Production Quantity (EPQ), Monetary unit lot size and non-instantaneous receipt model (Chapman *et al.*, 2017, p. 263).

Some limitations when using the EOQ are that it requires simplistic assumptions, it is not ideal for unstable or unpredictable demand and it can result in excess inventory of slower moving items, for example items that deteriorate or become obsolete (Slack and Brandon-Jones, 2019). It should also be mentioned that cost minimization is not necessarily an appropriate objective in all situations.

<u>POQ</u>

The period order quantity (POQ) rule uses the EOQ principle, together with expected demand in a given time period, to find the optimal order quantity (Chapman *et al.*, 2017, p. 265). It is particularly useful when demand is not uniform and calculates the economic time between orders. Although the economic time is calculated, it does not state when the orders are to be placed, but rather for what time period the ordered quantity will cover the demand for. The formula for POQ is as follows (Chapman *et al.*, 2017, p. 266):

$$POQ = \frac{EOQ}{Average\ weekly\ usage} \tag{3}$$

The period order quantity is a more suitable choice over the EOQ when demand cannot be assumed as uniform, or when replenishment cannot be assumed to occur all at once (Chapman *et al.*, 2017, p. 267). However, it is not necessarily ideal when demand cannot be predicted, as it takes expected demand into account.

<u>Lot-for-lot</u>

In the lot for lot policy only what is needed is ordered (Chapman *et al.*, 2017). Whenever demand changes, it allows for changes in the order quantity. This policy for order quantity requires real-time demand information to be provided. The advantage of using a lot-for-lot policy is that there is no inventory for unused items, further decreasing holding costs. It is therefore also an ideal policy for waste reduction.

<u>ROP</u>

The reorder point (ROP) ordering policy addresses the second question in inventory management of when to order. The ROP is stated in terms of a certain quantity of stock, where when this stock level is reached a new order should be placed. There are four factors affecting the ROP:

- Rate of demand
- Lead time
- Extent of demand or the lead time variability
- Acceptable degree of risk of stockout

For the acceptable degree of risk of stockout a measure can be the amount of safety stock needed. This is primarily based on the desired service level, the average demand rate and lead time, and demand and lead time variability (Stevenson, 2021, p. 526). To include both factors of cycle stock and safety stock, the ROP is a result of the expected demand during lead time (*DDLT*) and the amount of safety stock (*SS*) (Chapman *et al.*, 2017, p. 273).

$$ROP = DDLT + SS \tag{4}$$

To take the service level into account, a safety factor, z, is introduced in the formula for calculating the safety stock. The safety factor is defined as the number of standard deviations which should be provided as safety stock. A table of safety factors such as table 4 is often used to find the safety factor when calculating the safety stock and ROP.

Table 3: Table of safety factors. Adapted from Chapman et al. (2017).

Service level (%)	**Safety factor (*z*)**
50	0.00
75	0.67
80	0.84
85	1.04
90	1.28
94	1.56
95	1.65
96	1.75
97	1.88
98	2.05
99	2.33

The formula for calculating the ROP will differ slightly based on whether the lead time variation or the demand variation is taken into consideration. If only the demand is variable and the lead time is constant the formula is as follows (Stevenson, 2021), where $\bar{d}$ = average demand (daily or weekly), σ_d = standard deviation of demand (days or weeks), LT = Lead time (days or weeks):

$$ROP = \bar{d} \cdot LT + z\sigma_d\sqrt{LT} \tag{5}$$

If only the lead time is variable, and the demand is constant, the ROP is calculated as follows, where d = demand (daily or weekly), $\overline{LT}$ = Average lead time (days or weeks) and σ_{LT} = standard deviation of lead time (days or weeks):

$$ROP = d \cdot \overline{LT} + zd\sigma_{LT} \tag{6}$$

If both the demand and the lead time are variable, the following formula should be used for calculating the ROP:

$$ROP = \bar{d} \cdot \overline{LT} + z\sqrt{\overline{LT}\,\sigma_d^2 + \bar{d}^2\sigma_{LT}^2} \tag{7}$$

An advantage of using the ROP policy is that it is easily implemented, as the generation of orders is automatic when passing the given stock level. The ROP policy also explicitly takes service level into account, as it is included in the formula for determining safety stock. A limitation of using the ROP policy can be that it takes unpredictable demand and lead time into account, which can result in some varying levels of safety stock (Slack and Brandon-Jones, 2019). The ROP policy should be used together with a policy determining the ordering quantity.

One variation of the ROP policy is known as the Min-max system. Like the standard ROP policy, an order is to be placed when the stock level falls below the reordering point. There is a maximum level of stock decided upon, and the quantity to be ordered is the difference between the maximum level and the existing stock level at the time of ordering. A Min-max system based policy is noted in a study by Johansen (1999) as the best choice for increased demand uncertainty.

Fixed order quantity

In the fixed order quantity policy, the same quantity is ordered each time an order is placed (Chapman *et al.*, 2017, p. 257). This can be based on an EOQ, or another quantity, for example decided by the supplier, the size of the distribution vehicle, or the packaging size. This policy for ordering quantity is easily understood and implemented, but it does not necessarily minimize the costs related to inventory management. Fixed order quantities are optimal when there is no fixed setup cost for ordering and can be more suitable for easier coordination in regard to packaging and transportation (Zheng and Chen, 1992).

FOI

The fixed-order-interval (FOI) model (Stevenson, 2021, p. 530) is used when the orders are required to be put at set time intervals, such as weekly, monthly or quarterly. This requirement could be made by a supplier or a distributor. Since the question of when to order is predefined, the question of how much to order remains. With an FOI policy, the order quantity can vary from cycle to cycle. Since FOI is based on time and not quantity, it must have protection for both the lead time and the next cycle. This assumes that orders cannot be placed at any time and are set at the agreed upon time intervals. Therefore, more safety stock is needed when using this model, which increases carrying costs. On the other hand, the FOI model is ideal when close monitoring of inventory levels is not achievable, since only a periodic review of inventory levels before order placing is necessary. Grouping orders from the same supplier can also lead to economic benefits, such as savings in ordering, packing and distribution costs. A FOI policy is noted in one study by Hoshino (2001) as the optimal choice when the forecasting error is small.

Single-period

The single-period model is used for order-handling of perishable items and items with a short use-life, such as newspapers and spare parts for specialized equipment (Stevenson, 2021, p. 533). The period referred to is the period of time the product can be used, or the life cycle of the product. This assumes that the product cannot be used for any other purpose without a penalty. An example of this is that leftover baked goods can be sold at a reduced price the next day. There are two basic costs related to the single-period model. These are shortage costs, which are the costs related to not being able to supply the customers' demand, and excess costs, which are costs related to items left over at the end of the period.

Two-bin system

In the two-bin system the optimal order quantity of an item is kept in one bin and it is not used until the main stock in another similar bin is used up (Chapman *et al.*, 2017). The optimal order quantity can for example be based on the EOQ or on an ordering batch size with a quantity discount. When the main stock is used up, the other bin is taken out for use, and this triggers a replenishment order of the optimal order quantity. There are several versions of the two-bin ordering system, but in general, it is a simple, low-cost method of controlling inventory with the minimum number of resources and time required.

Limitations to the two-bin ordering system are that it typically requires more space since the policy often results in storing more inventory than other policies (Esmaili, Norman and Rajgopal, 2015). Storage could be difficult to implement for some products, due to the requirement of two bins. It is, however, a policy that is easily implemented operationally. It does not require counting of inventory and can lead to reduction of logistics costs and effort.

3.5 Healthcare inventory management

Within healthcare the tradeoff for inventory management is between lowering the cost of the necessary items, without sacrificing the availability of products and patient care, where the latter is seen as the essential objective (Rossetti, Buyurgan and Pohl, 2012, p. 10). Reaching high service levels and product availability can mean overstocking, which in turn leads to higher inventory holding costs, and potentially more waste, if products are not used before the sell-by date. Additionally, overstocking can use up space that could be spent on other critical products. It is, however, important to note that emergency orders in healthcare can cause supplementary labor costs, postponed patient treatment and possible life-threatening situations for patients (Ahmadi *et al.*, 2019, p. 3). In relation to this, backordering is generally not recommended when it comes to healthcare inventory (Saha and Ray, 2019).

3.5.1 Non-pharmaceutical hospital inventory

Most non-pharmaceutical hospital goods fall under the category of medical devices. A medical device is defined as any instrument, apparatus, software, appliance or material to be used specifically for therapeutic or diagnostic purposes for diagnosis, disease prevention, disease or injury monitoring, treatment, investigation or modification of anatomy or a physiological process, or control of conception (Battini, 2014). This includes disposable devices, reusable devices, special implantable devices, generic ward equipment, large capital machinery and temperature-controlled devices. Medical devices can incorporate medicinal substances but are not themselves considered medicinal products. Different types of medical devices have varying requirements regarding monetary value, time of use, type of packaging required due to sterility, type of maintenance process due to expertise, and type of sterilization process. Hospital inventory items which are not considered medical devices are, as mentioned, drugs and medicinal products, as well as human blood products, which are not included in the scope of this study.

One important characteristic of medical devices is their heterogeneity (Battini, 2014). Each hospital has their own practice regarding logistics, and they include many different patients, each with their own requirements and needs, resulting in many kinds of medical devices on the market. Medical devices also generally have very high capital costs, and a short life cycle as the innovation process is constant within the sector, but these characteristics are more fitting for large capital machinery, which are not the focus of this study. Lastly, fixed prices are a known characteristic of medical devices. Medical devices are usually classified based on a risk-based classification scheme, according to general criteria of invasiveness, duration of continuous contact, nature of the tissue contact, and distinction between non-active and active devices. These can be combined with a general logistics device classification based on criteria such as monetary value, reusability, maintainability, and packaging requirements.

The medical devices kept in non-pharmaceutical hospital warehouses can be subcategorized as medical consumables, which can be disposable, or equipment that is used several times before disposal or being used up (*CONSUMABLE | English meaning - Cambridge Dictionary*, 2022). Healthcare inventory items are often analyzed for their criticality based on patients' medical conditions and the specific treatment procedure which requires the inventory (Saha and Ray, 2019). This factor can be difficult to perceive completely. As for most products in the healthcare supply chain, it is also often challenging to forecast demand for medical consumables. Inventory demand problems under certainty may be used for items which are purchased in bulk, and that generally don't experience large variations in demand, compared to other critical items. Examples of such items can be examination gloves, certain intravenous fluids, and syringes. Inventory demand problems modeled under uncertainty typically assume a specific probability distribution of the random variables and are usually related to hospital activities in intensive care units, operating rooms, and emergency rooms. Some non-pharmaceutical hospital inventory items related to this can be surgical supplies.

3.5.2 Hospital warehouse ordering policies

A healthcare inventory's optimal stock level depends on the availability of space and the frequency of deliveries (Kumar and Kumar, 2015). A study conducted on inventory management at a university hospital showed how quality of patient safety was the most important indicator for improving healthcare inventory out of 14 sub-criterion within quality, time, financial and productivity factors (Sirisawat, Hasachoo and Kaewket, 2019). Therefore, inventory management decisions should be made with regards to the reduction of delays and errors negatively impacting hospital patient safety. One study presents the FOI-model for ordering as the most commonly used in healthcare, as it is simple to use, and pairs well with set ordering frequencies from suppliers (Ahmadi *et al.*, 2019, p. 6). Another study on modeling and analysis of inventory management systems in healthcare by Saha and Ray (2019) states that many healthcare systems use a combination of periodic and continuous review policies, in addition to joint replenishment criteria for several items. If real-time information is made available through the use of industry 4.0 technologies such as RFID, continuous review is considered as the preferable option (Fragapane *et al.*, 2019). Continuous review can, however, result in more frequent shipping, which means it is most ideal in a situation with a low cost per shipment.

One study using a simulation model of a hospital inventory system has shown that under shock demand conditions, a higher inventory review frequency is important for the success of operations (Duclos, 1993). Another policy for managing inventory at central warehouse hospitals was suggested in a study by Dellaert and van de Poel (1996), which is a combination of periodic and continuous review. It is known as the "(R, s, c, S) policy". There is a periodic review period, R, where if inventory levels have fallen below a level, c, an order up to level, S, should be released. The continuous review parameter is introduced where if the inventory at any time falls below s, an order up to level S must be made. The implementation of this model proved to be both efficient and simple to use.

The two-bin replenishment system has also proven to be an ideal inventory management system for medical supplies and office supplies in one study by Denton (2013). This investigation revealed that advantages of the two-bin system over periodic review systems include reductions in the average inventory level, reduction in time spent on ordering processes, reduction in product handling, built-in stock rotation and reduction of product expiration risk. RFID has been suggested as a technology for further improving the two-bin replenishment system. Expensive inventory items are recommended to be managed by a two-bin replenishment system, as this often supports reduction of inventory holding costs and an increased inventory turnover rate (Xu, Wermus and Bauman, 2011).

3.5.3 Supply and demand characteristics

Disruption risk and operational risk are known as the two main sources of uncertainty in a supply chain context (Ahmadi *et al.*, 2019). These sources can result in unwanted incidents such as shortage of capacity or necessary supplies. Sources of loss such as natural disasters, pandemics and environmental crises are all causes of disruption risk. Operational risk, on the other hand, is caused by uncertainty related to transportation time and cost, as well as uncertain demand and lead times. It has been suggested that the impact of disruption risk is greater than that of operational risk to the supply chain (Ahmadi *et al.*, 2019).

Due to the uncertainty in healthcare systems, the demand of inventory in hospital warehouses can be categorized as non-stationary (Saha and Ray, 2019, p. 5). Non-stationary demand is demand that varies unpredictably due to uncertainty in factors such as demand for medicines, lead times, availability from suppliers, differences in patient turnover rates, the length of hospital stays, conditions of patients, patients' response to various medicines and number of patients. To simplify the development of inventory management models, many studies have chosen to assume an independent and constant demand for healthcare items. Information about the consumption of supplies from POU inventories is generally lacking, exacerbating the difficulty in predicting demand (Fragapane *et al.*, 2019).

One study identifies demand related characteristics which should be taken into consideration when managing inventory in healthcare settings (Saha and Ray, 2019). The first characteristic presented is the changing condition of patients at hospitals. In addition to the different conditions of individual patients, each patient can develop new conditions throughout their stay, which further increases the uncertainty in demand for hospital goods. Second, the variability in the length of time each patient stays at a hospital will impact demand. Also, each patient can be transferred from one POU to another during their stay, due to changes in patient condition. Another important characteristic is the heterogeneity of both physicians and patients. Not only does each patient require a unique supply of healthcare items, but each physician has their own behavior regarding diagnosing and care for patients. These different behaviors will further impact demand for non-pharmaceutical hospital goods. Lastly, the study mentions the dependency of demand among items such as different medications, or medical devices that are interdependent because they can be used for preventing or treating similar diseases.

It is often challenging to predict the availability of items from suppliers, as information sharing between the supplier and the hospital is not always possible, in addition to the uncertainty of raw material availability (Saha and Ray, 2019). The continuously evolving and uncertain environment of healthcare often makes the availability of such goods undetermined. It is therefore vital to develop an inventory management system which can reduce the risks related to these challenges.

3.6 Summary

Inventory classification is a technique that is often used for simplification of inventory management tasks and supporting related decision-making, where management on an SKU level is not feasible or sufficiently efficient. Some methods for classifying inventory were presented in Section 3.3. It was found that the use of more than one criterion in classification of inventory may be more appropriate, as items often have more than one characteristic which can have an impact on inventory management decisions. However, too many criteria will reduce the benefit of a given classification scheme and further complicate the decision-making process. The ANP method, which is a generalization of AHP, is argued as a fitting method for inventory classification for inventory management decisions, since it allows for judgmental ranking of decision criteria, as well as dependencies between criteria and alternatives.

The main goal of inventory management in a hospital setting is found to be supplying the hospitals with adequate products so they can fulfill patient requirements, while concurrently keeping costs as low as possible. Hospitals are more willing to overstock than other industries if this means providing adequate patient safety. Overall, the literature states that quality of patient care is the main goal in hospitals, and any factor contributing to this goal should be prioritized in inventory management decisions at a central warehouse.

The unpredictability of demand in healthcare due to the diversity in patients' conditions is presented as a crucial factor to consider in inventory management of non-pharmaceutical hospital goods. The uncertainty in supply and demand due to both operational and disruptive risks is also important. Earlier studies have identified the criticality of inventory as a significant factor to consider when managing such inventory. Non-pharmaceutical hospital goods can be characterized as heterogeneous due to the variation in patients' conditions and doctor requirements. Additionally, demand dependency should be considered when making inventory management decisions for these products.

4 Case Study: Helse Midt-Norge Logistics Center

This chapter presents a selection of empirical information collected through discussions with the case organization's contact people and hospital warehouse purchasing managers, in addition to visits to the case warehouse and analysis of the data retrieved. First an introduction to the case organization is presented, followed by a description of inventory management characteristics of the central warehouse, including a more detailed account of their ordering policies, as well as the inbound and outbound material and information flows. Lastly, the inventory goods at the case warehouse are analyzed and characteristics of these are presented towards creating criteria for inventory classification. The case study is used for both the development of new theory through the framework and testing of the framework through simulation experiments.

4.1 Case organization introduction

St. Olav is the state-owned hospital in Trondheim, which cooperates in research with NTNU. The Helse Midt-Norge Logistics Center (HMN Logistics Center) is organized under the management of Helse Midt-Norge (HMN), which is the Central Norway Regional Health Authority. The authority is state-owned and responsible for operating hospitals in the Trøndelag and Møre- og Romsdal regions in central Norway. The previous local HMN warehouse, located near Trondheim, supplied only the St. Olav hospital. As a cost-reducing measure, HMN replaced local warehouses with the HMN Logistics Center, which is a regional logistics center at another location in Trondheim. Operations at the HMN Logistics Center began at the end of November 2022, supplying the St. Olav hospital in Trondheim, Orkanger and Røros. Hospitals in the northern Trøndelag region and Møre og Romsdal region are planned to be supplied by the HMN Logistics Center by the end of 2023. The centralization of this hospital warehouse structure inspired the initiation of the specialization project preceding this thesis. The HMN Logistics Center manages all non-pharmaceutical products supplied to the hospitals, medical centers, and doctor's offices in the area.

The HMN Logistics Center employs approximately 50 workers that process around 1200 individual orders per day. They use external suppliers for non-pharmaceutical hospital goods, and the warehouse additionally functions as a cross-docking facility. Goods arrive several times a day from suppliers, and the warehouse supplies their customers several times a day. The purpose of the HMN Logistics Center was not solely the centralization of the warehouse, but also modernization. The new warehouse has some state-of-the-art technological advancements aiding in efficiency and automation of logistics processes, such as vertical lift modules (VLM), iPads, and barcode scanners.

4.2 HMN Logistics Center inventory management

This section characterizes and describes the HMN Logistics Center's current inventory management practice. Firstly, the layout and management of inventory within the warehouse is presented briefly before the ordering policy is described. From a supply chain management perspective, both the inbound and outbound information and material flows are explored, to get a clearer picture of the existing inventory management at the case warehouse.

The main priority when making inventory management decisions at the case warehouse is patient safety and doctor requirements. The warehouse differentiates between safety stock and emergency inventory. Safety stock is the general excess stock of each SKU that is kept in case the cycle stock is not sufficient to meet the expected demand, or there are problems with suppliers. Emergency inventory, however, is the specific inventory kept only to be distributed in case of an emergency creating a disruption in the supply chain, such as a pandemic, a war, or a natural disaster. There is a separate stock room for this emergency inventory, as it is only to be used in special circumstances. Only specific products are stored here, and a supply covering 3 months of expected demand for these products should be available in case of emergency disruptions in the supply chain. These products usually remain untouched for around 5 years, at which point the items are reordered. There is virtually no turnover on these products, but during the Covid-19 pandemic, there was some turnover. The main storage area also has a sterile zone, which is kept at a positive air pressure and products going into this zone are air-washed before entering, to remove bacteria and microbes. Additionally, there is a separate room specifically for flammable products. This room can be cut off momentarily if there is a fire in any other part of the warehouse, minimizing the risk of explosion. Figure 8 shows a simple structure of the layout at the case warehouse. The areas for inbound and outbound material flow are highlighted in blue.

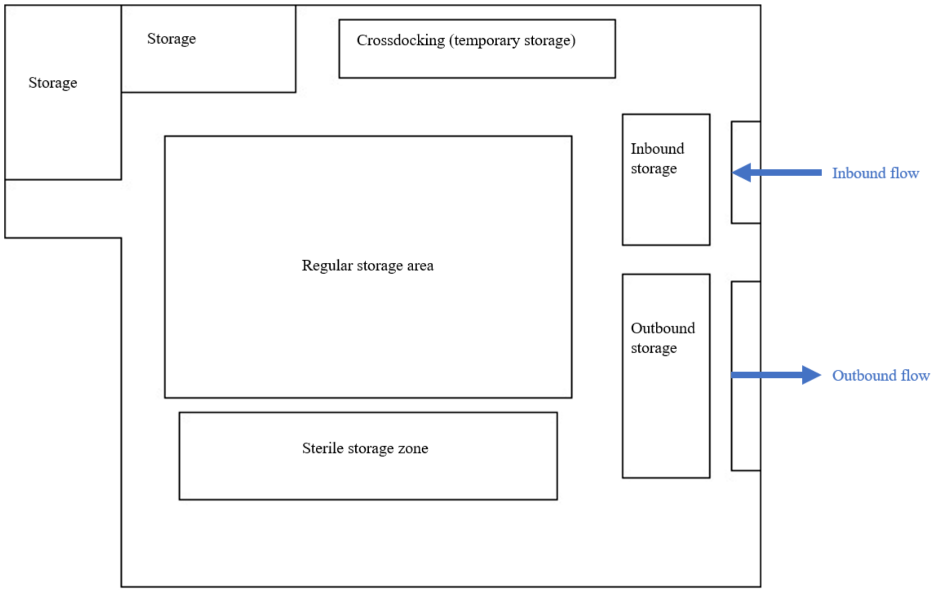


Figure 8: Simplified layout of case warehouse

4.2.1 Ordering policy description

The expiration date of products is not an issue when developing the case warehouse's ordering policy. This is because the products' shelf lives are longer than two years, the turnover rate is around 6 months, and a first-in-first-out (FIFO) method is used for storage within the warehouse. The current ordering policy at the case warehouse can be described as a form of ROP policy with a fixed order quantity. There is a minimum stock level for each SKU, where if the stock level falls below this point, a set quantity is ordered. This quantity is usually based on the expected demand for the product in one month, and not based on the ROP formulas presented in Chapter 3. The current ordering policy for the HMN Logistics Center as described is depicted in Figure 9. The warehouse uses ABC categorization for storing items within the warehouse, but this is not used for ordering policies. They do not currently practice classification of inventory for the purpose of ordering policy development.

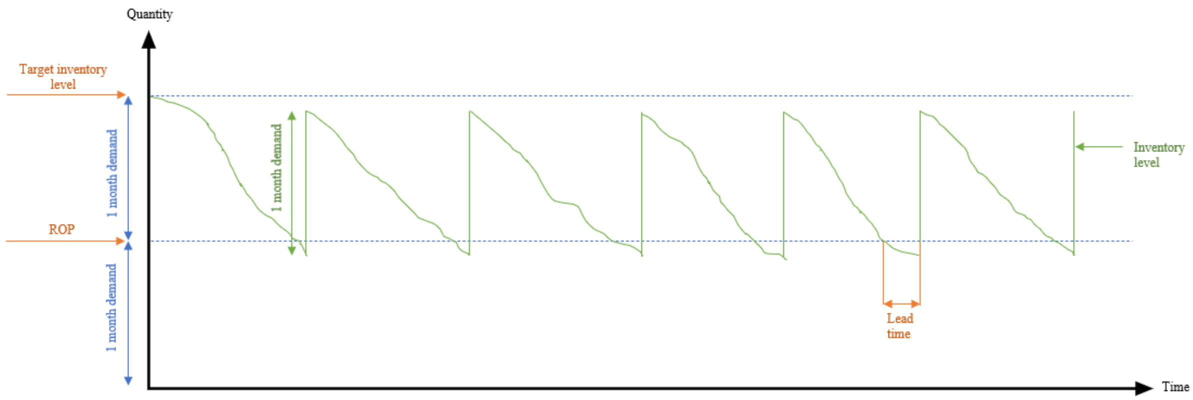


Figure 9: As-is ordering policy for the HMN Logistics Center

The safety stock levels for most inventory items in the case warehouse are not calculated using the traditional ROP formulas but are included in the set reordering points. Since most products are managed by ordering a months' expected demand when a month's expected demand is remaining, this means that the safety stock is included in the month's expected demand. The warehouse also has a list of certain products which are deemed more critical to patient safety than others and they are required to always keep coverage for at least 3 months of expected demand for these products. As a hospital warehouse, they are strongly discouraged to have backorder. The goal of the HMN Logistics Center is to avoid backorders as much as possible, but if they occur, they are forced to deal with them in an efficient manner.

4.2.2 Inbound material and information flow

Ordering quantities from suppliers can be changed, if necessary, but this requires manual registration. As they are required to keep enough products to cover the highest expected usage of each item for the given time period, they often need to purchase large amounts of stock from the suppliers. Based on a demand forecast set for each product, contracts with suppliers are typically signed for several years at a time, making it difficult to change the individual orders from suppliers. If the case warehouse suddenly changes their order, for instance by a significant increase in the order size, it could impact other hospital warehouses negatively. Healthcare suppliers need to allocate the resources evenly throughout the hospitals and corresponding warehouses in their area. Buildup of safety stock is therefore done over time, since sudden orders of large batches are not considered feasible. There is rarely a quantity discount when ordering from suppliers. According to the purchasing managers, toilet paper is one of the exceptions to this. The suppliers oversee product allocation. The hospital warehouses can place orders as desired, but they might not be fulfilled, since the suppliers have access to information on their requirements to meet demand in the course of the month. The suppliers attempt to even out the distribution of supplies, so that every hospital ward receives what is necessary.

Between the suppliers and the case warehouse there are different practices for deliveries. Some suppliers will operate with FTL policies and some use delivery companies or mailing services. Often the suppliers can send a truckload to several of their customers at once. There is a 3 day lead time set between the suppliers and the case warehouse, but, in practice, the lead time is usually between 3-5 days for all suppliers located in Norway. Any lead time longer than this is considered a deviation. As a hospital warehouse they are required to have backup suppliers for all goods in case of a shortage or scarcity with the main supplier.

4.2.3 Outbound material and information flow

The goal for the case warehouse is to keep the service level at a satisfactory level for the hospitals, ideally at 98%. It would also be preferable to have good financial and environmentally sustainable performance, but securing supplies to the hospitals is their main priority. The past few years with the pandemic have caused special circumstances at the case warehouse, where the focus has been on providing the hospital with what is required at the time it is required, but in the future, when the situation has stabilized, it would be favorable to spend more time and resources on improving efficiency of the hospital supply chains.

The case warehouse's customers, the hospitals, must place an order at least 4 hours before it is needed at the POU, due to the driving schedules. In practice, the time between placing an order and arrival at the POU is often longer, since not all trucks go to each hospital, and in some instances, trucks are already full. In some circumstances, the warehouse has the possibility to put in an extra truck to what is planned in the driving schedule, if this is required due to unforeseen demand from the hospital. Truckloads driving from the case warehouse to the hospitals are charged per truck and operate with a LTL loading policy, but the trucks are often full or close to full. Transport time between the case warehouse to the St. Olav hospital is set at one hour. This does not mean the driving time is one hour, but rather that to ensure the customer receives the product by 9am, the truck must leave the warehouse at 8am.

The case warehouse cross docking practice involves a separate catalog that the purchasers at the hospital can utilize to order directly to their wards. These products are typically not stored at the warehouse for long periods of time and most often they go through the warehouse the same day. These products are not a part of the warehouse's regular ordering system.

4.3 Inventory items at the HMN Logistics Center

This section delves into the analysis of the inventory items at the case warehouse using data on the demand from the hospital to the case warehouse in a two-year period, as well as information relating to each individual SKU in turnover at the case warehouse. This analysis will be used together with results from the literature study section for characterizing non-pharmaceutical hospital goods and framework development.

The non-pharmaceutical hospital inventory products kept at the case warehouse include medical consumables, such as plastic gloves and bandages, daily consumables, such as coffee filters, notebooks and toilet paper, some simple surgical instruments, and diagnostic tests, such as covid-19 tests. From the variety in usage areas of these products, it is safe to state that there is a variance in their criticality levels to the end patients at the POU in hospital wards. In the case of a medical emergency, it can be assumed that certain surgical instruments may be several levels higher in criticality to the patient than coffee filters, for instance.

The inventory demand data retrieved from the case warehouse was an Excel worksheet of approximately 950 000 rows of all outgoing orders from warehouse to the hospitals in the period of September 2020 to September 2022, with each order divided into separate SKUs. Each order of each SKU included information regarding the order number, material number, material name, order time, order size and total price of the order. After receiving the worksheet, Excel calculations were performed to compress the worksheet into 2588 individual SKUs. Calculations were performed to find the number of orders of each SKU in the period, the average order size, the average price per item, and the total number of items ordered.

As the data received were limited to orders from the warehouse to the hospitals, they did not give information on the actual demand at the POU, since there may have been orders placed and completed of products that did not result in use, and there may have existed demand that was not fulfilled by these orders. The data retrieved could therefore only give an approximate idea of the usage of these products by the hospitals in the region. Nevertheless, the ordering information gave an indication of the hospital's demand from the warehouse. The information on the unit cost and material name could, however, with certainty be used to make statements regarding the product characteristics.

Furthermore, the inventory items were categorized based on their usage area. The purpose of this was to gain understanding of the use of the products for characterization. One example of this was how approximately 50 separate SKUs of plastic gloves were gathered into one larger group of plastic gloves. This allowed for a clearer analysis of the product properties. It is important to note that the categorizations were done based on researching each product name and not on expert opinions and knowledge.

Products with the highest unit cost included some reusable surgical equipment, consumables related to large electrical medical devices, diagnostic catheters, and batteries for electrical devices. These products were ordered by the hospital in very small batches, often single unit sized, but had a varying ordering frequency. Products with the lowest unit cost included most disposables such as plastic gloves, face masks, coverings related to infection control, covid-19 tests, diapers, pads, and most bandages. These products were ordered by the hospital in larger batch-sizes, also with varying ordering frequency. The unit cost of the SKUs ranged from 0 NOK to 15 644 NOK. The average unit cost was 194 NOK, 92% of the products had a unit cost below 500 NOK and the cheapest 80% of the products were priced below 200 NOK. 72% of the SKUs were priced below 100 NOK and 32% were priced below 10 NOK. It can therefore be concluded that the products at the case warehouse are mainly low cost, with some outliers having a higher unit cost.

Products with a higher unit cost are more expensive to keep in the warehouse, due to capital binding. Capital binding refers to the amount of capital that is tied up or locked into a particular investment/asset, that cannot easily be converted into cash or used for other purposes. This is also related to the uneven demand for products with a higher unit cost.

Products with the largest order batch size included disposables such as plastic gloves, face coverings, most stationery, plastic bags, and bandages. Items with the smallest order batch size encompassed some stationery, syringes, cleaning supplies, dialysis-fluid, procedure packages, equipment for sutures or ligatures, plaster casts, and orthosis. Products with the highest order frequency included disposables such as plastic gloves and face masks, disinfectants, infusion fluid, syringes, and oxygen therapy equipment. Items with the lowest order frequency encompassed special bandages, certain stationery, fluid for dialysis, and equipment for specific types of surgery. The demand volume for each SKU per year ranged from 0.5 pieces to 1 566 600 pieces, where the average was 44 895 pieces. The average order size from the hospitals was 129 pieces per order and the order sizes ranged from 1 piece per order to 10 000 pieces per order. It can be worth noting that 93% of the orders were 100 pieces or less. Along with the average demand volume, this supports the notion that most of the products were ordered more frequently, in smaller batches. The average order frequency in the two-year time period was 368 orders, which corresponds to 184 orders per year. The range was 0.5 orders per year, to 4146 orders per year. The items with a higher ordering frequency are considered faster moving in the warehouse inventory.

4.4 Summary

Results from the data analysis supports characterizing products at the case warehouse as being of low unit cost. More expensive items were ordered in smaller batch sizes by the hospital and lower unit cost items were ordered in larger batch sizes. The ordering frequency, however, varied independently of the cost of the items. This supports demand variation not correlating with the unit cost of the product. However, findings from the case study indicate that costs should be considered when managing non-pharmaceutical hospital inventory, even though the service level to the hospital is the most important factor. As a government owned institution, there are certain obligations which must be upheld regarding keeping the costs at an appropriate level, as well as environmental considerations.

Based on the investigation of product usage areas the characteristic of heterogeneity of the inventory is supported due to the large variation in usage areas and high number of separate SKUs. Despite the large variation in usage areas, there are also several products which seem to be used for the same procedures, further supporting the characteristic of demand interdependency between the items. Varying criticality is also supported based on results from the data analysis. Additionally, this feature is already recognized by the hospital as a characteristic which should be accounted for when making inventory management decisions at the warehouse, as there exists a predefined list of the items which should be considered as the most critical to patient safety.

5 Inventory Management Framework

This chapter deals with the development of the inventory management framework for non-pharmaceutical hospital goods, based on findings from Chapter 3 and Chapter 4. Following the framework development, the definition of classification criteria levels is discussed.

5.1 Framework development

Non-pharmaceutical hospital goods vary in their criticality to patient care, and demand predictability is challenging due to variations in patient conditions and medical procedures. Heterogeneity and interdependency are defining characteristics of non-pharmaceutical hospital goods that affect the forecasting of demand, which can further have a defining impact on inventory management decisions. Most non-pharmaceutical hospital goods have a low unit cost, with a few outliers, such as certain surgical equipment and electrical devices. These characteristics are important to consider when making inventory management decisions and should therefore be translated to classification criteria.

The characteristic of varying criticality leads to the classification criterion of criticality with respect to the end patient in hospital wards. Varying demand predictability, with the higher the unpredictability, the closer that attention should be placed on the item, can be translated to the classification criterion of demand unpredictability. The characteristic of being low-cost items, with certain outliers, leads to unit cost as a classification criterion. Varying criticality and the need for the global healthcare supply chain to increase its resilience to unpredicted disruptions (Golan, Jernegan and Linkov, 2020) supports criteria related to uncertainty with suppliers and difficulty obtaining products. This leads to scarcity being chosen as a classification criterion. The resulting classification criteria for inventory classification are then translated to criteria for the optimal ordering policy for the given SKU that is classified.

A higher level of criticality of an item should lead to an ordering policy that provides a higher service level for the hospital and, ultimately, the patient. Therefore, service level is included as a criterion for the ideal ordering policy. Higher demand unpredictability requires flexibility in both the batch size and the ordering frequency, as it can be necessary to change these factors on short notice. Inventory with a high level of scarcity also requires ordering policies that are flexible in both ordering frequency and batch size, so that these parameters can change if a product becomes available on short notice. Less scarce products do not require as close attention as products with a higher degree of scarcity. For these reasons, batch size flexibility and ordering frequency flexibility are included as ordering policy criteria. The inventory classification criteria of unit cost require ordering policies that support both items with a higher unit cost and items with a lower unit cost. Therefore, the cost of the ordering policy should be included as a criterion. From the case study it is also shown that products with a higher unit cost generally have lower demand than low unit cost items. This also supports an ordering policy that allows for smaller batch sizes and flexibility in ordering frequency, as ordering and stocking unused items with a higher unit cost can lead to a greater financial loss.

The optimal ordering policy for a non-pharmaceutical hospital item can be determined with the help of the framework shown in Figure 10, which is inspired by the ANP method and general decision-making theory as described in Chapter 3. The item should first be classified based on the classification criteria. The higher the level of the criterion is for the item, the higher the importance of the correlating ordering policy criteria are for that item. For example, an item classified according to a higher level of criticality implies that the item is highly critical to patient safety, and therefore an ordering policy with a high service level should be prioritized. According to the inventory classification result, the ordering policy criteria are identified. The result is the optimal ordering policy for the given item.

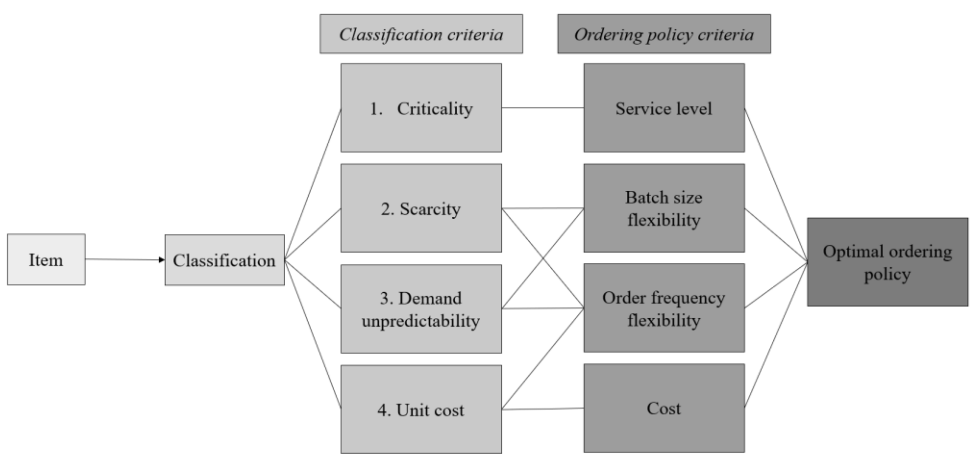


Figure 10: Inventory management framework for non-pharmaceutical hospital warehouses

Table 4 presents the suggested elements of ordering policies to consider for each level of ordering policy criterion. An ordering policy that assures a high service level can be an ordering policy taking the service level into account, such as a version of the ROP policy. No policies are directly correlated with a low service level, but some policies can lead to lower service levels than others in certain situations. One example of a policy that can lead to a lower service level is an ordering policy which does not keep adequate safety stock. For ordering frequency flexibility, elements of ordering policies which do not set requirements for the ordering frequency are suggested. Likewise, if the requirements for ordering frequency flexibility is low, one can use a policy which has a set ordering frequency, either by a set time interval or an ordering point. A similar reasoning is used for the criterion of batch size flexibility, where a higher batch size flexibility requires the ability to change the batch size upon request, whereas a lower batch size flexibility includes ordering policy elements of set batch sizes. For the criterion of cost in the ordering policy this depends on the situation. Usually, a policy that minimizes safety stock and logistics costs should be selected for lowering the cost of ordering policy implementation.

Table 4: Proposed resulting ordering policy elements based on criteria levels.

Ordering policy criterion		Proposed resulting ordering policies
Service level	High	ROP, as it secures adequate safety stock levels and takes the desired service level into account.
	Low	No policies overall lead to lower service levels, but certain policies can lead to lower service levels than others, depending on the situation.
Order frequency flexibility	High	EOQ, POQ, lot-for-lot, or Fixed order quantity.
	Low	FOI, Two-bin, or ROP.
Batch size flexibility	High	Lot-for-lot, ROP, or FOI.
	Low	Two-bin, EOQ, POQ, Fixed order quantity, or Min-max ROP.
Cost	High	No policies have a high overall cost, but certain policies can be more expensive than others depending on the situation.
	Low	EOQ, POQ, lot-for-lot, or other policies that minimize safety stock and logistics cost, such as two-bin.

To apply the framework in existing non-pharmaceutical hospital warehouses two main steps are identified:

1. Selection of the inventory classification criteria levels.
2. Selection of an ordering policy based on the inventory classification criteria levels.

Step 1 of the framework application will be discussed in the subsequent Section 5.2. Steps 1 and 2 of framework application are examined through the simulation study in Chapter 6.

5.2 Definition of classification criteria levels

The definition of the classification criteria levels should be done in a rigorous fashion and can vary depending on the warehouse in question. The framework for inventory management is initially designed to accommodate either low or high levels of each criterion, but as each of these can be seen as a spectrum, it is possible to adapt both the levels of the classification criteria and the ordering policy criteria to more than two different levels, such as low, medium, and high. It is important to note, however, that increasing the number of end groupings of inventory will also complicate the process further, which contradicts the main goal of classifying inventory with the aim of a simpler decision-making process in inventory management. Methods for how the levels for each classification criterion can be defined are discussed.

Criticality:

For the criticality criterion, one should utilize the knowledge of experts within the use of all products at the warehouse to determine which products should be considered more or less critical for the end patient in the hospital. This can be done through interviews with doctors/nurses/specialists or a combination of these professionals in focus groups. It can be reasonable to assume that items such as coffee filters do not have the same criticality as syringes and certain surgical equipment, but it is necessary to consult with specialists to determine anything more specific than this.

For the case warehouse, a list of the most critical products was provided. The list consisted of 98 products, which have been determined by medical practitioners as the most critical for hospital patients. These items included certain catheters, syringes, oxygen masks, infusion sets, fluid for dialysis and electrodes. These 98 items were then classified as being of high criticality. The remaining products were classified as being of low criticality. It is important to note that the products not included in the list of 98 most critical products could still be considered critical to patient safety, but the list represents the most crucial products as prioritized by experts in this situation.

Unit cost:

For the unit cost criterion, there may be predefined levels at the warehouse. However, there may often be instances where these are not yet defined. One possibility is for the level to be set at a point where there is a clear divide between the lower cost items and the higher cost items. It is also possible that consultation with experts on the product types can aid in determining what should be classified as having a low or high unit cost. Since the ordering policy selection can depend on the way the product is classified, it is also possible to examine the characteristics of the products regarding ordering policy decisions and see where this change is the most prominent. There may be a natural divide, which allows the division between two or even three different levels, but data analysis may also be needed to set the levels.

For the case warehouse, the products were plotted according to their unit prices in ascending order, in a cumulative fashion, in the graph shown in Figure 11, to visualize the unit price increase curve.

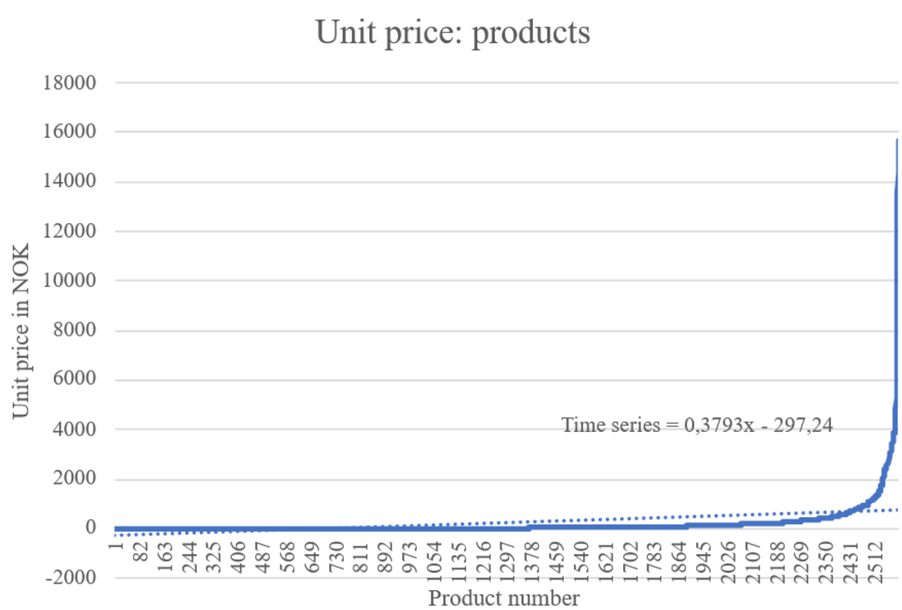


Figure 11: Cumulative unit price per product

This was done to get an overview of any large, sudden increases in the unit price. The graph visualizes how the unit price starts increasing more rapidly approximately where x = 400. Therefore, the level for low unit cost at the case warehouse is decided to be up to and including 400 NOK. Any product above 400 NOK is classified as high unit cost. The cheapest 2335 products are therefore considered low cost, as they are priced below 400 NOK. Accordingly, there are 253 SKUs at the case warehouse classified as high cost.

Scarcity and demand unpredictability:

The criteria for scarcity and demand unpredictability can be combined, as the levels of these will impact the ordering policy decisions in a similar way. Both a high level of scarcity and a high level of demand unpredictability require an ordering policy that allows for flexibility in the batch size and in ordering frequency as shown in the description of the framework. These are the most challenging criteria levels to determine, as they are concerned with the uncertainty of both supply and demand. Scarcity levels can be determined by looking at historical data of the scarcity of certain products or suppliers as predictions for future events. Similarly, the unpredictability of demand for products can be determined by looking at the past forecast demand in relation to the actual demand, to see if there are any existing patterns.

For the case organization, it was found through meetings with the purchasing managers that levels for scarcity and demand unpredictability were considered impossible to set at the time of the case study. The case warehouse did not possess a system for tracking the scarcity or demand unpredictability of products, so this level was not possible to set in a rigorous fashion for the framework testing. These criteria were still tested through simulations in Chapter 6 to determine the extreme levels of the criteria's impact on the ordering policy selection.

Classification process for case organization

After the classification criteria levels are set, the inventory classification process should be initiated. The following is an example of the process for inventory classification as it could be executed at the case warehouse:

1. Divide products into critical and non-critical based on the list of critical products. This results in two groups.
2. Divide subgroups into high and low cost, using the analysis of unit cost per item. This results in 4 groups.
3. Divide subgroups into high and low scarcity/demand unpredictability. This was done in preparation for the simulation study and should not be done in practice at the warehouse, as these criteria levels were not set in a rigorous fashion. Since it was impossible to determine what products could be classified as high or low scarcity/demand unpredictability at the case warehouse, the initial level for this criterion was found by

splitting the product groups in half, which meant 50% of the products in each of the 4 groups were considered high scarcity/high demand unpredictability and the remaining 50% were considered to have a low scarcity/demand unpredictability. After this step there should be 8 groups which require a separate ordering policy selection.

4. Ideally, one should go into detail for each SKU in each product group to not only determine the ordering policy selection, but also the selection of ordering policy parameters for the given SKU. As a simplification for the framework testing through simulation experiments, the ordering policy parameters were set at a group level. Even though ordering policies in practice should be determined on an SKU level, this was a reasonable simplification since the actual orders inbound and outbound from the warehouse are most often grouped together in truckloads and very rarely is there a truck delivering only one type of SKU either inbound or outbound from the warehouse.

Groupings:

As shown in Figure 12, the resulting product groups each have a different combination of the levels in the criteria of criticality, unit cost, and scarcity/demand unpredictability.

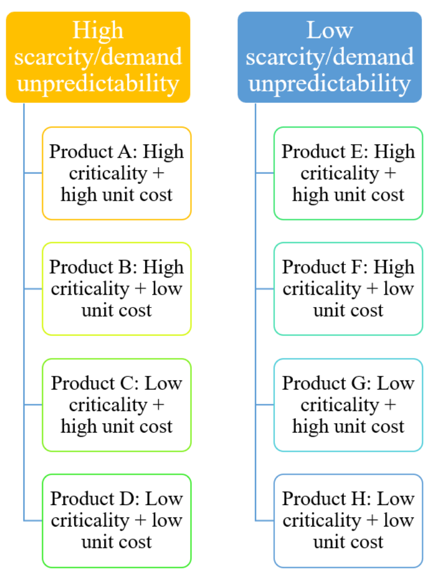


Figure 12: Product groupings at case warehouse

6 Simulation Study: Framework Application and Testing

This chapter presents the simulation study where the framework for inventory management of non-pharmaceutical hospital goods was tested using the proposed classification criteria levels from section 5.1 based on information and data retrieved from the case warehouse. First, a conceptual model was developed of the inventory management framework application at the case warehouse. Following this, the conceptual model was made appropriate for simulation experiments in anyLogistix software, together with demand modeling and ordering policy modeling. The scenarios depicted in the simulation experiments are described in detail before the simulation experiment results are presented.

6.1 Conceptual model development

The conceptual model for the simulation was developed using the framework for conceptual modeling as described in Chapter 2.

1. *Understanding the problem situation:* The problem situation consisted of investigating the use of inventory classification methods on ordering policy selection in non-pharmaceutical hospital warehouses. A more detailed description of the problem situation was presented in Chapter 1.
2. *Determining the modeling and general project objectives:* The general objectives for this conceptual model were threefold, based on the research questions: to test and validate the proposed framework for inventory management of non-pharmaceutical hospital inventory goods; to investigate the link between criteria level definition and ordering policy selection; and to test the proposed definitions of inventory classification criteria levels. The framework was described in detail in Section 5.1 and the definition of criteria levels was discussed in Section 5.2. To meet the general objectives for the simulation it is important to develop a model which is sufficiently accurate. Constraints to the conceptual model development included the time available for making the model and running the simulations, in addition to the limits of information and data available from the case warehouse.
3. *Identifying the model outputs:* The desired responses from this model were the relevant performance metrics of available inventory levels and service levels, shown in line graphs depicting the development throughout each simulation experiment. These performance

metrics were chosen based on the main goals of hospital warehouse inventories to maximize their service level for the hospital and to cater to patient safety requirements.

4. *Identifying model inputs:* The suggested ordering policies and their parameters were the experimental factors to be altered to meet the model objectives.
5. *Determining model content:*
   a. Demand modeling: In a stochastic nature, with a Normal probability distribution calculated from actual order information from the hospitals to the case warehouse.
   b. Truck loading policies: LTL for all trucks inbound and outbound.
   c. Lead time information: 3-5 from suppliers to warehouse and 1 hour from warehouse to customer, based on the transportation time.
   d. Simulation duration: 1 year (365 days) of operations at the warehouse.
6. *Identifying assumptions and simplifications:* A range of assumptions and simplifications were necessary to create this conceptual model, due to the limited information from the case warehouse and the time constraints of this research.
   a. *Assumptions:*
      i. There is only one ordering policy used to manage each product group.
      ii. No lot size or discount policy when ordering from suppliers or delivering to the customer.
      iii. Items are considered nonperishable.
      iv. The suppliers are assumed to have enough capacity to always satisfy the demand so that their inventory levels are modeled to be infinite.
   b. *Simplifications:*
      i. All suppliers were modeled as one supplier since the individual suppliers were not included in the scope of this research.
      ii. Only one customer was modeled in the simulation experiments, the St. Olav hospital in Trondheim.
      iii. Many simplifications were made regarding costs, for instance a fixed delivery cost between all actors in the supply chain. This was due to a lack of information available regarding costs, in addition to it not being a chosen performance metric of focus.
      iv. Unlimited capacity at the warehouse

v. Unlimited truck capacity

7. *Identifying data requirements:* The data requirements for this model were adequate demand information both in order to model the demand for the product groupings, and to model the ordering policies.

8. *Model Assessment:* A simple diagrammatic representation of the model is presented in Figure 13 to aid in understanding the model against its requirements for credibility, validity, utility, and feasibility. Figure 14 shows the simplified HMN Logistics Center supply chain simulation in anyLogistix according to the conceptual model and Figure 15 depicts the actors in the supply chain simulation.

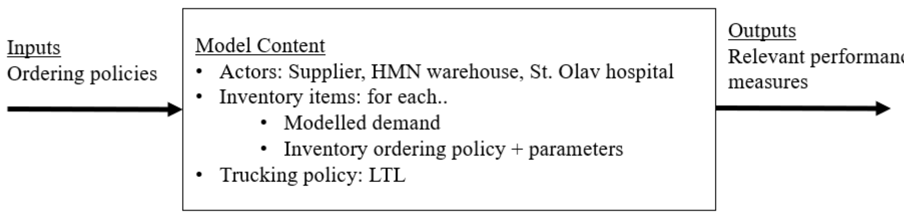


Figure 13: Simple diagrammatic representation of conceptual model for simulation

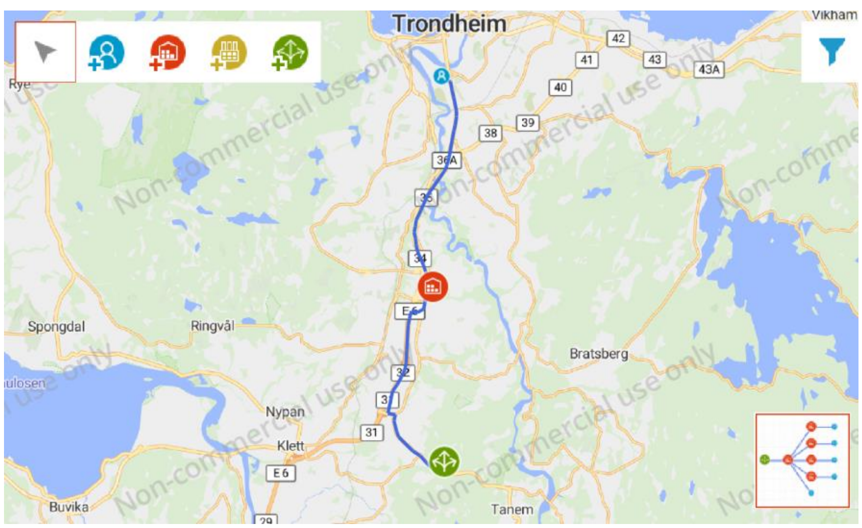


Figure 14: Screenshot of HMN Logistics Center supply chain simulation in anyLogistix

Figure 15: Actors in the HMN Logistics Center supply chain simulation in anyLogistix

6.2 Demand modeling

As presented in the conceptual model description the demand was modeled with a Normal probability distribution, according to findings in Chapter 3. The anyLogistix software allows for Normal distribution of both the order size and time between the orders. The raw demand data as described in the case study section were used to help create this probability distribution. The product classification groupings as presented in Section 5.2 were used to classify the individual orders into four different groups, based on their unit cost and criticality. As described previously, it was not possible to classify the products regarding scarcity or demand unpredictability, so it was not possible to classify the orders in the raw data based on this either. The scarcity and demand unpredictability criteria were therefore considered after the four groupings were demand modeled. The orders in each of the four resulting product groupings were then treated as orders for one type of product. Microsoft Excel software was used to calculate the mean and standard deviation (SD) of the time between orders, in addition to the order sizes outbound from the warehouse to the hospital. These numbers were then used for the modeling of demand in anyLogistix.

When calculating the time between orders, days where there was no activity at the warehouse, such as weekends and holidays, were not accounted for.

To take the scarcity/demand unpredictability levels into account, the mean of the resulting four groups were split in half, as well as the standard deviation, to create a mean and SD value for the 8 groups. Standard deviation and variance calculation rules state that:

$$\sigma^2_{X+Y} = \sigma^2_X + \sigma^2_Y \tag{8}$$

Where σ is the standard deviation of a value, X or Y. By using equation 8 and inserting $X = Y$, it was possible to find the standard deviation of a mean value split in half. This gave the two resulting groups the same mean and standard deviation values, which in turn meant their demand would be modeled the same way. Therefore, it was not necessary to test all groups A-H in the simulation experiments, but rather groups A-D and use resulting graphs for group A as graphs for group E and so on. Only product group A and E had a Normal distribution in the time between orders, as there were often several days between these orders. For the rest of the product groups there was a very high number of orders each day, and consequently, only the daily demand was modeled with a Normal probability distribution and the order intervals were assumed to be 1 day.

6.2 Ordering policy modeling:

To model the ordering policies in an appropriate fashion for anyLogistix it was necessary to find the fitting anyLogistix policy for each ordering policy for the groupings. An overview of possible ordering policies in anyLogistix is given in the table below:

anyLogistix inventory policy	*Description*
Min-max policy	This corresponds to the Min-max policy as described in Chapter 3. The parameters are min = ROP and max = order up to level, and safety stock if this is not considered in the ROP.
RQ policy	This corresponds to an ROP ordering policy with a fixed order batch size. The parameters are R = ROP and Q = order quantity.
Unlimited inventory	This policy assumes there is always enough stock to satisfy demand and subsequently there are no parameters to define.
Order on demand	For this policy the warehouse does not keep any products in stock and therefore there are no parameters to define. Products are only ordered from suppliers when the warehouse receives an order from a customer.
Regular policy	For this policy there is a fixed order interval and the parameter to set is Q for the quantity. It is also possible to set the time interval for when orders are to be made, for example once a day, week, or month.
No replenishment	For this policy the warehouse will not be replenished with inventory of the chosen product.
Cross-dock policy	For this policy the warehouse will not keep the inventory, but only transfer the products from one mode of transport to another.

Based on the available ordering policies in anyLogistix the simulation experiments were performed using the 6 ordering policies as described in Table 5. These 6 ordering policies were chosen as they represent a wide range and simultaneously the most common ordering policies used in inventory management as presented in Chapter 3.

Table 5: Description of ordering policies for simulation experiments

Ordering policy	Description
OP1	Min-max ordering policy, with min = ROP and max = ROP + EOQ.
OP2	RQ ordering policy, with R = ROP and Q = EOQ.
OP3	Order on demand.
OP4	Regular policy with safety stock based on ROP formula, periodic check every 30 days (once per month).
OP5	Regular policy with safety stock based on ROP formula, periodic check every 7 days (once per week).
OP6	Simulation of the current practice at the case warehouse. RQ policy with R = Q = expected demand for 1 month. Correlates with a two-bin ordering policy.

The required formulas for developing the ordering policies were, in addition to demand data from the case warehouse, the EOQ formula (equation 1), and versions of the ROP formula (equation 5, equation 6, and equation 7), as presented in Chapter 3.

EOQ calculation:

For the calculation of the EOQ for each product group the following elements were necessary:

- Annual demand: Calculated from the raw demand data Excel file.
- Ordering cost per order: Based on previous knowledge of ordering costs, a reasonable assumption was to place it anywhere between 150 NOK-1000 NOK. A middle ground value at 500 NOK was chosen. This assumption was deemed acceptable due to minimal impact on the core decisions of classification criteria levels and selected ordering policies.
- Holding cost: An assumption of 25% was decided on based on a multi-case study on inventory holding costs measurement by Azzi *et al.* (2014).

ROP calculation:

For the calculation of the ROP for each product group the following elements were necessary:

- Safety factor (z): Based on the case company's desired service level of 98% = 2.05, according to Table 3 in Chapter 3.
- Lead time: Normally distributed based on the case study with a mean of 4 days and SD = 1 day
- Demand: Mean average daily demand and SD of demand for the product groups with a Normal demand distribution.

6.3 Simulation experiment scenarios

An overview of the scenarios tested in the simulation experiments is presented in Table 6. Each product group was tested separately, as the ordering policies are in practice set on an SKU level.

Table 6: Overview of scenarios for simulation experiments

Parameter	Baseline scenario	Sensitivity analysis
Unit cost level	400 NOK	200 NOK, 1000 NOK, 2000 NOK
Average daily demand	Based on demand data	20% higher, 20% lower
SD of daily demand	Based on demand data	20% higher, 20% lower, No SD

In addition to the baseline scenario, 8 scenarios were run to perform a sensitivity analysis of the impact of changing criteria levels on the chosen ordering policy for each product group. The unit cost level was tested at 200 NOK, 1000 NOK, and 2000 NOK in addition to the baseline level of 400 NOK. This was possible as information regarding the unit price for all SKUs was available through data from the case warehouse. The only criteria level available for criticality at the case warehouse was the list of critical products provided. As there was no way to determine the levels for scarcity or demand unpredictability, it was not trivial to test the changing of these levels either. The significant parameters used for modeling the demand and the ordering policies were the mean value of the daily demand, in addition to the SD of the daily demand for each product group. These are the values which will change when the criteria levels for criticality, scarcity, and demand unpredictability change. Therefore, the variation of these parameters was tested to investigate the effects of changing criteria levels. A scenario with 20% higher daily demand and a scenario with 20% lower daily demand was tested in addition to the average daily demand based on the demand data. A scenario with 20% higher standard deviation of daily demand, a scenario with 20% lower standard deviation of daily demand and a scenario with no standard deviation (constant demand) were tested in addition to the standard deviation of daily demand based on demand data. It is important to note that the changing of the parameters for unit cost level, average daily demand and SD of daily demand were tested separately and the combinations of changing these parameters were not tested through the simulation experiments. Table 7 illustrates the data utilized for demand modeling and ordering policy modeling in the baseline scenario.

Table 7: Baseline scenario data

Groups	Daily demand (Units)	SD of daily demand (Units)	Unit cost (NOK)
A and E	0.79	2.72	2506
B and F	6847	2509	42
C and G	359	2256	1740
D and H	79688	198728	62

6.4 Simulation experiment results

The individual simulation experiment results are presented in Appendix A. A synthesis of the results from the simulation experiments is depicted in Table 8. Which ordering policy was selected based on the individual simulation experiment results is stated, together with a sensitivity analysis specifying whether the selected policy changed with variations in the criteria levels and if so, to which ordering policy.

Table 8: Results from simulation experiments

		Sensitivity analysis							
Group	**Baseline**	**200 NOK**	**1000 NOK**	**2000 NOK**	**Higher demand**	**Lower demand**	**Higher SD**	**Lower SD**	**No SD**
A: High C High UC High S/DU	OP6	OP4	OP2	OP2	No change	No change	No change	No change	No change
B: High C Low UC High S/DU	OP4	No change	No change	No change	No change	No change	No change	No change	No change
C: Low C High UC High S/DU	OP1	No change	OP4	OP4	No change	No change	No change	No change	OP4
D: Low C Low UC High S/DU	OP4	No change	No change	No change	No change	No change	No change	No change	No change
E: High C High UC Low S/DU	OP1	OP1, OP2	OP2	OP2	OP1, OP2	OP1, OP2	OP1, OP2	OP1, OP2	OP6
F: High C Low UC Low S/DU	OP5	No change	No change	No change	No change	No change	No change	No change	No change
G: Low C High UC Low S/DU	OP1	No change	OP2	No change	No change	No change	No change	No change	OP1, OP2
H: High C High UC Low S/DU	OP6	No change	No change	No change	No change	OP1	OP1	No change	No change

C = Criticality, UC = Unit Cost, S/DU = Scarcity/Demand Unpredictability

OP1 = Min-max OP4 = FOI monthly

OP2 = ROP with EOQ OP5 = FOI weekly

OP3 = Order on demand OP6 = As-is policy, two-bin with 1 month demand

For group A the service level was at 1 for OP1, OP4, OP5 and OP6. As this group has a higher unit cost, a reduction in the stock level should be aimed at, while keeping enough safety stock to cater to the scarcity and demand unpredictability of the group. The graphs from group A show how the available inventory steadily increased when using both OP4 and OP5. Therefore, these policies were not selected for this grouping. OP6 had a slightly higher level of safety stock than OP1. Therefore, OP6 was selected for group A. A lower unit cost level brought the service level for OP6 below 0.8. OP4 has a service level of 1, with adequate safety stock and was therefore selected. A higher unit cost level significantly impacted the service level negatively for all OPs so that the ordering policy with the optimal service level was changed to OP2. There was no change in the ordering policy selection based on changes in demand or SD.

For group B it was more acceptable to have a higher inventory level, due to lower unit cost. Both OP4 and OP5 provided a service level of 1. OP4 provided a higher level of safety stock, which is beneficial for the criticality and scarcity/demand unpredictability aspect of this group. Therefore, OP4 was selected. A lower unit cost level brought the service level for OP1 up to 1, but the safety stock was not adequate to alter the ordering policy selection. Results from the sensitivity analysis show that there was no change in the ordering policy selection for any changes in the parameters.

For group C it was less acceptable to have high levels of available inventory, as it is a high unit cost group, as well as the low criticality aspect, which means less safety stock is necessary. OP4 was the only policy providing a service level of 1, but the high available inventory levels brought this option down. OP1 was the policy which provided a slightly lower service level, but it was still above 95% throughout the whole period, and mainly around 98%. Therefore, OP1 was selected for group C. Both a higher unit cost level and no SD led to a lower service level for OP1. OP4 had a service level of 1 for this scenario also, and a lower available inventory, which made this the ordering policy selection. Other changes in the parameters had no effect on the outcome.

For group D the criticality did not need to be considered, and with a lower unit cost, a higher available inventory level was allowed. OP4 led to higher available inventory and was the only policy providing a service level of 1. Therefore, this was the ordering policy selected based on the simulation experiments. Changing the parameters had no effect on this outcome based on the sensitivity analysis.

For group E the high criticality required a higher service level, but higher unit cost and lower scarcity/demand unpredictability called for less available inventory. OP1 was the policy that provided the lowest level of available inventory for a service level of 1. A lower unit cost level led to OP2 being an equal selection to OP1. Changes in daily demand or a lower SD led to OP1 and OP2 both being the selected ordering policies in terms of service level and available inventory. With no SD the available inventory level for OP1 and OP2 was close to zero several times, so the selected policy changed to OP6.

For group F it was important to have a high service level due to high criticality. With low scarcity/demand unpredictability, a lower level of available inventory was acceptable. The simulation experiment results show this was provided by OP5. Changing the parameters did not change the outcome for the selected ordering policy according to the sensitivity analysis for this group.

For group G it was important to keep a lower available inventory level due to the high unit cost. Therefore, OP4 was not selected even though it had a service level of 1. The next best option regarding service level was OP1, which also provided significantly lower available inventory levels, making it the selected ordering policy for group G. Low criticality also allowed a slightly lower service level. A higher unit cost level at 1000 NOK brought the OP2 service level up above OP1, with a similar available inventory level. At 2000 NOK the service level was again more favorable with OP1 than with OP2. Removing the SD for group G made OP1 and OP2 both equal as selected ordering policies.

Product group H did not require close attention, as it has both a low criticality, low unit cost, and low scarcity/demand unpredictability. OP4 had the best service level at 1, but the available inventory level was higher than necessary for this degree of criticality and scarcity/demand unpredictability. With a low level of criticality, a lower service level was allowed if this meant a lower level of available inventory. OP6 had a near-perfect service level, with a significantly lower level of available inventory that catered to these requirements, making it the selected ordering policy. With either a lower average daily demand or higher SD, the service level dropped significantly in the last 100 days of the period with OP6. This changed the selected ordering policy to OP1, which consistently had a service level above 95% throughout the whole period.

7 Discussion

This chapter discusses the research questions in relation to the findings presented in Chapter 5 and Chapter 6. The simulation experiment results for each product group will be discussed compared to the suggested policy based on the theoretical framework from Chapter 5. Thereafter, the impact of the classification criteria levels on the ordering policy selection is discussed by examining the potential variations in selected ordering policies in the simulation experiments based on changes in the parameters. Lastly, the definition of the inventory classification criteria levels will be discussed by examining to what extent other simulation experiment scenarios relate to the suggested framework.

7.1 Inventory management framework validation

Based on the results from the simulation experiments, the optimal ordering policy for group A was OP6, which is a form of ROP-policy, where the reorder point is the expected monthly demand for that SKU. According to the suggested framework, this product grouping with high criticality, high unit cost, and high scarcity/demand unpredictability requires an ordering policy providing a higher service level, higher batch size flexibility, higher order frequency flexibility and supporting a lower ordering policy cost. ROP policies generally support a higher service level, as this secures adequate safety stock levels. However, ROP policies using the ROP formulas presented in Chapter 3 also take the desired service level into account, which the OP6 form does not, as it is not based on these formulas. According to the framework, a Min-max policy would be more appropriate for this group, as it uses ROP formulas and allows for batch size flexibility as well as setting a maximum stock level for these higher unit cost products, keeping the holding costs down.

Based on the results from the simulation study, OP4 was the selected ordering policy for group B, which is a form of FOI-policy with monthly ordering intervals. According to the suggested framework, this product group with high criticality, low unit cost and high scarcity/demand unpredictability a policy with an EOQ should be used, as this caters more to products with a lower unit cost. As the criticality is still high, the service level should be prioritized, and therefore the ROP policy can be used together with the EOQ ordering batch size according to the framework. This differs from the results of the simulation experiments.

According to the results from the simulation experiments, the optimal ordering policy for group C was OP1, which is the Min-max policy. Based on the developed framework, it is suitable to be more lenient when considering the service level for this product group. There should still be some safety stock as this is important with high scarcity/demand unpredictability, but there can be less than for the critical products. As a group with a higher unit cost there is a point in keeping the safety stock at a reasonable level, due to holding costs. This group should therefore use an ordering policy which allows for altering ordering batch sizes. A policy based on an ROP, with a lower service level consideration, fits in accordance with the framework recommendation for this group. This differs slightly from the simulation experiment results, as the service level used in the simulation experiments was 98% for all product groups.

Based on the results from the simulation experiment, the optimal ordering policy for group D was OP4, the FOI monthly policy with monthly demand order quantity. For this product group there is a low level of criticality as well as a lower unit cost. According to the framework, this allows for a more lenient policy with more regular orders. A policy with an FOI where the ordering interval can be subject to alteration, if necessary, in case the scarce product is suddenly available for order, fits these criteria. As the products are of low unit cost this allows for higher levels of available inventory. FOI together with a fixed ordering quantity fits these criteria. The simulation results were therefore in accordance with the framework's suggestion.

According to the results from the simulation study the selected ordering policy for group E was OP1, the Min-max ordering policy. For this product group it is important to consider the high criticality, as well as the high unit cost, but there is a lower level of scarcity/demand unpredictability. According to the framework, this requires an ordering policy which takes a higher service level into regard, such as the ROP policy, together with a fixed order Q, as it is not required to have flexibility with ordering batches. This correlates somewhat with the simulation results, as it is a form of ROP policy. However, the Min-max policy does not have a fixed ordering quantity.

Based on the results from the simulation study the selected policy for group F was OP5, which is the FOI weekly policy. According to the framework, a lower unit cost level does not require a policy with high flexibility in order frequency or ordering batch size. This is in agreement with the results of the simulation study.

The results from the simulation study indicated that the optimal ordering policy for group G was OP1, the Min-max policy. According to the framework, with low criticality and a low degree of scarcity/demand unpredictability, a policy with a low flexibility in both batch size and order frequency should be selected. Less safety stock is necessary due to the higher unit cost. Therefore, a FOI policy with less safety stock would have been appropriate according to the framework. This does not agree with the simulation study results.

Based on the results from the simulation study, the selected ordering policy for group H was OP6, which is a ROP policy with reordering point as monthly expected demand and order quantity as monthly expected demand. According to the framework, this product group is similar to group G, but has a lower unit cost, so it is possible to keep some extra safety stock without a high increase in holding costs. An FOI monthly policy coincides with these criteria, which differs from the results of the simulation study.

In summary, the simulation experiment results which were in complete agreement with the recommendations based on the framework were the results for groups D and F. The results from groups A, C, and E were somewhat like the recommendations based on the framework, whereas the simulation experiment results for groups B, G, and H differed from the recommendations based on the framework. Consequently, the total baseline scenario simulation experiment results were in partial agreement with the framework. OP6, the ordering policy which best represents the current practice at the case warehouse, was only selected as the ordering policy for two of the eight groups in the baseline scenario according to the simulation study results. This supports motivating existing warehouses to improve their inventory management practice by implementing elements of the framework.

One of the simplifications made when creating the conceptual model was unlimited capacity at the warehouse. Hospital warehouses have a limited capacity and therefore limits regarding the available inventory which can be kept. This could have affected the outcome for ordering policy selection due to the available inventory performance metric utilized in the simulation study. It is important to note that costs were not a focus of this research, and the simulation study could have yielded different results if costs were included as a performance measure and more information regarding this parameter was provided by the case company. Additionally, the ordering policies and their corresponding parameters were created for each grouping and not on an individual SKU basis, as is usually done in practice. This is another important factor to consider for framework application in a real warehouse setting. The next step is investigating the impact of criteria level definition on ordering policy selection, to increase understanding of the correct process for defining these levels.

7.2 Impact of criteria level definition on ordering policy selection

In discussing the effect of criteria level changes on ordering policy selection, it is important to relate it to the impact of placing a product in the wrong category according to the framework. Placing a product in the wrong category can mean a stockout at the hospital warehouse of that item, and that it will be unavailable to the end patient. The consequences of this can result in a negative impact on the hospital patients' health, if it is a high criticality item placed in a low criticality grouping. On the other hand, a high unit cost item placed in a low unit cost grouping can mean overstocking and increased capital expenditure. This will most likely not directly impact patients' conditions, but could contribute to lowering the hospital warehouse's efficiency, further lowering their ability to provide for the hospital's patients. The effect of placing a product in the wrong grouping according to scarcity or demand unpredictability depends on the classification of the product according to the other criteria of criticality and unit cost. A highly scarce product which is placed in a low scarcity category will negatively impact the end patients at the hospital at a much higher level if the product also is of high criticality. Similarly, a product with a high degree of demand unpredictability will cause more of an issue for the hospital if it also is of high criticality. For demand unpredictability it is also important to note that the demand can be stable, even if it is unpredictable. If a product with unpredictable, but stable demand, is placed in a category with lower demand unpredictability, it will most likely not impact the warehouse's service level negatively.

Regarding correlations between the simulation results, there were no changes in the selected ordering policy with changing parameters for groups B, D, and F. All these groups are characterized by a low unit cost. Both groups B and F are characterized by high criticality, but as these groups had the same input data for demand and ordering policy modeling, this is not a surprising result. All groups B, D, and F possessed either the highest SD of daily demand values or the second highest value. However, there does not seem to be a correlation between the ratio of daily demand to SD of daily demand and changes in selected ordering policy based on criteria level changes.

Looking at the groupings which possessed variations in selected ordering policy due to changing criteria levels, correlations are not as apparent. The selected ordering policy for group A only changed based on variations in the unit cost level. Group C's optimal ordering policy also changed based on alterations of the unit cost level, but also with no standard deviation in demand. Similarly, group G's optimal ordering policy changed with a slightly higher unit cost level and no standard deviation. One possible explanation for this is that the standard deviation for groups C and G were significantly larger than the daily demand values. The optimal ordering policy for group E changed for all variations in the parameters. This indicates that group E is highly sensitive to criteria level changes. Group H's optimal ordering policy was changed solely for variations in daily demand. Even though only one parameter change impacted the selected policy in the simulation study, several criteria level changes could potentially impact the selected policy for this group, as several classification criteria can have levels which lead to changes in daily demand. However, since variations in the unit cost level have been tested, it is more likely that variations in the criteria level definition for criticality, scarcity, or demand unpredictability will affect the selected policy.

In the simulation study the parameters were altered one at a time and it is important to note that these changes most likely will occur simultaneously in real life situations. Since changes in criteria levels had different impacts based on the groupings, it is difficult to predict what the combined effects would be in a simulation study where multiple parameters are varied simultaneously.

In summary, the changing parameter levels do not seem to impact the ordering policy selection for most low unit cost items but mainly seem to impact higher unit cost items. Since findings in the literature study and case study both suggest that criticality of products is the most important characteristic to consider when classifying non-pharmaceutical hospital inventory items, the classification criterion of criticality becomes the most significant to consider when applying the framework. As high criticality items are of both high unit cost and low unit cost, findings in this study indicate that criteria levels do have a significant impact on ordering policy selection, but that the effect of the criteria level changes is difficult to quantify exactly when only certain parameters relating to the criteria levels are varied one at a time.

7.3 Definition of inventory classification criteria levels

From the simulation experiment results for group A, it was shown how the changing criterion level for unit cost has an impact on the ordering policy selection, but changing the average daily demand or the standard deviation has no impact. A higher unit cost level changed the selected ordering policy to OP2 which is an ROP-based policy with a fixed ordering batch size based on the EOQ. This is in partial agreement with the framework suggestion, as it is an ordering policy which utilizes the ROP formulas, but on the other hand, it does not have a high flexibility in terms of batch sizes. A lower unit cost level changed the optimal ordering policy to OP4, which is a form of FOI-policy with a fixed order batch size. This is not in agreement with the framework suggestion, as it has no batch size flexibility or order interval flexibility. One possible explanation for this result is that OP4 still used safety stock based on the ROP-formula, which provided protection against demand uncertainty. Another level of safety stock might not have yielded the same result.

The sensitivity analysis in the simulation study indicated some changes in the selected ordering policy for group C when altering the classification criteria levels. OP4, the FOI policy with monthly ordering intervals, was the selected ordering policy with a higher unit cost level and with no standard deviation based on the simulation experiment results. This does not coincide with the recommendations from the framework, which differ from the results of the baseline simulation experiments. This suggests that the unit cost level of 400 NOK from the baseline scenario is more appropriate for this grouping.

With a lower unit cost level, changes in average demand, increase in standard deviation and decrease in standard deviation, OP2 became equal to OP1 as the selected ordering policy for group E based on the results from the sensitivity analysis in the simulation study. When increasing the unit cost level, the ordering policy selection was OP2. OP2 is in better agreement with the recommended policy based on the framework than OP1. With constant demand and no standard deviation, the selected ordering policy based on the simulation results was OP6, which is the ROP policy with reorder point as the monthly expected demand. This correlates somewhat with the recommendations based on the framework, as it secures adequate safety stock levels as well as fixed batch sizes.

The selected ordering policy for group G based on the simulation results changed to OP2, the ROP with fixed order quantity, with a slightly higher unit cost level of 1000 NOK. With constant daily demand without standard deviation the selected policy based on the simulation study was both OP1 and OP2. Like the results from the simulation of the baseline scenario, these changes are not in agreement with the recommendations based on the framework. With lower demand or higher standard deviation, the selected policy according to the simulation study for group H was OP1, the Min-max policy. Like the results from the baseline scenario, this does not agree with the recommendation based on the framework. The sensitivity analysis in the simulation study indicated no change in the selected ordering policy with varying criteria levels for groups B, D, and F.

Table 9: Framework correlation with simulation experiment results

		Sensitivity analysis							
Group	**Baseline**	**200 NOK**	**1000 NOK**	**2000 NOK**	**Higher demand**	**Lower demand**	**Higher SD**	**Lower SD**	**No SD**
A									
B									
C									
D									
E									
F									
G									
H									

A summary of the correlations of the simulation experiment results is presented in Table 9. Green indicates agreement with the developed framework, yellow indicates a partial agreement and red indicates no agreement. Variations in the parameters did not generally change the degree to which the simulation results agreed with the recommendations based on the developed framework for any groups except for group C and E. In group C the selected ordering policy based on the simulation results changes from partial agreement, to not at all with a unit cost level above 1000 NOK. For group E the same criteria level variation of a higher unit cost level above 1000 NOK yields simulation experiment results agreeing with the framework, as opposed to partial agreement in the baseline scenario results. As described in Section 7.1, the baseline scenario results did not completely match the recommendations based on the framework. The variations in the parameters did not seem to have an impact on the degree to which the framework agreed with the simulation experiment results.

The simulation results for groups B, G and H did not for any experiment run agree with the recommendations based on the framework. As these groups represent both high and low levels of all the criteria, this suggests that definition of criteria levels for all the classification criteria in the inventory management framework should be investigated further to determine the ideal framework application approach.

8 Conclusion

The objective of this study was to investigate how inventory classification methods can support the selection of ordering policies in non-pharmaceutical hospital warehouses. First, a framework was developed based on a case study and a literature study by identifying what classification criteria should be used and how these would relate to the ordering policy choice. Practical implementation of the framework requires both a selection of the classification criteria levels, and a selection of the optimal ordering policy based on these criteria levels. For this reason, an overview of how the classification criteria levels should be selected was suggested and discussed in detail. Lastly, a simulation study was performed to validate the developed framework, assess the impact of the changing criteria levels on the chosen ordering policy and validate the suggested set of classification criteria levels.

8.1 Research questions and contribution

The aim of the first research question was to investigate the possibility of utilizing inventory classification methods to simplify the selection of ordering policies in non-pharmaceutical hospital warehouses. First, the defining characteristics of non-pharmaceutical hospital goods were found to be varying criticality, heterogeneity, interdependency, varying demand predictability and low cost. These characteristics were used to find the classification criteria of criticality, scarcity, demand unpredictability, and unit cost. Based on these inventory classification criteria, the ordering policy criteria were found to be service level, order frequency flexibility, batch size flexibility and cost. Ordering policies to meet the different levels of these criteria were suggested and presented in the resulting framework.

The aim of the second research question was to investigate the effects of varying classification criteria levels on the selected ordering policy. Findings from the simulation study indicate that high unit cost items are the most affected by the changing criteria levels. As criticality is the most significant criterion for classification and high criticality items are both high cost and low cost, it can be concluded that the variation of classification criteria levels have a significant impact on the ordering policy selection and therefore also on the performance of the warehouse for the hospital.

The aim of the third research question was to investigate how the inventory classification criteria levels should be defined when applying the developed framework by validating a suggested set of classification criteria levels based on the case study. Results from the simulation study indicate that the baseline scenario method attempted for testing the framework is in partial agreement with the suggestions based on the developed framework. Results from the sensitivity analysis also indicate that scenarios with parameter variations are in agreement with the framework to the same degree. However, results for three out of 8 groups did not correspond to the framework for any simulation runs, which indicates that the suggested set of classification criteria levels, in total, exhibited only limited agreement with the framework.

The main contribution to research provided by this study is the developed framework, which extends the scope in the hospital inventory management research area. Previous research has focused on biological and pharmaceutical inventory management in hospital warehouses. The framework may be used in further development of processes for ordering policy selection in hospital warehouses. A more developed framework based on the research in this study should be able to be used to aid purchasing managers of hospital warehouses in ordering policy decisions for non-pharmaceutical items. It should also enable hospital warehouse managers to examine their ordering policies and make the changes required to better accommodate the end customer, the patient at the hospital. The framework could also help hospital warehouses support the healthcare supply chain in being better equipped and prepared for significant disruptions such as pandemics, wars, or natural disasters. The proposed research questions have been answered and the goal of this thesis research has been met.

8.2 Study limitations

One of the limitations of this research was that it involved a single case study of one case organization, making generalizing more challenging. Additionally, the case study took place at the same time as the initiation period of the new warehouse, so the availability for discussions with the case organization was constrained. Therefore, the case study is limited in terms of information retrieved from the case warehouse, leading to a lower level of detail in the simulation study.

Another limitation was the time constraint, as the thesis research was conducted over a short period of 5 months. This also impacted the depth and extent of the research. Several assumptions and simplifications were necessary to create the simulation model due to constraints in both time and available information. These assumptions and simplifications have been mentioned in Chapter 7 as to how they may have impacted the simulation experiment results. Lastly, there may exist more potentially optimal ordering policies which have not been tested due to the inability to model them using the anyLogistix software.

8.3 Further research

Limitations to this research can be examined together with the study conclusions to guide the further research agenda based on this study. As inventory management of non-pharmaceutical hospital goods and inventory classification of such items is an area of research not previously focused on in the literature, there are several possibilities for further research.

Further testing of the framework through simulations based on data and information from more case warehouses could be beneficial, as it could aid in generalization of the results. Additionally, information and data from other case warehouses could introduce alternative methods of defining classification criteria levels which can aid in framework validation. Other simulation tools should be investigated for their potential to validate and further develop the framework and the classification criteria levels with a higher degree of detail in both input and output of the conceptual model.

Based on the findings in the study the classification criteria levels of scarcity and demand unpredictability should be investigated further, as these were identified as the most challenging levels to define. The use of emerging technologies such as data analytics, big data, and Internet of Things (IoT) together with for example historic data regarding forecasting error should be researched for their potential to aid in defining the levels for both scarcity and demand unpredictability.

References

Ahmadi, E. *et al.* (2019) 'Inventory management of surgical supplies and sterile instruments in hospitals: a literature review', *Health Systems*, 8(2), pp. 134–151. Available at: https://doi.org/10.1080/20476965.2018.1496875.

Azzi, A. *et al.* (2014) 'Inventory holding costs measurement: a multi-case study', *The International Journal of Logistics Management*, 25(1), pp. 109–132. Available at: https://doi.org/10.1108/IJLM-01-2012-0004.

Battini, D. *et al.* (2014) 'LOGISTICS IN THE HEALTHCARE SECTOR: KITTING, PACKAGING AND WAREHOUSING', p. 26.

Battini, D. (2014) 'Medical Device: THE ROLE OF LOGISTICS', p. 36.

Battini, D. *et al.* (2020) 'Centralised healthcare supply networks for efficient and sustainable drug management: an Italian case study', *International Journal of Integrated Supply Management*, 13(4), p. 394. Available at: https://doi.org/10.1504/IJISM.2020.110744.

Benkő, J. (no date) 'MODELING SUPPLY CHAIN WITH SIMULATION', 4.

Chapman, S.N. *et al.* (2017) *Introduction to Materials Management*. Eighth. Essex, England: Pearson.

Chen, Y., Li, K.W. and Liu, S. (2008) 'A comparative study on multicriteria ABC analysis in inventory management', in *2008 IEEE International Conference on Systems, Man and Cybernetics*. *2008 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Singapore, Singapore: IEEE, pp. 3280–3285. Available at: https://doi.org/10.1109/ICSMC.2008.4811802.

Chopra, S. (2019) *Supply Chain Management: Strategy, Planning, and Operation*. Pearson Education Limited.

CONSUMABLE | English meaning - Cambridge Dictionary (2022). Available at: https://dictionary.cambridge.org/dictionary/english/consumable (Accessed: 29 November 2022).

Dellaert, N. and van de Poel, E. (1996) 'Global inventory control in an academic hospital', *International Journal of Production Economics*, 46–47, pp. 277–284. Available at: https://doi.org/10.1016/0925-5273(95)00110-7.

Denton, B.T. (ed.) (2013) *Handbook of Healthcare Operations Management: Methods and Applications*. New York, NY: Springer New York (International Series in Operations Research & Management Science). Available at: https://doi.org/10.1007/978-1-4614-5885-2.

Derbel, M. *et al.* (2013) 'Measuring the impact of (s, S) ordering policy on the bullwhip effect by means of simulation optimization', in *2013 International Conference on Advanced Logistics and Transport*. *2013 International Conference on Advanced Logistics and Transport (ICALT)*, Sousse, Tunisia: IEEE, pp. 482–487. Available at: https://doi.org/10.1109/ICAdLT.2013.6568506.

Døhlsmo, I.K. *et al.* (2021) 'FORBEREDT PÅ NESTE KRISE?'

Duclos, L.K. (1993) 'Hospital Inventory Management for Emergency Demand', *International Journal of Purchasing and Materials Management*, 29(3), pp. 29–38. Available at: https://doi.org/10.1111/j.1745-493X.1993.tb00016.x.

Esmaili, N., Norman, B. and Rajgopal, J. (2015) *A Heuristic for Selecting Multi-item Inventory Review Policies*.

European Commission issues 2021 Ageing Report | www.europeactive.eu (2021). Available at: https://www.europeactive.eu/news/european-commission-issues-2021-ageing-report (Accessed: 20 May 2023).

Fragapane, G.I. *et al.* (2019) 'Medical Supplies to the Point-Of-Use in Hospitals', in F. Ameri et al. (eds) *Advances in Production Management Systems. Towards Smart Production Management Systems*. Cham: Springer International Publishing (IFIP Advances in Information and Communication Technology), pp. 248–255. Available at: https://doi.org/10.1007/978-3-030-29996-5_29.

Golan, M.S., Jernegan, L.H. and Linkov, I. (2020) 'Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic', *Environment Systems and Decisions*, 40(2), pp. 222–243. Available at: https://doi.org/10.1007/s10669-020-09777-w.

Gupta, R. *et al.* (2007) 'ABC and VED Analysis in Medical Stores Inventory Control', *Medical Journal Armed Forces India*, 63(4), pp. 325–327. Available at: https://doi.org/10.1016/S0377-1237(07)80006-2.

Hautaniemi, P. and Pirttilä, T. (1999) 'The choice of replenishment policies in an MRP environment', *International Journal of Production Economics*, 59(1–3), pp. 85–92. Available at: https://doi.org/10.1016/S0925-5273(98)00026-7.

Heckmann, I. (2016) *Towards Supply Chain Risk Analytics: Fundamentals, Simulation, Optimization*. Wiesbaden: Springer Fachmedien Wiesbaden. Available at: https://doi.org/10.1007/978-3-658-14870-6.

Hjemås, G. (2019) 'Fremskrivninger av etterspørselen etter arbeidskraft i helse- og omsorg mot 2060'.

Hoshino, K. (2001) 'On switching-type mixed-ordering policy based on monitoring forecasting error', *International Journal of Production Economics*, 71(1–3), pp. 373–380. Available at: https://doi.org/10.1016/S0925-5273(00)00134-1.

Johansen, S.G. (1999) ‘Lot sizing for varying degrees of demand uncertainty’, *International Journal of Production Economics*, 59(1–3), pp. 405–414. Available at: https://doi.org/10.1016/S0925-5273(98)00107-8.

van Kampen, T.J., Akkerman, R. and Pieter van Donk, D. (2012) ‘SKU classification: a literature review and conceptual framework’, *International Journal of Operations & Production Management*, 32(7), pp. 850–876. Available at: https://doi.org/10.1108/01443571211250112.

Karlsson, C. (ed.) (2016) *Research methods for operations management*. Second Edition. New York: Routledge.

Kelle, P., Woosley, J. and Schneider, H. (2012) ‘Pharmaceutical supply chain specifics and inventory solutions for a hospital case’, *Operations Research for Health Care*, 1(2–3), pp. 54–63. Available at: https://doi.org/10.1016/j.orhc.2012.07.001.

Keshavarz Ghorabaee, M. *et al.* (2015) ‘Multi-Criteria Inventory Classification Using a New Method of Evaluation Based on Distance from Average Solution (EDAS)’, *Informatica*, 26(3), pp. 435–451. Available at: https://doi.org/10.15388/Informatica.2015.57.

Ketkar, M. and Vaidya, O.S. (2014) ‘Developing Ordering Policy based on Multiple Inventory Classification Schemes’, *Procedia - Social and Behavioral Sciences*, 133, pp. 180–188. Available at: https://doi.org/10.1016/j.sbspro.2014.04.183.

Kumar, D. and Kumar, D. (2015) ‘Modelling hospital inventory management using interpretive structural modelling approach’, *International Journal of Logistics Systems and Management*, 21(3), p. 319. Available at: https://doi.org/10.1504/IJLSM.2015.069730.

Landry, S. and Beaulieu, M. (2013) ‘The Challenges of Hospital Supply Chain Management, from Central Stores to Nursing Units’, in B.T. Denton (ed.) *Handbook of Healthcare Operations Management*. New York, NY: Springer New York (International Series in Operations Research & Management Science), pp. 465–482. Available at: https://doi.org/10.1007/978-1-4614-5885-2_18.

Longitudinal studies - PMC (2022). Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4669300/ (Accessed: 31 October 2022).

March 23, 2005 - Rattling the Supply Chain: The Opportunity for Supply Chain Management in Healthcare - Smarter Health Seminars 2004 - 05: Emerging Solutions - The infraNET Project (2005). Available at: https://infranet.uwaterloo.ca/index.php?MenuItemID=83 (Accessed: 20 May 2023).

More than a fifth of the EU population are aged 65 or over - Produit Actualité Eurostat - Eurostat (2021). Available at: https://ec.europa.eu/eurostat/fr/web/products-eurostat-news/-/ddn-20210316-1 (Accessed: 20 May 2023).

Nyoman Pujawan, I. (2004) ‘The effect of lot sizing rules on order variability’, *European Journal of Operational Research*, 159(3), pp. 617–635. Available at: https://doi.org/10.1016/S0377-2217(03)00419-3.

Obsolete inventory - definition and example - Market Business News (2022). Available at: https://marketbusinessnews.com/financial-glossary/obsolete-inventory-definition-meaning/ (Accessed: 29 November 2022).

Parsa, H. *et al.* (2011) 'HEALTHCARE INVENTORY AND SUPPLY CHAIN MANAGEMENT: A LITERATURE REVIEW', 1(2).

Partovi, F.Y. and Burton, J. (1993) 'Using the Analytic Hierarchy Process for ABC Analysis', *International Journal of Operations & Production Management*, 13(9), pp. 29–44. Available at: https://doi.org/10.1108/01443579310043619.

PRODUCT SUBSTITUTION - Cambridge English Dictionary (2022). Available at: https://dictionary.cambridge.org/dictionary/english/product-substitution (Accessed: 29 November 2022).

PSQ Newsletter (2022). Available at: https://www.psq.co.za/news25.htm (Accessed: 18 December 2022).

Ramaekers, K. and Janssens, G.K. (2012) 'Service-oriented decisions on inventory levels in the case of incomplete demand information', *Logistics Research*, 5(1–2), pp. 33–46. Available at: https://doi.org/10.1007/s12159-012-0076-y.

Ramos, K.G. *et al.* (2021) 'Suez Canal blockage and its global impact on healthcare amidst the COVID-19 pandemic', *International Maritime Health*, 72(2), pp. 145–146. Available at: https://doi.org/10.5603/IMH.2021.0026.

Robinson, S. (2008a) 'Conceptual modelling for simulation Part I: definition and requirements', *Journal of the Operational Research Society*, 59(3), pp. 278–290. Available at: https://doi.org/10.1057/palgrave.jors.2602368.

Robinson, S. (2008b) 'Conceptual modelling for simulation Part II: a framework for conceptual modelling', *Journal of the Operational Research Society*, 59(3), pp. 291–304. Available at: https://doi.org/10.1057/palgrave.jors.2602369.

Rossetti, M.D., Buyurgan, N. and Pohl, E. (2012) 'Medical Supply Logistics', in R. Hall (ed.) *Handbook of Healthcare System Scheduling*. Boston, MA: Springer US (International Series in Operations Research & Management Science), pp. 245–280. Available at: https://doi.org/10.1007/978-1-4614-1734-7_10.

Russo, R. de F.S.M. and Camanho, R. (2015) 'Criteria in AHP: A Systematic Review of Literature', *Procedia Computer Science*, 55, pp. 1123–1132. Available at: https://doi.org/10.1016/j.procs.2015.07.081.

Saaty, T.L. (1984) 'The Analytic Hierarchy Process: Decision Making in Complex Environments', in R. Avenhaus and R.K. Huber (eds) *Quantitative Assessment in Arms Control*. Boston, MA: Springer US, pp. 285–308. Available at: https://doi.org/10.1007/978-1-4613-2805-6_12.

Saaty, T.L. (2006) ‘The Analytic Network Process’, in *Decision Making with the Analytic Network Process*. Springer US (International Series in Operations Research & Management Science), pp. 1–26. Available at: https://doi.org/10.1007/0-387-33987-6_1.

Saha, E. and Ray, P.K. (2019) ‘Modelling and analysis of inventory management systems in healthcare: A review and reflections’, *Computers & Industrial Engineering*, 137, p. 106051. Available at: https://doi.org/10.1016/j.cie.2019.106051.

Sbai, N., Benabbou, L. and Berrado, A. (2020) ‘Comparison of MCDM Methods for Multi-echelon Inventory System Selection Problem’, in *Proceedings of the 13th International Conference on Intelligent Systems: Theories and Applications*. *SITA’20: Theories and Applications*, Rabat Morocco: ACM, pp. 1–7. Available at: https://doi.org/10.1145/3419604.3419783.

Scarcity | National Geographic Society (2022). Available at: https://education.nationalgeographic.org/resource/scarcity (Accessed: 1 December 2022).

SCM Definitions and Glossary of Terms (2022). Available at: https://cscmp.org/CSCMP/Educate/SCM_Definitions_and_Glossary_of_Terms.aspx (Accessed: 1 November 2022).

Sirisawat, P., Hasachoo, N. and Kaewket, T. (2019) ‘Investigation and Prioritization of Performance Indicators for Inventory Management in the University Hospital’, in *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Macao, Macao: IEEE, pp. 691–695. Available at: https://doi.org/10.1109/IEEM44572.2019.8978700.

Slack, N. and Brandon-Jones, A. (2019) *Operations Management (9th edition)*. Pearson.

Stevenson, W.J. (2021) *Operations Management*. 14th edn. New York, NY: McGraw-Hill.

STOCKOUT | English meaning - Cambridge Dictionary (2022). Available at: https://dictionary.cambridge.org/dictionary/english/stockout (Accessed: 13 October 2022).

‘Supply Chain Optimization and Simulation: Technology Overview’ (2023).

Tiacci, L. and Saetta, S. (2009) ‘An approach to evaluate the impact of interaction between demand forecasting method and stock control policy on the inventory system performances’, *International Journal of Production Economics*, 118(1), pp. 63–71. Available at: https://doi.org/10.1016/j.ijpe.2008.08.010.

United Nations (2018) *World Population Ageing 2017: Highlights*. United Nations. Available at: https://doi.org/10.18356/10e32e81-en.

United Nations (2019) *Global Sustainable Development Report 2019: The Future is Now - Science for Achieving Sustainable Development*. UN (Global Sustainable Development Report). Available at: https://doi.org/10.18356/5d04ad97-en.

Vaz, A. *et al.* (2020) ‘Order Frequency as a Variable to Determine Slow Moving D Items in ABC Inventory Categorization’, 9(2), p. 9.

Volland, J. *et al.* (2017) ‘Material logistics in hospitals: A literature review’, *Omega*, 69, pp. 82–101. Available at: https://doi.org/10.1016/j.omega.2016.08.004.

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

Xu, E., Wermus, M. and Bauman, D.B. (2011) ‘Development of an integrated medical supply information system’, *Enterprise Information Systems*, 5(3), pp. 385–399. Available at: https://doi.org/10.1080/17517575.2011.566630.

Yin, R.K. (2003) *Case Study Research: Design and Methods*. 3rd Edition. Thousand Oaks, CA: Sage.

Zheng, Y.-S. and Chen, F. (1992) ‘Inventory policies with quantized ordering’, *Naval Research Logistics*, 39(3), pp. 285–305. Available at: https://doi.org/10.1002/1520-6750(199204)39:3<285::AID-NAV3220390302>3.0.CO;2-T.

Appendices

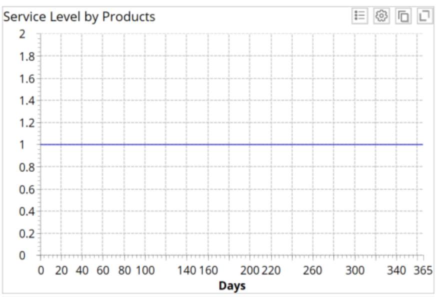
Appendix A: Simulation experiment result graphs

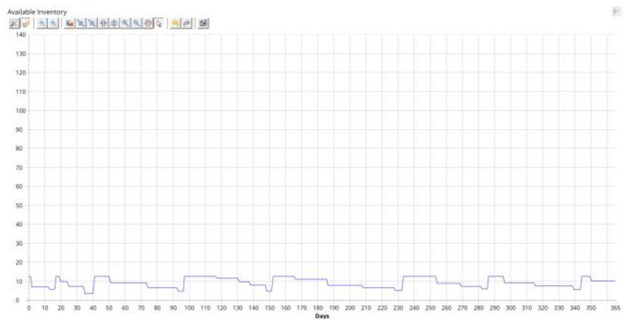
This appendix presents the results of all the simulation experiments. It is structured by showing the results for each ordering policy, for each scenario, for each group at a time. For each simulation run the service level is presented in the graph to the left and the available inventory is presented in the graph to the right. As mentioned, only results from groups A-D are presented, as these are also used as results for groups E-H. Results for OP3, order on demand, is only shown for the baseline scenario, as this was never the selected ordering policy due to plummeting service level graphs.

Simulation experiment results for group A

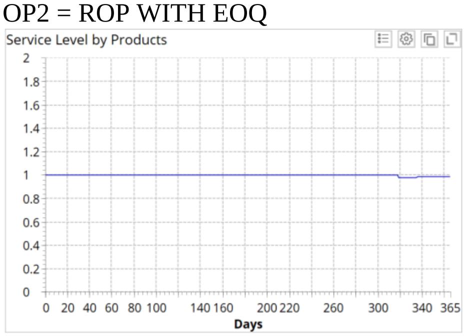
Baseline scenario

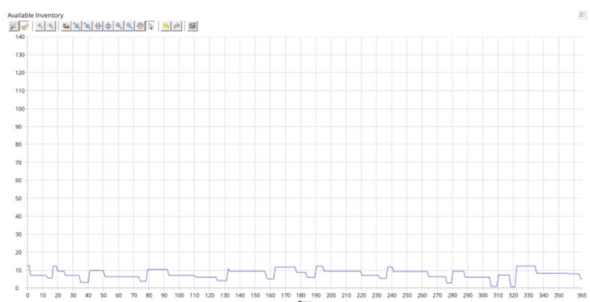
OP1 = MIN-MAX



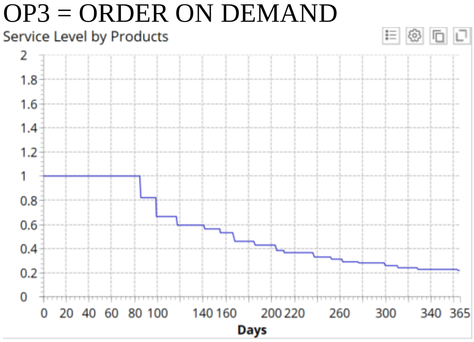


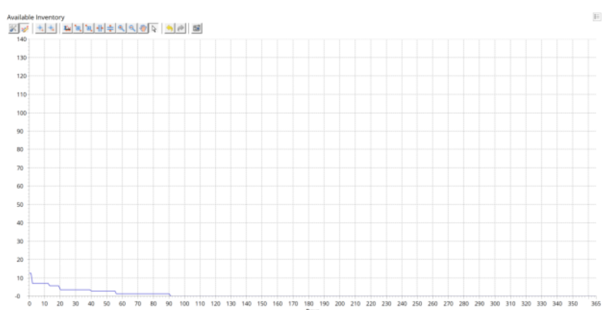
OP2 = ROP WITH EOQ



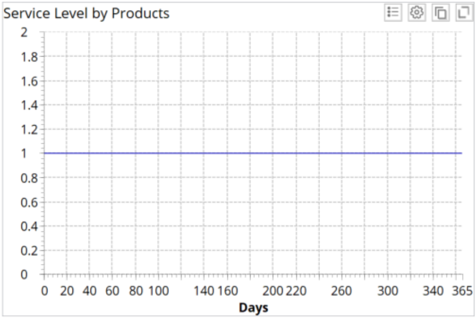


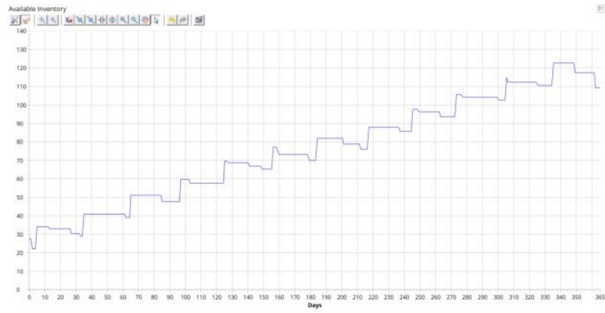
OP3 = ORDER ON DEMAND



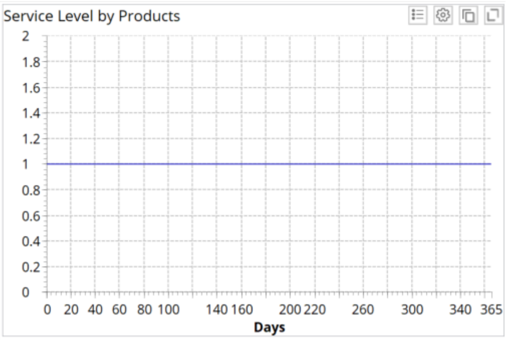


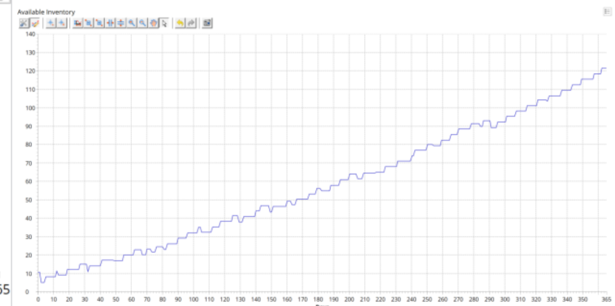
OP4 = FOI MONTHLY



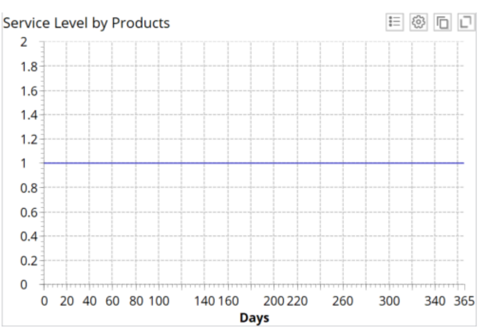


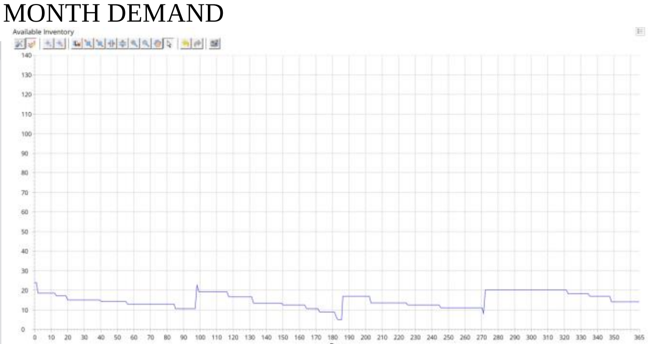
OP5 = FOI WEEKLY





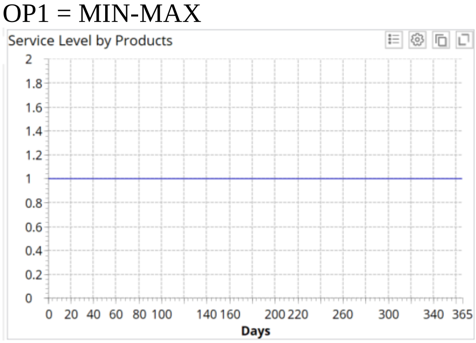
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



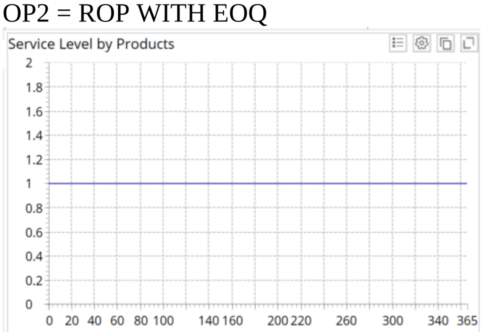


200 NOK unit cost level

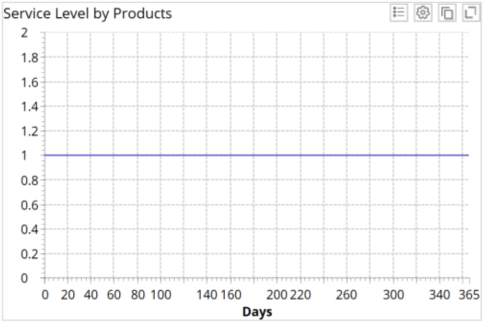
OP1 = MIN-MAX

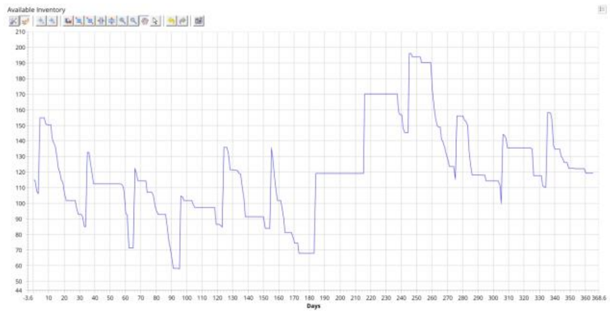


OP2 = ROP WITH EOQ

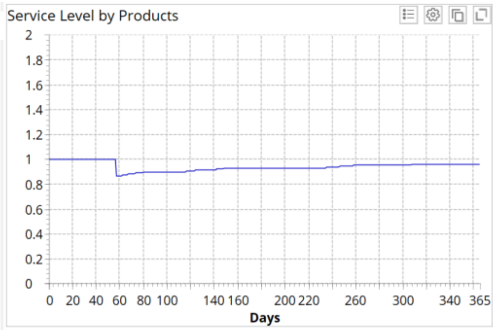


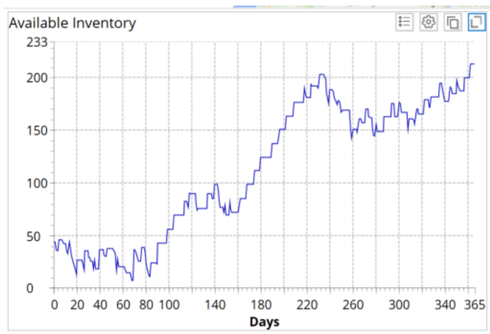
OP4 = FOI MONTHLY



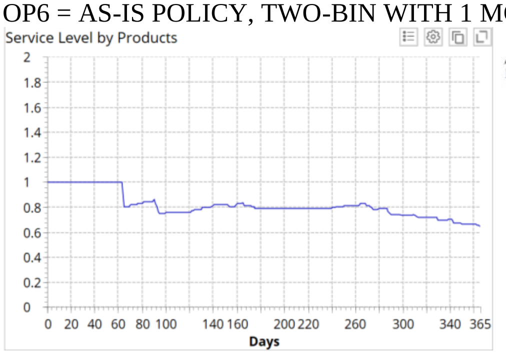


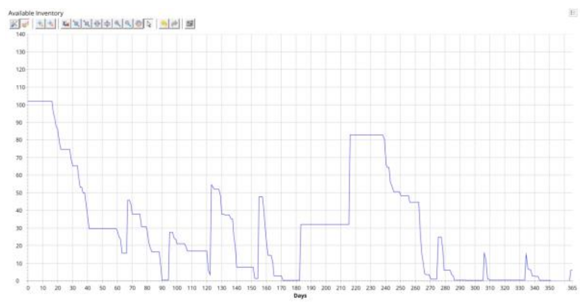
OP5 = FOI WEEKLY





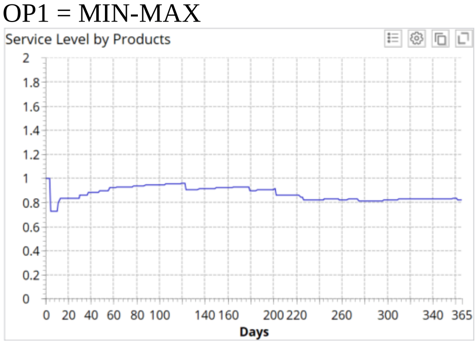
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

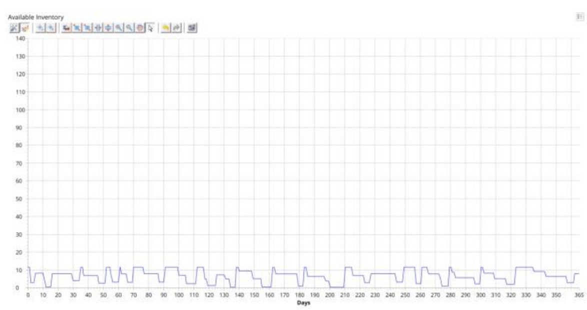




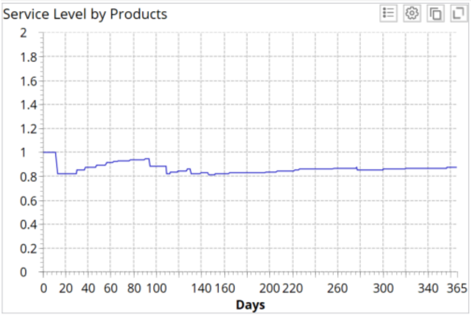
1000 NOK unit cost level

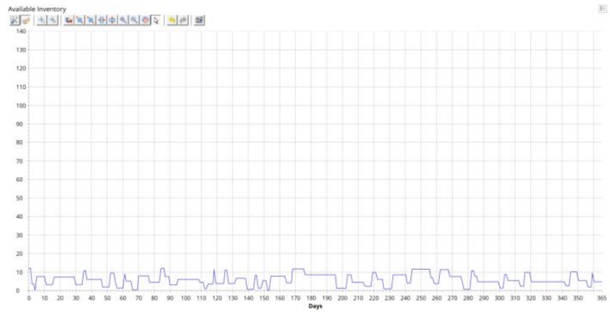
OP1 = MIN-MAX



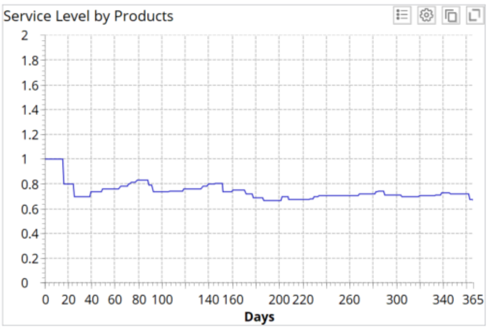


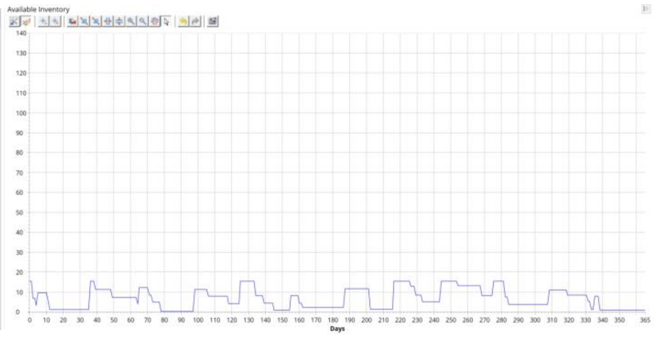
OP2 = ROP WITH EOQ



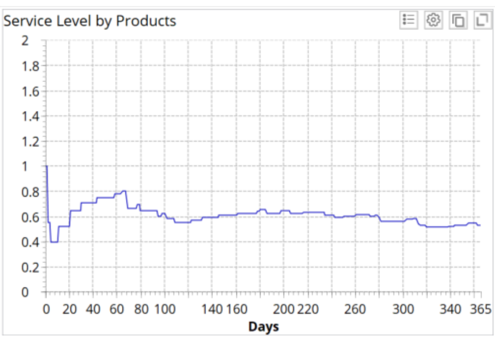


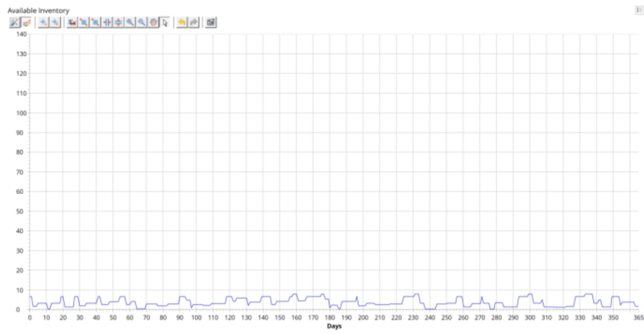
OP4 = FOI MONTHLY



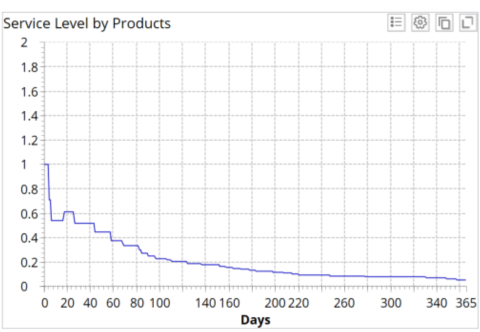


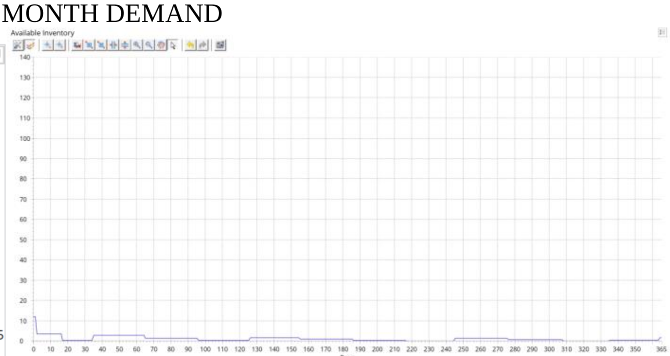
OP5 = FOI WEEKLY





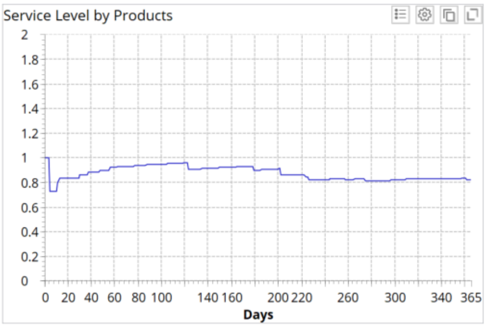
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

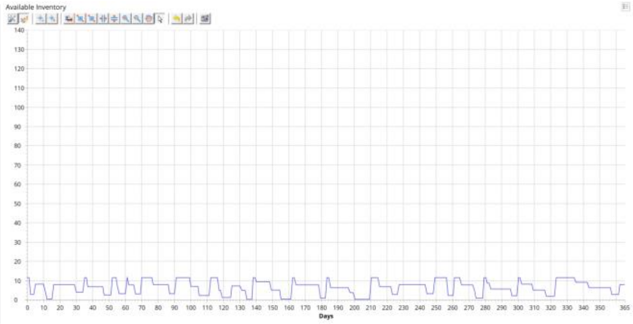




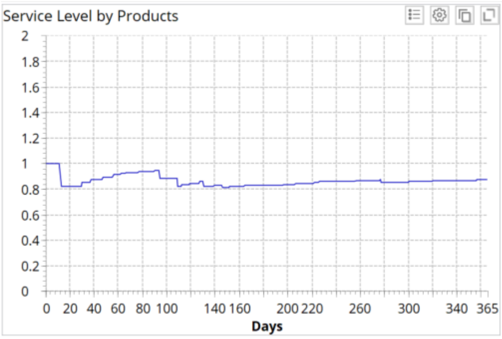
2000 NOK unit cost level

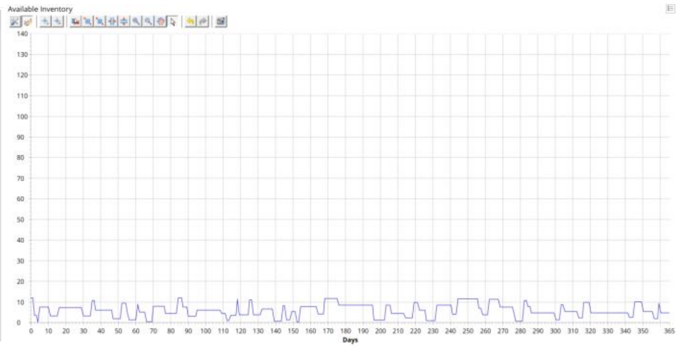
OP1 = MIN-MAX



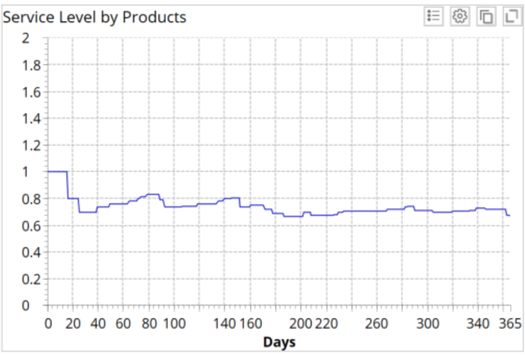


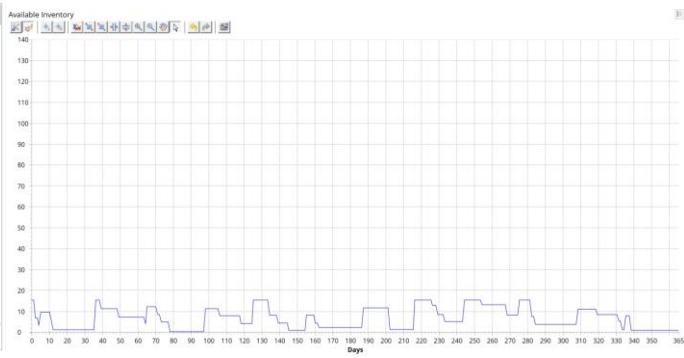
OP2 = ROP WITH EOQ



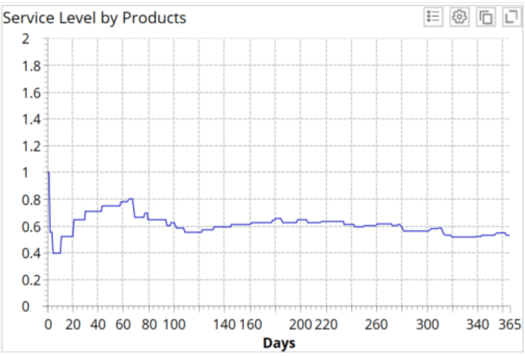


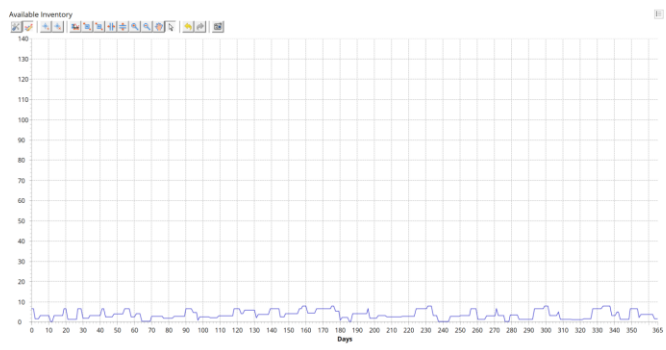
OP4 = FOI MONTHLY



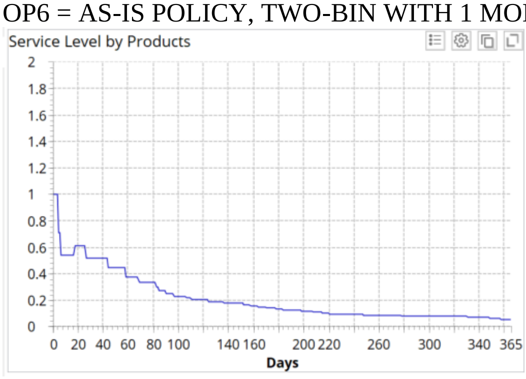


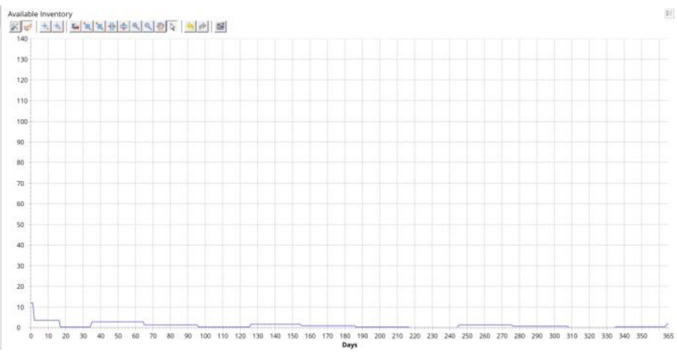
OP5 = FOI WEEKLY





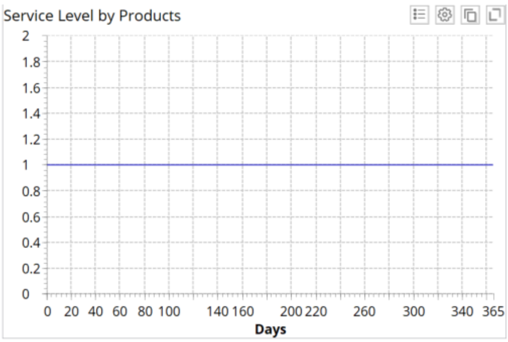
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

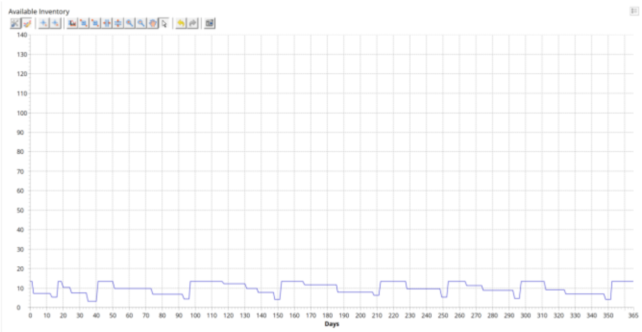




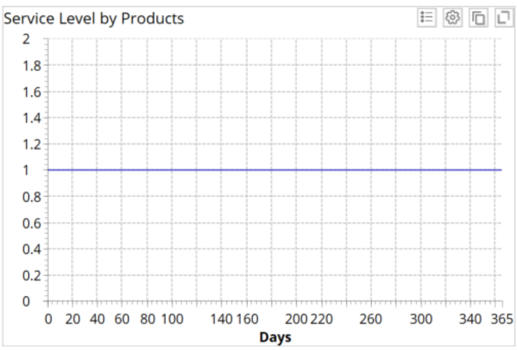
20% higher daily average demand

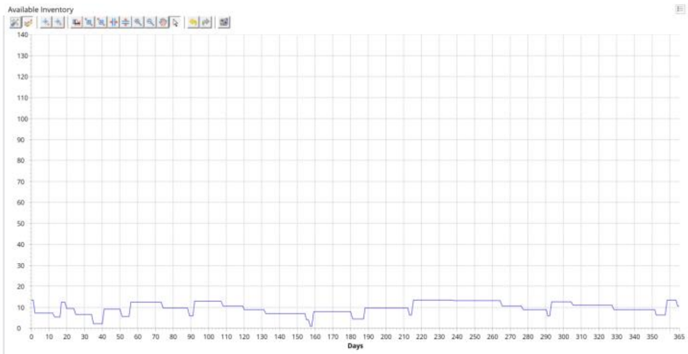
OP1 = MIN-MAX



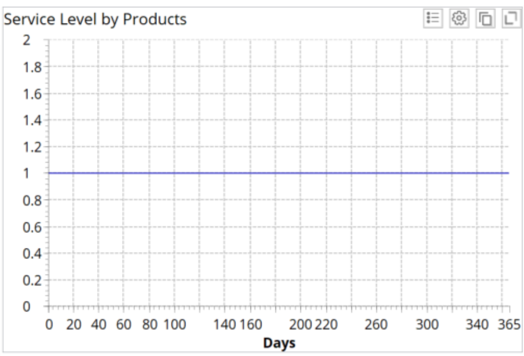


OP2 = ROP WITH EOQ

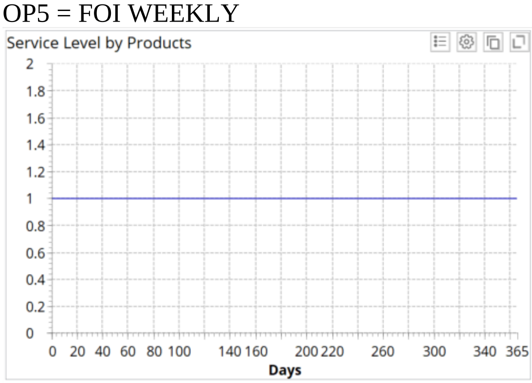


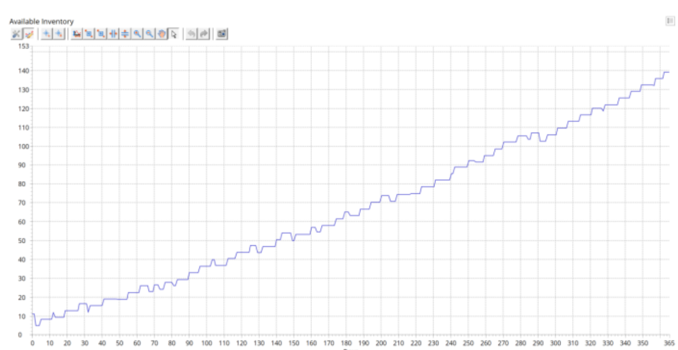


OP4 = FOI MONTHLY

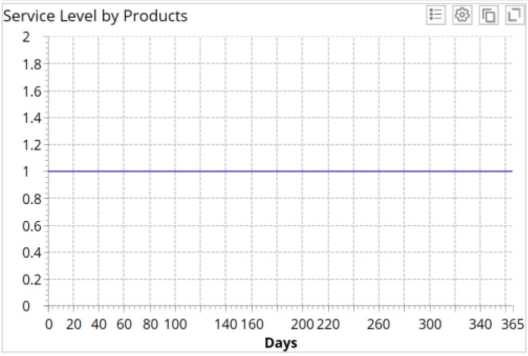


OP5 = FOI WEEKLY



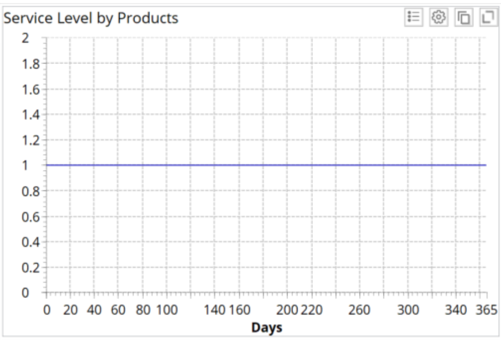


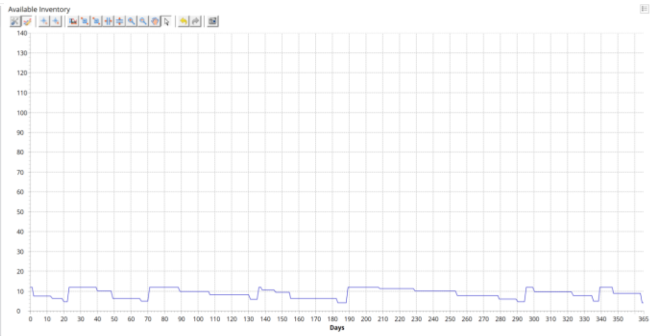
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



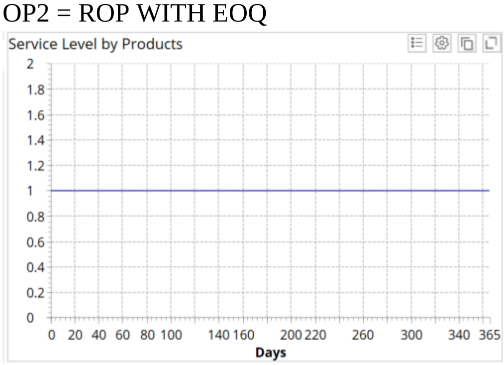
20% lower daily average demand

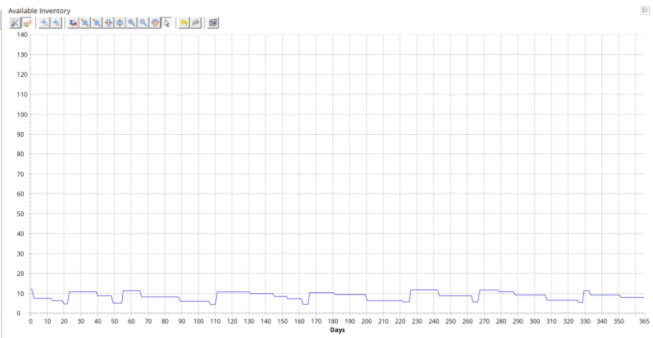
OP1 = MIN-MAX



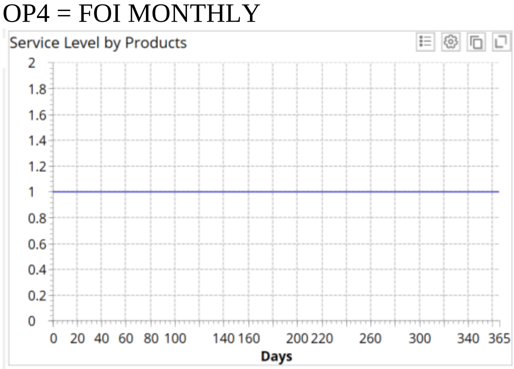


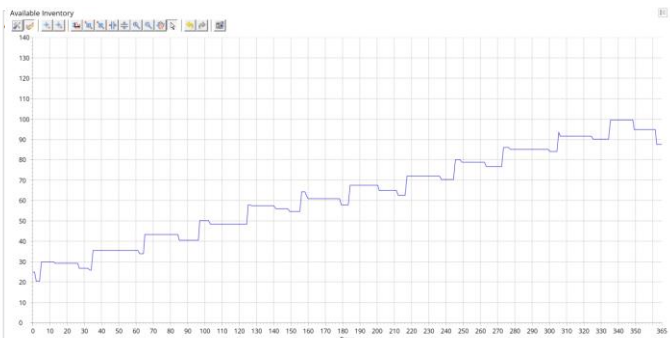
OP2 = ROP WITH EOQ



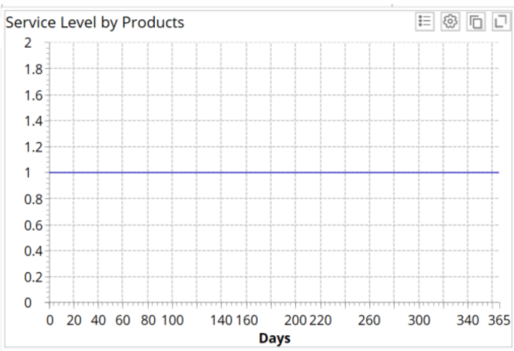


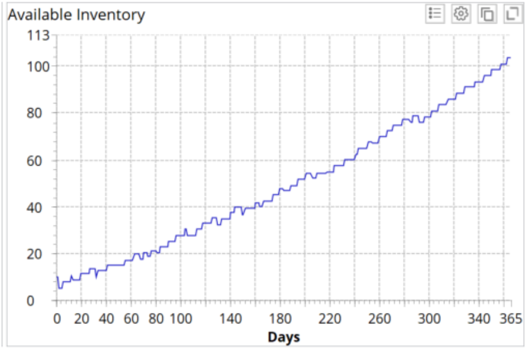
OP4 = FOI MONTHLY



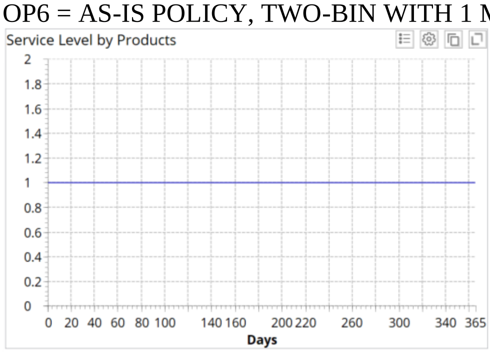


OP5 = FOI WEEKLY



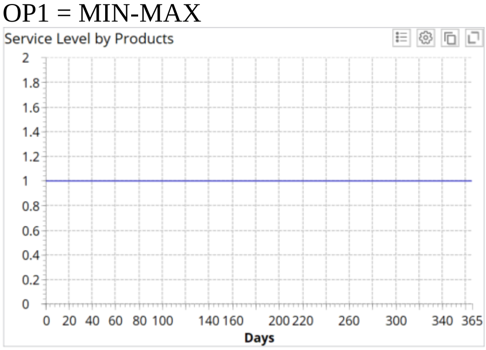


OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

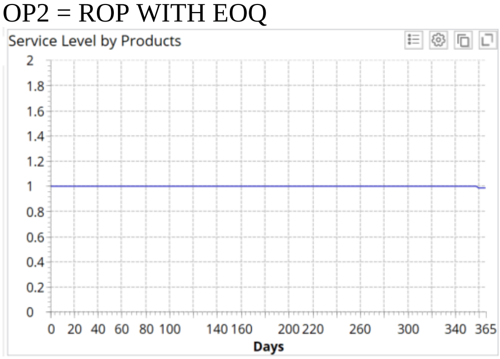


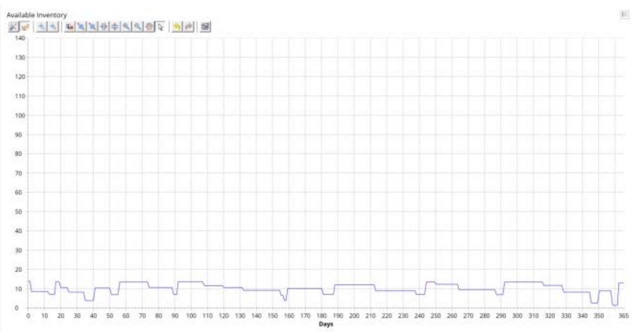
20% higher daily standard deviation of demand

OP1 = MIN-MAX

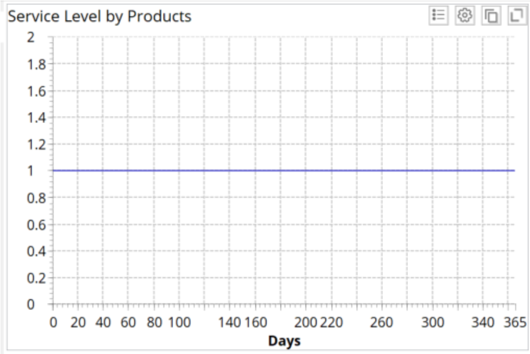


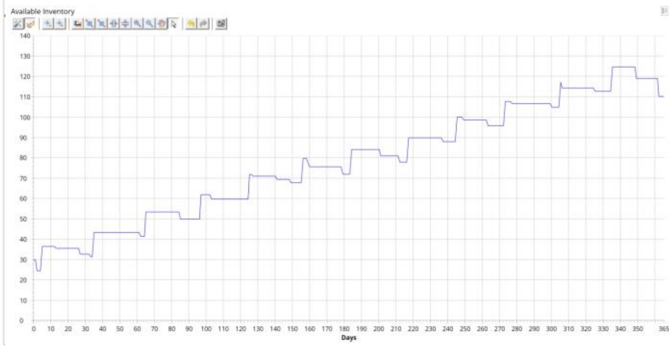
OP2 = ROP WITH EOQ



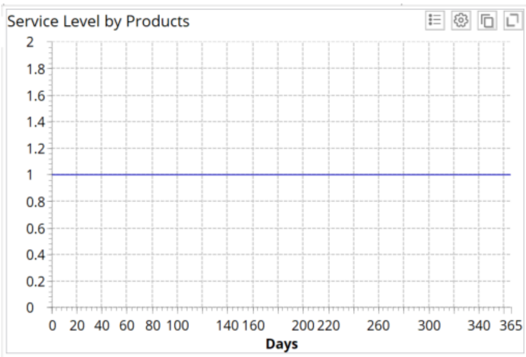


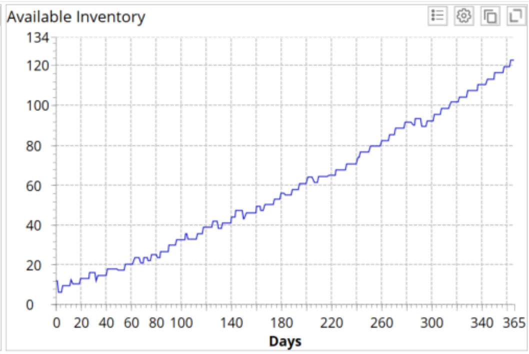
OP4 = FOI MONTHLY



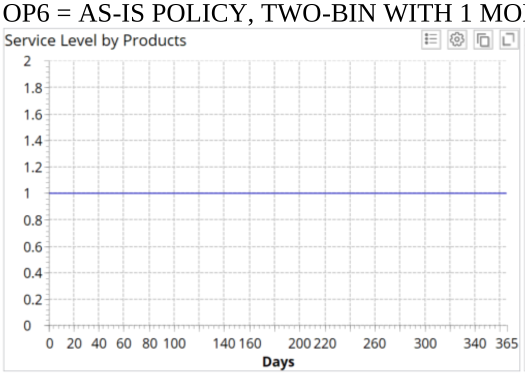


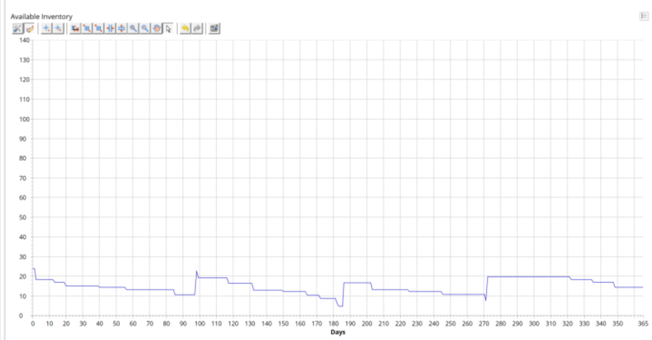
OP5 = FOI WEEKLY





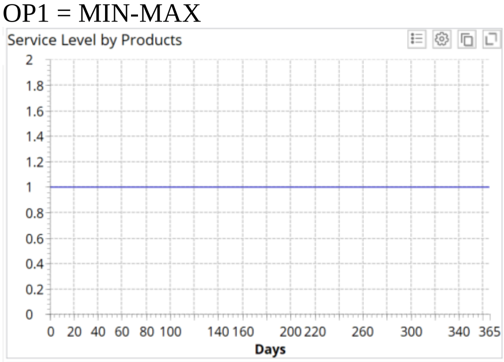
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



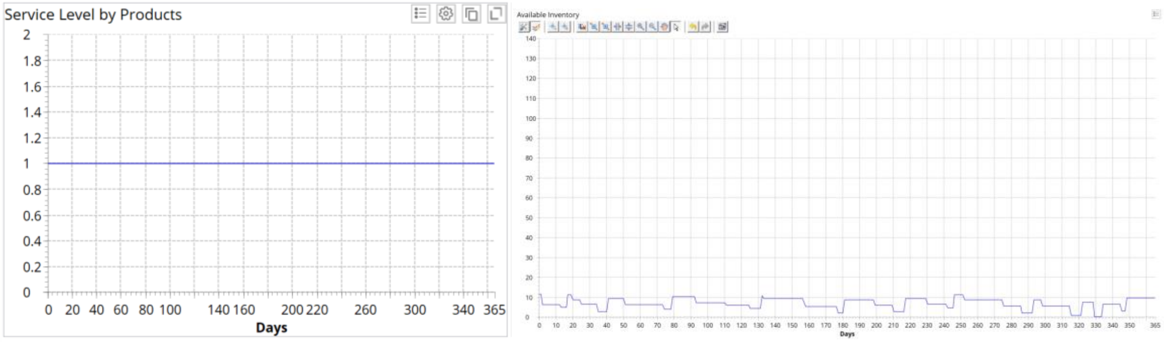


20% lower daily standard deviation of demand

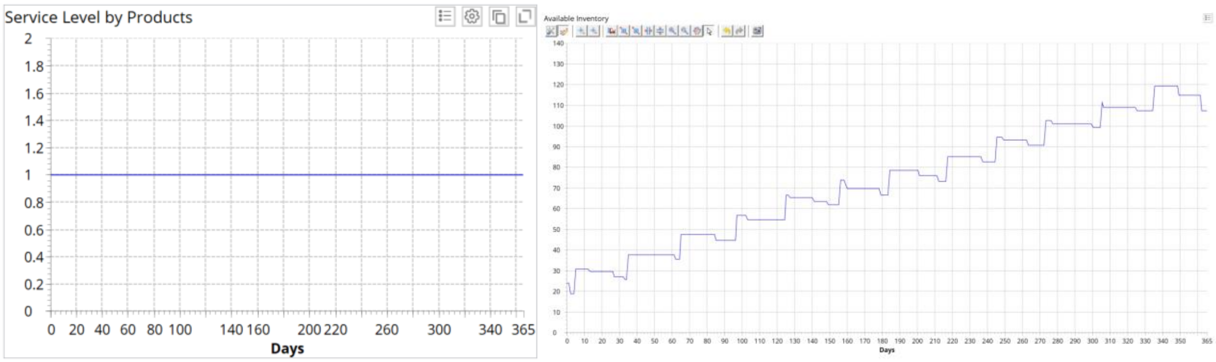
OP1 = MIN-MAX



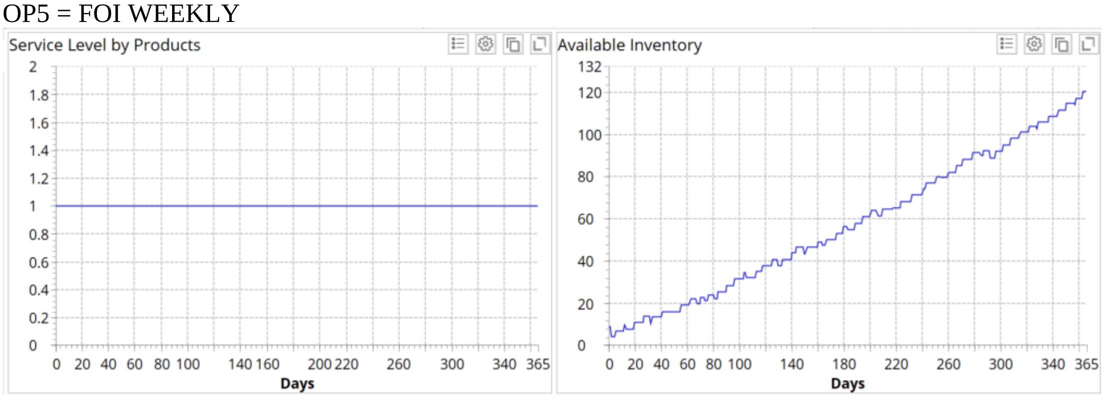
OP2 = ROP WITH EOQ



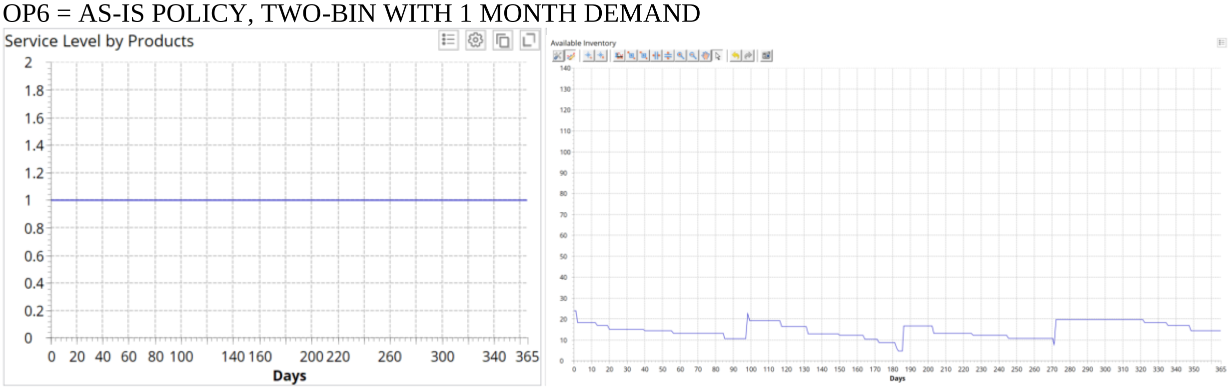
OP4 = FOI MONTHLY



OP5 = FOI WEEKLY

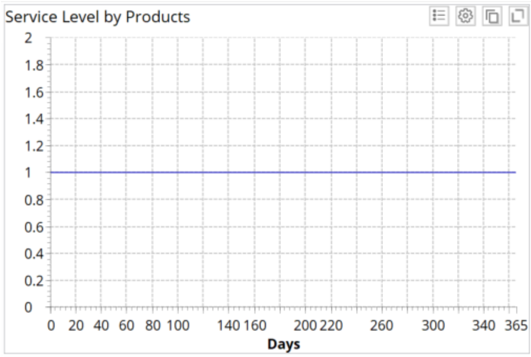


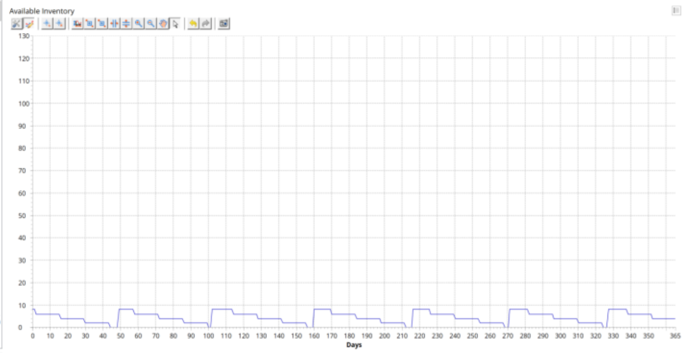
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



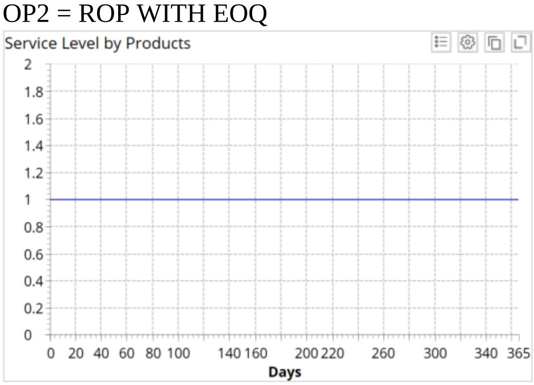
No standard deviation of demand

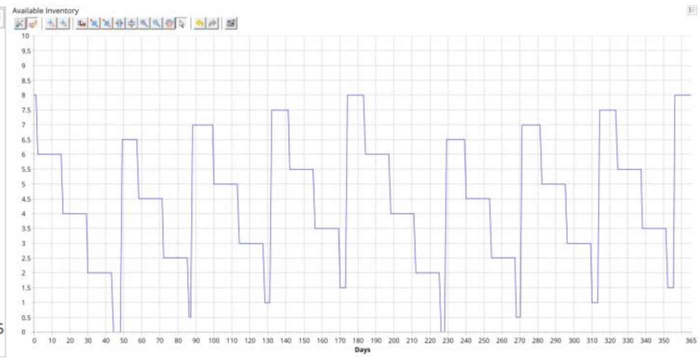
OP1 = MIN-MAX



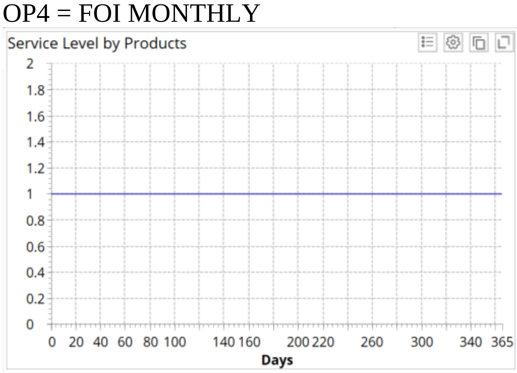


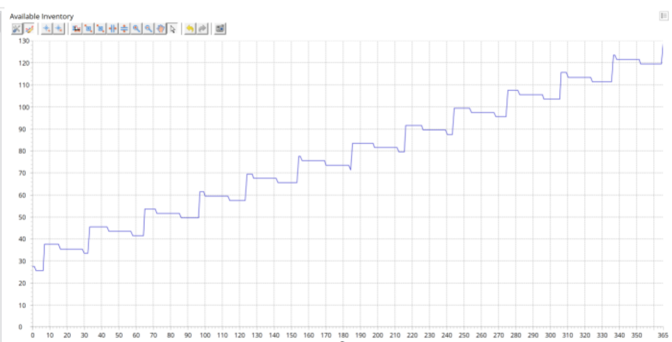
OP2 = ROP WITH EOQ



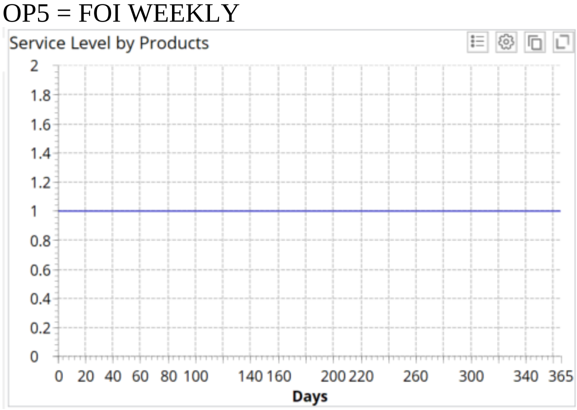


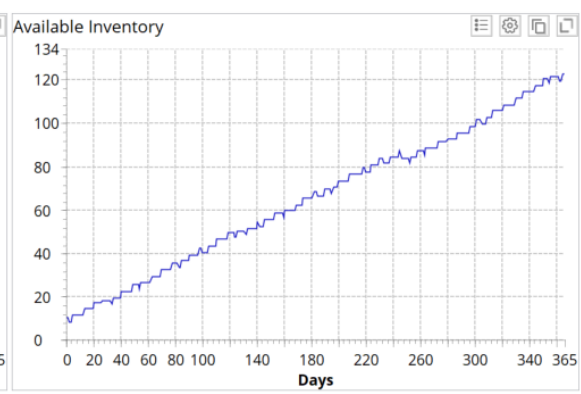
OP4 = FOI MONTHLY



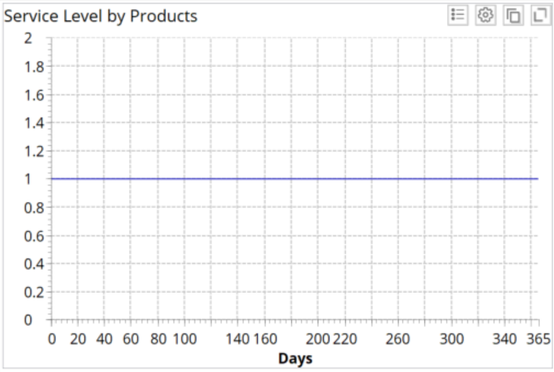


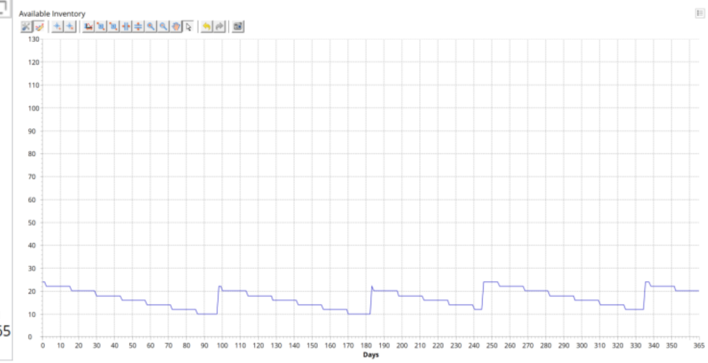
OP5 = FOI WEEKLY





OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

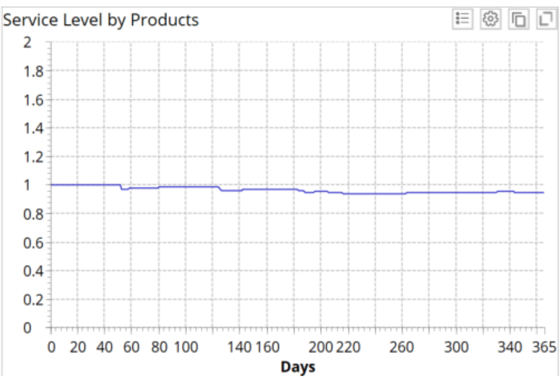


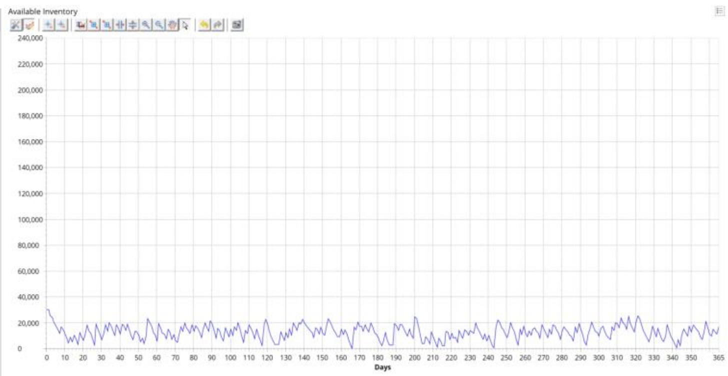


Simulation experiment results for group B

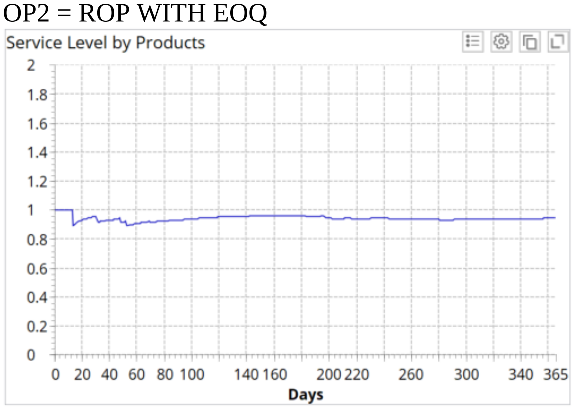
Baseline scenario

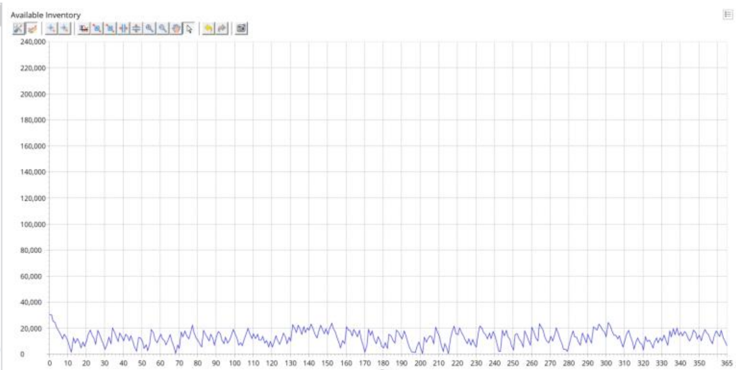
OP1 = MIN-MAX



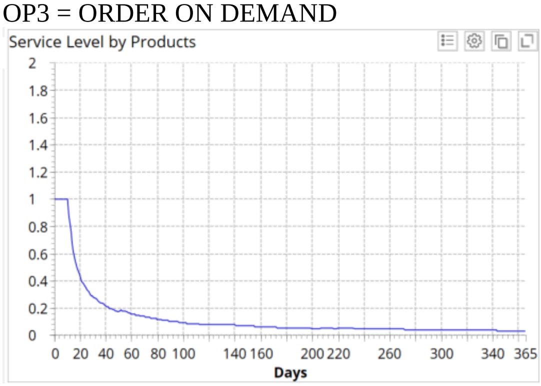


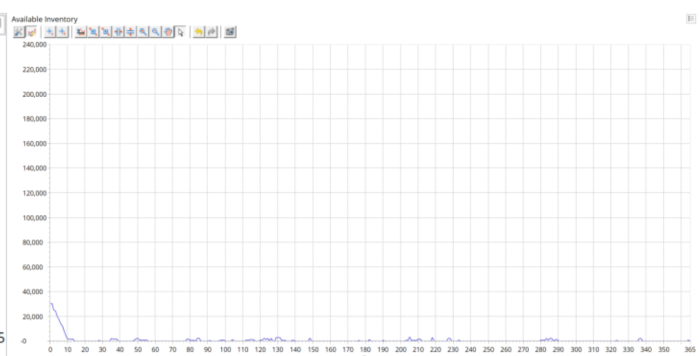
OP2 = ROP WITH EOQ



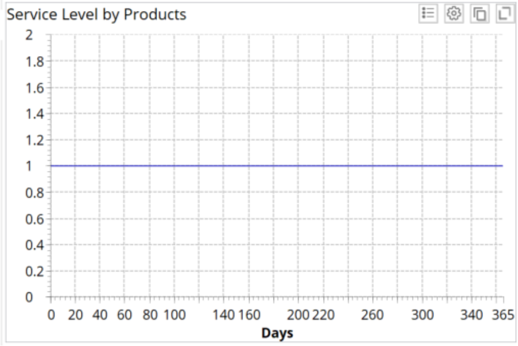


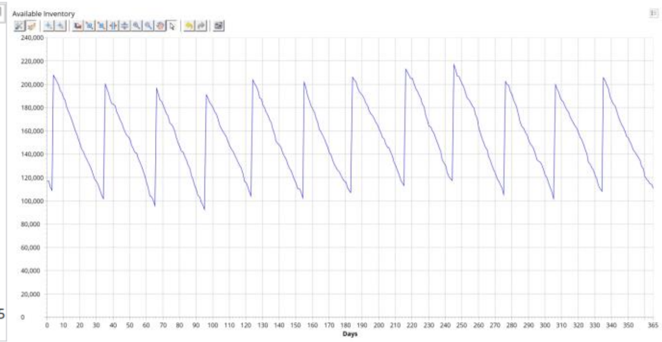
OP3 = ORDER ON DEMAND



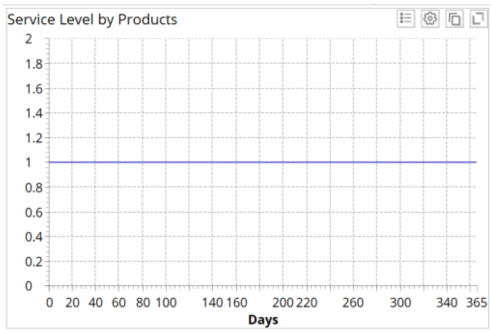


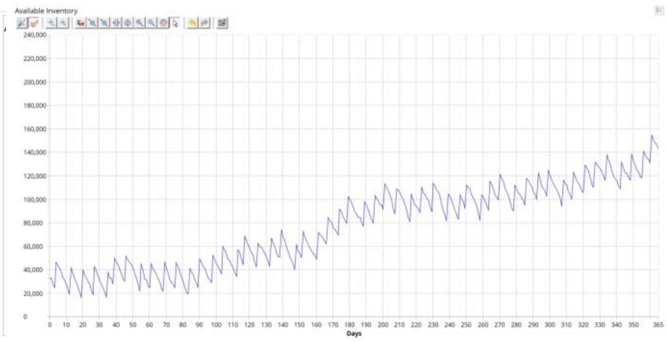
OP4 = FOI MONTHLY



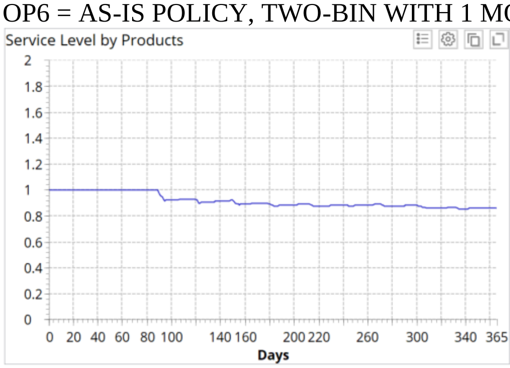


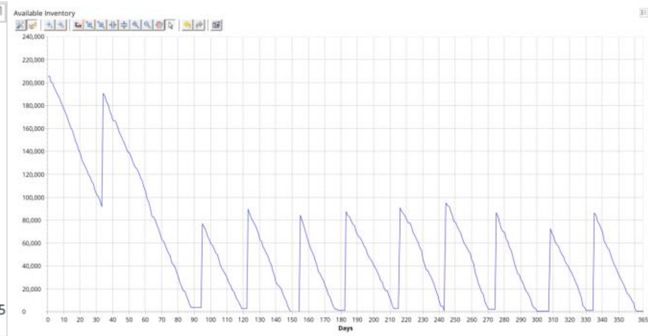
OP5 = FOI WEEKLY





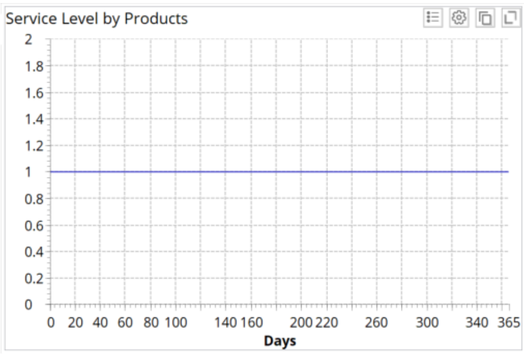
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

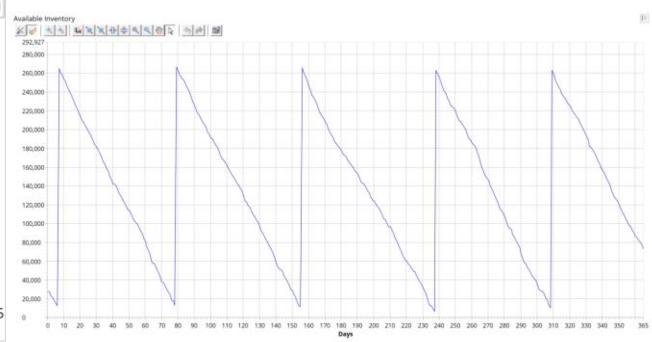




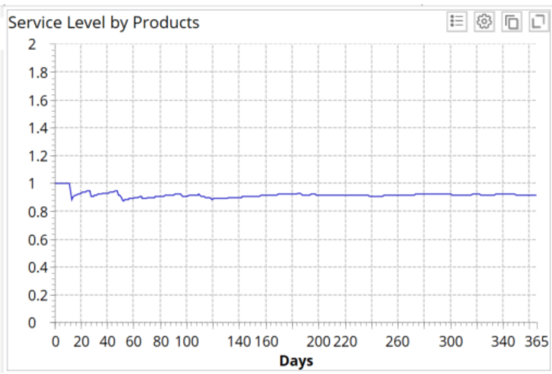
200 NOK unit cost level

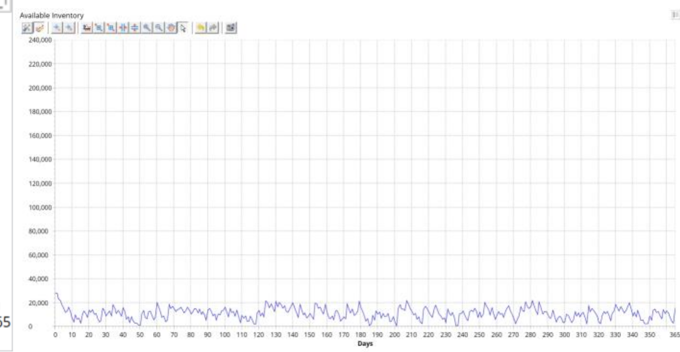
OP1 = MIN-MAX



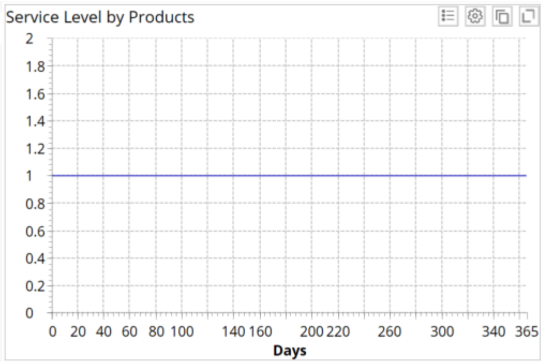


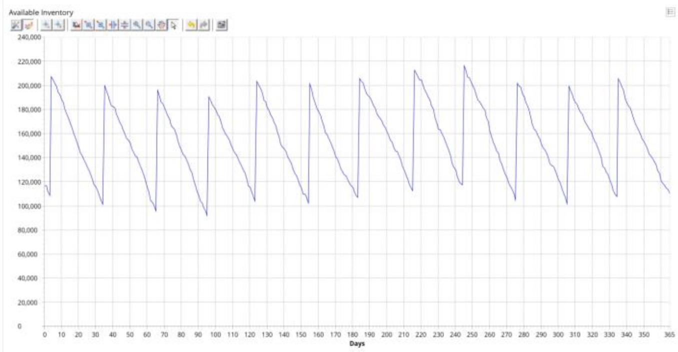
OP2 = ROP WITH EOQ



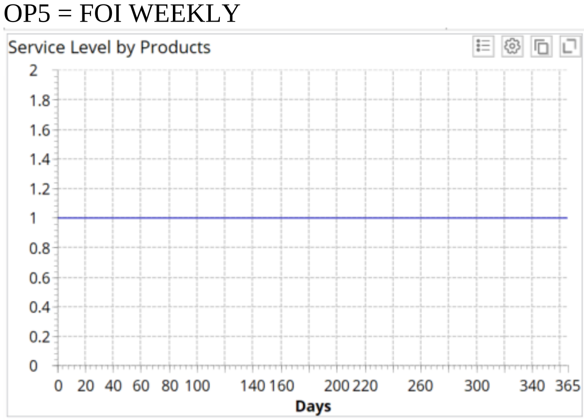


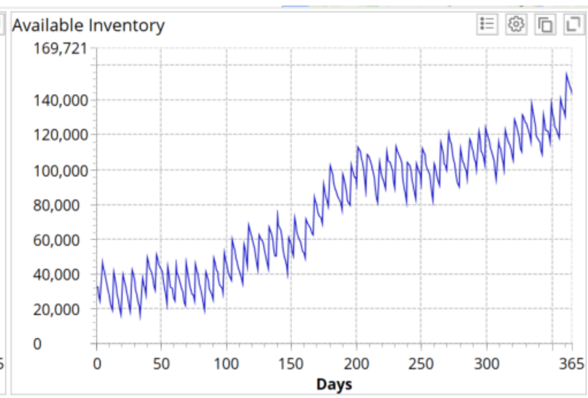
OP4 = FOI MONTHLY



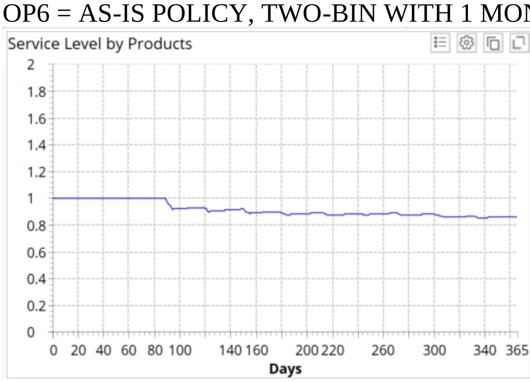


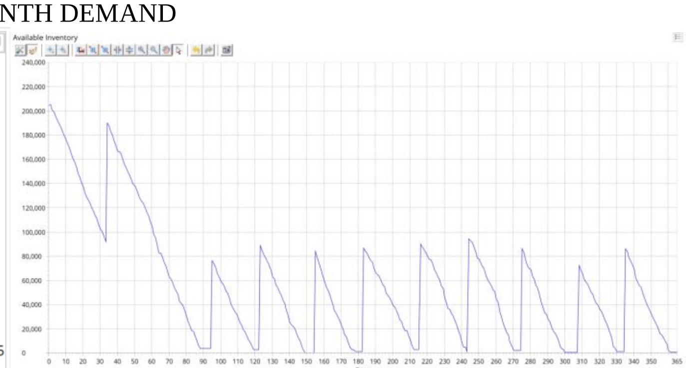
OP5 = FOI WEEKLY





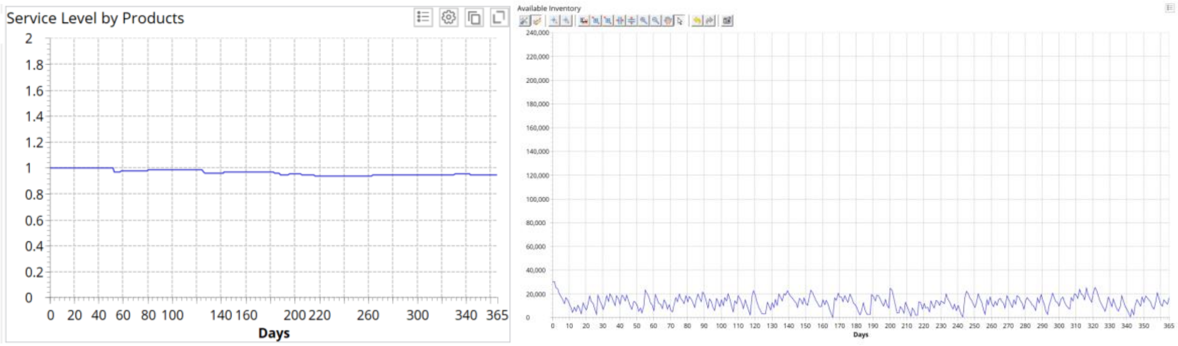
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



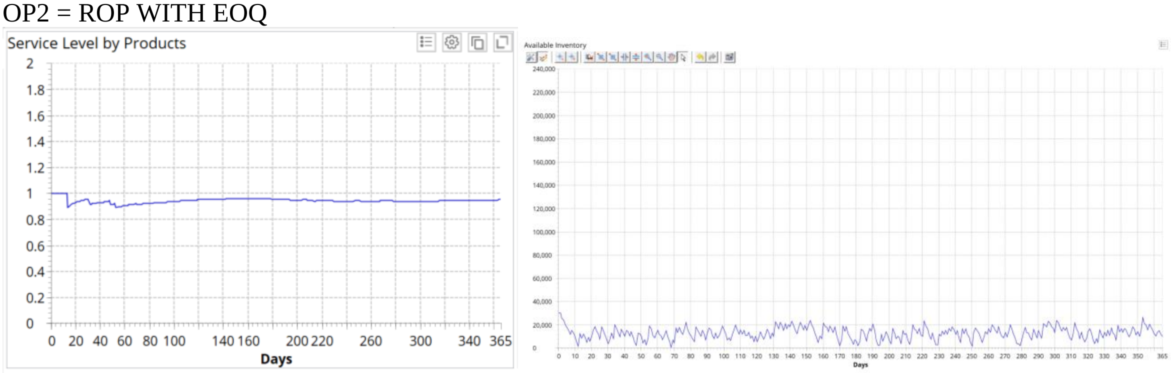


1000 NOK unit cost level

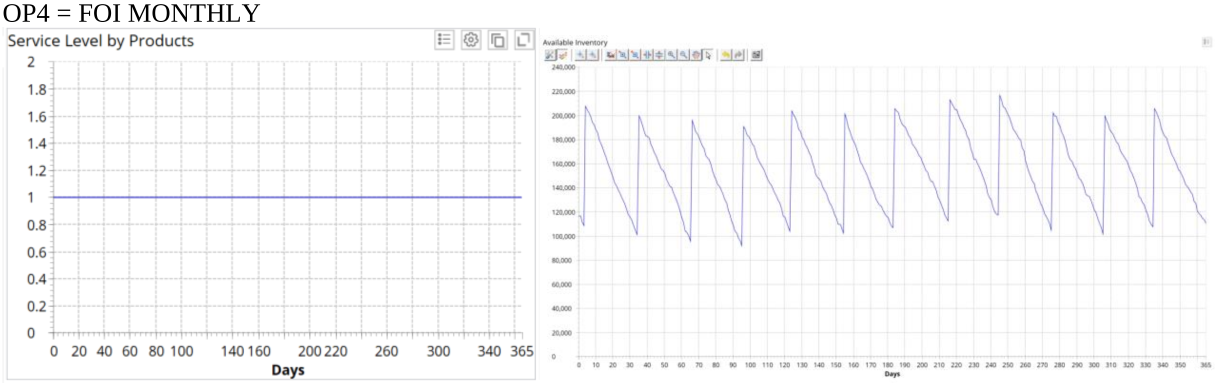
OP1 = MIN-MAX



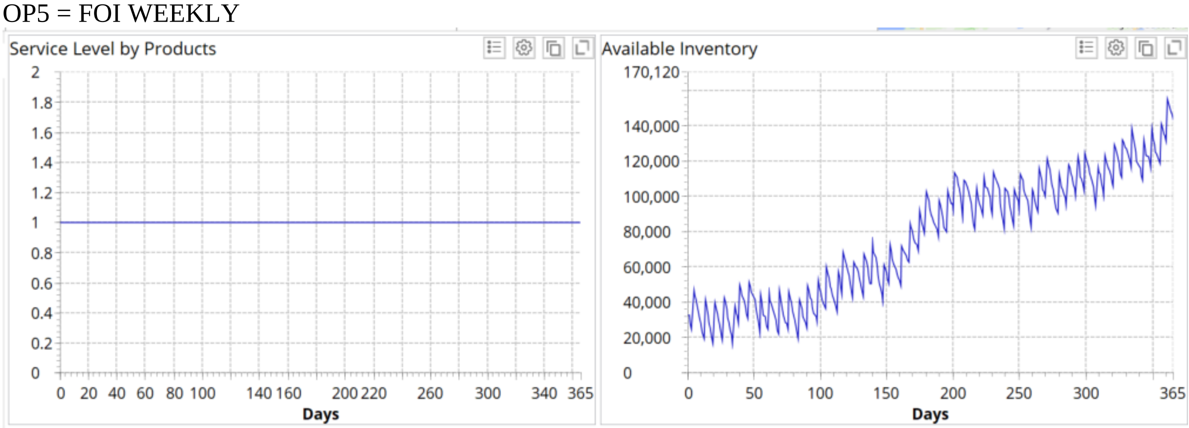
OP2 = ROP WITH EOQ



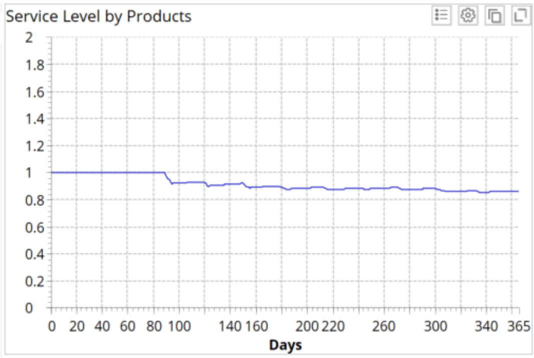
OP4 = FOI MONTHLY

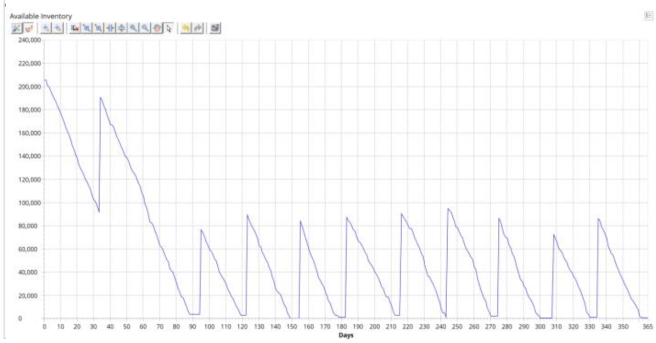


OP5 = FOI WEEKLY



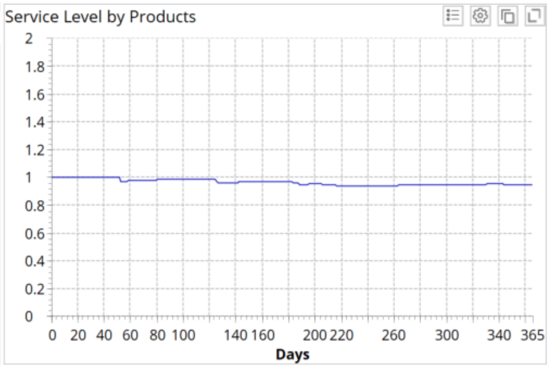
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

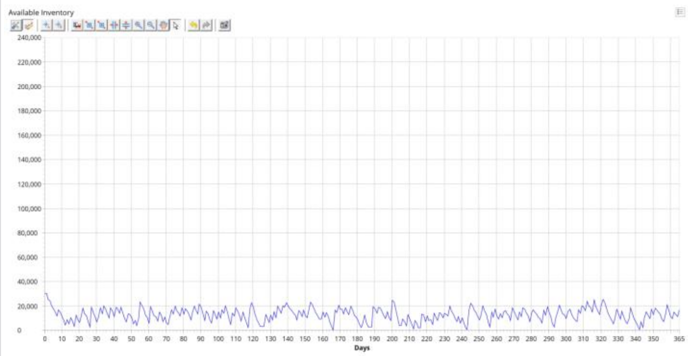




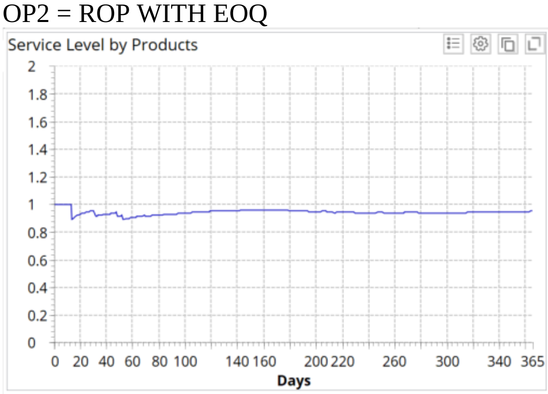
2000 NOK unit cost level

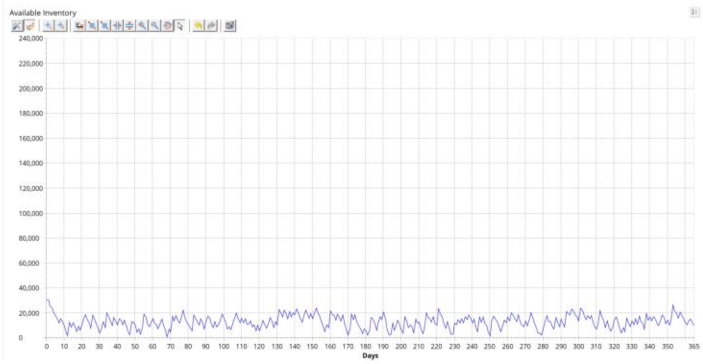
OP1 = MIN-MAX



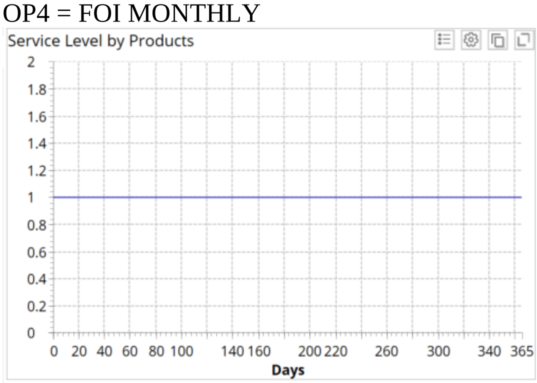


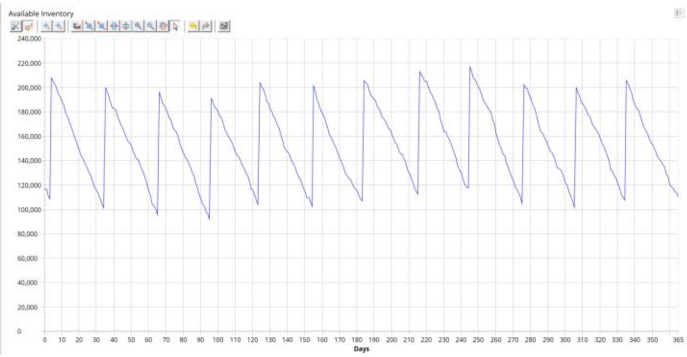
OP2 = ROP WITH EOQ



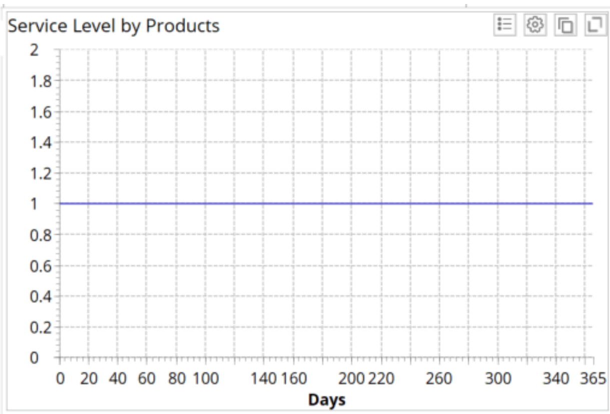


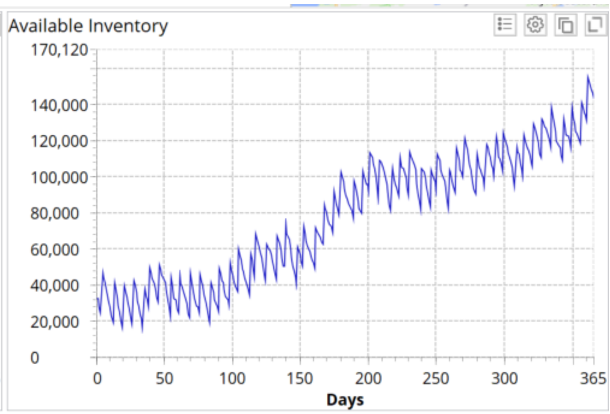
OP4 = FOI MONTHLY



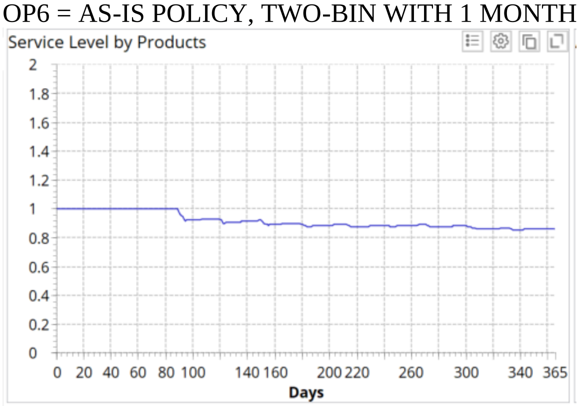


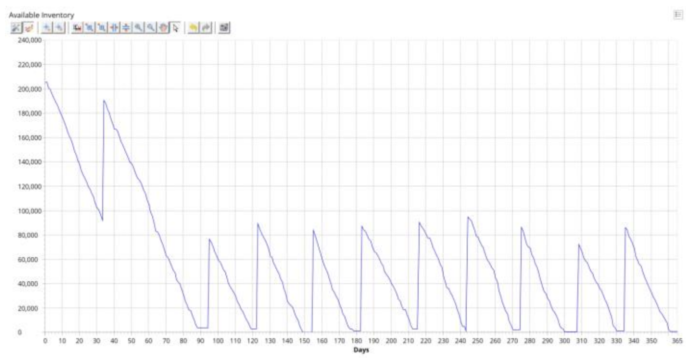
OP5 = FOI WEEKLY





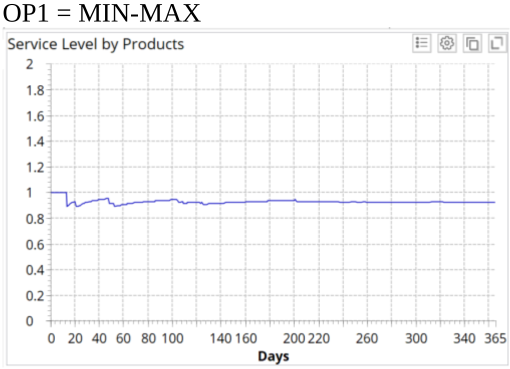
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

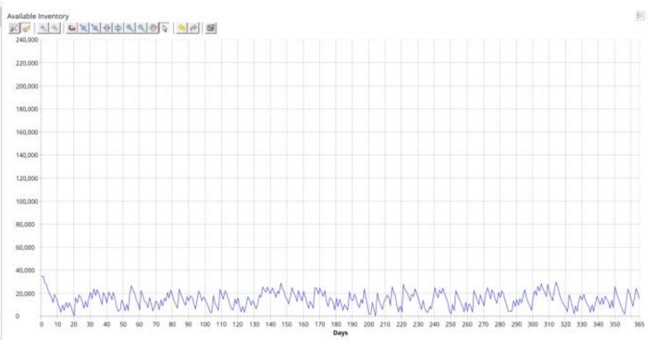




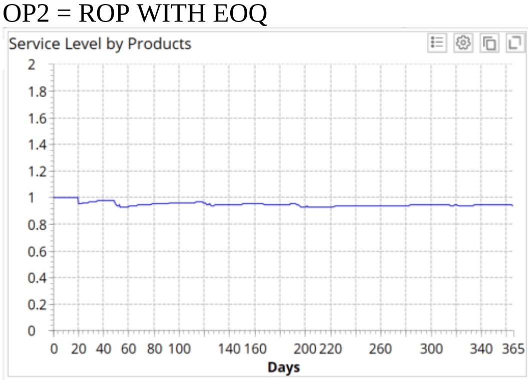
20% higher daily average demand

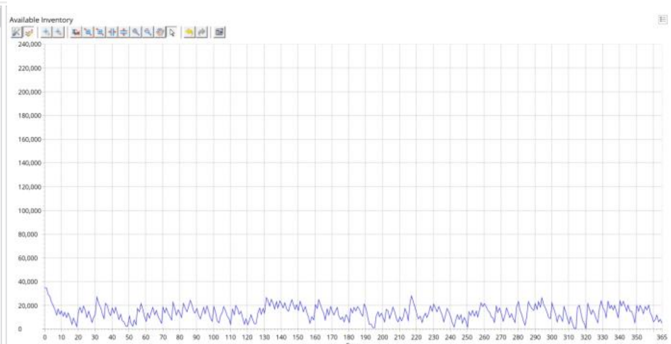
OP1 = MIN-MAX



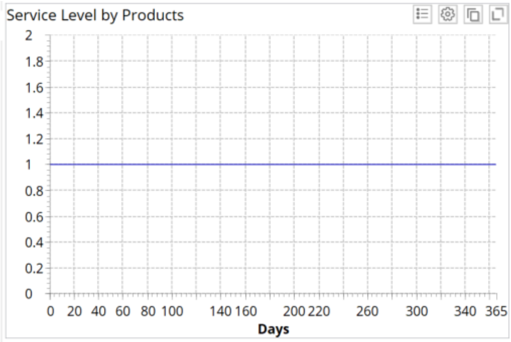


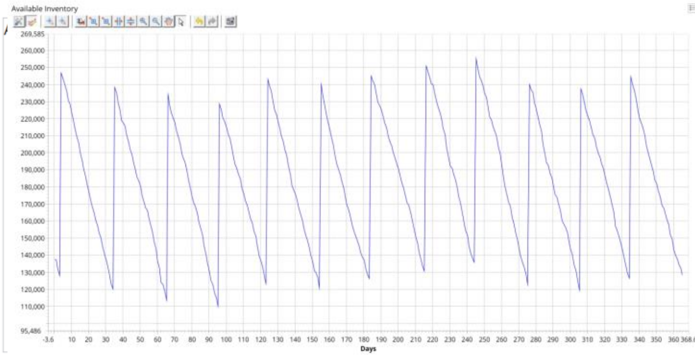
OP2 = ROP WITH EOQ



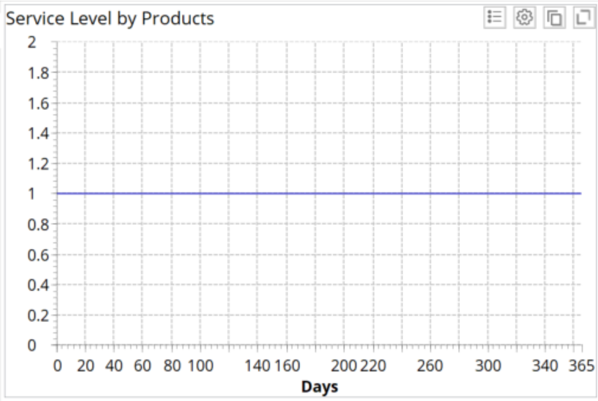


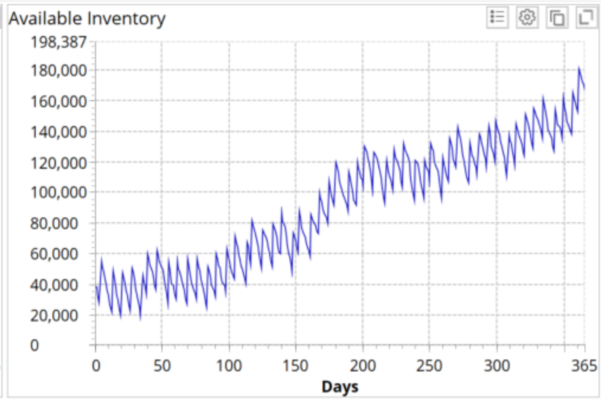
OP4 = FOI MONTHLY



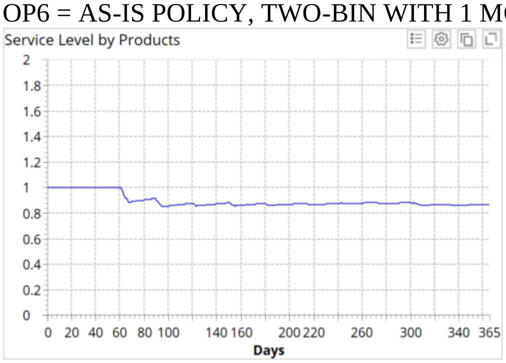


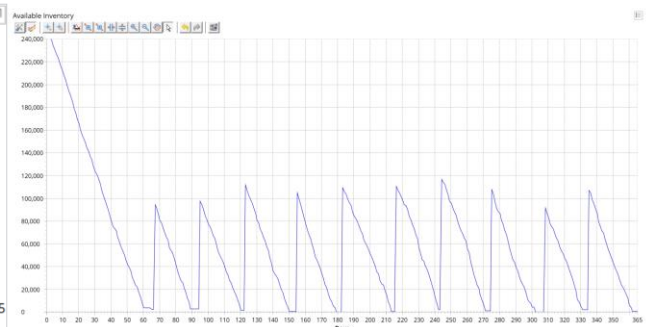
OP5 = FOI WEEKLY





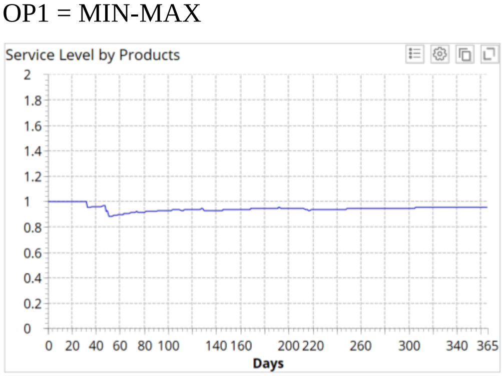
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

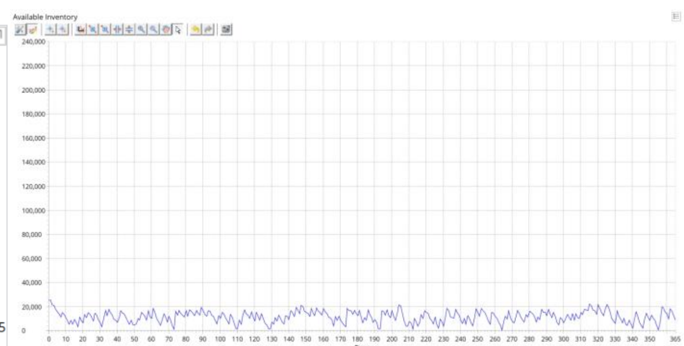




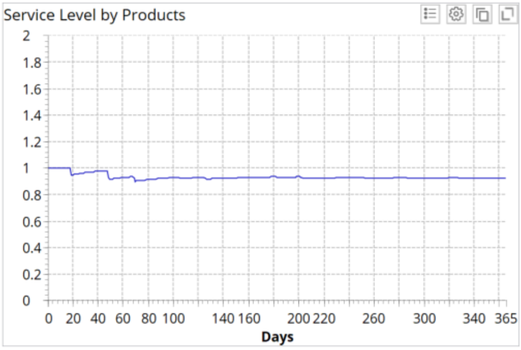
20% lower daily average demand

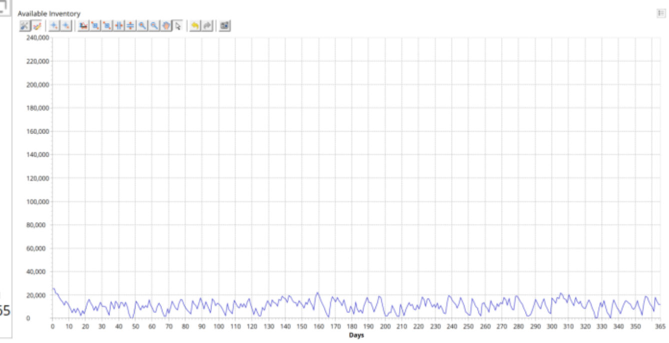
OP1 = MIN-MAX



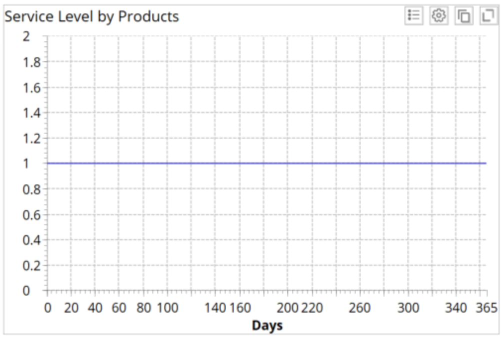


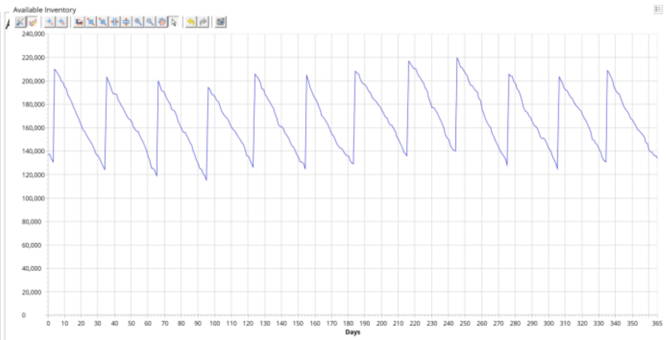
OP2 = ROP WITH EOQ



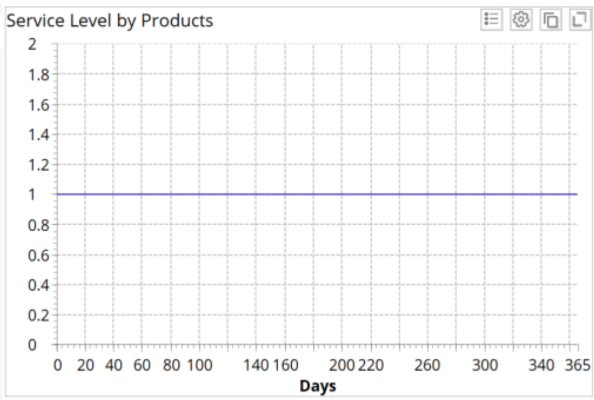


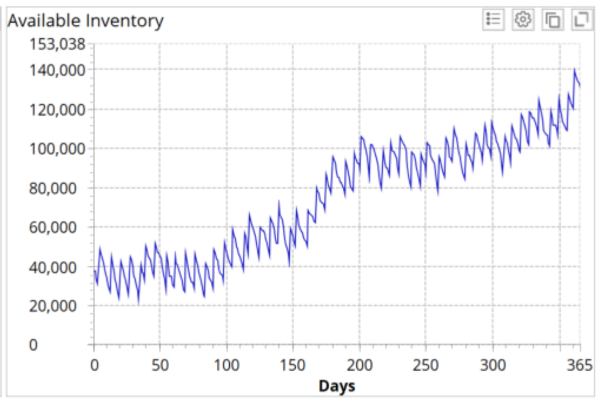
OP4 = FOI MONTHLY



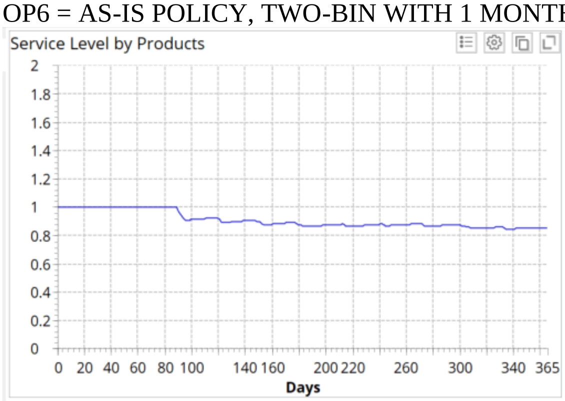


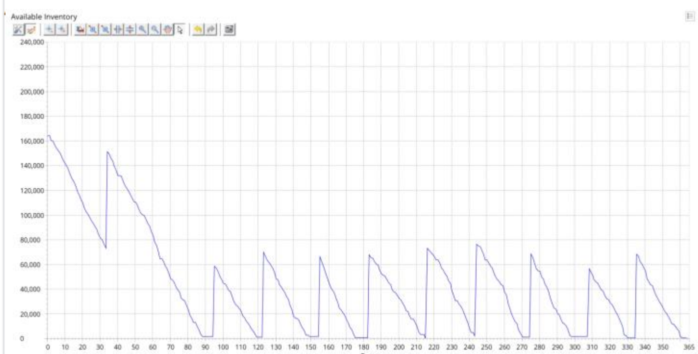
OP5 = FOI WEEKLY





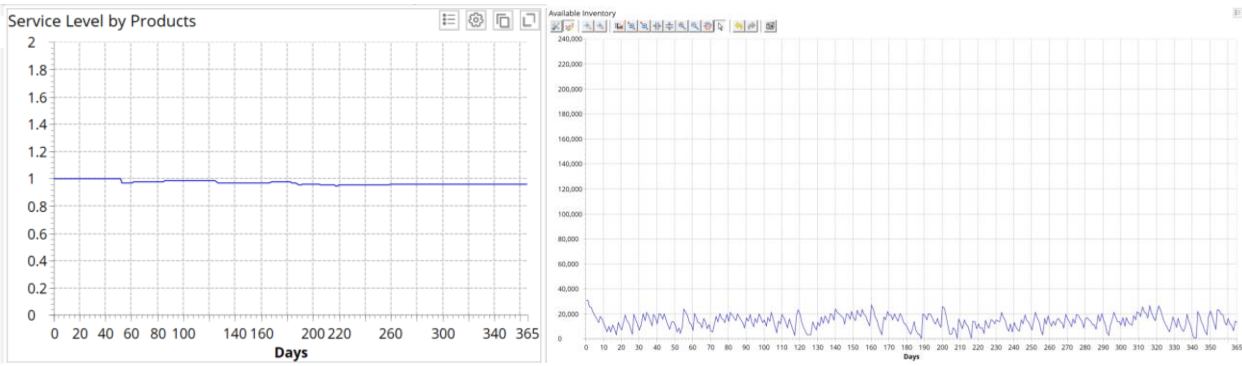
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



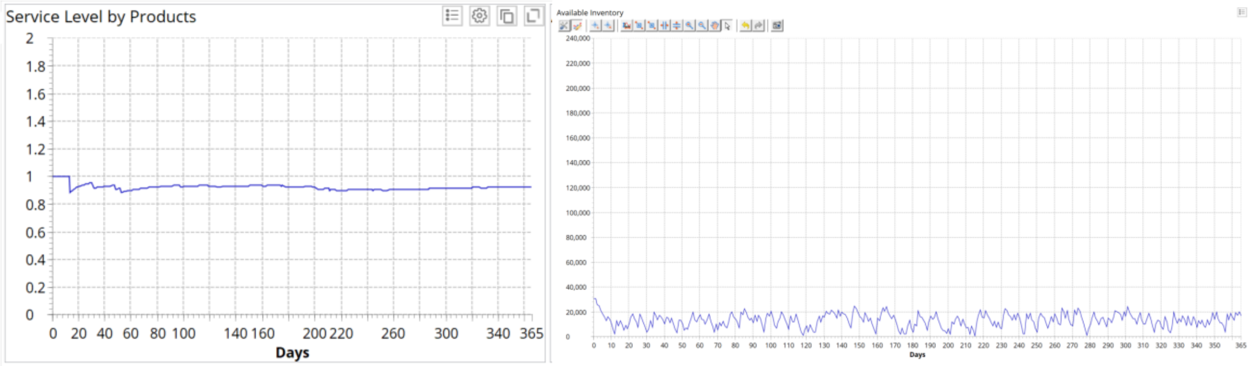


20% higher daily standard deviation of demand

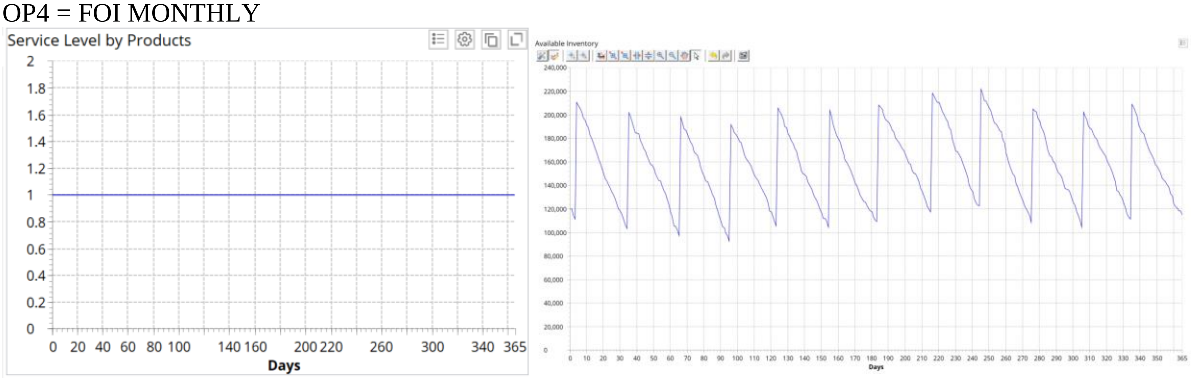
OP1 = MIN-MAX



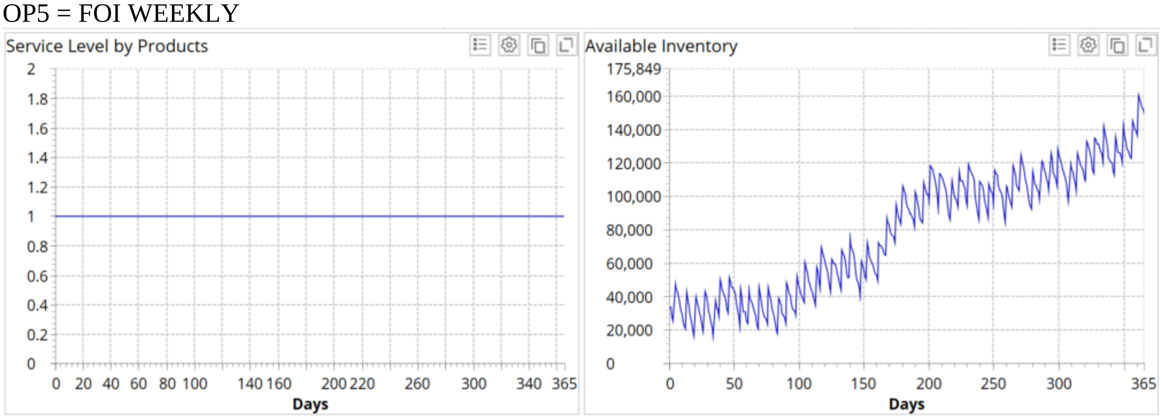
OP2 = ROP WITH EOQ



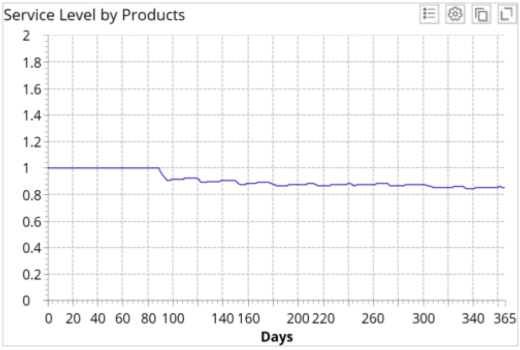
OP4 = FOI MONTHLY

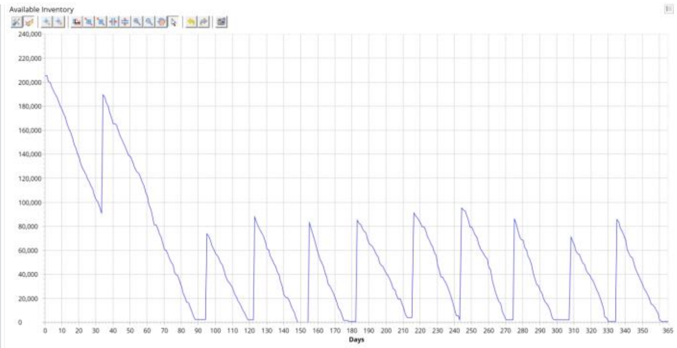


OP5 = FOI WEEKLY



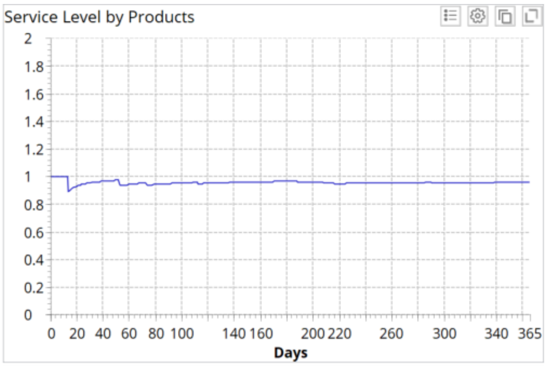
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

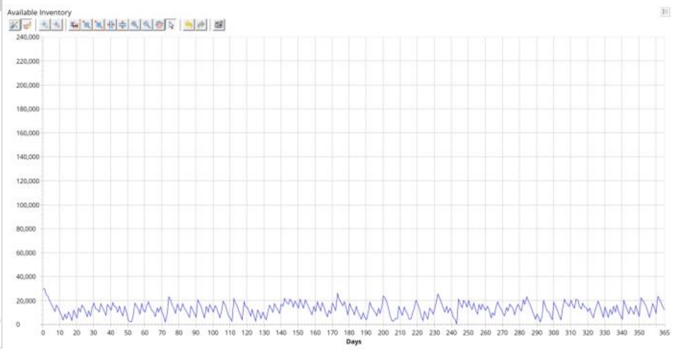




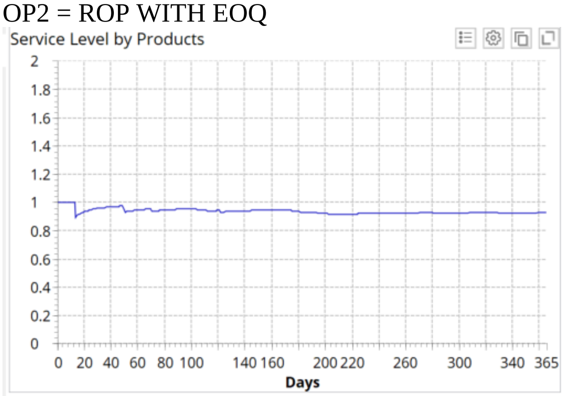
20% lower daily standard deviation of demand

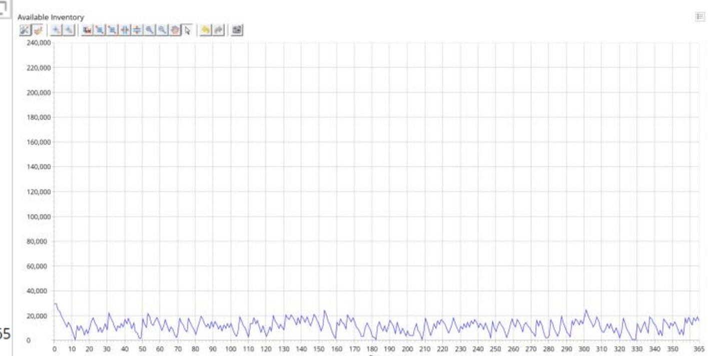
OP1 = MIN-MAX



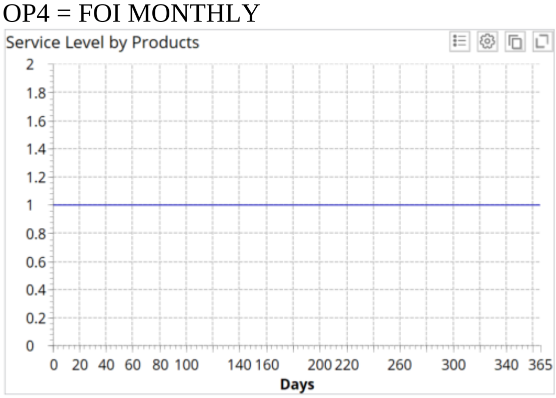


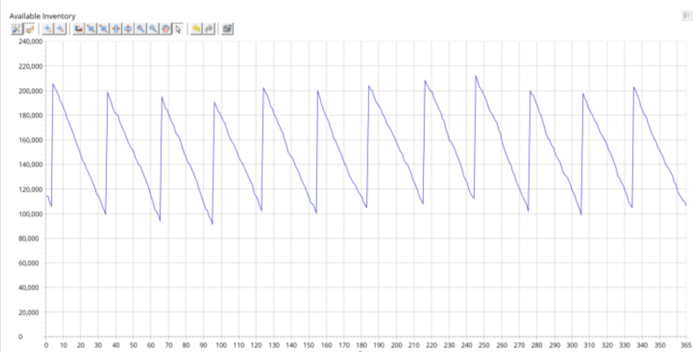
OP2 = ROP WITH EOQ



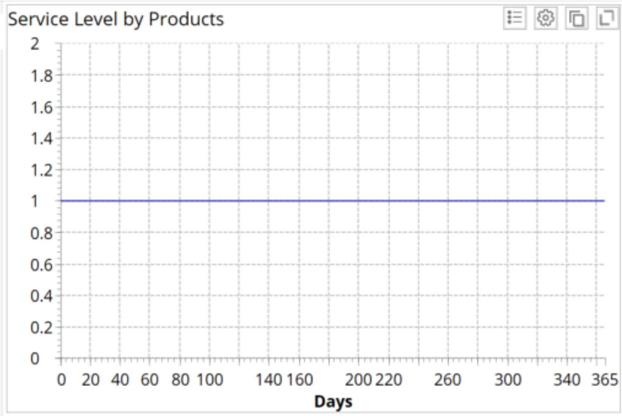


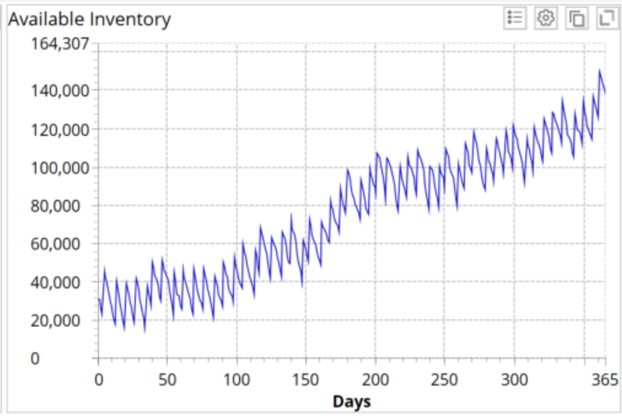
OP4 = FOI MONTHLY



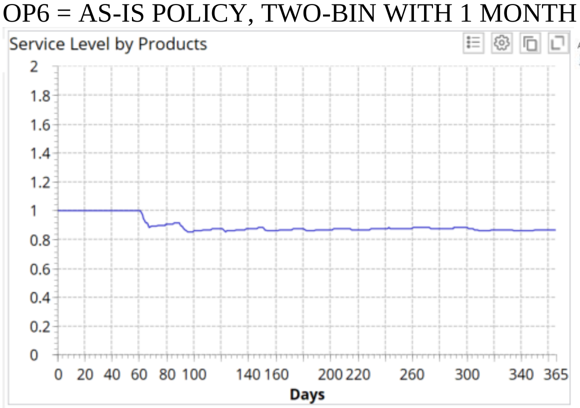


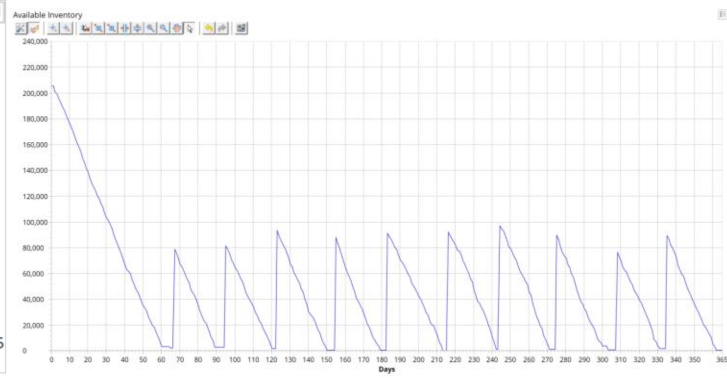
OP5 = FOI WEEKLY





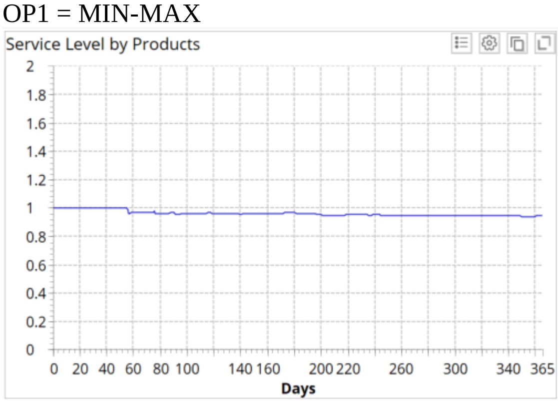
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

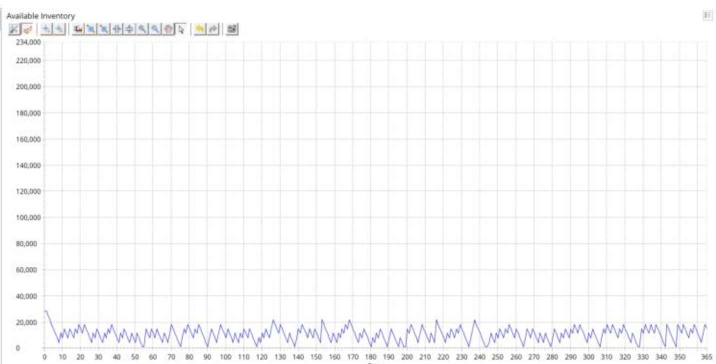




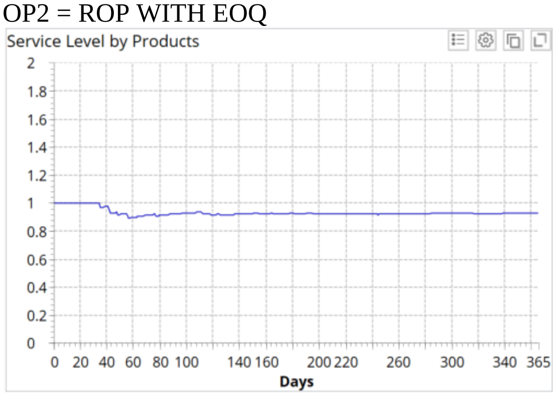
No standard deviation of demand

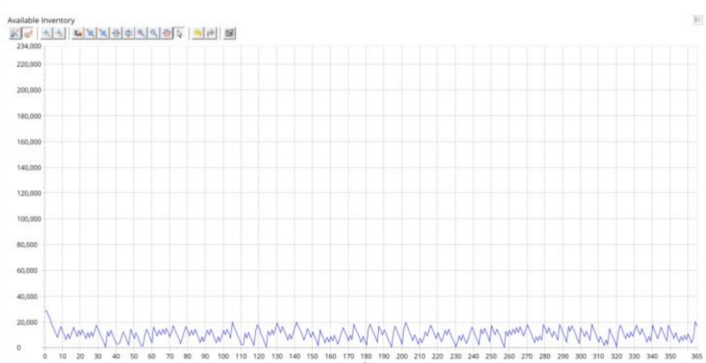
OP1 = MIN-MAX



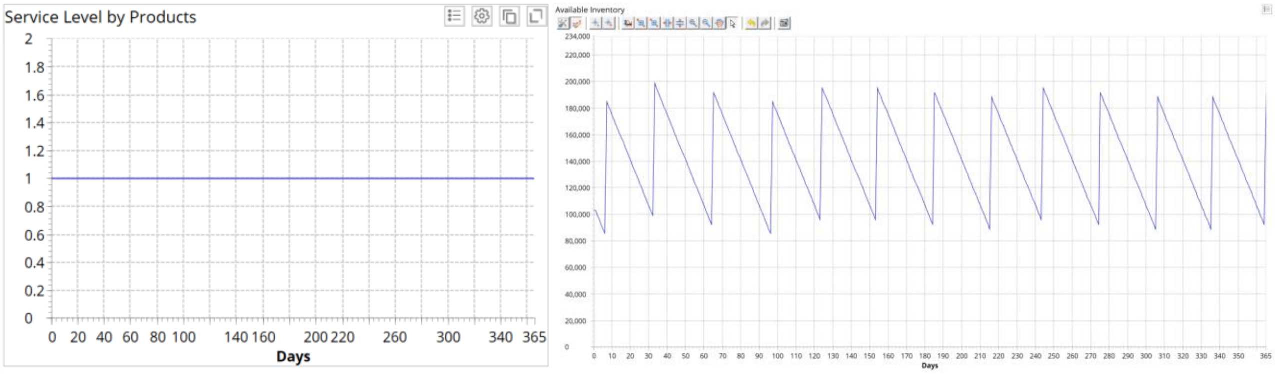


OP2 = ROP WITH EOQ

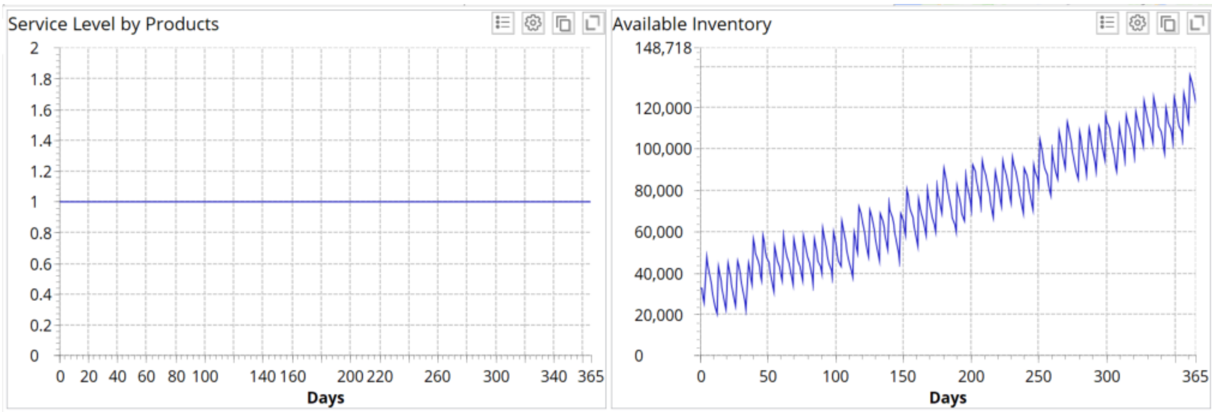




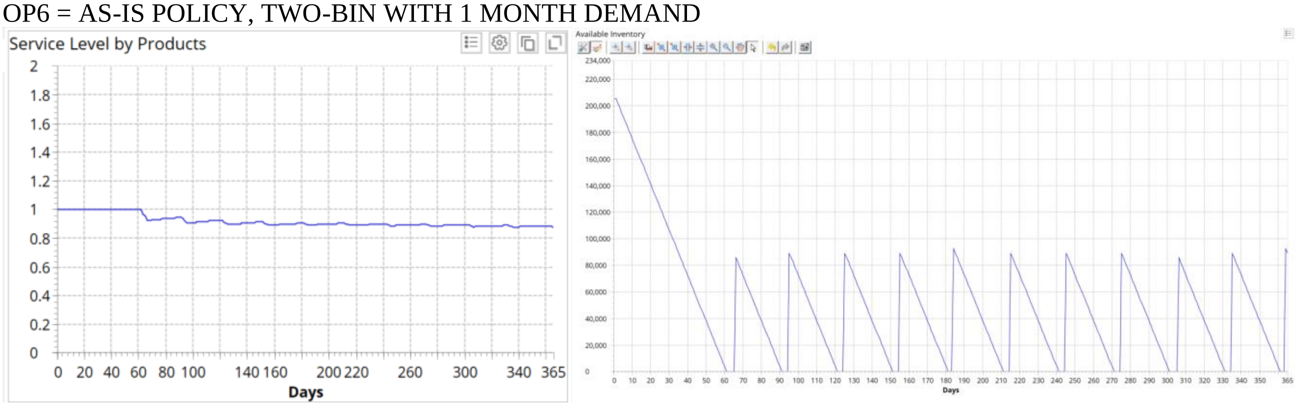
OP4 = FOI MONTHLY



OP5 = FOI WEEKLY



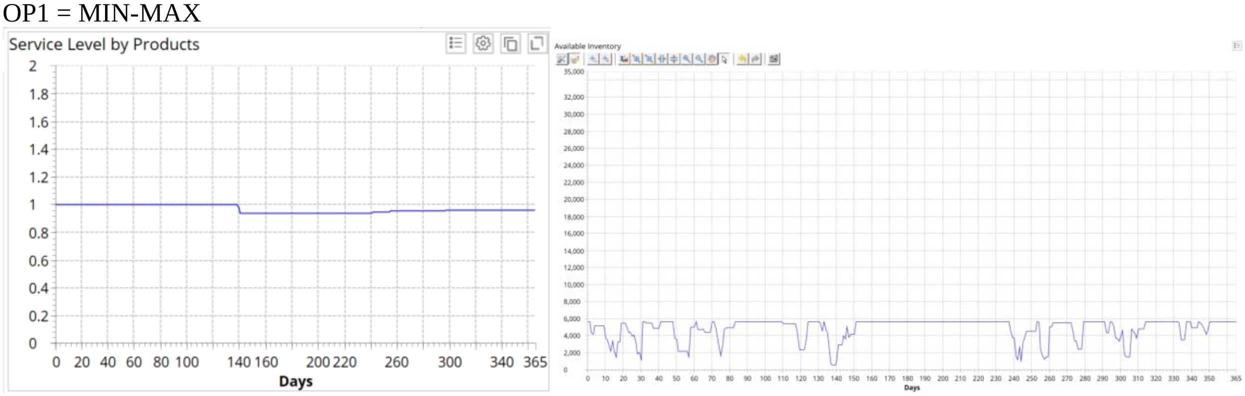
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



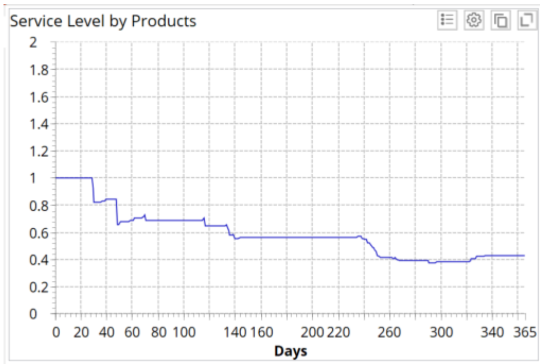
Simulation experiment results for group C

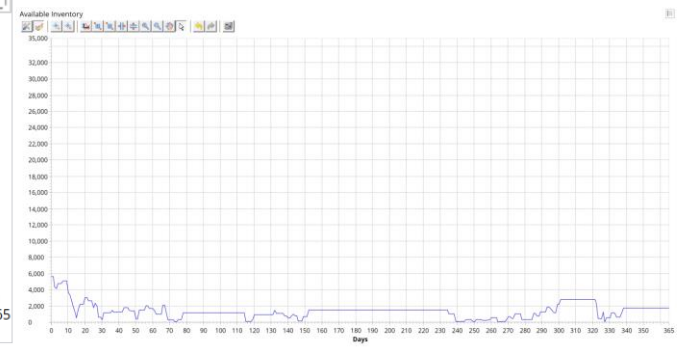
Baseline scenario

OP1 = MIN-MAX

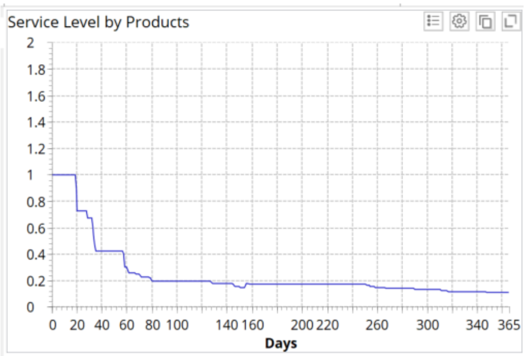


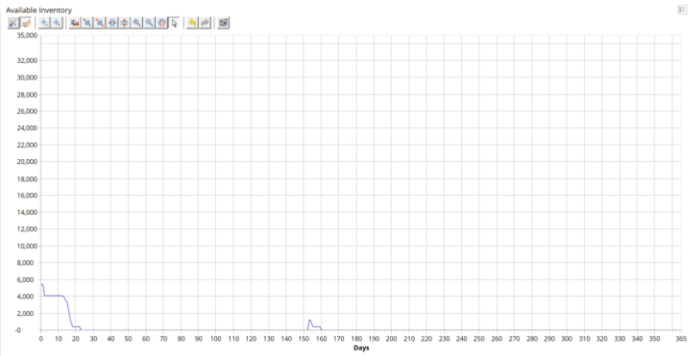
OP2 = ROP WITH EOQ



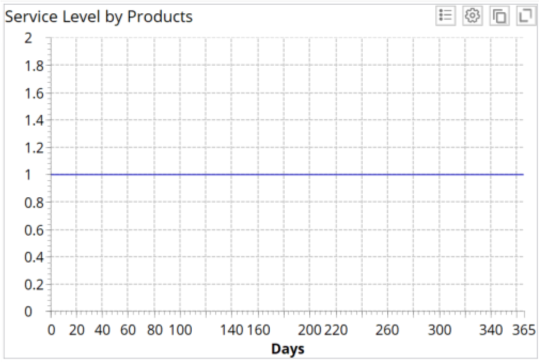


OP3 = ORDER ON DEMAND

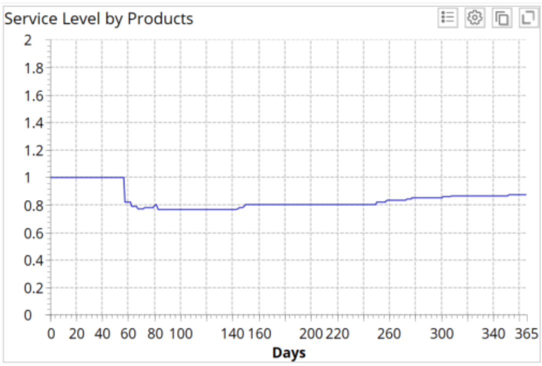


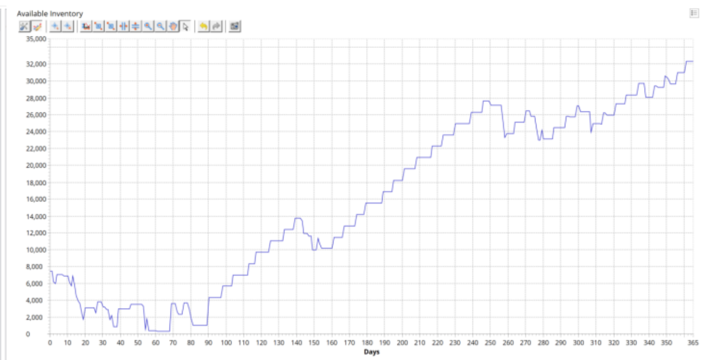


OP4 = FOI MONTHLY

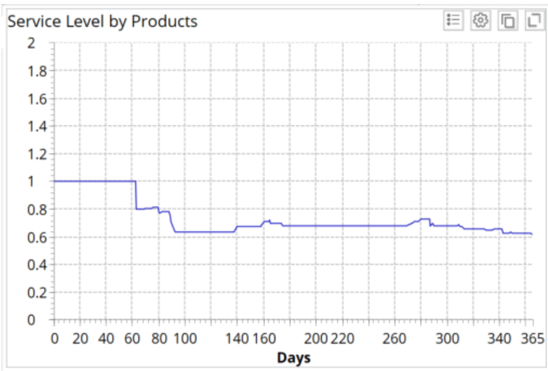


OP5 = FOI WEEKLY



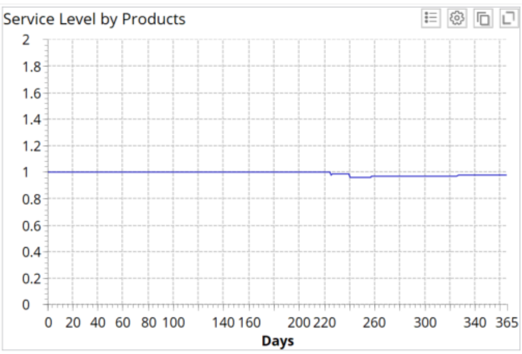


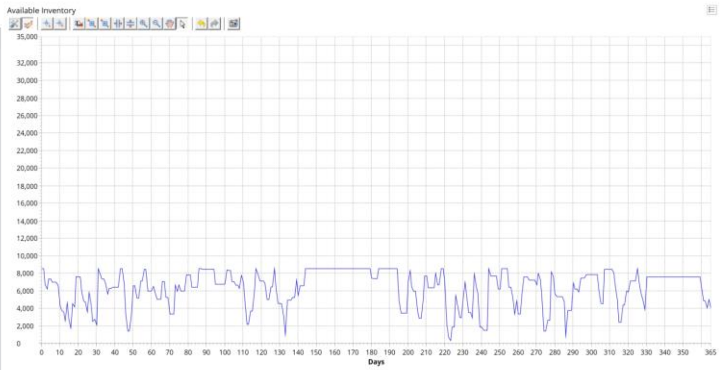
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



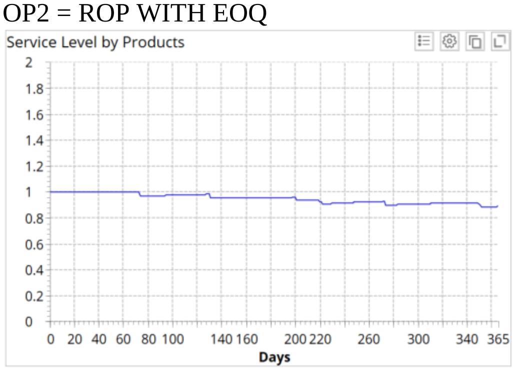
200 NOK unit cost level

OP1 = MIN-MAX

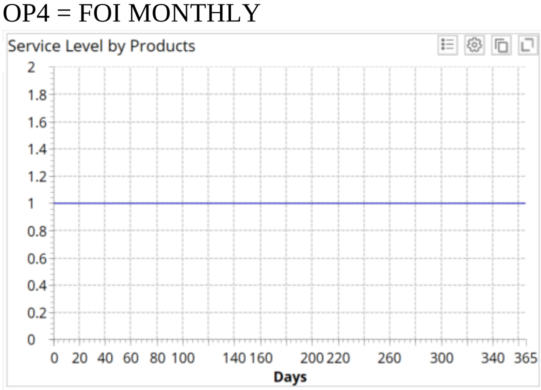


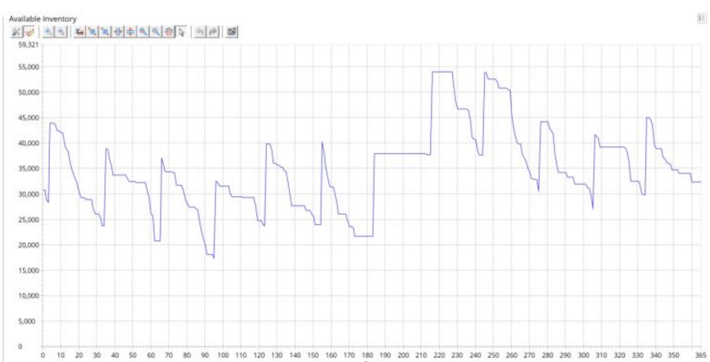


OP2 = ROP WITH EOQ

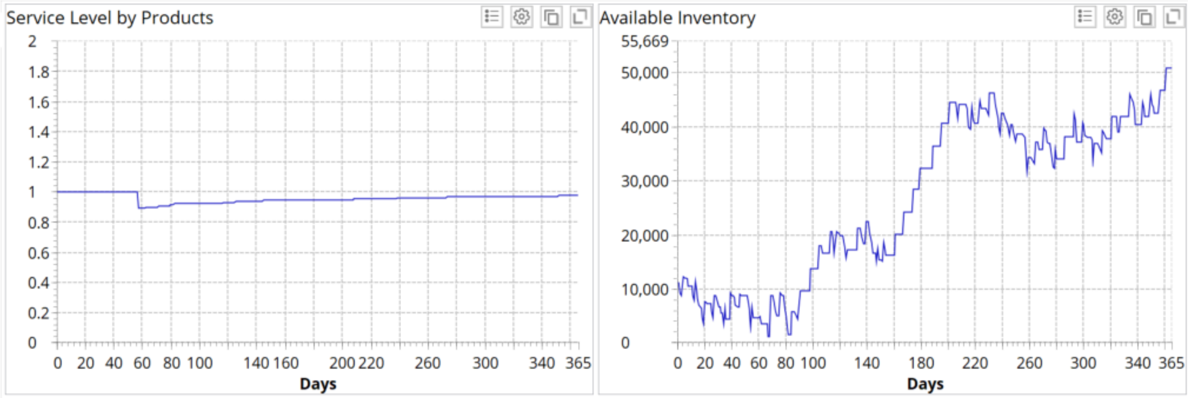


OP4 = FOI MONTHLY

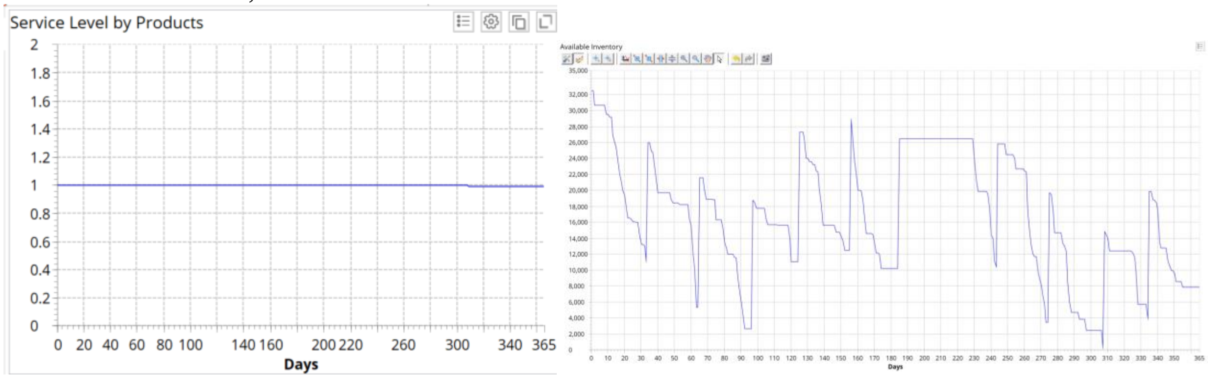




OP5 = FOI WEEKLY

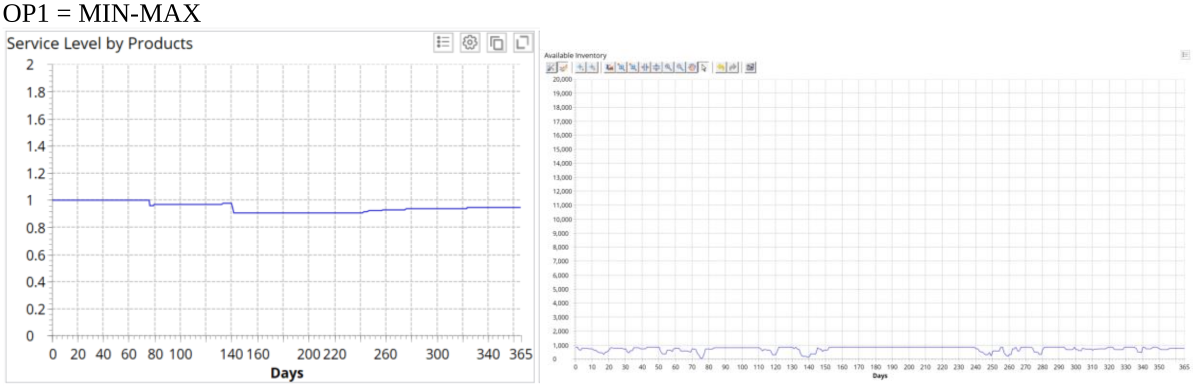


OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

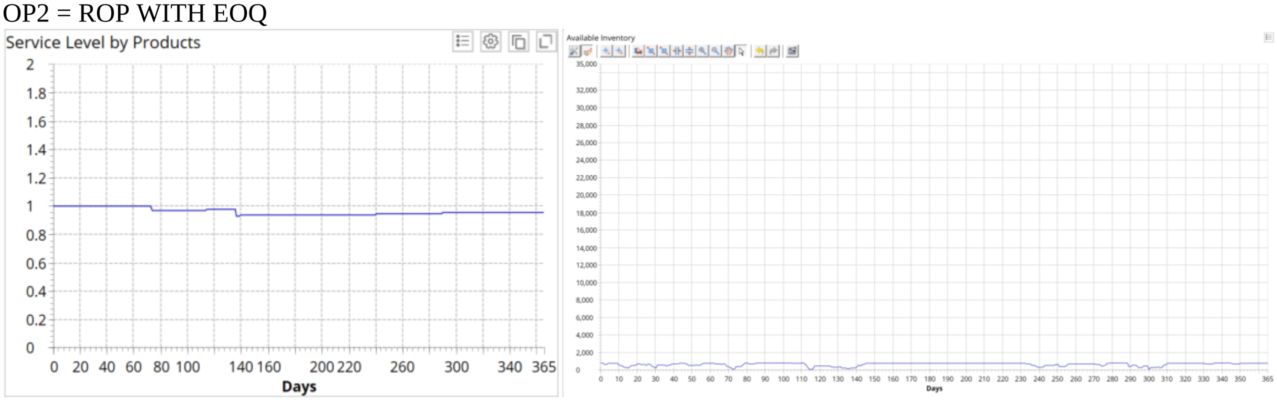


1000 NOK unit cost level

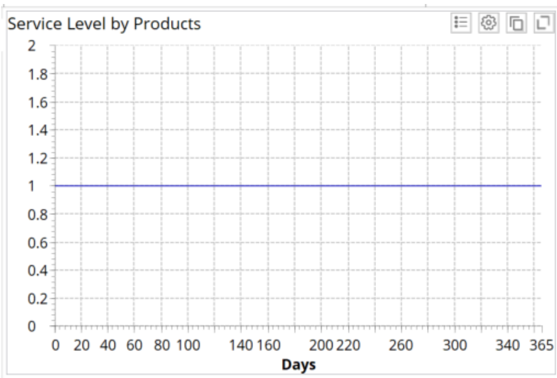
OP1 = MIN-MAX

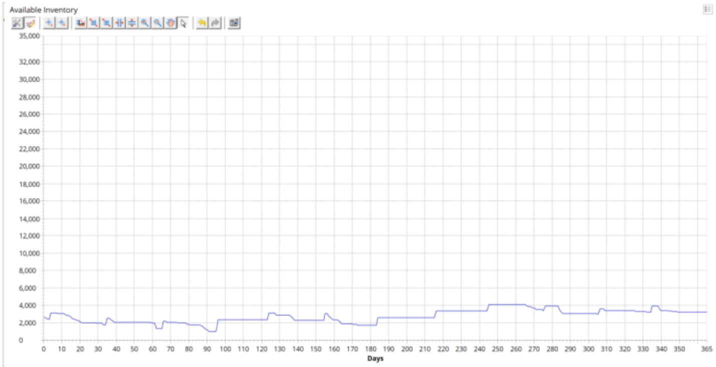


OP2 = ROP WITH EOQ

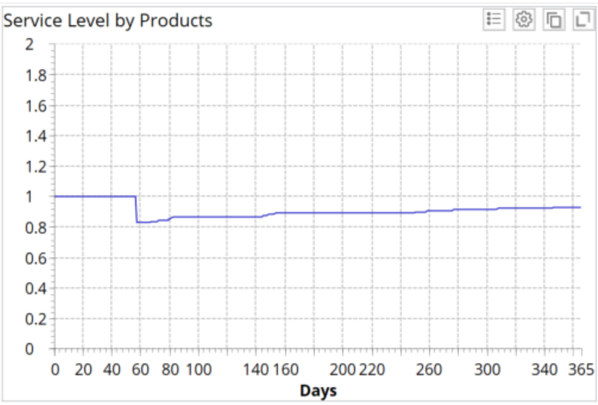


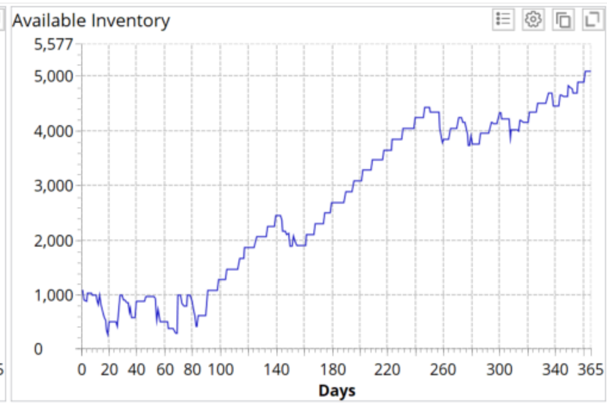
OP4 = FOI MONTHLY



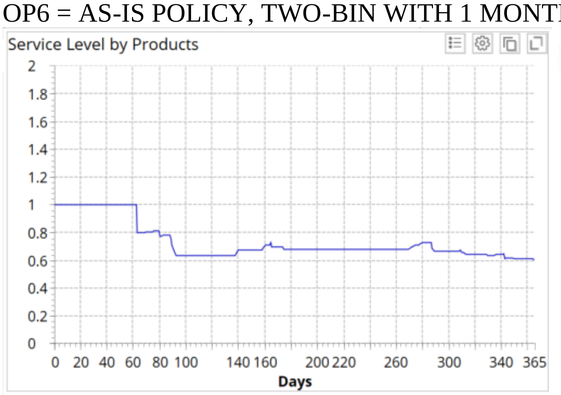


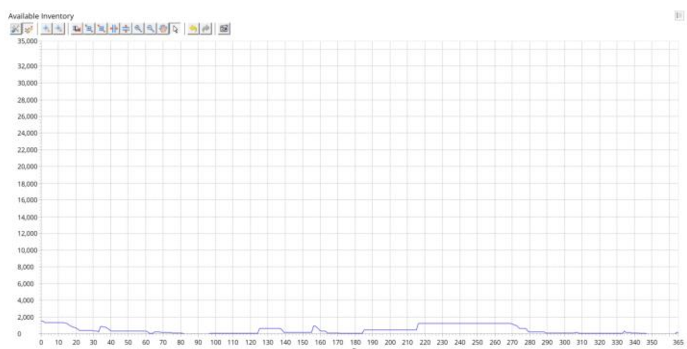
OP5 = FOI WEEKLY





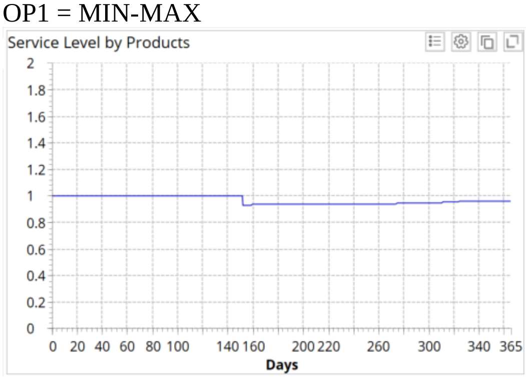
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

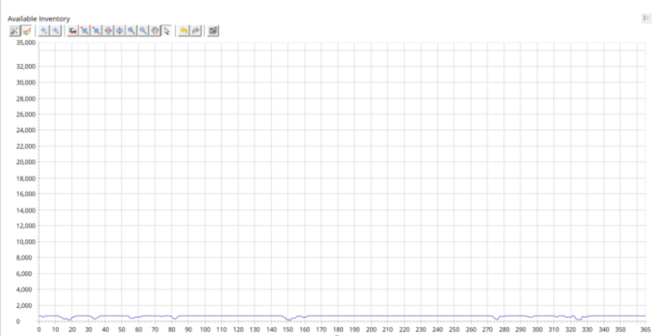




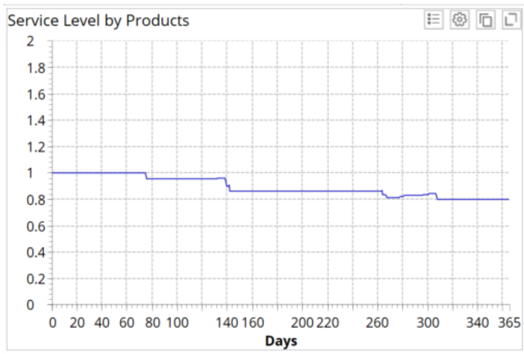
2000 NOK unit cost level

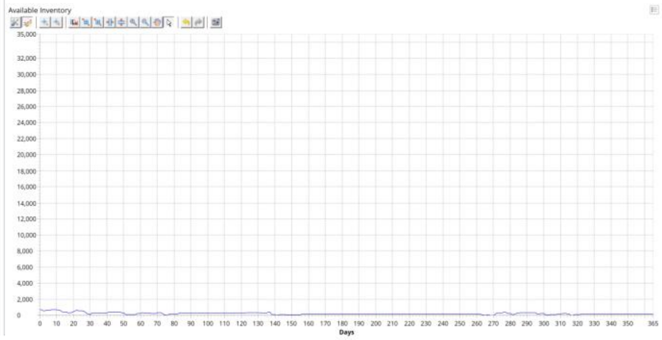
OP1 = MIN-MAX



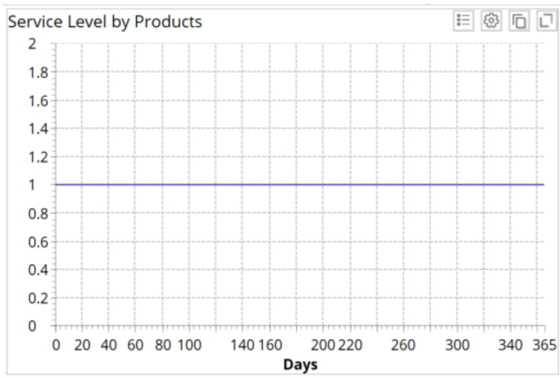


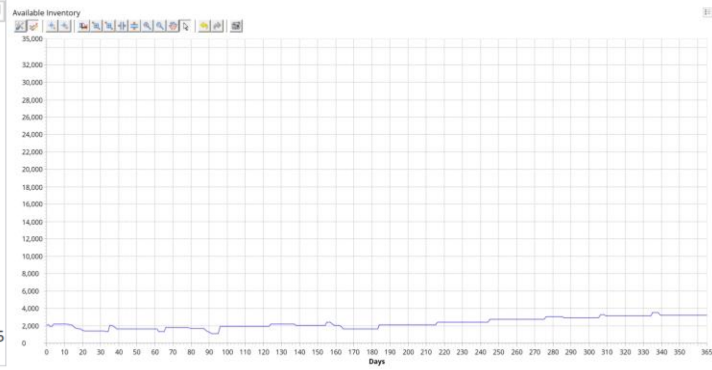
OP2 = ROP WITH EOQ



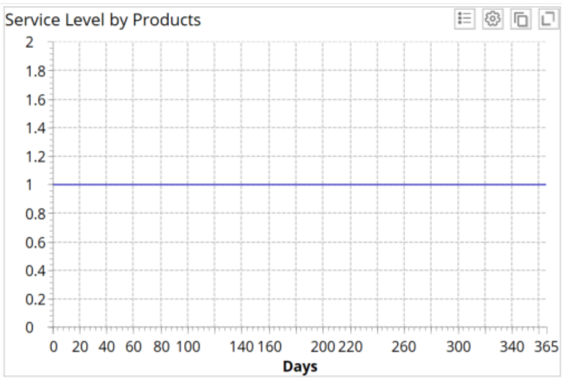


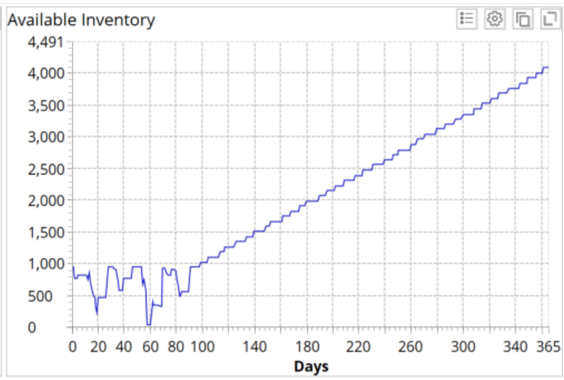
OP4 = FOI MONTHLY



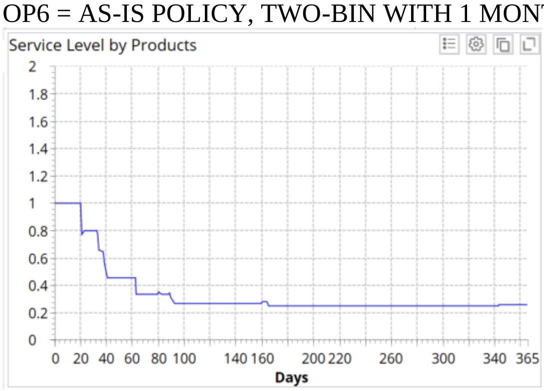


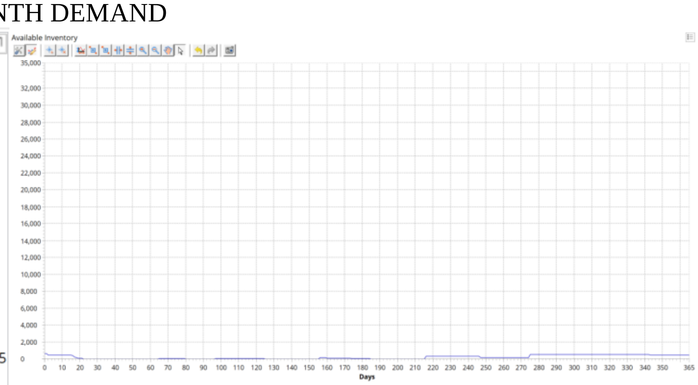
OP5 = FOI WEEKLY





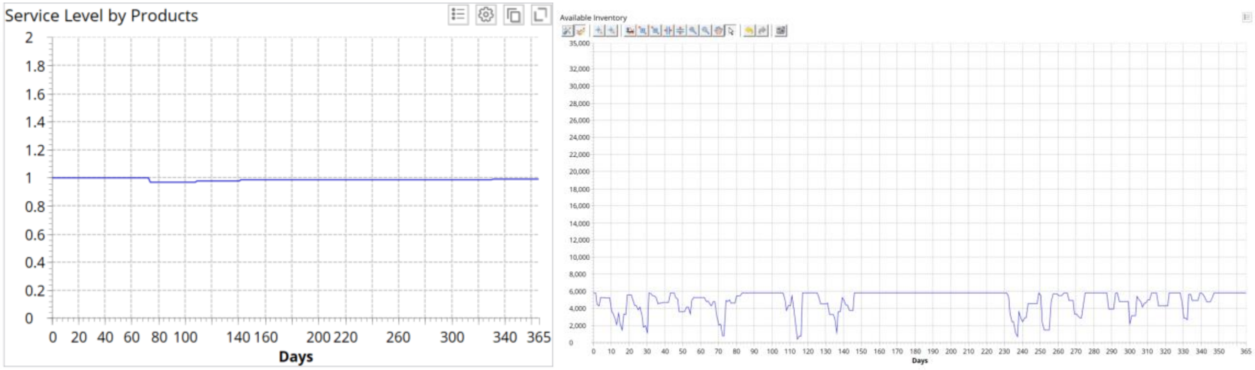
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



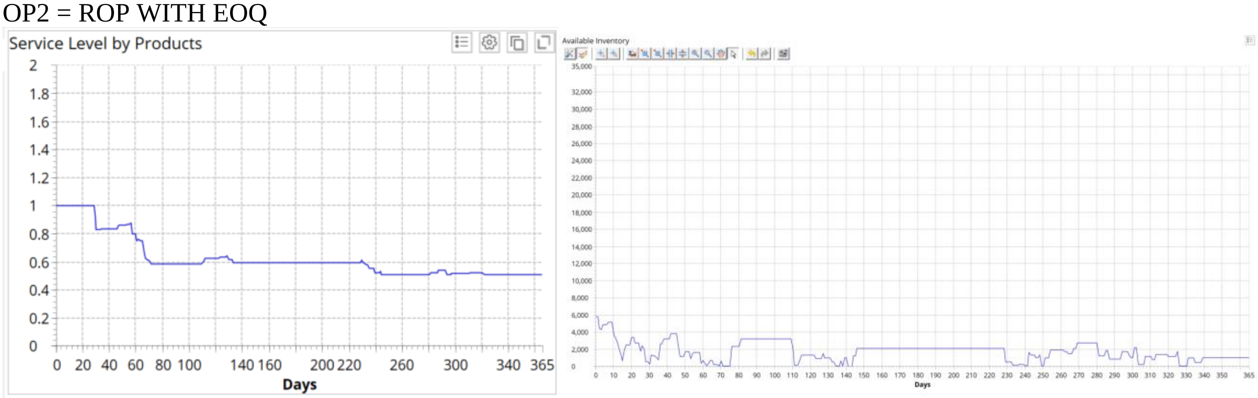


20% higher daily average demand

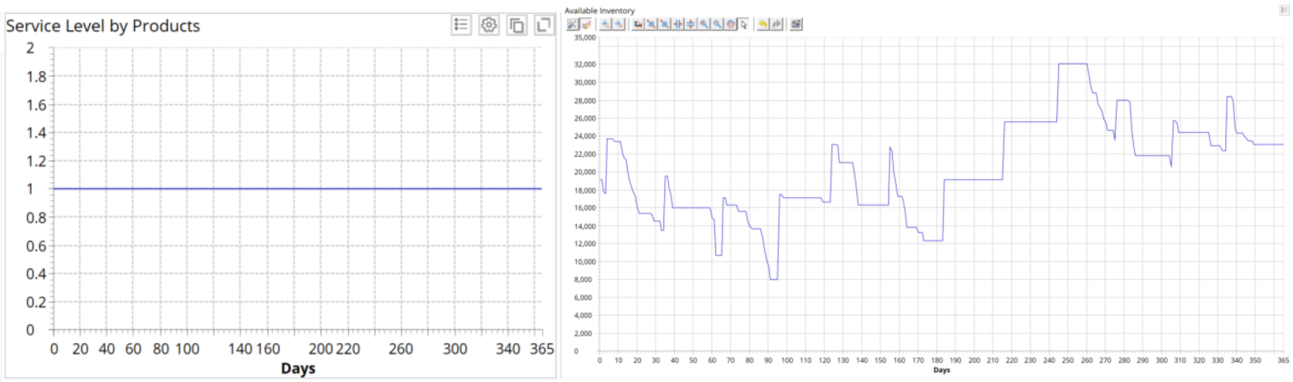
OP1 = MIN-MAX



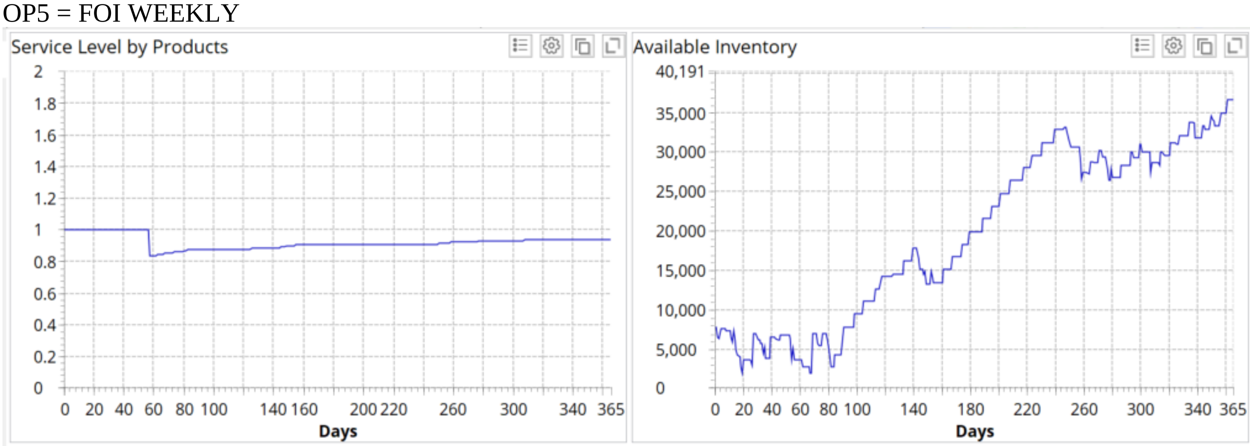
OP2 = ROP WITH EOQ



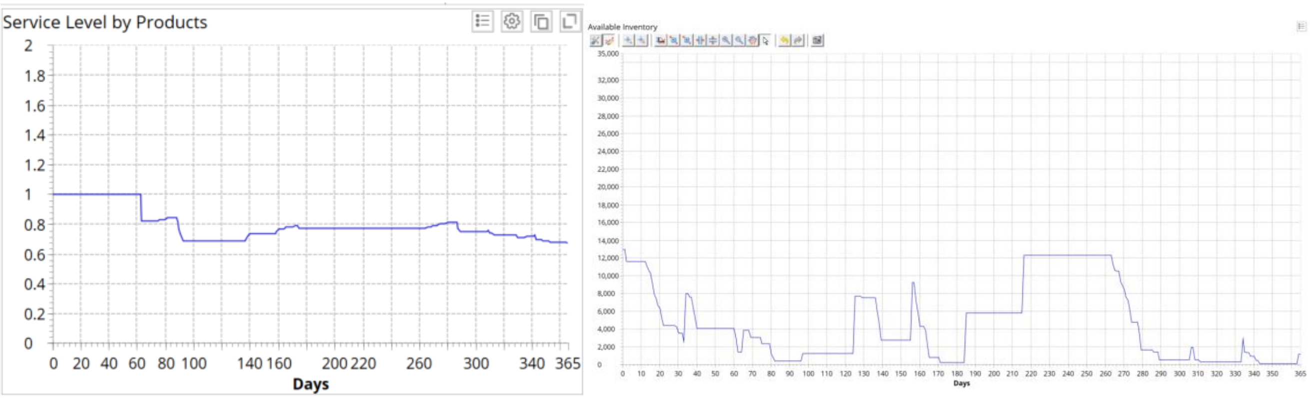
OP4 = FOI MONTHLY



OP5 = FOI WEEKLY

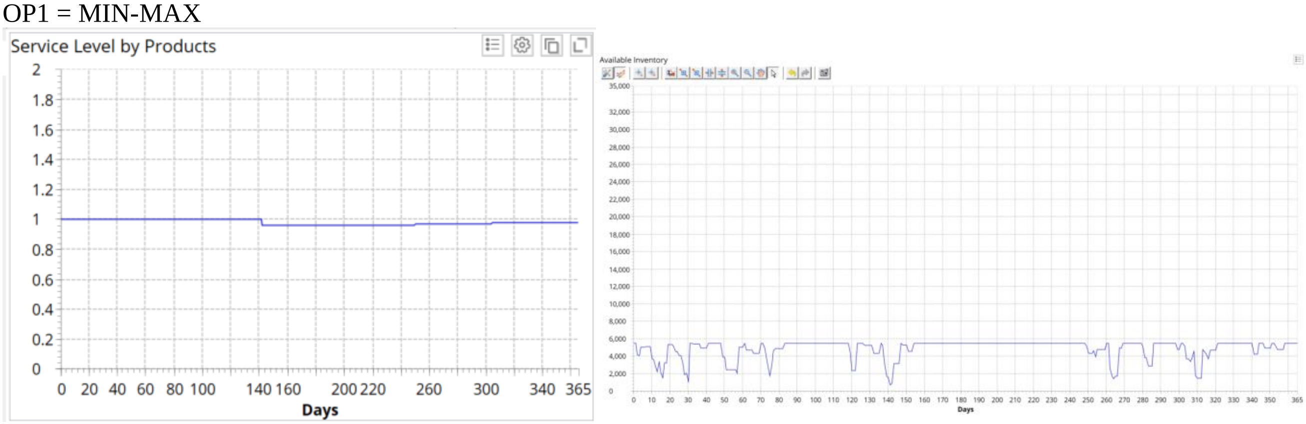


OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

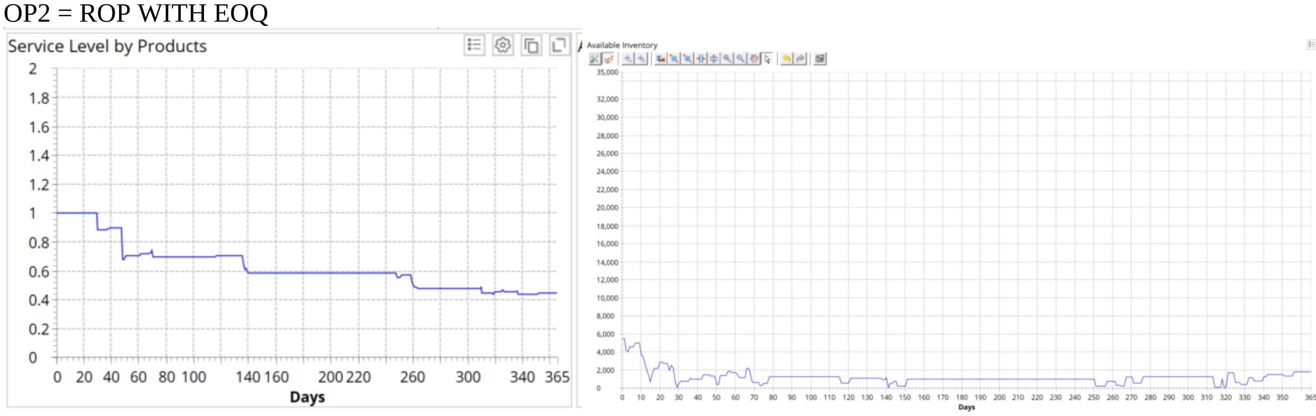


20% lower daily average demand

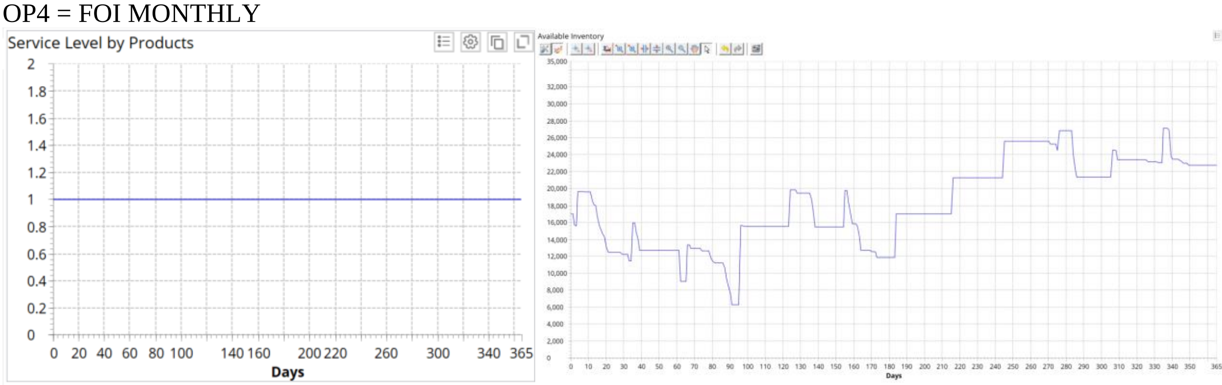
OP1 = MIN-MAX



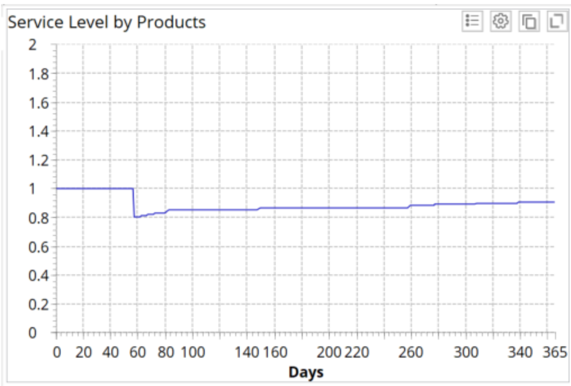
OP2 = ROP WITH EOQ

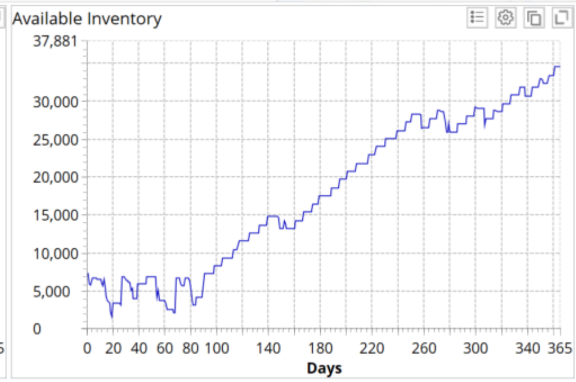


OP4 = FOI MONTHLY

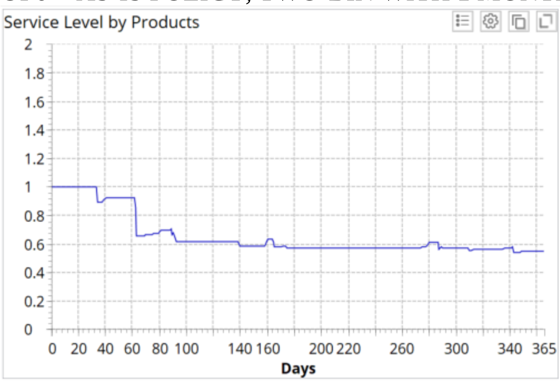


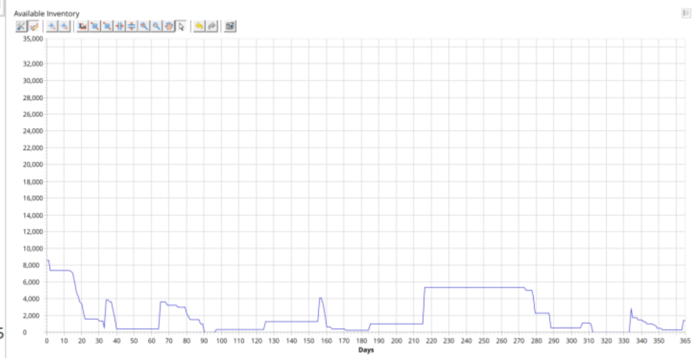
OP5 = FOI WEEKLY





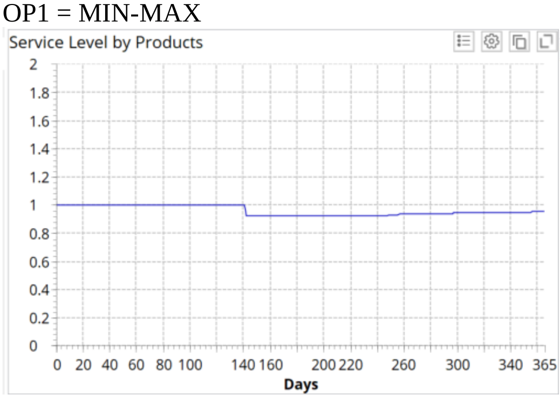
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

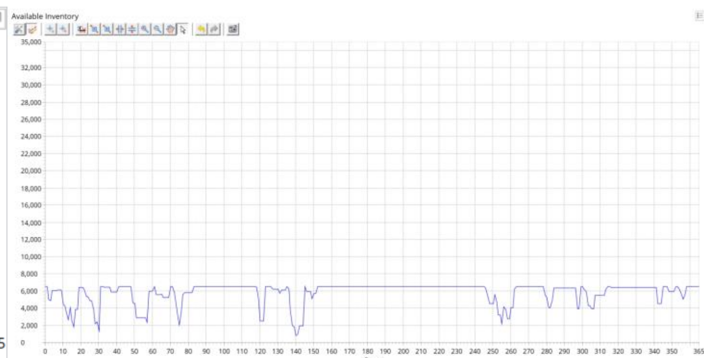




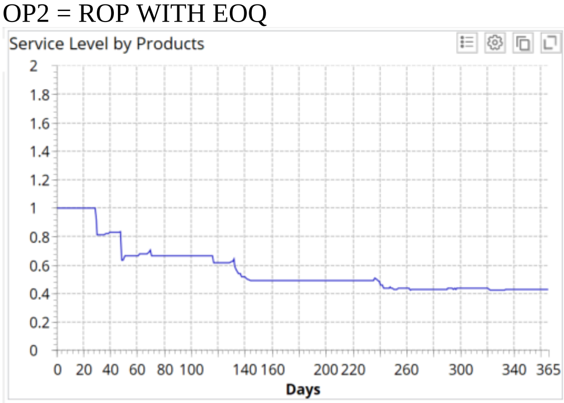
20% higher daily standard deviation of demand

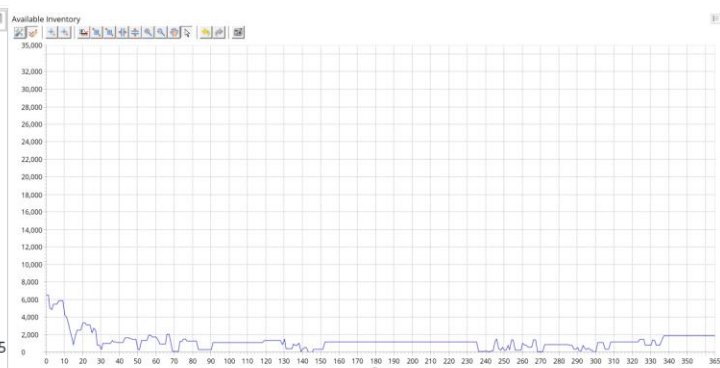
OP1 = MIN-MAX



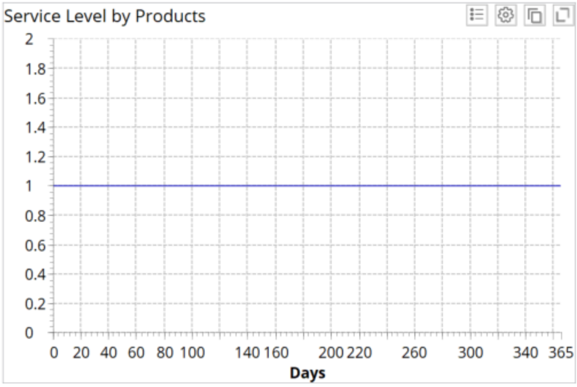


OP2 = ROP WITH EOQ

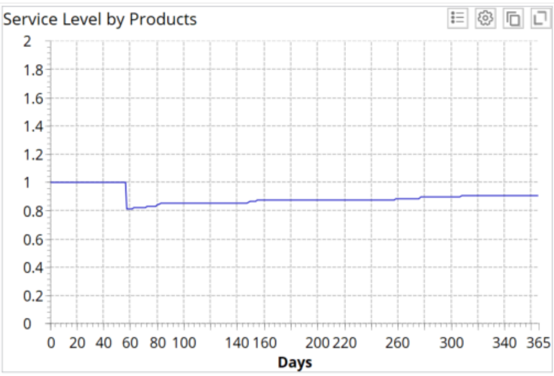


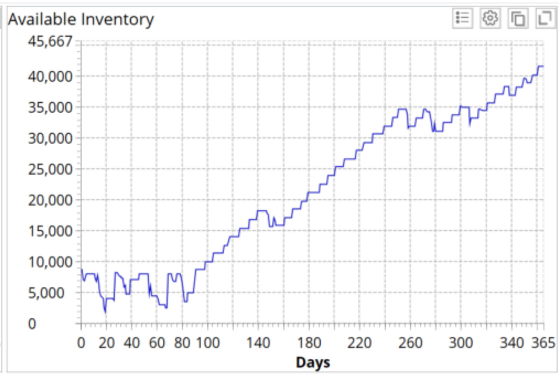


OP4 = FOI MONTHLY

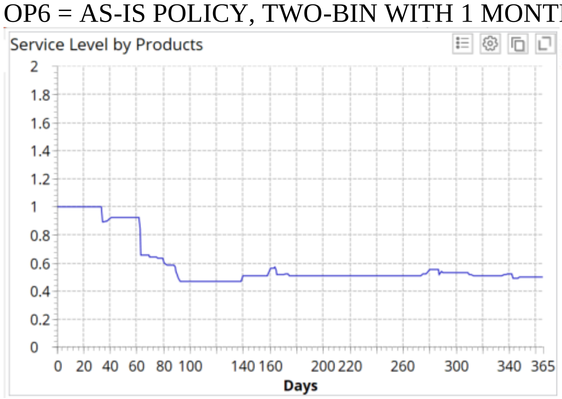


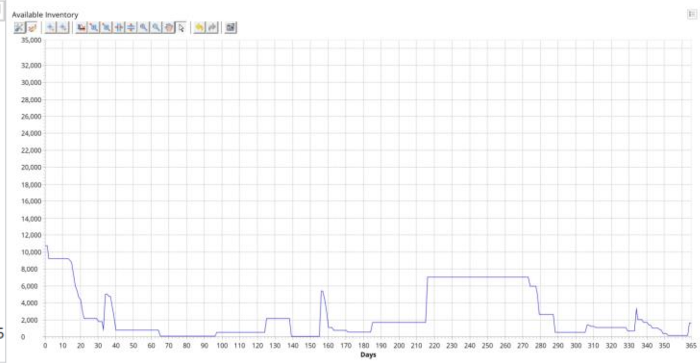
OP5 = FOI WEEKLY





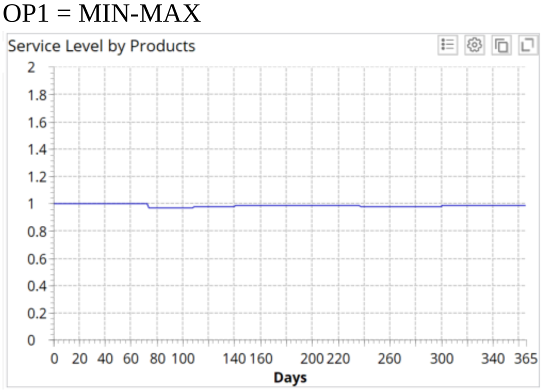
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

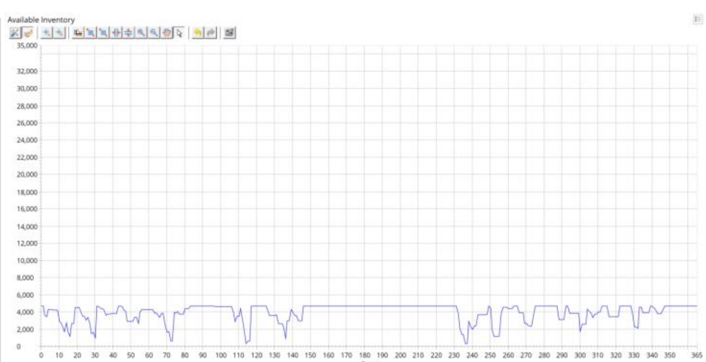




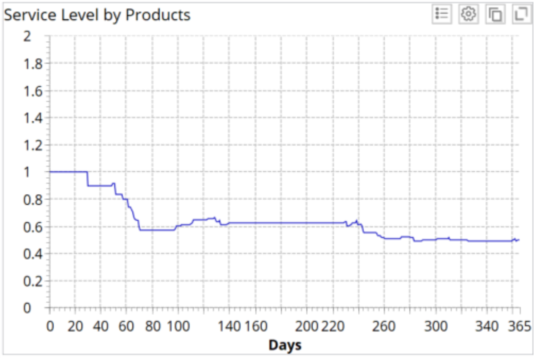
20% lower daily standard deviation of demand

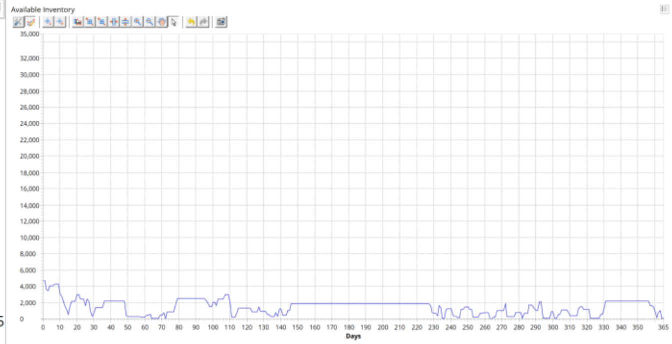
OP1 = MIN-MAX



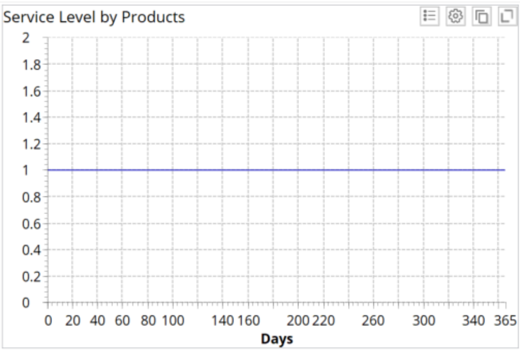


OP2 = ROP WITH EOQ

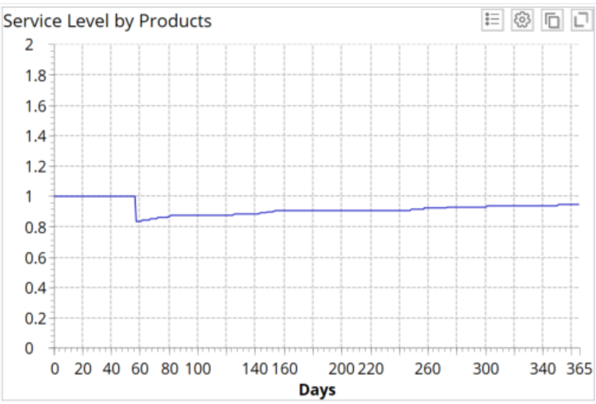


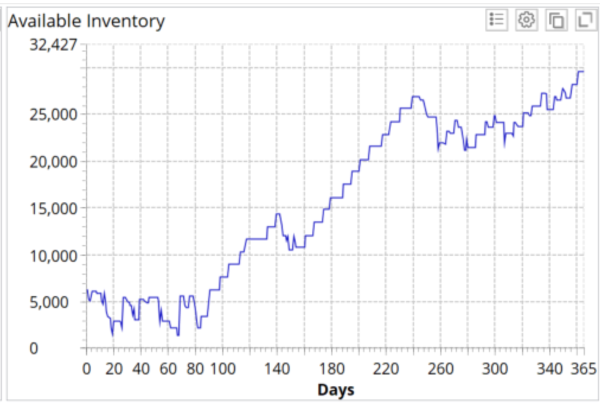


OP4 = FOI MONTHLY

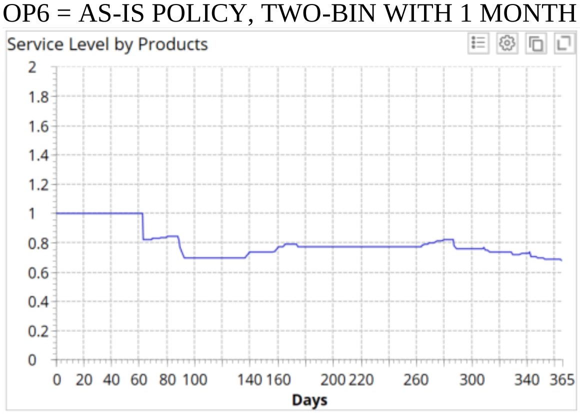


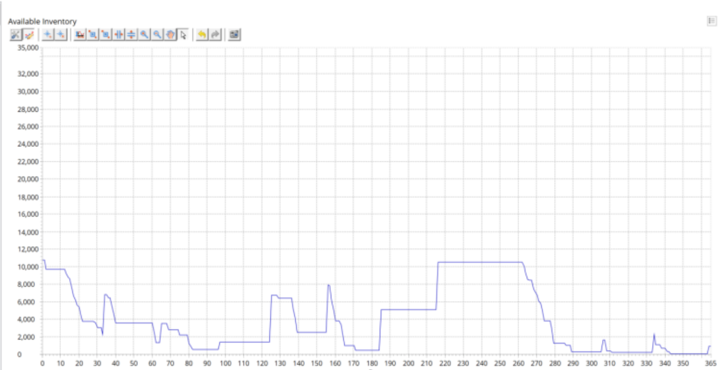
OP5 = FOI WEEKLY





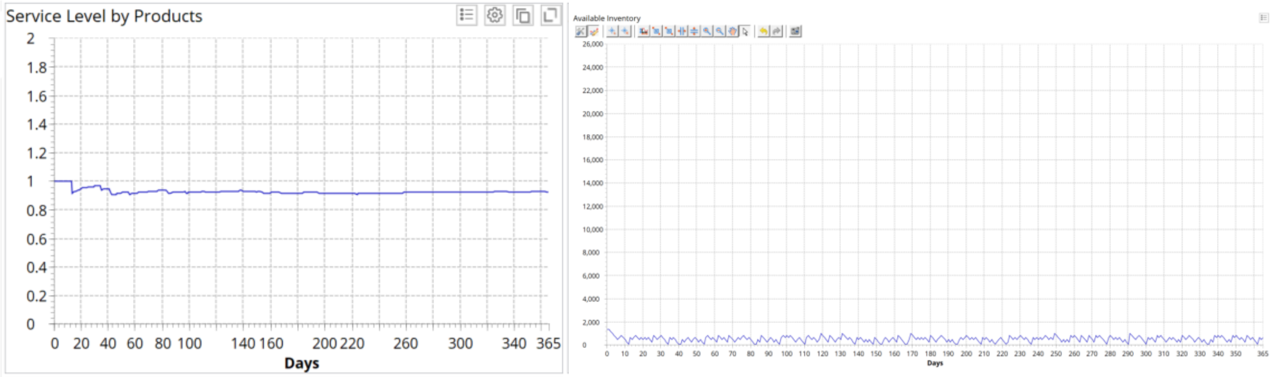
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



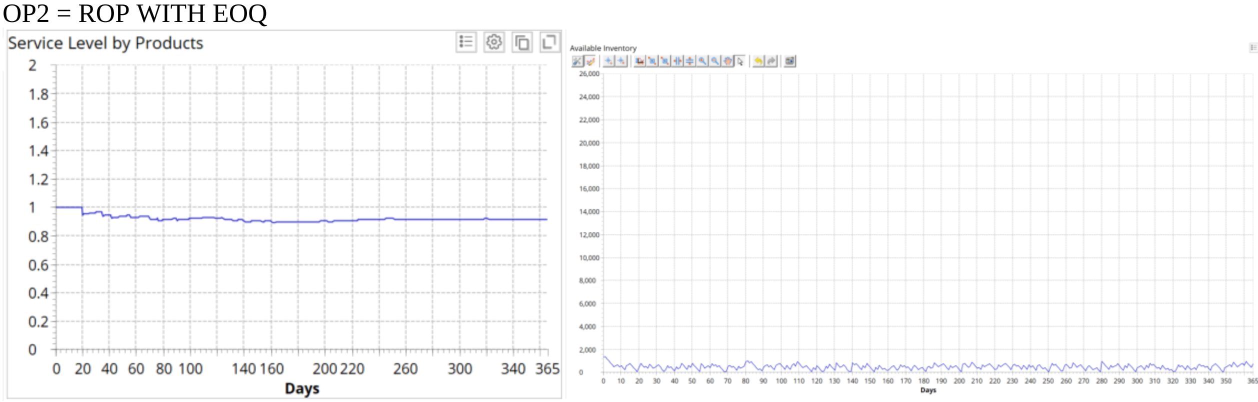


No standard deviation of demand

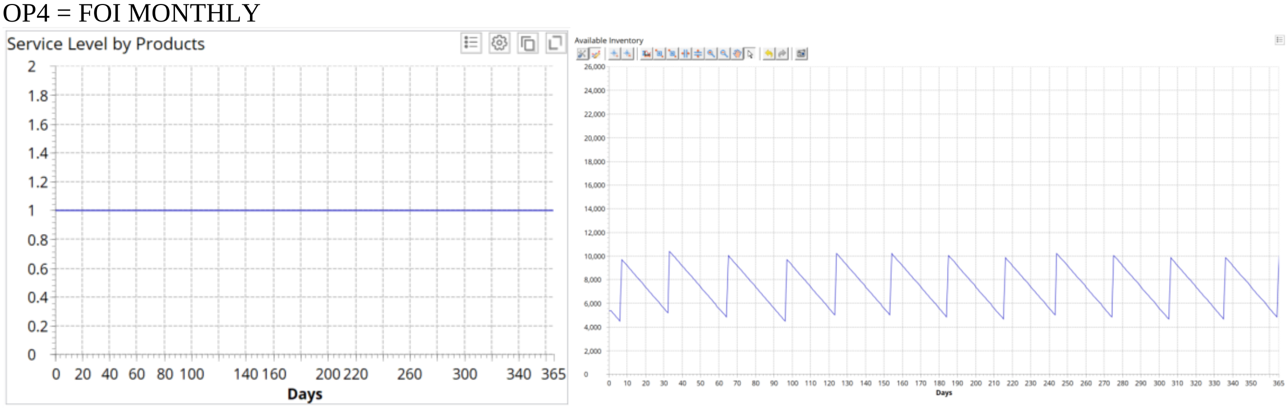
OP1 = MIN-MAX



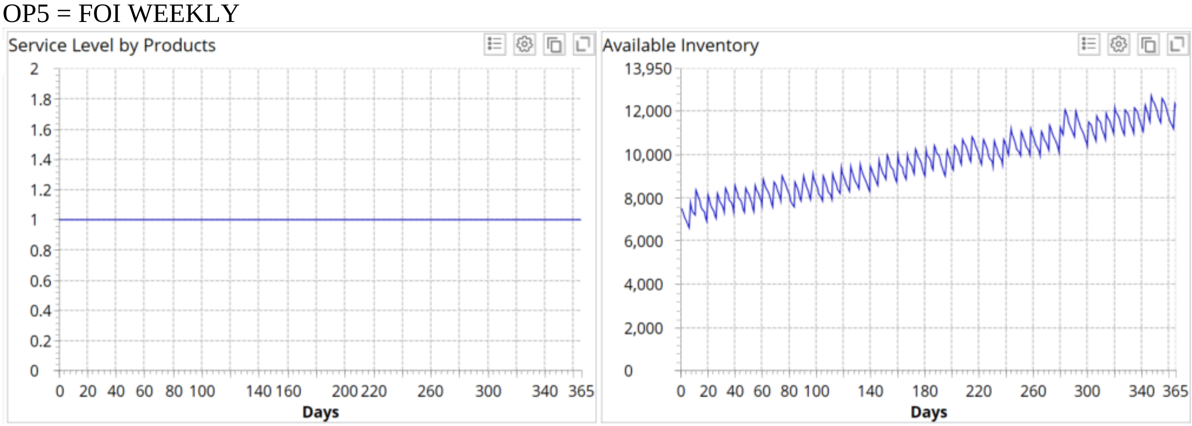
OP2 = ROP WITH EOQ



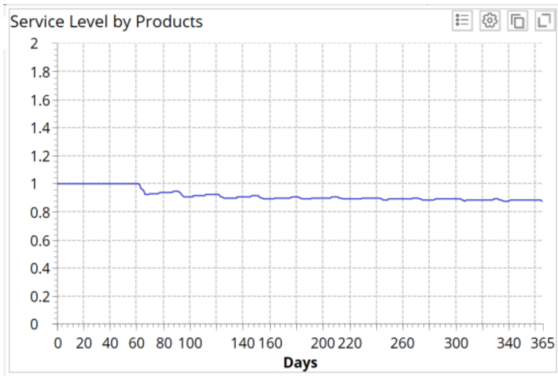
OP4 = FOI MONTHLY

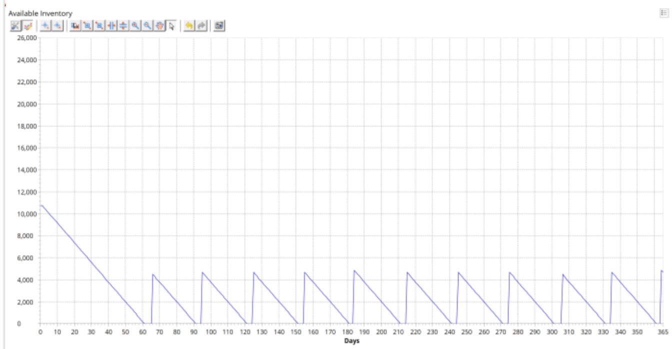


OP5 = FOI WEEKLY



OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

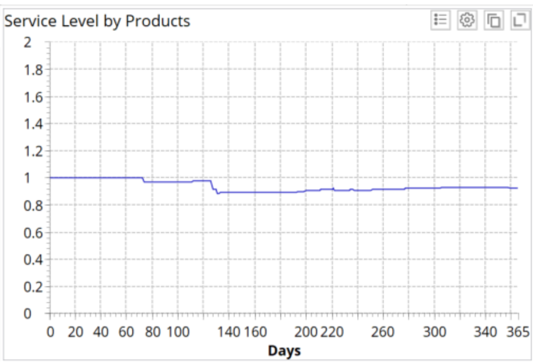


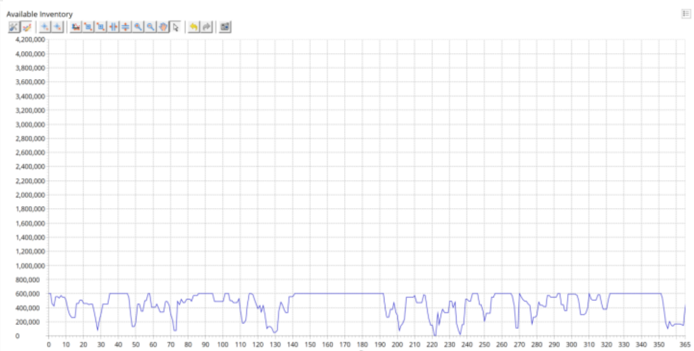


Simulation experiment results for group D

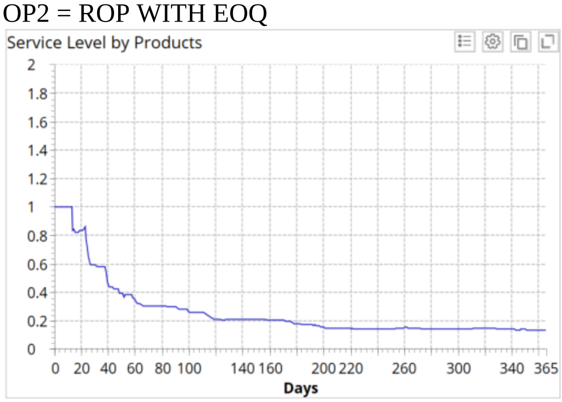
Baseline scenario

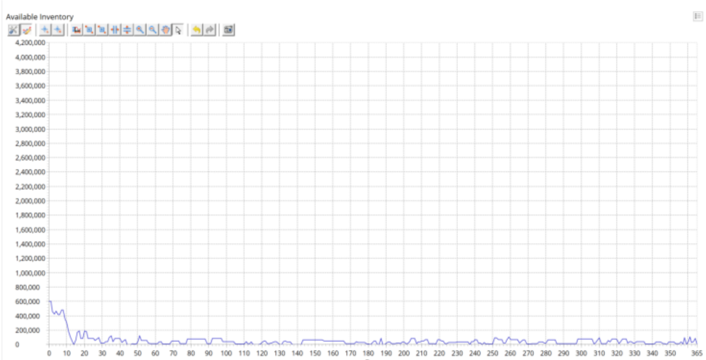
OP1 = MIN-MAX



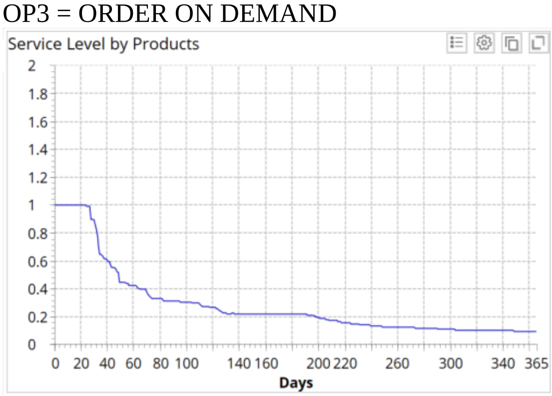


OP2 = ROP WITH EOQ

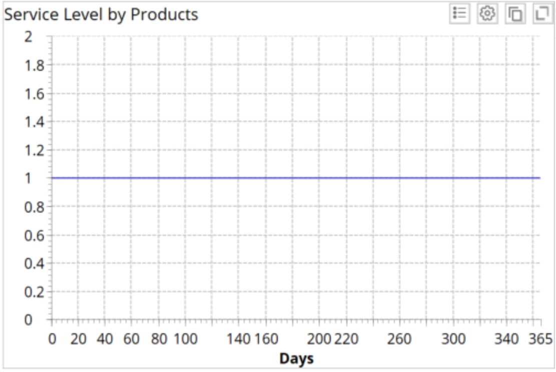


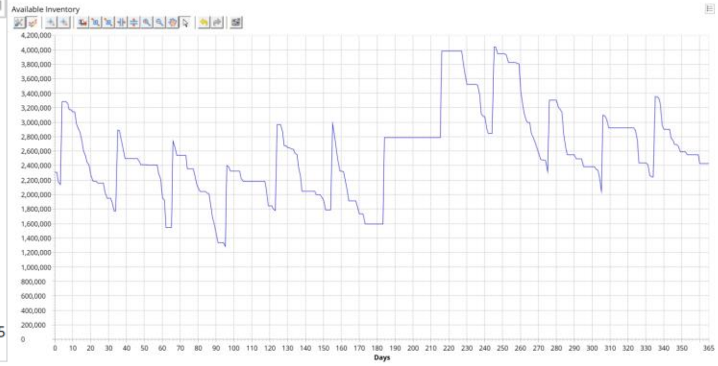


OP3 = ORDER ON DEMAND

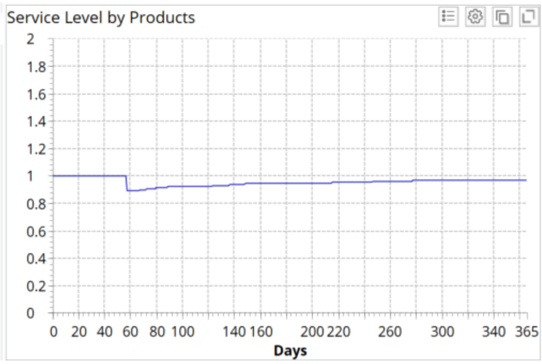


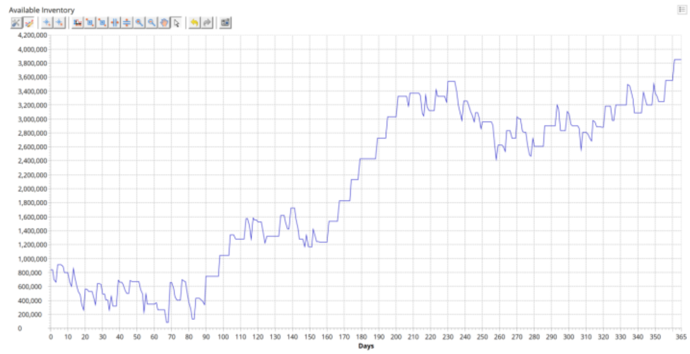
OP4 = FOI MONTHLY



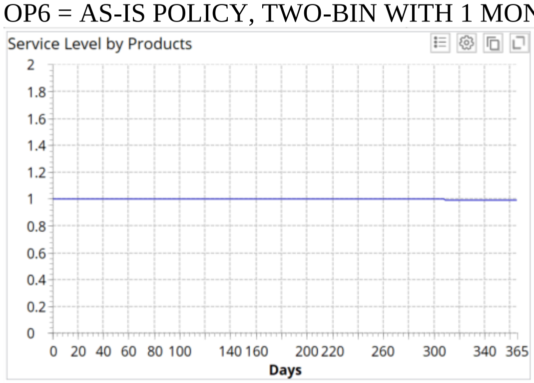


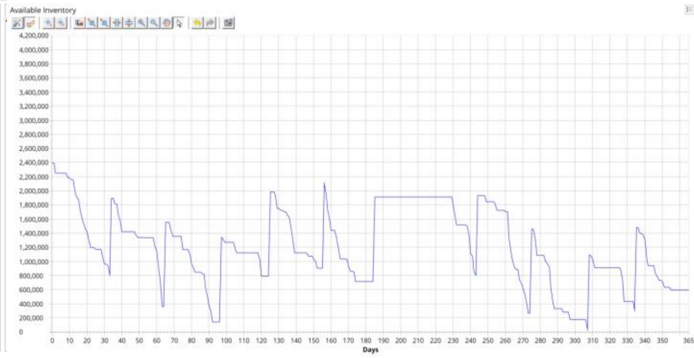
OP5 = FOI WEEKLY





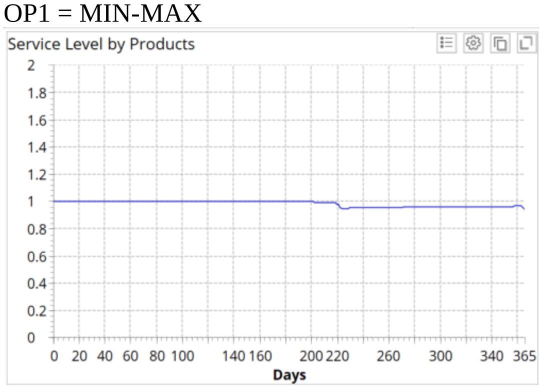
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



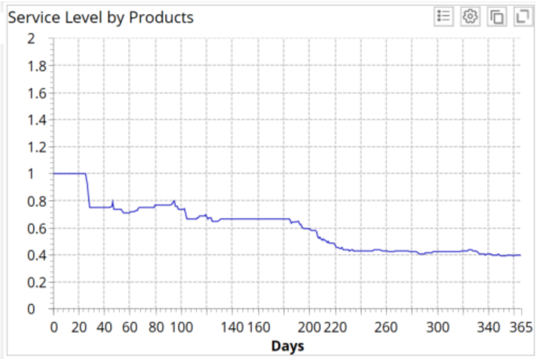


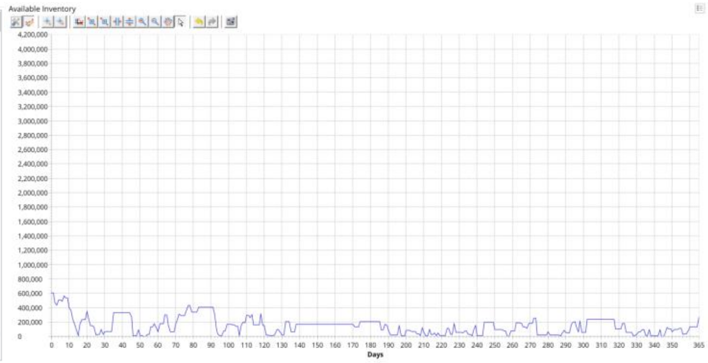
200 NOK unit cost level

OP1 = MIN-MAX

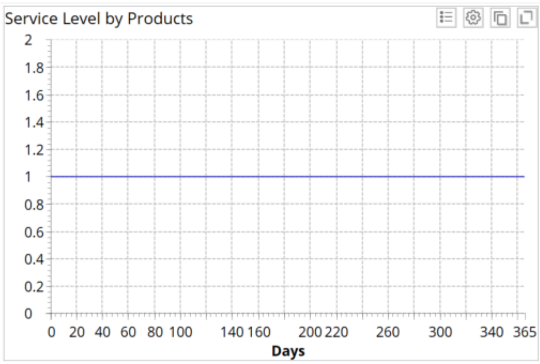


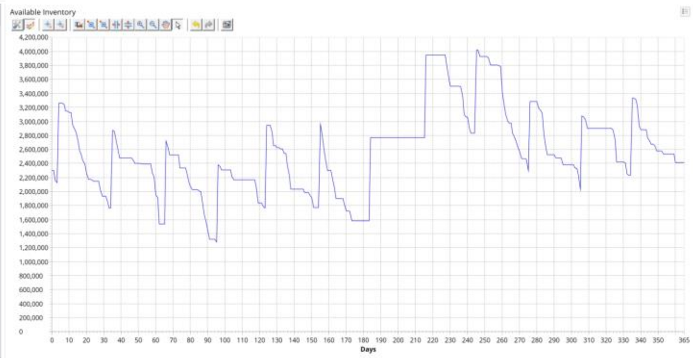
OP2 = ROP WITH EOQ



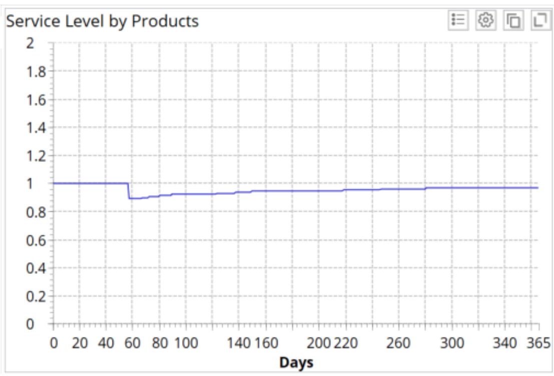


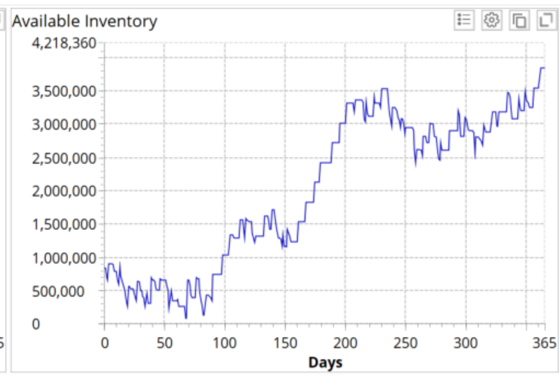
OP4 = FOI MONTHLY



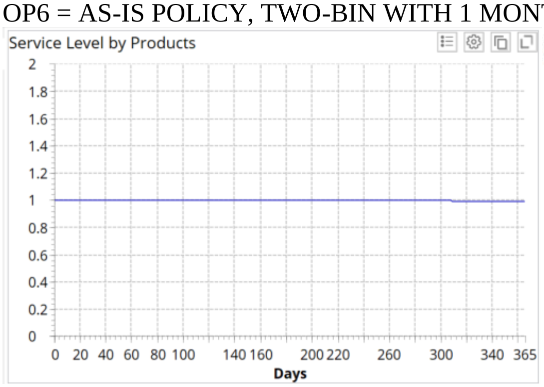


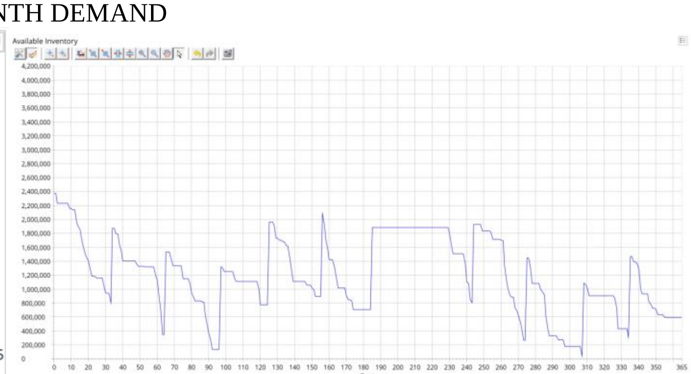
OP5 = FOI WEEKLY





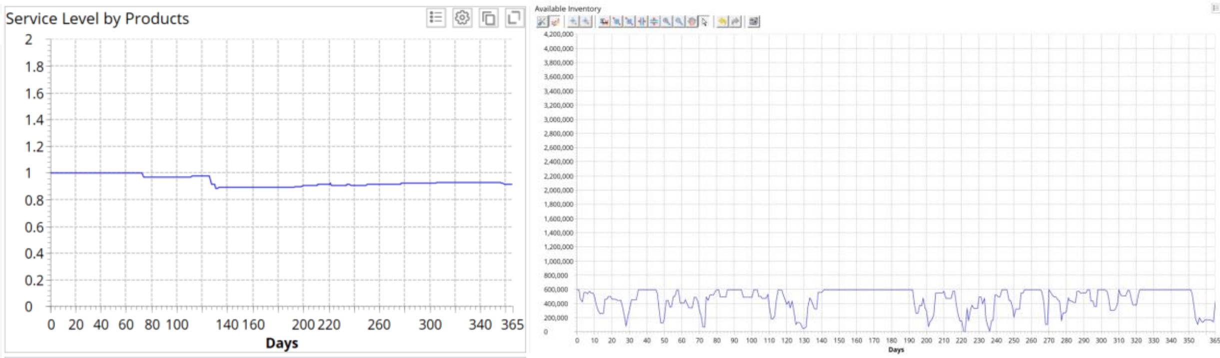
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



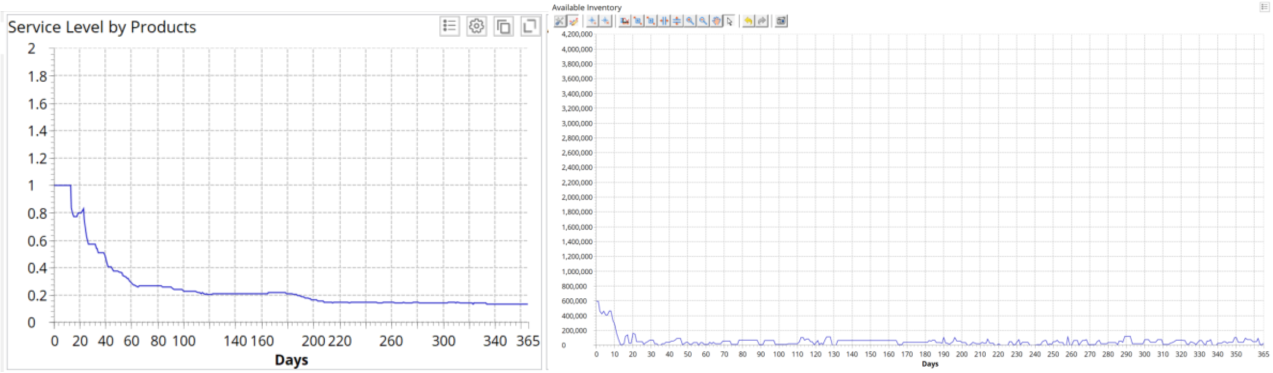


1000 NOK unit cost level

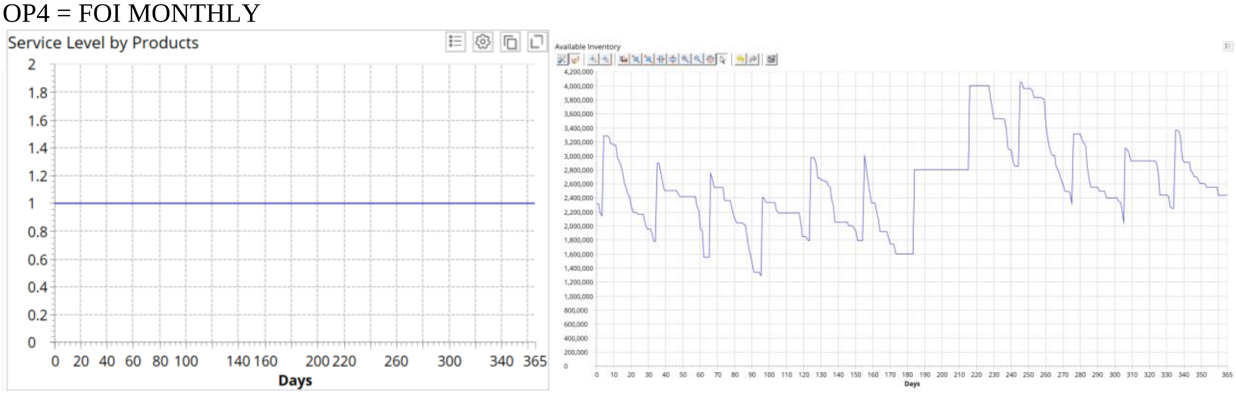
OP1 = MIN-MAX



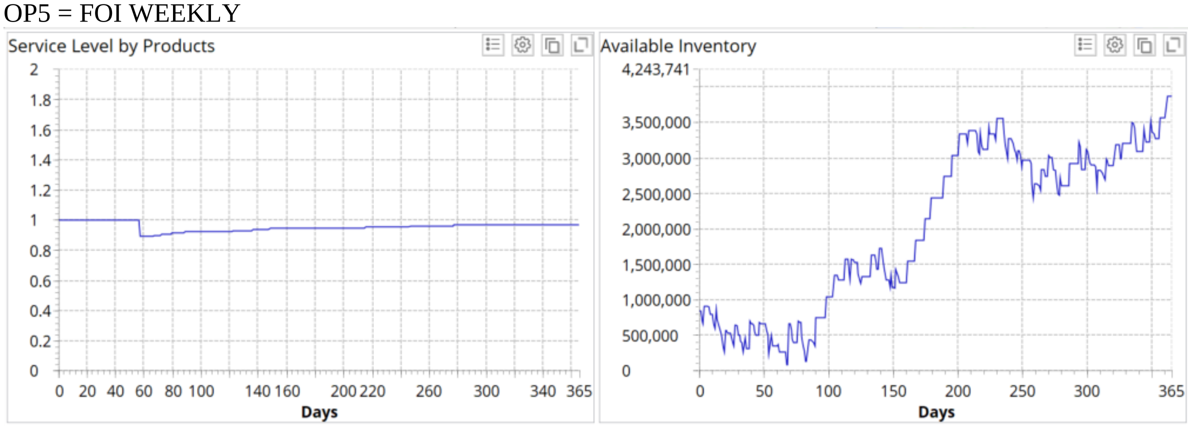
OP2 = ROP WITH EOQ



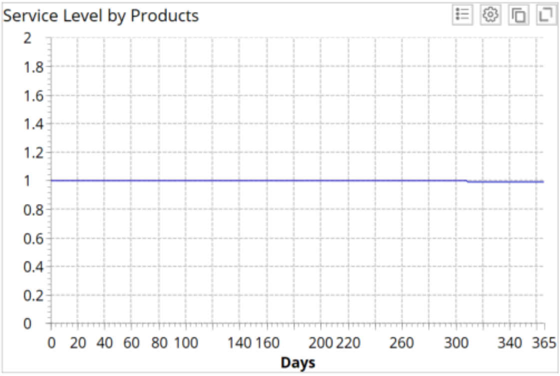
OP4 = FOI MONTHLY

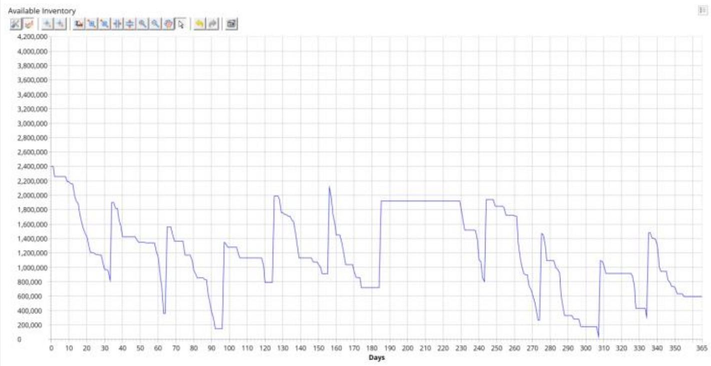


OP5 = FOI WEEKLY



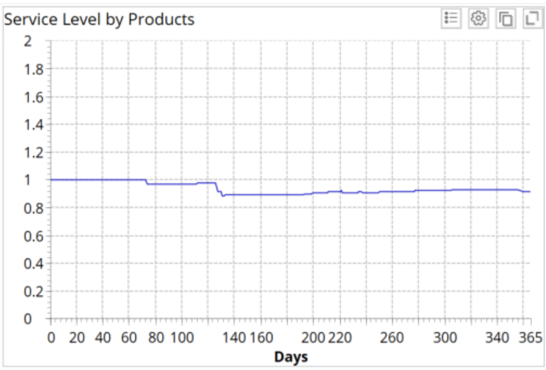
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

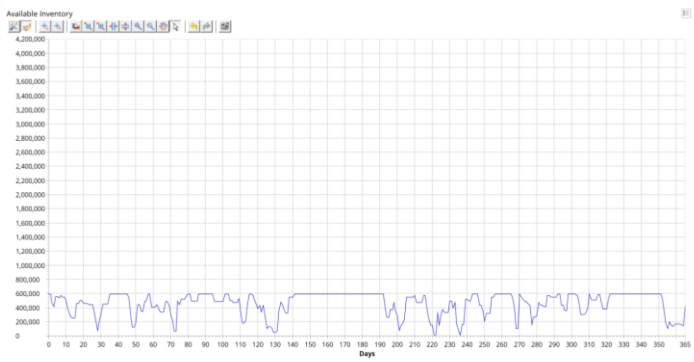




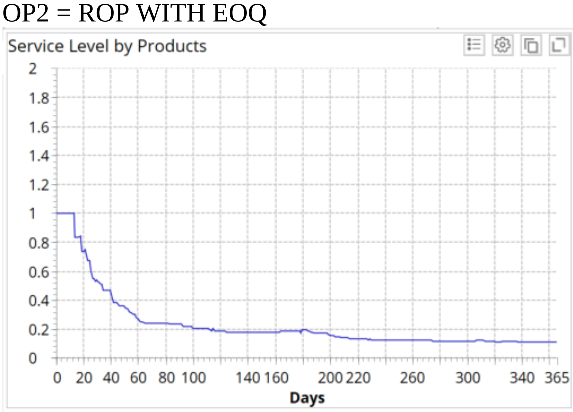
2000 NOK unit cost level

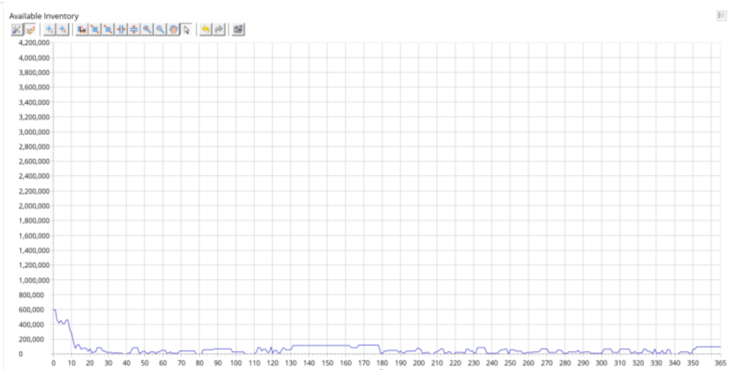
OP1 = MIN-MAX



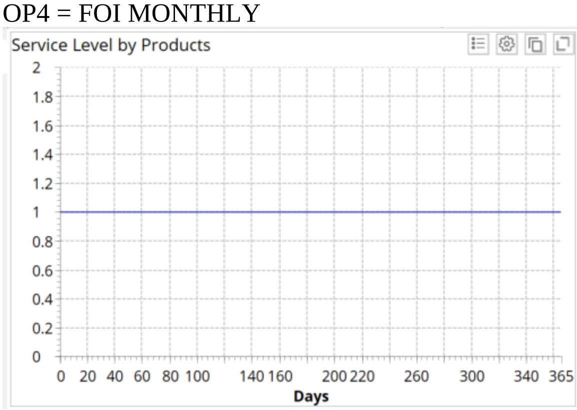


OP2 = ROP WITH EOQ

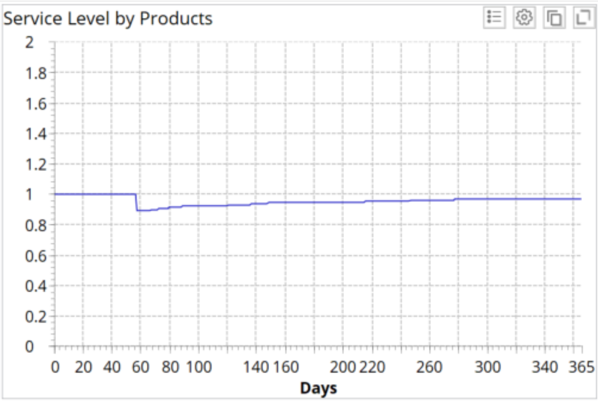


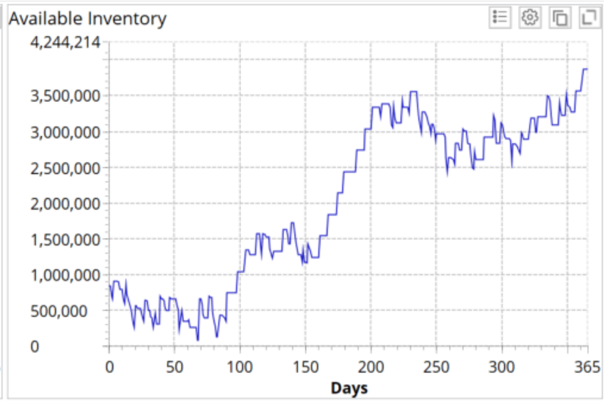


OP4 = FOI MONTHLY

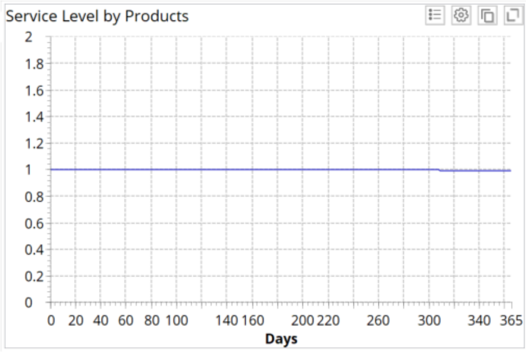


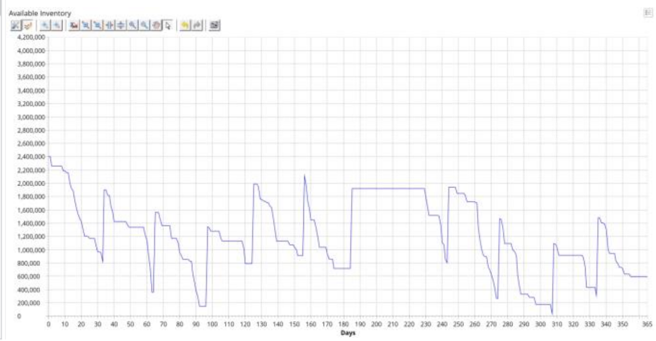
OP5 = FOI WEEKLY





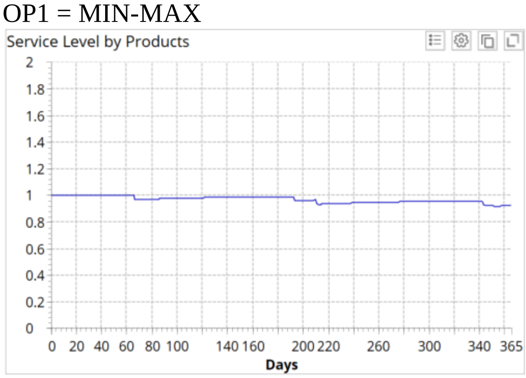
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

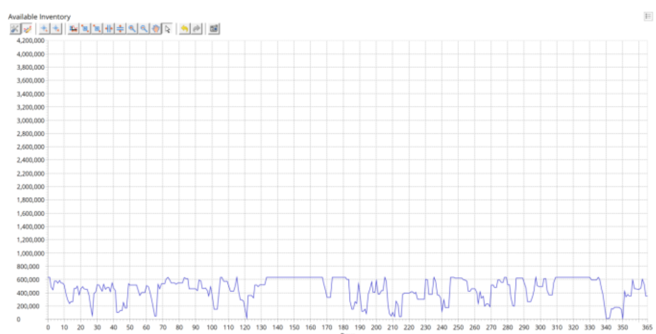




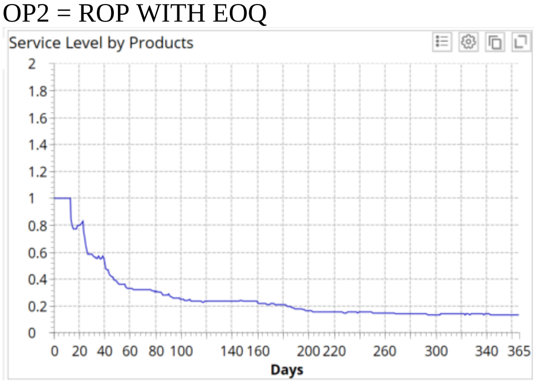
20% higher daily average demand

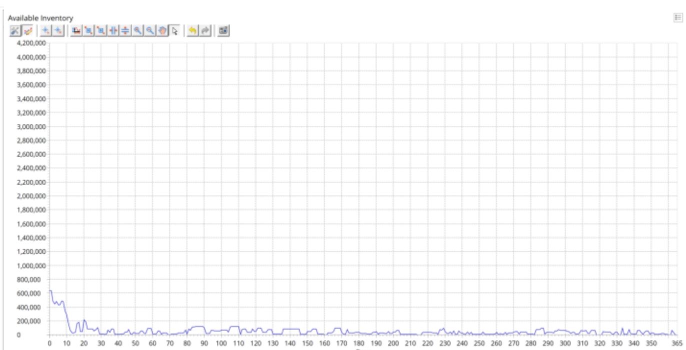
OP1 = MIN-MAX



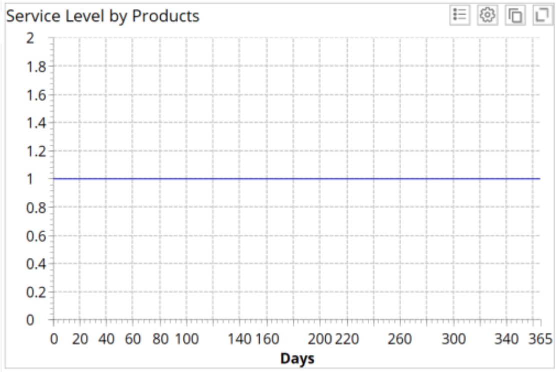


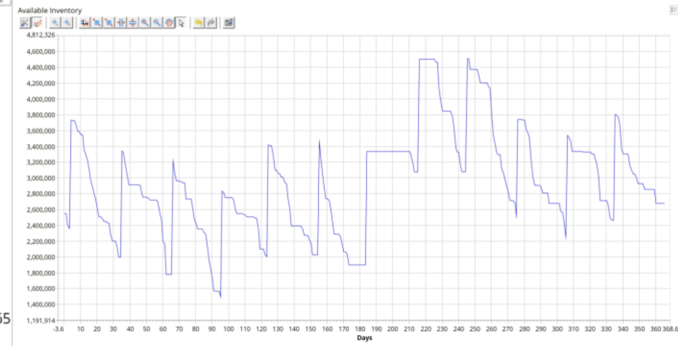
OP2 = ROP WITH EOQ



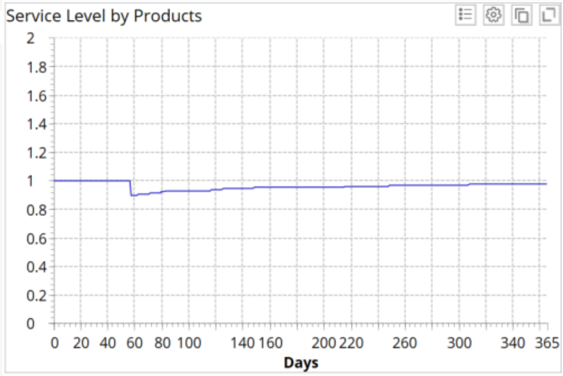


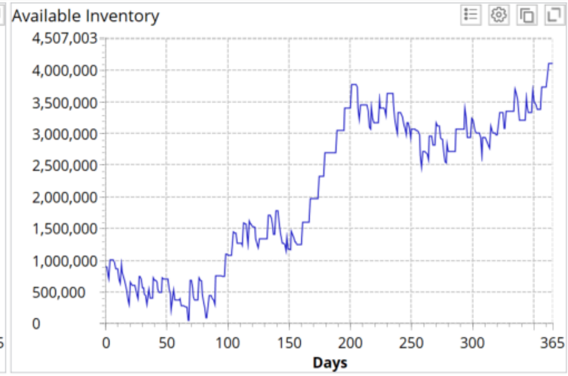
OP4 = FOI MONTHLY



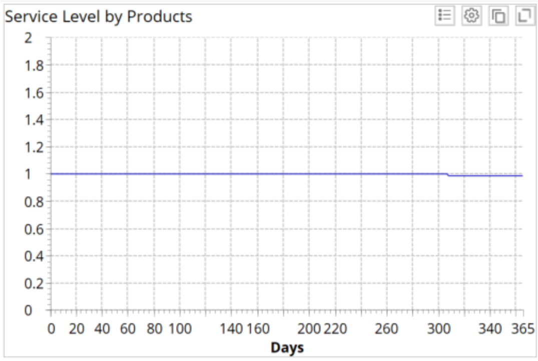


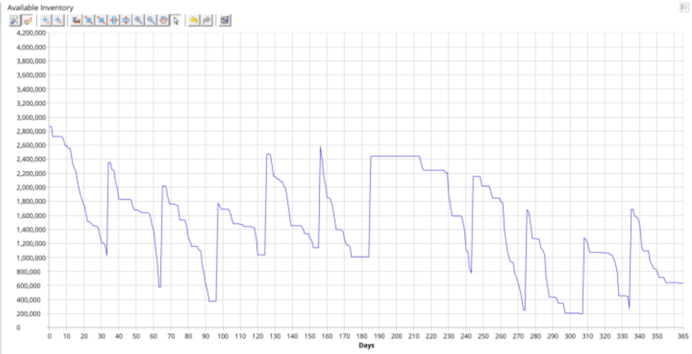
OP5 = FOI WEEKLY





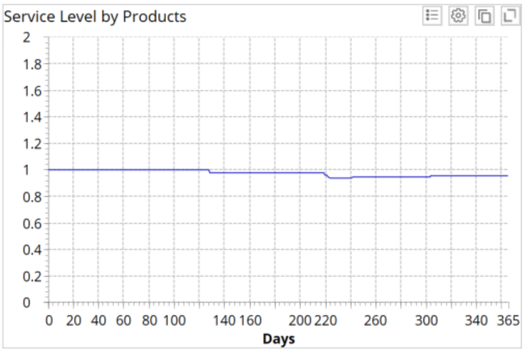
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

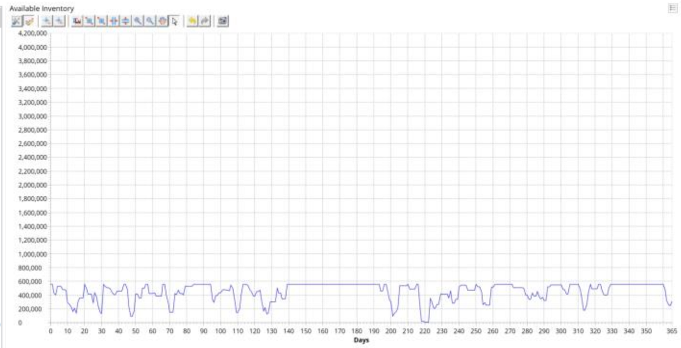




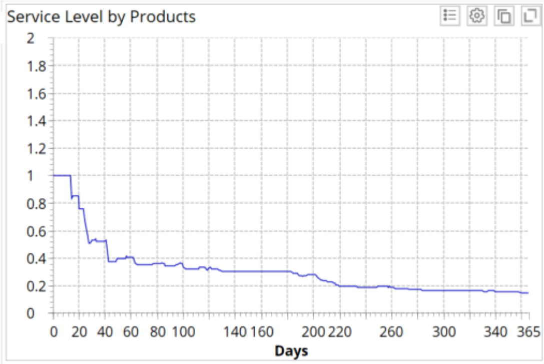
20% lower daily average demand

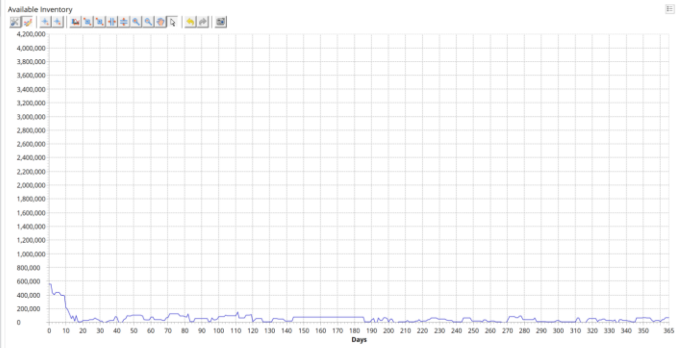
OP1 = MIN-MAX



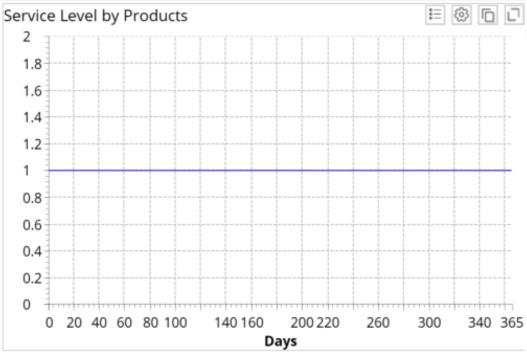


OP2 = ROP WITH EOQ

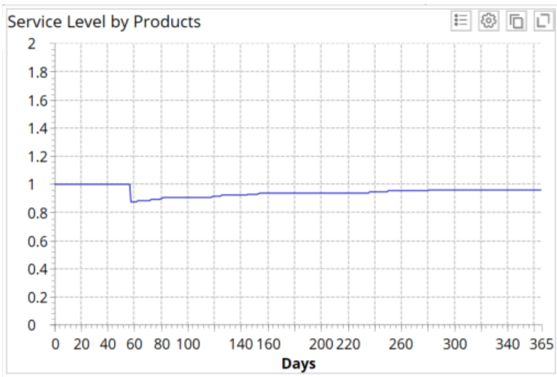


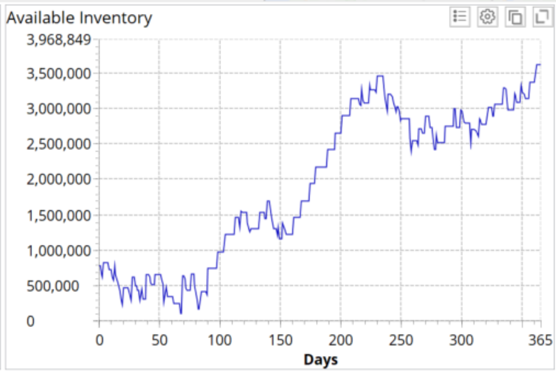


OP4 = FOI MONTHLY

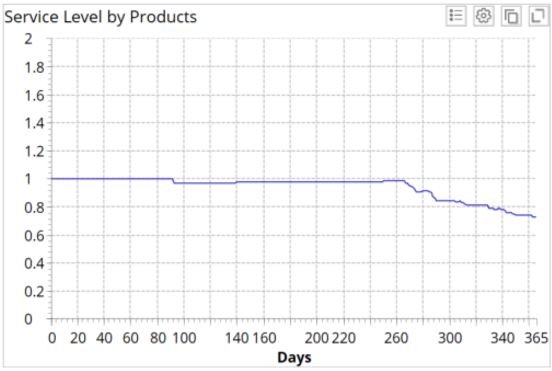


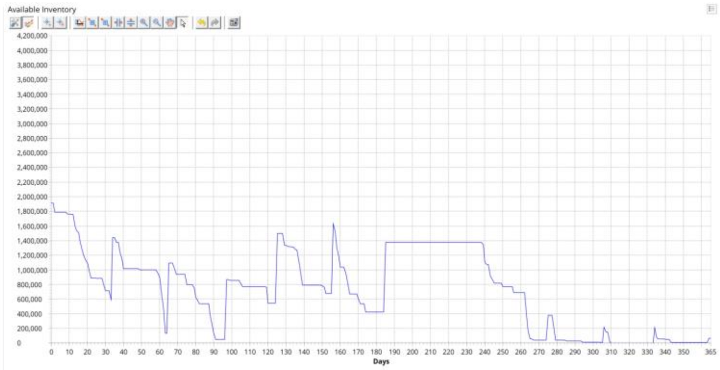
OP5 = FOI WEEKLY





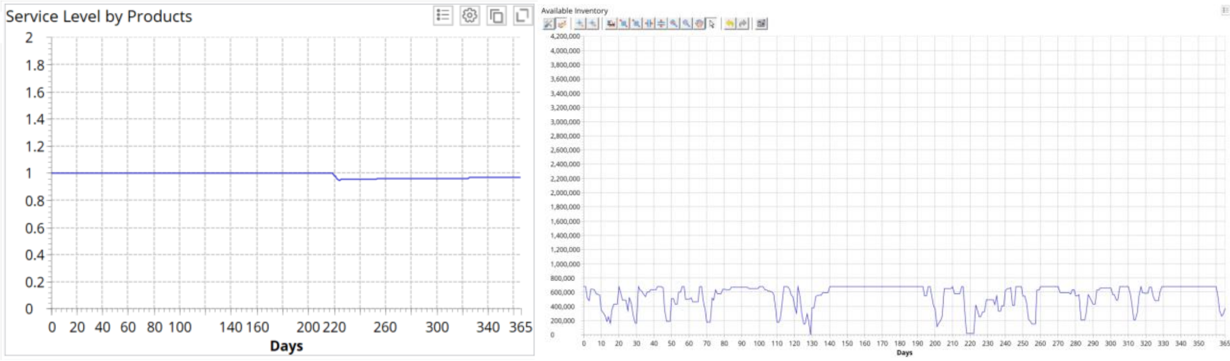
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND



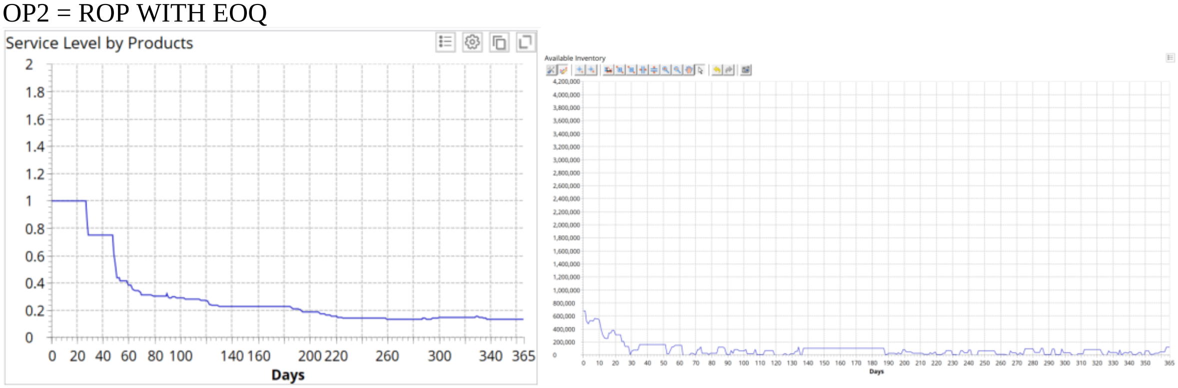


20% higher daily standard deviation of demand

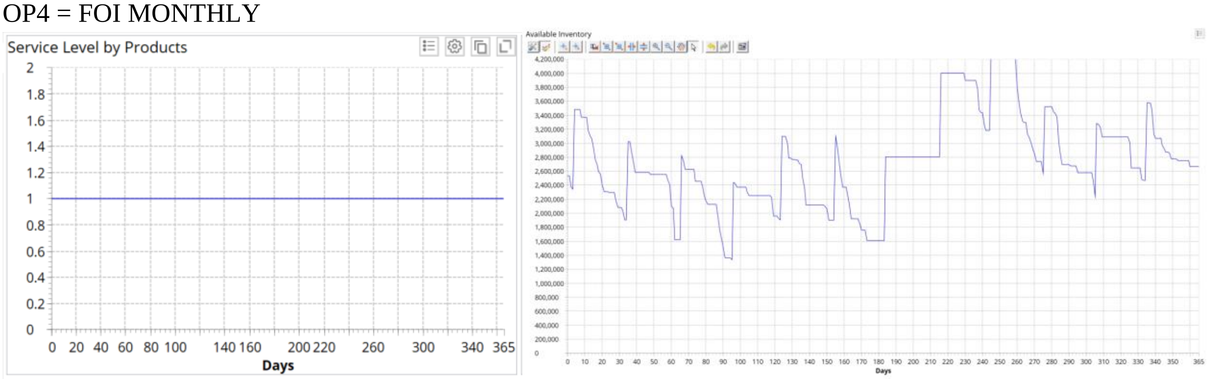
OP1 = MIN-MAX



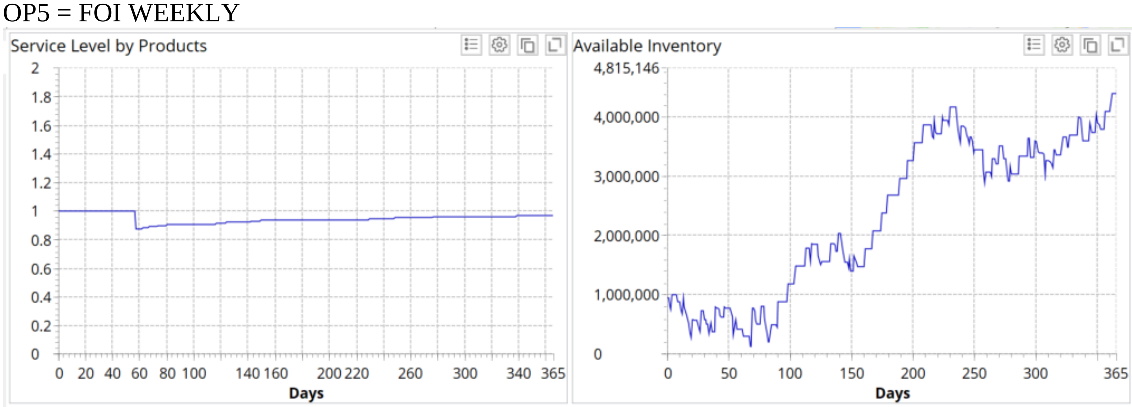
OP2 = ROP WITH EOQ



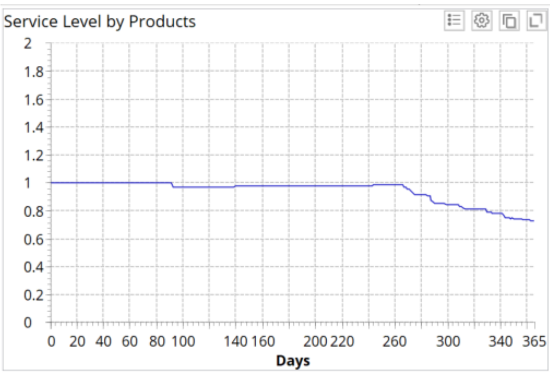
OP4 = FOI MONTHLY

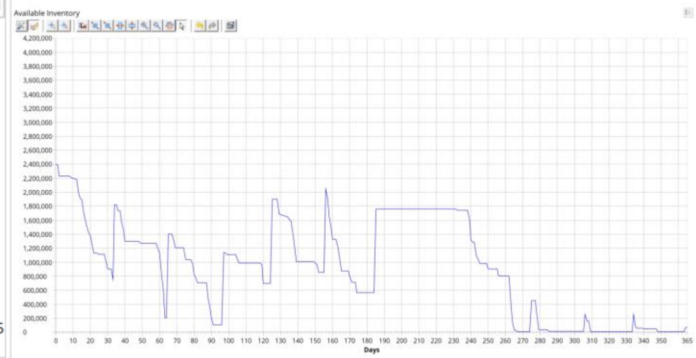


OP5 = FOI WEEKLY



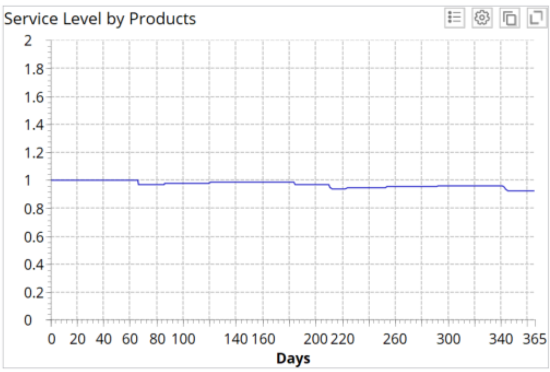
OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

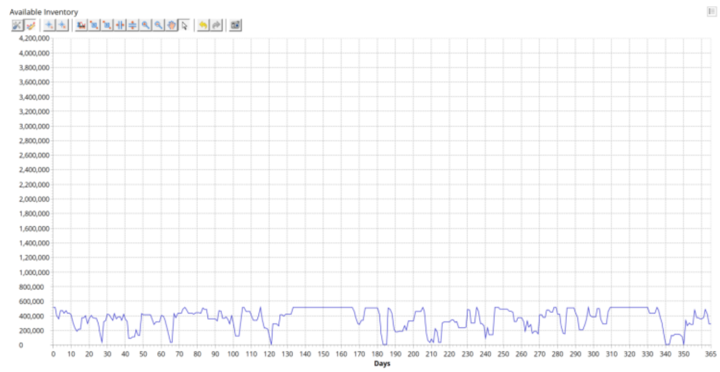




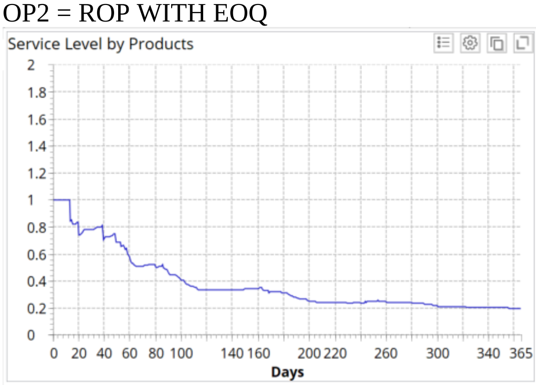
20% lower daily standard deviation of demand

OP1 = MIN-MAX

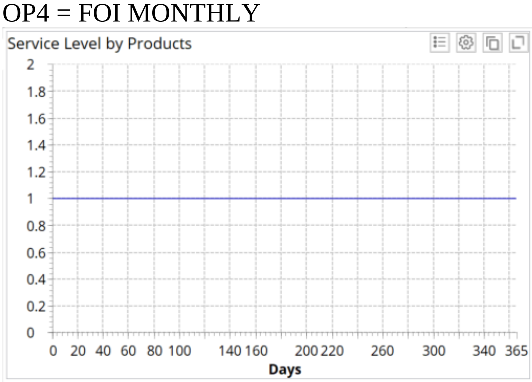




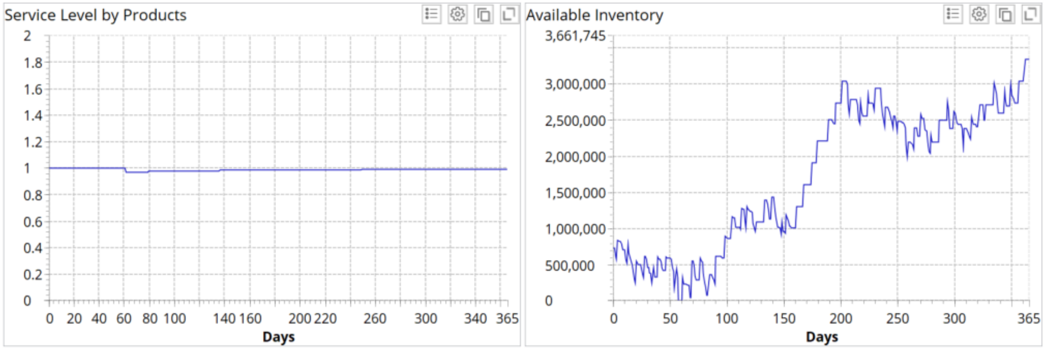
OP2 = ROP WITH EOQ



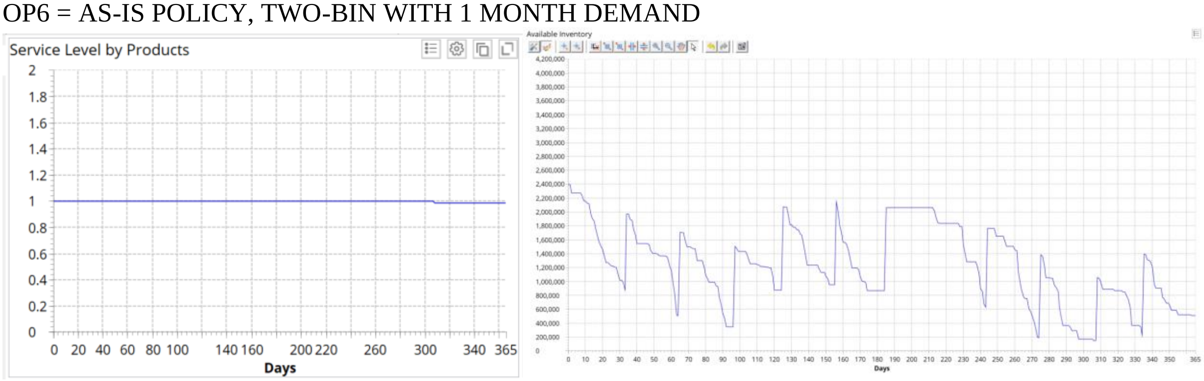
OP4 = FOI MONTHLY



OP5 = FOI WEEKLY

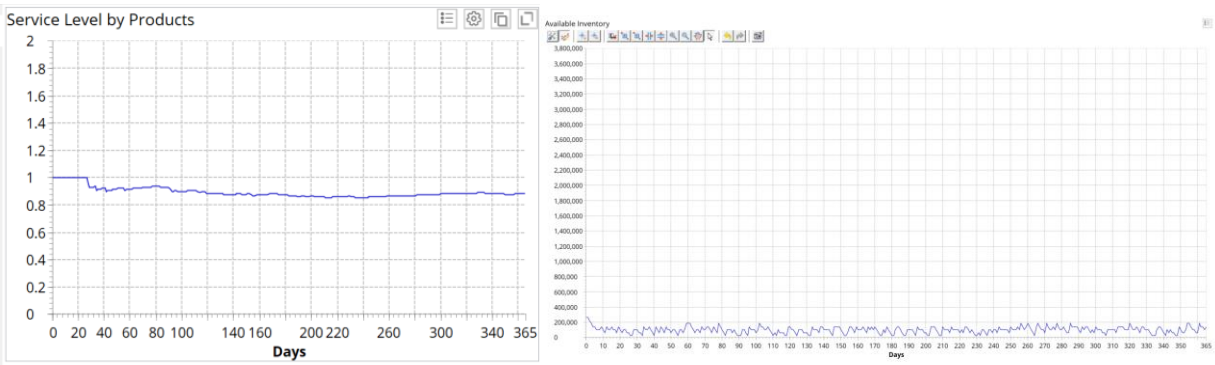


OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND

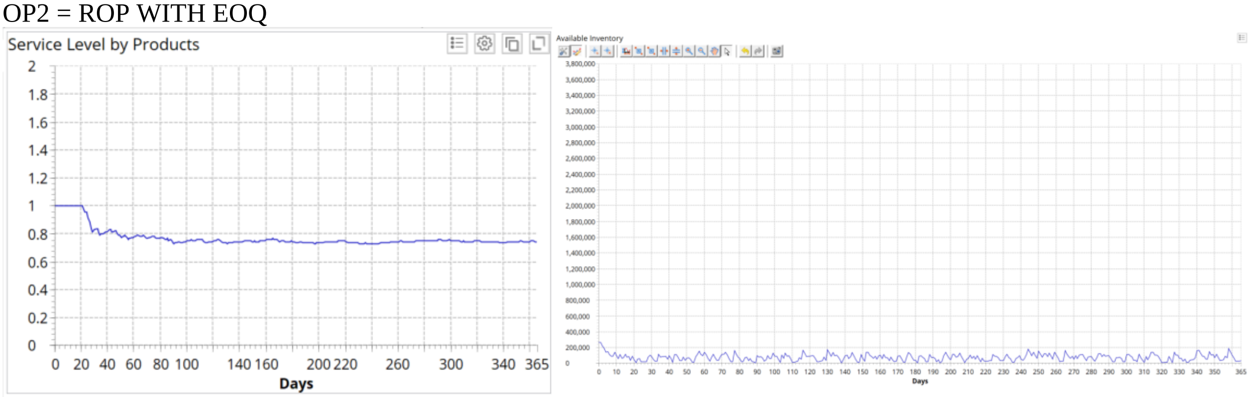


No standard deviation of demand

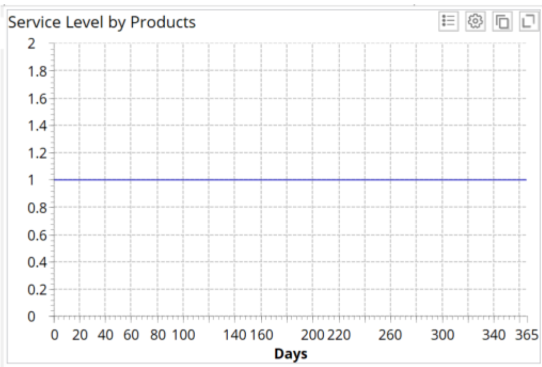
OP1 = MIN-MAX

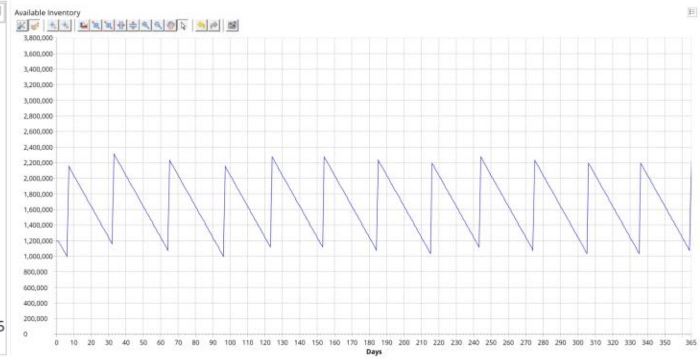


OP2 = ROP WITH EOQ

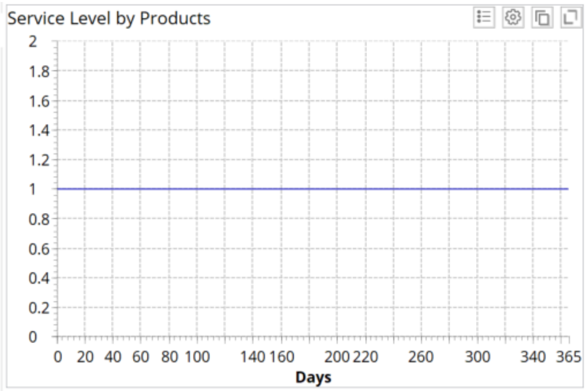


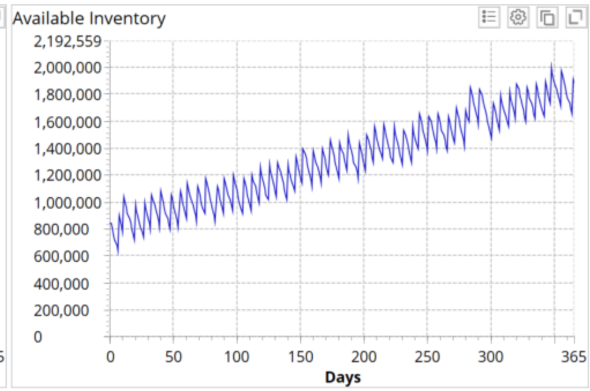
OP4 = FOI MONTHLY



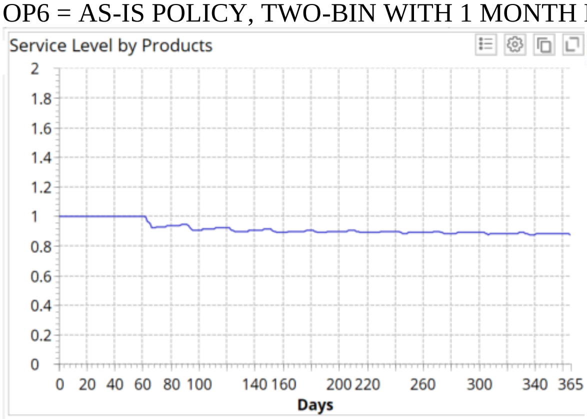


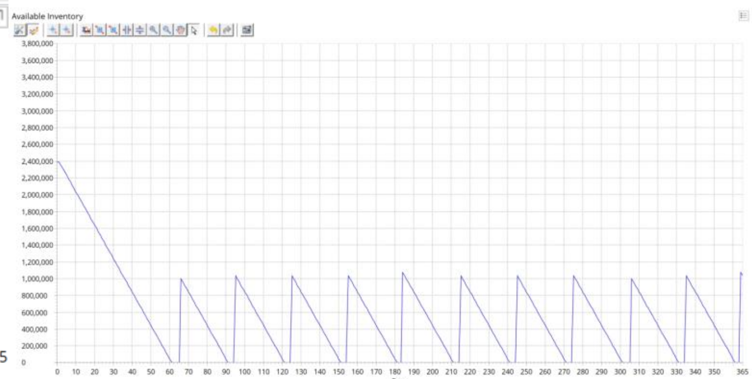
OP5 = FOI WEEKLY





OP6 = AS-IS POLICY, TWO-BIN WITH 1 MONTH DEMAND





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