UNIVERSITY OF TWENTE

MSC THESIS

A continuous review inventory model for the improvement of material logistics in hospitals

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Leon van Beek *Enschede, April 2023*

Management Summary

Problem definition

In this research we focus on the scan-relevant items stored at the OR department of Isala. Scan-relevant items are surgical supplies that remain in the body after the procedure, and thus need to be scanned and linked to the patient. Analysis of the current situation at Isala identified the following issues the OR department faces:

- A lack of mathematically substantiated inventory levels, causing high stock levels.
- SKUs not meeting minimal service level requirements, where 12 out of 837 do not reach 99.9% availability.
- Not keeping to predetermined order sizes.
- A lack in storage space due to high stock levels.
- Unnecessary emergency ordering by the OR department.

Following, the objective of this research is:

"To design and assess an inventory model for the scan-relevant items stored in the operating room department that reduces inventory level and decreases emergency orders, whilst maintaining, or improving, the current material availability."

Solution design

This research creates an *(s,S) inventory system* that is optimally solved using a *stochastic program*. The constructed stochastic program is a scenario-based program that incorporates uncertainty in future demand and lead times in the current decision making, and determines optimal order points (s), order-up-to levels (S), and emergency-order-points. The objective function minimises both costs and total inventory, as the OR departments storage space is limited. Two models are constructed. One that optimises the order-up-to level and the emergency-order-point with a calculated s, and a second model that uses a joint optimisation of the levels s, S, and the emergency-order-point.

It is found that it is hard to determine optimal stock levels for products with low intermittent demand, a characteristic of the scan-relevant items with average daily demand ranging from 0.0006 to 0.55 units. The issue is demand generation. In order to include enough demand such that all scan-relevant items need to be ordered causes the scenario tree and time frame to be increased to sizes that are not solvable anymore. A heuristic is constructed that determines good inventory levels for items with these demand characteristics.

A variety of experiments are performed on the stochastic program and the heuristic. To test the performance of the stochastic program for other departments with larger demand sizes a case with large demand is created, with daily demand ranging between 1 and 500 units. The experiment compares performance with a calculated value for s and an optimal one. The heuristic experiments on a variety of emergency-order-points, where the emergency-order-point is the order point s times a decimal ranging from 0 to 0.5. Lastly, a heuristic experiment is conducted that determines the benefits of decreasing lead time variability.

Results

The evaluation simulation of the optimally solved large demand case looks promising and achieves a CSL of 94.09% using the joint optimisation including the level s. When larger computing power is used to run the stochastic program, using a bigger scenario set and time span, an increase in performance is expected. The experiments show that using an optimised value for the order point is preferable over a calculated value yielding an expected inventory decrease of 35.49% with similar costs.

The heuristic experiment ensures that all SKUs achieve their desired CSL. Since 12 out of 837 SKUs currently fail to meet their minimal CSL of 99.9% the costs increase slightly. The results show that an expected cost increase of 3.24% to 9.91% yields an inventory decrease of 11.17% to 56.62%, dependent on the emergency-order-point, and achieves the minimal CSL requirement for all SKUs. The best experiment according to us increases costs with 4.52%, and decreases inventory with 37.61%, using an emergency order factor of 0.3. The increase in costs is in part countered by an expected decrease in obsoletes, with obsoletes being €92,462 (3.12% of costs) annually.

When decreasing the lead time variability of the scan-relevant items the heuristic determines than an additional decrease of 2.76% in stock level can be obtained. However, close cooperation and contact with suppliers is necessary to obtain more accurate lead times.

Practical contribution

The heuristic provides Isala with good inventory levels for the scan-relevant items of their OR department, significantly decreasing stock levels and increasing availability. Stocks decrease with 37.61%, with a costs increase of 4.52% using the proposed emergency-order-point factor of 0.3. Furthermore. the heuristic shows that it is beneficial to decrease lead time variability, should Isala think that the effort is worth the expected stock decrease of 2.76%.

The stochastic program shows potential to be applied to large demand cases. Isala can run the stochastic program using more computational power on data of a department or product type that is similar to the large demand characteristics of the test case.

Lastly, the research at Isala shows that there are improvement possibilities in the inventory management of hospitals. The results can help convince healthcare professionals that there is room for improvement, hopefully increasing their willingness to accept alterations to their current method of working. This research is a stepping stone to implementing more advanced inventory management methods, such as incorporating surgery schedules, or a multi-echelon inventory optimisation.

Scientific contribution

This research introduces a new problem where a joint optimisation is performed on the levels s, S, and an emergency-order-point, by means of the optimal solving of a stochastic program under variable lead time and demand. The stochastic program combines point-of-use inventory systems with the introduction of an emergency-order-point that to the best of our knowledge has not been regarded in literature before.

The use of a heuristic is proposed to be better suited to SKUs with low intermittent demand, as their demand characteristics make it hard to calculate optimal values. The proposed heuristic achieves a significant decrease in stock level, and ensures that all SKUs achieve their minimal CSL requirements.

Lastly, this research adds to the sparse publications focused on material logistics in the healthcare sector.

Contents

Chapter 1

Introduction

This thesis aims to improve the inventory management of the operating room department of the Isala clinics. The following chapter is an introduction and considers the context of the research setting. *Background* is provided on the relevance of the research in Section 1.1, the *context* is discussed in Section 1.2, the *problem identification* is given in Section 1.3, the *research objective* is stated in Section 1.4, Section 1.5 describes the *research questions* that will be answered in this research.

1.1 Background

The healthcare sector is and has always been a sector that continues to increase in costs due to technological innovation [1]. When focusing on Dutch healthcare expenditure, the largest part of the budget is spent on hospital care, with costs expected to increase to 96 billion a year by 2060 (with an annual growth of *2.8%* per year). The percentage of the Gross Domestic Product (GDP) going towards the healthcare sector is projected to grow from *12.7%* in 2015 to *19.6%* by 2060 (with an annual growth of *1.7%*) [1]. This shows that healthcare expenditure is expected to have a higher cost increase compared to economic growth. These numbers indicate the need for cost reduction within the healthcare sector.

From these increasing costs, approximately *30-40%* of total hospital costs are spent on inventory, this being the second highest expense after personnel costs [2]. This indicates that proper inventory management has the potential to substantially decrease costs. While in industry inventory management is a widely studied topic, the healthcare sector remains behind. For example, when looking at research that focuses on inventory management within hospitals, only 66 relevant sources up to 2014 are found according to Jonas Volland et al., and an increase in publications is observed between 2012 and 2014, compared to the years before [3]. Compared to the vast amount of research conducted on inventory management for manufacturing companies, it is apparent that there is still a lot unknown about inventory management within the healthcare sector, although the attention given to material logistics in the healthcare sector is increasing [3]. Next to research, it can also be seen that little of the already conducted research is implemented at the moment. This shows the need, in addition to increased research initiatives, to implement appropriate inventory management approaches.

1.2 Context

This section describes the context in which this research is conducted. The research is carried out at *Isala Clinics* located in *Zwolle, the Netherlands* for their purchasing department. Furthermore, the research focuses on one specific care unit, the *Operating Rooms (ORs)*.

FIGURE 1: Top levels of Isala's strategy pyramid (2019-2022). Adapted from [5].

1.2.1 Isala

The research is carried out at the Isala Clinics located in the region of Zwolle, the hospital group includes the hospital located in Meppel. The hospital has 6,797 (5,081 Full Time Equivalent (fte)) employees, including 427 (394 fte) medical specialists, and holds 1,250 beds. At location Zwolle there are 14 clinical Operating Rooms (ORs), where eight are dedicated to the OR department. Furthermore, Isala has six day treatment ORs; in comparison, location Meppel has five ORs in total [4]. A hospital of this size is relatively large for the Netherlands, and Isala is considered one of the largest hospitals in the country, with a significant catchment area.

The policy of Isala is based upon their strategy, which they envision in blocks of three years. Figure 1 shows a translation of the six highest levels of their strategy pyramid. Costs and waste are one of the main focus points of Isala, but less important than patient care itself denoted in the upper levels of the pyramid. In trying to reduce costs, Isala looks at waste, and not only in the form of materials. They also consider whether the offered care will actually benefit the patient. The main question is whether the cost of care outweighs the expected health benefit. Here the cost of care refer to the actual costs made, together with the treatment side effects for the patients. Furthermore, Isala is increasingly moving care to the patients' homes, instead of treating them at the hospital, aiming to offer 10% of all care at the patients' homes by the end of 2022 [6].

In conclusion, Isala wants to focus on the costs they have incurred and the waste associated with it. However, in their strategies, there is no mention of improving the efficiency of existing processes, such as their inventory management system, and whether there is still improvement to be made in this aspect. This research investigates the manner in which Isala manages their inventory in greater depth to determine whether they can improve.

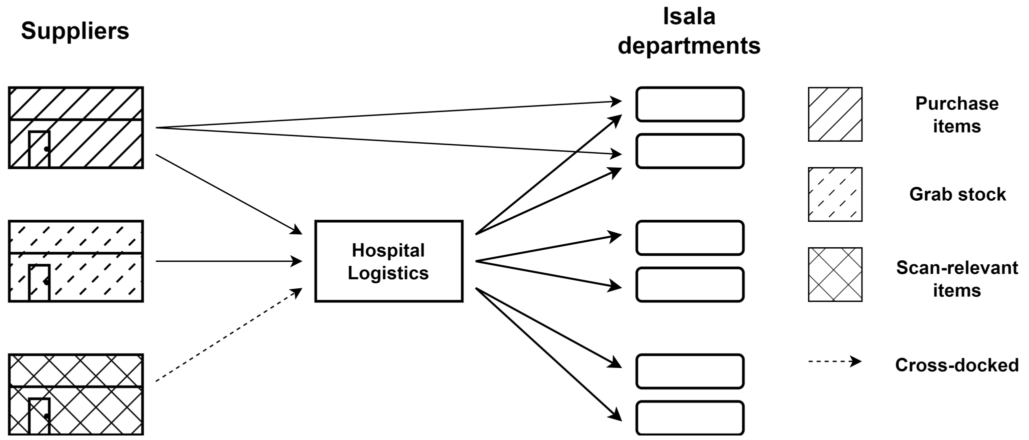


FIGURE 2: The supply chain of Isala's logistics per item type

1.2.2 Hospital Logistics

When Isala moved into their new building in 2013 the building was built with the goal of having a *Just-In-Time* (JIT) inventory management system. The aim is to optimally use the building for patient care and to reduce the space needed for stock and other ancillary practices. Due to the JIT management strategy a logistical partner, Hospital Logistics, is contracted to handle most of the material deliveries. Hospital Logistics can supply materials with a variable lot size, ranging from one unit to many, based on Isala's needs. Figure 2 shows an overview of Isala's current material delivery system. Isala distinguishes between three different types of materials, further explained upon in Section 1.2.3.

Inventory management is highly dependent on the delivery of materials. It is thus important to have a proper view on delivery quantities and lead times. For Isala there is improvement to be made in the delivery process of their supplies. Currently, their logistic partner, Hospital Logistics (HL), sends deliveries to Isala four times a day. The HL warehouse for the Isala Zwolle location is based in Apeldoorn. Four deliveries a day are more transportation movements between Isala and HL than deemed necessary by HL, increasing emissions and costs. When meeting employees of HL they indicated that they would like to reduce these deliveries to at most two times a day, as it is deemed to be sufficient to deliver all materials.

1.2.3 Operating Rooms

This research focusses on the inventory management of the Operating Room (OR) department. Hospital ORs can be seen as cost centres, as they are responsible for about *60%* of total hospital cost [7]. In the OR, a variety of surgeries are carried out. Multiple medical specialties use the operating rooms, which requires the availability of a wide variety of materials. The OR department of Isala consist of 8 ORs. Materials that may be required during surgery are stored near the ORs in various storage rooms. Initially the allocated storage space, with the JIT management style, proved to be too small. To create more space, some break rooms and other rooms are additionally turned into storage spaces. This causes the OR department to have 32 smaller storage spaces that differ in shape. The large number of smaller storage spaces makes it hard to keep overview of all the materials. The OR department is located on two floors that are immediately above each other. The OR department tries to divide the storage in such a way that there is little transportation between the first and second floors. However, sometimes materials need to be transported between the two floors by stairs. In addition, all materials must be collected prior to surgery by the logistic staff working for the OR department. These employees often need to visit multiple rooms to retrieve all materials, which is time-consuming.

The OR is resupplied three times a day, with one supply time of HL being for another department. The logistical department of Isala receives the goods and transports them to the OR. Here the logistics department of Isala put all goods in the designated on-site cabinets for the other departments, the OR does this themselves, as they have their own logistical staff and method of working. Therefore, the Isala logistics department transports the materials to the OR airlock in wheeled containers, and from there the goods are transported and unpacked by the logistic staff of the OR itself. The OR department does not have any Key Performance Indicators (KPIs) that measure their performance with respect to their material logistics. For the scan-relevant items waste records are kept, but this information is not used in planning and control.

Isala distinguishes between three different "types" of materials.

Scan-relevant items are mostly materials that remain in the patient after surgery is complete or very expensive products that are frequently used and Isala wants to keep track of. All scan-relevant materials that are implants and remain in the patient after surgery need to be linked to their respective patient. So, when a scan-relevant item is used, it is scanned during the procedure before being used. The OR department, however, concluded from the data that about *3%* of all scan-relevant items is not scanned during the procedures. This is caused by complications that occur during surgery, which causes a quick need for materials, or by employees slacking off. It is possible to scan the items after the surgery is concluded, but this is also not always done correctly or at all. It is thus approximately known what scan-relevant items are used per surgery.

In total, there are $4,457$ scan-relevant Stock Keeping Units (SKUs) at the OR department. The average usage for the period 2017-2022 is $20,375.27$ products per year. These statistics do need the side note that many of the articles are used only zero to five times per year, and that there are on average 74.2 articles that are used 50+ times a year. Meaning that 74 of $4,457$ SKUs constitute *18%* of total usage.

For all scan-relevant items an automated ordering process is in place. Each scan-relevant item has a *min* and *max* stock; when the *min* stock is reached in the system, an automated order is placed that replenishes stock up to the *max* level. Often the *min* and *max* are the same level, meaning that a replenishment order is placed immediately after one item is used. This inventory system resembles an *(s,Q) inventory system* with a reorder point s and an order quantity Q, under continuous review. This can also be modelled as an *(s,S) system*, where S is the order-up-to level. Since products are ordered unit by unit, both models are identical [8]. Scan-relevant items are delivered within 24 hours if Hospital Logistics has them in stock, and otherwise within 48 hours if the product is ordered directly at the supplier. However, often the OR department does not keep to the predetermined order points and quantities, and mostly orders based on experience. Furthermore, the *min* and *max* levels are determined arbitrarily.

Grab stock includes basic articles that are often needed during surgeries, but do not remain in the body after completion. The grab stock is indicated by yellow card labels on their bins. Since grab stock is used often and in high quantities Hospital Logistics keeps a sufficient stock level of these materials, and they are delivered within a day of ordering (or sooner when an emergency order is placed). The grab stock has a variable assortment, ranging from rubber gloves to syringes to bandages. This type of stock is kept using a two-bin system. Each basket is separated into two compartments similarly to two different bins. Once the first compartment is empty it is refilled from the second compartment, and a new order is placed to restock the product. For all items a minimum amount is determined that when reached should be replenished up to double this amount. The inventory level of the grab stock is checked every morning when the OR logistics department checks all stock locations. Thus, for the grab stock an *(R, s, S) inventory system* is in place, with a review period of 1 day, a reorder point s, and an order up to level S that is double the amount of s [8].

The ordering of these items is done by scanning the barcodes associated with the product. For each item, a barcode is added to the bin where the product is stored. Next to this barcode a number is written, this is the minimum amount that should always be in stock s. When the barcode is scanned, this minimum amount is ordered. The stock should never exceed double this minimum amount S. However, occasionally more than the maximum amount S is in stock. This happens as physicians sometimes request more materials, or the cards are scanned too often. In theory, the logistical employee needs to count all the materials already on-stock, and only order if level s is reached. However, employees sometimes do not really count the materials in stock, but just place a replenishment order to ensure that enough material is in stock. This causes materials to not fit into their designated storage spot, or materials to go to waste as they cannot be used before they expire. Lastly, the lack of overview in storage spaces previously mentioned can cause employees to occasionally not scan grab stock cards that need to be replenished, causing emergency orders to increase.

Purchase items are products that are used irregularly and in low quantities. Due to the characteristics of these items Hospital Logistics does not keep them in stock, as this would take up too much space for the profit that they bring. The purchase items are recognisable by the blue cards placed on their bins. These items are ordered directly by Isala at the retailer. Most purchase items are still delivered to HL, who acts as a cross-dock for Isala and ships the products together with the next order. There are, however, products that are delivered to Isala directly from the retailer, mainly products that need specific types of transportation (e.g. cooling). The flow of material between the supplier, HL, and Isala is shown in Figure 2. Due to the JIT inventory system of Isala the quantities of the blue cards are often 2 units. It is mentioned that the lead time for these types of products is typically 48 hours. The inventory model for purchase items is an *(s,Q)* or *(s,S)* inventory system with unit-by-unit ordering, the same as for grab stock. Although the lead time is longer.

The research focuses on improving the material logistics of ***scan-relevant*** items. When all scan-relevant materials are stocked up to their maximum level, the total monetary value of stock is €5,654,586.54 for the OR department. The various types of items require different inventory management approaches. Max (2023) focused on the grab stock and purchase items, thus the combination of the two researches considers the inventory of the entire OR department [9].

1.3 Problem Identification

In the past years, no, or only a few, surgeries were delayed or cancelled due to stock shortages caused by incorrect inventory management. Recently, some procedures got delayed due to the unavailability of products caused by the current global shortage of materials, this is, however, out of scope for this research. In a normal situation it is the case that when stock runs out, an emergency order is placed in order to refill this stock and ensure no cancellations. Facilitating emergency ordering causes the OR to place many (unnecessary) emergency orders, which are quite expensive.

Other factors that increase the number of emergency orders are the behaviour of employees, and a lack of understanding the ordering process. Hospital employees are very risk-avoiding;

should there even be the slightest possibility of a stockout, an emergency order is placed. Furthermore, employees do not properly understand what counts as an emergency order. Due to their contract with HL, an order already counts as an "emergency" when it is placed at the wrong time. When placing an order within 1.5 hours of delivery it already counts as this first level of emergency order, as it takes HL additional time, and thus costs, to add this order to the next shipment. With HL delivering 4 times a day, these time windows take up a large part of the day. Employees do not realise that when they order products at the wrong time, this triggers an emergency order cost. Most products that are scanned within these time intervals do not need to be used immediately, thus increasing the number of unnecessary emergency orders.

An emergency order costs €21.66 in employee costs for HL orders and €34.50 for orders from other suppliers, and costs increase if the emergency order cannot be delivered immediately [10]. Next to the emergency order costs there are the expiration costs, if too many products are on-stock they might expire and need to be discarded. Hospital logistics does not charge any additional costs for an emergency order of scan-relevant products as the emergency order comes from an external supplier and they crossdock it [10]. The external supplier does charge an additional emergency order cost.

Appendix A shows the problem cluster and the associated core problem that is selected. The problem is stated as follows: "There is no optimised inventory management system". There are min / max levels for the scan-relevant products, however, these boundaries are set arbitrarily based on experience and not updated. When products are consistently unavailable it is noticed and the min and max margins will be increased. However, it is expected that when there is too much stock of certain products, these parameters are not lowered, as the employees do not experience problems with these products. This shows the lack of an inventory management system, and shows that most of the ordering is based on experience. Furthermore, there is no calculated amount of safety stock.

Over the period of 2019-2021 an average of €92,462.73 a year is thrown away due to products being expired. These costs can be reduced when unnecessarily high inventory levels are lowered for certain products.

Another problem that increases the stock and emergency orders is the "risk-avoiding behaviour of employees", hospital employees rather order products too soon to decrease the risk of running out. However, the hospital has very little storage space, so the products do not fit in their designated cabinets. In general there is more than enough products in stock, especially since the OR department gets restocked multiple times a day. With the frequent restocking there is often no need to place emergency orders on products that have short lead times and low demand. However, these emergency orders are frequently placed. This behaviour causes waste, storage space problems, and emergency order costs to increase.

The behaviour of employees, and the inefficient inventory management system of the OR department, can be linked to the theory on the operations management (OM) triangle shown in Figure 3. Hospitals can be seen as capacity oriented, as everything else in the organisation should support the highest throughput of patients. Isala focuses on capacity, but they do not regard inventory and information as something that can support decision making in this aspect. Making a trade off between the different components of the OM triangle, and actively consider the influence of the components on each other, will improve performance and profitability [11]. Especially since Isala aims to have a lean inventory management the coordination of the OM triangle factors is required.

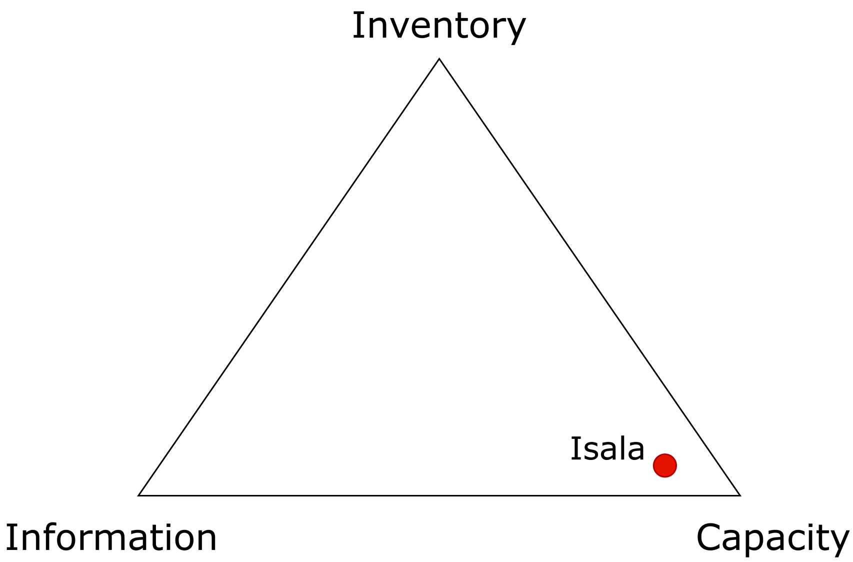


FIGURE 3: The operations management triangle. Adapted from [11]

1.4 Research Objective

The objective of this research is to formulate an inventory model that minimises the total costs of the scan-relevant items of the OR department in such a way that emergency ordering and expiration decrease, while maintaining the current level or increasing the material availability. In this way, the main Isala strategy shown in Figure 1 is maintained, as costs and waste are minimised while maintaining patient value with its associated quality at the level. From the core problem identified in Section 1.3 the following main research objective is stated:

To design and assess an inventory model for the scan-relevant items stored in the operating room department that reduces inventory level and decreases emergency orders, whilst maintaining, or improving, the current material availability.

The research objective addresses the lack of mathematically substantiated inventory management, and creates an advanced inventory model for the OR department. Since the OR department is currently lacking any form of numerically substantiated inventory management the created model will probably be too advanced to be properly implemented in the current situation. Another aim of this research is thus to set up some rules-of-thumb for inventory management that can immediately be implemented, with the suggestion to implement the advanced inventory model once this proves to be possible and beneficial.

1.5 Research questions

This section discusses the structure of this thesis with accompanying sub-research-questions that are answered. Figure 4 shows the outline of the report. Following the objective and core problem of this research the following question needs to be answered: *How can we design and implement an inventory management system for the scan-relevant items of the OR department of Isala?* To answer this question we formulate the following sub-questions:

Chapter 1 discusses the background of this research, the problem identification, and research questions are constructed that will be answered in this research.

1. *What inventory models with a continuous review period are known in literature and apply to the case of Isala?*

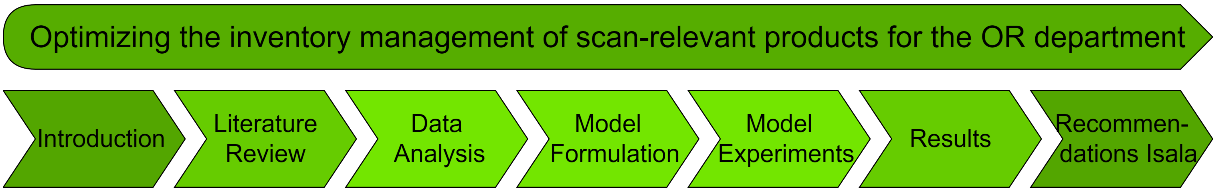


FIGURE 4: Research outline

2. *What type of modelling can be used to assess the performance of different inventory policies?*

Chapter 2 discusses research questions one and two, where a semi-structured literature review on the state of the art on hospital material management is conducted that identifies what type of inventory model suits this research best.

3. *What is the mathematical model formulation, and what are the associated parameters?*

Chapter 3 formulates the mathematical model and determines the objective value based upon the literature review.

4. *What is the current situation at Isala with regards to their inventory policy, performance on KPIs, and minimal stock levels?*

Chapter 4 discusses the data available at Isala, and introduces the hospital as a case study to assess the performance of the mathematical model constructed in Chapter 3.

5. *How should the experiments be designed to reflect the expected real-world performance of the model as accurately as necessary?*

6. *What are the different scenarios that need to be modelled?*

Chapter 5 discusses the different experiments to be run on the model to assess the performance.

7. *What is the performance of the different experiments and what are the advantages and disadvantages?*

Chapter 6 discusses the results from the experiments and assesses the performance of the model.

8. *Which recommendations can be given to the OR department of Isala to improve their inventory management?*

Chapter 7 gives conclusions and recommendations based on all previous chapters. The final conclusions will cover the proposed inventory model, as well as easy to implement rules that can immediately be used.

Chapter 2

Literature review

This chapter discusses the current application and theory on hospital material logistics in Section 2.1. Section 2.2 describes solutions and models from other industries. Section 2.3 describes a variety of modelling approaches that have applications to solve this problem. Lastly, Section 2.4 concludes this chapter providing a solution approach and the literature gap. Appendix B shows the search and exclusion criteria used in the selection of relevant sources.

2.1 Material logistics in healthcare

Inventory costs in hospitals amount to approximately *30-40%* of total costs, the second highest expense after personnel costs [2]. Furthermore, hospital material management is identified as a key cost containment lever and is considered one of the costs that can be reduced to combat the steady increase in healthcare spending that developed countries are currently faced with [3]. Chapter 1 showed the lack of research focused on material logistics in the healthcare sector. This lack of focus is explained by the fact that material logistics is not an independent research stream and that in many cases material logistics within hospitals is a cross-departmental issue that makes it harder to address [12]. In the period 2014-2017, it is observed that the number of publications on optimisation techniques for material logistics in the healthcare sector has reached levels that have not been seen before, with up to 27 publications per year [3, 12]. Over the last decade, a new planning level is identified for healthcare planning, the tactical planning level, which aims to execute a strategic goal over the middle to long term [13]. The goal of the tactical planning level is to give direction to organisations on how to actually achieve their strategic goals and to be a bridge to link the strategic goals to their daily operations. Approximately half of hospital logistic costs are eliminated by efficient logistics management [3]. To determine which products to focus on, an ABC or VET classification can be used, where VET classifications require a detailed knowledge of product characteristics and are thus harder to implement [3].

We consider the supply chain for material delivery in hospitals a multi-echelon system, with a central warehouse that receives goods from suppliers. This central warehouse regularly delivers to point-of-use inventories that are close to patient care locations. This being the "traditional" system. Next to this system, there are two other distribution systems that are applied to practise, a "semi-direct delivery", where there is no central warehouse and all suppliers deliver directly to the point-of-use locations, and a "direct delivery", which is closest to a Just-In-Time (JIT) system, where materials get delivered based upon daily demand, with the goal being to minimise stock levels. This means that the supplier is responsible for reacting to changes in demand and stocking the point-of-use storage accordingly [3]. Furthermore, it is mentioned that a warehouse that supplies multiple hospitals can create significant cost savings for the entire supply chain [14].

Currently, many hospitals work with a two-bin system where two baskets of stock are kept, and should one become empty, an order is placed to replenish the empty basket [12, 15, 16]. These two-bin systems have been an innovation over the past decade for inventory management within hospitals. It is proven that two-bin systems work best under continuous review, with cost reductions of up to *50%* [15]. Only when the cost per stock-out occurrence is very low, the periodic review system may be able to outperform the continuous model in terms of costs [15].

A JIT inventory strategy can reduce costs for hospitals. However, it is necessary for the hospital environment to adapt to such an inventory strategy. The important pillars for the correct implementation of a JIT inventory system are *Supplier selection*, where suppliers must deliver a high quality product within short lead times. Additionally, the number of suppliers needs to be kept as low as possible. Secondly, *Strategic partnerships* long-lasting, good, relationship with your suppliers is necessary. And lastly, *Adequate information sharing and communication*, where suppliers and buyers communicate with one another about their needs and inventory wishes [17]. Furthermore, for the implementation of a JIT inventory system to be successful, it requires an integrated network that shares information with each other. The development and application of information systems that share data on stock levels, and the real-time monitoring and tracking of the purchase, storage and delivery of hospital materials have been stated to be key to achieving JIT mode [17]. The numerical analysis of Bhosekar et al. [16] indicates that, in general, coordination of surgical instruments and material handling decisions can potentially improve the service levels provided by operating rooms. Furthermore, a JIT delivery of surgical supplies in short-duration surgeries leads to lower inventory levels without jeopardising the service level provided [16].

The focus on pharmaceutical products is outside the scope of this research as the pharmacy often does its own inventory management independent of other hospital processes [18, 19, 20].

2.2 Methods from other industries

Since the healthcare sector has only recently seen an increase in attention to improving its material logistics, methods from other industries can possibly be applied [3]. A stochastic demand, single item, continuous review inventory model with short lead times and the objective of having a high service level whilst maintaining an as low as possible stock is constructed [21]. An optimal solution proves to be obtainable in polynomial time, furthermore the model shows that slight deviations from this solution can lead to a big decrease in performance, and an increase in reorder point is less disadvantageous than decreasing it [21].

In addition to conventional $(s, Q) models$, Chiang [22] proposes the addition of a parameter R. R is regarded as the "expedite-up-to-level" and is the order point where an emergency order is placed. The addition of the variable R has been shown to yield significant cost savings, especially for organisations with high service levels, large demand variability, low emergency order costs, and long manufacturing lead times. The proposed model implements this only for a single item and has not yet been applied to operation-wide inventory management [22]. Since hospitals often have the option of emergency ordering, and this occurs with regularity, the introduction of a new parameter can help determine whether it is really necessary to emergency order.

Ouyang et al. [23] propose a model with fuzzy lost sales with partial information about lead time demand. The case of fuzzy lost sales is not applicable in a hospital context, as all postponed surgeries need to be rescheduled and are thus not lost. The uncertainty in lead time demand is a factor that is relevant to hospitals, as the requirements for materials are patient, procedure, and physician specific. Furthermore, they show that a reduction in lead time can lead to significant cost reductions [23, 24].

Due to supply disruptions in recent years many corporations are struggling with material unavailability and backorders. Poormoaied et al. [25] propose to introduce the possibility of placing an emergency order just before a supply disruption occurs. Their model uses different ordering and order-up-to levels for periods with and without supply disruption. This requires close cooperation and good communication with all suppliers [25]. Furthermore, models are developed that consider the inventory control system of perishable goods with relatively short lifespans. These models are often applied to pharmaceutical or food products [19, 20].

2.3 Modelling approaches

In this section different modelling approaches are discussed that have applications to continuous review inventory models in hospitals. Most models regard a (s, Q) inventory model where the reorder point s is the safety stock ss plus the demand under lead time DL. The safety stock is the safety factor z, which depends on the desired service level, times the standard deviation σ times the square root of the lead time $\sqrt{L}$. This combined formula gives the following for determining the reorder point: $s = DL + z\sigma\sqrt{L}$ [26]. Furthermore, an (s, Q) model is stated to be faster in run-time compared to (s, S) models due to the lower complexity. The proposed model has a linear complexity and, thus, a fast runtime. The model uses unit-by-unit ordering, similar to the case of Isala [27].

When including uncertain demand and lead time in (s, S) systems a different calculation of the level s is needed that incorporates this uncertainty. The addition of demand uncertainty increases the level of s compared to models without demand uncertainty, as an increase in safety stock is needed to cope with the increased uncertainty. The expression including these uncertainties is shown in Equation (1).

$$s = E(DL) + z\sqrt{E(L) \cdot var(D) + \ [E(D)]^2 \ \cdot var(L)} \tag{1}$$

The expected demand over the lead time $E(DL)$ is added with a safety factor z times the square root of the expected lead time $E(L)$ times the variance in demand, $var(D)$, plus the expected demand squared, $[E(D)]^2$ times the variance in lead time $var(L)$ [8]. Furthermore, the Economic Order Quantity (EOQ) is often used to determine the level of S in (s, S) systems. The EOQ determines the optimal quantity to order based on the expected demand, $E(D)$, the ordering costs, C^O, the SKU cost C^M, and the cost of holding inventory h [8]. The EOQ is expressed in the Equation (2).

$$EOQ = \sqrt{\frac{2 \cdot E(D) \cdot C^O}{C^M \cdot h}} \tag{2}$$

In theory there are two types of service levels, a level α also known as the cycle service level, and a level β known as the fill rate [28]. α measures the number of cycles in which a stockout does not occur, and its calculation shown in Equation 3.

$$\alpha = \frac{\#\, of\ cycles\ without\ stockout}{total\ \#\, of\ cycles} \tag{3}$$

The cycle service level measures the times that there is a stockout, not the total inventory quantity of the stockout. It does not differentiate between 1 unit, or 100 units short. The fill rate β does take into account the number of units, as this is a measure of the fraction of demand that is satisfied from inventory [28]. The calculation for β is shown in Equation (4)

$$\beta = \frac{Total\ volume\ of\ orders\ supplied}{Total\ demand\ ordered} \tag{4}$$

In general using β achieves a higher service level compared to α. In some cases with high demand and variability in lead time, the service level of α can exceed β due to large stockout volumes [28]. For hospitals, it seems that the cycle service level is a more appropriate measure, as a stockout is unfavourable for patient safety and the number of cancellations.

A Poisson distribution is often used to model (hospital) demand [21, 22, 27, 29, 30]. Akcan et al. [29] states that stochastic demand is widely regarded in literature, and mentions that there is still a lack of models considering lead time variability. There is no widely accepted standard distribution for modelling lead time variability. Various distributions are used to make lead times stochastic, such as, *exponential*, *normal*, *erlang*, and other *general distributions* [29]. Appendix C shows a table with some sources and whether they used a stochastic demand or lead time accompanied by their respective distributions.

A simple simulation can be used in a continuous review inventory policy for healthcare systems. The model varies the values of s and S in an (s, S) inventory system and determines the optimal values for a single item [30]. The entire model is simulation-based and takes a long time to run due to the many iterations for the values of s and S, since these values only need to be calculated periodically; a simulation with a longer run time is possible. Other simulation models also incorporate the surgical schedule to determine an optimal order policy [16]. Research on inventory simulations for healthcare applications is still sparse compared to the vast literature that covers simulation for ordering systems in other industries [30].

Another approach to hospital inventory management is the *dynamic drum-buffer-rope (DDBR)* replenishment model, which tries to overcome the drawbacks of existing reorder approaches by using a demand-pull replenishment approach [2]. The model is implemented using a system dynamics approach and adopts Powell's conjugate gradient search algorithm [31] to determine optimal buffer sizes and replenishment quantities with fast runtimes. The *DDBR* model aims to have no stock-out occurrences. The proposed model incorporates the logistics of single care units, together with the deliveries to and from a central warehouse. It does, however, require very accurate demand predictions and is modelled as a periodic review system.

Other models regard a periodic review period, but do give some useful insights into hospital material management. Bijvank et al. [32] compare models that maximise a service level under limited storage capacity and models that minimise capacity under a hard service level constraint. Easy to understand rules-of-thumb are given to hospital staff. The reorder point for each SKU is set based upon some specific SKU characteristics regarding the demand over the lead time or review period, and the available capacity. Furthermore, most of the literature on inventory theory cannot be used in a hospital context, because other industries typically focus on backorder models, opposed to lost-sales models [32].

Zhang et al. [12] mention that the healthcare sector often lacks the training for non-technical personnel on healthcare logistics. There are four different types of simulation modelling identified that can be used to train this personnel. The aim of these models is to identify rules-of-thumb, or efficient methods of working, that non-technical personnel can implement. There is a lack of complex modelling and simulation in the healthcare industry. For the future, agent-based and participatory simulations are promising approaches to increase performance in healthcare logistics given current societal trends [12].

2.4 Conclusion

In this section, the literature review performed is related to Isala. The two sub-questions addressed in this chapter are *"What inventory models with a continuous review period are known in literature and apply to the case of Isala?"* and *"What type of modelling can be used to assess the performance of different inventory policies?"*. These questions have been answered throughout the chapter, and the final conclusions and a choice of model are given in this section.

First of all, Isala strives to operate under a JIT system with HL as the main supplier. To achieve an effective JIT strategy, much collaboration with suppliers and information sharing systems is needed. Together with real-time information on inventory levels, adequate data sharing, and adaptation to fluctuation in demand [17]. Isala is lacking in these aspects as there is no insight in stock levels, in house or at HL, and there is no demand forecasting. Furthermore, there is a lack of data sharing between HL and Isala about their stock levels, possible stock outs, and their needs and wishes. There is a lot of improvement potential, and in this research we will focus on improving the insights into the material usage of Isala and design an inventory model for managing the inventory for scan-relevant items.

A continuous review inventory policy is preferred, as the literature shows that these models consistently outperform periodic review inventory models. Since every scan-relevant item needs to be scanned during the procedure, the stock levels are already automatically tracked. This enables Isala to implement a continuous review policy, if they want to make some adaptions to their *Enterprise Resource Planning (ERP)* system. When an automated ordering system proves to be beneficial in terms of costs and inventory levels, there is the possibility to include more products in the continuous review inventory system. These products then do need to be scanned before usage. Furthermore, an exact solution approach is preferred over simulation based solutions. A better solution is obtained by optimally solving a mathematical program, and performing a small simulation to show performance, then by only simulation study. Multiple models include a central warehouse that is optimised together with point-of-use locations. For our case at Isala, we will implement the proposed model without optimising the central warehouse, which can be HL.

Currently many unnecessary emergency orders occur to ensure product availability at Isala. The introduction of an expedite-up-to, or emergency order level, that determines when it is necessary to place an emergency order can decrease these numbers. The introduction of this parameter seems contradictory to the aim of constructing an inventory model, as the goal is to prevent stock outs and emergency orders; however, the addition of the emergency order level can help educate employees that these orders are not always necessary.

Following the above reasoning the aim of this research is to construct an inventory model that is optimally solved by a mathematical program. A continuous review (s, S) inventory model is preferred, due to it outperforming other types of models. The level of s will be initialised using the previously described formula with lead time and demand uncertainty in Section 2.3. Furthermore, the order-up-to level S and the emergency order point are the variables to be optimally solved by the constructed mathematical program.

The gap in literature that is addressed is the lack of a point-of-use inventory model incorporating lead time and demand uncertainty with the addition of an emergency order level. The goal is to develop a model that decreases unnecessary emergency ordering and that copes with lead time uncertainty, which is currently common due to global material shortages. Since the distribution of lead time uncertainty has no golden standard in literature it is determined by means of data analysis.

As a service-level measure, the *Cycle Service Level (CSL)* is used. It measures the number of cycles without stockout. The CSL is suited to a hospital context due to the risk avoiding behaviour of physicians, and the need for surgical products to always be available. Furthermore, for the demand a Poisson distribution is used, as it is determined to be best practice.

Chapter 3

Modelling

In this chapter the mathematical model is constructed. The model can be adjusted to have two objectives with varying weight. The objectives of the model is for one, to minimise costs, and second to minimise the total required storage space. Section 3.1 introduces the stochastic program that is constructed by means of Mixed Integer Programming (MIP), the mathematical notation is denoted in Section 3.2, the assumptions are denoted in Section 3.4. Lastly, Section 3.5 concludes this chapter and reflects on the constructed mathematical model.

3.1 Introduction

From Chapter 2 it becomes apparent that the best suited inventory management system for the given context is an (s, S) inventory system where a replenishment order is placed that replenishes the inventory up to level S, should the inventory position drop below the level s. In order to determine the levels S and s a stochastic programming approach is used that provides optimal levels for these parameters. The constructed model is a scenario-based stochastic program that incorporates uncertainty in future demand and lead times in the current decision making. Furthermore, the model proposes an emergency-order-level that determines when one should place an emergency order for a product, to counter unnecessary emergency ordering that is currently common practice at Isala. The proposed model adds to the currently available literature as there is sparse research into the optimisation of restocking point-of-use locations, especially for consumable goods in the healthcare sector. Furthermore, incorporating an emergency-order-point and lead time variability has to the best of our knowledge, not been considered in the literature before. In this research two variants of the model are constructed. One model uses a stationary s and an upper bound for the level S that consist of the level s plus the EOQ. The second model includes the value of s in the optimisation, and sets an upper bound for S high enough.

The objective of the stochastic program model is twofold. First, the model aims to minimise the costs. Second, the model minimises the total space usage as the hospital often copes with a lack of available storage space. There is also the possibility to assign weights to the two objectives such that they are both accounted for, this is however further elaborated on in Chapter 5 where experiments are conducted.

The first model uses a set value for s based on the expected lead time demand, the desired service level, and the lead time and demand variability [8]. This according to the following formula, previously mentioned in Chapter 2:

$$s = E(DL) + z\sqrt{E(L) \cdot var(D) + \ [E(D)]^2 \ \cdot var(L)}$$

The level s serves as a lower bound for the order-up-to level S, which is optimised by solving the stochastic program. Furthermore, to set a bound for the maximum value of S the level s plus the Economic Order Quantity (EOQ), previously mentioned in Chapter 2, of the respective SKUs is used. As the EOQ gives high restocking values because it does not take into account

FIGURE 5: An example of possible s, S, emergency-order-point and inventory position level changes by the model over time periods t

the SKU lead time. Since the hospital desires JIT inventory management with low lead times the level of S is expected to achieve better performance if the value is lower than s plus the EOQ, causing $s + EOQ$ to be a good maximum value for S. Next to the order-up-to level the model also calculates an optimal value for the emergency order point. The emergency order point is bounded between 0 and the level s, as it could be possible that emergency orders are never needed, or for products of which the demand is low it can be optimal to immediately emergency order and keep less stock. The amount that is emergency ordered is the expected demand over the lead time. This is a logical value as emergency orders only occur if a normal order is placed simultaneously, or in a previous time period, as the emergency order level is lower than the level s. It is thus not needed to order a larger amount to replenish stock.

An example on possible model performance for a random SKU is shown in Figure 5. The figure shows that when the current on-hand inventory drops below the emergency order point, an emergency order is placed. Furthermore, when the inventory position (IP) drops below the reorder point s an order is placed to replenish the stock up to the order-up-to level S. The levels of the emergency order point and S vary over time, as the model adjust these levels based on various demand scenarios. In case of the second model the reorder point s is also optimized, and can thus differ over time. Do note that for illustration purposes the inventory position and on-hand inventory are viewed as the same. It is possible for an emergency order to be placed should the on-hand inventory drop below the emergency order level, whilst there is already inventory in the pipeline.

Furthermore, the model draws for every time period t a number of k different demand scenarios, as illustrated in Figure 6, where two time steps are denoted with their demands d1 and d2 respectively. Furthermore, the figure is expanded to include the entire range $t \in T$ and $k \in \kappa$. The model takes into account these multiple demand scenarios and optimises based on all the possible demand realisations. The demand in the scenarios is drawn using a Poisson distribution [8], as previously mentioned in Chapter 2. Since the demand for the next time period is independent of the demand realisation of the current period the same set of possible demand realisations k is used for every branch of the scenario tree at time t. For every time period t a new set of possible demand realisations is drawn.

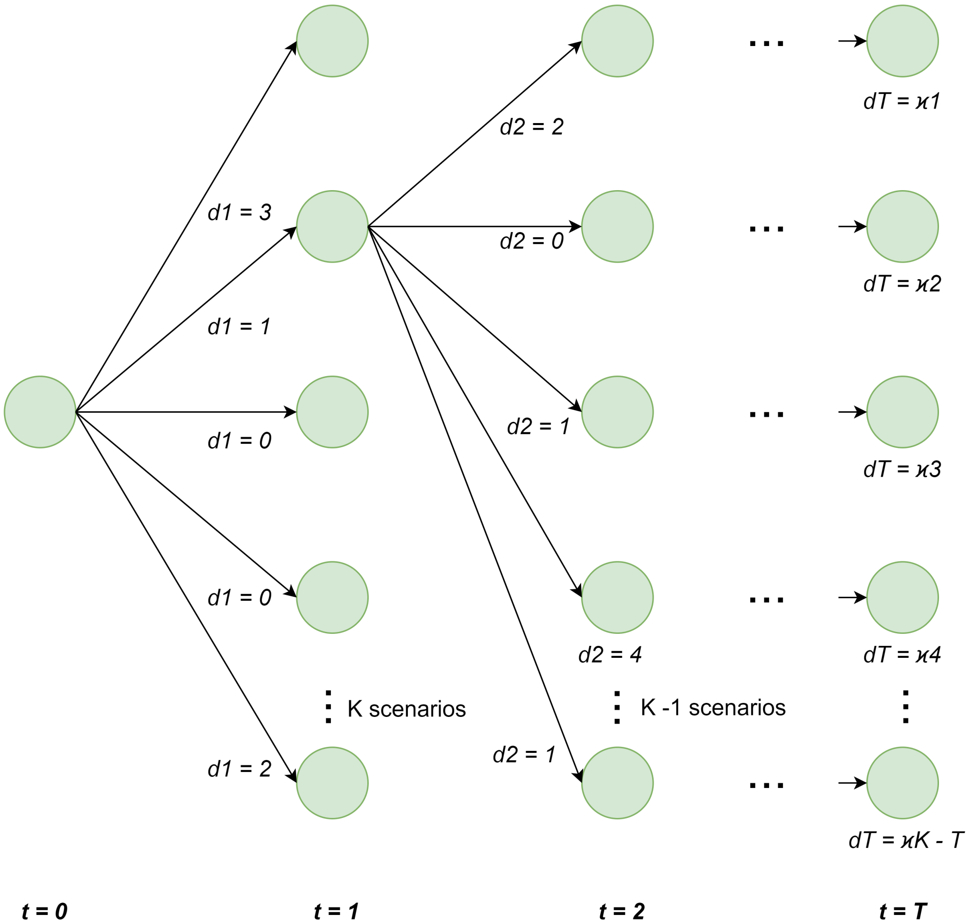


FIGURE 6: Scenario tree with possible demand realisations $k \in \kappa$ per time step $t \in T$ for a single SKU

In order to increase running times the scenario set depicted in Figure 6 will decrease with time, as expected demand in a later time period is less important than possible demand realisations in the next time step, and since most SKU lead times are short. The scenario set will decrease with one for every time period, until the scenario set has a length of one. Meaning that when the number of time periods is larger than the initial length of the scenario set that for these last time steps every node has one demand realisation.

3.2 Mathematical formulation models

In this section the two different inventory models are mathematically denoted. For the second model just the changes are denoted, as most of the constraints are similar.

3.2.1 Model 1: stationary s and EOQ

In this section the mathematical model formulation in given. First the different indices, parameters, constant, and decision variables are described. Hereafter the objective function is explained and the levels s, EOQ, and the scenario set determined. Following, the constraints are denotes, ending with the model parameters.

Indices

t	Index for the time period (t = 1, 2, .. , T)
m	Index of SKU (m = 1, 2, ..., M)
k	Index of scenario (k = 1, 2, ..., K)

Parameters

s_m	Reorder point of SKU m
EOQ_m	Economic Order Quantity of SKU m
$E(D_m)$	Expected demand for SKU m during period t
$E(D_m^L)$	Expected demand for SKU m during its lead time L
$E(L_m)$	Expected replenishment lead time from external suppliers to hospital per SKU m denoted in the unit of time periods t before arrival
σ_m^L	Standard deviation of the lead time of SKU m
σ_m^D	Standard deviation of demand D of SKU m
I_m^{Init}	Initial inventory of SKU m
$C_m^M at$	Cost of one unit of SKU m
$C_m^U O$	Emergency ordering cost of SKU m
UO_m^L	Emergency order lead time of SKU m
κ_{mtn}	Scenario set containing the demand scenarios k dependent on the previous node n in time period t for SKU m

Constants

C^O	Ordering cost of the external supplier (€/ batch)
C^D	Delivery cost of logistic partner (€/ delivery)
h	Fraction of SKU cost C_m as holding cost per time period t
CSL^{min}	Required minimum cycle service level
z	Safety factor associated with the CSL
PF	High penalty value for stockout (€/ stockout)
$BigM$	Large value used to set binary variables
K	Initial size of the scenario set
p_t	Probability of scenario k for every SKU m in time period t

Decision variables

R_{mtk}	Replenishment quantity of SKU m in time period t and scenario k
R_{mtk}^{ord}	Replenishment quantity ordered, but yet to arrive of SKU m in time period t and scenario k

S_m	Order-up-to level of SKU m in time period t and scenario k
UOP_m	Emergency / urgent order point of SKU m in time period t for scenario k
O_{mtk}	Binary variable indicating an order for SKU m in time period t and scenario k
O^{quan}_{mtk}	Order quantity for SKU m in time period t and scenario k
UO_{mtk}	Binary variable indicating an emergency, or urgent, orders for SKU m in time period t and scenario k
UO^{quan}_{mtk}	Emergency order quantity for SKU m in time period t and scenario k
I_{mtk}	Inventory of SKU m at the end of time period t and scenario k
SO_{mtk}	Binary variable indicating a stockout for SKU m in time period t and scenario k
M^C_{mtk}	Total material cost of all SKUs m in time period t and scenario k
O^C_{mtk}	Total ordering cost of all SKUs m in time period t and scenario k
I^C_{mtk}	Total inventory holding cost for SKUs m in time period t and scenario k
UO^C_{mtk}	Total emergency order cost of all SKUs m in time period t and scenario k
SO^C_{mtk}	Total stockout cost for all SKUs m in time period t and scenario k

Objective function

The objective Z to be minimised is the total costs incurred by the material handling of the hospital and is shown in Equation (5). The total cost incurred by the hospital is the sum with respect to SKU m, time t, and scenario k, of the various cost components M^C_{mtk}, O^C_{mtk}, I^C_{mtk}, UO^C_{mtk}, SO^C_{mtk} multiplied with the scenario probability p_k. The value is weighed by a factor α. The second part of the objective function regards the lack of available space for material storage at the hospital. This part of the function minimises the total maximum inventory of the hospital by summing with respect to SKU m, time t, and scenario k, over the order-up-to level S_m times the scenario probability p_k, and is weighted with value β.

$$Minimize\ Z = \underbrace{\alpha \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{k=1}^{K}}_{\substack{\text{Weight factors}\\ \text{and summation}}} p_k \overbrace{(M^C_{mtk} + O^C_{mtk} + I^C_{mtk} + UO^C_{mtk} + SO^C_{mtk})}^{\text{Different cost components}} + \underbrace{\beta \sum_{m=1}^{M} S_m}_{\substack{\text{Minimisation of storage}\\ \text{space usage}}} \tag{5}$$

Decision variables

Constraint (6) bounds the level of S to be above s, as the order-up-to level should always exceed or equal the reorder point. To clarify, an order is placed when the inventory drops below the level s, therefore the possibility for s and S to take the same value.

$$S_m \geq s_m \quad \forall \quad m \tag{6}$$

To reduce the solution space we also set an upper boundary for the level S. Since the EOQ provides relatively high values for the level S we take the level s plus the EOQ of its respective SKU m, EOQ_m, as an upper bound. This constraint is shown in Equation (7).

$$S_m \leq s_m + EOQ_m \quad \forall \quad m \tag{7}$$

The Emergency Order Point (UOP) is determined by the stochastic program. The variable is bounded to be less than or equal to the reorder point s in Constraint (8).

$$UOP_m \leq s_m \quad \forall \quad m \tag{8}$$

Non-negativity constraint

Furthermore the UOP_m, I_{mtk}, and R^{ord}_{mtk} must be a non-negative integer. Constraints (9), (10), (11) bounds these variables.

$$UOP_m \ \geq 0 \quad \forall \quad m \tag{9}$$

$$I_{mtk} \ \geq 0 \quad \forall \quad m, t, k \tag{10}$$

$$R^{ord}_{mtk} \ \geq 0 \quad \forall \quad m, t, k \tag{11}$$

Nonanticipativity constraints

We must ensure that no knowledge of future events is taken into account when solving the stochastic program. This is incorporated by ensuring that the taken decision is the same for all scenarios stemming from the same nodes of the previous time steps. Since the levels S_m and UOP_m are determined by the stochastic program the following nonanticipativity constraints are incorporated in the model. Constraint (12) denotes that for every SKU m in time period t with previous scenario tree node n the same decision must be made for all scenarios k and previous tree nodes in κ_{mtn}.

$$S_m^{CurNode} = S_m^{Node(n)} \quad \forall \quad m, t, k \in \kappa_{mtn} \tag{12}$$

Furthermore, constraint (13) determines that the emergency-order-point needs to be equal for every SKU m in time period t with previous tree node n for every scenario k in κ_{mtn}.

$$UOP_m^{CurNode} = UOP_m^{Node(n)} \quad \forall \quad m, t, k \in \kappa_{mtn} \tag{13}$$

For each scenario the demand of future periods cannot be known by the model, and thus not used in determining the levels for S_m and UOP_m in the current time period. Since every demand scenario is independent of previous demand scenarios for every time period the same samples are used for every branch of the scenario tree. Furthermore, since predicting the far future becomes less important due to the in general fast delivery times the number of scenarios taken into account decreases over time. This gives the following set of demand scenarios κ_{mt}, that consist of $K - t$ values with demand scenarios for SKU m in time t with previous node n, with a minimum of one demand scenario in later time steps if t is larger than K. K is the initial size of the scenario set as mentioned in the constants. Each demand scenario is denoted by ξ_{mtk}, the set of demand scenarios is denoted mathematically in Equation (14).

$$\kappa_{mtn} \ \in \ [\xi_{mtn\ k=1};\ \xi_{mtn\ k=2};\ ..;\ \xi_{mtn\ K-t}] \quad \forall \quad m, t, n \tag{14}$$

Variables

The number of units emergency ordered for SKU m in time period t is determined in Equation (15). The equation consists of the binary variable UO_{mtk} on whether an emergency order is placed, times the expected demand over the order lead time.

$$UO_{mtk}^{quan} \geq E(D_m^L) \cdot UO_{mtk} \quad \forall \quad m, t, k \tag{15}$$

Equation (16) and (17) denote the inventory I_{mtk} for SKU m at the end of time period t for scenario k. The first time step the inventory is initialised to I_m^{Init}. The inventory at the end of a time period t is the inventory from the previous time period $I_{m,t-1,k}$, plus the replenishment quantity R_{mtk}, minus the demand of the current period ξmtk, plus the quantity emergency ordered with emergency lead time $E(UO^L)$ periods ago $UO_{m,t-E(UO^L),k}^{quan}$. Lastly, in case of a stockout the demand for that scenario is replenished. When $t = 0$ the initial inventory for each SKU m is I_m^{Init}.

$$I_{m0nk} = I_m^{init} \tag{16}$$

$$I_{mtk} = I_{m,t-1,k} + R_{mtk} - \xi_{mtnk} + UO_{m,t-E(UO^L),k}^{quan} + SO_{mtk} \cdot \xi_{mtk} \tag{17}$$

Whether SKU m is ordered in time period t in scenario k is denoted in Equations (18) and (19). Should the current inventory I_{mtk}, plus the amount already ordered R_{mtk}^{ord} drop below the level s, then another order is placed.

$$s_m \geq I_{mtk} + R_{m,(t-1),k}^{ord} - BigM \cdot (1 - O_{mtk}) \tag{18}$$

$$s_m \leq I_{mtk} + R_{m,(t-1),k}^{ord} + BigM \cdot O_{mtk}) \tag{19}$$

Equation (20) denotes the quantity ordered of SKU m in time period t. The amount that is ordered is the difference between the order-up-to level S and the current inventory on hand, minus the amount already ordered in previous time periods, minus the amount emergency ordered. This ensures that SKU m gets restocked up to le vel S. An order is only placed if the current inventory position drops below the reorder point s.

$$O_{mtk}^{quan} \geq O_{mtk} \cdot (S_m - I_{mtk} - R_{m,t-1,k}^{ord} - UO_{mtk}^{quan} - UO_{m,t-1,k}^{quan}) \quad \forall \quad m, t, k \tag{20}$$

Equation (21) and (22) sets the emergency orders binary in time period t to 0 or 1 dependent on whether the on-hand inventory I_{mtk} plus the amount emergency ordered drops below the emergency order point UOP_m. The maximum number of emergency orders to occur is one per time period.

$$UOP_m \geq (I_{mtk} + \sum_{i=t-E(UO^L)}^{t} UO_{mik}) - BigM \cdot (1 - UO_{mtk}) \tag{21}$$

$$UOP_m \leq (I_{mtk} + \sum_{i=t-E(UO^L)}^{t} UO_{mik}) + BigM \cdot UO_{mtk} \tag{22}$$

Equation (23) is a variable that determines the replenishment quantity for SKU m in time plus expected lead time $t + N_1(E(L_m), \sigma_m^L)$. Where a normal distribution is used to draw a lead time based on the mean and standard deviation. The replenishment quantity is applied to all scenarios k in that time step for all nodes originating from the initial node.

$$R_{m,\ t+N_1(E(L_m),\sigma_m^L),\ k} \geq O_{mtk}^{quan} \quad \forall \quad m,t,k \tag{23}$$

Equation (24) determines the number of units of SKU m already ordered in time period t, but not yet received. This number is based on the number of units already ordered in the previous time period $R_{m,t-1,k}^{ord}$, minus the received replenishment order R_{mtk} and the emergency order that arrives $UO_{m,t-L(UO),k}^{quan}$, plus the amount ordered O_{mtk}^{quan} and the amount emergency ordered UO_{mtk}^{quan} . Furthermore, since this parameter can become negative, we need to add a non-negativity constraint shown in Equation 25.

$$R_{mtk}^{ord} \geq R_{m,t-1,k}^{ord} - R_{mtk} + O_{mtk}^{quan} + UO_{mtk}^{quan} - UO_{m,t-UO_m^L,k}^{quan} \quad \forall \quad m,t,k \tag{24}$$

$$R_{mtk}^{ord} \geq 0 \quad \forall \quad m,t,k \tag{25}$$

Equations (26) and (27) set the stockout binary SO_{mtk} 1 if a stockout occurs for SKU m in time period t for scenario k. Otherwise this value is set to 0. A large penalty factor is associated with a stockout, as this is a health risk for the patients in the hospital. This cost factor is applied in Equation (35).

$$0 \geq (I_{mtk} - 1) - BigM \cdot (1 - SO_{mtk}) \tag{26}$$

$$0 \leq (I_{mtk} - 1) + BigM \cdot SO_{mtk} \tag{27}$$

Lastly, Equation (28) denotes the probability of each scenario in time step t. Since every scenario is equally likely to occur, and are distributed i.i.d., the value of p_t is one divided by the number of nodes in the current time step denoted by $Nodes_t$. The number of nodes in time step t, denoted in Equations (29) and (30), is the number of scenarios in the initial set, minus t, plus one, times the nodes in the previous time step, as the size of the scenario set decreases with one every time step. Once t becomes larger than the length of the initial scenario set the scenario set will be size one for all following time periods, and keep the same node probability. The while and else statements are possible, as the node probability table is calculated before running the model and used as static input, thus having no influence on linearity.

$$p_t = \frac{1}{Nodes_t} \tag{28}$$

$$Nodes_t = \begin{cases} Nodes_{t-1} \cdot (K - t + 1) & while\ t <= K\ and\ t > 0 \\ Nodes_{t-1} & else \end{cases} \tag{29}$$

$$Nodes_0 = 1 \tag{30}$$

Cost parameters
The material cost for every SKU m in time period t and scenario k is considered in Equation

(31). The SKU material costs is the SKU price $C_m^M at$ times the ordered quantity, O_{mtk}^{quan}.

$$M_{mtk}^C \geq C_m^{Mat} \cdot (O_{mtk}^{quan} + UO_{mtk}^{quan}) \quad \forall \quad m,t,k \tag{31}$$

Equation (32) determines the ordering cost per time unit t for SKU m in scenario k. The ordering cost is incurred if an order is placed at the hospital during time period t. The ordering cost include the transportation and transaction cost of as well the external supplier and hospital logistics. The ordering cost in period, O_{mtk}^C, is the ordering cost C_m^O plus the delivery cost C_m^D, times whether SKU m is ordered O_{mtk}.

$$O_{mtk}^C \geq O_{mtk} \cdot (C_m^O + C_m^D) \quad \forall \quad m,t,k \tag{32}$$

The cost of inventory per time period t for SKU m and scenario k are determined in Equation (33) and denoted by I_{mtk}^C. The inventory costs amount to the fraction of SKU cost as holding cost h times the SKU cost C_m times the inventory at the end of time period t, I_{mtk}.

$$I_{mtk}^C \geq h \cdot C_m \cdot I_{mtk} \quad \forall \quad m,t,k \tag{33}$$

The emergency ordering costs per time period t for SKU m in scenario k, UO_{mtk}^C, is denoted in Equation (34). These costs amount to the emergency order cost for SKU m, C_m^E, times the binary UO_{mtk} that denotes whether an emergency order is placed for SKU m in time period t.

$$UO_{mtk}^C \geq C_m^U O \cdot UO_{mtk} \quad \forall \quad m,t,k \tag{34}$$

The stockout cost per time period t for SKU m in scenario k is denoted in Equation (35) as SO_{mtk}^C. The stockout cost is the the binary variable SO_{mtk} that denotes whether there was a stockout in period t for SKU m and scenario k, times the stockout penalty factor PF.

$$SO_{mtk}^C \geq SO_{mtk} \cdot PF \quad \forall \quad m,t,k \tag{35}$$

3.2.2 Model 2: Optimised s and order quantity

This section denotes the changed made to the initial model in order to make s a variable that is optimised by the MIP. The inclusion of s is necessary when SKUs with low erratic demand and variation in demand and leadtime provide unrealistically high values for a stationary s. The need for application of the second model is further elaborated on in Chater 5 where the conducted experiments are denoted. The changes to model 1 needed to make s a decision variable that can be optimised are the following.

- Parameter s_m becomes a decisions variable of the model. The non-anticipativity is applied to s_m in the same manner as to S_m and UOP_m.
- The decision variable s_m is bounded to be one or higher, as an order is placed when the inventory level drops below the level s. The level s is bounded in Constraint (36).

$$s_m \geq 1 \quad \forall \quad m,t,k \tag{36}$$

- The EOQ is removed from the model. Constraint (7) that bounds the level S based on the EOQ is altered. S is now bounded large enough to expect to incorporates all optimal values. A check is performed after the optimisation if values of S reach the upper limit.

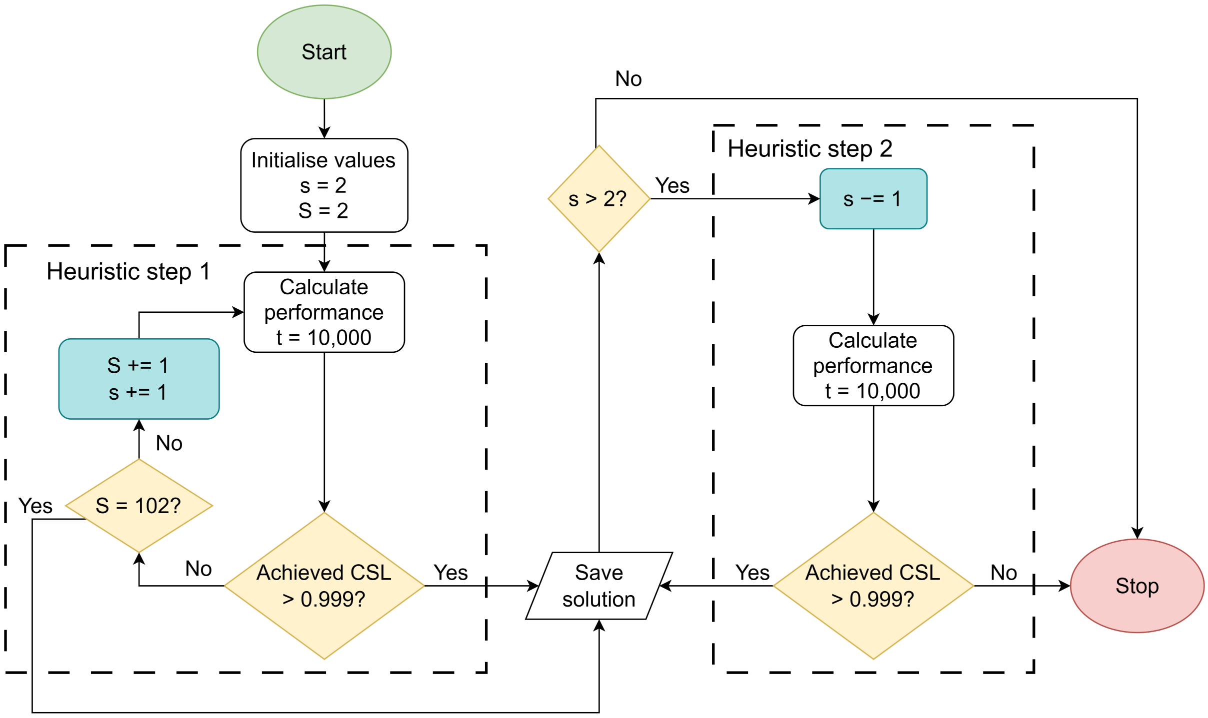


FIGURE 7: Flowchart depicting the heuristic solution approach, separated in a first and second step.

3.3 Heuristic

Since the stochastic programs proved to be unable to solve for data sets with small intermittent demand within reasonable time frames a heuristic is constructed to provide solutions for inventory systems with these characteristics.

Figure 7 shows the constructed heuristic and the steps it takes to calculate inventory levels. Initially the levels of s and S are set to two, as this is the lowest acceptable value due to stock outs occurring should there be demand and one unit of inventory. Performance is calculated over 10,000 time steps for the current levels for s and S. When a CSL of 99.9% is reached the level is deemed adequate and the solution is saved, otherwise the algorithm increases both levels with one. The algorithm is bounded on a maximum level for S and s of 102, to prevent infinite run time should a 99.9% CSL be impossible to obtain. The second step of the heuristic decreases the order point s by one if the order point is larger than two, and calculates performance. Should the achieved CSL still be above 99.9% the solution is saved and s is decreased further. If the CSL drops below the threshold the algorithm stops, and the last levels for s and S that achieved a CSL of above 99.9% is chosen as final solution.

3.4 Assumptions

All relevant assumptions with accommodating explanations are listed below.

1. Only one (emergency) order can be placed per time interval

Since lead times are short, with even faster emergency deliveries, a maximum of only one (emergency) order per time period is placed.

2. Larger SKUs are more expensive

Due to the limited storage space larger SKUs need to be penalised more than smaller SKUs. The holding cost is a penalty cost for having stock, it penalises more expensive SKUs as the holding cost is a percentage of SKU value. We assume that larger products cost more, as they are more extensively packaged, or generally bigger.

3. The ordered quantity is also the delivered quantity

The model assumes that all ordered SKU quantities are also delivered. From the experience of Isala it is proven that in reality it sometimes is the case that this does not happen. So, should the model be implemented, there also needs to be an additional check whether the ordered quantities are actually the delivered quantities.

4. All scan-relevant items are scanned during the procedure, and thus subtracted from the inventory position

Occasionally it is the case that items are not scanned during procedures, whilst it is obligatory by law. The model assumes that all products get scanned, so periodic checks are necessary to ensure that inventory levels do not decrease.

3.5 Conclusion

In this chapter the sub-question *"What is the mathematical model formulation, and what are the associated parameters?"* is answered. Two different mathematical models are constructed in Section 3.2. One that optimises the order-up-to level S and the emergency order point UOP with a stationary order point s. The second model includes s in the optimisation, and can be used if SKUs with low erratic demand give unrealistically high values for s, and values of 0 and 1 for the EOQ. The chapter describes the constructed heuristic that is applied to the small intermittent demand of the scan-relevant items. Lastly, the relevant assumptions are listed in Section 3.4.

Chapter 4

Case study: OR department Isala

In this section, the case of the OR department of Isala is discussed and analysed using available data. First, the data is validated and exclusions for this research are made in Section 4.1. Section 4.2 discusses the current performance of Isala, and illustrates problems previously identified. Section 4.3 discusses the available data on demand and illustrates the characteristics of the sporadic demand for scan-relevant items. Section 4.5 discusses the conclusions that can be drawn from the case study.

4.1 Data validation, preparation, cleaning

The data contained some missing or incorrect values. Furthermore, some assumptions are made and data is excluded.

Items not in stock anymore, the data between 2017 and 2022 contains many SKUs that are not in stock anymore because they became unavailable or are replaced with other SKUs. Of the total of 4,788 SKUs in the dataset, 3,634 SKUs are no longer used. This leaves us with 1,154 SKUs that are currently being used at the OR department.

1-1 level product are products that have a minimum and maximum stock level of 1. These products have an average demand of 0.0688 units over their respective lead times and amount to a total of 316 SKUs. Since only one of each of these products is in stock, it is always the case that an emergency order is placed should demand occur. The sporadic use of these products and the risk-avoiding behaviour of physicians causes the need to emergency order every one of these products. It is chosen to exclude these SKUs from the dataset as this research focuses on the inventory management itself, and not the change management required to implement it. 317 out of the remaining 1,154 SKUs had an 1-1 inventory level, and are thus removed. This leaves 837 SKUs in the dataset.

Negative average lead time, or an average lead time of 0 days, is present in the dataset for some SKUs. For both cases, the values are modified to the average lead time in the dataset. The number of orders that had incorrect data was low, so these values are assumed to be small data discrepancies. These values are not possible, and thus deemed faulty data.

SKUs ordered once in the dataset do not have a standard deviation in lead time. The standard deviation in lead time of these SKUs is set to the average standard deviation of all SKUs.

Wrong order data is present in the data sheets. A total of 3 order sizes have been altered since they were abnormally large. Three orders in the database consisted of 1000+ units. Upon further investigation, the average order size for these SKUs was 1, and abnormally large values are altered to this number. The next largest order size was about 30 units, and not inconsistent with other orders of this SKU type. So we can assume that all order size outliers are now removed.

Data analysis from this point in the report forward is conducted with the dataset after the previously mentioned exclusions, which amounts to a total of 837 SKUs.

4.2 Current performance

Chapter 1 identified the problems that arise at Isala and determines the scope of the research. In this section the posed problem is substantiated with numerical examples, and it shows that the identified problem is supported by findings from the data.

4.2.1 Usage vs stock levels

Figure 8 plots the maximum stock level determined for ten SKUs compared to their average yearly orders. The figure shows the five SKUs that have the least usage, and the five SKUs with the largest ordering quantity. The SKUs with the least usage have significantly higher maximum stock levels than yearly order quantity. Furthermore, the five products that have the highest deviation in ordering and maximum stock level have vastly lower stock levels compared to their ordering. On average 30% of all SKUs deviate more that 5 units with their maximum stock level. The figure confirms our suspected flaws with the current inventory management system described in Chapter 1. Data shows that 94.7% of orders arrive within 11 days. Furthermore, it becomes apparent that 803 of the 837 SKUs have a higher maximum stock level than their demand over a two-month period. This confirms the expectation that stock levels are relatively high and can be lowered.

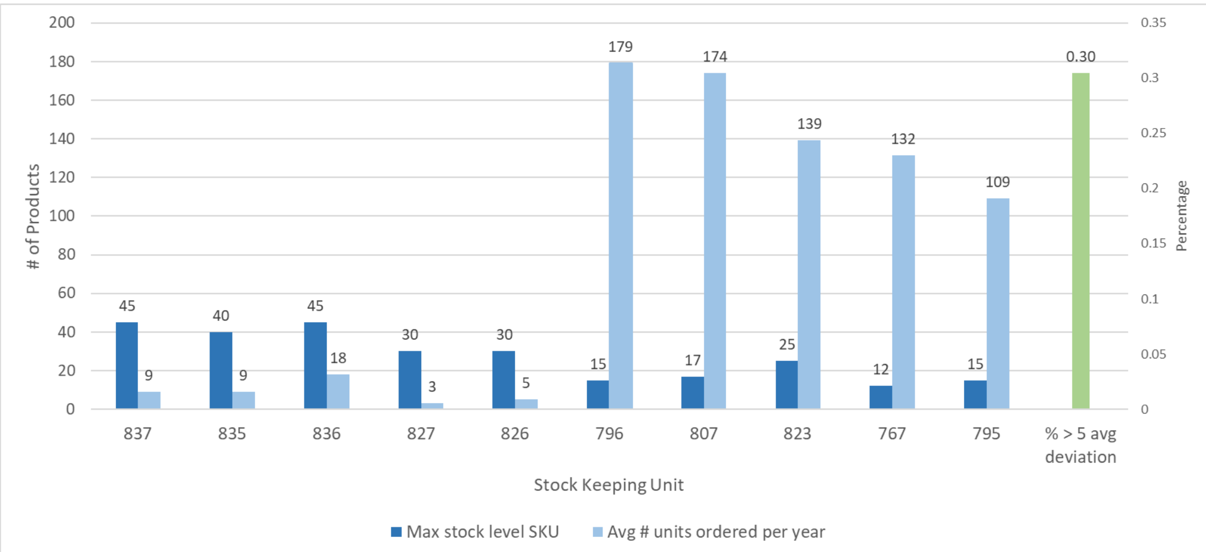


FIGURE 8: The maximum stock levels versus the average yearly orders for the 5 most deviating SKUs in the least and most usage. Including the fraction of SKUs on average deviating more than 5 units per order.

4.2.2 Order sizes

Figure 9 shows the five most deviating SKUs in terms of order size in deviation per order. From the min and max levels a predetermined order size is calculated. However, from the figure it becomes apparent that the current ordering policy does not follow these predetermined levels. Figure 9 shows an average order size for the five most deviating products to be about 1 to 4, whilst a vastly larger order size should be used according to the data. This illustrates

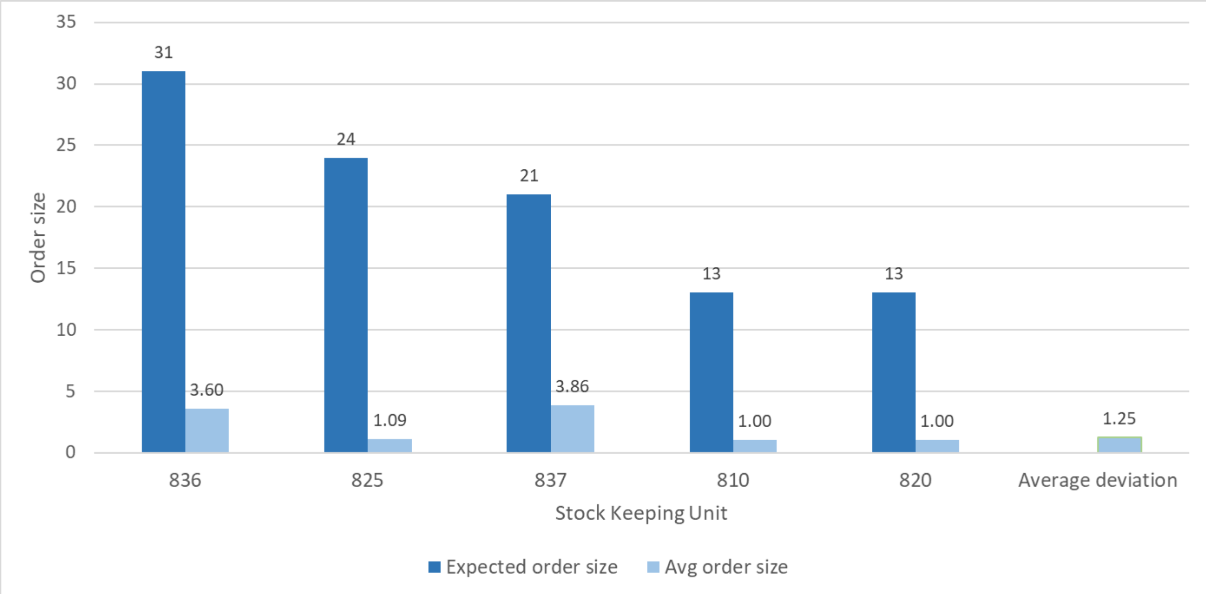


FIGURE 9: Predetermined order sized versus the actual order sizes from data for the five most deviating SKUs, including the average over all SKUs.

the risk-avoiding behaviour and the distrust in the inventory system of employees. Once a mathematically substantiated system is constructed, it is important that employees follow this system. Furthermore, the average deviation between the expected and actual order sizes is 1.25. The value seems low, however, as most orders sizes consist of single product orders an average deviation of 1.25 units is substantial.

The OR department does not work with set Key Performance Indicators (KPIs) to measure their performance. The general consensus is that when there are units in stock, it is going well, without digitally monitoring the stock levels. The OR department does keep some safety stock in order to accommodate emergency surgeries. However, this number is not a determined value, but based on experience. The absence of KPIs and mathematically substantiated inventory systems or safety stocks emphasises the need for an optimised inventory management system. Furthermore, of the included SKUs, 12 do not reach the required CSL of 99.9%.

4.3 Demand

The demand for scan-relevant products is for many SKUs sporadic. There are 228 products of 837 that have orders of equal to or less than 2 per year for the period of 2017 to 2022. Only 23 our of the 837 products are ordered weekly, with the most popular product having an average of 179.17 units ordered per year. The other SKUs have orders between 2 and 52 units per year. Although the demand for scan-relevant products is low, the total value of these products is high because most SKUs are highly patient-specific and of high quality. The total value based on the current maximum stock levels of all included SKUs amounts to €2, 062, 322.34, with the total amount of stock being 4, 675 units. Over the years 2019-2022, waste is known. The average waste over this period amounts to €92,462 annually and is caused by products that go past their due date.

TABLE 1: Performance of the current method of inventory management averaged over the years 2017-2022.

Cost /Factor	Avg per year
S	4,603
E(CSL)	99.97%
nr. SKUs CSL < 99.9%	12
Inventory	€ € 545,000
Ordering	€ 100,000
Material	€ 2,114,000
Emergency	€ 201,000
Stockout	€ 916,000
Total costs	*€ 3,877,000*
Total costs wo Stockout	*€ 2,960,000*

4.4 Costs current inventory policy

In order to compare the model performance to reality the average annual costs of the current inventory management method are calculated and the findings are reported in Table 1. The values are the average costs over the period of 2017-2022. The level S is determined by taking the maximum stock levels of all SKUs currently stored at the OR department. Furthermore, the current cycle service level is estimated by drawing a Poisson distribution with the average on stock inventory and the expected demand over the lead time.

Table 1 shows that the current inventory policy of Isala achieves high values for the cycle service level and on average keeps to their stated wish to have a Cycle Service Level (CSL) of 99.9% to ensure product availability. The stock level S is high, since the average demand per year for all products amounts to 5,839.17 units annually, averaged over the years 2017-2022. This means that the maximum stock level is 78.83% of the annual demand, or 4,099% of the weekly demand. With the majority of lead times ranging from 1 to 10 days it is unnecessary to keep stocks of this quantity, which leads to increasing inventory costs, and being the main cause of the problems the OR department experiences with limited storage space. Note that the maximum stock level is not the stock that is on average in the inventory. However, with the frequent ordering of Isala, the average stock level will be near this maximum. The stockout costs are calculated using the achieved average cycle service level of 99.97%, where 3 out of every 10,000 days each SKU has a stockout. Since stockout costs are an artificial cost based on a penalty factor determined in this research the total not including these costs is included in the table.

4.5 Conclusions

In this chapter we have answered the sub-question *"What is the current situation at Isala with regards to their inventory policy, performance on KPIs, and minimal stock levels?"* The current inventory management system most resembles an (s, Q) system with automatic orders should an SKU drop below level s, if the employees do not intervene with the ordering. However, this is done frequently, as becomes apparent from the expected order sizes and the actual order sizes displayed in Figure 9. Furthermore, the levels s and Q are arbitrarily determined and are not calculated or checked for revision. It can thus be concluded that the OR department of Isala does not use any kind of mathematically substantiated inventory model for their SKUs. Furthermore, the hospital does not use any KPIs, which means that they are not measuring their performance in any way. Lastly, there are minimal stock levels per SKU to accommodate emergency surgeries, but these stocks are not a calculated value.

The current performance of Isala in terms of costs, maximum inventory levels, and CSL is calculated. The average annual costs for the OR department amounts to €3,709,714.91, with a CSL of 99.97% and the maximum amount of inventory in stock being 4,603 units. The unnecessarily high maximum stock levels are identified to be the main cause for the issues the OR department experiences with limited storage space. Furthermore, the OR department has 12 SKUs that do not meet their CSL requirements.

Chapter 5

Model Experiments

In this chapter the various inputs to the stochastic program are determined in Section 5.1. After the input the experiments on the first stochastic model are discussed in Section 5.2. The first stochastic model included the stationary levels for s and the EOQ. Following this, the experiments of model two are discussed in Chapter 5.3, where the level s is determined by the model, and there is no upper bound for the order-up-to level S. The heuristic experiments are denoted in Section 5.4. The chapter is concluded in Section 5.5.

5.1 Model input

5.1.1 Time period and scenario set

In this subsection the sampling approach is discussed. The levels for the time steps t and the maximum size of the scenario set κ are determined. Since we encounter memory issues when running the different models the time step and scenario size is chosen such that it still fits within the memory of the computer, whilst having the largest possible amount of demand realisations. The results of these experiments can be seen in Table 2. It can be observed that all experiments with a scenario set that is larger than four caused a memory error. An increase in scenario set size drastically increases the number of nodes that needs to be calculated. When the scenario set would be increased from four to five this would mean five times as many nodes for the model to calculate. When the size of the scenario set is determined, experiments are run on the largest possible value of t that the model can run. The model started to increase in run-time when using twenty time steps. Since $(t = 20)$ incorporates more than 95% of lead times, as determined in Section 5.1.3, this number of time steps is determined to be adequate. The model ideally needs to be able to place orders that arrive within the time steps, and this is achieved with a time horizon of twenty days.

5.1.2 Demand

The demand distribution implemented into the model uses a simple exponential smoothing over the years of 2017-2022 to be used as expected yearly demand. The choice of simple

TABLE 2: Experiments time step and scenario size.

Experiment	Scenarios	Time steps	Runtime
1	10	20	N/A
2	6	10	N/A
3	5	10	N/A
4	4	10	3:28
5	4	15	3:34
6	***4***	***20***	***40:32***

smoothing is based on the fact that most SKUs do not have a clear upwards or downwards trend, and average yearly order sizes also vary. Since the demand seems random, the choice for simple exponential smoothing is made, as this smooths the fluctuation in demand, without needing a trend. Reasonable values for the smoothing factor α range between 0.1 and 0.3 [8]. Since on visual inspection the demand fluctuation seems quite random, an α level of 0.3 is chosen. This gives more weight on demand of recent years, as these are deemed more significant with erratic demand patterns. The formula used for exponential smoothing is denoted below. x_t denotes the realised demand from the previous period, and $\hat{x}_t$ is the expected demand for the next time period, in our case the year 2023.

$$\hat{x}_t = \alpha * x_t + (1 - \alpha)\hat{x_{t-1}}$$

With the expected demand for the year 2023 a daily demand is calculated. The model draws demand realisations based on a Poisson distribution as described in Chapter 2. Since the variance of all demand realisations are above one a Poisson distribution is deemed a good fit [8].

The demand for many SKUs is low. When running the model at memory limits there is still a significant part of SKUs without demand. When the SKUs in the model have little to no demand the model is unable to determine optimal stock levels for these SKUs. 100 runs of demand generation are performed, and in these runs an average of 560.82 SKUs do not have any initial demand. SKUs in the model that do not have any initial demand according to the Poisson distribution will get assigned a demand realisation of one in a random time step for a random scenario. This ensures that all SKUs in the model have demand, and thus the possibility to be ordered. Next to the demand generation, it is chosen to exclude all SKUs below 0.15 units of expected demand over their lead time, as the model will not yield results for these SKUs due to no demand occurring within the models time steps. This leaves 241 out of the initial 837 SKUs that are optimised by the mathematical model. Since the demand over the lead time for the excluded SKUs is low the maximum and minimum stock levels are set to two, such that when there is demand for these SKUs, there is still one unit in stock to prevent emergency orders and stock outs. Should demand for one unit occur, a replenishment order of size one is placed.

5.1.3 Lead time variability

The lead time for most SKUs is not the expected lead time. The lead time ranges from 1 to 15 days for *95%* of the orders. The data shows that from the period of 2017 to 2022 $12,946$ out of $24,217$ orders had a different delivery date than expected. This amounts to *53.45%* of orders having a deviation in delivery date. A factor influencing this deviation is that the scan-relevant SKUs are not in stock at HL. These products are cross-docked and have longer lead times. This since the products move from supplier, to HL, to Isala.

When an order is placed the mathematical model draws a lead time. This lead time is assumed to be normally distributed, and is based on the SKUs average and standard deviation. The lower bound for the lead time is at least two days, as this is the number of days it takes before an emergency order arrives. Demand over the lead time is calculated by taking the average demand per day over the years that the product has been ordered, and multiplying the value with the average SKU lead time.

Figure 10 shows the absolute days of deviation in lead time from the expected delivery date for all orders from 2017 to 2022. In order to determine outliers, the interquartile range (IQR) is calculated, and all values above $1.5 * IQR$ are excluded. In this manner, all values above 49 days and below -28 days of deviation are not considered in the determination of SKU lead time. The figure shows a steady decrease in the number of orders when the days of lead time deviation

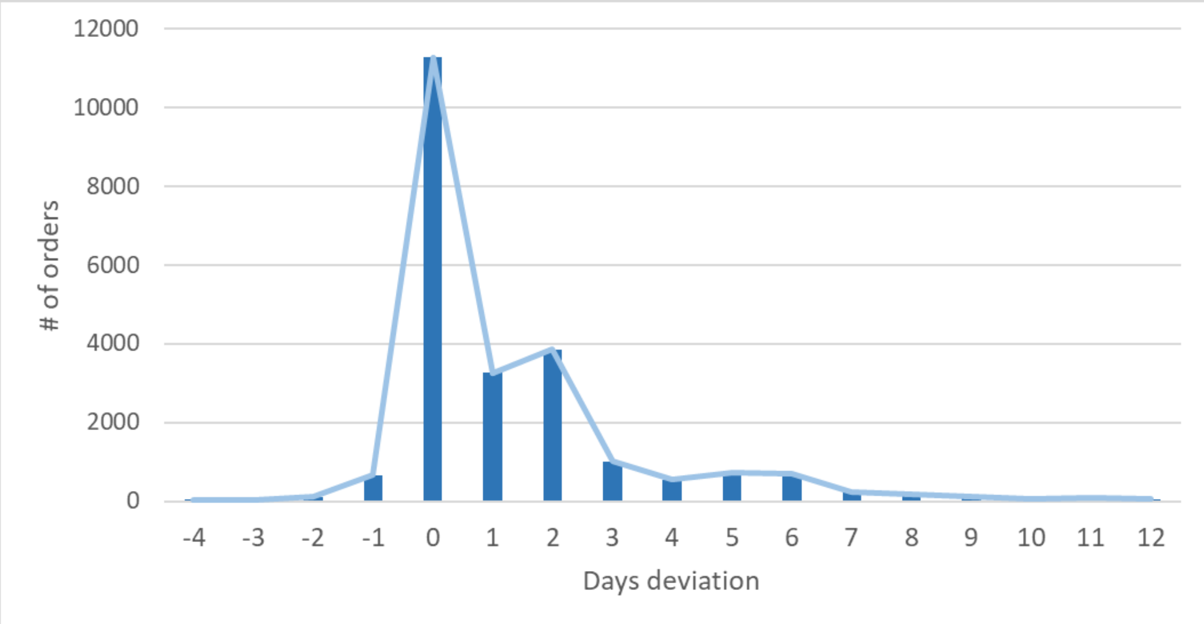


FIGURE 10: The days deviation of planned delivery date and actual delivery date.

increases or decreases. Thus, it can be concluded that the largest part of SKUs deviated at most 1 to 7 days from their expected delivery date.

5.1.4 Ordering and stockout costs

The costs need to be estimated, as the HL cost are not known exactly. For ordinary orders the average ordering costs amount to €23.89 per order. We assume the costs incurred by HL as a cross dock to be €1 per order.

The costs for emergency ordering are zero for HL as they cross dock the scan-relevant SKUs. Furthermore, the emergency ordering of scan-relevant items is done automatically by the system, and thus no personnel costs are incurred for these emergency orders [10]. We assume the emergency order costs to be double that of the order costs for a regular order. This amounts to €49.78 per emergency order.

For the stock out costs a high value of €9999 is taken. This value is substantially higher than the emergency ordering costs, as stockouts are highly undesirable. The high stockout cost discourages the model to use stockouts as policy to reduce inventory levels.

5.1.5 Number of replications

For the number of replications an adequately large number of runs is performed for every dataset that is experimented on. The number of replications is deemed adequate if the relative error is smaller than gamma prime (γ'). Where gamma prime is $\gamma/(1+\gamma)$. The mathematical formulation is denoted in Equation 37. S^2 denotes the sample variation and $\bar{X}$ the sample average. We take an α of 0.001, as the required CSL is 99.9%. Furthermore, a γ of 0.025 is used, giving $\gamma' = 0.02439$. Should the value of the left hand side of the equation be lower than the right the number of replications is deemed adequately large.

$$\frac{t_{0.9995,n-1} \cdot \sqrt{S^2/n}}{\bar{X}} \leq \gamma' \tag{37}$$

5.1.6 Model 1 specific inputs

Level s

The reorder point s is derived to be used as input value for every SKU in the optimisation algorithm for model 1. Equation (38) determines the initial levels of s for every SKU m. This level is based on the expected demand over the lead time $E(D_m^L)$, plus the safety factor z times an expression that incorporates the demand and lead time variability [8].

$$s_m = E(D_m^L) + z \cdot \sqrt{E(L_m) \cdot (\sigma_m^D)^2 + (E(D_m))^2 \cdot (\sigma_m^L)^2} \quad \forall \quad m \tag{38}$$

EOQ

To set a bound on the order-up-to level S, the Economic Order Quantity (EOQ) is used. Equation (39) shows how the EOQ is calculated. The EOQ denotes the optimal order size based on the expected demand per time period t, $E(D_m)$, the cost of ordering C^O, the cost of SKU material C_m^M and the fraction $(h \cdot 365)$ of SKU value as the holding cost fraction per day. The EOQ sets a maximum bound for the level S_{mt}. The MIP will thus consider all values of S_{mt} between s_m and EOQ_m. Since the EOQ can be a decimal number, all values will be rounded up before being loaded into the model.

$$EOQ_m = \sqrt{\frac{2 \cdot E(D_m) \cdot C^O}{C_m^M \cdot (h \cdot 365)}} \quad \forall \quad m \tag{39}$$

5.1.7 Constants

Below the constants of the mathematical model are listed. All experiments are run with these constant values. The values are obtained through data analysis, and in collaboration with employees of the OR department.

$C^O =$ €23.89	Ordering cost of the external supplier
$C^D =$ €1	Delivery cost of Hospital Logistics
$C_m^{UO} =$ €49.78	Emergency order cost
$h = 0.3/365$	Fraction of SKU cost C_m as holding cost per time period t
$z = 3.01$	Safety factor associated with the CSL
$PF = 9999$	High penalty factor for stockout
$UO_m^L = 2$	Emergency order lead time
$S_m^B oundSmall = 50$	Upped bound for S for the the scan-relevant data
$S_m^B oundLarge = 2000$	Upped bound for S for the large demand case

5.2 Experiments model 1

In this section, experiments performed with model 1, using calculated stationary values for s and EOQ, are discussed. Data analysis shows that for SKUs with low intermittent demand, the calculations for the value of s and EOQ are not representative, as high values are obtained due to demand and lead time variability. Since all scan-relevant SKUs have this low demand a second mathematical model is constructed, with its experiments denoted in Section 5.3. The number of replications needed for the large demand case are determined to be three following the method described in Section 5.1.5.

5.2.1 Large demand case

To test the performance of model 1 a larger demand case is constructed. The daily demand for the scan-relevant items is multiplied by a factor 1,000 and run for 20 time steps and an initial scenario set of 4. Since the scan-relevant items have longer lead times and larger standard deviations than in general items that are more frequently ordered the average lead time of the SKUs is set to two, with a standard deviation of one, similar to deliveries items in stock at Hospital Logistics. Emergency orders are set to be delivered in one day.

With this increase in demand, a stationary reorder point s is calculated. Furthermore, the EOQ is calculated to set a maximum bound for the order-up-to level S. The performance on scenarios with larger demand probability determine whether the constructed model has applications in other departments, or for other product types, with higher demand characteristics. If the model yields good results on a large demand case it opens opportunities for implementation in different departments.

When running experiments, the large demand case model could not be solved to optimality within ten hours. To obtain optimal solutions, another experiment is performed described in Section 5.2.2.

5.2.2 Optimally solved large demand case

Since the large demand case generates enough demand to provide all SKUs with initial demand, it is possible to reduce the initial size of the scenario set κ from 4 to 2. This enables the stochastic program to be solved optimally within reasonable time frames. The experiment uses the same input settings as in the large demand case described in Section 5.2.1.

5.3 Experiments model 2

This section described the experiments performed on model 2. To recall, model 2 is the stochastic program that determines the order point s itself. Furthermore, the model still determines levels for S and the UOP.

5.3.1 Scan-relevant dataset experiments

α and β experiments

To assess the influence of the levels of α and β on the objective function denoted in Equation 5 in terms of costs and maximum inventory a variety of different levels are input to the model. The variety of weight factors is used to make a trade-off between the lowest costs and the lowest stock for the scan-relevant items. Based on the results, Isala can select the weight factors of their preference and set their inventory levels accordingly. The different experiments are listed in Table 3.

TABLE 3: Values for α and β experiments.

Experiment	α	β
1	0	1
2	0.2	0.8
3	0.4	0.6
4	0.6	0.4
5	0.8	0.2
6	1	0

The initial inventory levels from the data set are quite high, and would not enable the model to order units as the majority of demand can be satisfied from stock. Thus, the initial inventory for all SKUs is set to $max(2, 3 * E(D_L))$. A minimal inventory of two is chosen as an inventory level of one would mean that every demand occurrence in the first time steps would cause a stockout.

Initial inventory

An experiment is conducted on a variety of initial inventory levels. The stochastic program runs for three different initial inventory scenarios. The initial inventory is determined by multiplying the initial inventory of the experiment α, β by factors [0.5, 1.5, 2]. The settings that are run with these initial inventories is the settings with the best performance from the α, β experiment. Best performance is measured in terms of costs, CSL, and total maximum inventory. A choice is made based on these findings.

5.3.2 Large demand case

In order to compare the performance of model 1 to model 2, the large demand case is optimised by model 2. The expectation is that, when able to be optimally solved, the performance of model 2 will be better, as model 2 gives more freedom to the stochastic program in determining optimal stock levels. Three replications are run as mentioned to be adequate in Section 5.2.

5.3.3 Validation simulation large demand case

In order to test expected real-life performance a validation simulation is performed on the optimally solved large demand case. The values for S, s, and emergency order point UOP determined by the model are used as stationary inputs. The model is run for 10,000 time steps and three replications, indicating performance should the model be implemented for a large demand scenario. Three replications are deemed sufficient for this experiment.

5.3.4 Toy instance emergency-order-point

Since the experiments with model 1 and model 2 showed that the stochastic program solves optimally without using an emergency order point an experiment is performed on a toy instance to show that the mathematical model does emergency order when needed. For this instance the input parameters are set such that emergency ordering in the first time steps will always benefit the program. The toy instance uses the following inputs:

- $M = 20$ (20 SKUs optimised)
- $I_M^{Init} = 4$
- $E(D_M) = Random(3, 5)$

- $E(L_m) = 4$
- $\sigma_m^L = 0$

With these input settings, and an emergency order lead time of one day, it is always beneficial to emergency order in the first time steps, as otherwise stockouts will occur.

5.4 Heuristic experiments

Since the stochastic programs are unable to determine optimal inventory levels for the scan-relevant items the heuristic algorithm is constructed. The experiments with this heuristic use the dataset of the scan-relevant items of the hospital and includes all 837 SKUs.

5.4.1 Emergency order point

As an experiment the heuristic uses a variety of factors to determine the emergency order point. The emergency order point is the rounded multiplication of the factor s in the heuristic algorithm. The factors that are used as experiment are $[0.0, 0.1, 0.2, 0.3, 0.4, 0.5]$. In total six experiments. The required number of replications for this experiment is six, following the method described in Section 5.1.5.

It is possible that the six experiments have different values for s and S due to the randomness of demand and lead time. The rounded average level of s and S is taken as the optimised value of the heuristic.

5.4.2 Lead time variability

SKUs are ordered a few times or only once a year, causing some SKU lead time variances to be large. This experiment determines whether a decrease in lead time variability would improve performance. Should it be the case that a lower lead time variability yields significant improvement Isala can choose to approach their suppliers and try to set more accurate lead times.

This experiment uses the stochastic program with an emergency ordering level of 0.3. Furthermore, the standard deviation in lead time is set to one for all SKUs.

5.4.3 Validation simulation

Since there is the possibility that the different replications produce different levels for s and S a validation simulation is performed to assess heuristic performance using the average values for s and S rounded up. The validation simulation is run for 10,000 time steps with six replications.

The model that is run with these initial inventories is the model with the best performance from the urgent-order-point experiment. Best performance is measured in terms of costs, CSL, and total maximum inventory.

5.5 Conclusion

In this chapter the subquestion *"How should the experiments be designed to reflect the expected real-world performance of the model as accurately as necessary?"* is answered. The experiments for the two stochastic programs are determined, together with their relevance. To estimate the expected real-world performance a validation simulation is constructed that determines the performance of the model over a long time period using values for S, s, and UOP determined by the model. Furthermore, experiments for the heuristic approach are described. The heuristic uses the dataset of the scan-relevant items exclusively.

The next subquestion that is answered,"*What are the different scenarios that need to be modelled?*", the chapter discusses the various experiments that need to be performed in order to determine model robustness should input factors change. The model is tested to a variety of scenarios with adequate replications. A large demand scenario is run for model 1 to see whether the model yields good results, and if the model might be applicable to departments with larger demand. For model two the robustness of the model is measured by experimentation on the different weight factors α and β, and the initial inventory. Model two also incorporated the large demand case, to determine whether a stationary or optimised value of s is preferable.

Chapter 6

Results

In this chapter the experiments described in Chapter 5 are discussed. First the results of model 1 are discussed in Sections 6.1. Next the results of model 2 are discussed in Section 6.2. Section 6.4 denotes the conclusions drawn from the analysis of the results. All experiments are run on an AMD Ryzen 5 2600H (6 cores, 12 processors) with 16 GB of DDR4 RAM, with solver Gurobi.

6.1 Model 1 results

The model used for all model 1 experiments uses a cost factor α of 0.8, and a total inventory factor β of 0.2, this to balance between reducing costs, and inventory. The main priority is decreasing the total costs, and a small factor for inventory level minimisation is used to restrict the model in using unrealistically high inventory levels to prevent stockouts. The initial inventory for all experiments is the level s plus the EOQ. To recall, in model 1 a stationary calculated value for s and the EOQ is used.

6.1.1 Model 1: Results large demand case

The experiment ran five replications with a maximum runtime of two hours per run. This yielded an average optimality gap of 77.26%, with an average CSL of 60.18%.

6.1.2 Model 1: Results optimally solved large demand case

Figure 11 shows the results of the experiment, with average runtime being around 30 minutes. The average cycle service level of the experiment does not achieve the goal of 99.9%. The cause of this is that the calculated values for s and EOQ for some SKUs cause stockouts. Stockout costs are not displayed in the graph as these costs are an artificial cost penalising a lower CSL, since the CSL is included the stockout costs are not.

For 113-121 SKUs the emergency order point is set to a value of one. However, the model does not need to emergency order due to optimised levels for S. Furthermore, an emergency order point of one is not expected to increase performance, as most SKUs, except eight, have an expected daily demand that is vastly larger than one.

6.2 Model 2 results

As discussed in Section 5.1.2 241 of the initial 837 SKUs are optimised by the mathematical model for the experiments in Section 6.2.1, for all other experiment all SKUs are included.

6.2.1 Model 2: Results (α, β) and initial inventory experiment

The results for the two experiments can be seen in Table 4. Note that for all experiments, except the experiment with ($\alpha = 0,\ \beta = 1$), yield no optimal solutions after running the model for two

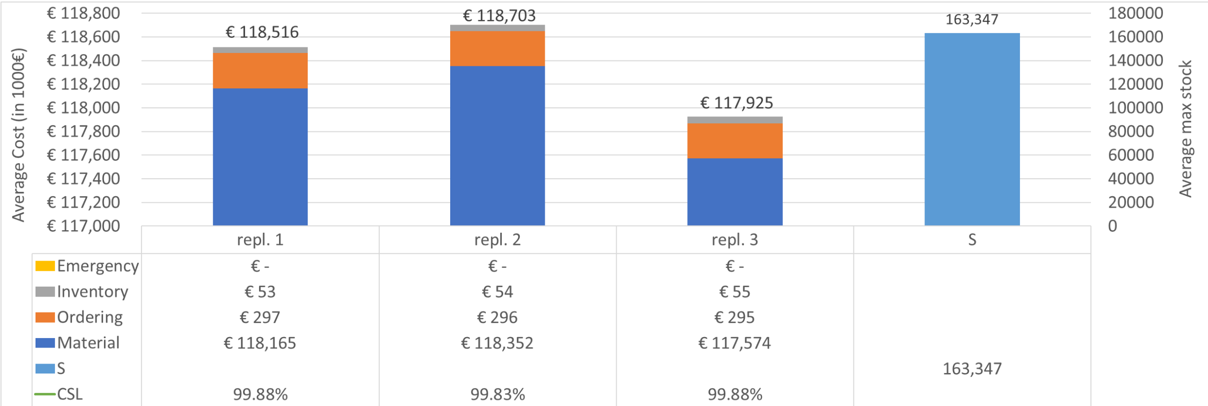


FIGURE 11: Three replications and average level S of the optimally solved model 1 with the large demand case, including achieved CSL

hours. An 10 hour run is performed where the model was still not able to to solve optimality with similar performance to the two hour run. On average, 100.8 of the 241 SKUs did not receive an initial demand in the model. This is unexpected, as most SKUs with lower demand have already been removed from the dataset. The fact that there are still many SKUs without initial demand shows that the demand probability for the included SKUs is still too low to generate enough demand for the model to place orders within its time frame. This causes the cycle service levels to be unrealistically high values as most SKUs can satisfy all demand from their initial inventory. The initial inventory experiment confirms this as a cycle service level of 100% is achieved for the experiments with larger initial inventory. The initial inventory experiment shows that with lower initial inventory more SKUs need to be ordered, causing the stochastic program to set larger values for s and S.

Since the stochastic model is unable to optimally solve within reasonable runtime for the data set of scan-relevant items a heuristic approach is used to determine stock levels, with result denoted in Section 6.3.

TABLE 4: Results for the α, β and initial inventory experiment, which cannot be solved optimally for the scan-relevant items.

Experiment	*run*	*Total costs*	*Max stock*	*CSL*	*Optimality gap*
α and β	($\alpha = 1, \beta = 0$)	€ 132,000	717	99.99%	50.05%
	($\alpha = 0.8, \beta = 0.2$)	€ 96,000	632	100.00%	75.36%
	($\alpha = 0.6, \beta = 0.4$)	€ 176,000	552	99.90%	82.37%
	($\alpha = 0.4, \beta = 0.6$)	€ 192,000	697	99.99%	15.77%
	($\alpha = 0.2, \beta = 0.8$)	€ 108,000	619	99.99%	15.04%
	($\alpha = 0, \beta = 1$)	€ 976,000	242	97.77%	0.00%
Initial inv	Inv. Factor 0.5	€ 858,000	1845	99.92%	22.72%
($\alpha = 0.8, \beta = 0.2$)	Inv. Factor 1.5	€ 58,000	440	100.00%	53.95%
	Inv. Factor 2	€ 35,000	382	100.00%	32.99%

6.2.2 Model 2: Large demand case

Figure 12 shows the results of optimally solved large demand case. When comparing the performance of the large demand case with an optimised value for s and S to the performance of model 1 (Section 6.1.2), model 2 that uses a joint optimisation of important decision variables performs significantly better. The average cycle service level in model 1 is 99.86% for the optimally solved model, whilst model 2 achieves 99.99%. The costs are increase slightly, with an

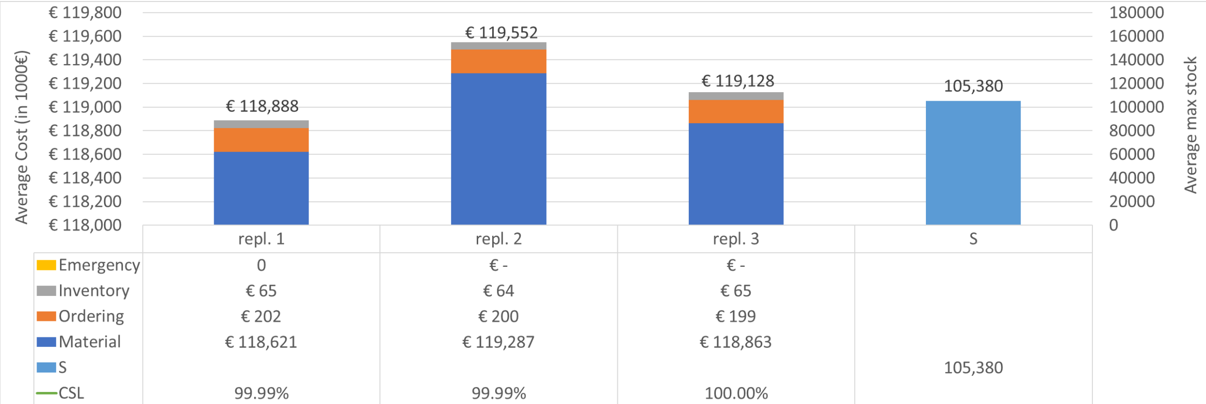


FIGURE 12: Three replications and average level S of the optimally solved model 2 with the large demand case, including achieved CSL.

average inventory decrease of 35.49%. This shows the stochastic program solving all decision variables outperforms the program with a static reorder point.

The optimally solved large demand case identifies 16 SKUs where the emergency order point is increased. The stochastic program, however, prevents emergency ordering by optimising the levels s and S.

6.2.3 Model 2: Evaluation simulation large demand case

Figure 13 shows the performance of the evaluation simulation for model 2 with the large demand case, including confidence intervals in Table 6.2.3. The evaluation simulation shows a drop in cycle service level when evaluating the policy over a long time period. The drop in cycle service level indicates that the time frame of the stochastic program is not large enough to ensure good long term performance. The stochastic program fails to identify peak demand outliers, which cause stockouts.

The stockouts caused by occasional peak demand can possibly be prevented by an emergency order point. However, since the time frame of the model failed to include these peak demand levels no emergency order point was set for most SKUs. Figure 12 shows some emergency ordering, as the stochastic program did set an emergency order point for some SKUs. The stochastic program is promising, the expectation is that when model 2 is run for more scenarios and time steps, that include occasional peak demand, the performance increases.

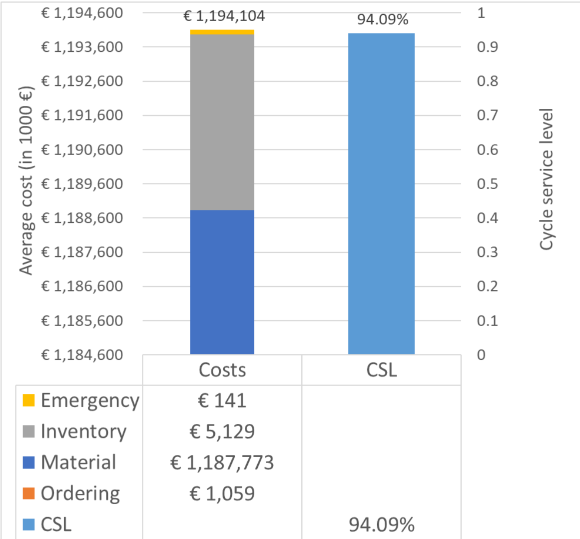


FIGURE 13: Average costs and CSL of the large demand evaluation simulation solved with model 2 for the large demand case.

	Costs (in 1000€)	*UOP*
99.9% CI	[€1,172,454; €1,215,755]	-
Avg	€ 1,194,104	94.09%
CIHW	€ 21,650,456	0.00058244

TABLE 5: The 99.9% confidence interval of the large demand case evaluation, including averages and the confidence interval half-width (CIHW)

6.2.4 Model 2: Toy instance emergency-order-point

Figure 14 shows the results of the toy instance experiment. In this experiment an instance is created where emergency ordering is in general beneficial due to low initial inventory. we conclude that the proposed mathematical model does set an emergency order point should the SKU characteristics be such that it is necessary.

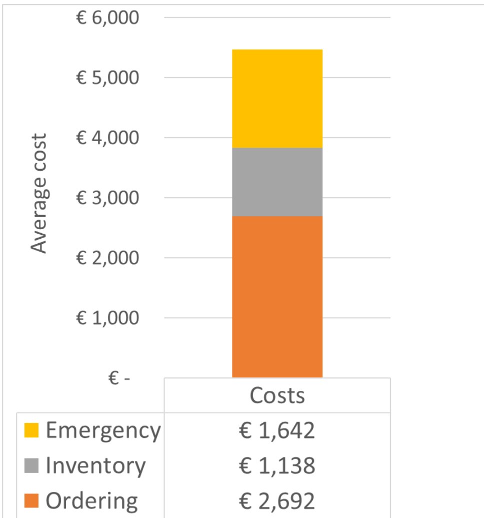
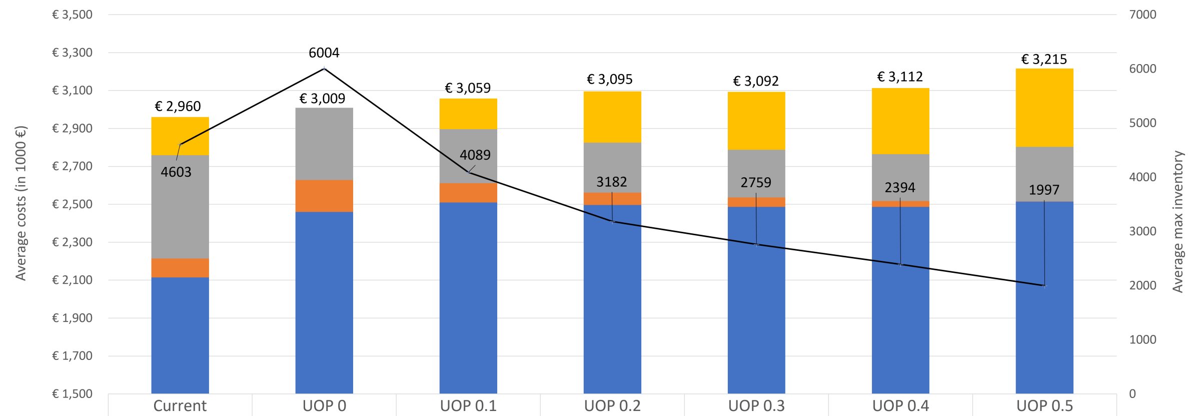


FIGURE 14: Three replications and average costs of the toy emergency order point experiment.

6.3 Heuristic scan-relevant items

In this section the results of the heuristic performance is described. Two experiments and a validation simulation are performed. One experiment shows heuristic performance under various different emergency order levels, and the second experiment shows performance should lead



	Current	UOP 0	UOP 0.1	UOP 0.2	UOP 0.3	UOP 0.4	UOP 0.5
Emergency	€ 201	€ -	€ 162	€ 271	€ 305	€ 349	€ 413
Inventory	€ 545	€ 381	€ 284	€ 263	€ 252	€ 247	€ 288
Ordering	€ 100	€ 168	€ 102	€ 66	€ 50	€ 31	€ 1
Material	€ 2,114	€ 2,460	€ 2,510	€ 2,496	€ 2,486	€ 2,486	€ 2,514
CSL	99.97%	99.83%	99.97%	99.97%	99.97%	99.97%	99.98%
S	4603	6004	4089	3182	2759	2394	1997

Contains SKUs with < 99.9% CSL

FIGURE 15: Heuristic results emergency order point experiment normalised on 365 days including the current performance in €1,000.

time variability decrease. Furthermore, the most promising emergency-order-point experiment is validated.

6.3.1 Emergency order point

Figure 15 shows the average heuristic performance of six replications of six experiments using various levels of emergency-order-point factors. The current performance and the experiment without emergency order point still have SKUs with an CSL lower than 99.9%. For all other experiments the desired service level is achieved. As the SKUs that currently do not meet these requirement need to be ordered more frequently there is no expected decrease in costs. However, the inventory level of the OR department can be reduced significantly. for an expected cost increase of 3.24% to 9.93% the total inventory is decreased by 11.17% to 56.62% dependent on the desired UOP, whilst achieving the desired CSL of 99.9% for all SKUs.

6.3.2 Lead time variability

This experiment is performed with an UOP factor of 0.3, as the results from the experiment with this level are the most promising. An UOP of 0.3 reduces inventory levels significantly, for a relatively low cost.

Figure 16 shows the results of the lead time experiment, showing the average values over six runs. With Table 6.3.2 showing the 99.9% CI for the costs and maximum stock level S. The costs can be observed to be similar to the costs from the emergency-order-point experiment, whilst the inventory level is reduced. The reduction in lead time variance leads to an expected decrease of 76 units, or 2.76%. Should Isala want to reduce their inventory levels further they can decide to convene with suppliers and try to reduce this variance.

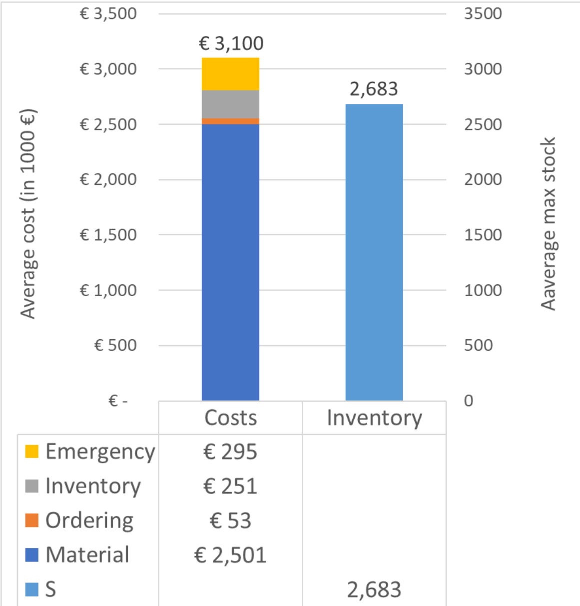


FIGURE 16: Heuristic results lead time variability experiment normalised on 365 days in €1,000.

	Costs (in 1000€)	*S*
99.9% CI	[€3,112 ; €3,088]	[2667 ; 2699]
Avg	€ 3,100	2683
CIHW	€ 12.16	16

TABLE 6: The 99.9% confidence interval of the heuristic lead time experiment, including averages and the confidence interval half-width (CIHW)

6.3.3 Evaluation simulation

The evaluation simulation is performed for the experiment using an emergency-order-point factor of 0.3, as these results achieve significantly lower stock levels and the required CSL for all SKUs, with a slight cost increase.

The first replications of the evaluation simulation showed that 43 out of the 837 SKUs fell just below the required CSL. These SKUs were SKUs with reduced levels for s by the heuristic. For these SKUs the level s is set equal to the level S, and the evaluation simulation is repeated. This gives the results shown in Figure 17 and Table 6.3.3, with accompanying proposed inventory levels in Appendix D. With these settings all SKUs are validated by the simulation to have a CSL larger than 99.9%. With yearly costs expecting to increase to €3,100,000 and maximum stock levels dropping from 4603 to 2872. Compared to the current situation this is a cost increase of 4.52%, to ensure that all SKUs are sufficiently available, and a maximum inventory reduction of 37.61%, whilst achieving an average CSL of 99.99%.

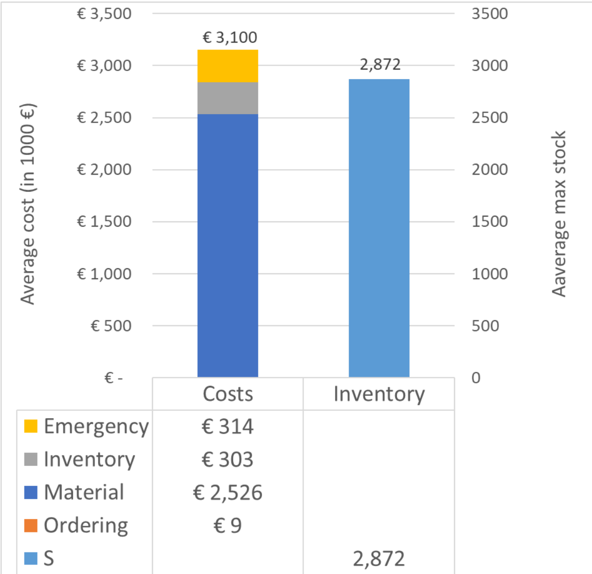


FIGURE 17: Heuristic results evaluation simulation normalised on 365 days in €1,000.

	Costs (in 1000€)
99.9% CI	[€3,138 ; €3,170]
Avg cost	€ 3,154
CIHW	€ 15.955

TABLE 7: The 99.9% confidence intervals of the heuristic evaluation simulation, including average costs and the confidence interval half-width (CIHW)

6.4 Conclusions

In this chapter we answered the sub-questions *"What is the performance of the different experiments and what are the advantages and disadvantages?"*. The large demand case is solved optimally by both models. The results show that model 2 outperforms model 1 when solved optimally, increasing the average CSL, and significantly decreasing total inventory. The validation simulation showed that the time frame for the stochastic program is too small to include demand outliers in the optimisation, causing stockouts. Should the model be able to run for a larger scenario set and time period the performance is expected to increase. A toy instance was able to set emergency order points, validating that the model does emergency order should it be beneficial.

The constructed heuristic provides stock levels that Isala can implement at their OR department. The costs for the OR department do increase slightly, this is however necessary as currently not all SKUs achieve their required CSL. The proposed stock levels achieve the required CSL for every SKU, and furthermore decrease inventory significantly. The proposed levels use an emergency-order-point factor of 0.3, and is expected to increase costs by 4.52% whilst reducing inventory by 37.61% and ensuring that all SKUs achieve their required CSL of 99.9%.

The increase in costs is in part countered by the decrease in products going past their due date. As mentioned, currently €92,462 worth of product is thrown away each year. When implementing mathematically substantiated, lower, stock levels this value is expected to decrease.

Chapter 7

Conclusions and Recommendations

This chapter concludes our research in Section 7.1. Recommendations to Isala are given in Section 7.2. Discussion about the limitation of the research are discussed in Section 7.3. Possibilities for future research are denoted in Section 7.4.

7.1 Conclusions

In Chapter 1 we formulated the following research objective: *"To design and assess an inventory model for the scan-relevant items stored in the operating room department that reduces inventory level and decreases emergency orders, whilst maintaining, or improving, the current material availability."*. Analysis of the current situation at Isala identified the following issues the OR department faces:

- A lack of calculated inventory levels, causing high stock levels for scan-relevant items.
- SKUs not meeting minimal service level requirements, where 12 out of 837 do not reach 99.9% availability.
- Not keeping to predetermined order sizes.
- A perceived lack in storage space.
- Unnecessary emergency ordering by the OR department.

Due to a lack of mathematically substantiated inventory levels at the OR department they maintain high stock levels to counter the anxiousness of stockout. This increases costs and causes a lack of storage space at Isala. The optimisation of inventory levels will ensure that all SKUs reach their required availability, and reduce stock levels.

In this research a *stochastic program* is constructed for *(s,S) inventory systems* that to the best of out knowledge is not previously regarded in literature. The constructed stochastic program is a scenario-based program that incorporates uncertainty in future demand and lead times in the current decision making, and determines optimal emergency-order-points. The innovation to literature is the combination of point-of-use inventory systems with the introduction of an emergency-order-point for healthcare institutions. The program optimises based on two weights in the objective function. One being the total costs that need to be minimised, and the second the total inventory, as the OR departments storage space is limited. The provided model aims to reduce inventory levels. Having unnecessarily high inventory is common practise at the OR department and other hospitals, as hospitals are in the capacity point of the Operations Management triangle [11]. The optimisation of inventory levels aims to reduce emergency ordering, and achieve the high cycle service levels (CSL) desired. Two models are constructed with the stochastic program, model 1 that has a calculated value for the order point s and model 2 that uses an optimised value for s.

The research shows that for many of the low intermittent demand SKUs the constructed mathematical model is not able to solve to optimality. To test the model a large demand case is constructed that does yield optimal inventory levels. The evaluation simulation of the optimally solved large demand case looks promising and achieves a CSL of 94.09% for model 2. When larger computing power is used to run the stochastic program, using a bigger scenario set and time span, an increase in performance is expected. The experiments show that using an optimised value for the order point (model 2) is highly preferable over a calculated value (model 1). This yields an expected inventory decrease of 35.49% with similar costs. Both models did not need an emergency-order-point to minimise their objective function. A toy instance is created that proves that the stochastic program does emergency order should it be beneficial.

For the scan-relevant items with low intermittent demand a more simplistic methods of setting the inventory parameters is better suited. A heuristic is constructed to calculate the order points and order-up-to levels for these items. The heuristic experiments on a variety of emergency-order-points, where the emergency-order-point is the order point times a decimal ranging from 0 to 0.5. Since 12 out of 837 SKUs fail to meet their minimal CSL of 99.9% the costs increase slightly. The heuristic shows that an expected cost increase of 3.24% to 9.91% yields an inventory decrease of 11.17% to 56.62%, dependent on the emergency-order-point, and achieves the minimal CSL requirement for all SKUs. The best experiment according to us increases costs with 4.52%, and decreases inventory with 37.61%, using an emergency order factor of 0.3. The scan-relevant items have large lead time variances, this research show that when variance is reduced, stocks can decrease an additional 2.76%. The heuristic provides mathematically substantiated inventory levels that can immediately be implemented at the OR department decreasing their inventory and increasing availability. The heuristic results denote the practical contribution of this research, and proposed inventory levels per SKU are denoted in Appendix D.

The heuristic experiments show that the introduction of an emergency order point reduces inventory and increases cycle service levels. The optimisation of emergency order points has little mention in literature. This research shows that mathematically substantiated emergency order points improve performance significantly, and that additional research into this topic is necessary. The other addition to literature is the creation of a heuristic calculating inventory levels for (s, S) point-of-use inventory systems under variable demand and lead time, using a calculated emergency order point. This type of inventory system is to the best of our knowledge not yet discussed in literature before.

Concluding, the formulated stochastic program shows promising results for large demand cases, but is not able to achieve the desired CSL when running for the current time frame. Performance is expected to increase when running the model with more computing power for a larger set of scenarios and time steps. To provide mathematically substantiated inventory levels to Isala a heuristic is constructed and evaluated for the scan-relevant items. The resulting inventory levels ensure that all SKUs fulfil their minimal CSL requirement, and decrease total inventory with 37.61%.

7.2 Recommendations

We recommend that the OR department implements the inventory levels provided by the heuristic, using an emergency-order-point factor of 0.3. Furthermore, the OR department is advised to run the heuristic (half) yearly to see whether stock levels change based on recent demand realisations. In the ideal situation, Isala should implement an inventory management system in their ERP system that updates the inventory levels real-time.

Since the results of the large demand case are promising Isala can run the stochastic program using more computing power, and use a bigger scenario set and time span. If the performance of the stochastic program is adequate, they can implement it at departments that suit the characteristics of the large demand case, where daily demand ranges between 1 and 500 units. The stochastic program cannot be altered by the employees of the OR department itself, as this requires programming and mathematical skills, but the integral capacity management team, or other skilled employees, can be requested to apply the model.

Isala strives to have a Just-In-Time (JIT) management of their material logistics. To achieve this they should focus on improving contact and information sharing with their suppliers, as mentioned to be essential in Chapter 2. More accurate agreements on delivery dates and delays are necessary to implement an effective JIT management strategy, decreasing safety stocks, and thus inventory.

Lastly, the OR department is recommended to start collecting data on demand realisation as opposed to recording order data. With more accurate historical demand data it is possible to more accurately forecast future demand, which will increase the accuracy of mathematical models calculating stock levels.

7.3 Discussion

As mentioned in Chapter 4 the scan-relevant items have obsoletes amounting to a value of €92,462 annually. Since the model does not incorporate the best-before date of SKUs, savings in reducing the waste are not included in the results. Obsoletes, however, are expected to decrease significantly, should maximum stock levels be reduced. This counters the necessary cost increase.

When experimenting with the stochastic program on the scan-relevant, intermittent demand, items a random demand of one was generated if the SKU did not receive any demand from the model. The goal being to force the model to have demand for every SKU, and thus optimise the stock values. However, the assigning of a random demand of one unit does not have the desired effect, as low demand realisations still not force the model to order, and thus not to optimise model parameters. In the future an exact solution approach is not advisable for items with very low intermittent demand as it is computationally intensive to optimally solve, and more simple solution methods are sufficient.

7.4 Possibilities for future research

Determine a policy for SKUs with a maximum stock level of one. These SKUs are always emergency ordered when demand occurs. The SKUs with this characteristic are excluded from the model experiments, but since the demand for the SKUs is very low the emergency ordering may not be necessary.

This research focused solely on improving the inventory system of Isala as a single echelon system. When Isala uses an inventory management model for their stock levels it can be beneficial to incorporate Hospital Logistics and model them as a central warehouse. A multi-echelon optimisation is expected to yield lower overall inventory levels and costs, and is beneficial to both involved parties.

Connecting the surgery schedule of Isala to their inventory management systems. If for medical procedures it is known or estimated what supplies are needed, then the ordering and stock levels can be dependent on the procedures scheduled the coming weeks. This does require data analysis and the integration of multiple IT systems Isala is currently working with.

Bibliography

[1] RAA Vonk, HBM Hilderink, MHD Plasmans, GJ Kommer, and JJ Polder. "Toekomstverkenning zorguitgaven 2015-2060 : Kwantitatief vooronderzoek in opdracht van de Wetenschappelijke Raad voor het Regeringsbeleid (WRR). Deel 1: toekomstprojecties". In: (2020). DOI: 10.21945/RIVM-2020-0059.

[2] Li-chih Wang, Chen-yang Cheng, Yatsai Tseng, and Yi-fang Liu. "Demand-pull replenishment model for hospital inventory management: a dynamic buffer-adjustment approach". In: *International Journal of Production Research* 53 (Nov. 2015), pp. 1–14. DOI: 10.1080/00207543.2015.1102353.

[3] Volland Jonas, Fügener Andreas, Schoenfelder Jan, and O. Brunner Jens. "Material logistics in hospitals: A literature review". In: *Omega* 69 (2017), pp. 82–101. ISSN: 0305-0483. DOI: https://doi.org/10.1016/j.omega.2016.08.004.

[4] *Feiten en cijfers*. URL: https://www.isala.nl/over-isala/bestuur-en-organisatie/feiten-en-cijfers/ (visited on 10/15/2023).

[5] *Isala strategie 2019-2022*. URL: https://www.isala.nl/over-isala/strategie-2019-2022/ (visited on 10/16/2023).

[6] *Isala strategie kosten*. URL: https://www.isala.nl/over-isala/strategie-2019-2022/kosten/ (visited on 10/16/2023).

[7] Ehsan Ahmadi, Dale T. Masel, Ashley Y. Metcalf, and Kristin Schuller. "Inventory management of surgical supplies and sterile instruments in hospitals: a literature review". In: *Health Systems* 8.2 (2019), pp. 134–151. DOI: 10.1080/20476965.2018.1496875.

[8] Edward A. Silver, David F. Pyke, and Thomas J. Douglas. *Inventory and Production Management in Supply Chains*. 4th ed. CRC Press, 2016.

[9] Max Kloosterman. "Increase the on-hand availability of surgical supplies at the Operating Room department by improving inventory management". In: (2023).

[10] Muller Bente. "Surgical supplies demand forecasting". In: (2021). URL: http://essay.utwente.nl/88113/.

[11] Glen Schmidt. "The OM triangle". In: 1 (Jan. 2005).

[12] Cevin Zhang, Thomas Grandits, Karin Härenstam, Jannicke Hauge, and Sebastiaan Meijer. "A systematic literature review of simulation models for non-technical skill training in healthcare logistics". In: *Advances in Simulation* 3 (Dec. 2018). DOI: 10.1186/s41077-018-0072-7.

[13] Elias W. Hans, Mark van Houdenhoven, and P.J.H. Hulshof. "A Framework for Healthcare Planning and Control". English. In: *Handbook of Healthcare System Scheduling*. Ed. by Randolph Hall. International Series in Operations Research and Management Science. Netherlands: Springer, 2012, pp. 303–320. ISBN: 9781461417330. DOI: 10.1007/978-1-4614-1734-7_12.

[14] Mohammed Almanaseer and Guoqing Zhang. "The Preference of VMI Contract on Traditional RMI System in an Optimal Healthcare Supply Network: A Comparative Study". In: *Proceedings of the Eighth International Forum on Decision Sciences*. Ed. by Xiang Li and Xiaofeng Xu. Singapore: Springer Singapore, 2021, pp. 59–68. ISBN: 978-981-16-1380-7.

[15] R. Rosales Claudia, Magazine Michael, and Rao Uday. "The 2Bin system for controlling medical supplies at point-of-use". In: *European Journal of Operational Research* 243.1 (2015), pp. 271–280. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2014.10.041.

[16] Amogh Bhosekar, Sandra Eksioglu, Tuğçe Işık, and Robert Allen. "A discrete event simulation model for coordinating inventory management and material handling in hospitals". In: *Annals of Operations Research* (Jan. 2021), pp. 1–28. DOI: 10.1007/s10479-020-03865-5.

[17] Wen Yan, Liu Zixian, and Liu Junlan. "Logistics mode reengineering of hospital materials based on JIT theory". In: *2010 International Conference on Logistics Systems and Intelligent Management, ICLSIM 2010* 2 (Jan. 2010). DOI: 10.1109/ICLSIM.2010.5461113.

[18] Raffaele Iannone, A. Lambiase, Salvatore Miranda, Stefano Riemma, and Debora Sarno. "Modelling Hospital Materials Management Processes". In: *International Journal of Engineering Business Management* 5 (June 2013), pp. 1–12. DOI: 10.5772/56607.

[19] Chaaben Kouki, Zied Jemai, Evren Sahin, and Yves Dallery. "Comparison between continuous review inventory control systems for perishables with deterministic lifetime and lead time". In: Apr. 2013, pp. 1–6. ISBN: 978-1-4673-5812-5. DOI: 10.1109/ICMSAO.2013.6552713.

[20] Peter Kelle, John Woosley, and Helmut Schneider. "Pharmaceutical supply chain specifics and inventory solutions for a hospital case". In: *Operations Research for Health Care* 1.2 (2012), pp. 54–63. ISSN: 2211-6923. DOI: https://doi.org/10.1016/j.orhc.2012.07.001.

[21] Herbon Avi. "Replenishing an inventory system permitting lost sales under Poisson demand and short lead times: Explicit performance and an efficient algorithm". In: *Computers and Industrial Engineering* 137 (2019), p. 105998. ISSN: 0360-8352. DOI: https://doi.org/10.1016/j.cie.2019.07.055.

[22] Chiang Chi. "An order expediting policy for continuous review systems with manufacturing lead-time". In: *European Journal of Operational Research* 203.2 (2010), pp. 526–531. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2009.08.012.

[23] Ouyang Liang-Yuh and Chang Hung-Chi. "A minimax distribution free procedure for mixed inventory models involving variable lead time with fuzzy lost sales". In: *International Journal of Production Economics* 76.1 (2002), pp. 1–12. ISSN: 0925-5273. DOI: https://doi.org/10.1016/S0925-5273(01)00142-6.

[24] Ilkyeong Moon and Sangjin Choi. "A note on lead time and distributional assumptions in continuous review inventory models". In: *Comput. Oper. Res.* 25 (1998), pp. 1007–1012.

[25] Saeed Poormoaied and Ece Demirci. "Analysis of an inventory system with emergency ordering option at the time of supply disruption". In: *OR Spectrum* 43 (Dec. 2021). DOI: 10.1007/s00291-021-00636-x.

[26] C. Velmurugan and Uthayakumar Ramasamy. "Optimal shipment policy with ordering constraint for multi items in healthcare industries". In: *International Journal of Mathematics in Operational Research* 8 (Jan. 2016), p. 203. DOI: 10.1504/IJMOR.2016.074855.

[27] Awi Federgruen and Yu-Sheng Zheng. "An Efficient Algorithm for Computing an Optimal (r, Q) Policy in Continuous Review Stochastic Inventory Systems". In: *Operations Research* 40.4 (1992), pp. 808–813. DOI: 10.1287/opre.40.4.808.

[28] Anshul Agarwal. "Validation of Inventory models for Single-echelon Supply Chain using Discrete-event Simulation". In: (June 2018).

[29] S. Akcan and A. Kokangul. "A new approximation for inventory control system with decision variable lead-time and stochastic demand". In: *The International Journal of Industrial Engineering: Theory, Applications and Practice* 20 (Jan. 2013), pp. 262–272.

[30] Nidarsha Attanayake, Rasha Kashef, and Tariq Andrea. "A simulation model for a continuous review inventory policy for healthcare systems". In: May 2014, pp. 1–6. DOI: 10.1109/CCECE.2014.6901005.

[31] Michael J. D. Powell. "An efficient method for finding the minimum of a function of several variables without calculating derivatives". In: *The Computer Journal* 7.2 (Jan. 1964), pp. 155–162. ISSN: 0010-4620. DOI: 10.1093/comjnl/7.2.155.

[32] Marco Bijvank and Iris Vis. "Inventory control for point-of-use locations in hospitals". In: *Journal of the Operational Research Society* 63 (Apr. 2012), pp. 497–510. DOI: 10.1057/jors.2011.52.

Appendix A

Problem Cluster

In Figure A.1 the problem cluster is displayed. It shows the initial problems of Isala, and the core problem that stems from these initial problems.

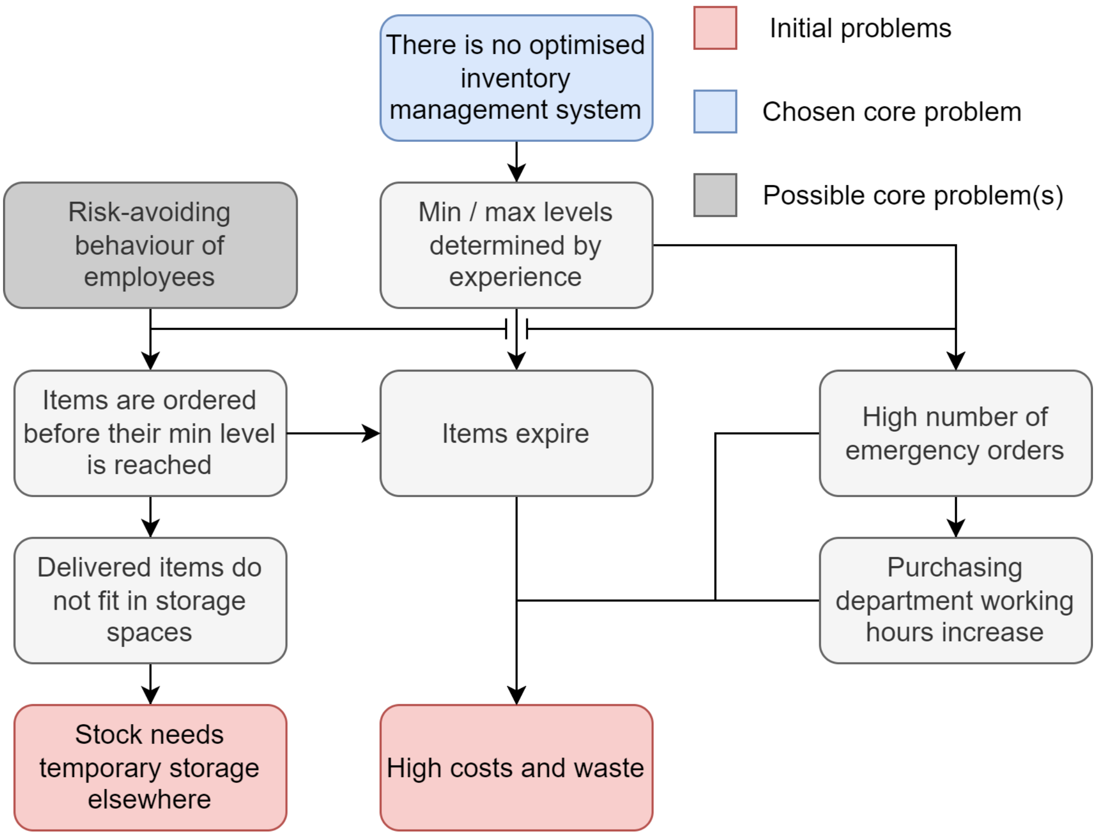


FIGURE A.1: Problem cluster

Appendix B

Semi-systematic literature search on inventory management (models) within, and outside of, the healthcare sector

We used a semi-systematic search construction for the literature search. We used a variety of search strings to obtain relevant results. Since we wanted results from within the healthcare sector, as well as applications from other industries, this required a variety of search strings. Table B.1 shows the search process and exclusion criteria, with as a result a set of of sources reviewed for this research.

TABLE B.1: Overview of search results with regards to material logistics

Search keywords	**# of sources**
WebOfScience	
(Inventory AND model) AND (continuous AND review) AND ((healthcare) OR (health AND care))	18
(inventory AND model) AND (continuous AND review) AND (low AND lead-time)	20
(inventory AND model) AND (continuous AND review) AND (operating AND room)	0
(material) AND (hospital AND logistics)	40
Additional results (snowballing / sporadically found)	6
Backward search	7
Exclusions	
Not relevant for this research	-65
Total remaining sources	**25**

The initial search results in 90 sources. However, since many sources regarded medical applications, or the inventory policies of pharmaceutical or blood products many were excluded after initial scanning. The 25 sources that remain regard periodic and continuous inventory policies with appliances in healthcare and within different sectors. Furthermore, some literature reviews, and research specifically focused on low-lead-time and JIT inventory models are included in the selection of papers.

Appendix C

Stochastic distributions table

Table C.1 shows some sources on whether they used a deterministic or stochastic demand and leadtime. It can be seen that a Poisson distribution is common practice for demand variability, and that for lead-time there is no distribution that is commonly used.

TABLE C.1: Table taken from [29] showing distributions for stochasticity in demand and lead-time.

	Inventory Control			
	Demand		*Lead Time*	
Authors (Year)	***Deterministic***	***Stochastic***	***Deterministic***	***Stochastic***
Satır and Cengiz (1987)		Normal	+	
Cakanyildirim et al. (2000)	+			Exponential
Salameh et al. (2003)	+			Normal
Seifbarghy and Jokar (2006)		Poisson	+	
Axsater (2006)		Normal	+	
Chen and Levi (2006)		Poisson	Equal to zero	
Mohebbi and Hao (2006)		Poisson		Erlang
Hill et al. (2007)		Poisson	+	
Hill (2007)		Poisson	+	
Kopytov et al. (2007)		Poisson		Normal
Darwish (2008)		1.Uniform 2.Normal	+	
Babai, Jemai and Dallery (2010)		Poisson		General distribution

Appendix D

Proposed inventory levels

The SKU numbers included in this report do not correspond with the article numbers of Isala, this in order to ensure animosity.

SKU	*old_s*	*new_s*	old_S	new_S
0	1	2	2	2
1	2	2	2	2
2	2	2	2	2
3	2	2	2	2
4	2	2	2	2
5	2	2	2	2
6	2	3	2	3
7	2	3	2	3
8	2	2	2	2
9	2	2	2	2
10	2	3	2	3
11	2	4	2	5
12	2	4	2	4
13	2	2	2	2
14	2	2	2	2
15	2	3	2	3
16	2	2	2	2
17	2	3	2	3
18	2	5	2	5
19	2	2	2	2
20	2	2	2	2
21	2	4	2	4
22	2	2	2	2
23	2	2	2	2
24	2	4	2	4
25	2	2	2	2
26	2	4	2	4
27	2	2	2	2
28	2	4	2	4
29	2	2	2	2
30	2	2	2	2
31	2	2	2	2
32	2	2	2	2
33	2	4	2	4
34	2	2	2	2
35	2	4	2	4
36	2	2	2	2

37	2	2	2	2
38	2	2	2	2
39	2	2	2	2
40	2	2	2	2
41	2	2	2	2
42	2	2	2	2
43	2	2	2	2
44	2	2	2	2
45	2	2	2	2
46	2	2	2	2
47	2	3	2	3
48	2	3	2	3
49	2	2	2	2
50	2	2	2	2
51	2	4	2	4
52	2	2	2	2
53	2	2	2	2
54	2	2	2	2
55	2	2	2	2
56	2	2	2	2
57	2	3	2	3
58	2	2	2	2
59	2	2	2	2
60	2	2	2	2
61	2	2	2	2
62	2	2	2	2
63	2	4	2	4
64	2	3	2	3
65	2	3	2	3
66	2	2	2	2
67	2	2	2	2
68	2	4	2	4
69	2	2	2	2
70	2	2	2	2
71	2	2	2	2
72	2	3	2	3
73	2	2	2	2
74	2	2	2	2
75	2	2	2	2
76	2	6	2	6
77	2	2	2	2
78	2	3	2	3
79	2	2	2	2
80	2	3	2	3
81	2	2	2	2
82	2	2	2	2
83	2	4	2	4
84	2	2	2	2
85	2	2	2	2
86	2	3	2	3
87	2	2	2	2

88	2	3	2	3
89	2	2	2	2
90	2	2	2	2
91	2	2	2	2
92	2	2	2	2
93	2	4	2	4
94	2	2	2	2
95	2	2	2	2
96	2	2	2	2
97	2	3	2	3
98	2	2	2	2
99	2	2	2	2
100	2	2	2	2
101	2	2	2	2
102	2	2	2	2
103	2	2	2	2
104	2	2	2	2
105	2	2	2	2
106	2	4	2	4
107	2	2	2	2
108	2	2	2	2
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124	2	2	2	2
125	2	2	2	2
126	2	2	2	2
127	2	3	2	3
128	2	3	2	3
129	2	3	2	3
130	2	2	2	2
131	2	2	2	2
132	2	2	2	2
133	2	2	2	2
134	2	2	2	2
135	2	2	2	2
136	2	2	2	2
137	2	2	2	2
138	2	2	2	2

139	2	2	2	2
140	2	3	2	3
141	2	2	2	2
142	2	3	2	3
143	2	2	2	2
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145	2	2	2	2
146	2	4	2	4
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184	2	2	2	2
185	2	4	2	4
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239	2	2	2	2
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243	2	2	2	2
244	2	2	2	2
245	2	4	2	4
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343	3	3	3	3
344	3	4	3	4
345	3	2	3	2
346	3	4	3	4
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377	3	2	3	2
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387	3	2	4	2
388	3	2	4	2
389	3	2	4	2
390	3	2	4	2
391	3	3	4	3
392	4	2	4	2
393	4	2	4	2

394	4	5	4	5
395	4	3	4	3
396	4	2	4	2
397	4	7	4	7
398	4	4	4	4
399	4	4	4	4
400	4	4	4	4
401	4	3	4	3
402	4	7	4	7
403	4	7	4	7
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407	4	2	4	2
408	4	7	4	7
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413	4	4	4	4
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419	4	5	4	5
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421	4	3	4	3
422	4	3	4	3
423	4	2	4	2
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425	4	2	4	2
426	4	4	4	5
427	4	3	4	3
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429	4	4	4	5
430	4	4	4	4
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433	4	3	4	3
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436	4	4	4	4
437	4	4	4	4
438	4	2	4	2
439	4	2	4	2
440	4	2	4	2
441	4	7	4	7
442	4	4	4	4
443	4	4	4	4
444	4	4	4	4

445	4	4	4	4
446	4	4	4	4
447	4	2	4	2
448	4	5	4	5
449	4	3	4	3
450	4	3	4	3
451	4	3	4	3
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453	4	3	4	3
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538	5	7	5	7
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541	5	9	5	9
542	5	5	5	5
543	5	3	5	3
544	5	7	5	7
545	5	3	5	3
546	5	4	5	4

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549	5	4	5	4
550	5	7	5	7
551	5	7	5	7
552	5	5	5	5
553	5	4	5	4
554	5	5	5	5
555	5	2	5	2
556	5	3	5	3
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