OPTIMISING THE USE OF PYXIS MEDSTATIONS IN THE MEDICAL SPECTRUM TWENTE

Medisch Spectrum Twente
een santeon ziekenhuis

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Preface

You are about to read my bachelor thesis "Optimising the use of Pyxis Medstations in the Medical Spectrum Twente". With this thesis, I aimed to help the MST in making optimal use of their automated medication dispensing systems. During my time at the MST, I have gotten to know numerous people and every one of them supported me in their way. I have learned a great deal and I am grateful for the opportunity.

I would like to thank Mirije en Mirjam for taking time out of their always-busy schedules to discuss ideas and provide feedback. The meetings were always efficient and clear. Your insights in the processes at the MST helped me immeasurably and without them, I would not have come where I am today.

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Enjoy the read.

Kind regards,

Casper Jacobs

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Management summary

The Medical Spectrum Twente uses automated medication dispensing systems (AMDS) in their nursing units. However, currently, these systems are not used optimally, and the reason this thesis was initiated was that nurses felt like they had to walk to the clinical pharmacy too often to pick up medications that were unavailable in the AMDS'. After performing a thorough problem analysis, this problem was not found throughout the nursing units. The average CSL was found to be 99.75% and the average FR is around 99.33%. These high inventory performances were the result of incredibly high inventory levels (a minimum of 2 weeks and a maximum of 4 weeks of demand). Apparently, another problem was in play here. This other problem manifested itself to be poor inventory accuracy. In several test samples taken, the average percentage of refills where the inventory level did not have to be adjusted by hand was 65%. These discrepancies were caused by underlying problems, such as disconnected patient systems and mechanical failures. This thesis focusses on developing a method for making these new (and reduced) inventory models, granted that the underlying problems are tackled as well.

A method is developed to create fitting inventory models for a complete nursing unit. This method takes demand data from these AMDS' and makes an inventory classification. Then, a fitting inventory policy is chosen, as well as the desired cost and service objectives. Statistical distributions are fitted to the demand and finally, decision rules are used to calculate new reorder points and order-up-to levels. By decreasing the inventory, a cost decrease is expected and room in the AMDS' is freed up for an extended assortment. With this new assortment, nurses will have to walk to the CP less often. Additionally, a tool is included to automate as much of the method as possible.

To check how the method performs and obtain a rough estimate of how much savings could be achieved, a numerical experiment is performed for which the A5 nursing unit was evaluated. For FR levels roughly similar to the current situation (99.5%), an average inventory reduction of approximately 19% in number of medications could be obtained on the A5. Here, order sizes were rounded off to logical and/or package sizes. Due to this reduction, at least several extra SKUs could be added to the assortment of the AMDS, depending on the total usage of these new SKUs. The data used, however, have very high variability. Therefore, sensitivity analyses were performed which looked at the average total inventory needed for several CSL and FR levels, and a changing variety in the data. The former analysis yielded results according to expectations: with rising CSL and FR levels, the average total inventory levels increased exponentially. For decreasing variability, the average total inventory also decreased, supporting the notion that if somehow the variability in the data could be lowered, more accurate inventory models could be made that require less inventory to be kept, thus creating even more room for additional SKUs.

To get more SKUs into the assortment of the Pyxis', the inventory levels of the SKUs already in the Pyxis' should be reduced. This is possible with the method described in this thesis. However, these lower inventory levels can only be implemented if inventory management and inventory accuracy are improved. This task was considered outside of the scope of this thesis, but suggestions on what to improve can be made. Perhaps one of the most important suggestions is to connect the patient system and the Pyxis systems, which will allow faster and more accurate medication retrieval. On top of that, EAV packages should be ordered as much as possible.

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List of important abbreviations

CP	=	Clinical Pharmacy
COW	=	Computer On Wheels
A5	=	A5-Thorax nursing unit
CSL	=	Cycle Service Level
SKU	=	Stock Keeping Unit
NU	=	Nursing Unit
PRS	=	Periodic Review System
CRS	=	Continuous review system
FR	=	Fill Rate
ADPRC	=	Average Demand per Replenishment Cycle

1)Research Methodology

1.1) Company Introduction

The MST is one of the largest non-academic hospitals in The Netherlands. In 1990 the MST was founded after the merger of hospital organisations ‘Ziekenzorg’ and ‘Sint Joseph Stadsmaten’ from Enschede, the St. Bernardushospital from Losser, the Sint Antoniushospital from Haaksbergen and ‘Heil der Kranken’ from Oldenzaal. Including their location at Oldenzaal, the total amount of beds comes to 1070. Furthermore, they have over 220 medical specialists and circa 3000 total employees. In 2019, the hospital had almost 30,000 intakes and processed more than 400,000 outpatient visits.

In the MST, a large clinical pharmacy (CP) is present. This CP facilitates almost all medications for patients in the clinical departments. From this central storage room, daily streams of medications go to the departments. On each nursing unit, however, some safety stock is present in so-called “*Pyxis Medstations®*” (called “Pyxis” for the rest of the thesis). These Pyxis’ form a decentralised storage system which aims to facilitate easier stock keeping.

1.2) Background knowledge

The CP has a large, central, storage where the bulk of the stored medication is placed. From this storage, there are a lot of different in- and outflows of medication, that mostly, but not completely, finish at the patients in the hospital. A flowchart has been made to visualise the different flows. This flowchart can be found in Appendix A. Now, a short description of the different flows will be given.
The first and foremost medication flow is that via the COWs (computers on wheels). COWs are carts containing patient-specific drawers where one COW often covers all patients on a specific nursing unit. These COWs are filled in a separate storage room close to the main storage before being brought out to the different nursing units at around 15:30. Should any more medication requests come in after that time, the corresponding medications are put into green boxes for which there is one for each nursing unit. These boxes are then brought to their corresponding floors at around 16:30, being the last scheduled delivery of the day.
Moving on to the nursing units, every unit has some medication stock. This stock is present in multiple different ways. Firstly, small emergency suitcases are present on every nursing unit. These cases only contain vital medications and other products to help a patient in the first moments after a complication or emergency. Therefore, emergency cases contain mostly different SKU’s than the Pyxis’ or COWs. The emergency cases, aptly named, can only be used in actual emergencies.
Secondly, and more importantly, some stock is placed in Pyxis’. In these Pyxis’ a selection of SKU’s is placed that is adapted to the nursing unit it is on, as some nursing units use more of a certain medication or different medications in general. The idea behind the stock in these Pyxis’ is that whenever a sudden and unforeseen need for medication occurs, nurses do not have to walk to the CP, but can instead take it out of the Pyxis. As mentioned before, these Pyxis’ have their own, decentralised, storage system and require a nurse or employee to log in with a personal login and register for which patient they are taking medication and exactly how much of which medications they take. That way, patients do not get double doses and it makes sure data is collected about which patient received which medications when. The combination of these makes for improved security for patients. Both through regulated and automatically checked medication selection, and through perpetually monitored stock levels meaning, in theory, the chance of stockouts is very low. Therefore, patients should almost always receive adequate care. However, in practice, this turns out to be less accurate than hoped.
One of the problems encountered is that nurses have to walk to the CP to retrieve some medication that is not in the Pyxis. This takes a long time and keeps nurses from their actual tasks: taking care of patients. Also, there are too many stockouts for how high the current inventory levels are. This indicates

that inventory management and accuracy might be problematic. To give a better overview of all the problems that are in play here, a problem cluster has been created after rigorous problem discovery.

1.3) Problem cluster and motivation of core problem

Figure 1: Problem cluster

In Figure 1 the problem cluster can be seen. From this problem cluster, five root problems are found:
1. Inventory levels are based on old models/data
2. Some medicine is (temporarily) not available for purchase from the supplier
3. Prescribed patient medication is not shown in the Pyxis, so nurses have to select the correct medication manually for each patient
4. Mechanical failures occur routinely, needing to be resolved before medication can be retrieved
5. Medication is packaged per strip instead of apiece. Meaning a whole strip needs to be retrieved for each patient

1.3.1) Choosing the core problem

In this chapter, the root problems are analysed, and the most appropriate root problem is chosen as the core problem.

- Root problem 1 is about the inventory levels being too high. They have been determined before the big move in 2016 and have barely been changed since, even though the nursing units and their needs have changed drastically. Due to the size of the inventories, the number of different SKU's in each Pyxis (the assortment) is limited. This is taken as the root problem because by making new inventory models and a new assortment, more space can be created for more different SKU's, thus reducing the number of times a nurse has to go to the CP to pick up a specific medication. It is the most academically relevant and is the problem that can be solved the best with the time, knowledge, and resources available.

- Root problem 2 can in certain cases be a real problem, but for most medications, an alternative can be found. This is not a core problem since it is largely out of the hands of the CP.
- Root problem 3 is a problem that has a large impact on especially the nurses. This problem means that retrieving the proper medication for the proper patient takes a lot longer. It is one of the biggest reasons so many discrepancies occur, and this should be fixed if the new inventory models are to be implemented effectively. Sadly, the current Pyxis system does not support integration with the patient information system. This problem will not be chosen as the core problem, but it will be discussed more thoroughly in the scope and discussions since it needs to improve for the initial problem to be solved through new inventory models.
- Root problem 4 is about mechanical failures in the Pyxis. This happens on all NUs, with some Pyxis' being over 15 years old. This problem causes a lot of annoyance and decreases the willingness to keep the inventory accuracy high. It also increases the time needed to retrieve medications, because the error needs to be fixed first. As with root problem 3, this problem will be discussed in more detail later on. Although it is not as pressing as root problem 3, it needs to be addressed as well.
- Root problem 5 is about less medication being packaged EAV (Eenheids-Afleverings-Verpakking) by suppliers. EAV means that every pill is packaged separately, with its expiration date. Without this, whole strips need to be retrieved per patient to make sure the expiration date can be checked in a later stage of the distribution process. This problem can also not be the root problem because again it is almost completely out of the CP's hands how suppliers package their products.

1.4) Research objective and motivation

The research objective of this thesis is to reduce the number of times nurses must walk from the nursing units to the clinical pharmacy. To attain this, new inventory models will be made through which the inventory size is expected to be reduced. This will free up room for additional SKU's in the Pyxis': the assortment will grow and less often medication will have to be picked up at the CP. To achieve this result, though, the number of discrepancies will have to be reduced as well. Recommendations about how to do this will be given in Chapter 7.2.

The Pyxis system has a lot of potential benefits if kept well maintained. However, if left unattended it can be the cause of several problems too. Currently, the stock levels are too outdated and too often a discrepancy between the expected and actual stock occurs. Due to this, the cycle service levels (CSLs) are not what they are supposed to be and too much effort and time go into keeping the inventory levels this high. Hence, the MST wishes to reduce the total average inventory, both to reduce work and to create space for extra SKUs. Additionally, the number of discrepancies between projected and actual stock levels is sought to be reduced. This will be done by making a method for determining new inventory levels. On top of that, an Excel tool will be provided to automate a large part of that method.

After consulting the pharmacists responsible for the Pyxis', old stock models are a recurring problem on all nursing units. However, on certain nursing units inaccurate stock management poses a notable problem as well. One that should be solved if a new stock model is to show improvements in those nursing units. This will largely be done by composing recommendations.

1.5) Research Questions

In this chapter, the research questions to be answered in the thesis are put forward. They will provide the backbone for the thesis and each chapter will attempt to answer a sub-question until the main question can be answered.

1.5.1) Main question

The main research question taken for this thesis is:

"For a fixed CSL, how can inventories be reduced and the assortment expanded in a decentralised, automated dispensing system, so that less often pickups at the CP are necessary?"

This means that a certain CSL will be sought after, to ensure optimality for the nurses. Then, inventory will be reduced as much as possible, also reaching an optimal solution for the management. This will be done by classifying the SKU's in the Pyxis' and by re-determining the inventory policies (e.g., re-order points and order-up-to-levels). To fully answer this main question, it has been divided into multiple steps, each with corresponding sub-questions that will be answered per chapter.

1.5.2) Sub questions

1. What is the current situation like?
    a. Which of the suggested core problems is the most relevant?
    b. What are the current inventory policies or models in use?
    c. What are the current attained CSLs and FRs of the Pyxis'?
    d. What data is available regarding the demand, inventory performance, inventory accuracy, and CSL of the Pyxis'?
    e. Who are stakeholders to these Pyxis' and in what ways are they influenced by the planned research?
2. What can be learned from the literature regarding inventory policies of AMDS' in a hospital?
    a. What KPI's and methods can be found in the literature regarding the efficient use of AMDS'?
        i. What are the strengths, weaknesses, opportunities and threats of these KPI's and/or methods?
        ii. What data that is needed is not yet collected
3. How can the findings from the literature be implemented into the specific case of the MST?
    a. What simplifications and/or assumptions need to be made?

    b. Constraints
        i. What are constraints coming from the CP?
        ii. What are the constraints coming from the nursing units?
        iii. What are the constraints coming from other sources?
4. What are the expected improvements regarding the KPI's?
    a. Which reduction in average total inventory can be expected by implementing the proposed method?
5. How can the found solution be implemented further?
    a. What is needed to make the found solution applicable to the rest of the nursing units?
    b. Which further steps can be explored in future research?

1.6) Scope

To make sure a project of the right scale is taken on, it is decided to focus only on the Pyxis'. That means that other medication streams are left out of consideration for now. Their supposed influence is assumed to be almost nought for the scale of this assignment.

The method to be produced and the accompanying tool will be able to produce inventory levels for all Pyxis. There are, however, certain NUs that fill their COWs themselves from the Pyxis'. Meaning that almost every medication distributed to patients on that NU comes from the Pyxis on that NU. If the demand data is extensive enough, the model should be able to create appropriate inventory models for these NUs as well.

Demand forecasting based on expected patient inflow is an aspect not included in this thesis. Only forecasting based on historical demand data will be used for creating the new inventory models. Additionally, in the case inventory levels are reduced and space is freed up for additional SKUs, determining the completely new assortment of the Pyxis' will not be in the scope of this thesis.

Lastly, the Pyxis' themself have some issues that require solving from another source. Therefore, these need to be left out of consideration as well. An example would be the root problem "Some medications are (temporarily) not available for purchase from the supplier". This problem could still be looked at to costs regarding the Pyxis, but it is in such a different scope that it is better to exclude it completely from this research.

1.7) Theoretical framework and research design

1.7.1) Theoretical framework

After determining the research question and subquestions, it becomes clearer what the theoretical framework should look like. To reduce the number of times nurses will have to walk to the CP, new inventory levels will need to be determined, together with an update of the assortment. This will require the use of supply chain management, specifically inventory management, and operations research. "Inventory management refers to the process of ordering, storing, and using a company's inventory." (Hayes, A., 2019) And Operations Research is described as: "a scientific approach to decision making that seeks to best design and operate a system, usually under conditions requiring the allocation of scarce resources" (Winston, 2004). Both of these fields will help with answering (part of) the research question by providing relevant information, models or theories.

1.7.2) Research method

Answering all the sub-questions stated above will require using multiple different research methodologies. One major research method used will be quantitative research. According to (Bhat, A., n.d.), “Quantitative research is defined as a systematic investigation of phenomena by gathering quantifiable data and performing statistical, mathematical, or computational techniques.” This research method is suitable for this thesis because the goal is to analyse and optimise a certain phenomenon (Pyxis usage) with the help of quantifiable data and draw conclusions out of that. Because in this research, the aim lies in finding a systematic method for (re)determining stock levels in Pyxis, quantitative research is appropriate. Next to that, data will be analysed to find a trend and make a model for the future. Inductive research is a term that describes quite closely the way this research will be shaped.

The first research question, about the current situation, will require the exploration of the available data and knowledge present in the hospital. There is always one main Pyxis pharmacist present, which will know the most about the Pyxis, what data there is and where to find it. He/she will be consulted to find out about the current situation. Also, there are multiple Pyxis assistants, who mainly refill the Pyxis. They often have more practical experience with the Pyxis’ than the main Pyxis pharmacist, thus they are a valuable asset to get information and experiences from. Collected data will be used to determine the current norm and reality.

The second research question, regarding literature, will be answered by doing an extensive literature study concerning AMDS’ in hospitals and inventory management. The literature study will be conducted according to a systematic literature review. It will focus on finding the correct methods of demand forecasting, inventory management and which medications to have in the inventory.

The third research question, which is about implementing the found literature into the MST case, requires careful analysis of found data and close communication with staff from the MST to make sure an adequate fit can be found. Some generalisations or specifications will need to be made to find a tailored solution for the MST. Then, a method can be developed, specifically tailored to the MST to create new inventory models.

The fourth research question is about expected improvements. To be able to see if any improvement has been made by implementing the newly found solution, an analysis will have to be done. On top of that, a sensitivity analysis will be done to be able to determine how the output reacts on changing input parameters.

Finally, the fifth research question. To find out how the found solution can be implemented further, thorough discussions need to be held with the staff and problems not covered should be mentioned explicitly. The scope of the thesis can be used as a foundation upon which suggestions for future research can be built. Also, the deliverables will be designed so that easy implementations into the other Pyxis’ (and possibly another type of AMDS) can be made.

1.7.3) Operationalisation of key variables

As can be read above, the optimisation of the use of the Pyxis’ is the goal of this research. To measure if the found solution has been successful afterwards, some key variables need to be determined and operationalised.

When looking at inventory processes, the CSL and FR are often used KPI’s. Also, total inventory costs are generally looked at as an indicator of the performance of an inventory process. Unfortunately, the total inventory costs consist of many different costs, which are not all defined within the MST. Therefore, the total average inventory will be taken as a KPI. The total average inventory is calculated by taking the reorder point s plus half of the order size Q. It is the value exactly between the min (s) and the max (S). It is relevant because the goal of the method will be to calculate new inventory models, which decrease the average total inventory. After all, the goal is to reduce average total inventory so the assortment can be expanded.

The CSL and FR are KPIs for how the current system is doing but are also counted as the input variables for the method. The management will want to set the desired CSL and/or FR level for which the optimal inventory model will be created. Then, this model will be compared to the old model using the average total inventory.

1.8) Stakeholders

Increasing the efficient use of Pyxis' has multiple different parties that can be regarded as stakeholders. Stakeholders here are not only regarded as parties benefiting but those that are in general affected by the process or outcome of this assignment.

Stakeholder group	**Outcome of improved efficiency Pyxis**
The pharmacists and (Pyxis) assistants	Positive: less work
The clinical pharmacy	Positive: less spillage, more accurate demand forecasting
The nurses	Positive: medications more often at hand
The patients	Positive: better quality care
The hospital	Positive: fewer costs

Table 1: Stakeholders

1.9) Intended deliverables

The focus of this research is to deliver something applicable and usable for the CP. It is intended to re-determine the stock items and stock levels of a certain Pyxis. To conclude, the deliverables will be along the lines of:

- A method to calculate new inventory models for the MST. Optimally, the method will be applicable to all NUs with a Pyxis.
- A tool that will largely automate the method. This is so that repetitive work is removed, and the inventory optimisation can be carried out more often to stay up to date.

2) Situation analysis

In this chapter the sub-question: “What is the current situation like” will be addressed. This will be done by analysing the current situation in the MST to see if the problem can be quantified and problem hotspots can be identified. For this, several NUs have been asked for their view on the problem and data is taken to see if it is in line with the problems proposed by management and the nurses.

2.1) Available data

The Pyxis Medstations have a separate information system in which all stock levels are continuously updated and a lot of reports on different subjects are available. Some examples of available reports are discrepancies, refill activities, loading, empty drawers, etc. There also is a server which stores all the daily activities of every Pyxis. The data files on this server go back to the 5th of October 2019, with some individual data files going back as far as 2015 and 2012. In one such a daily file, thousands of lines of actions are recorded containing the date, the time, the medication code, the type of action, the employee number, the patient number, the old stock level, the amount retrieved/added/etc., the new stock level, and last but not least, the min stock level and the max stock level for that medication.

2.2) Current Inventory policy

When filling a new Pyxis, the assortment of medication was taken from historical usage data. No real algorithm or method was found that the MST used to calculate which SKU’s should or should not be in the Pyxis’ or what the inventory levels should be. There is no distinction between higher or lower priority medications. When these high inventory levels first became clear, it was quite surprising, considering there are on average 10 stockouts per day in the hospital.

In 2016 most nursing units (NU’s) received their Pyxis’ and inventory levels needed to be determined. The min and max levels had been determined based on usage data of half a year and ultimately, the min and max levels were chosen to be two and four weeks of average demand, respectively. After analysing the demand data, it appears that for many, if not all, SKUs these values do not hold any more. The min and max are, respectively, on average 9.4 and 20.4 days. For the A class, they are 5.0 and 11.0 days, the B class 8.3 and 18.8 days and for the C class 11.0 and 23.5 days.

The selection of SKU’s for the Pyxis’ was made based on this same usage data and refined by hand. This policy was implemented with some haste because the MST was on the brink of a large moving. Other than the CP, most NUs were also going to move, merge or change in size. The plan was to re-evaluate inventory levels after the moving, however, this plan was never executed. The previously determined levels were adhered to and sometimes refined by hand afterwards.

While in use, the inventory levels might sometimes be adjusted. This is done by performing a rudimentary analysis on usage data of the medications from the past couple of months (the precise time frame varies, depending on what is most readily available or when a new check is done) and highlighting potential candidates for removal or addition. This is then checked by hand by the hospital pharmacist responsible for purchasing. She ultimately decides which medications to add or remove. Of the process described above, nothing is done according to formulas, algorithms, or calculations, but instead, this pragmatic approach is purely based on experience, gut feeling and instinct.

The Pyxis’ track inventory levels continuously. All medications in the Pyxis’ have a max and min level and once a medication’s inventory level reaches that min level, an order is put outsized just so that the inventory should be raised to the maximum level (max). This policy of continuous monitoring and filling to a certain value is called an (s, S) inventory policy. Here ‘s’ is the min value and ‘S’ is the max value.

However, even though the system recognises the medication level dipped below the s value immediately and should thus be restocked, the actual refill process is only started when the restocking lists are printed out in the morning. Therefore, an (R, s, S) model would be more appropriate. This model adds the 'R' variable, which denotes the period after which the inventory is checked. In this case, R is taken to be one day. The (R, s, S) inventory policy will be discussed in more detail in Chapter 3.

2.3) Current restocking method

At the MST there are two different types of NUs. There are NUs where patient-specific medication is prepared at the CP and put out to the NUs using the aforementioned COW's. On other NUs the nurses fill these COW's directly from the Pyxis' on the NUs itself. A first analysis of all NUs will show if there are certain units where the problem is more prominent or if all units cope with the same problem to the same degree.

Whenever the inventory of a medication in the Pyxis' falls below the min level, it is added to the order list. Every morning, the Pyxis assistants print out the order lists of the NUs and use that to collect the correct medications from the CP inventory and refill it in the corresponding Pyxis. Should, during the day or the night, a medication in a Pyxis is completely depleted, a stockout list is printed immediately in the CP. During the day, there is always an assistant present to respond to these stockouts. This takes 30 minutes on average. Should a stockout happen during the night, the NU will generally borrow the medication from another unit, if possible and the medication will be restocked during the morning run. This requires almost no extra costs. If the medication is not available elsewhere and acutely needed, a pharmacist is called and has to come to the hospital to provide the needed medication. This is very expensive for the hospital.

2.4) Current problems

In Chapter 1, the core problem of having outdated inventory models was put forward. However, it was also mentioned that there are underlying problems, such as inventory inaccuracies. In this section, an analysis will be performed to see in what order of magnitude which problems contribute to the main problem.

Three NUs were asked about their experiences with these problems. The A5, IC, and C4 NUs were asked. The A5 and IC NUs were asked because according to the Pyxis assistants, these have the most frequent stockouts and discrepancies. The C4 was chosen as a control group because in general, the Pyxis assistants felt it performed relatively well.

After that, data that is available is also analysed to see if it is in line with what the NUs feel about the causes of the problem. With this analysis, we can check the extent of the problem, but also whether it occurs on all NUs, or just on certain ones.

2.4.1) Walking to the CP

After informing about it, neither of the aforementioned three NUs see walking to the CP as a major problem in their daily operations. The reason that nurses sometimes have to walk to the CP, is for special medications that are not in the assortment of their Pyxis. For stockouts, they do not need to go to the CP, since Pyxis assistants will come and refill it immediately. If the medication is needed on shorter terms, they will often borrow it from another NU.
Asking the pharmacy assistants that work behind the booth, so where nurses have to pick up the requested medication, yielded the same results. They explained that they have nurses coming to pick up medication a couple of times a day, but nothing out of the ordinary.

Unfortunately, no data is available on how often requests from NUs come in at the CP. The requests that do come in are written down on a small piece of paper. As soon as said request is granted, it is thrown away.

2.4.2) Stockouts

The NUs do not see the frequency of stockouts on their NU as a problem. It is acknowledged that poor inventory management on their part can lead to discrepancies. However, large inventory levels and (too) frequent restocking from the CP make it so that this does not manifest into a large number of stockouts. Thus, a large part of the effort is shifted from the NU to the Pyxis assistants.

Station	# SKUs	# Cycles	# Stockouts	% Stockouts	CSL
A5-THORAX	202	31916	121	0.38%	99.62%
A6-MDL	210	33180	48	0.14%	99.86%
AOA-A6	267	42186	77	0.18%	99.82%
AOA-BG	264	41712	62	0.15%	99.85%
B3-INTENS	54	8532	3	0.04%	99.96%
B4-ORTRAKA	95	15010	10	0.07%	99.93%
B4-PAAZ	119	18802	6	0.03%	99.97%
B4-PAAZMPU	141	22278	9	0.04%	99.96%
C3-CCU	194	30652	49	0.16%	99.84%
C3-EHH	162	25596	16	0.06%	99.94%
C3-TH-OK	5	790	5	0.63%	99.37%
C4-VAAT	177	27966	121	0.43%	99.57%
C5-STROKE	217	34286	89	0.26%	99.74%
C6-LONG	236	37288	112	0.30%	99.70%
E4-CHI/ONC	232	36656	119	0.32%	99.68%
E5-URO-NEU	224	35392	71	0.20%	99.80%
E6-HIC	138	21804	34	0.16%	99.84%
E6-INTERNE	283	44714	127	0.28%	99.72%
H1-NEO	49	7742	13	0.17%	99.83%
H1-VERLOS	68	10744	52	0.48%	99.52%
H2-KRAAM	102	16116	30	0.19%	99.81%
H3-KINDER	131	20698	40	0.19%	99.81%
ICUNITA	180	28440	83	0.29%	99.71%
ICUNITD	199	31442	147	0.47%	99.53%
ICUNITE	195	30810	116	0.38%	99.62%
OPIATEN	21	3318	17	0.51%	99.49%
SEH	162	25596	30	0.12%	99.88%

Table 2: Cycle Service Levels of the Nursing Units

This can also be seen in the data. To better put the number of stockouts in perspective, the CSL and FR will be addressed.

The CSL per NU was found by multiplying the number of cycles per SKU during the measuring period of 158 days by the number of SKUs on the NU. These numbers are shown in the third column of Table 2. Column 4 shows the number of stockouts recorded on that NU. The CSL is then simply calculated by doing: $1-\frac{\#\,cycles}{\#\,stockouts}$. As can be seen, the CSLs are very high. This is in line with the current inventory models and the experiences from the NUs. Please note that an assumption is made that no SKUs will stockout in the same cycle/day.

NU	# Stockouts	Average per order	Missed Demand	Total Demand	Fill Rate
A5-THORAX	121	3.44	416	106384	99.61%
A6-MDL	48	1.94	93	14012	99.34%
AOA-A6	77	1.61	124	30783	99.60%
AOA-BG	62	1.67	103	43441	99.76%
B3-INTENS	3	1.54	5	1548	99.70%
B4-ORTRAKA	10	2.27	23	2329	99.03%
B4-PAAZ	6	2.06	12	5303	99.77%
B4-PAAZMPU	9	2.01	18	11698	99.85%
C3-CCU	49	1.61	79	20522	99.62%
C3-EHH	16	1.52	24	8360	99.71%
C3-TH-OK	5	2.33	12	386	96.99%
C4-VAAT	121	2.31	279	31774	99.12%
C5-STROKE	89	2.04	182	42459	99.57%
C6-LONG	112	1.88	210	23816	99.12%
E4-CHI/ONC	119	2.22	265	34656	99.24%
E5-URO-NEU	71	2.31	164	13649	98.80%
E6-HIC	34	1.72	58	5887	99.01%
E6-INTERNE	127	2.65	336	31401	98.93%
H1-NEO	13	1.50	20	4844	99.60%
H1-VERLOS	52	2.17	113	7773	98.55%
H2-KRAAM	30	2.42	73	12501	99.42%
H3-KINDER	40	1.74	70	15600	99.55%
ICUNITA	83	1.80	149	36832	99.59%
ICUNITD	147	1.70	250	40558	99.38%
ICUNITE	116	1.35	157	34583	99.55%
OPIATEN	17	5.19	88	36225	99.76%
SEH	30	1.48	44.29	14661	99.70%

Table 3: Fill Rates of the Nursing Units

Evaluating the current FR is a little harder because no records are kept of missed demand. It is possible, however, to make an estimation using the average order size per NU and taking that as a rough estimate of demand missed. Multiplying the number of stockouts by this average demand (or missed demand) will give us the total amount of demand missed. This can then be used to calculate the fill rate by dividing it by the total demand on that NU. The results are shown in Table 3. Please note that this is a crude estimate because stockouts might occur more frequently for SKUs with low inventory and low average demand, or the other way around.

2.4.3) Discrepancies

The NUs are aware of discrepancies occurring on their unit, but they rarely experience the negative effects because the CP restocks so quickly. The discrepancies still occur because using the Pyxis' exactly according to the book is too ponderous and often takes time the nurses don't have.

After asking further, there are several problems with the Pyxis' that largely explain the poor inventory management (and thus the discrepancies). The first, and perhaps the biggest, is that the patient system is not connected to the Pyxis system. This means that the Pyxis does now know which medications are prescribed to which patient. To retrieve medication for a patient, a nurse needs to search in the complete list of medications present. This is of some annoyance in regular daily activities, of larger annoyance for NUs with more Pyxis usage, but largest for NUs where a whole COW needs to be filled. Here, nurses often fill these during the night and must manually enter all medications for all patients. Especially during this stage, a lot of inventory inaccuracies occur, because nurses take out multiple boxes of medications to speed up the COW-filling process. Afterwards, the correct amount of medications retrieved rarely is logged, resulting in the discrepancies.

The second example of how regular discrepancies form mainly takes place in the Intensive Care Units. Here, patients lie that, as the name suggests, require intensive care. In frequently occurring situations patients require a certain set of medications immediately. Since the Pyxis does not know which medications are prescribed to which patient, it does not matter for the nurses which patient they select to retrieve medications for. This data is stored, but not compared periodically to the patient files to see if the medications retrieved from the Pyxis' per patient are the same as those prescribed. Connecting the patient system with the Pyxis system would both add a check that only the correct medications can be retrieved for the correct patients and make the process of retrieving medications easier.

Thirdly, suppliers deliver medication more and more in strips instead of separate packaging. The strip then contains only one expiration date, instead of every individual pill having one. This forces the NUs to put a whole strip in a COW-tray, even if the patient only needs one or two. Struggles arise about how many retrieved medications need to be logged; the whole strip or just the amount the patient is going to use? The inventory level will need to be readjusted after the strip is returned (if the strip is returned). Often, NUs reuse the strip for other patients as well since it is easier than retrieving a new strip from the Pyxis.

Lastly, the Pyxis cupboards sometimes cope with mechanical problems: doors or drawers not opening or closing correctly. According to the system, this needs to be resolved before additional medications can be retrieved. These problems slow and hinder the NUs in their work and decrease overall satisfaction and willingness to correctly work with the Pyxis.

Discrepancies are handled in reports available from the Pyxis system. They are, however, not summarised in a single overview, but rather need to be counted by hand. For this reason, only several samples will be taken to get a general idea of the number of discrepancies. Four random test samples were taken. The samples were taken from the IC-E, A5, C4 and E6 NUs. The first three to see if the data aligns with the feedback from the NUs themselves. The E6 was taken at random. The duration of the sample data was shorter for busier NUs and longer for NUs with less Pyxis activity. This was done to ensure an approximately equally large sample size of total refill activities. The results can be seen in Table 4.

Nursing Unit	Sample duration	Number of refill activities	Number of discrepancies	Inventory accuracy
IC-E	16-01-2020 to 18-01-2020 (2 days)	22	12	45%
A5	01-02-2020 to 02-02-2020 (1 day)	15	9	40%
C4	13-02-2020 to 17-02-2020 (4 days)	25	10	60%
E6	13-02-2020 to 17-02-2020 (4 days)	54	10	81.5%

Table 4: Samples of discrepancies across different NUs.

The first three have an incredibly low inventory accuracy. The E6 does better on this front, but its inventory accuracy is still very low. The discrepancies happen because of the aforementioned reasons and these samples show that it is a real problem on the NUs. Please note that these percentages are only rudimentary estimations and are only meant to assess whether or not there potentially is a problem or not. These sample tests definitely suggest there is, but for exact figures, a more extensive analysis should be performed.

2.4.4) Inventory levels

The assortment and the inventory levels are seen as adequate by all three NUs. The data suggests the same: the inventory levels of two and four weeks of demand for most medications is very high and should be adequate for the NUs. The number of stockouts is also low enough that high satisfaction is expected.

2.4.5) Assortment

The assortment of the Pyxis' is perceived as good by the three NUs that were asked. It does occur sometimes that, when a new patient arrives, a medication is not in their assortment and they have to go and pick it up at the CP. Nevertheless, everyone understands that the space in the Pyxis' is not infinite and thus not everything can be in there.
The data suggests that with an improved inventory model, the needed inventory can be reduced and the assortment in most Pyxis' could be expanded.

2.5) Stakeholders

There are numeral stakeholder groups, which are listed in Table 5.

Population group	Outcome of renewed inventory models and improved inventory management
The pharmacists and (Pyxis) assistants	Positive: less work
The clinical pharmacy	Positive: less spillage, more accurate demand forecasting
The nurses	Positive: medications more often at hand, less work
The patients	Positive: better quality care

The hospital	Positive: fewer costs

Table 5: A table of all the stakeholders

2.6) Summary

- The MST does not use any inventory classification as of yet.
- The MST currently uses an (R, s, S) inventory policy, with $R = 1\,day$, $s = 2\,weeks\ of\ average\ demand$ and $S = 4\,weeks\ of$ average $demand$ for all SKUs.
  - Since $R + L = 1\,day$, about 13 days of safety stock is kept. That should, normally, mean no stockouts occur.
  - The fact that some stockouts still occur, can mostly be explained by poor inventory management and accuracy.
- The current average overall CSL is 99.75% and the current average overall FR is 99.33%
- The initial problem of nurses having to walk to the CP too often is not a widespread concern. On average, only once or twice a day does a NU need to pick up a medication from the CP.
- Rather, poor inventory accuracy and inventory management make for these high inventory levels to be required.
- Solving the other Pyxis problems falls outside the scope of this thesis, so inventory models and assortments will be updated

3) Literature study

In this chapter, the sub-question: "What can be learned from the literature regarding inventory policies of AMDS' in a hospital" will be addressed. For this, literature will be analysed to build the theoretical framework or methodology for inventory planning and assortment in the MST. Theory or terms that have been discussed during the bachelor Industrial Engineering and Management will be discussed only very briefly. More detailed information on these subjects can be found in Appendix B.

"The fundamental purpose of a replenishment control system is to resolve the following three issues or problems:

1. How often the inventory status should be determined
2. When a replenishment order should be placed
3. How large the replenishment order should be"

(Silver et al., 2017, p. 240)

These problems can be solved by answering the following questions:

1. How important is the item?
2. Can, or should, the stock status be reviewed continuously or periodically?
3. What form should the inventory policy take?
4. What specific cost or service objectives should be set?

(Silver et al., 2017, p.240)

These questions will be answered one by one in the following paragraphs.

3.1) Inventory classification

Inventory is often classified into subgroups to divide energy and resources adequately between these subgroups. The classification can happen based on several criteria or a combination of them. The most common inventory classification is the ABC classification, which bases the classification on dollar usage, the usage multiplied by the cost of the product (Silver et al., 2017). See Appendix B for more detail on the ABC classification.

3.2) Continuous or periodic review

A system where inventory levels are continuously monitored is called a continuous review system (CRS). The other option is checking the inventory levels only at pre-specified times: a periodic review system (PRS). There are some advantages and disadvantages to both systems, to be explained here. In a PRS, after making an inventory classification, logical groups of products can be reviewed according to the same interval. Also, PRS allows for easier workload prediction and a more even workload. For CRS a replenishment could be needed at practically any point in time. Another disadvantage of CRS is that it is overall more expensive, especially considering reviewing costs and reviewing errors. The reason CRS is still used is that it requires less SS for the same CSL. (Silver et al., 2017, p. 241)

3.3) Different inventory policies

The form of inventory policy can be determined once the item class has been chosen, and a choice was made between a CRS and a PRS. The inventory policy form will help answer <u>when</u> and <u>how large</u> of an order should be placed. There are four major inventory policies, discussed below. (Silver et al., 2017, p. 245)

3.3.1) (s, Q) systems

This is a CRS ($R = 0$), where Q is the fixed order size and s is the reorder point. So, Q items are ordered whenever the inventory level drops below s.
This type of system is sometimes also called a 'two-bin system'. Two bins are used and whenever the first bin is empty, a reorder is triggered.
Advantages: Simple to understand and implement. Production requirements are relatively predictable.
Disadvantages: With large individual transactions, one order of Q units might not be enough.

3.3.2) (s, S) systems

Again, continuous review is used in this system. As in the previously covered system, an order is placed when the inventory position drops to or below s. The difference, however, is that now the order is sized so that the inventory will be raised to S, the order-up-to level.
Advantages: This system has the potential to lower total costs.
Disadvantages: The calculations of optimal s and S values require a lot more computation than the values for an (s, Q) system. Also, fixed order sizes are often preferred by suppliers and make for smaller chances of making mistakes.

3.3.3) (R, S) systems

The (R, S) system is a PRS, where R denotes the review period. Every review period, the inventory level is raised to S.
Advantages: This system can be efficient by combining the ordering of related items. Also, because after each review period R, the S level could be adjusted to changing demand, it is flexible for systems where demand might vary.
Disadvantages: The (R, S) system produces higher carrying cost and has varying order sizes.

3.3.4) (R, s, S) systems

This is a combination of the (s, S) system and the (R, S) system. After every period of R units of time, if the inventory position is below s, an order is placed to raise it to S. In theory, the (s, S) system is a special case where $R = 0$, and the (R, S) system where $s = S - 1$. This system is seen often when R is selected based on convenience (e.g., 1 day), even when continuous review is possible.
Advantages: Has the potential to produce the lowest total cost of all systems.
Disadvantages: The computation of three parameters requires more work and the system is more difficult to understand.

Silver et al. (2017) also put forward a rule of thumb for choosing appropriate inventory policies based on the type of review available (PRS or CRS) and the class the item is in. It is displayed in Table 6.

	Continuous review	Periodic review
A items	(s, S)	(R, s, S)
B items	(s, Q)	(R, S)

Table 6: Rule of thumb for selecting the form of the Inventory Policy

3.4) Cost and service objectives

In the case of probabilistic demand, there is always a chance of not being able to fully satisfy all demand. This is countered by keeping a safety stock (SS, see Appendix B). Determining the size of this SS can be done based on four different criteria, often taking in mind what the customer finds important. The four criteria are: (Silver et al., 2017, p.246)

1. SSs are determined by a simple-minded approach. Using this method often saves time and effort, but rarely produces excellent results.
2. SSs are based on minimizing cost. This method looks at the costs of all aspects involved and makes a trade-off determining the policy which produces the lowest costs.
3. SSs are based on customer service. An extra constraint is added in this method: the CSL (or the FR). For this method, the total costs are minimised again but subjected to a minimum CSL or FR.
4. SSs are based on aggregate considerations. "The idea of this general approach is to establish the SSs of individual items, using a given budget, to provide the best possible aggregate service across a population of items. Equivalently, the selection of the individual SSs is meant to keep the total investment in stocks as low as possible while meeting the desired aggregate CSL." (Silver et al., 2017, p. 246)

There are no clear rules for determining which objective is best in what circumstances. Choosing one or the other should oftentimes depend on the (competitive) environment of the company.

For this thesis, the choice is made to focus on the FR. This way, the MST can keep track of how severe stockouts are, instead of only being able to count the frequency. Also, medication that has a stock of 1 will not be counted as a stockout when retrieved. Since all demand was still satisfied from shelf, the FR stays untouched.

3.5) Demand distribution

Now that the process of determining an inventory control system has been described, the parameters must be determined. The formulas to calculate these parameters do not only vary based on the inventory control system chosen, but also on the statistical distribution the demand most closely follows. Therefore, the demand distribution needs to be determined before calculations can be made.

The complete process of fitting a distribution to data can be explained by the following three steps: (Robinson, S., 2004)

- Selecting a statistical distribution
- Determining the parameters
- Testing the goodness-of-fit

3.5.1) Selecting a statistical distribution

There are several rules of thumb for selecting a distribution to a demand pattern, and not always does the goodness-of-fit need to be tested. For some SKUs, it is not worth to execute that rather resource-intense plan. With that in mind, different rules of thumb have been described for different inventory classes. They will be discussed below.

3.5.1.1) A class

The potential benefits of using a more accurate representation are higher for A class items (Silver et al., 2017). Therefore, even though the normal distribution is often still taken as the expected distribution, Silver et al. (2017, p. 352) suggest that if the average demand per replenishment cycle (ADPRC) is less than 10 units, a discrete distribution is more appropriate. A Poisson distribution should be considered when the observed standard deviation during lead time σ_{R+L} is within 10% of $\sqrt{\hat{x}_{R+L}}$. Should that not be the case, a more complicated discrete distribution, such as the negative binomial, should be considered. If the ADPRC is more than 10, the ratio $\sigma_{R+L}/\hat{x}_{R+L}$ should be checked. Should this ratio be larger than 0.5 or when the data is skewed, the normal distribution is likely not the best-fitting distribution. Instead, a gamma distribution will probably be more fitting.

Should the fit of the selected distribution still be inadequate, the following can be tried. Firstly, the data should be visualised to get a clear overview. A histogram is an often-used aid to see the rough shape of the distribution. Secondly, the process from which the data originates often has known properties that suggest certain distributions.

3.5.1.2) B class

B class items rarely warrant extensive distribution fitting processes. The rules of thumb described above provide an accurate enough idea of what distribution to fit the found demand data: if the ADPRC exceeds 10, a continuous distribution should be used. If the ratio $\sigma_{R+L}/\hat{x}_{R+L}$ is smaller than 0.5, the normal distribution should be used. Otherwise, the Gamma distribution might provide a better fit. If the ADPRC is less than 10, a discrete distribution should be used. The Poisson distribution is the first choice, except for when the observed standard deviation during lead time is not within 10% of $\sqrt{\hat{x}_{R+L}}$. In the latter case, a negative binomial distribution should be used.

3.5.1.3) C class

For C class SKUs, a more rudimentary approach is suggested by literature (Silver et al., 2017, p. 360). With low ADPRC, a discrete distribution is suggested. The Poisson distribution gives an adequate approximation most of the time, but due to increased computing power in PCs, the calculations from the B class could be extended to the C class, if the data suggests they have the same distribution. If needed, sometimes a more generalised approach can be used, encompassing most, if not all SKUs. Or individual exceptions can be made to tailor specific SKUs based on experience or other observations.

3.5.2) Determining distribution parameters

The parameters that need to be determined depend on the type of distribution that is tested for. For a normal distribution only the mean and standard deviation need to be estimated, while for a gamma distribution α and β need to be estimated using the following: (Silver et al., 2017, p. 745)

$$\alpha = \frac{\hat{x}_{R+L}^2}{\sigma_{R+L}^2} \quad (1)$$

$$\beta = \frac{\sigma_{R+L}^2}{\hat{x}_{R+L}} \quad (2)$$

For a Poisson distribution, the two parameters are: (Silver et al., 2017, p. 352)

$$\hat{x}_{R+L} = D * L \quad (3)$$
$$\sigma_{R+L} = \sqrt{\hat{x}_{R+L}} \quad (4)$$

Please note that for a continuous review system, $R + L$ should be replaced with L.

For a negative binomial distribution, the parameters are r (the number of failures until the experiment is stopped) and p (the chance of success). These parameters can be calculated with the mean $\hat{x}_{R+L}$ and the variance σ_{R+L}^2 using the following relationships:

$$r = \frac{\hat{x}_{R+L}^2}{\sigma_{R+L}^2 - \hat{x}_{R+L}} \quad (5)$$

And

$$p = 1 - \frac{\hat{x}_{R+L}}{\sigma_{R+L}^2} \quad (6)$$

(Van der Heijden, M., n.d.)

3.5.3) Testing the goodness-of-fit

Thirdly a check needs to be performed to see how well the chosen distribution fits the empirical data. This can be done using a goodness-of-fit test. The most common goodness-of-fit test is a chi-square goodness-of-fit test. The formula used in this test is as follows:

$$\chi_c^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{7}$$

Here c refers to the number of degrees of freedom, O_i is the observed value and E_i is the expected value according to either handpicked values or the expected value from a certain distribution. The test checks if the null hypothesis, that the empirical data does follow the suggested distribution, should be rejected or not. If the chi-square value is less than the critical value (level of significance), then the proposed distribution cannot be rejected as a good fit (Robinson, S., 2004, p.112-118).

3.6) Decision rules

Once an inventory classification has determined which SKU's warrant detailed and sophisticated inventory policies, and once the demand distribution has been determined, the variables from the chosen policy can be calculated. The decision rule to use depends on various factors, including the inventory policy, the cost and/or service objectives and the demand distribution. In Chapter 4 it is stated that the used policy will be an (R, s, S) policy, for a CSL and/or FR service objective. Therefore, the decision rules explained below will focus on those alone.

For all decision rules, it is assumed that the order quantity, lot size or order size Q has been predetermined. This is most often done using the EOQ formula (sometimes also known as Camp's formula).

3.6.1) Normally distributed demand

In case of a fill rate constraint for an (R, s, S) policy, s is selected to satisfy:

$$\sigma_{R+L}^2 * J_u\left(\frac{s - \hat{x}_{R+L}^2}{\sigma_{R+L}}\right) - \sigma_{R+L}^2 * J_u\left(\frac{s - \hat{x}_L^2}{\sigma_L}\right) = 2(1 - P_2)\hat{x}_R^2\left(S - s + \frac{\sigma_R^2 + \hat{x}_R^2}{2\hat{x}_R^2}\right) \tag{8}$$

Where
$S - s$ is assumed to be predetermined (e.g., by the EOQ, or maybe package size) and
$J_u(k) = \int_k^\infty (u_0 - k)^2 f_u(u_0) du_0$ is a special function of the unit normal distribution.
(Silver et al., 2017, p.335)
This formula can be simplified if: the desired FR is high enough ($P_2 \geq 0.9$), the demand pattern is relatively smooth and R is not too small compared with L. In this case, the second term in the left-hand side of Formula 8 can be ignored. Then, if:

$$s = \hat{x}_{R+L} + k\sigma_{R+L} \tag{9}$$

the decision rule is reduced to selecting k as to satisfy:

$$\sigma_{R+L}^2 * J_u(k) = 2(1 - P_2)\hat{x}_R\left(S - s + \frac{\sigma_R^2 + \hat{x}_R^2}{2\hat{x}_R}\right) \tag{10}$$

Using a table of $J_u(k)$ versus k, makes finding the appropriate k not difficult.
According to Silver et al. (2017, p. 745), $J_u(k)$ can also be expressed as an excel function:

$$J_u(k) = (1 + k^2)\big(1 - NORMDIST(k, 0,1, TRUE)\big) - k * NORMDIST(k, 0,1, FALSE) \qquad (11)$$

Additionally, for a given value of $J_u(k)$, the desired value of k can be found in excel using the following:

$$k = \frac{a_0 + a_1 z + a_2 z^2 + a_3 z^3}{b_0 + b_1 z + b_2 z^2 + b_3 z^3} \qquad (12)$$

Where for $0 \leq J_u(k) \leq 0.5$

$$z = \sqrt{\ln\left(\frac{1}{Ju(k)}\right)^2}$$

$$a_0 = -4.18884136 \times 10^{-1}$$
$$a_1 = -2.5546970 \times 10^{-1}$$
$$a_2 = 5.1891032 \times 10^{-1}$$
$$a_3 = 0$$

$$b_0 = 1$$
$$b_1 = 2.1340807 \times 10^{-1}$$
$$b_2 = 4.4399342 \times 10^{-2}$$
$$b_3 = -2.6397875 \times 10^{-3}$$

And for $J_u(k) > 0.5$

$$z = Ju(k)$$

$$a_0 = 1.1259464$$
$$a_1 = -1.3190021$$
$$a_2 = -1.8096435$$
$$a_3 = -1.1650097 \times 10^{-1}$$

$$b_0 = 1$$
$$b_1 = 2.8367383$$
$$b_2 = 6.5593780 \times 10^{-1}$$
$$b_3 = 8.2204352 \times 10^{-3}$$

This can easily be implemented in Excel to find the value of k, which is in turn used to find s using Formula 9. Lastly, S is found simply by doing $s + Q = s + (S - s) = S$.

3.6.2) Gamma distributed demand

If the demand follows a gamma distribution, then formulas change slightly.
The probability of a stockout in a replenishment cycle (CSL) given a certain reorder point is calculated according to the following formula:

$$Probability\ of\ a\ stockout = 1 - P_1 = 1 - GAMMADIST(s, \alpha, \beta, TRUE) \qquad (13)$$

$GAMMADIST$ is a function in excel, using the input variables seen in Formula 13. If the reorder point is wanted, the following formula is used instead:

$$s = GAMMAINV(P_1, \alpha, \beta) \qquad (14)$$

To calculate the reorder point for a given FR, first the Expected units Short per Replenishment Cycle (ESPRC) is determined according to:

$$ESPRC = \mathrm{Q} * (1 - \mathrm{P}_2) \tag{15}$$

Then, the reorder level can be found by solving:

$$ESPRC = \alpha * \beta * [1 - GAMMADIST(s, \alpha, \beta, TRUE)] - s * [1 - GAMMADIST(s, \alpha, \beta, TRUE)] \tag{16}$$

Lastly, the order-up-to-level S is calculated by doing: $S = s + Q$.

3.6.3) Discrete distribution: Poisson

Discrete distributions are more suitable for slow-moving items, as was made clear in Chapter 3.5.1.1. The decision rules are quite easily calculated similarly to the Gamma decision rules. However, in excel, there is currently no function for the inverse Poisson. So, using a very basic VBA script, a function was created. It takes the desired CSL and the mean of the data and outputs the first x for which $POISSON(x, mean, TRUE)$ is equal to or larger than the desired CSL. Using this, the reorder point can be calculated. This can be explained by the fact that the CSL describes the chance that no stock out occurs in the replenishment cycle. The cumulative percentage depicts the chance that the found value is the maximum demand during the replenishment cycle and can thus be interpreted as the chance that demand does not overshoot the found value (= the chance of a stockout).

Alternatively, the FR can be calculated similarly to the gamma distribution. First, Formula 15 is used to find the ESPRC for the desired FR. Then, the following formula is solved for s.

$$ESPRC = mean[1 - POISSON(s - 1, mean, TRUE)] - s[1 - POISSON(s, mean, TRUE)] \tag{17}$$

(Silver et al., 2017, p.747)
Again, S can be found by doing $S = s + Q$, where Q is assumed predetermined.

3.6.4) Discrete distribution: negative binomial

For a negative binomial distribution, the same applies as for the Poisson, discussed in Chapter 3.6.3. Again a simple script is written to create the inverse of the negative binomial function:

$$s = INV.NEGBIN.DIST(CSL, r, p) \tag{18}$$

The value of s can be found using the desired CSL, and r and p, which can be calculated as described in Formulas 5 and 6 in Chapter 3.5.2.

Alternatively, as with Poisson distributed demand, Formula 15 is used to find the ESPRC for a certain FR, and then the following formula is solved for s.

$$ESPRC = \frac{r * p}{1 - p}[1 - NEGBINOM.DIST(s - 1; r + 1, p, TRUE)] - s[1 - NEGBINOM.DIST(s; r, p, TRUE)] \tag{19}$$

3.7) Verification and Validation

Starting with their definitions: “verification is the process of ensuring that the model design has been transformed into a computer model with sufficient accuracy.” (Davis, P., 1992) “Validation, on the other hand, is the process of ensuring that the model is sufficiently accurate for the purpose at hand.” (Carson, J., 1986)

3.7.1) Conceptual model

The conceptual model needs to be checked against the project specifications to see if it covers all requirements. This involves frequent discussions with the supervisor and the people who have detailed knowledge of the process(es).

3.7.2) Data validation

There are numerous verification and validation methods, of which not all apply to this thesis since no actual model is made. Calculations are made according to established methods, using substantiated assumptions about distributions in the data. This data, however, proves to be a point of interest from a validation point of view.

Data serves as input for a model as well as the method developed in this thesis. The quality of the data can make or break the quality and usability of the output of the method singlehandedly. The sources for the data should always be investigated to determine their reliability. Additionally, the data itself should be studied to see if any inconsistencies or any other cause for concern arise. (Robinson, S., 2004, p.215)

3.7.3) Comparison with the real system

To see whether a system represents the real world to a sufficient degree, outputs should be similar to real-world outputs, given the same conditions (inputs). (Robinson, S., 2004, p.217) This proves to be challenging, as it is dependent on the quality of the data as well. With insufficiently accurate data the results of comparing the model with the real world will not be alike.

3.8) Summary

- The literature study shows a method for determining new inventory rules that are most likely very applicable to the MST, including:
    - Determining how important the item is and how many resources should be dedicated to designing its inventory control system (ABC classification)
    - Determining what is possible and what the inventory policy for that item should be
    - Determining what variable should be optimised by the inventory control system
- Most aspects of the method will be easy to implement in the situation of the MST. The data found in Chapter 2 is adequate for making the calculations
- To model demand as accurately as possible, the demand data will be fitted to a statistical distribution. This can be done according to the rules-of-thumb described, or with professional programs. Also, goodness-of-fit tests will need to be performed
- The desired cost and service objectives will be determined by the management, but an objective Fill Rate service level is recommended.
- There is no literature included about assortment determination. This will have to be done according to heuristics.

4) Bringing theory into practice

In this chapter, the sub-question: "How can the findings from the literature be implemented into the specific case of the MST?" will be addressed. The goal of the method, as well as the excel tool provided, is to, with sufficiently accurate input data, construct new inventory rules that better fit the demand pattern and the situation in the MST. The method and tool enable the CP to review the inventory levels periodically and with less effort.
At first, the requirements and prerequisites for the method are described. Then, the main body of the method, where the actual new inventory rules are determined, is discussed. Lastly, method validation and verification are covered.

4.1) Input data

The first step in creating a new methodology for inventory planning and assortment determination is collecting input data. The input data is the foundation of the methodology because every conclusion and/or result will be based on that data.
The input data will need to be an accurate representation of all demand on a certain NU, with clear distinction of which medications were retrieved from the Pyxis' and which portion of demand came from patient-specific medications delivered by the CP. The demand will have to be available per review cycle to get a good estimation of the mean and standard deviation per replenishment cycle.

4.2) Inventory classification

The first thing to do is to perform an inventory classification. The goal of this ABC-classification is to segregate the SKUs in a specified number of classes based on their importance, or in this case, their number of uses. This way, energy and other resources can be focused on where they have the most impact. See Chapter 3.1 and Appendix B.3. For the MST, the number of inventory classes was chosen to be three. This is enough to accurately separate SKUs so that the amount of effort going into determining inventory rules will reflect the expected payoff.
The ABC-classification will be done based on the total number of uses, as per the request of the MST. The dataset is sorted with the medications with the most total uses during the collection period on top. The next step in the inventory classification, after determining the criterion, is to set boundaries for the classes. The boundaries can be defined from two standpoints: the cumulative percentage of SKUs, or the cumulative percentage of uses. As can be read in Appendix B.3, the usual boundaries lie at 5%-10% of the cum. percentage of SKUs for the A class and around 20%-30% for the B class, depending on the steepness of the ABC-curve. Normally, different classes warrant different inventory models. However, as stated below in Chapter 4.3, all classes will be outfitted with an (R, s, S) model. The difference between the classes will be expressed largely by the fact that a better fitting distribution will be used for A class SKUs and that these SKUs will be handled more meticulously, both with determining and with implementing the new inventory models.
In the excel tool, the boundaries can be freely chosen by the user. The choice of whether the boundaries are placed on certain percentages of the number of SKUs or percentages of uses is also available to the user. This way, total freedom is given to enable the user to get the desired results.
Chapter 5.10 will discuss a numerical experiment where specific values for the boundaries are chosen and advocated.

4.3 Inventory models

Once an inventory classification is performed, an appropriate inventory model will be selected. This will start with determining the review period, as described in Chapter 3.2. The current Pyxis system in use at the MST is capable of continuous review of the inventory levels. However, because the Pyxis

assistants who are tasked with refilling the Pyxis, also have other tasks to attend to, the conscious choice was made to implement a periodic review period of one day. Every morning, lists are printed containing which medications dipped below their s (reorder point) during the past 24 hours.
For the method, the same review period will be used. Partly because the system that is in place works well: utilising a continuous review period would require a lot more work from the assistants. And partly because implementing a new review system will be a lot of work.

Once the review period is determined, the rules of thumb from Silver et al. (2017), as seen at the end of Chapter 3.3, can be used to determine fitting inventory models. With the periodic review system, the rules of thumb suggest that the (R, s, S) system would be a logical choice for A class items and the (R, S) system for B and C class items.
Even though this rule of thumb generally works for inventory systems where the review period is longer or the restocking procedure is less time-consuming, for the case of the MST an (R, S) inventory model would be very unhandy. In Chapter 2.2, it is shown that the MST currently uses an (R, s, S) system for all medications in their Pyxis cupboards. This inventory policy will be kept, because, unlike the current parameters, the system itself is the right choice. The number of Pyxis assistants is not that large, and they do not have a lot of time for refilling the Pyxis, which costs a lot of time. With an (R, S) system, every medication is refilled every day, even if demand during the last replenishment period was not substantial. It saves a lot of precious time if the assistants only have to refill medications when it truly needs refilling. On top of that, most medications come in packages or strips of 10 or a multiple of 10, making it extremely unpractical to have to refill smaller amounts than that. The refill quantity (or order quantity Q) will also be pragmatically adapted to this. This will also be incorporated in Chapter 5.
In conclusion: the (R, s, S) policy is currently used for all SKUs and will be used for the A class, but also the B and C classes.

In an inventory model, the cost and/or service objective determines what criterion the formulas should be minimised for. The MST set the desired CSL to 95% so that the total average inventory is minimised for that CSL. This is relatively low, especially looking at the currently attained CSL from Chapter 2.4.2. As mentioned before in Chapter 3.4, the FR is seen as a better service objective, as it also entails the severity of stockouts. Therefore, the numerical experiment will start with calculating the decision rules for a FR of 95%. After that, a sensitivity analysis will be done to see what the average total inventory will be for other FR levels. This is especially useful because the current FR is estimated to be around 99.6%, and with the sensitivity analysis, it can be checked whether improvement on the current situation can be suggested for a FR that is close to the current FR.

4.4) Demand distribution

Before calculations can be made to determine the decision rules, the demand distribution per SKU needs to be determined, together with the corresponding parameters.
This is done using the rules of thumb from Chapter 3.5.1. After that, the appropriate parameters of the found distributions will be calculated in excel. For the A class, a goodness-of-fit test can be performed (in Excel or another program).
For the A5 NU chosen in the numerical example in Chapter 5, this means that the first 14 of the 32 A class SKUs are fitted with a gamma distribution. The remaining 18 follow a negative binomial distribution more closely. The B and C class SKUs all have low enough ADPRC and high enough variability to warrant a negative binomial distribution as well. These choices will be worked out in more detail in Chapter 5. There, the distribution parameters will be calculated as well.

4.5) Decision rules

As described in Chapter 3.6, a lot size Q is expected to be predetermined, usually using the EOQ. In this case, however, there were not enough resources available, both in data and time, to calculate these values. Instead, lot sizes were chosen heuristically, using old lot sizes and average daily demand to help determine them. These lot sizes are always rounded off to multiples of 10 or package sizes since it is of no use to refill 8 pills when there are 10 in a strip. In the sensitivity analysis performed at the end of Chapter 5, varying values of Q are taken to see the effect on the reorder point and average total inventory. A more in-depth analysis of the effect of other lot sizes will be performed in Chapter 5.10.3.

Now that all necessary variables are defined, the actual decision rules can be applied to find the needed input parameters of the chosen inventory system. Using the formulas from Chapter 3.6, the reorder point, order-up-to level, and safety stock can be calculated.
Once these variables have been calculated, their values are compared to current values to get an idea of potential inventory reduction.

Using the resulting new inventory levels from the method described above, a new assortment could be established. Especially the first time these new inventory policies will be implemented, a large reduction in inventories is expected, freeing up room for potential additional SKUs in the Pyxis. Also, a clearer view of the current usage is given, partly due to the inventory classification. There are likely to be several SKUs not used regularly which can be removed from the Pyxis' to free up space for other, more frequently used SKUs. This will have to be determined by the pharmacists, as other factors that are not considered by the method could play a role.
Even though the method will provide a suggested reduction in inventories, it does not offer up which SKUs would be appropriate to add to the Pyxis assortment: that will have to be determined by the pharmacists and the nurses.

4.6) method validation and verification

4.6.1) Conceptual model

The conceptual model needs to be checked against the project specifications to see if it covers all requirements. This involves frequent discussions with the supervisor and the people who have detailed knowledge of the process(es). (Robinson, S., 2004, p. 214-215)
This was done with the department head of clinical pharmacy, the process manager of clinical pharmacy, the pharmacists assistant focussing on the Pyxis systems, and several other pharmacists and Pyxis assistants. Also, nurses from the nursing department were included in this process. There were some suggestions about the visualisation of the medication flows in the hospital and which NUs would most likely be the most promising to potential improvements. Also, additional requests, such as broadening the range of SKUs for the model, were made.

4.6.2) Data validation

The data collected will have to be as accurate as possible. The data source should be checked to see if it is reliable and accurate. For example, the Pyxis data is not always accurate, because of the discrepancies explained in Chapter 2.4.3. Sometimes more medication was taken out than was registered, or sometimes the other way around. At other times, it might be tried to rectify these discrepancies by counting and adding a phantom 'retrieval' to set the expected stock equal to the actual stock again. This will give a higher demand for that specific day (or another review period) than in actuality, resulting in a higher standard deviation of the data.
Additionally, some medications have a max (S) set to 9999 for an unknown reason. These must be excluded to prevent them from corrupting the quality.
All of these inventory inaccuracies might degrade the quality of the data and should be kept under close watch.

4.6.3) Comparison with the real system

To make a comparison with the real system, the current reorder point and the order-up-to point will be taken as input and the output of CSL and/or FR will be checked against the values found in Chapter 2.

4.7) Summary

- Due to the good fit between theory and practice, the appropriate inventory policies can be determined relatively well.
- Heuristics will be applied to determine lot sizing, instead of the usual process including the EOQ.
- The extent of the demand data is adequate, although the credibility could be improved.

5) Numerical experiment

In this chapter, the sub-question: "What are the expected improvements regarding the KPI's?" will be addressed. This will be done by carrying out a numerical experiment using the method described in the previous chapter. All steps from the method will be followed to arrive at a potential new set of inventory rules. After that validation will be done to check if the method is a good impression of the real world and if the found results can be considered usable. Lastly, a sensitivity analysis will be performed to see whether additional improvements could be made with other data or other input parameters.

5.1) Input data

As input data for this numerical experiment, we take a dataset containing all usage data concerning Pyxis. This dataset contains 303,883 data entries from 04/10/2019 until 09/03/2020 (158 days). The A5 NU was chosen for this numerical experiment because previous research and talks with staff suggest large improvements could be achieved here. After filtering for the A5 and only retrieval actions, the dataset contains 30961 data points. The categories include retrieval date, retrieval time, medication ID, inventory before action, inventory after the action, min (s), max (S). There were some other categories, but they were not needed and thus removed from the dataset.
The average demand per replenishment cycle here was calculated by dividing the total demand recorded by 158 (total number of days of which the data set consists) and then multiplying by the number of days in a review period. The standard deviation was calculated using Excel's in-built function, including zeroes on days no demand was recorded. The found standard deviation is lastly multiplied by the square root of the review period.

5.2) Inventory classification

As described in Chapter 4.2, the tool prompts the user to select boundaries for the inventory classification. For this experiment, the chosen boundaries were based on the per cent of total uses: A-B boundary: 70% of total uses, B-C boundary: 90% of total uses. The tool automatically sorts the SKUs in descending order based on the number of uses and separates the classes using colours. In the A class are the first 32 SKUs (16% of the total number of SKUs), the B class contains the next 45 (22%), and the C class contains the last 124 SKUs (62%), making the total SKUs in the A5 Pyxis 201.
A button is displayed for copying the SKUs in ranking order to the next worksheet. The SKUs in class A and B can be found in Appendix D.

5.3) Inventory models

As described in Chapter 4.3, the replenishment period $R + L$ is taken to be one day. According to Chapter 4.3, the current (R, s, S) system is the most viable inventory policy for the MST, for all classes. The review period cannot be changed to continuous because that would mean that the Pyxis assistants would have to be available for refill activities during the whole day (and night). So, a periodic review period of $R = 1$ will be kept (for the A and B class. More about this in Chapter 5.5.2).

According to Silver et al. (2017), the (R, s, S) policy would be the better choice for the A class, but for the B class, an (R, S) system would often be the better option. However, if the Pyxis assistants would have to refill every B class SKU (and possibly even the C class SKUs), it would result in an overwhelming amount of work due to the high number of SKUs. On top of that, the amounts to be refilled resulting from an (R, S) policy would oftentimes be very small and thus be unpractical for strip-packaged medications.

As mentioned in Chapter 4.3, the MST expressed the desired CSL to be 95%. However, an FR is a better representation of the sought-after service objective. Also, 95% is probably on the low side looking at the attained FR from Chapter 2.4.2. For that reason, the sensitivity analysis will look at how a different FRs will influence the resulting inventory size and/or assortment.

5.4) Demand distribution

5.4.1) A class

For the A class, we have two cases: since the ADPRC is above 10 for about half of the SKUs, and below 10 for the others in class A, we start with assuming a continuous distribution: the normal distribution for the upper half. Upon observing the fact that the data is skewed and the σ/μ ratio is larger than 0.5 for all cases in said upper half, we assume, as described in Chapter 3.5.1.1, that the demand is following a gamma distribution instead. Their parameters were calculated in excel using Formulas 1 and 2. The results can be seen in Table 7.

MedID	α	β
1087452	3.68	37.43
851078	3.08	8.59
2239671	2.95	8.13
1117238	2.29	8.14
693332	1.81	7.68
858099	0.83	16.41
1045318	1.56	8.62
2266725	1.29	10.21
2202182	1.59	7.93
2710455	2.77	4.52
858609	1.54	7.85
1791613	1.13	10.64
866407	0.75	15.90
1791621	2.12	4.90

Table 7: Distribution parameters of the A-class SKUs with gamma distributed demand

After performing a goodness-of-fit test for these SKUs, we can see with the help of P-P plots that some demand patterns follow the gamma distribution quite nicely. Not all SKUs do, however. Some SKUs have a lot of low values, which fall outside of the expected range of values. The question here is whether the gamma distribution is the correct distribution after all, or if the dataset contains errors/irregularities. For now, it is assumed that the quality of the input data is at fault and a gamma distribution is fitted as well as possible.

The second half of the A class has a too-small ADPRC to use a continuous distribution. Instead, discrete distributions are considered. Then, the variance-to-mean ratio is checked, to see if a Poisson or negative binomial distribution is more appropriate. The average of this ratio across both the remaining half of the A class and the B class is 8.36, with no values below 1. Therefore, the negative exponential distribution is deemed most appropriate. The parameters are subsequently calculated by using Formula 5 and 6. The values for r and p found for the rest of the A class can be found in Table 8.

MedID	r	p
90900799	47.22	0.17
1839950	2.65	0.79
1196049	1.31	0.88
857793	1.26	0.88
90940172	11.03	0.45
2198096	0.93	0.90
2239698	1.49	0.84
619116	0.77	0.91
2303116	2.55	0.75
2264714	1.52	0.82
1762397	0.96	0.88
2124572	1.05	0.86
1828630	2.54	0.72
1114506	0.75	0.90
1137719	0.90	0.87
78069	1.03	0.85
412953	1.56	0.78
1088882	2.03	0.73

Table 8: Distribution parameters of A-class SKUs with Negative Binomial distributed demand

Again, a goodness-of-fit test must be executed, to see whether the negative binomial distribution fits these demand patterns. This can be done in Excel easily using the built-in Chi-Squared test. The goodness-of-fit test showed that some SKUs had a good fit with the negative binomial distribution and others less so. Again, the question of the accuracy of the data comes into play. Additionally, there are some SKUs which are ordered almost exclusively in round numbers (e.g., 5, 10, 15, 20), which suggests an empirical distribution might be a better choice.

5.4.2) B class

All SKUs in the B class are given a negative binomial distribution as well. Because the tool automates a large part of the process, the B class distribution parameters were determined the same way as the A class SKUs. The difference is that for the B class, no goodness-of-fit test was performed. Since the ADPRC is below 10 for all of the SKUs, ranging from $\hat{x}_{R+L} = 5.39$ to $\hat{x}_{R+L} = 1.70$. Again Formulas 5 and 6 were used to calculate the r and p, just as in Chapter 5.4.1. The resulting distribution parameters can be found in Appendix E.

5.4.3) C class

The C class items had such a low demand rate that ADPRC for $R = 1$ is below 1.7 for all items. In some instances, a very high variance was observed, most probably because these medications are seldom used, but if used, a patient will need multiple of them. This process could be fitted to a compound Poisson distribution. A compound Poisson distribution describes a process where a new 'patient' enters according to a Poisson distribution and needs several medications that follow another distribution. This could describe the demand for C class SKUs very well but will have to be looked into further at a later time.

Because of this high variance, the distribution parameters take on strange values. To counter this, a new review period was chosen for the C class items. Instead of checking every day if the inventory position dropped below s, it is checked once a week. Therefore, $\hat{x}_{R+L}$ is multiplied by 7 and σ_{R+L} is multiplied by $\sqrt{7}$. This gives more reasonable numbers to work with. Now the maximum ADPRC is 11.87 in class C and the minimum is 0.44. Even though the maximum value exceeds the rule of thumb for a continuous or discrete demand distribution, for simplicity all C class SKUs are assumed to follow a negative binomial demand distribution. Their distribution parameters are calculated accordingly. Because of excessive repetition, the results will not be displayed in a too-long table in an Appendix. Instead, some remarkable cases will be examined to show possible manual decision rules.

5.5) Decision rules

5.5.1) A class

5.5.1.1) Gamma distribution

The final stage of the method is about finding the actual new (and hopefully improved) inventory rules. As discussed before, for now, the lot sizes Q are chosen to be the same as in the current situation. We use Formula 15 from Chapter 3.6.2 to calculate the ESPRC. Then, Formula 16 is solved to find s. The results can be seen in Appendix E.1.

5.5.1.2) Negative binomial distribution

Firstly, the ESPRC is calculated, again using Formula 15. Then, using the found distribution parameters, the reorder point s is calculated by solving Formula 19. Then, the found values of s are added to their respective Q's, to get our order-up-to point S. The results can also be seen in Appendix E.1.

5.5.2) B & C class

Since a negative binomial distribution was fitted on the B and C class SKUs as well, the decision rules are the same as in 5.7.1.2. The reorder points, order quantities and order-up-to levels for the B class can be found in Appendix E.2.

With the change of the review period to be 7 days for C class items, the decision rules produce much nicer values. Instead of restocking one or two pills for certain medications, the amounts are a little bit more manageable and the reorder points are a bit higher. This does mean that for most C class SKUs, the average inventory level ($s + \frac{1}{2}Q$) will be a little higher. On the other hand, when a patient comes in that needs that specific medication, it is less likely to be out of stock immediately. And because the C class items have such low demand when compared to the A class SKUs, the reduction in the A & B class easily outweighs this slight increase. Additionally, with this increase in the review period, some SKUs fit a Poisson distribution better now, instead of the Negative Binomial. Here as well the ESPRC is calculated using Formula 15. And after that Formula 17 is solved for s. Again, the results are displayed in Appendix E.

For some C class SKUs, especially in the lower ranges, parameters take on weird values. All SKUs with total demand lower than 10 are suggested to be excluded from the Pyxis' assortment, as having to walk to the CP to pick up that medication once or twice in 158 days is unlikely to outweigh the space one package of that medication would take up in the Pyxis. Or, if it is known a patient will be brought in who requires said medication, it can be put on the schedule instead of having to be taken out of the Pyxis. For low usage medications needed in certain emergencies, the emergency cases should be used.

5.6) Validation

The current min and max are taken and inputted in the model to check if the CSLs and FRs outputted by the model are similar to those found in practice. For all A class SKUs, the average CSL outputted is 97.59%, which is on the low side. The outputted FR, however, is 99.64%, which is almost the same as the current FR. The difference in CSL might be explained by incorrect counting or recording of the recorded stockouts, or because the percentage of 99.62% given in Chapter 2.4.2 is an estimation.

5.7) Results

The results are expressed in average inventory level, being $s + \frac{1}{2}Q$. The average inventory level is compared between the method output and the current situation and a percentage reduction is calculated. The following results are for a FR of 95%. In the next chapter, more feasible FRs will be analysed.

The A class experienced a percentual decrease of 35.75%. The B class a reduction of 49.94%. Lastly, the C class, even though for some SKUs more inventory will be kept because of the 7-day review period, there still was a suggested reduction of 46.34%.
This drives the total average inventory level on the A5 from 6227 medications to 3554: a decrease of 42.92%. This would mean that an approximate 43% of the space in the Pyxis would be freed up for potential other SKUs. This is under the assumption that these ‘other SKUs’ take up roughly as much space as the SKUs currently in the Pyxis. To draw more conclusions about how many new SKUs can be added with these new inventory models, more information about physical medication size is needed.

Nevertheless, it should be recognised that this inventory reduction estimation was made based on the assumption that the FR is ‘only’ 95% and based on the current dataset. To see what the output of the model will be when the FR is the same level as it currently is, a sensitivity analysis will be done. In this sensitivity analysis, the variability of the current demand data will be analysed as well, to sketch what improvements a dataset with less variability will give. Lastly, the sensitivity analysis will look at different values of Q.

5.8) Sensitivity analysis

Three variables will be looked at in this sensitivity analysis: the FR, the variability of the demand data, and the lot sizes Q. For simplicity, one variable will be varied per analysis. This means that it is not known if certain variables might have certain relationships. This will have to be analysed in additional research.

5.8.1) FR

6 values other than the starting value of 95% were chosen, representing reasonable FR values. The higher values might be considered high, but in a hospital often very high FR values are desired. For this analysis, the variability of the data is kept the same and the lot sizes Q are also kept the same as the old values (as was used in 5.9).

FR	90%	92.5%	**95%**	97.5%	98%	99%	99.5%
Average inventory	*3133*	*3287*	***3554***	*3961*	*4103*	*4543*	*5023*
% reduction	*49.69%*	*47.21%*	***42.92%***	*36.39%*	*34.10%*	*27.04%*	*19.33%*

Table 9: Average inventory for different FR levels

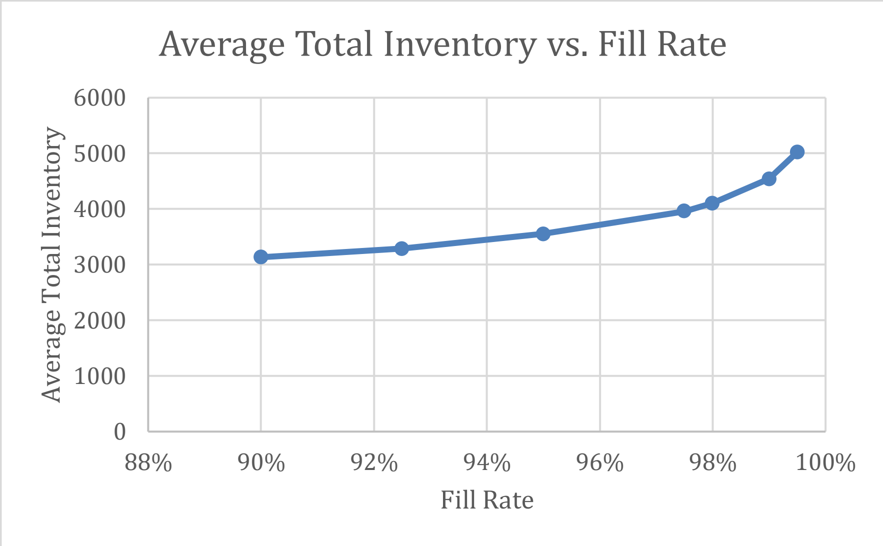

Figure 2: Average Total Inventory vs. Fill Rate

As can be seen in Figure 2, the average total inventory increases exponentially as the FR increases. This is according to expectations. Table 9 shows that even for 99.5% FR, still a reduction of 19.33% could be achieved, which is substantial. After seeing Table 9 and Figure 2, the management of the MST should reconsider their desired CSL/FR now that they would have a better idea of how much reduction could be possible for certain FR levels.

5.8.2) Variability of data

It has been mentioned before that the dataset contains a high variability across almost all SKUs. In this chapter, a sensitivity analysis is performed on the variability of the Pyxis demand data. This analysis is done for a FR of 99.5%, to best show possible additional reductions for the same FR as in the current situation.

The variability of the data will be altered compared to the current variability. So, a percentage of the current variance of the demand during $R + L$ for each SKU will be taken, starting with 10% of the current variance, then 25%, 50%, 75%, 125% and lastly 150%. Upon changing the variance, some SKUs might follow a different distribution better. This is taken into account and calculations will be made according to the method in Chapter 4. Only the final outputs will be displayed here, in the form of average total inventory.

% of Variance (FR = 99.5%)	10%	25%	50%	75%	**100%**	125%	150%
Average Total Inventory	*3739*	*3866*	*4230*	*4600*	***5023***	*6227*	*5743*
% Reduction	*37.96%*	*37.91%*	*32.07%*	*26.13%*	***19.33***	*13.11%*	*7.77%*

Table 10: Average inventory for different levels of Variance

For the variance levels of 50%, 25%, and 50%, some SKUs followed a Normal or Poisson distribution. The formulas described in Chapters 3.6.1 and 3.6.3 were used for these instances.

As can be seen from Table 10 and Figure 3, a lower variance reduces the total inventory needed significantly. This is according to expectations. It is most definitely a good idea for the MST to see if it is possible to reduce the variance in their data. At this point, it is unclear whether the variance is due to inventory inaccuracies and poor inventory management or due to the true nature of demand in the hospital. For the first, improvements in variance might be made using the implementation plan in the next Chapter. For the latter, a solution might lie in better forecasting what types of patients might come to the hospital.

5.8.3) Lot size Q

Lastly, an analysis of how sensitive the average total inventory is to the lot sizes. The calculations so far have been made with lot sizes that are the same as the current situation. However, some of those seem outdated or make little sense. Therefore, now some suggested lot sizes are tested. Firstly, lot sizes will be a certain number of days of average demand. Starting with all classes having a lot size of 2 days of demand (rounded off to the nearest multiple of 10). After that, lot sizes of 4 and 7 days will be tested. Then a slightly more sophisticated heuristic will be used, where the A class will have lot sizes of 2 days of demand, the B class 4 days and the C class 7 days. These distributions might prove feasible since daily demand for A class SKUs is higher, so having fewer days of demand for those is a big deal. The C class SKUs can have lot sizes of multiple days of demand since that rarely amounts to significant amounts of medications. Lastly, lot sizes of 4 days, 7 days and 14 days for A, B and C class SKUs respectively will be tried. The FR will be kept at 99.5% for previously mentioned reasons. The variance is not altered from what was recorded. The results (in average total inventory) are displayed below, in Table 11.

Lot sizes Q	A:2, B:2, C:2	A:4, B:4, C:4	A:7, B:7, C:7	A:2, B:4, C:7	A:4, B:7, C:14
Average total inventory	4465	4945	5881	4970	6271
Reduction in %	28.30%	20.59%	5.56%	20.19%	-0.70%

Table 11: Average inventory levels for different lot sizes

As stated in Chapter 3, the optimal lot sizes should be calculated by using the EOQ. These lot sizes are a heuristic solution and therefore inherently non-optimal. It can be said, however, that compared to the 19.33% decrease in average total inventory for a FR of 99.5% with lot sizes equal to their current values, three of the suggested scenarios suggest a higher reduction. The most reduction is suggested for lot sizes of approximately two days of demand. While this would attain significant suggested reductions, it is not very likely having to refill every medication every two days is feasible. Therefore, two options remain: all SKUs having 4 days of demand as lot sizes, or the option where the A class SKUs have smaller lot sizes and the C class SKUs larger ones. In theory, both scenarios have the same FRs, so should perform equally well. The difference here is that for the first option, A class SKUs will have to be refilled less often and C class SKUs more often. Also, the average total inventory for A class SKUs will be larger, and those for c class SKUs smaller. The EOQ takes into account how much the holding cost of a medication and fixed cost of a refill are, thus being able to say more accurately if lot sizes (and thus average inventory) should be small and order frequency high, or the other way around. Because no clear data was found on this (as stated in Chapter 4.5), no clear conclusions can be drawn on this. For future research, this method will need to be used after the correct EOQ values have been determined to arrive at the optimal order policies.

5.8.4) Optimal solution

Combining these three analyses, we could say something about the optimal values of the variables tested, within the tested value range. For the FR, 99.5% would still be adhered to, to make sure (about) the same service level is reached as in the current situation. About the variability of the data, it has been speculated that it could decrease by collecting data more accurately and perhaps implement patient forecasting. For this ‘optimal solution’, a reduction in variability of 50% is deemed reasonable. Lastly, lot sizes of 2, 4 and 7 days of average demand were taken for the optimal lot size value, because it minimises the A class inventory and is most likely the most reasonable scenario.

All of these combined give a total suggested reduction of 35.33%. The average total inventory goes from 6227 to 4027. The A class would reduce by 45.81%, the B class by 50.63% and the C class by 8.82%. This is according to expectations because larger lot sizes are taken for the C class, whilst the A class is optimised as much as possible.

5.9) Summary

- Data from 158 days of demand was taken as input. The A5 nursing unit was used for the numerical example. The inventory was classified into three classes based on the number of uses. The A class contained the first 70% of cumulative uses, the B class the next 20%, the C class the rest.
- The review period for the A and B class is set to one day since that is the most logical choice and already the case currently at the MST. Their replenishment period is also set to one day for simplicity. Because of the extremely low demand of C class SKUs, their review period and replenishment period are set to 7 days.
- Because of physical constraints, the (R, s, S) policy was chosen for all inventory classes. Additionally, the objective of the method is to create inventory policies with inventory levels as low as possible, while still adhering to certain CSL and FR.
- For the current data set, about half of the A class is fitted with a gamma distribution: the variance is too large to allow a normal distribution fit. The other half has a too-small average demand per replenishment cycle and thus was fitted with a discrete distribution: the negative binomial. The B and C classes were also fitted with a negative binomial distribution, due to their high variance. All distribution parameters were calculated and for the A class SKUs a goodness-of-fit test was conducted.
- Decision rules were used to calculate new s and S levels for all SKUs. Taking the average between those two, the average inventory on hand could be calculated and compared with the current situation.
- A suggested reduction of approximately 19.33% is devised for a FR of 99.5%, with the current variability in demand and the currently used lot sizes.
- A sensitivity analysis was performed, showing that, for 99.5% FR, if demand variability is reduced to 25% of the current variability, and lot sizes are 2, 4 and 7 days of average daily demand for A, B and C class SKUs respectively, a reduction of 35.33% could be achieved.

6) Implementation plan

In this chapter, the sub-question: “How can the found solution be implemented further?” will be addressed. In short, an implementation plan will be described. The implementation of the findings from this thesis requires several steps. These steps are described below.

6.1) Better inventory management

First, the overall inventory accuracy should be increased. At the moment, it is very low, and a lot of discrepancies occur, as well as stockouts that should not happen. To increase inventory accuracy, medication retrieval should be logged more strictly. Suggestions on how to improve this are: connect the patient information system with the Pyxis system so that nurses can select the desired patient and his/her prescribed medication or reduce mechanical failures in the Pyxis cupboards by performing proactive maintenance (see the last point made in Chapter 2.4.3). The other problems that would increase accurate inventory management are listed in Figure 1.
On top of this, data collection should be intensified as well. During the writing of this thesis, often data sources proved deficient. By logging and saving more data, more diverse analyses can be performed, and the implementation of the method becomes easier.

6.2) Lower inventories needed

Once inventory accuracy has increased through better inventory management, less inventory is needed to keep the same FR. Before these new inventory levels can be calculated using the method and tool from this thesis, the input parameters of the method should be determined by management. These include the desired FR, but also the criteria and boundaries of the inventory classification.

In theory, only one person with moderate knowledge of Excel and inventory theories could calculate new inventory rules for all NUs in a matter of minutes. The complete implementation will take longer but should still be manageable. Of course, this will have to be checked by a pharmacist afterwards, to make sure results make sense and are according to expectations. Again, these lower inventory levels mean stockouts are more likely to occur with inaccurate inventory management. Therefore, it is essential to make sure everyone adheres to the inventory rules. To help this along, the proposed changes should be thoroughly discussed with everyone involved, to create understanding.

6.3) Lot sizes

As described in Chapter 4.5, there was too little data and too little time present to accurately calculate the EOQ for all medications on all NUs. When implementing the method, this EOQ (or another suitable method, such as the Wagner-Whitin-algorithm (Silver et Al. p.205)) should be used to get more accurate inventory policies. This would most probably improve the suggested inventory policies even further, compared to the heuristics used in this bachelor’s assignment.

6.4) More room for additional SKUs

Once inventory levels have been updated, it is most likely that some room (see Chapter 5.7) is freed up in the Pyxis, making room for additional SKUs. This way the assortment of the Pyxis’ on the NUs can be expanded. In this thesis, no additional assortment is determined, because of a lack of data. Instead, pharmacists should confer with nurses to determine what additional SKUs are required in the Pyxis or could look at historical data for candidates.

6.5) Less walking to the CP

With a more extensive assortment in the Pyxis', less often will the nurses find a patient requiring some medication that is not in the Pyxis. This means that overall, fewer trips to the CP will be needed.

6.6) Afterwards

As mentioned before, the demand data coming from the Pyxis contains a lot more variance than is expected. This limits the potential reduction in inventories, as can be seen in Chapter 5.10.2. The question remains whether this variance is inherent to this process, or if it can be reduced by performing, for example, a more in-depth patient inflow analysis. The prediction is that, with a better forecast of patient type inflow and better demand logging, this variance can be decreased severely. Therefore, the MST is advised to analyse this 'problem' in-depth to try and solve it.

The situation and demand patterns in the hospital are ever-changing and should not be treated as stationary. Therefore, the inventory policies must be monitored and updated regularly. For example, with good data collection it would be reasonable to check the performance (e.g., CSL, FR and stockouts) of three or four NUs each month and apply changes if necessary. It speaks for itself that this should also be done if (structural) changes are in effect or expected.

If more advanced decision rules for determining s and S for discrete distributions are wanted, Zheng and Federgruen (1991) have developed a fast algorithm which can be developed in a programming language or macros in Excel. More extensive coding knowledge is needed compared to the current method.

7) Conclusions, recommendations, and discussions

In this chapter, conclusions will be drawn, and recommendations will be made. Also, some discussion will be made about the thesis in general. The conclusions will answer the main research question:

<u>For a fixed CSL, how can inventories be reduced and the assortment expanded in a decentralised, AMDS, so that less often pickups at the CP are necessary?</u>

7.1) Conclusions

- Current inventory levels are too high, emphasizing underlying problems that need to be tackled before inventory reductions can be realised.
- The numerical example showed that using the created method and tool to create new inventory policies, inventories could be reduced by roughly 19% for similar FR levels, the same lot sizes and the same variability in demand data.
- This 19% of freed up space can be used to expand the Pyxis' assortments to house an undefined number of additional SKUs and provide better overall medication coverage.
- To improve the effectiveness and results of the method, the lot sizes can be calculated properly, but most importantly reduction in demand variability should be sought.

7.2) Recommendations

- Calculate the EOQ to use as lot sizes in the method.
- Connect the patient information system with the Pyxis system so that medication retrieval will be multiple times faster and easier.
- Proactive maintenance should be performed on the Pyxis', to decrease the number of mechanical problems
- The purchasing department should order EAV packages as much as possible to keep medication retrievals flexible.
- Use the method and tool to implement new inventory policies if and only if confident that inventory management is accurate.
- The inventory performance should be monitored monthly at least, and improvements should be made regularly to ensure that the inventory policies stay up to date.
- There should be regular feedback sessions between the CP and the NUs to make sure both parties understand each other's needs and wants.
- For a better understanding of the demand patterns, hourly demand could be compared (e.g., demand during the night vs during the day).
- Additionally, patient forecasting could add to demand forecasting and reduce demand variability.

7.3) Discussion

Determining the actual problem that caused the perceived negative effects took longer than anticipated. This is because the problem lies deeper and consists of multiple aspects. Added on to that is the fact that there are obstacles that can only be solved by a higher level of management. These include, but are not limited to, obstacles that require a large investment for new machines. All of these combined make for a thesis that was more focused on problem exploration than problem-solving. Hence a lot of suggestions and propositions are made to use or to build on in further research.

Once the direction of the thesis was determined, the problem of data availability occurred. The Pyxis system is very old and does not even integrate with any Microsoft Office programs. Eventually, a usable data set was found, but it had some major flaws as well. Firstly, because of the aforementioned problems, it is very likely that the collected data is not 100% accurate. Currently, medications are sometimes retrieved while the door is opened for another medication, or medication is returned without registering it. This would certainly explain (part of) the large variability in the dataset. Additionally, in the dataset were several SKUs that were not medications at all. Due to time constraints, it was not possible to filter all of these out. Therefore, it might be possible SKUs have been used in the numerical experiment that should not be in there. Last but not least, the collection period of the data is a discussion point as well. Data was collected from 158 days, which did provide a lot of individual data points, but no seasonal factors can be distinguished from this data. This might be a factor that plays a role in a hospital (e.g., flu season).

One shortcoming of the method is that it does not incorporate the size of packages very well. Since no EOQ was calculated, the current lot sizes were taken. Additionally, in the sensitivity analysis, other lot sizes were tried, but all were multiples of 10. Data about package sizes were only available per medication, and not per list. Therefore, only the package sizes of the A class SKUs were looked at. It appeared that most, if not all, could easily be distributed in multiples of 10. For this reason, lot sizes were often rounded off to these multiples, but true package sizes were not looked at for all SKUs.

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Appendices

Appendix A: Medication flowchart

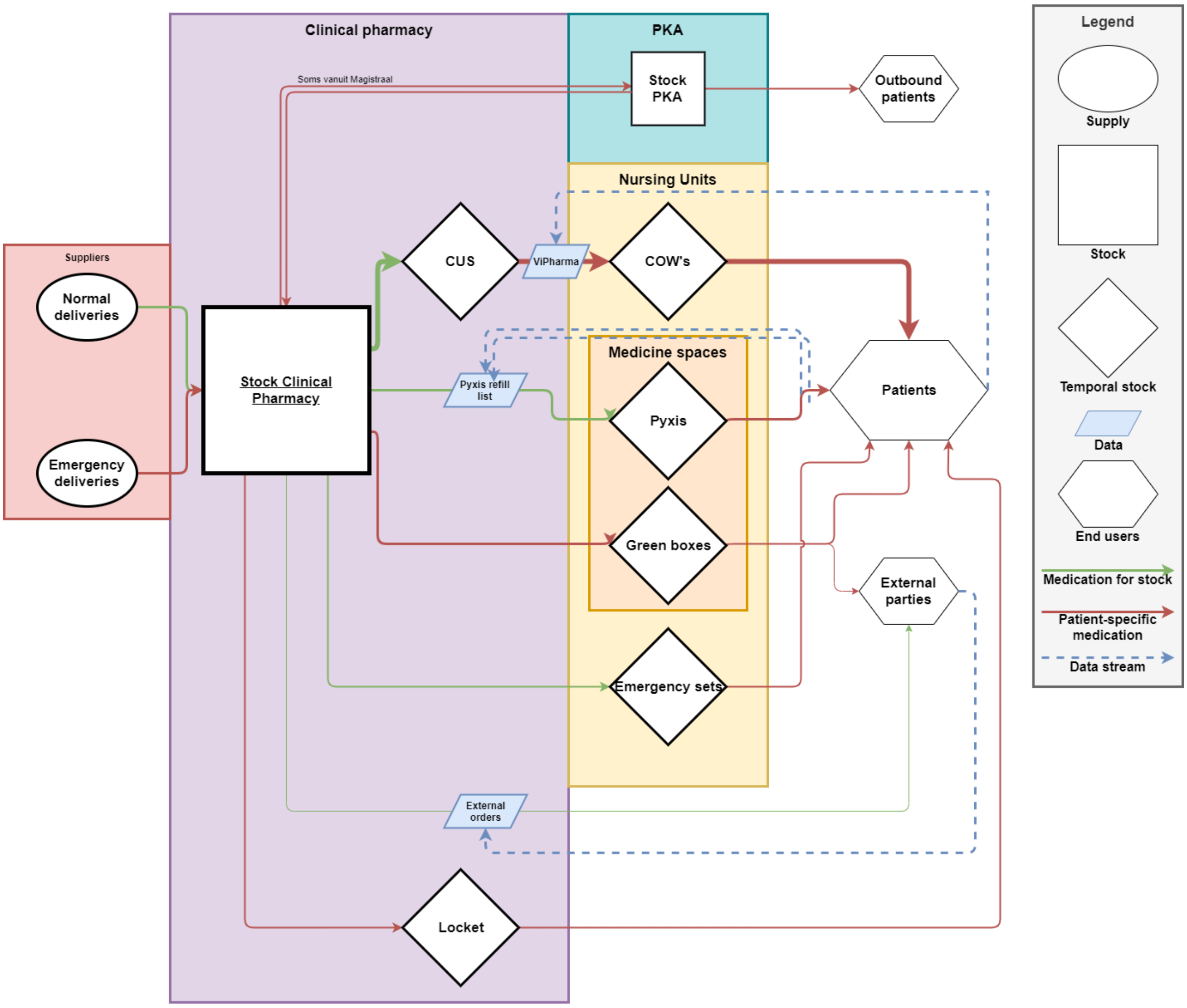


Figure 3: A flowchart of all medication flows in the MST

Appendix B: additional literature

B.1) Inventory

“Inventory exists in the supply chain because of a mismatch between supply and demand.” (Chopra, S., Meindl, P., 2016) Or another way to put it would be: “perhaps the most fundamental role that inventory plays in supply chains is that of facilitating the balancing of demand and supply.” (Esper, T., Waller, M., 2014) The role of inventory is to make sure the expected or unexpected gap between supply and demand can be countered and profits can be optimised.

B.1.1) Types of inventory

According to Chopra and Meindl (2016), the following inventory types are important for creating a more responsive and efficient supply chain:

- **Cycle inventory** - Cycle inventory is half of the average lot size. Together with safety inventory, it forms the average inventory. It exists mainly because it is cheaper to order larger lots at a time, due to economies of scale. To calculate the cycle inventory, the following formula is used:

$Cycle\ inventory = Q/2$, Where:
$Q = lot\ size$

- **Safety inventory** - This is inventory held to make sure orders exceeding the expected demand can still be fulfilled. Safety inventory would not be needed if everything was perfectly predictable. This is stock kept for unknown demand increases; to avert most stockouts. Do note that safety inventory is not meant to prevent all stockouts, just the majority of them. As mentioned before, trying to achieve a 100% CSL is rarely a viable option.

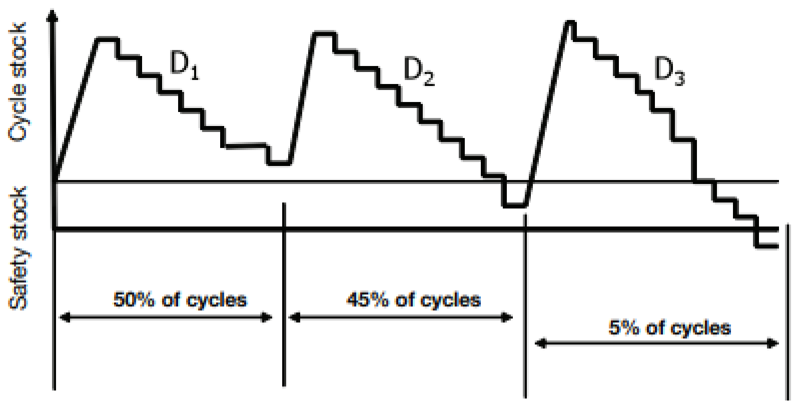


Figure 4: Visualisation of cycle service level

Safety inventory is affected by the following three factors: demand variability, lead time variability and the desired CSL. According to (King, P., 2011), the most pertinent formula to calculate safety inventory depends on whether demand variability or lead time variability are large concerns.

If <u>demand variability</u> is the largest threat to your inventory model, the formula to best protect against that with the adequate safety inventory is:

$Safety\ inventory = Z * \sqrt{L} * \sigma_D$, where:

$$Z = Z - score$$
$$L = Lead\ time$$
$$\sigma_D = Standard\ deviation\ of\ demand$$

Should the most protection be needed from lead time variability, the following formula for safety inventory is more adequate:

$Safety\ inventory = Z * \sigma_{LT} * D_{avg}$, where:

$$\sigma_{LT} = Standard\ deviation\ of\ lead\ time$$
$$D_{avg} = Average\ demand$$

If in your inventory model, there is both demand and lead time variability and they are independent, a combination of the formulas above needs to be used:

$$Safety\ inventory = Z * \sqrt{(\frac{PC}{T_1} * \sigma_D{}^2) + (\sigma_{LT} * D_{avg})^2}$$

This can also be read as the Z-score times the square root of the sum of the squares of the individual variables.

- **Seasonal inventory** - Sometimes demand might differ in different parts of the year. If this is the case, a seasonal inventory can be built up to make sure enough is available to fulfil the known increased demand. This is stock kept for known demand increases.

B.2) Demand Forecasting

Forecasting of demand is incredibly important as one of the largest supply chain decision drivers. There are some characteristics to note regarding demand forecasting according to (Chopra, S., Meindl, P., 2016). Firstly, forecasts will always have some sort of inaccuracy. Also, “long term forecasts are usually less accurate than short-term forecasts”. This is through the help of current information. Next to that, disaggregate forecasts are often less accurate than aggregate forecasts. Lastly, the distance the company is from the customer amplifies information distortion and forecast error.
There are several factors impacting demand forecasting: (Chopra, S., Meindl, P., 2016)

- Past demand
- Lead time of product replenishment
- Planned advertising or marketing efforts
- Planned price discounts
- State of the economy
- Actions that competitors have taken

Some factors might play a bigger role in certain companies than for others. In the case of this thesis, the MST has little to no advertising or marketing efforts or planned price discounts. But past demand and lead time are very important factors.

B.2.1) Forecasting types

There are four main types of forecasting methods, each with different strengths and weaknesses (Chopra, S., Meindl, P., 2016).

1. **Qualitative** - This forecasting method is mainly subjective and depends on human judgement. It is most often used when little historical data is available. This method can prove inaccurate when wrong human judgement is used. It appears this forecasting method has been used by the MST, while there is plenty of historical data available.
2. **Time series** - When enough historical data about demand is available, it can be used to make a forecast. This method assumes that the basic demand pattern will not change a lot from one

year to the next and that, therefore, demand history can be used as an indicator for future demand. This forecasting method does not take into consideration any external factors such as changing trends or, in the case of the MST, new medication developments or older medications disappearing from the market.

3. **Causal** - Certain factors in the environment can be correlated with the demand forecast. If this is believed to be the case, causal forecasting methods can be used to, for example, determine the impact of price promotions on demand. Causal methods need a correlation between environmental factors and demand. If these are not clear or not present, this type of forecasting method is difficult to use.
4. **Simulation** - Simulation forecasting methods are "a combination of time-series and causal methods to imitate consumer choices that give rise to demand to arrive at a forecast." Simulation can be a very powerful tool, but a lot of assumptions are needed and if they are not correct, the whole simulation model could give the wrong outcomes.

B.3) Inventory classification

Within a company, logically, there are SKU's that are more important and SKU's that are less important. Making the same managerial decisions for all SKU's is a sub-optimal and should not be done. "After examining a large number of actual multi-SKU inventory systems, a useful statistical regularity in the usage rates of different items was found." (Silver et al., 2017) Oftentimes, only 20% of the SKUs make up around 80% of the annual dollar usage. This principle can be visualised in a distribution by value (DBV) curve. Such a curve depicts the cumulative percentage of the total number of SKU's versus the cumulative percentage of total dollar usage. The total dollar usage is simply the demand or usage multiplied by the SKU's value. A typical DBV curve is shown in Figure 5. (Silver et al., 2017)
This classification can greatly help improve the handling of disaggregate inventories by making a clear distinction between SKU's that are more important and less important ones. (Silver et al., 2017) This

is done by dividing the SKU's into several classes. Starting with the A-Class, this is the class where the

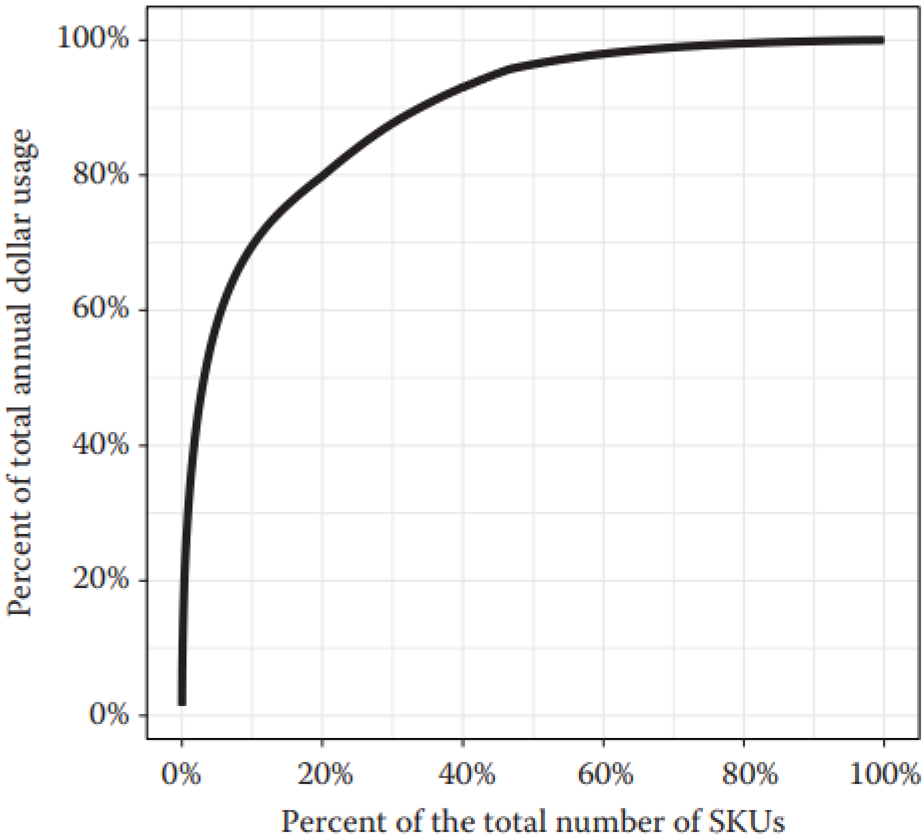


Figure 5: A typical DBV curve.

most important SKU's are placed in. (Silver et al., 2017) suggest putting the first 5%-10% of the highest-ranking SKU's in Class A, with exceptions up to 20%. Usually, this should account for around 50% of the total dollar usage in the A-Class. They say Class B items require a "moderate but significant amount of attention". Often more than 50% of the SKU's fall into this group, according to (Silver et al., 2017) accounting for most of the remaining 50% of annual dollar usage. It is discussed that some other sources recommend putting a smaller portion of SKU's in the B-Class, but since computers have increased the available calculating and monitoring power, as many SKU's as possible should be monitored and controlled."

Armstrong, (1985) in an older article, suggests taking 50% of the total dollar usage from a sorted list, with whatever % of the total number of SKU's that comes, for the A-Class. Then take 50% of the lowest total dollar usage SKU's and put those in the C-Class. The rest belongs in the B-Class.

Appendix C: Tool manual

The Excel-tool (hereafter: tool) requires input data containing at least: the date on which the medication was dispensed, the medication ID, the mutation (the amount of medication taken out), the nursing unit/Pyxis from which it was retrieved, and lastly whether the medication was dispensed from the Pyxis or the CP. This last requirement allows the tool to make different models depending on if the NU will put out their medications or if the CP will do that.

The first step in implementing the literature findings into the case at the MST, an inventory classification needs to be made. As mentioned earlier, it is futile and often impossible to make detailed and well-fitting inventory policies for all SKUs. Therefore, an ABC classification based on medication usage is made. All of the data collected is put into a table in the excel file in the “DataIn”-sheet, where redundant columns or information is filtered out by hand, as well as outliers or wrong data points. The tool has a start button and after pressing it a userform shows up, as can be seen in Figure 7.

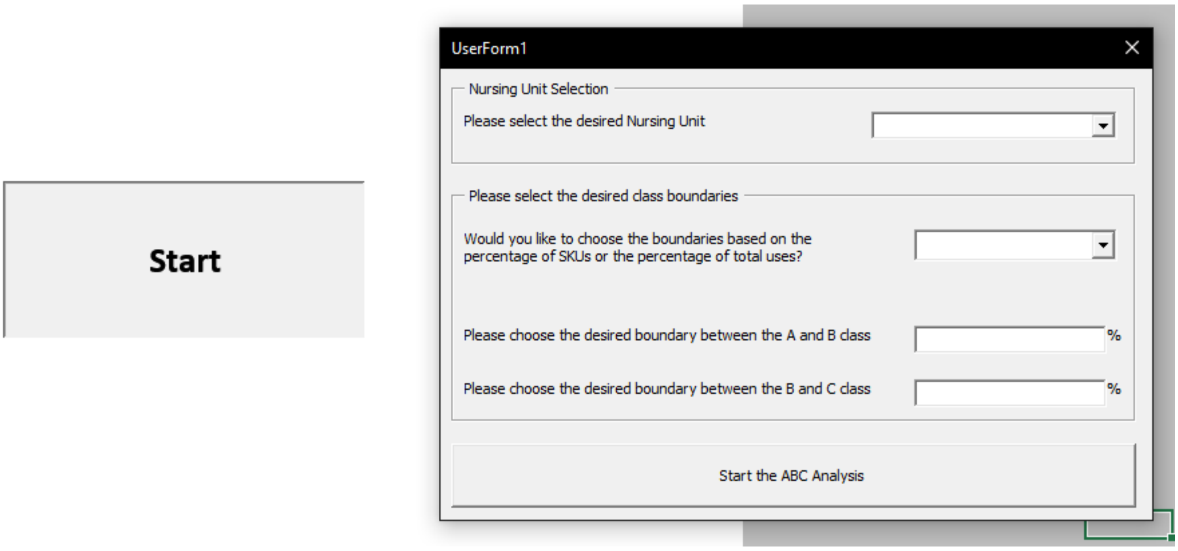


Figure 6: The start button and first userform.

On this userform, the user can select a NU to apply the ABC classification to, chosen from a dynamic range that can be altered by the user manually, or be drawn from the data. Additionally, the user can choose the desired bounds between the A and B class, and between the B and C class. As is described in Appendix B, the usual boundaries of these classes lie around 60% of total usage and 80% of total usage for the AB-boundary and the BC-boundary, respectively. Usually, this results in the A class containing around 5%-7% of the total number of SKUs, the B class around 10%-12%, and the C class the rest of the SKUs. In the tool, the SKU’s with their uses are sorted, coloured, and labelled with a class depending on the chosen boundaries. An example of an ABC classification for the AOA A6 NU, based on 60% and 80% of total uses boundaries is shown in Figure 8.

ABC-Analysis

Selected Nursing Unit:	Selected boundaries:	Percent of total SKUs	Percent of total uses
	AB-Boundary	3%	**60%**
Nursing Unit AOA A6	BC-Boundary	15%	**80%**

Total number of SKU's:	Total number of Uses:	Number of SKU's in class					
726	56007	A	24	B	85	C	617

Demand Distribution

Copy Data

SKU	Sum of Mutation	Cum. % of # of SKU's	Cum. of # of Total Uses	
90941101	7500	0.14%	13.39%	A
01087452	4508	0.28%	21.44%	A
90950860	3500	0.41%	27.69%	A
01771108	3090	0.55%	33.21%	A
00415219	2060	0.69%	36.88%	A
00625523	1550	0.83%	39.65%	A
00570583	1490	0.96%	42.31%	A
00565369	1357	1.10%	44.74%	A
01114506	1040	1.24%	46.59%	A
01678876	1000	1.38%	48.38%	A
00598968	750	1.52%	49.72%	A
02264714	624	1.65%	50.83%	A
02239671	501	1.79%	51.73%	A
01043110	499	1.93%	52.62%	A
02127563	483	2.07%	53.48%	A
01045318	482	2.20%	54.34%	A
02264749	442	2.34%	55.13%	A
02266725	440	2.48%	55.91%	A
00619116	400	2.62%	56.63%	A
02239698	400	2.75%	57.34%	A
02010259	360	2.89%	57.99%	A
01791613	340	3.03%	58.59%	A
01107151	325	3.17%	59.17%	A
00633267	322	3.31%	59.75%	A
02127113	289	3.44%	60.26%	B
00579548	267	3.58%	60.74%	B
00693332	254	3.72%	61.19%	B

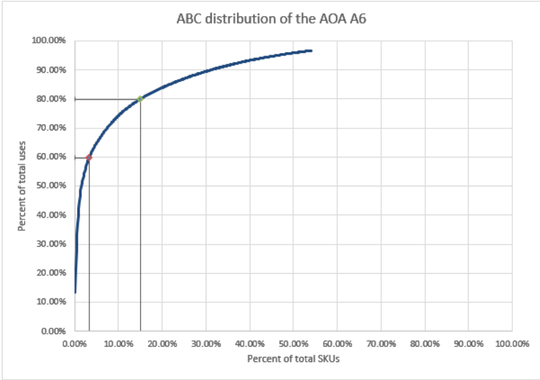


Figure 7: The worksheet containing the ABC classification, both in list and graphical form.

Next to that, the total number of SKUs and the total number of uses are displayed, together with the number of SKUs in each class. Of course, a neat graph is shown that presents the distribution graph and the boundaries of the classes. This graph includes a dynamic title that displays the current NU being looked at.

After the NU and the boundaries have been chosen and an inventory classification has been created, the user can then copy the data to the next sheet. In this next worksheet, a large table is shown with the demand per SKU per day from the chosen NU. If scrolled to the right, a table will be visible showing statistical figures of these demand patterns. Most of these columns are filled in automatically. The replenishment cycle is set to 7 if the average demand per day drops below 1. This can, of course, be changed. The average demand per research cycle is then automatically changed to the replenishment cycle duration. Also, FR values can be chosen here. This value will only need to be filled in the first row and will copy automatically to all rows. A beginning of a fitting statistical distribution is then made based on the rules of thumb from Chapter 3. Also, the distribution parameters are calculated automatically, depending on the distribution. Note that the goodness-of-fit of the distributions is not checked yet; this will have to be done manually or by another program. Lastly, the decision rules are all calculated as well. Please note that the lot sizes Q will have to be filled in manually.

Once all the values have been filled in, the button "Solve s for FR" can be pressed, which loops the Excel solver tool overall necessary rows to calculate s. Note that for normally distributed SKUs, the reorder point s should be calculated using Formula 9. If everything works well, k should be calculated automatically. The process of calculating all s values can take a little time. One can check if this is done properly if the rightmost column, called "0" actually has 0 everywhere. This is a check that an optimal solution has been found. Sometimes the solver can bug out a bit, coming up with no answer or a wrong answer. In that case, it is suggested to adjust the s value by hand and either manually use the solver on that value or start the whole process again by clicking the button. In the lower rows, sometimes "#NUM" can appear. This often means that values lower than 1 have to be used in the calculation of the ESPRC, which is not allowed. Since the values are rounded off to 1, it is advised to just accept these values as 1.

Depending on the number of SKUs in the chosen NU, the table might have to be extended or retracted by hand. Also, to the right of that table is another table making a rough estimate of the average total demand as done in Chapter 5.7 and 5.8. This is not an essential part of the method, more of a rough check.

Of course, even though a large part of the method is automated with the use of the tool, all steps should still be checked by hand. Errors could still occur.

Appendix D: Additional figures and tables

1087452	A	412953	A	1089749	B	220418	B	1024906	B
1771086	A	78069	A	90952561	B	858102	B	1516167	B
851078	A	1148427	A	709239	B	1090194	B	1163086	B
1771108	A	2397943	A	1828258	B	90923184	B	2703130	B
2239671	A	570583	A	1822527	B	90951956	B	1503103	B
1117238	A	1171534	A	1104969	B	1651544	B	1630156	B
858099	A	1017217	A	2031418	B	2551896	B	2275090	B
693332	A	2735245	A	2753383	B	869260	B	616842	B
858609	A	1523244	A	868930	B	1815571	B	1034332	B
2202182	A	2264749	A	415227	B	792659	B	1046128	B
2266725	A	673390	A	1678876	B	1199722	B	2010259	B
1045318	A	1127039	A	579548	B	598690	B	1754300	B
2710455	A	1170015	A	888567	B	571016	B	2673746	B
1791613	A	2182416	A	1763571	B	2364654	B	1440187	B
866407	A	90923435	A	2303108	B	700096	B	1089528	B
90925381	A	2399083	A	1516175	B	1721968	B	2532735	B
1839950	A	2239728	A	1012371	B	1613065	B	821195	B
415219	A	856126	A	1098063	B	837121	B	1884042	B
1791621	A	1112740	B	2264730	B	641081	B	236276	B
1196049	A	1414763	B	2116626	B	2002922	B	2198088	B
1114506	A	2177129	B	840483	B	709433	B	1139649	B
2239698	A	1051385	B	1113771	B	1146149	B	2268094	B
619116	A	463175	B	2110318	B	2017423	B	2458616	B
857793	A	1107151	B	719374	B	2040964	B	210536	B
2198096	A	2121441	B	1566407	B	90950151	B	2195666	B
1762397	A	618918	B	1600923	B	804533	B	700061	B
598968	A	849170	B	2703149	B	2118769	B	2182483	B
2303116	A	636525	B	2121573	B	2173107	B	1700944	B
2124572	A	2127121	B	1458973	B	797197	B	846392	B
1828630	A	1493493	B	2127148	B	1036386	B	90950674	B
651230	A	2081725	B	824453	B	1652567	B	90922366	B
1137719	A	2217252	B	1996495	B	2139715	B	1051423	B
2264714	A	2198118	B	1805789	B	596698	B	90923443	B
1024728	A	415235	B	57711	B	1643126	B	1836625	B
90952200	A	415200	B	874965	B	2371855	B	90933761	B
1088882	A	1036211	B	1613057	B	2589451	B	90950860	B

Figure 8: The A & B class of the A5 NU with class boundaries of 70% and 90% of total number of uses

Appendix E: Statistic values, parameters and decision rules of A & B class SKUs

E.1 A class

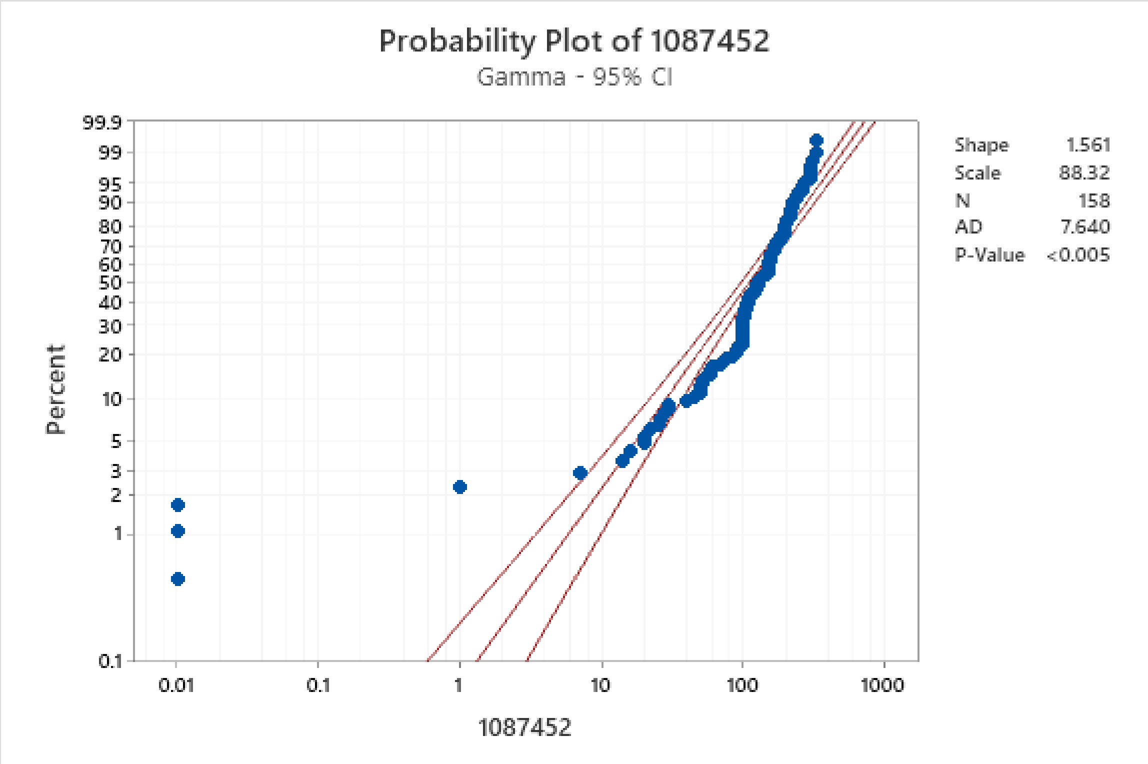
MedID	Review Period	D	x	StDev	Var	Dist.	FR	StDev/x	V/X	α	β	r	p	E	s (FR)	ESPRC	Q	S
1087452	1	21781	137.85	73.70	5431.31	Gamma	99.50%	0.53		3.50	39.40			1.50	308	1.50	300.00	608
851078	1	4177	26.44	15.07	227.00	Gamma	99.50%	0.57		3.08	8.59			0.25	64	0.25	50.00	114
2239671	1	3794	24.01	14.06	197.69	Gamma	99.50%	0.59		2.92	8.23			1.25	42	1.25	250.00	292
1117238	1	2944	18.63	12.32	151.66	Gamma	99.50%	0.66		2.29	8.14			0.45	43	0.45	90.00	133
693332	1	2197	13.91	10.39	107.96	Gamma	99.50%	0.75		1.79	7.76			0.25	39	0.25	50.00	89
858099	1	2146	13.58	14.89	221.65	Gamma	99.50%	1.10		0.83	16.32			0.50	51	0.50	100.00	151
1045318	1	2128	13.47	10.93	119.41	Gamma	99.50%	0.81		1.52	8.87			0.30	40	0.30	60.00	100
2266725	1	2085	13.20	12.01	144.15	Gamma	99.50%	0.91		1.21	10.92			0.15	52	0.16	31.00	83
2202182	1	1988	12.58	10.03	100.51	Gamma	99.50%	0.80		1.58	7.99			0.50	31	0.50	100.00	131
2710455	1	1978	12.52	7.65	58.52	Gamma	99.50%	0.61		2.68	4.67			0.25	28	0.25	50.00	78
858609	1	1907	12.07	9.74	94.79	Gamma	99.50%	0.81		1.54	7.85			0.45	31	0.45	90.00	121
1791613	1	1898	12.01	11.33	128.37	Gamma	99.50%	0.94		1.12	10.69			0.25	43	0.25	50.00	93
866407	1	1880	11.90	14.11	198.97	Gamma	99.50%	1.19		0.71	16.72			0.30	55	0.30	60.00	115
1791621	1	1639	10.37	7.41	54.91	Gamma	99.50%	0.71		1.96	5.29			0.25	26	0.25	50.00	76
90900799	1	1553	9.83	3.45	11.88	Neg Bin	99.50%		1.21			47.22	0.17	0.25	14	0.25	50.00	64
1839950	1	1541	9.75	6.88	47.33	Neg Bin	99.50%		4.85			2.53	0.79	0.30	22	0.30	60.00	82
1196049	1	1464	9.27	8.75	76.48	Neg Bin	99.50%		8.25			1.28	0.88	0.25	31	0.25	50.00	81
857793	1	1426	9.03	9.29	86.33	Neg Bin	99.50%		9.57			1.05	0.90	0.20	35	0.20	40.00	75
90940172	1	1418	8.97	4.09	16.69	Neg Bin	99.50%		1.86			10.44	0.46	0.26	14	0.25	50.00	64
2198096	1	1348	8.53	9.55	91.19	Neg Bin	99.50%		10.69			0.88	0.91	0.25	34	0.25	50.00	84
2239698	1	1260	7.97	7.29	53.21	Neg Bin	99.50%		6.67			1.41	0.85	0.38	21	0.38	75.00	96
619116	1	1257	7.96	9.38	87.97	Neg Bin	99.50%		11.06			0.79	0.91	0.19	37	0.19	50.00	87
2303116	1	1232	7.80	5.66	32.01	Neg Bin	99.50%		4.11			2.51	0.76	0.35	17	0.35	70.00	87
2264714	1	1097	6.94	6.51	42.41	Neg Bin	99.50%		6.11			1.36	0.84	0.25	21	0.25	50.00	71
1762397	1	1074	6.80	7.93	62.93	Neg Bin	99.50%		9.26			0.82	0.89	0.10	35	0.10	20.00	55
2124572	1	1043	6.60	7.03	49.41	Neg Bin	99.50%		7.49			1.02	0.87	0.35	21	0.35	70.00	91
1828630	1	1038	6.57	4.98	24.85	Neg Bin	99.50%		3.78			2.36	0.74	0.08	20	0.08	15.00	35
1114506	1	1014	6.42	8.49	72.09	Neg Bin	99.50%		11.23			0.63	0.91	0.45	24	0.45	90.00	114
1137719	1	985	6.23	7.13	50.86	Neg Bin	99.50%		8.16			0.87	0.88	0.10	30	0.10	20.00	50
412953	1	888	5.62	6.28	39.46	Neg Bin	99.50%		7.02			0.93	0.86	0.20	21	0.20	40.00	61
78069	1	888	5.62	5.22	27.29	Neg Bin	99.50%		4.86			1.46	0.79	0.50	12	0.50	100.00	112
1088882	1	858	5.43	4.70	22.08	Neg Bin	99.50%		4.07			1.77	0.75	0.25	14	0.25	50.00	64

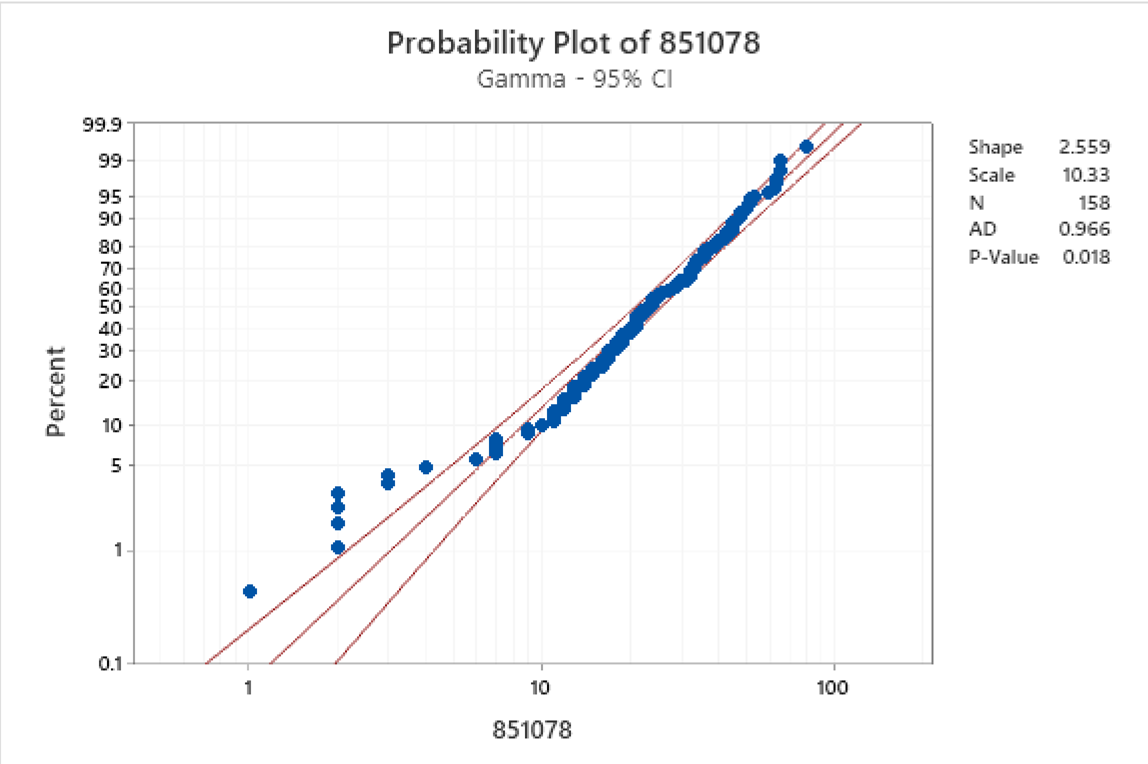
E.2) B class

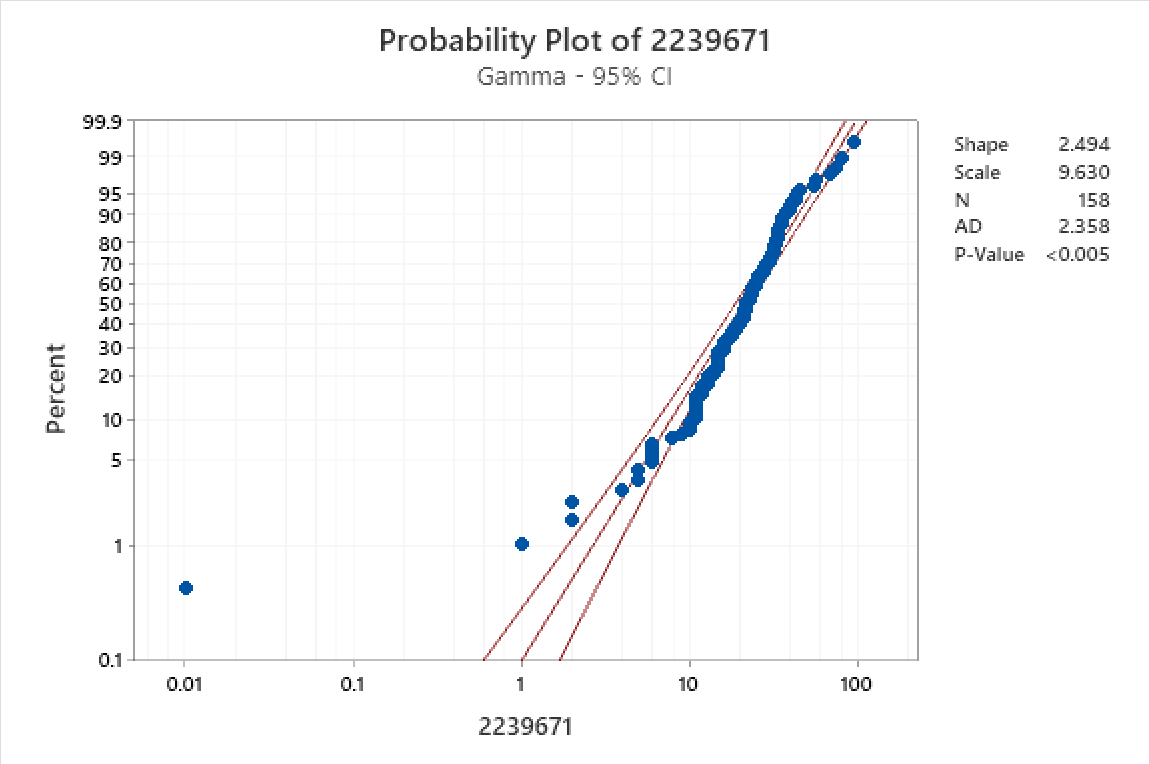
MedID	Review Period	D	x	StDev	Var	Dist.	FR	StDev/x	V/X	α	β	r	p	E	s (FR)	ESPRC	Q	S
651230	1	852	5.39	4.23	17.92	Neg Bin	99.50%		3.32			2.32	0.70	0.20	13	0.20	40.00	53
2735245	1	832	5.27	4.52	20.43	Neg Bin	99.50%		3.88			1.83	0.74	0.10	16	0.10	20.00	36
1171534	1	731	4.63	4.75	22.53	Neg Bin	99.50%		4.87			1.20	0.79	0.25	14	0.25	50.00	64
1148427	1	717	4.54	5.07	25.74	Neg Bin	99.50%		5.67			0.97	0.82	0.17	17	0.18	35.00	52
2182416	1	703	4.45	5.27	27.80	Neg Bin	99.50%		6.25			0.85	0.84	0.10	21	0.10	20.00	41
1024728	1	696	4.41	7.68	58.94	Neg Bin	99.50%		13.38			0.36	0.93	0.15	33	0.15	30.00	63
2264749	1	659	4.17	4.14	17.12	Neg Bin	99.50%		4.11			1.34	0.76	0.25	11	0.25	50.00	61
856126	1	654	4.14	6.18	38.16	Neg Bin	99.50%		9.22			0.50	0.89	0.25	20	0.25	50.00	70
1017217	1	653	4.13	6.55	42.87	Neg Bin	99.50%		10.37			0.44	0.90	0.25	22	0.25	50.00	72
2397943	1	646	4.09	3.04	9.22	Neg Bin	99.50%		2.25			3.26	0.56	0.32	7	0.30	60.00	67
1523244	1	641	4.06	5.76	33.18	Neg Bin	99.50%		8.18			0.57	0.88	0.08	26	0.08	15.00	41
1414763	1	623	3.94	5.30	28.11	Neg Bin	99.50%		7.13			0.64	0.86	0.15	19	0.15	30.00	49
2303108	1	583	3.69	3.99	15.90	Neg Bin	99.50%		4.31			1.12	0.77	0.25	11	0.25	50.00	61
1170015	1	563	3.56	3.94	15.56	Neg Bin	99.50%		4.37			1.06	0.77	0.22	11	0.23	45.00	56
2217252	1	545	3.45	8.27	68.33	Neg Bin	99.50%		19.81			0.18	0.95	0.25	34	0.25	50.00	84
2399083	1	543	3.44	4.66	21.75	Neg Bin	99.50%		6.33			0.64	0.84	0.10	18	0.10	20.00	38
1127039	1	541	3.42	4.34	18.87	Neg Bin	99.50%		5.51			0.76	0.82	0.20	13	0.20	40.00	53
1112740	1	539	3.41	4.24	18.01	Neg Bin	99.50%		5.28			0.80	0.81	0.25	11	0.25	50.00	61
463175	1	505	3.20	11.10	123.23	Neg Bin	99.50%		38.55			0.09	0.97	0.15	74	0.15	30.00	104
2121441	1	497	3.15	4.14	17.11	Neg Bin	99.50%		5.44			0.71	0.82	0.07	17	0.08	15.00	32
1090194	1	485	3.07	7.81	61.03	Neg Bin	99.50%		19.88			0.16	0.95	0.25	31	0.25	50.00	81
2239728	1	477	3.02	3.95	15.60	Neg Bin	99.50%		5.17			0.72	0.81	0.07	16	0.08	15.00	31
1051385	1	469	2.97	3.09	9.52	Neg Bin	99.50%		3.21			1.34	0.69	0.13	9	0.13	25.00	34
1828258	1	431	2.73	4.25	18.05	Neg Bin	99.50%		6.62			0.49	0.85	0.25	11	0.25	50.00	61
1089749	1	421	2.66	2.78	7.73	Neg Bin	99.50%		2.90			1.40	0.66	0.25	6	0.25	50.00	56
1036211	1	392	2.48	3.18	10.14	Neg Bin	99.50%		4.09			0.80	0.76	0.12	10	0.13	25.00	35
618918	1	389	2.46	2.67	7.12	Neg Bin	99.50%		2.89			1.30	0.65	0.25	6	0.25	50.00	56
1493493	1	389	2.46	2.28	5.21	Neg Bin	99.50%		2.11			2.21	0.53	0.05	8	0.05	10.00	18
2081725	1	385	2.44	2.91	8.48	Neg Bin	99.50%		3.48			0.98	0.71	0.05	11	0.05	10.00	21
636525	1	383	2.42	2.46	6.05	Neg Bin	99.50%		2.50			1.62	0.60	0.13	7	0.13	25.00	32
2127121	1	383	2.42	2.27	5.16	Neg Bin	99.50%		2.13			2.15	0.53	0.05	8	0.05	10.00	18
849170	1	374	2.37	2.52	6.34	Neg Bin	99.50%		2.68			1.41	0.63	0.07	8	0.08	15.00	23
1104969	1	364	2.30	3.12	9.72	Neg Bin	99.50%		4.22			0.72	0.76	0.20	8	0.20	40.00	48
2753383	1	351	2.22	2.49	6.19	Neg Bin	99.50%		2.78			1.24	0.64	0.16	6	0.15	30.00	36
1678876	1	351	2.22	3.39	11.52	Neg Bin	99.50%		5.19			0.53	0.81	0.15	10	0.15	30.00	40
2031418	1	334	2.11	2.25	5.07	Neg Bin	99.50%		2.40			1.51	0.58	0.05	8	0.05	10.00	18
1113771	1	330	2.09	2.56	6.58	Neg Bin	99.50%		3.15			0.97	0.68	0.03	11	0.03	5.00	16
888567	1	317	2.01	3.68	13.53	Neg Bin	99.50%		6.75			0.35	0.85	0.10	14	0.10	20.00	34
1516175	1	310	1.96	2.30	5.31	Neg Bin	99.50%		2.71			1.15	0.63	0.12	6	0.13	25.00	31
2116626	1	290	1.84	1.97	3.88	Neg Bin	99.50%		2.12			1.64	0.53	0.12	5	0.13	25.00	30
868930	1	284	1.80	3.39	11.49	Neg Bin	99.50%		6.39			0.33	0.84	0.12	12	0.13	25.00	37
2127148	1	279	1.77	2.08	4.32	Neg Bin	99.50%		2.45			1.22	0.59	0.08	6	0.08	15.00	21
2121573	1	275	1.74	2.32	5.39	Neg Bin	99.50%		3.10			0.83	0.68	0.12	6	0.13	25.00	31
858102	1	274	1.73	2.07	4.27	Neg Bin	99.50%		2.46			1.18	0.59	0.10	6	0.10	20.00	26
1458973	1	269	1.70	2.08	4.34	Neg Bin	99.50%		2.55			1.10	0.61	0.13	5	0.13	25.00	30

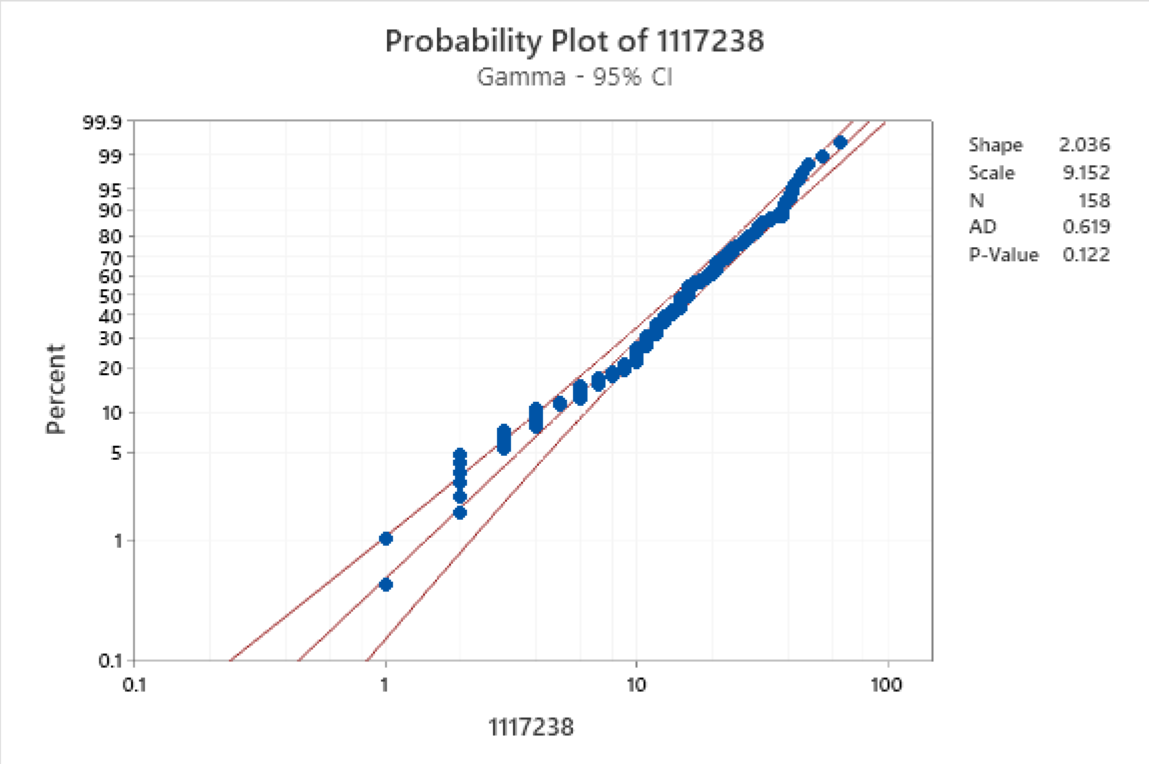
Appendix F: Goodness of fit test results

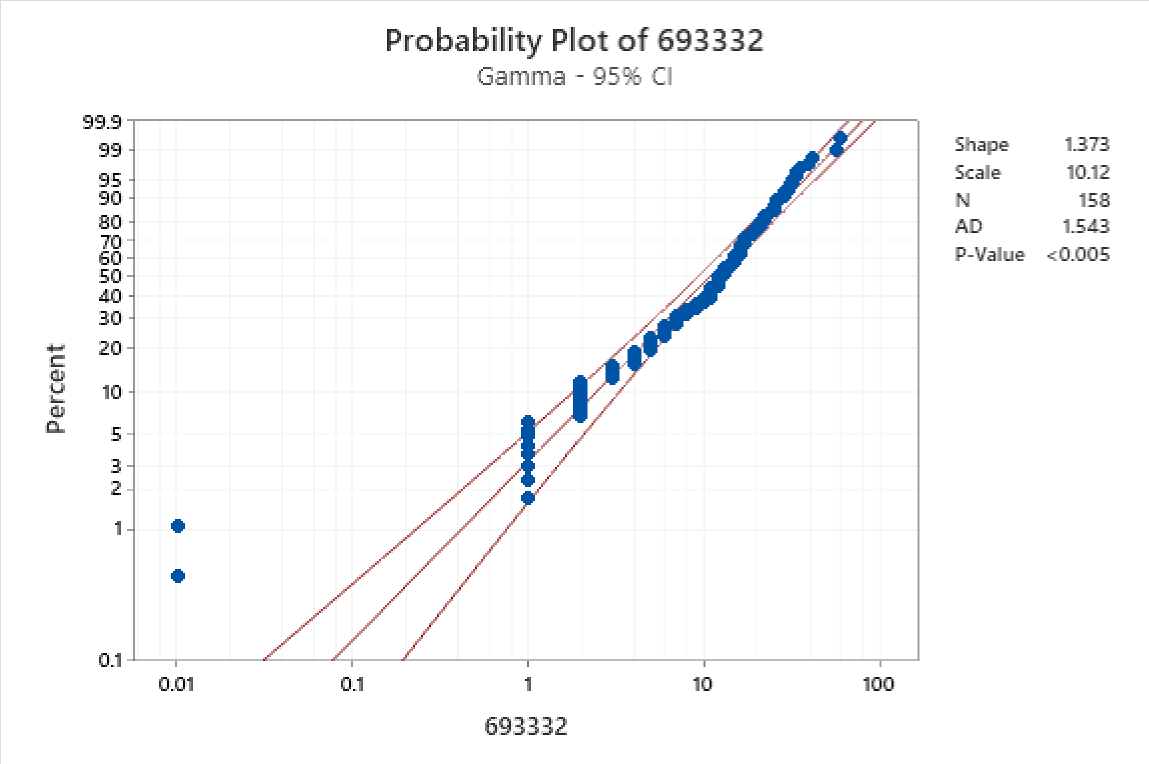
Probability plots of gamma distributed A class SKUs

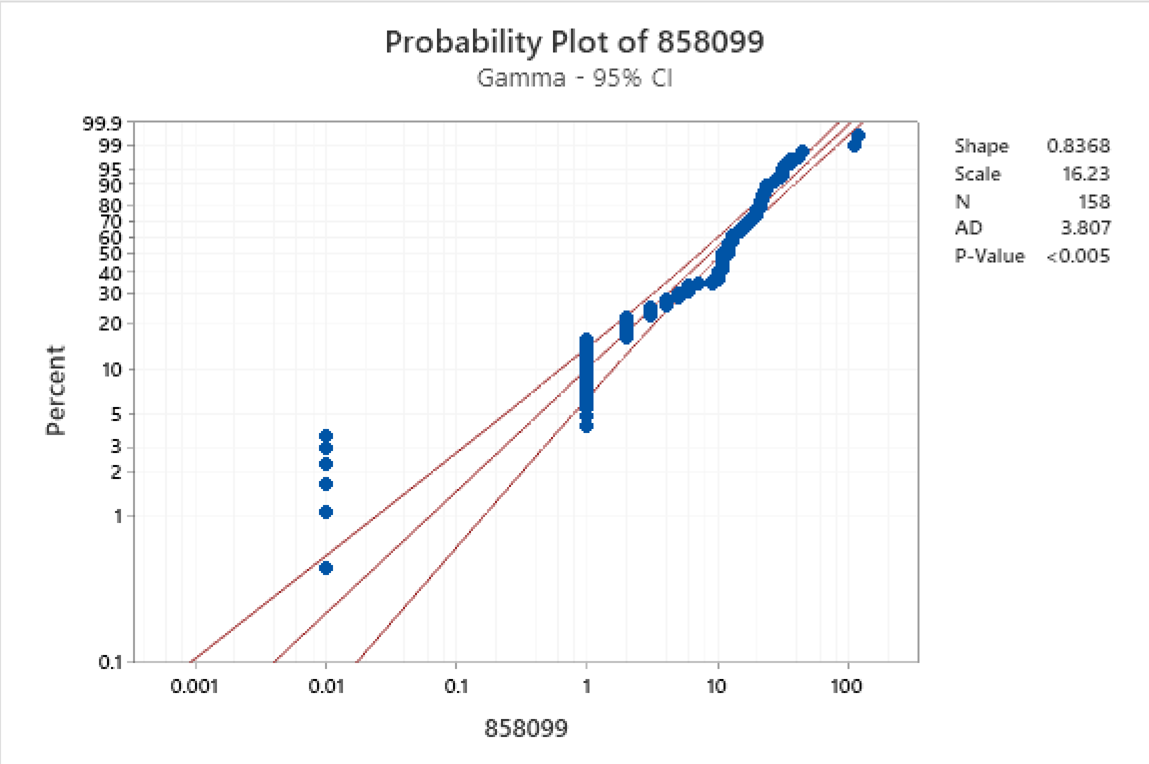


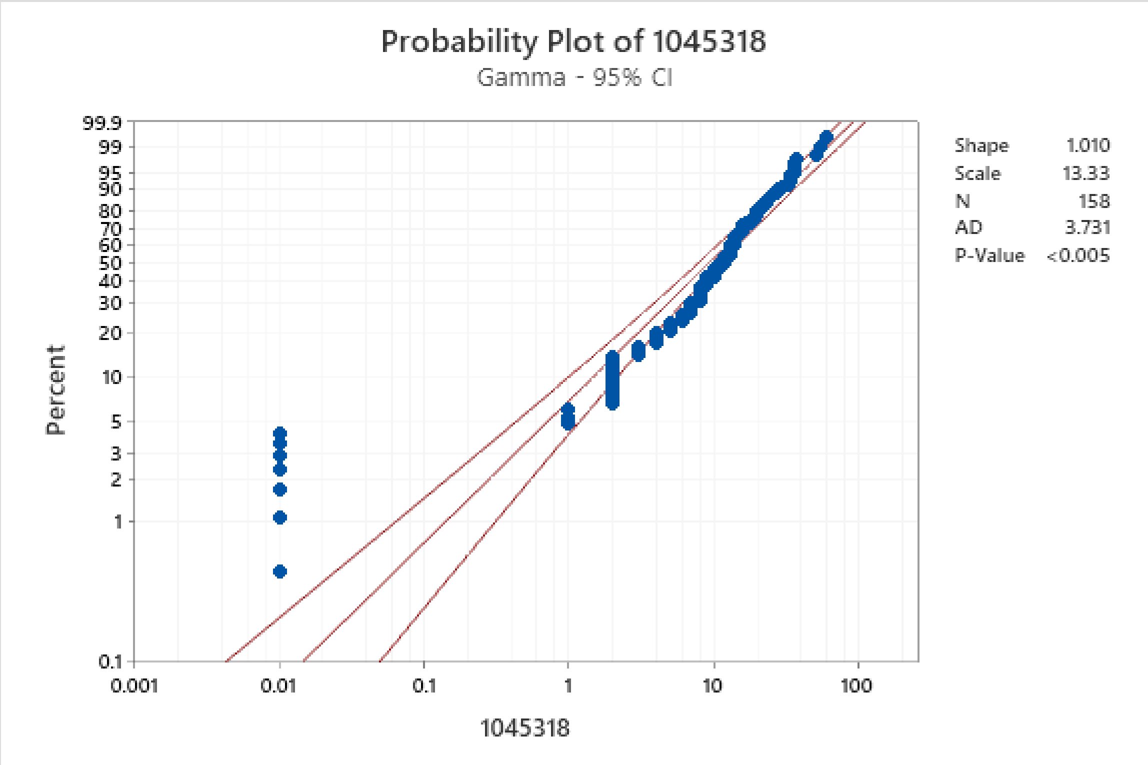


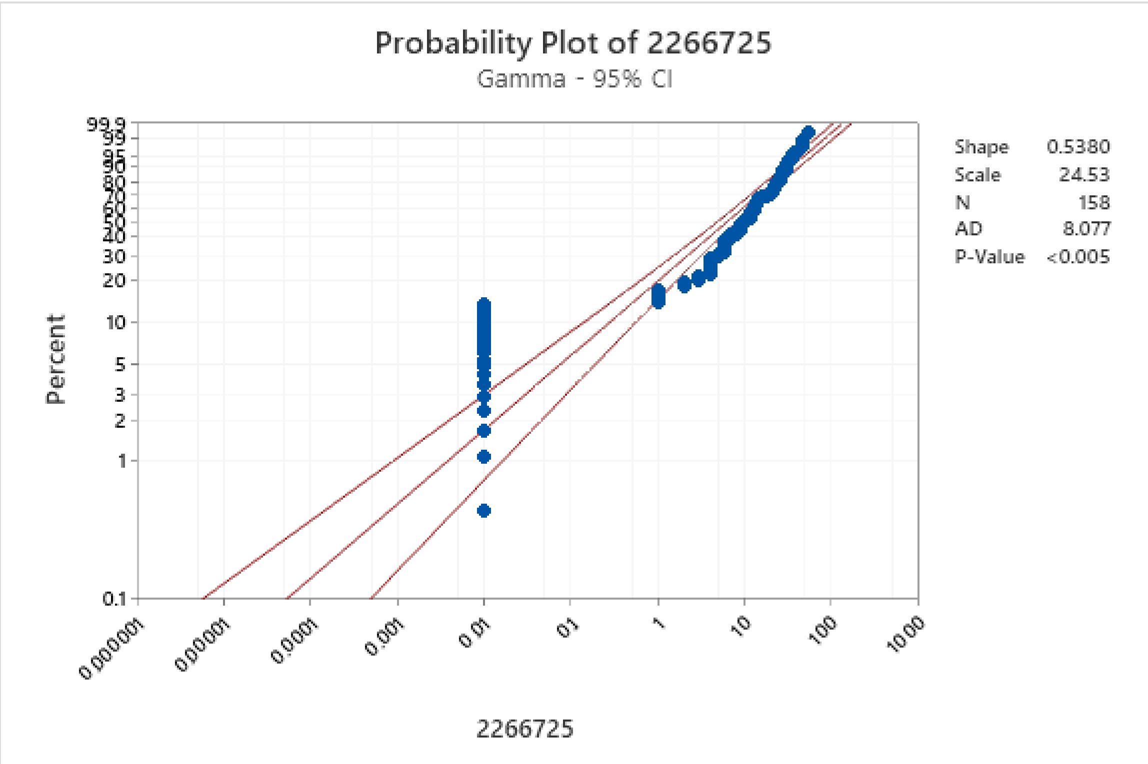

Probability Plot of 2239671
Gamma - 95% CI
99.9
99
95
90
80
70
60
50
40
30
20
10
5
1
0.1
Percent
0.01
0.1
1
10
100
2239671
Shape 2.494
Scale 9.630
N 158
AD 2.358
P-Value <0.005

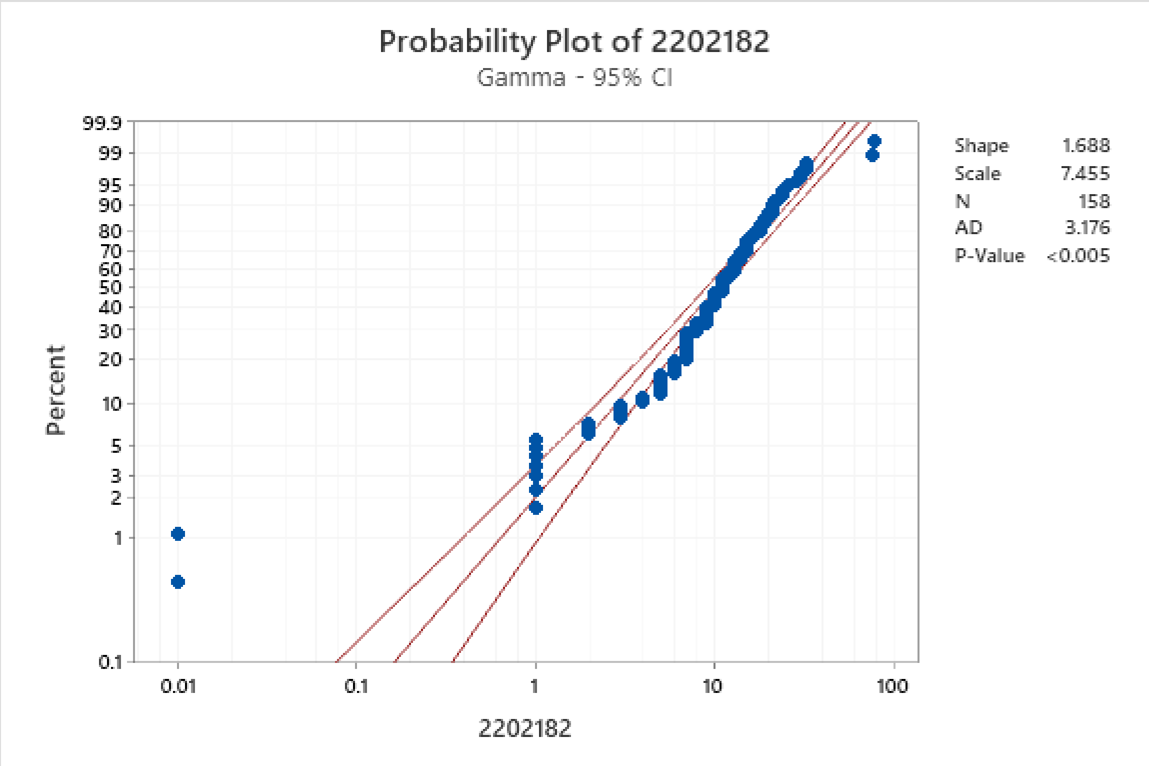

Probability Plot of 1117238
Gamma - 95% CI
99.9
99
95
90
80
70
60
50
40
30
20
10
5
1
0.1
Percent
0.1
1
10
100
1117238
Shape 2.036
Scale 9.152
N 158
AD 0.619
P-Value 0.122

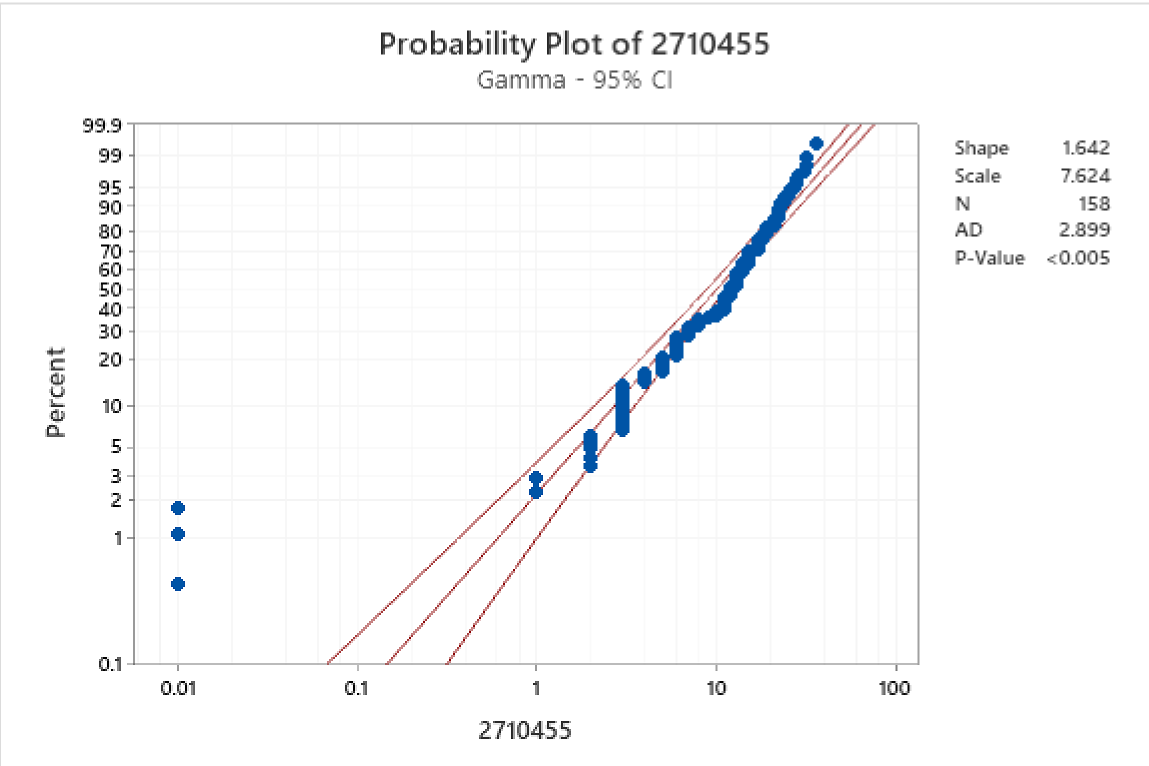

Probability Plot of 693332
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.01
0.1
1
10
100
693332
Shape 1.373
Scale 10.12
N 158
AD 1.543
P-Value <0.005

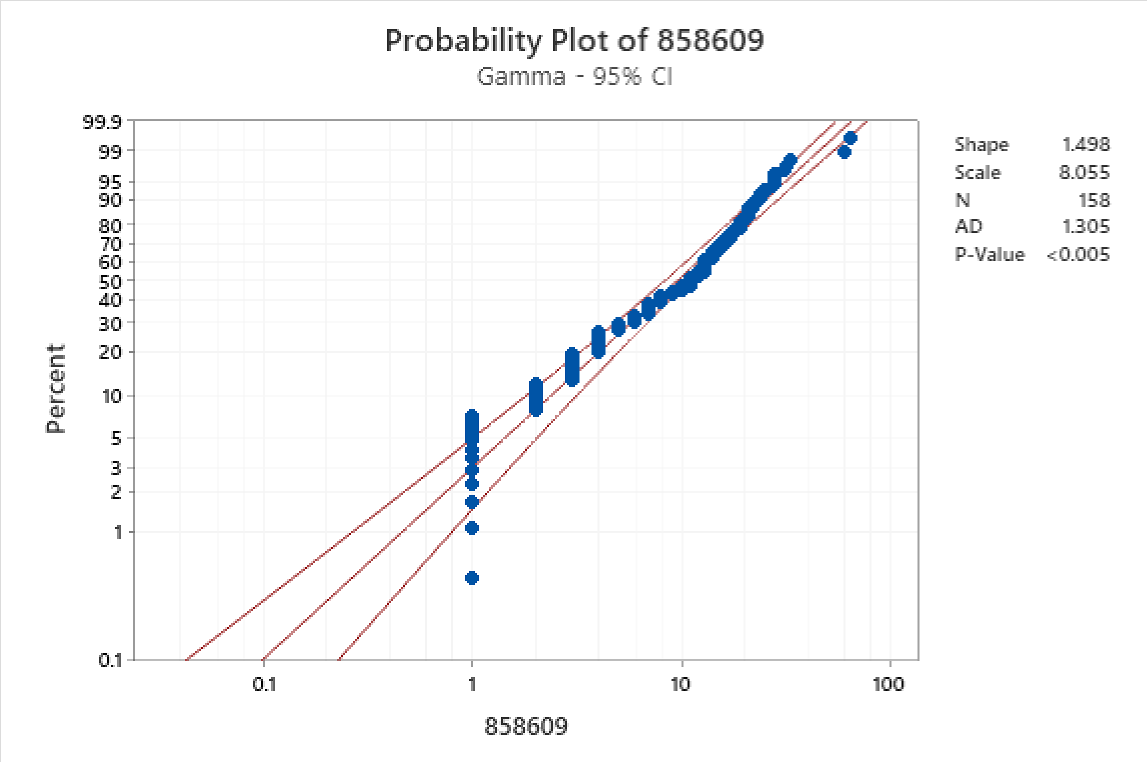

Probability Plot of 858099
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.001
0.01
0.1
1
10
100
858099
Shape 0.8368
Scale 16.23
N 158
AD 3.807
P-Value <0.005

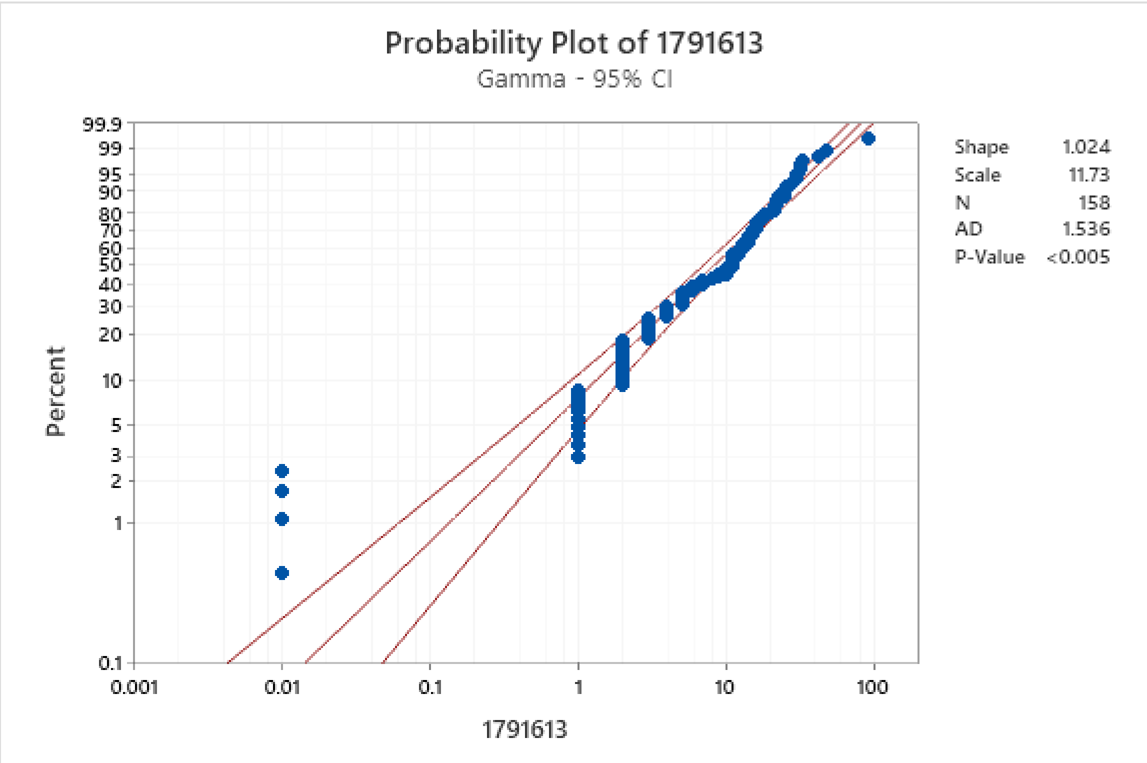

Probability Plot of 1045318
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.001
0.01
0.1
1
10
100
1045318
Shape 1.010
Scale 13.33
N 158
AD 3.731
P-Value <0.005

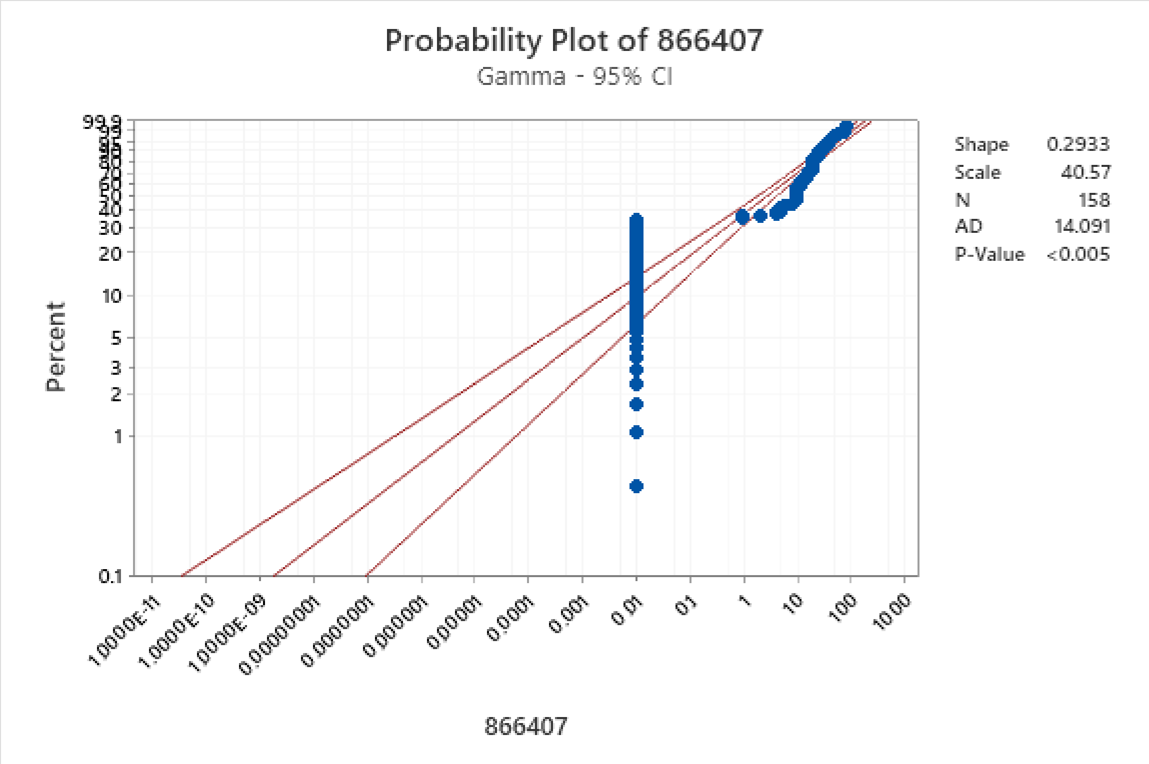

Probability Plot of 2266725
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.000001
0.00001
0.0001
0.001
0.01
0.1
1
10
100
1000
2266725
Shape 0.5380
Scale 24.53
N 158
AD 8.077
P-Value <0.005

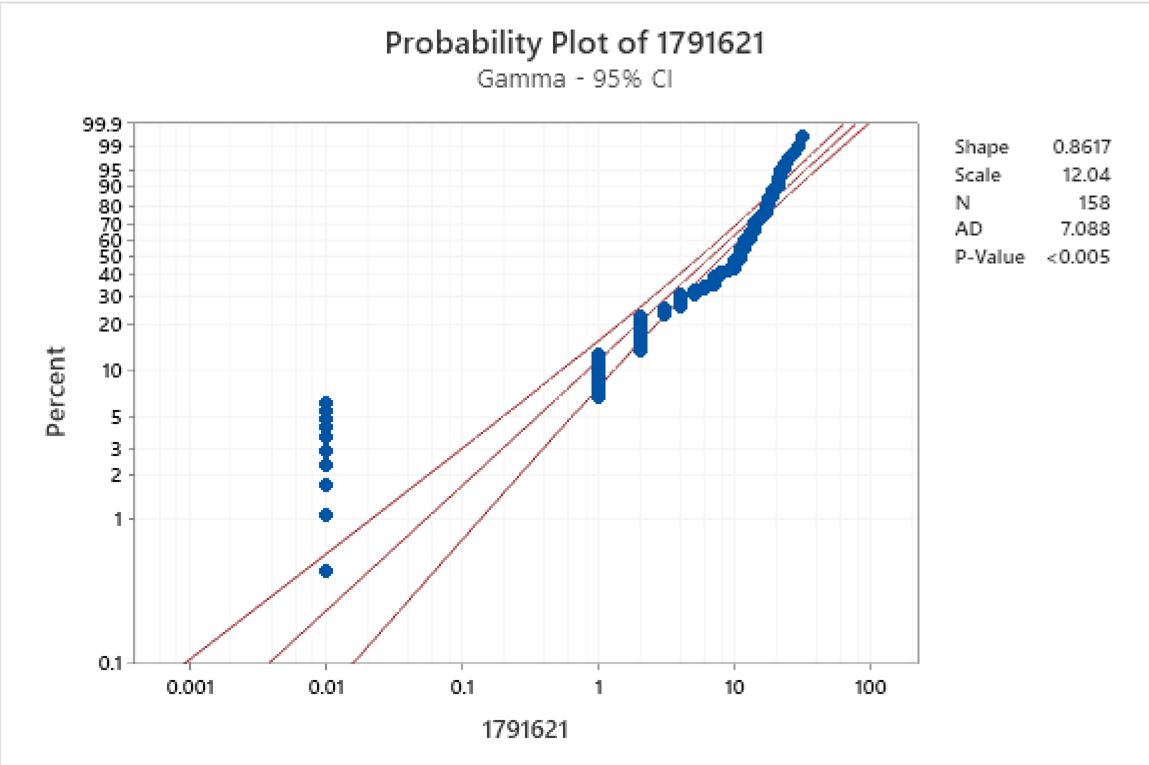

Probability Plot of 2202182
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.01
0.1
1
10
100
2202182
Shape 1.688
Scale 7.455
N 158
AD 3.176
P-Value <0.005


Probability Plot of 2710455
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.01
0.1
1
10
100
2710455
Shape 1.642
Scale 7.624
N 158
AD 2.899
P-Value <0.005


Probability Plot of 858609
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.1
1
10
100
858609
Shape 1.498
Scale 8.055
N 158
AD 1.305
P-Value <0.005


Probability Plot of 1791613
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.001
0.01
0.1
1
10
100
1791613
Shape 1.024
Scale 11.73
N 158
AD 1.536
P-Value <0.005


Probability Plot of 866407
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
1,0000E-11
1,0000E-10
1,0000E-09
0,0000000001
0,0000001
0,000001
0,00001
0,0001
0,001
0,01
0,1
1
10
100
1000
866407
Shape 0.2933
Scale 40.57
N 158
AD 14.091
P-Value <0.005


Probability Plot of 1791621
Gamma - 95% CI
Percent
99.9
99
95
90
80
70
60
50
40
30
20
10
5
3
2
1
0.1
0.001
0.01
0.1
1
10
100
1791621
Shape 0.8617
Scale 12.04
N 158
AD 7.088
P-Value <0.005