Improving Inventory Policy within Thales Supply Chain

THALES

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UNIVERSITY OF TWENTE.

Master Thesis

Jasper Leonard van Harten

Industrial Engineering & Management

Production & Logistics Management

Improving Inventory Policy within Thales Supply Chain

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Author
Jasper Leonard van Harten
S1818252
Msc Industrial Engineering & Management
JLvanharten@gmail.com

Thales Hengelo
Zuidelijke Havenweg 40,
7554 RR Hengelo
The Netherlands

University of Twente
Drienerlolaan 5
7522 NB, Enschede
The Netherlands

Supervisor Thales Hengelo
Willem-Jan Haarman
Manager Master Planning

Supervisor University of Twente
Dr. I. Seyran Topan
Faculty BMS

Management Summary

Thales, a high advanced radar company, operates with the help of its complex supply chain. They face unique challenges due to being a high mix and low volume industry. For their warehouse this essentially means that for producing a single product, many different components are required since there is almost no standardization in the parts used over all product classes. Over the past few years Thales stock value has been increasing substantially. One notable reason for this is the increase in the demand for their products. Other reasons exist, like minimum order quantities, however a notable outcome of this stock increase is the accumulation of dead and excess stock within their warehouses. Overall Thales is looking for ways to reduce stock since the increase in stock value has become significant and this is not sustainable in the long term.

Currently Thales relies on the Material Requirements Planning (MRP) system to procure its parts. However, while using MRP where procurement and demand should be in balance, a lot of excess stock has entered the system. This suggests a potential gap in the implementation of inventory policies. Looking at the data it is shown that only a small percentage of all items are monitored and procured using some sort of inventory policy. Hence, this Thesis focuses on creating a more tailored made approach given Thales' complex supply chain and inventory situation. To address these challenges, a mathematical model is designed to integrate a many different classification methods, inventory policies and other input factors to ensure the complexity of Thales is served. The goal of this model is to show that through experiments a significant stock reduction can be realized while maintaining stockout probabilities. The latter is very important since Thales demand has risen substantially and production schedules and thus the availability of parts is of most importance.

To couple observe how the inventory policies perform first demand data is linked to statistical distributions. The unpredictability of Thales item demand can not be linked to a single distribution. Hence all items are tested for different statistical distributions. These distributions are tested through the chi-square test to ensure that the demand patterns are validated. Furthermore various methods of ABC classification are considered. The classifications range from simple, like the annual dollar volume, to more advanced multi criteria inventory classification. The latter shows promise as it can include both qualitative and quantitative input data. Lastly, different inventory models are included namely, the (R, s, S) system, Lot-for-Lot, Just in Time and Base stock. Thales environment is modeled and the baseline of the model uses none of the included classification and inventory models.

Experimental simulations are conducted using the mathematical model shows positive results. The potential stock value savings are substantial and can lead to almost 8 million. Note that these stock value savings are achieved without tanking the stockout probabilities. Hence, it is shown savings can be realized while maintain operational efficiency. Furthermore, different classification methods can significantly impact the inventory costs, stockout probability and class sizes. Thales current method of solely looking at item price is sub optimal.

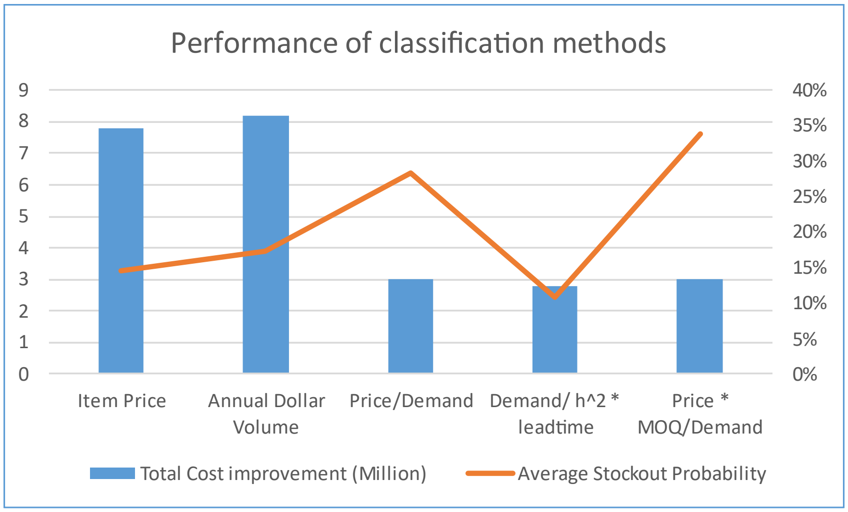

Figure 33- Comparison between classification methods

It is shown in figure 33 that all other classification methods lead to cost reduction. that other methods are more fruitful. Moreover, an alternative to traditional methods like annual dollar volume is explored. The MCIC shows a potential more nuanced approach to the classification problem. Alternative metrics like 'on stock date' and 'risk' are incorporated into the classification method and more strategic results are possible. While multi criteria inventory classification offers strategic flexibility, the traditional method ADV still outperforms it. By understanding and optimizing these elements, Thales can realize even more cost savings.

Looking at the data some insights of the mathematical model can be summarized. The model hints at reducing inventories for all subclasses for the B and C item classes. In the contrary, due to stockout probability of the items within the fast-moving A sub-class the model suggests to increase the stock of these items. Furthermore, the experiments show that the base stock inventory policy increases savings within the B and C class. In addition, the L4L and JIT inventory policies also increase savings for the slow-moving A class.

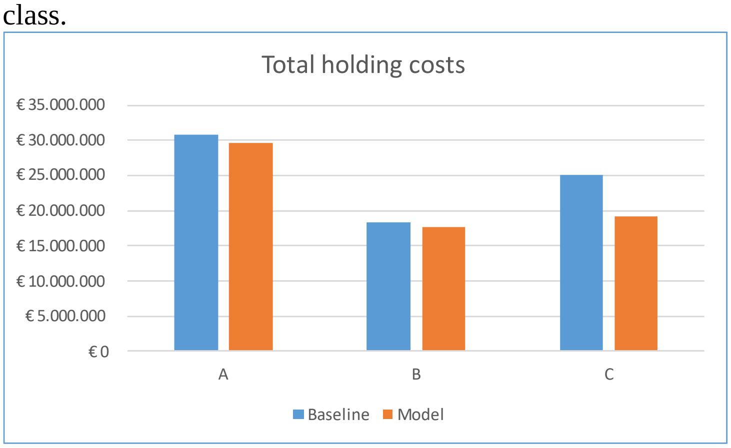

Figure 31- Comparison of holding costs between baseline and mathematical model

Looking at figure 31, a potential reduction in holding costs of around 11% can be realized. The total holding cost reduction can lead to €7.8 million euros. Furthermore, the performance of the KPI's increases as the model facilitates a more efficient stocking situation. In the figures 35 and 36, the Days inventory Outstanding and Inventory turn over ratio both increase in performance. The DIO decreases due to the fact that less stock is required and the ITR increases due to more efficient warehouse and the eradication of dead stock.

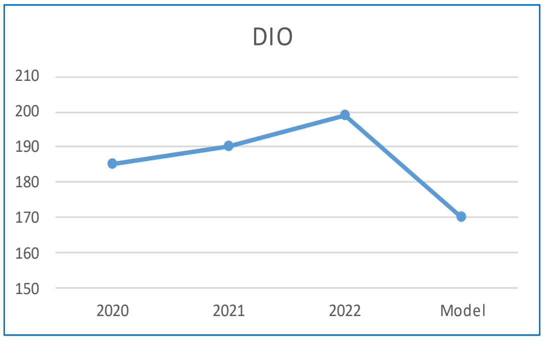

Figure 35- Performance of DIO

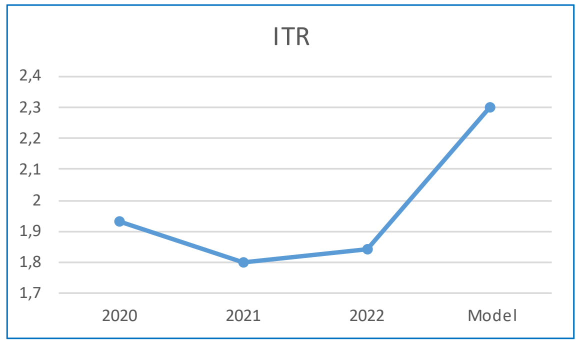

Figure 36 – Performance ITR

This thesis shows solutions to the inventory challenges faced by Thales. As Thales inventory increases the urgency to create a more balanced and efficient inventory system increases as well, as the capacity of the warehouse is not infinite. During the high times of business, the implications of increasing inventory costs might seem trivial, but in tight business circumstances, they can escalate into substantial pains for management. Hence, affecting the financial stability and health of the whole organization.
Within Thales inventory, multiple critical findings are present indicating improvements are possible.
Among these critical findings were the substantial amount of dead stock and excess stock. Overall, by addressing Thales complex inventory situation with a mathematical model and a pragmatic approach through experiments, Thales' diverse inventory landscape can be incorporated, and big improvements can be realized.

Besides the improvements within inventory, the developed model serves as a potential tool for inventory managers and decision makers. It increases the visibility of existing inventory problems and by tweaking its configuration and strategies, solutions can be found. The model hints at improvements that should be made to further enhance the current inventory situation. It does this by showing that almost €8 million can be saved in stock value without reducing stockout probabilities. Within the thesis it is indicated how these improvements can be realized. If used well, Thales can take a step towards a more organized inventory structure, and possibly ensuring a healthier bottom line. Concluding, this thesis shows the way towards less inventory costs and a more resilient management system.

Pre Face

I am honored to present my master's thesis completed at Thales Hengelo. I want to thank Willem Jan Haarman, my supervisor at Thales, whose support was invaluable in doing this research. I look back happily at my times at Thales. I have gained a lot of experience doing my thesis and working within their business. Lastly, I want to thank Ipek Seyran Topan, my academic supervisor, for her insightful feedback and support. After 6 years I will leave the life being a student behind. I have grown a lot as a person, and I look back fondly at my time at the university of Twente.

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Chapter 1 - Introduction

In this chapter a general introduction of Thales is given in section 1.1. Afterwards in section 1.2 the main problem is shown. Then in section 1.3 the problem statement and its core problems are analyzed. Through section 1.4 to 1.6 the research objective, scope and approach are explained and lastly in section 1.7 the deliverables are discussed.

1.1 Company Description

Thales, formerly Thomson-CSF, is an aviation, weapon manufacturing and information technology company. Market leader in sensor technology. Thales Hengelo, one of many locations in the world, specifically focusses on Naval Technology. They specialize in radar systems for ships for foreign governments and are known for their state-of-the-art radar/IR systems. Hollandse Signaal BV. was bought by Thales in 1990 and is currently their Hengelo Location. With over 1500 employees working and a yearly revenue nearing 1 billion, it is one of Thales' biggest locations.

1.2 Problem Context

Compared to former years, the number of sales orders is increasing significantly. Due to the increasing number of sales, Thales' main focus is to keep up with customer order delivery dates. To be able to meet rising demand, production is increased. A side effect of this is a rise in inventory levels (WIP, finished goods) and this is starting to become problematic. At the start of 2022, as shown in figure 1, total stock value surpassed 130 million and in May 2022 stock value nears 180 million.

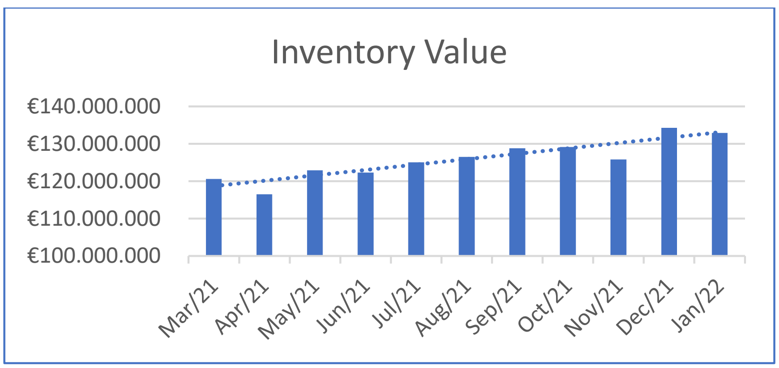


Figure 1 - Inventory value March 2021 to January 2022

High inventory levels impact profit cash flows. For example, high inventory values are associated with high depreciation costs. While in times of economic success, these costs can be overlooked. However, in economic downturn high inventory costs could hurt the company significantly. To reduce future inventory costs and lowering the probability of stock levels becoming a burden, Thales is looking for a way to reduce inventory positions and ultimately positively impact the inventory KPI's: Inventory turnover ratio (ITR) and Days inventory on hand (DIO). Thales' long-term targets for these KPI's are ITR > 2.5 and DIO < 400 days.

Thales Hengelo has an intricate inventory system. Its production process is high mix/low volume with many different product lines. However, product parts are not confined to single product lines, some parts are used in different products while other parts are only used in one. Hence, standardization of inventory polices is hard due to diversification. To create at least some standardization, all parts are divided into three main categories: Work in progress, stock build and common stock, the latter can be divided into two categories.

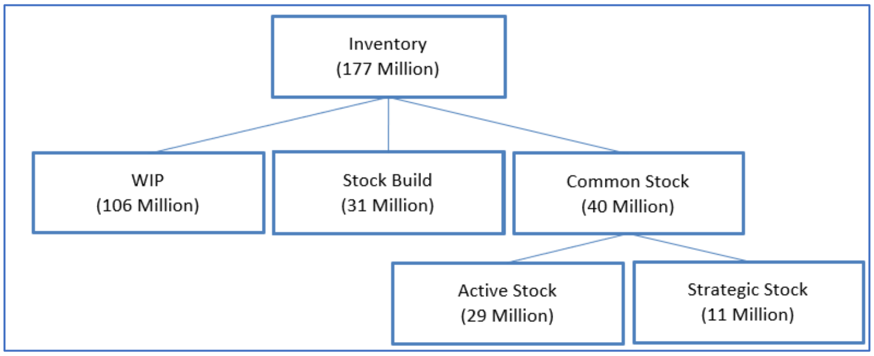


Figure 2 – Overview of stock categories with stock value

- *Work in progress stock (WIP)*

WIP contains all items that are allocated to a sales order number. This means that all these items are reserved for a specific customer/project, also called hard pegging. WIP stock is demand driven, meaning that if product X is ordered, all parts within product X are then ordered and eventually kept in stock. Thus, WIP has a one-on-one relation with demand. This means that the parts are already paid for by the customer and therefore do not accommodate financial risk. As can be seen in Figure 2, WIP accommodates for around 60% of total stock value.

- *Stock Build*

Just as WIP, stock build is allocated to sales order/project numbers. The difference between stock build and WIP is that stock build is not specifically related to customers, it is linked to a specific location instead. Some locations within Thales' warehouse are reserved for specific projects. For example, a newly introduced product, without a yet streamlined production process, has all its parts on the same location to improve its production process.

- *Common Stock*

Common stock items are freely available within Thales. These items are not linked to a location or project/sales order number. Within Thales this is also called soft pegging. Soft-pegged items range from small screws to big, printed circuit boards. When necessary, planners can reserve these items from the free (common stock), to projects and its customers. Once reserved, in other words hard-pegging, these items are not freely available anymore. Finally, common stock can be subdivided into two subcategories:

- *Active Stock*

Free/readily available stock.

- *Strategic Stock*

Some Thales products have a life cycle of over 25 years. Thales has service agreements that ensure that during its systems lifecycle it can be maintained and repaired when necessary. Some parts can not be bought after for example 5 years. If this is the case, extra stock is bought to reduce the probability of stockout.

1.3 Problem description

Stock value is increasing as shown in figure 1. Besides increasing sales orders and customer demand, other reasons exist that increase stock levels. For example, Thales must comply with minimum order quantities (MOQs) set by its suppliers. Often, Thales only needs 1 or 2 specific screws for production, while suppliers only sell them per 1000, resulting in excessive stock. Over estimation of demand is another reason of increasing stock. In these cases, more parts are purchased than necessary, or more parts are baselessly reserved to avoid stockout. In some cases, items are ordered early to ensure production can begin on time while contract negotiations are not finished yet. This is called ‘for release’ or ‘Bids’. Now and then these contracts are lost and thus items are ordered without customer demand, again resulting in excessive stock. Not only purchasing excess stock is linked to the rising stock value, but some policies that promote this behavior are in place deliberately. For example, Thales stays competitive due to its strong R&D of new radar systems. It happens that parts are purchased for testing and eventually not included in the final product. It is unclear what happens to these items since they are not linked to a specific customer project or project location. Furthermore, due to continuous improvement of Thales’ product roster, new versions of the same product are introduced. These are called ‘Engineering changes’ and ensure that the bill of material is slightly altered to accommodate for the newest technology. These changes can occur after parts are already ordered or build. In these cases, items are kept in stock.

In all these cases amount of inventory is increased, and this happens every day. In addition, due to the nature of Thales’ ERP system, items in stock are linked to projects or sales order numbers, if linked at all. When items are not linked, it is very hard to backtrack why a specific item is in stock. And because Thales’ current focus is to increase production and deliver products, people are very hesitant to throw items away when they are unsure if it is important or not, or worse keep procuring more items since they think current stock levels are necessary for future demand. The costs associated to production being halted due to parts not supplied are significantly higher compared to higher inventory costs. Hence, within Thales there exists a culture that prefers to keep items in stock ‘just to be save’. Once a year however, towards the end of the year, there exists a general scrapping procedure. Items that have no demand and have not been used in the last 5 years are up for inspection. However only a small portion of items that are up for inspection are scrapped. This has many reasons: items becoming soon obsolete, uncertainty of item usage, uncertainty of demand stochasticity, uncertainty of ERP data. Ultimately, due to information uncertainty there is not a lot of confidence and to be safe items are kept in stock. The latter results in ever increasing stock levels.

Other, yet smaller reasons for the increasing stock levels are for example unoptimized economic order quantities, better purchasing prices while buying in bulk, risk averse behavior of spare item purchasing policies and excessive strategic stock by the obsolescence department due to the so called ‘last time buys’ (LTB). LTB are where items are bought, sometimes in excessive quantities, one last time before the item becomes obsolete. Finally, with over 1500 Thales employees interfering at some degree with inventory levels, one can find countless of issues. To avoid unnecessary complexity, only high-level structural reasons are considered. These issues are put together in a problem cluster in figure 3 to help identify the core problem.

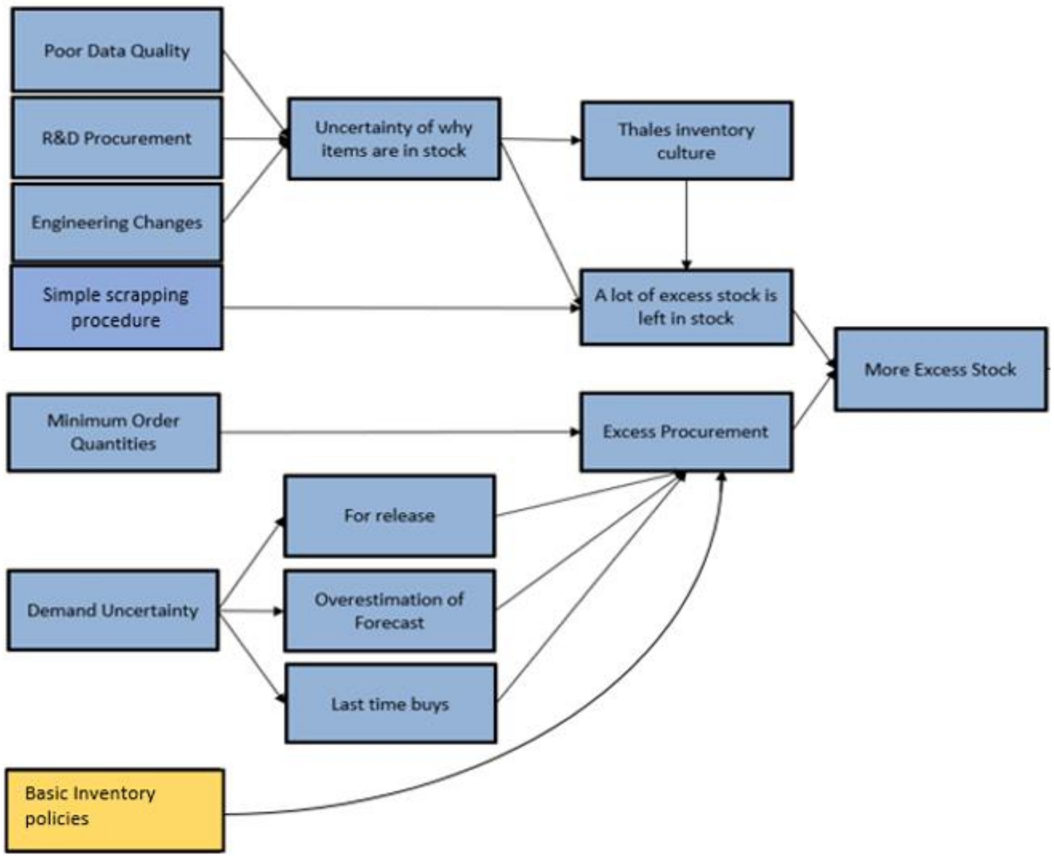


Figure 3 - Problem cluster

It is important to know which problems are solvable within the scope of this thesis and which are not. Looking at figure 3, multiple potential core problems can be identified. Using the definition of a core problem: A problem is only considered a core problem if it can be solved, (Heerkens et al., 2012). Multiple problems are ignored. For example, MOQs are put in place by suppliers hence Thales cannot influence these. The same is true for demand uncertainty, while Thales could improve demand forecasting, there will always be some form of uncertainty. Furthermore R&D procurement and engineering changes are necessary for Thales to maintain a competitive advantage. These can be considered as the cost of doing business. These problems would probably be less of an issue if Thales would increase its ERP data quality. For example, if unused R&D equipment is listed somewhere it is easier to backtrack for which reasons certain items are kept stock and thus can be more easily scrapped. Better ERP data quality is something Thales can implement themselves and although strongly recommended, not something this thesis can achieve.

Core problem

The biggest gains can be gained by improving Thales' current inventory policies and scrapping procedures. In the current scrapping policy, only items that have no demand and have no utilization in the last 5 years are considered. This so called 'dead stock' amounts to only 5,8% of total stock value, excluding strategic stock. Additionally, due to risk averse scrapping only a small fraction of this 5,8% is actually scrapped. Thales does have some current Inventory policies. Due to its engineer-to-order business, stock policies are mainly based on what is already in pipeline or committed. Furthermore, not all finished goods translate to sub system or item forecast. Not knowing how much of an item needs to be in stock to avoid stockouts, makes scrapping items scary. Hence, improving Thales' inventory management capabilities improves inventory transparency and boosts confidence to scrap items or procure less when inventory positions are too high. Currently, there is a big mountain of excessive stock but no data that shows what is excess and what is not. By improving Inventory policies, this becomes clearer and excess stock can be reduced by scrapping or selling. Ultimately, Thales should use better strategies for their purchasing policies. Overall, the core problem this thesis tackles, is to improve inventory management and provide more transparency into its stock levels by doing so.

1.4 Research Objective

The main objective of this thesis is to improve Thales' current inventory policies. By improving this, more items can be confidently scrapped which results in less excessive stock and ultimately reduces inventory levels in the long term. Since Thales current culture towards inventory, it is also important that it boosts inventory transparency. Due to Thales' high-mix, low-volume and engineer-to-order business, a one size fits all inventory policy will not be enough. Good segmentation and categorization of items is necessary to ensure the right decisions are made. It does not make sense to reduce stock for items that are still in pilot period (very new technological items), chances are they will be used in the next few years. On the other hand, items that are in stock for 10 years and still without demand, should probably be scrapped. Ultimately the objective of this thesis is twofold:

- *Improve inventory methods and increase inventory management*
- *Show necessity of items in stock more clearly*

Reality to norm

The preferred situation that this thesis achieves is described as follows: Thales knows when items are excessively in stock based on item policies. Currently 81% of items make us of their MRP planned policy (shown in chapter 2), which does not a good enough job to keep stock levels stable. The goal of this thesis is that all items get a fitting inventory policy assigned to counteract excess stock. When this is the case, Inventory managers can decide to scrap or resell excess items. Reaching this new norm requires a model that indicates what the inventory position should be for all items in scope. This inventory position number is calculated based on forecast methods inventory parameters and KPI's as service level targets, overall days on hand or turnover ratio. More extra parameters exist and will be explored further in this thesis. To ensure the model reflects Thales' business as appropriate as possible, parameters should be able to be changed by decision makers based on their preferences.

1.5 Research Scope

As described in section 1.3, hard-pegged items are allocated to single projects. Hence, these items need to be kept in stock if the project is still in progress. All hard-pegged items are one on one accounted for through demand, meaning that all items are used and often not left in stock when the project is finished. Items that are left in stock go from hard-pegged to soft-pegged, as the project no longer exists. Because of the nature of hard-pegged items, they are out of scope of this thesis. Hence, only soft-pegged items are included in the model. This means that Work in progress and Stock build items are out of scope, only common stock is considered.

Common stock can be subdivided into active and strategic stock. Strategic stock is in stock for specific reasons, it is not considered as excess stock or waste. This is why strategic stock is out of scope, and active stock is within the scope.

1.6 Research Approach & Research Questions

This research is done through different phases with accompanying research questions. The research is done in the order of the phases 1 to 5. All steps are done to answer the following main research question:

What inventory policies should be implemented to improve inventory management for all Thales common stock items?

I. **Analysis of current inventory, current inventory methods, Thales' current performance and classification of inventory**

To obtain a complete picture of the current situation, all in scope items should be evaluated. It is useful to investigate what and where items are in inventory, what procedures exist and impact the situation constantly. Therefore, the following sub-research questions should be answered.

1. *How much items are in stock? What is the nature of these items regarding size, value, demand, days in inventory?*
2. *When do items get sold or scraped? What items are not considered and why?*
3. *What is the performance of Thales' inventory regarding the main KPI's?*

II. **KPI dimension analysis, Inventory Strategies, Strife value implementation**

In the second phase all the characteristics of the current situation are known. Hence, the current performance can be substantiated by using literature and the outcome of the first phase. This can later be used to build and evaluate the model. In addition, multiple inventory strategies or methodologies from literature are evaluated to find the best fit for Thales.

1. *What statistical distributions fit current demand patters? What inventory strategies fit these demand patterns?*
2. *How can inventory management be improved?*
3. *What item classification exist? Which would be beneficial for Thales?*
4. *What inventory policies or strategies exist? Which are applicable to Thales? Would these policies benefit Thales?*

III. **Applying chosen solution approaches**

In this phase multiple inventory policies are evaluated, and its effect is analyzed. Besides analyzing the impact of these improvements, it is also important to validate the solutions themselves. Based on these findings, recommendations and the proposed inventory methods can be implemented.

4. *How do proposed policies impact the performance of Thales inventory? How much do KPI's improve? What other changes happen next to KPI changes?*
5. *What settings/methods lead to the biggest increase in performance or reduction in inventory?*

IV. **Implementation of the new plan**

The final phase of this research is to provide recommendations on how this model should be implemented. It should show how the model works and how inputs and outputs should be interpreted.

1.7 Deliverables

To ensure Thales can make use of this research, alongside this thesis other deliverables are given.

This thesis outlines the new proposed inventory policies, as well as how they are implemented in Thales current situation. Currently, Thales makes use of a lot of Excel data files. Besides this Thesis, a macro enabled excel file is created. This excel file ensures that Thales can load in its data and after calculations are made an overview is created of all current items in stock. This overview shows the current stock levels, expected demand (calculated and from ERP), recommended inventory policy, policy parameters and lastly it points out whether a SKU stock level is within acceptable bounds given the inventory policy. This last point ensures Thales has a good understanding of why or when a stock is too low or too high.

In the appendix E, instructions can be found that show how this Excel tool works.

Chapter 2 – Analyzing the current situation

In this chapter the current situation in regard to the items in stock is analyzed. First the characterization of items is discussed in section 2.1. Afterwards multiple policies and current practices are discussed and elaborated on in section 2.2. Furthermore, demand specifics of these stock keeping units is analyzed in section 2.3. Section 2.4 shows the current depreciation of items as financial risk and section 2.5 shows the KPI performance of the Thales stock. Lastly, 2.6 concludes this chapter.

2.1 Item Characteristics

There are currently over 23 thousand different items in stock. Ranging from bolts and screws to big assembled parts. To distinguish the items. Items are sectioned by the terms active, strategic (also called obsolete) stock, dead and not dead. Thales is worried that a lot of stock is dead stock. Healthy stock policies ensure that overall stock cost and stockout probabilities are minimized. Dead stock costs Thales money, either by taking up valuable warehouse space, or by extra handling costs without return. Dead stock is stock that does not pull its weight and will pull the business down in the long-term. (Kakarlamudi, 2018) There are different types of dead stock. Excess stock is one example where too much stock is procured and after order is finished excess stock stays in inventory. However, stock that sits around for a long time does not have to be bad. In Thales case a significant part of un-moving stock is strategic stock (items that are obsolete). To get better insight into what items cause problems and which are necessary for business, Thales uses 2 categories:

- *Dead and not Dead: Dead stock are items that are without demand and no usage in the last 5 years and not dead items are when this is not the case.*
- *Strategic and Active: Strategic items are unavailable for purchase on international markets and active items are readily available for purchase.*

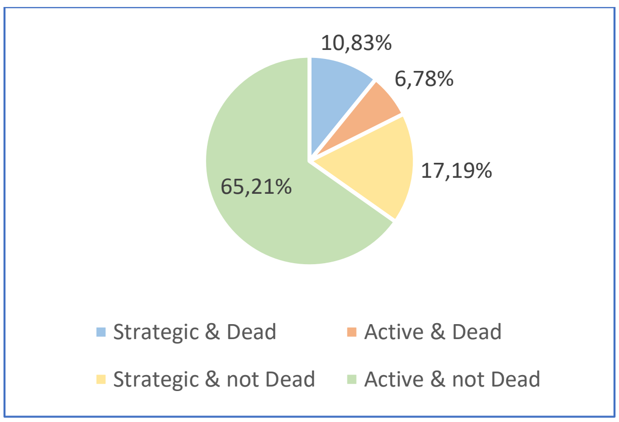


Figure 4 – Distribution of items in stock (Common Stock)

According to the 2 categories, the distribution of items is shown in figure 4. The worst category is active & dead stock, as this stock does not move and is readily available on the market, hence if currently necessary one could simply procure it. This category accounts for almost €3 million of total stock value. In the contrast to the latter category, active & not dead accounts for the majority of stock value and 1/4th is strategic stock. Note however that within figure 4 does not tell the whole story. While 65% (€26 Million) is active stock, due to Thales definitions excess stock is included. When an item has not been used for the last 4 years and has no demand, it is still considered active while in fact all that it could be excess items left over from a transaction 4 years ago.

To obtain more insight into the nature of items in stock, Thales does use some form of classical ABC classification. While classical methods from (Teunter et al. 2009) rank SKUs based on their value and revenue Thales just considers inventory value only, since for many items relevant revenue data is missing. Based on the ranking, the items are divided according to the Pareto distribution 80%, 15%, 5%.

Table 1 – ABC Classification of items in stock

Classification	Percentage of total value
A	80%
B	15%
C	5%

The distribution results in the following cumulative distribution of inventory value.

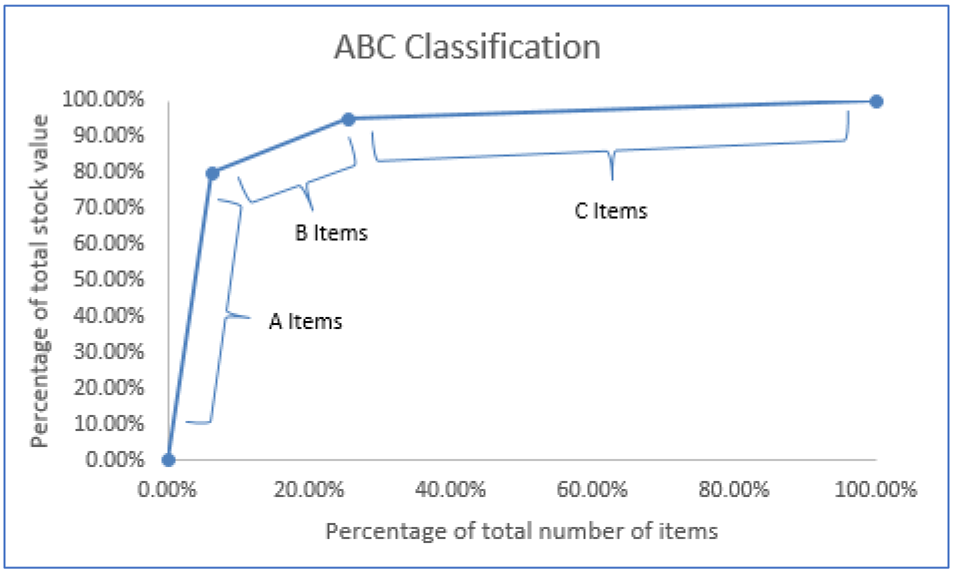


Figure 5 – ABC classification cumulative distribution

Due to the chosen subsets of items the characteristics of these classes are shown in table 2.

Table 2 –Summary ABC Classification

Classification	A	B	C
Max Value	€3.200.000	€12.000	€2000
Min Value	€12.000	€2.000	€0
#items (%)	6.2%	19.2%	74.5%

When looking at the summary, the number of items in Class A is relatively small. This can be explained due to the nature of Thales' products that are sold. Products often have only a few high value sub parts, and this is represented in its stock. It would be interesting to see if a high percentage of these A parts are considered 'dead'. On the other hand, the majority of items are C items. One could ask the question if this amount of C items is necessary for business or that a lot of these items are 'leftover' or excess. In the next section, more insight is given into the item sets.

2.1.1 Dead stock

Using the ABC classification, the characteristics of the items in stock are further explored. The most interesting category is dead stock, since these assets do not convert to revenue. Dead stock amounts up to 17% of total stock. To improve inventory turnover ratio, eradication of dead stock is one of the first logical improvement areas.

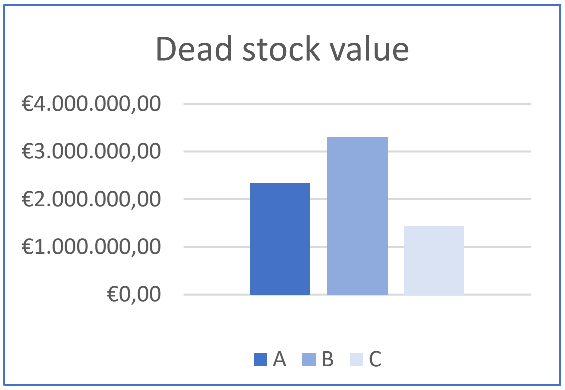


Figure 6 – Dead inventory value

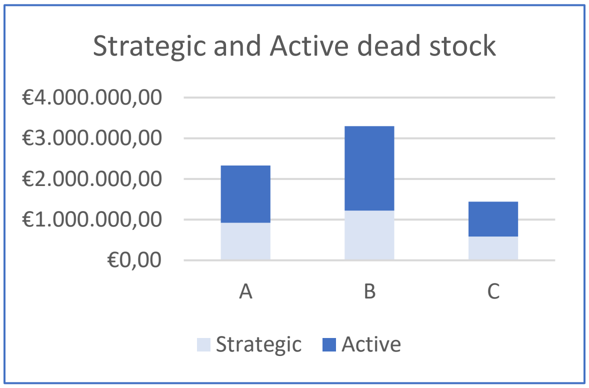


Figure 7 – division of strategic and active stock

Figure 6 shows the distribution of dead <u>common</u> stock according the ABC classification. To further elaborate on dead stock, figure 7 shows the composition of dead stock in regards to strategic and active stock. First, the B-item class looks to be the biggest contributor regarding inventory value. Oddly A items are a significant part of total dead items. These items cost thousands of euros. A-items contain items like circuit boards. Are these expensive items still usable after being on the shelf for 5 years? Furthermore, in figure 7, the majority of 'dead' items are still active. Hence, they do not need to be kept in stock as they are still available to be bought. Reselling or scrapping of these items could lead to reduction in inventory value.

2.1.2 Not dead stock

While dead stock logically would be the biggest negative contributor to inventory KPI's. 'Not dead' stock is not without fault. As mentioned, Thales 'best' subclass (not dead & active) does contain excess items and in theory it is still possible the majority of these items are left unused for years.

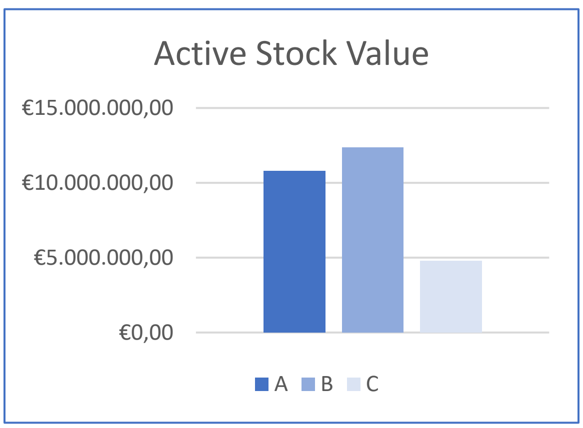


Figure 8 – Active inventory value

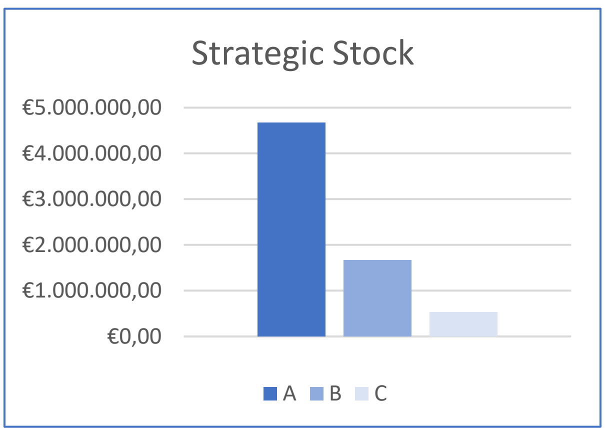
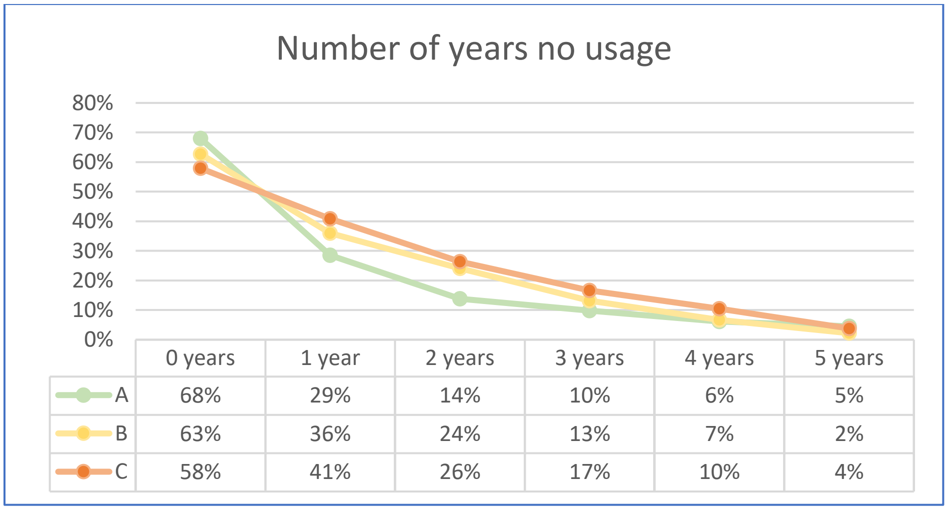


Figure 9 - strategic stock value

Figure 8 shows the distribution of active <u>common</u> stock. In comparison to dead stock, the difference between A and B items is less. However, in both cases, even when A items are far more expensive, B items are the majority of stock value in common stock. Interestingly to note however, is that in contrast to dead strategic stock, the majority of not dead strategic stock are A items. That A item segment is more represented in not dead stock is interesting. This is could intuitively be explained that there is more attention for A items and thus less likely to be left on the shelf for too long.



	0 years	1 year	2 years	3 years	4 years	5 years
A	68%	29%	14%	10%	6%	5%
B	63%	36%	24%	13%	7%	2%
C	58%	41%	26%	17%	10%	4%

Figure 10 - Active (not-dead) inventory, years not used.

While not dead stock is 'in use' according to the definitions set by Thales. Figure 10 shows that around 63% across the three item classes is recently used. A connection can be seen between importance of item class and steepness of the no usage curve. High value A items are more likely to have recent usage and are less likely to be unused for a longer time period. While figure 10 is based on not dead active inventory, it is interesting that around 25% of B and C items have not been used in the last 2 years. It is even a bit odd with the knowledge that most items have a lead time of less than a year. In these cases, one could choose to resell these items and when demand rises, more can be bought.

2.1.3 Excess stock

In the previous section, the usage of active un dead stock is discussed. Usage alone does not tell the complete story as items that are used may still be plentiful in stock.

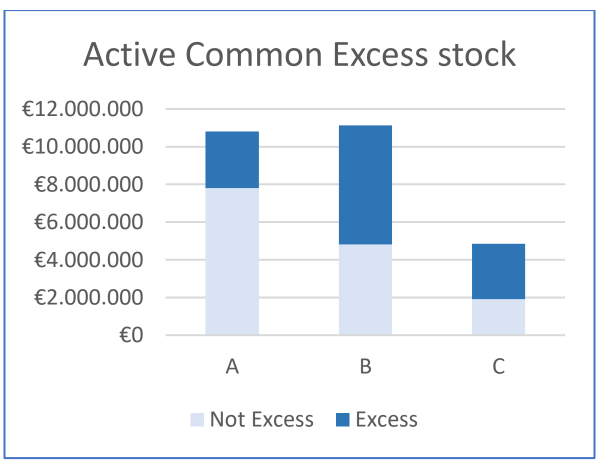


Figure 10 – Active stock build-up (excluding strategic stock)

Figure 10 shows us the amount of excess stock in regards to total stock of figure 8. Note that excess stock is calculated as follows:

$$Excess\ Stock\ value = Max((Current\ inventory - Demand) * piece\ price, 0)$$

Looking at figure 10, it becomes clear that for B and C items, more than 50% of stock is excess. It is impossible for Thales to completely remove excess stock coming in. Things like MOQ's and Engineering Changes are the cost of doing business. However, having over €12 million excess stock can negatively impact inventory performance. In Thales' situation excess stock is not 100% bad. In the way excess stock is currently calculated, it includes safety stock. While Thales lacks inventory policies that calculate safety stocks for a lot of items, moreover in section 2.2, extra safety stock reduces the probability of stockout. However, how much safety stock is required is currently not calculated for the majority of SKUs.

2.1.4 Probability of demand of 'dead' inventory

As the Thales' prescription of dead demand dictates: No future demand and no demand in the last 5 years. Using this definition, a lot of inventory is assigned this label. In most cases items that are not used for 5 years do not have and will not have new demand. To find the probability of future demand given demand in the past, demand behavior is analyzed. It is interesting to see whether the 5-year 'dead' period is appropriate to say something about future demand. For example, it could be that items that are not used in the last 3 years, will not have any future demand. Due to the big emphasis on R&D, parts are replaced often. Hence, the longer an item is unused, increases the probability that it has been interchanged, and thus future demand of this item will decrease. Because the probability of years unused and demand are dependent Bayes' Theorem is a suitable method to calculate the relation between usage and demand.

$$\mathrm{P}(\mathrm{D}|U) = \frac{\mathrm{P}(\mathrm{U}|\mathrm{D})P(D)}{\mathrm{P}(\mathrm{U})}$$

The probability of demand (D) is calculated given the usage (U) of the items in stock.

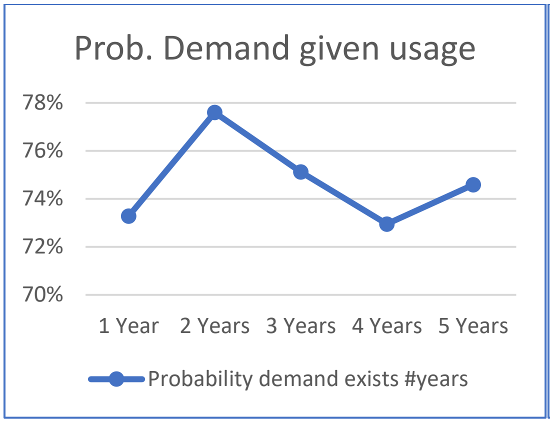


Figure 11 – Demand given usage

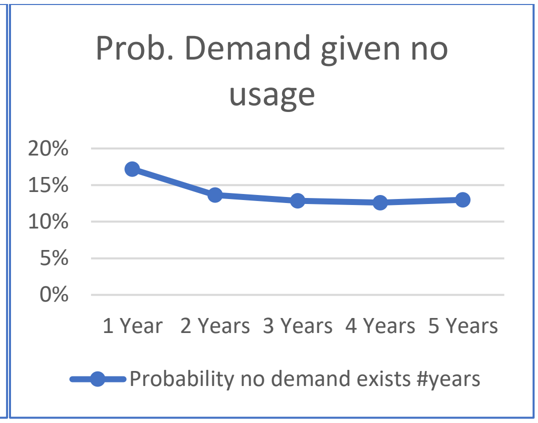


Figure 12 – Demand given non-usage

In figure 11, the analysis shows that the probability increases of demand when an item has been used in the last 2 years. An item that is used once (for 1 year) has a lower probability on future demand than items that are used multiple years. Considering Thales' long lead times this is logical, even 3 years of usage gives a higher probability of future usage. In figure 12 the probability of demand is given in regards to consecutive years of no usage. No usage in year 1 corresponds to a demand probability of 17%. This number lowers for the next 2 non-usage years and then stays stable. This indicates that the probability of demand is not changed when an item has not been used in the last 3 years than if it was not used in the last 5 years. Additionally, the probability of demand given 4 years of usage is lower than 3 years of usage (figure 11). Together, this indicates that the arbitrary 5-year period might be too long. A 3-year period indicates a similar promise of future demand and makes the group of dead stock bigger.

2.2 Inventory Parameterization

There are currently over 21 million items in stock. It is known that the value of inventory is increasing. From January to August total inventory value has risen by €14 million.

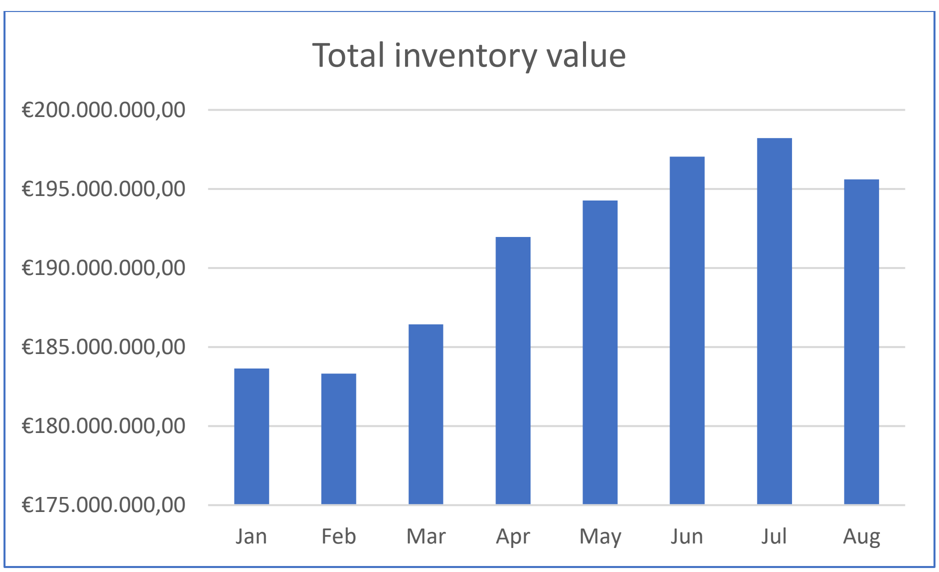


Figure 13 - Total inventory value

2.2.1 Inventory Policies

Current inventory policies are very basic. This makes it hard to check whether your stock levels are justified or not. When looking at the current situation only a few policies are found. The items in inventory can be subdivided into two main categories, MRP planned and inventory Min-Max policy. MRP planned means that the items are procured based on the internal MRP planning. Thus, these items are only procured when the product is currently in the production pipeline. This procurement policy happens for the vast majority of items as shown in figure 12. Note that the number of units MRP procured is equal to the demand, however this is not the case for items which contain a MOQ/EOQ or safety stock. In this case the number of units procured often exceeds the demand. So, items where EOQ/MOQ or safety stock calculations are used, are still MRP planned but use a different inventory policy.

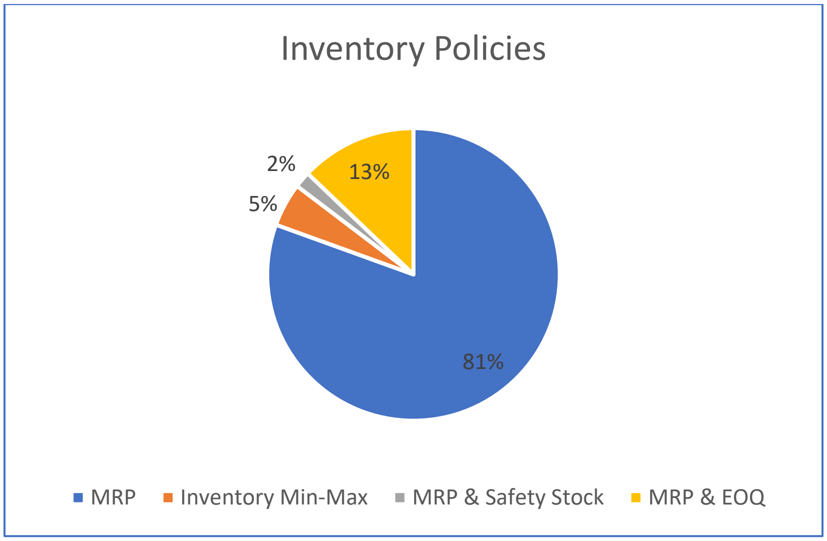


Figure 14 – MRP planning vs Inventory min-max policy

Besides MRP planned, Min Max is another used policy. Inventory Min Max corresponds to one of the common inventory control systems. Min/Max can be seen as a (R, s, S) policy, moreover in chapter 3.

2.2.2 EOQ and Safety Stocks

EOQ calculation are only done for fast movers, moreover in the next section. These items are often in multiple products. EOQ's are calculated following traditional EOQ formula:

$$Q = \sqrt{\frac{2DK}{h}}$$

Where:
Ordering costs K = €200
Holding costs h = 0,2

While most items follow the formula, exceptions are made.
If MOQ > EOQ then the MOQ is used as the EOQ, furthermore, if the EOQ > average yearly demand, then the EOQ = yearly demand.

Safety stocks are only calculated for a few items. In appendix A an overview of Thales' current safety stock calculations is shown.

2.2.3 Demand during lead time

As Thales wants to reduce inventory value while not reducing stockout probability, demand during lead time plays a big role. However, some items are produced/demanded in such low volumes and occurrences that the need for stock is neglectable. Looking at MRP planned only, demand next year is known for these items. Still, a lot of items are kept in stock while the time before next demand < lead time. Meaning that for some items, the next time they are needed for production is in 2023. And with a lead time of less than 100 days, there is still a lot of time for procurement processes to get them in stock on time. So, when looking at items that have no demand for the next 6 months and a lead time of less than 100, table 3 shows the resulting stock value. In theory, over €11 million could be procured later as these items are not needed yet and thus reducing current stock value significantly.

Table 3 – Stock value of items that could be procured or made later

No Demand and Lead time < 100 days	**Stock Value**
Make items	€70.931
Buy items	€11.432.931

2.3 Demand Characteristics

While Thales keeps track on the number of products it will sell in the coming years. They do not look at individual items. Thus, future demand is clear based on what is already in contract (MRP planned), no other methods are used to improve inventory policies like forecast based purchasing and safety stocks. Doing this does come with some challenges. Thales is a low-volume High-mix company. And their items in stock range from basic bolts to very complex expensive products. There is no single demand distribution that fits all items. In this section, all different demand characteristics found within Thales are discussed.

According to (Boylan et al., 2008) a demand framework is given to categorize the different demand types. The framework is based on average demand size μ, interval between demand events and coefficient of variation σ/μ.

Fast movers (demand during lead time > 10)

- Fast moving: Regular demand/small inter-demand intervals ($\sigma/\mu < 0.5$)
- Erratic: Highly variable demand size (High $\sigma/\mu > 0.5$)

Slow movers (demand during lead time < 10)

- Slow moving: Low average demand per period or low demand size
- Intermittent demand: infrequent demand occurrences ($\sigma/\mu < 0.5$)
    - Lumpy: intermittent demand with highly variable demand size (High $\sigma/\mu > 0.5$)
    - Clumped: intermittent with constant demand

As seen in figure 15, the division of fast and slow items is around 50/50.

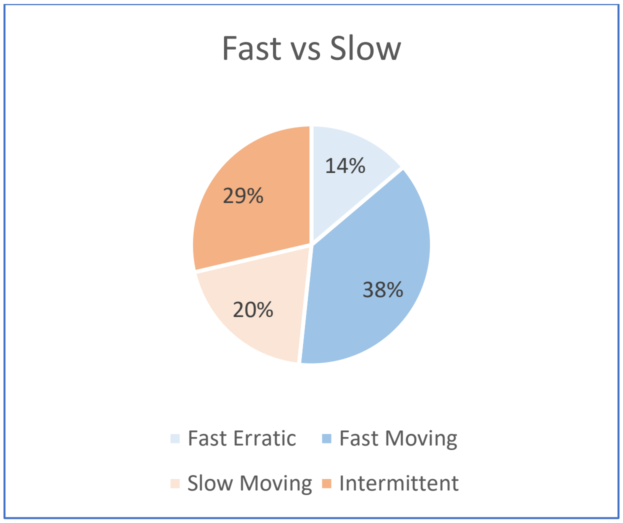


Figure 15 – Fast vs Slow moving items

Figure 15 shows that most demand is relative predictable. Nearly 60% of total demand is predictable ($\sigma/\mu < 0.5$). As mentioned in section 2.2.1, the majority of items do not use any inventory policy, this is odd since the biggest subgroup have fairly predictable demand patterns.

2.3.1 Erratic/Lumpy Demand

Lumpy and Erratic demand is less plannable. Due to bigger variance of demand sizes, the demand during lead time is more unpredictable. To reduce the probability of stockout occurrences, bigger safety stocks need to be in place than with regular demand. Taking a look at the distribution of the coefficient of variation over all the items.

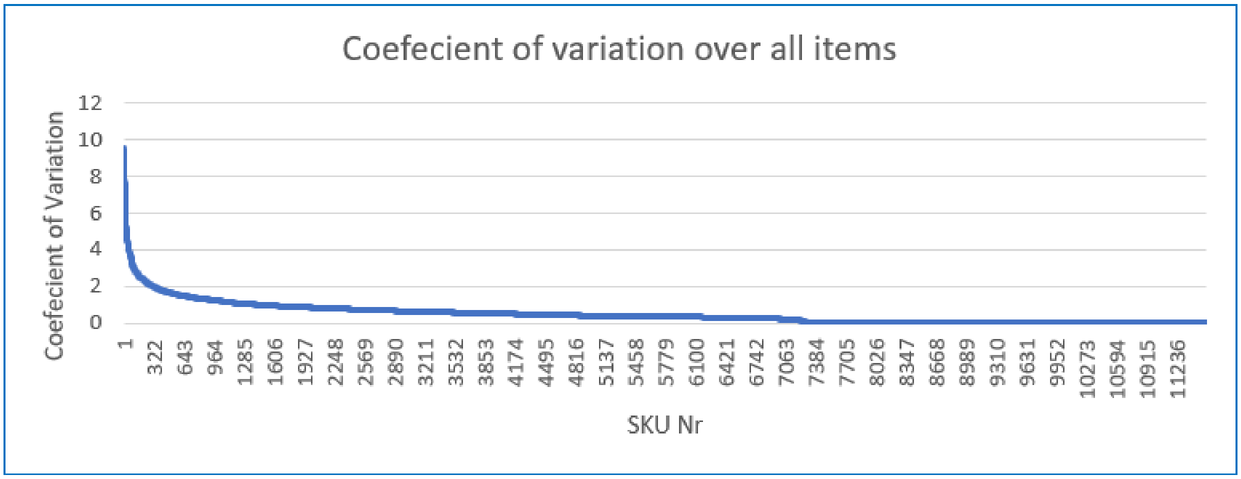


Figure 16 – Coefficient of variation of demand sizes per item

It becomes clear from figure 16 that while a lot of items have a coefficient of variation of over 0.5, only a few items are very unpredictable. In Appendix C, a few items are illustrated as an example as of how these items behave. Ultimately these items contain such high CV's due to one or two big deviations. Possibly, these deviations could be filtered in a model.

2.3.2 Intermittent Demand

Intermittent demand amounts up to 29% of total demand. Intermittent demand is characterized as having infrequent demand occurrences, however what is infrequent? Due to relative long lead times (average lead time of all Thales items equals 97 days), demand is characterized as intermittent if and only if the average days between consecutive demand occurrences is ≥ 100 days. Note that this value could be altered in a model. Examples of intermittent demand are shown in Appendix D. For 16% of all intermittent items, the time interval between consecutive demand occurrences is bigger than their lead time. Similar to section 2.2.3, stock value might be decreased through later procurement in these cases.

2.4 Financial risk

Having items in stock for a long time ensures that items at some point are depreciated. Within Thales this is part of their financial risk. Based on a lot of specific characteristics, a risk percentage is given. The risk is based on things like depreciation, obsolescence, shelf life, intricate materials. Items that have assigned 100% financial risk are fully depreciated and Thales reserved 100% of the cost on their balance sheet. The latter, meaning the item has fully been paid for since Thales assumes the item will not give any more returns. Considering this, it is interesting to see how much of current stock is 'fully depreciated'.

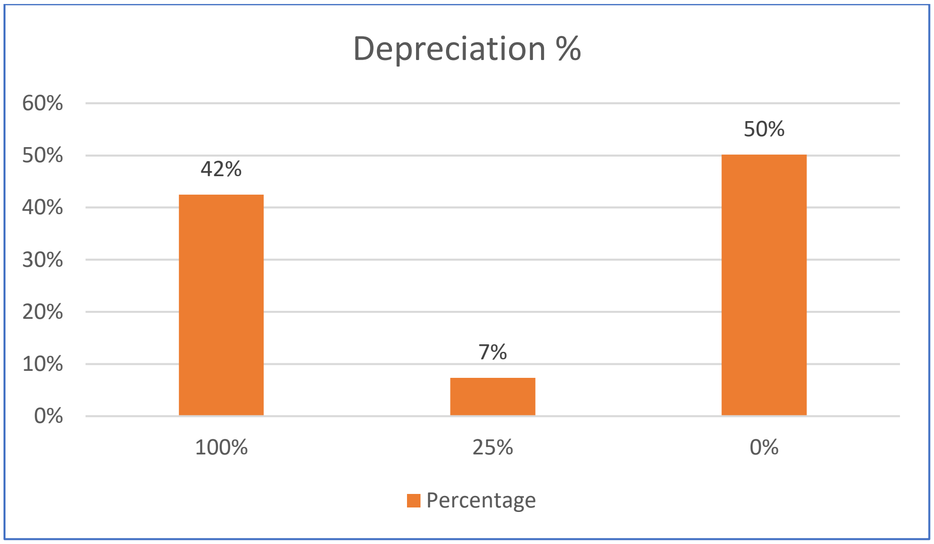


Figure 17 – Percentage of items that are depreciated

Luckily as seen in figure 17, most items in stock are not depreciated. Oddly, almost a third of all common stock is 100% depreciated. The figure presented above is without Strategic stock. Hence, the stock above is still available on the market. Thus, when something is completely depreciated and still available, why is so much of it in stock?

Table 4 – Stock value corresponding to financial risk

Item Class	**Stock Value**
A	€3,693,132.25
B	€4,683,833.43
C	€2,472,872.75
Total	**€10,849,838.43**

As a result, table 4 shows the stock value corresponding with the financial risk. More than a quarter (27%) of total common stock is depreciated. Interesting to see that the sub class B contributes the most to the overall depreciated stock.

2.5 KPI performance

To give insight into the performance of the overall stock performance, Thales uses two main KPI's, DIO and ITR. In figure 17 it is shown that although most stock is ordered fairly recently, still a large chunk of items have been sitting in stock for over 10 years.

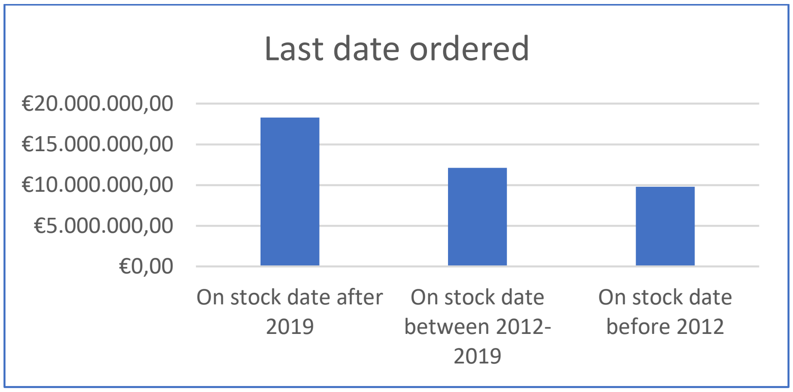


Figure 18 – Stock value by on latest stock date

Having a lot of dead/idle stock ultimately has a negative impact on DIO and ITR. The DIO and ITR are calculated using the following formulas:

Days inventory on hand = Average Inventory / (Cost of Goods Sold (COGS) / Days in period)

Inventory Turnover Ratio = (Cost of Goods Sold (COGS) / Average inventory

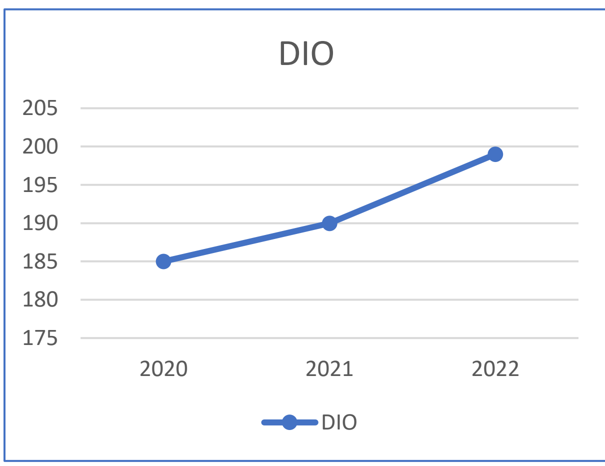


Figure 19 – DIO period 2020-2022

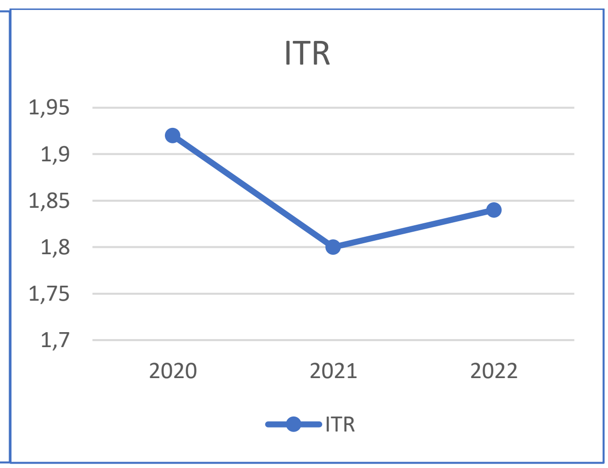


Figure 20 – DIO period 2020-2022

Looking at the two KPI's, DIO is still worsening year on year. A possible reason could be the significant amount of excess and old items in stock. The ITR does improve compared to 2021, one of the reasons for this is that a new inventory manager started in 2022. As stated in chapter 1, a mathematical model will be developed that tries to improve inventory policy and improves KPI performance. Hence, these KPI's will be used to verify when improvements are realized given the created model in this thesis.

2.6 Analysis Conclusion

Ultimately, the number of items in stock can be improved upon. It is shown that around 1/5th of stock is dead or idle. For some item classes, like B-items, over half of its stock is excess stock and overall inventory value is increasing. Inventory performance has been deteriorated in the last few years, which results in millions of euros spending in depreciation. Other problems could arise due to increasing inventory like increasing inventory handling costs, increases warehouse utilization and worsens KPI's.

In chapter 1 some reasons are given for how inventory performance could worsen. Think of MOQ's and LTBs. However, some assumptions made by Thales like the 5-year dead stock rule are counterproductive. For example, lowering this to 3 years, indicates that a lot more items are assigned 'dead'. And it is a lot easier to scrap dead stock than active stock. Lastly, section 2.2 shows that while inventory performance worsens, only a small percentage of items actually have inventory strategies besides MRP planning. For example, as seen in section 2.3, a lot of items have very irregular demand and currently no policies exist within Thales to effectively deal with them. Overall, the stock policy is very reactive instead of predictive. Most items are purchased according to MRP planning. In theory, these items do not need forecasting, while the procurement is based on known order. Still, due to many different reasons, items are procured and left in stock unused, hence there is need for additional checks whether an item should be stocked or not. While current problems are not painfully felt on the financial balance, not improving the current situation could deteriorate the current situation and give new problems or bigger costs in the future.

Chapter 3 – Literature

In this chapter different statistical distributions are discussed that can be linked to specific demand characteristics. In the second part, different item classifications are listed. After classification, it is important to know what to do with these classes regarding inventory control. Hence, in the last part of this chapter different inventory strategies are discusses as methods that improve item inventory control for specific classes.

3.1 Demand Distributions

To improve inventory policies, one must account of the unpredictability of demand. As demand is stochastic, statistical distributions help predict the incoming demand. The item demand characteristics over all different items within Thales's stock differentiate a lot, one demand distribution does not fit all. Using the cumulative distribution functions (CDF) of demand during lead time is a standard method for inventory policies. To evaluate inventory policies, standard CDFs are often used. For example, normal and gamma are popular for fast-moving items. And Poisson, negative binomial and compound Poisson distributions are often used for slow-moving or intermittent items (Boylan, J.E, 2008). In practice however, fitting some of these probability distributions to actual demand patterns can give errors.

3.1.1 Fast-Movers

According to research, the normal probability distribution is often used to predict fast-moving demand in various industries. This distribution is particularly effective for forecasting demand for SKUs with a coefficient of variation around 1 and a lead time demand greater than 20 (Chopra & Meindl, 2015). However, one limitation of the normal distribution is that it allows for a probability of negative lead time demand, which is not physically possible. When this probability is too high, the Gamma distribution may be a more suitable choice as it accounts for the fact that negative demand is not possible (Axsäter, S. 2006) and tends to not result in lower safety stock estimates. Often the Coefficient of variation is used in literature to help choosing a distribution (Winston, 2004). Gamma distribution is mostly used when the CV > 0.5, while Normal probability works well when CV <0.5.

On the other hand, in cases where demand is very high, the Gamma distribution may give an overly high probability of demand. In these situations, the lognormal distribution may be more appropriate as they are better equipped to model high demand accurately.

3.1.2 Slow-Movers

It has been shown that when lead time demand is lower than 20, the Poisson distribution performs better than the Normal distribution as a model for slow moving items. One reason for this is that the Poisson distribution is well-suited to modelling discrete data, hence low numbers, such as the number of units sold per month, while the Normal distribution assumes a continuous distribution of data. In addition, the Poisson distribution has the property of being skewed to the right, which is often observed in real-world demand data due to outliers.

When the variance to mean ratio is less than 1, the Binomial distribution is a better choice for modelling demand data. This is because the Binomial distribution is specifically designed to model binary outcomes, such as the number of successes in a fixed number of trials. In this case, the mean and variance of the Binomial distribution are equal, making it well-suited to modelling data with a low variance to mean ratio (Ross, 2014).

On the other hand, when the variance to mean ratio is greater than 1, the Negative Binomial distribution performs better as a model for demand data. The Negative Binomial distribution is a generalization of the Binomial distribution that allows for an additional parameter, which can be used to model overdispersion in the data (Ross, 2014). In this case, the mean and variance of the Negative Binomial distribution are not equal, making it more suitable for modelling data with a high variance to mean ratio.

3.1.3 Intermittent Demand

Intermittent demand is characterized by fluctuations in demand over time, with periods of high demand followed by periods of low demand. The Poisson and compound Poisson distributions are well-suited for modeling intermittent demand patterns because they can capture the variability in demand over time and the likelihood of rare events. Intermittent demand forecasting first was talked about by John Croston in 1972. It took 20 years for research to gain popularity, since faster item forecasting were much more popular. (Boylan et. Al 2021)

The Poisson distribution is a discrete probability distribution that is often used to model the number of occurrences of a particular event over a given time period, such as the number of customer purchases of a product. The compound Poisson distribution is a continuous probability distribution that is derived from the Poisson distribution and is often used to model the number of occurrences of a particular event over a given time period, taking into account the variability in the rate at which the events occur (Adelson (1966). Compound is thus very suitable for stocks that have a high variability in demand sizes.

3.1.4 Goodness of fit test

The goodness of fit test is a statistical procedure used to evaluate the fit of a model to a set of observed data. This test allows researchers to determine whether the model accurately represents the underlying patterns in the data. One such procedure is the Chi-square test. The Chi-square test groups data in bins and compares the amount of observed bin data versus the expected bin data. Another option is the Kolmogorov-Smirnov test. The advantage of this test is that it does not need bins, which does require less computations. However, the Kolmogorov does need the demand data to be continuous and thus it is not useful for slower moving demand or discrete demand data (syntetos et al., 2011). The test shows if a statistical distribution fits certain data with a confidence percentage. To calculate the Chi-square test the following formula is used:

$$X^2 = \sum_{i=1}^{N} \left(\frac{(O_i - E_i)^2}{E_i} \right)$$

Where E_i is the expected count of a distribution and O_i the observed count.

While the goodness of fit test often works well, there are also some limitations to the goodness of fit test. For example, the chi-squared statistic is sensitive to the sample size and may not accurately reflect the fit of the model for smaller samples (Williams, 1950). Low sample size fits discrete distributions and due to the nature of slow movers the Poisson distribution is chosen for these demand types. Additionally, the goodness of fit test assumes that the observed data are independent and identically distributed, which may not always be the case in real-world situations.

Overall, the goodness of fit test is a valuable tool for evaluating the fit of a model to a set of observed data. While it has some limitations, it can provide useful insights into the accuracy and reliability of a model and can help researchers to improve their predictions.

3.2 Classification

As Thales' items come in all shapes and sizes, a classification can be useful for efficient inventory management. Most widely used is the ABC classification (Teunter et al 2010). The ABC classification is a method of categorizing inventory items based on their relative importance and value to the business. This classification system typically divides inventory items into three categories: A items, which are the most valuable and important; B items, which are less valuable but still important; and C items, which are the least valuable and least important.

While the most common approach is to rank the classes according to the so-called annual dollar volume. There are many practices in how SKU's can be divided. The following additional criteria can be used to classify stock keeping units according to literature (Jiaxi Li et al, 2016; Teunter et al 2010)

- Lead time (Items with long lead times are less responsive, hence can have an impact on production when its supply certainty is not reliable. Delays will be long and costly.)
- Obsolescence (In high-tech industry, single parts can change quickly and thus obsolescence can have a big impact on availability)
- Substitutability (Items that can easily be interchanged need less maintenance since when these items are out of stock, other items can be substituted)
- Minim order quantity (MOQs can result in high inventory since demand and supply can be vastly different when MOQs are very high.)
- Piece price (Obviously the impact of piece price on inventory value and company cash flows is great. High stocks of expensive SKU's can hurt a company's balance statement)

To increase inventory classification performance more criteria can be added to better fit item segments. However, the main reason for adding and choosing criteria is to not complicate inventory management (Flores et al, 1992). One main criterion can be a result of multiple sub criteria. Eventually weights should be added to correctly prioritize the impact of each criterion.

In addition to multiple criteria, classification can be effectively enhanced with the number of classes. Typically, researchers use 3 classes as ABC is most common. However, increasing the number of classes can lead to a reduction of overall inventory costs. (van Wingerden, 2016). Note, this does not work for all scenarios. When item characteristics are of high diversity and in big numbers, additional classes can capture the more specific needs of smaller sub classes. While high item differentiation can maybe be better captured with more classes, extra classes does complicate overall inventory management.

In a paper from Flores (1992), multiple subclasses are created through matrices. In this case the classes AB, BC, AC, CA are created to increase inventory control. In other studies, the B class is eliminated since it is found to be unnecessary. In some cases, B items can be seen as cheap A or expensive C items. However, this only works when the item characteristics are similar. A items are expensive, unique, MRP scheduled. C items on the other hand are cheap, non-unique and offered by many suppliers. They are bought in bulk and its inventory can easily be controlled by simple Min/max or re-order-point policies. In high mix low volume companies more often than not, more classes increase complexity however since its products and SKUs are very different, they can capture the complexity of SKU's better.

3.2.1 Classification Methods

While the number of classes can improve overall inventory management and capture more complexity. Different methods exist as of how to classify the items into these classes. In this section, an overview is given on the different methods to classify SKUs.

- Item price

Thales currently classifies its SKUs according to their item price. This method is the least complex as it only accounts for one criterion. While this method emphasizes the most expensive items, as the most expensive items are ranked first, it has its shortcomings. In a complex environment, as is the case for Thales, there are more indicators like demand or lead time for 'important items' which this method does not include.

- Annual dollar volume

ADV is the most traditional used classifier. ADV is ranked by multiplying the number of SKUs demanded with the SKU price. This ensures that less expensive but more demanding SKUs are ranked higher. (Prakash et al. 2017) However, a shortcoming of this method is by multiplying these factors, it could lead to a bias for cheap items. Often, cheap items are demanded a lot more than expensive items. A C-item of 1 euro could be thousand times more demanded than 1 expensive item. This method could lead to this cheap item outranking the expensive items, while in practice this should not be the case.

- Price/Demand

To counteract the shortcoming of ADV, instead of multiplying the criteria, the ratio between the two can be calculated. The price demand ratio ensures that the bond between the two criteria is still observable while keeping expensive items still in more important classes.

- Pareto analysis

This method very common in a lot of industries. It uses the pareto principle, which states that a small number of items (usually around 20%) account for a large proportion of total value or revenue. In ABC classification, the top (80% of total value) makes up the A-class, 15% of value the B-class and lastly 5% of value the C-class.

- Demand versus holding costs and lead time

This method ranks SKUs higher according to the following formula (Zhang et al., 2001): $\frac{\mathrm{D}}{h^2 * \mathrm{L}}$

If the demand rate is larger or if the holding costs are smaller. Furthermore, in contrast to other methods the order quantity has no effect on the SKU rank while the lead time does. In businesses where order quantities are similar across SKU's, this criterion can outperform other methods.

- Price * MOQ/Demand

This method elaborated on price/demand and adds the minimum order quantity into consideration. Since MOQs can disrupt inventory control, giving a bigger emphasize on items that have one, can improve overall inventory management.

3.2.2 Multi criteria inventory classification (MCIC)

In section 3.2.1, a list of the most used classification methods is given. Often these methods only take a few criteria into account. For complex environments this might not be sufficient. As the number of criteria increases, so does the need to use multi-criteria inventory classification methods to classify items. Gajpal et al. presents the analytical hierarchy process (AHP) as a method to incorporate multiply criteria into an ABC inventory classification. This method ensures quantitative as well as qualitative criteria can be implemented. In other literature a weighted linear optimization model is used to classify (Ramanathan, 2006)). The proposed model uses a scalar score based on all the criteria to evaluate the performance of the

SKU. Some implementations of classification incorporate multiple classification methods. Vancheh et al. first used multiple criteria as ADV, lot cost and lead time ranking. Afterwards a technique called data envelopment analysis (DEA) is used to calculate criteria weights and thus eventually item scores. AHP and DEA can both make use of quantitative and qualitative data, which increases the performance of item classification since decision makers can input their qualitative input. Yet in this thesis, only quantitative data is considered. DEA also has a disadvantage; computational time increases significantly as the number of items increases, as for every item a decisions value y_{ij} is calculated (Hatefi et al., 2010). With thousands of items this takes a lot of computational effort to solve.

As knowing the relative weights of each criterion is a major step into solving classification. A less computational expensive method could be more practical. Among several methods in literature Shannon's entropy method is very popular (Zhao et al., 2010). This method includes the use of entropy. Entropy is widely used to compute uncertainties, from social sciences, physics but also in MCDM problems. In chapter 4, the steps of Shannon's entropy method are shown. In the contrary to a more overall method like DEA, using entropy only gives us criteria weights. Ranking items afterwards is a new problem. A lot of different MCDM methods exist, from AHP, ELECTRE to DEA and others. Given the amount of data TOPSIS is an effective approach (Van Harten, 2019). TOPSIS is based on the principle that the best solution has the shortest Euclidean distance from the ideal solution and the most negative the farthest. This can easily be calculated using the outcome from Shannon's entropy. After ranking all items, classification is the last step. The steps of Shannon's entropy (Zheng et al., 2017), are illustrated next:

A multi-attribute problem is defined as a matrix with m items and n evaluation criteria.

$$D = \begin{Bmatrix} X_{11} & X_{\dots} & X_{1n} \\ X_{\dots} & X_{\dots} & X_{\dots} \\ X_{m1} & X_{\dots} & X_{mn} \end{Bmatrix}$$

First matrix D is normalized:

$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$ ∀. i and j

Step 2 computation of the entropy measure

$$E_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij}$$

Where,

$$k = \frac{1}{\ln m}$$

Step 3 Define the objective weight based on the entropy.

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n}(1 - E_j)}$$

Step 4 calculate the general form of entropy weight if the decision maker assigns subjective weights sj. By considering sj, the previous formula transforms into the following:

$$w_j^* = \frac{s_j w_j}{\sum_{j=1}^{n} s_j w_j}$$

Step 5
Lastly, the overall score of items I is calculated using the comprehensive score value calculated by the following formula:
$Score_i = \sum_{j=1}^{J} w_j p_{ij}$

Furthermore, the overall score of the items is used to classify them into the classes A, B, C.

3.3 Inventory Strategies

After classification it becomes clear what items are more important than others. The next step is to decide what to do with these items and classes. Service level is the main performance indicated for inventory control. Often A-class items get the highest service level targets as they are critical for production and stockouts are most expensive. However, most of the surveyed works use the classification of items only to choose the demand forecasting model instead of the inventory control method (Roberto et al., 2011)

As shown in section 3.2, most literature focusses on creating weights and classifying items for efficient inventory control, but not what inventory policies to link. In this section, a couple of inventory policies are discussed as they could provide a way of efficiently improving service levels or decreasing stockout probabilities while decreasing inventory costs for the item classes.

3.3.1 To stock or not to stock

Traditional inventory control methods often assume that stocking items is necessary. As stockouts can be costly for business, the far lower cost of holding inventory is often preferred. However, are storage costs always worth it, even when regarding a single unit? There are methods that focus procuring items only under demand, ensuring that the time a single unit needs to be kept in stock is minimal. (Johnson, 1962) illustrates 2 ideas: only storing items that are purchased upon demand and secondly stocking items to keep baseline stock levels. The latter is often justified for fast moving items, as demand frequency is high, and the holding costs are relatively low compared to the revenue. Slow moving items however, are more a predicament. In Tavares et al. (1983) a case is considered where slow-moving item demand follows a Poisson distribution. The model evaluates two options. Option 1: hold inventory and regular ordering costs. Option 2: eliminate holding costs and increase ordering costs as emergency purchasing is expected to increase. In this paper option 2 shows lower cost only when average demand is greater than the lower bound demand of its specific demand formulation. Other research suggest that a single item should be kept in inventory if its annual storage costs is greater than the expected annual shortage cost. Ultimately, there is no literature wide consensus on when to stock. Business characteristics and other practical specifics makes it impossible to create a one size fits all method. The correct decision is bound by implicit formulations of the business.

3.3.2 Classic models

Classical inventory models that are affiliated with high demand is a well-researched topic in operations management. These models can be divided into three main models. Continuous review, Periodic review, and Base Stock. Thales already uses a Min/Max inventory policy which corresponds well with the first two categories of the following methods (Chopra & Meindl, 2013) shown in table 5.

Table 5 – Inventory control policies

	Periodic review	**Continuous review**
Fixed replenishment quantity	(R, s, nQ)	(s, Q)
Variable replenishment quantity	(R, s, S)	(s, S)

In general, inventory policies can be differentiated on two main axes. The review period and replenishment quantity.

The variables given in table 5 are defined as follows.

- Review period (R), the time between consecutive inventory position evaluations.
- reorder level (s), when inventory position drops below s, inventory is replenished.
- Integer (n), number of times lot size is ordered.
- Lot size (Q), the number of products ordered in a replenishment order. In thales' case often yearly demand.
- Order-up-to-level (S), when replenishment order arrives, inventory position is replenished up to the inventory level S.
    - Thales' Min Max policy is a (R, s, S) inventory policy where:
- R = 1 week
- s (Min) = demand during lead time + safety stock
- S (Max) = s(min) + Q – undershoot

Where standard demand characteristics (Chopra & Meindl, 2015) are calculated as follows:

- Undershoot $Z = \frac{\sigma_r^2 + x_r^2}{2x_r}$.
- $SS = k * \sqrt{Lead\ time * \sigma_D^2}$
- K = safety factor
- σ_D^2 = variance of demand

In practice periodic review is more often used as continuous review requires a well setup software systems that keep track of all SKU's. This is not the case within Thales' business, hence periodic review is more applicable.

3.3.3 Just in time / L4L

For expensive items other approaches might be fruitful in comparison to classic models. One of those is Just in time (JIT). Expensive A class items, which are tightly controlled, are a good fit for a JIT inventory policy. JIT ensures that replenishments are tightly correlated to the production process. Items are frequently replenished in small quantities. Advantages of this approach is that it requires less stock as items are tightly correlated with the production process and thus a lot of stock is not required.

While this approach decreases inventory value and cost for high value items, it can only work under certain circumstances (K. Sing, 2013). Instead of normal supplier contracts, suppliers of these items need to be tightly collaborated with. External as well as internal activities need to be closely connected with the suppliers. In addition, suppliers need to be reliable in quality, deliverability, and delivery time. Suppliers often only consider such a kind of collaboration if this relationship can deliver a considerable fraction of total demand. It is assumed that JIT items do not require safety stock. This is in line with literature as JIT works through tight collaboration with suppliers and minimizing lead time variability. For modelling purposes reliable suppliers are assumed and lead time variability is set to zero. While safety stock is assumed to be zero, lead time demand still exists. If JIT were approached as an R, s, S system, the reorder point of a JIT item is equal to the lead time demand (D_L). Some supplied items in the mathematical model have MOQ's hence the item stock variation can be described as [D_L, D_L + MOQ]. In non-MOQ cases the stock range is set to [D_L, D_L + 1] to simulate the low volume, high frequency order behavior.

If the requirements for close JIT collaboration is not met, or if it is impossible due to a lack of consistent raw materials, businesses can opt into a less intensive collaboration. One of such policy is called Lot-for-Lot (L4L). The difference between JIT and L4L, is that while JIT is based on actual production schedules, L4L is based on the planned production horizon. L4L ensures that the quantity ordered is based on an amount of demand periods ahead. Hence, a bit more leeway is created. Note that both these policies are not suitable for cheap items, as the reduction in holding costs do not outweigh the increase in ordering costs and increase in stockout risk.

3.3.4 Base stock

While Continuous and periodic review is more suitable for items with high consistent demand, base stock could be applied to items with very low demand. Base stock ensures that when a mutation in stock is made, the same amount is immediately ordered to maintain a base stock level (Harris, 1913). This is applicable to items when often only one or a few items are ordered on the same time.

As the idea of the base stock policy is to keep a constant base stock level of inventory, the parameters are set in such a way to reflect this behavior. The reorder point or “base stock” level is calculated similarly to (R, S, S):

- Base stock = Safety stock + lead time demand.

3.4 Literature Conclusion

Improving inventory policies asks for an understanding of the demand characteristics. To effectively model demand, fitting the correct statistical distributions is a necessity. Specific distributions are more suitable to fast or slow-moving items. The Gamma distribution is favored when negative demand probabilities are high. And the Poisson distribution shows superior performance when lead time demand is lower than 20 which captures the variability in intermittent demand patterns. After demand characteristics are clear, a good inventory management program prioritizes. Hence, classification is another important step. A lot of classification methodologies exist in literature, however for more complex inventory environments multi criteria classification can incorporate this complexity. The use of entropy in Shannon’s Entropy method is one approach that can yield beneficial outcomes in a less computationally demanding manner in a multi criteria classification problem. Lastly several inventory policies exist that control item stocks. In general, these seems to be a gap in literature regarding the linkage between these classification systems to specific inventory policies. Incorporating these classification methods to specific inventory policies can lead to advancements in improving service levels or mitigating stockout probabilities. Ultimately, demand forecasting/characterization models, classification and inventory policies can greatly enhance inventory management.

Chapter 4 – Inventory model

In this chapter the inventory model workings are explained. From how everything is programmed to what decisions or assumptions are made to ensure it is working and fitting to the practical situation. In section 4.1, a model overview is given. Section 4.2 elaborates on the demand data and distribution, furthermore section 4.3 discusses the input variables used within the model. As the inputs are discussed the Settings dashboard is shown in section 4.4. Lastly, the verification, validation and conclusion of the model are shown in section 4.5, 4.6 and 4.7 respectively.

4.1 Model overview

Thales' information system is very complex. Thales makes use of a lot of different information sources. Their main source of information is the ERP system. However, taking information out of this system leads to an excel file. Thus, Thales has an excel file for everything which makes merging all the information not an easy task. In figure 20 an overview is given of all information flows.

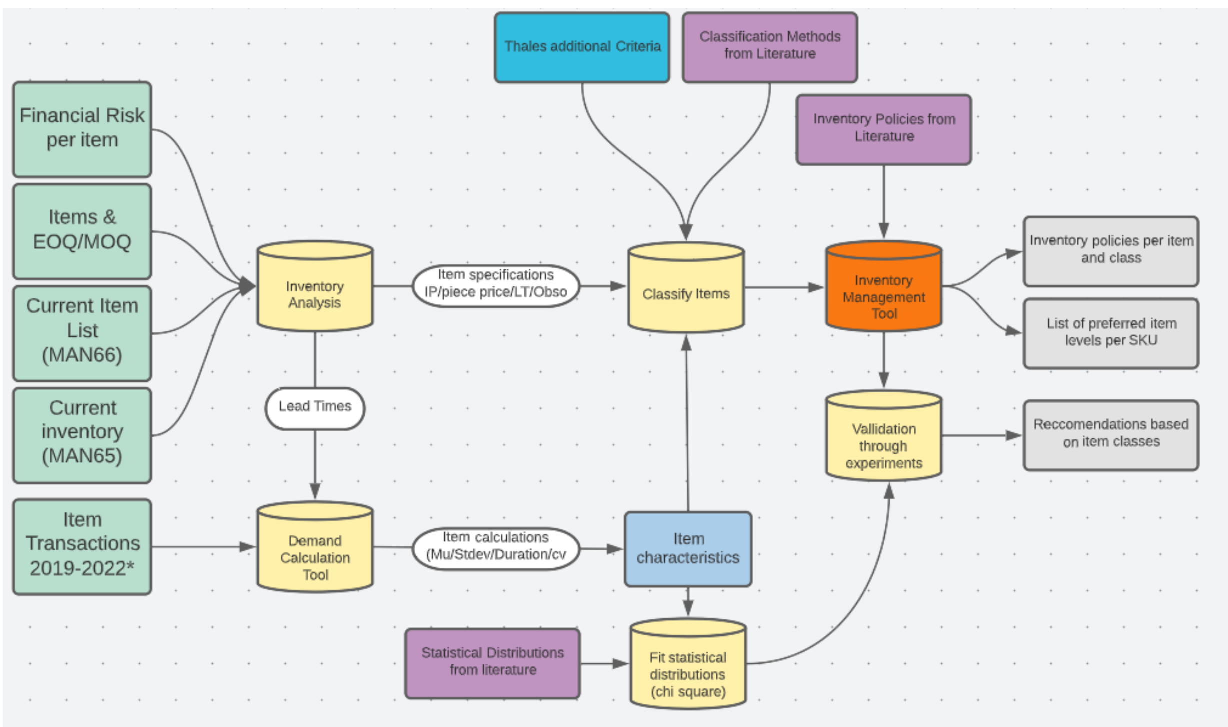


Figure 20 – The information and process flow from data inputs of this thesis to its outputs

- Inventory Analysis

The green squares indicate different excel data sources. First the inventory analysis incorporates 4 excel files. Inventory analysis ensures that stock levels, item risk, demand and other important attributes are combined. The item code is used as a unique key to merge all files.

- Demand calculation Tool

The item transaction files are multiple files where all transactions are registered. The transactions are sorted to their respective dates to get an overview of the item demand over the period 2019-2022. Afterwards the lead times from the inventory analysis is added to the correct items. After the demand is registered multiple calculations are done as calculating the average demand, standard deviation, correlation of variation.

- Classify items

As the name suggests, all classification methods noted in Chapter 3 are implemented here. This part of the information flow is within the inventory management tool. However, since the classification step is before the inventory policies it is regarded as a separate database. Some classification methods make use of some demand characteristics as average or standard deviation hence item characteristics are a input for the classification.

- Chi Square

In this step the item characteristics and statistical distributions from literature are combined to link the distributions to the items using the chi square test, moreover in the next section (4.2).

- Validation

While the demand characteristics through CDF's are used as input for the model. The CDF's are also used for validation as the behavior of the CDF's are known and thus the impact on the stock performance can be calculated.

- Inventory management tool

The inventory management tool incorporates all of the above. Based on the demand characteristics and classification specific inventory policies implemented. Moreover in section 4.4.

4.2 Demand data and distribution

As shown in chapter 2 the demand data is very diverse. Therefore, it is essential to validate the accuracy and reliability of demand data before making decisions based on it. Using the chi-squared test, the fit of the predicted statistical distribution is tested. By applying the chi squared test to the demand data, it can be ensured that the distributions or patterns identified are not due to chance but are indeed reliable.

The hypothesis to be tested is that of the predicted statistical distribution. Where the chi square test is used to test whether the observed demand can be explained by the predicted (distribution) demand.
For all items the demand data is divided into 9 bins based on its minimum and maximum value. Where the size of the bins is defined by bin size ={max(observation)-min(observation)}/9 bins. So for example if the bin size is equal to 10 then the observations between 0 and 10 are put in bin 1 and 10 to 20 in bin 2. After the observed demand is put in the corresponding bins, expected quantities according to the hypothesized distribution are put in bins as well. Finally, the bins are compared according to the chi square formula in chapter 3 given a critical probability of 0.05 and 8 degrees of freedom. The full code of this process can be found in Appendix H. When the test gives a probability lower than 0.05 the expected and observed quantities are too different and there exists significant evidence that they are not the same thus the predicted distribution is rejected.

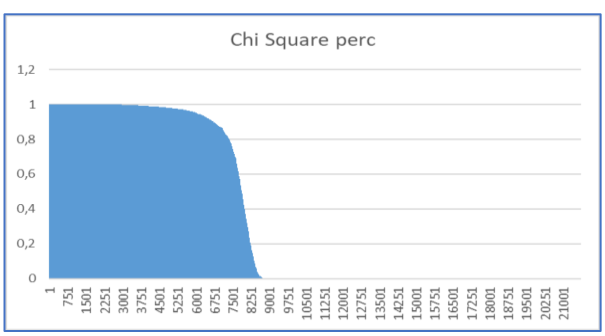


Figure 21 – Chi square test performance over all items

As shown in Figure 21, for around 40% of the items the hypothesized statistical distribution from chapter 3 is not rejected. Hence, the hypothesized distribution significantly predicts the behavior of the demand data and can thus be used to model the demand.

Table 6 – Acceptance ratio per statistical distribution

Distribution	**Acceptance Ratio**
Normal	15,8%
Poisson	42,4%
Gamma	53,3%
Negative Binomial	95,3%

In table 6 the statistical distributions according to the literature are tested. Where the normal and gamma distribution are tested for fast movers, negative binomial for slow movers and Poisson for intermittent demand. Interesting to see is that the normal distribution is rejected most of the time. Looking at the data this is because most "normal" items have a relative low amount of datapoints. When limiting these calculations only to items with more than 5 datapoints the acceptance ratio of the normal distribution goes to 90%. The same happens for all the other distributions, when items of less than 5 datapoints are removed, the average acceptance ratios increase significantly (Table7).

Table 7 – Acceptance ratio per statistical based on data with more than 5 datapoints.

Distribution Data points >5	**Acceptance Ratio**
Normal	90,5%
Poisson	77,0%
Gamma	58,1%
Negative Binomial	99,6%

After finding all statistical distributions, the stockout probability can be calculated for these distributions. For example, the stockout probability can be calculated given a distribution and a reorder point of for example 10. The stockout probability is equal to the probability where the demand exceeds the available inventory in this case: $P(X > 10)$. While these stockout probabilities are useful to compare the old and new situation for Thales, in reality stockouts do not occur, rather their production planning is changed to avoid stockouts.

4.2.1 Demand exclusion criteria

As seen in section 4.2, excluding parts of the demand data (number of observations less than 5), it has a big impact on the model. Thus, to avoid dramatic outliers that influence the outcome of the model unrealistically, two exclusion criteria are added to the model.

Number of demand data points

The number of datapoints corresponds to the number of demand observations in the data. Hence an item with 3 datapoints corresponds to a demand file with only 3 demand occurrences in the last 3 years.

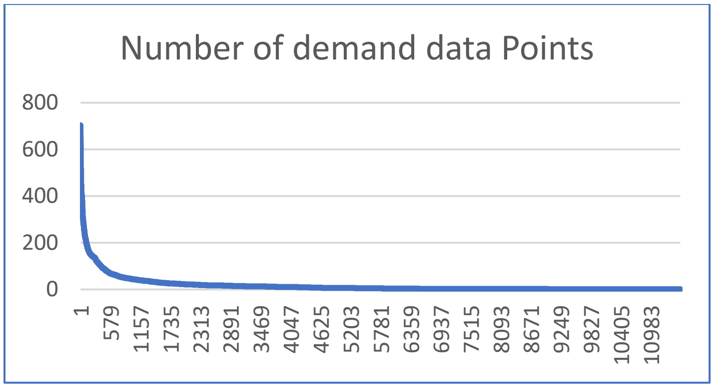


Figure 22 – Number of demand datapoints per ite (demand occurrences per item)

In figure 22 the number of datapoints for the items where demand data is found is given. Immediately it becomes clear that only a small selection of all the items have considerable amount of demand occurrences/data points registered. When looking at the performance of items with low amount of datapoints, the performance becomes a lot worse. In figure 23 an example is given of unreliable demand data. Ultimately it is found that from around 5-10 datapoints, the performance stabilizes, and most outliers are gone.

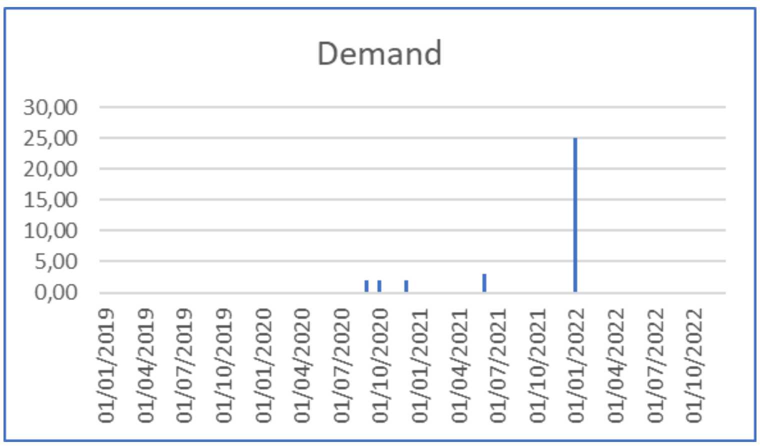


Figure 23 – example of item low data points

As shown in figure 23, this item has 5 datapoints/demand occurrences. When put in the inventory model this item has a lot of costs associated with it. This is because of safety stock calculations. Safety stock is calculated using lead time demand. In this specific case the lead time demand is very inflated due to one outlier, point 5 in figure 23. Since Thales has a very long average lead time of 100 days, this ensures that often a lot of safety stock is allocated. Items with more datapoints have a bigger chance to counteract a single outlier. Thus, a minimum number of data points is required to get reliable results. It is a tradeoff however, increasing the minimum number of data points results in less included items in the inventory model. When increasing the minimum requirement to 600 data points, only 3 items are included in the model.

Coefficient of variation

The second exclusion criterium is the coefficient of variation. Often low amount of data points go hand in hand with high cv. Some items however have very irregular behavior, see Appendix C. This irregular demand leads to more risk and thus safety stock calculation allocate a lot of safety stock which negatively impacts the overall performance. In reality, this irregular behavior is due to human error or backtracking. Where backtracking means that once a year a correction is done in the ERP system, resulting into all the demand of a period is set on a single day. Both cases should be voided since it unrealistically influences the model. In section 4.4 the impact of excluding low and high cv's is illustrated.

4.2.2 Discount factor

For some items there exists a big gap in their demand data. Mostly because the item has been used a lot a few years ago, however for some reason the last 2 years it has not been ordered. The inventory model calculates mean and standard deviations based on demand data. But it does not take this gap of no demand into account. To account for this, a discount factor is introduced as this can be an effective way to correct demand data in the future (or in this case, in the past) (Giraitis et al. 2012). The discount factor is used to adjust historical demand data to better reflect current conditions. This is because items that have not been demanded in the last few years should not be expected to have high mean demand. For example, take an item with an average demand of 50, 2 years prior and demand of 0, in 1 and 0 years prior. If the average demand of 50 is taken to calculate safety stock. The safety stocks are too high. To adjust the expected demand the discount factor is introduced through the formula below:

$$Adjusted\ Demand = Demand * \ \beta^{t}$$

Where β is the discount factor and t correspond to the demand data gap in years, hence Demand (old demand data) is adjusted to ensure demand characteristics are not inflated.

4.3 Input variables

The inventory model integrates demand characteristics, classification methods and inventory policies from literature. However, in Thales real-world situation other input variables have impact in the performance of the model. To ensure the model aligns with Thales's specific circumstances input parameters have been incorporated. For example, holding costs have a big impact on the financial situation of items held in stock. In this section, the input parameters are discussed. Note that initial values are based on Thales' situation, however for analysis purposes these values can be altered by decision makers to see the impact of these values.

4.3.1 Safety Factor

To calculate the safety stock a safety factor is used. Note that this safety factor is the same for all items and policies. For all items that currently use safety stock within Thales current policies, they do not differentiate with different safety factors. The impact of the safety factor is discussed in section 4.4. However, from theory it is known that increasing the safety factor will reduce the stockout probability while increasing stocking costs. By carefully balancing these factors, companies can normally optimize their inventory levels. However due to the nature of Thales business stockouts are different. Often when items are not available their planning pipeline is changed. While some safety margins are effective at lowering stockout or planning costs, without stockout data it is hard to calculate the optimal safety factors. This is why the model takes a single safety factor to calculate all safety stocks. Currently Thales uses a safety factor equal to 1.5 if safety stock is considered. The effects of this number and increasing or decreasing it are researched in chapter 5.

4.3.2 Holding cost

Items in stock have costs associated with them. Direct costs like storage expenses or depreciation, but also indirect costs like opportunity cost of tying up capital in inventory. In Thales' case it is estimated that once an item is in stock for over 6 years it is no longer profitable. Given that Thales has a lot of strategic and dead stock, holding costs are high. To account for these costs Thales currently has set the holding cost rate to 20% of item value per year.

4.3.3 Ordering cost

Ordering costs refer to the expenses incurred by Thales when placing an order for materials. These costs can include various expenses like transportation costs or administrative costs. The economic order quantity (EOQ) considers holding costs and ordering costs. By minimizing the total cost of ordering and holding inventory, Thales can improve its overall inventory efficiency. While Thales does not have specific ordering costs per item, they do have some items where ordering costs are free and some items where ordering costs can go up to 100 euros or more. After analysis within Thales' business, it is estimated that ordering costs between 10 to 50 euros is near practical situation. Note that the ordering costs can be changed by decision makers if it is too high or too low.

4.4 Dashboard

The inventory model has many settings. There are classification methods, inventory policies, input parameters and exclusion criteria. To accommodate all these inputs and enable testing of different input settings, a settings dashboard is created. Figure 24 shows this dashboard with red markings to elaborate.

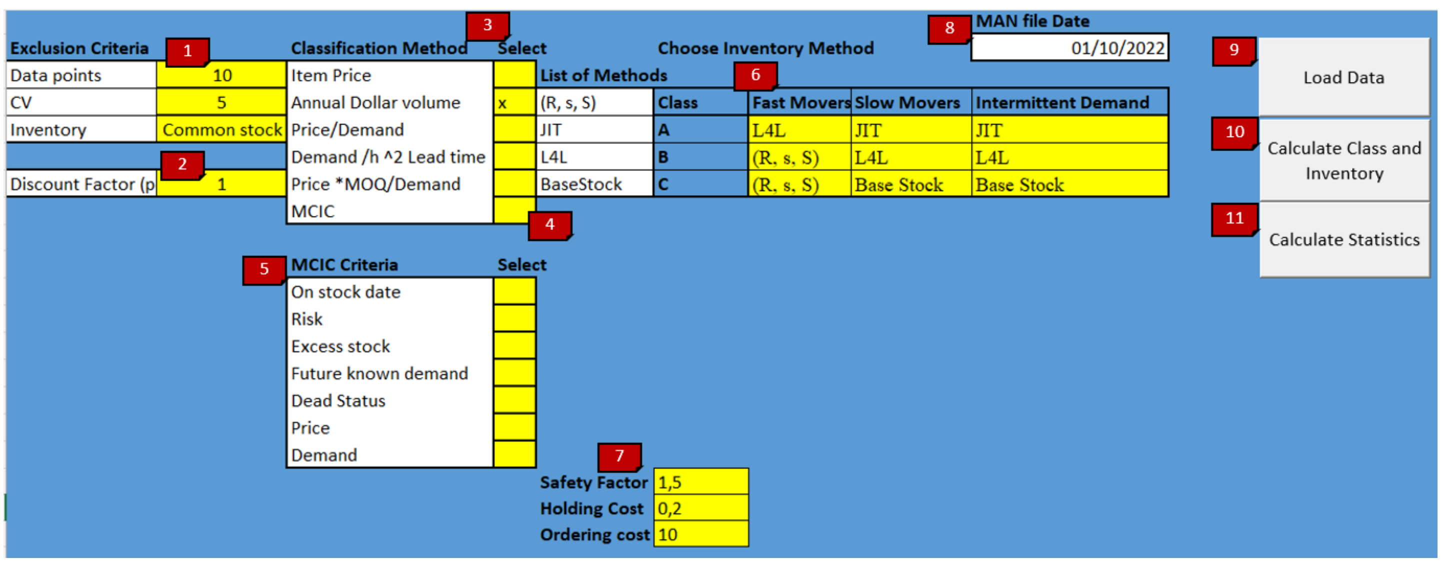


Figure 24 – overview settings dashboard inventory model with red indicators

The red markings 1-11 are listed and explained below and yellow cells represent changeable input parameters. Note that the values within the yellow cells are examples and can be altered in later experiments in chapter 5:

- *1 – Exclusion Criteria*

This is the exclusion criteria of the demand data. In figure 21 the value 10 means that only items with at least 10 demand occurrences are considered. The value 5 means that only demand with a CV of less than 5 is considered. Inventory (currently Common) is the stock type that is considered. As mentioned in Chapter 2, Thales has different stock types. Currently only common stock is considered. However, decision makers could change this value to accommodate more stock types. Note that these values must be set to the preferred values before you load data into the model (number 9).

- *2 – Discount Factor*

The discount factor that corrects demand data if gap years exist, see section 4.2. The discount factor should range from 0 to 1 as average demand of items with gap years should be reduced. Given one full year of no data, a discount factor of 0.8 means that the predicted average demand is reduced by 20%.

- *3 – Classification method*

This is a list of all classification methods listed in chapter 3. Put an 'x' in one yellow cell on the right. This ensures that when clicking on button (number 10) this specific classification method is used to classify all the items.

- *4 – MCIC*

When selecting this classification, the table (number 5) should also be filled in. Selecting MCIC as classification method enables the choice of criteria in the table below.

- *5 – MCIC Criteria*

When MCIC is selected as classification method. The user can select one or more criteria which are considered during the MCIC calculation. To enable one criterion put an 'x' in one the yellow cells on the right For MCIC calculation see Chapter 3.2.2.

- *6 – Inventory method table*

As the items are categorized by their class and demand specification, users can select an inventory policy per segment. The yellow cells should contain one of 4 inventory policies. When clicking on the button "calculate class and inventory" (number 10), the inventory policies are selected for the specific item category.

- *7 – input parameters*

These are the input parameters as discussed in section 4.3.

- *8 – MAN file date*

When loading Demand data, this date shows the latest date found within the demand data source file. This is used to calculate the number of years where no data is found and used to discount data (number 2).

- *9 – Load data*

When clicking this button demand data and demand characteristics are loaded and combined. First the code asks the user to select a file where all demand parameters are found. Secondly, the code asks the user to select the demand data. These files are shown in figure 20 in section 4.1 as 'Inventory analysis' and 'Demand calculation Tool' respectively.

- *10 – Calculate Class and inventory*

After clicking this button, the main code executes. First ensure all input parameters are filled before executing. First the class of all items is calculated based on numbers 4 and 5. Then using numbers 6 and 7 the inventory characteristics are calculated.

- *11 – Calculate Statistics*

This button executes the code that calculates the performance of the inventory system and publishes the outputs on another sheet. These outputs are used in chapter 5.

4.5 Verification of the model

Verifying the model ensures that the mathematical model is correctly implemented and thus the proposed inventory model behaves as expected.

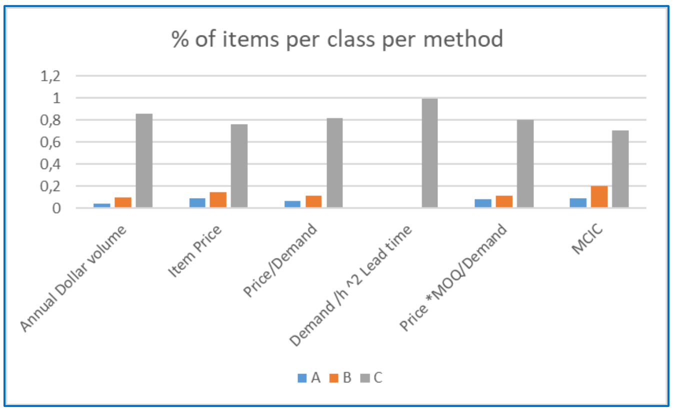


Figure 25 – Number of items in classes per classification method

The model's classification mechanisms effectively follow the Pareto principle. In all classification methods the A class is the smallest, as shown in figure 25 This is because only a small number of items amount to over 80% of the total scoring value within the classification method. A items are the most valuable, hence they should be managed most intensively. Note the method which includes de holding cost and lead time shows barely an A class. As Thales has only a few items with very high demand, while lead time is similar for all items (very long), it is expected that the A class would be tiny for this policy.

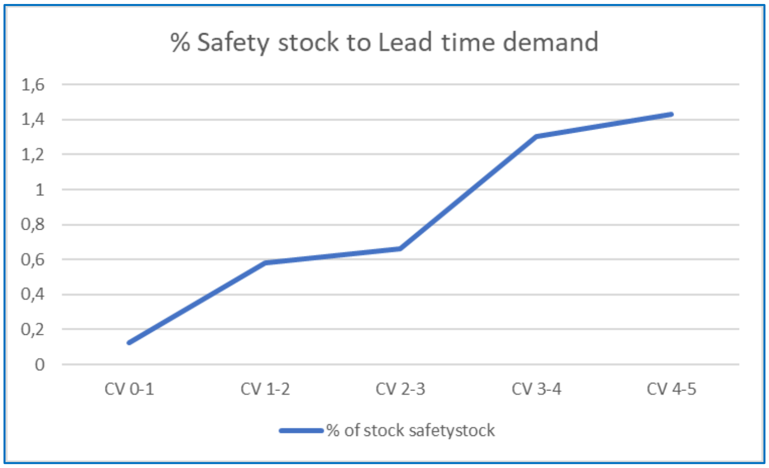


Figure 26 – Connection of safety stock to coefficient of correlation in demand

Upon verifying the proposed inventory model it is observed that the model behaves as expected. When demand uncertainty rises, the model assigns more safety stock to account of this uncertainty. Figure 26 shows that it increases more safety stock when CV increases. This increased allocation of safety stock contributes to the robustness of the system, guarding against potential stockouts. Interestingly, while the increased safety stock allocation for uncertain demand, the overall inventory level across all items is reduced by over 40%. This indicates that the model enhances efficiency in stock allocation and can reduce costs in a real-world inventory.

4.6 Validation of the model

The model accurately represents the real-world situation at Thales. Given that Thales is a high-mix, low-volume business, it is crucial the model incorporates a very diverse range of products and items in stock and assign inventory efficiently to these items. The validation of the model reveals that the model is able to represent Thales' operations. Particularly, the model predicts the possibility of the significant reduction in stocks. This outcome aligns with the observations made in chapter 2, the existence of a lot of excess stock, and it is also in line with literature. Thales had no inventory policies and literature emphasizes that effective inventory management necessitates the implementation of inventory policies to optimize stock levels.

However, while stock reductions are cost effective, avoiding stockouts is equally important. Striking this delicate balance is a complex task. Interestingly, while the model overall makes big stock cuts for classes B and C, in some cases it suggests increasing stock levels for some A items than Thales currently has in stock. This outcome validates the model's realistic representation of Thales' operations as it shows diverse solutions to the diverse products and items.

4.7 Model Conclusion

This chapter shows the workings of the mathematical model. The demand data's diverse nature is tested using a chi-squared test. Hence the predicted statistical distributions are accurately linked to the demand. Additional input parameters are integrated to adjust the model which offers decision makers the ability to alter these variables for impact analysis. Furthermore, the model demonstrates that it can make a balance between reducing stock levels while increasing stock if the demand irregularity calls for it. In conclusion, the model efficiently merges demand characteristics, classification methods and inventory policies, validating that the model can create a tailor-made solution for Thales unique real-world situation.

Chapter 5 – Results

In this chapter the results are shown and elaborated on. First the performance of the model is discussed in reference to the old situation. Furthermore, the classification and inventory policies are compared and in section 5.2 different inputs are discussed. In section 5.3 a small selection of items are shown in more detail to look at the behavior of the model. In section 5.4 the overall impact of the model is shown as well as its impact on several KPI's. In section 5.5 a sensitivity analysis is done to evaluate the input parameters. Lastly, section 5.6 summarizes the results.

5.1 Performance and experiments

As mentioned in section 3.3.1, stocking items is always a tradeoff between either reducing holding costs or reducing stockout probability. Hence, to show the performance of the model the two KPI's; total holding costs and average stockout probability are compared. Additionally, as shown in chapter 2 currently Thales does not use inventory policies, except for a small number of items, and Thales does not keep track of stockout probabilities as mentioned in chapter 1. If items are not in stock in time, they make changes in their production schedule instead of registering a stockout. To effectively compare these two situations a baseline scenario is setup and used to compare the model to.

The baseline scenario is created by using a couple of assumptions regarding reality:

- A snapshot is made of current stock levels within Thales' supply chain and these stock levels are used to compare the financial difference and stockout probability between using an inventory policy or not.
- The classification of items, as is Thales' reality, is done by solely looking at the item price. Thus, A items are the most expensive items, B less expensive and C items the cheapest items.
- Other input variables as discussed in chapter 4.3: safety factors, holding costs, ordering costs, discount factors, Minimum data points and max cv are equalized through the different experiments. Note that holding costs are known and set to be 0.2. The other variables, safety factor, ordering cost and discount factor, minimum data points and max cv are set somewhat arbitrarily to 1.5, 10, 1, 10, and 5 respectively. The impact of these input variables is on the other hand shown in the sensitivity analysis in chapter 5.5. Note that as decision makers get a better understanding of these variables, they can change these in the model settings.

Baseline scenario performance

The total stock investments of the baseline scenario are equal to €74 million. The average stockout probability is equal to 20,66%. The classification of the baseline scenario is shown in table 8.

Table 8 – Distribution classes and demand

Class	*Fast Movers*	*Slow Movers*	*Intermittent Demand*
A	4%	5%	1%
B	5%	9%	2%
C	31%	37%	8%

When looking at the classes it is interesting to compare the stockout probabilities. As shown in figure 27, it becomes clear that A-items have a significantly worse stockout probability. One explanation for this is that the snapshot of item stock levels is taken at a random moment in time within the replenishment cycles of these items. This random moment does not take the pipeline of ordered items into account and since on average more expensive items are more tightly controlled with less excess stock, see section 2.1.3, it is intuitive that the stockout probability would be higher. In the contrary, cheaper items are stocked more in bulk/excess than expensive items because cheap items have more often certain procurement agreements like MOQ's, and the stocking costs of excess stock is cheap which results overall in lower stockout probability.

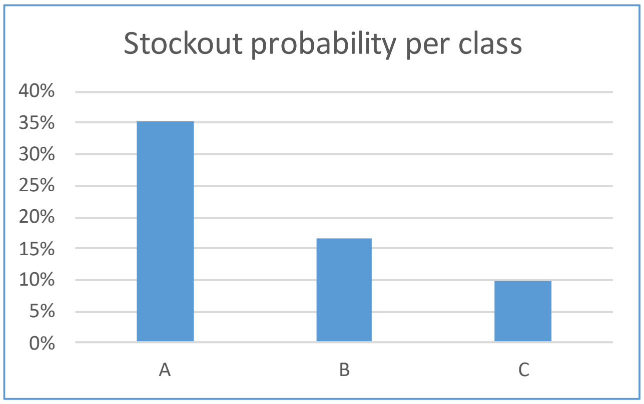


Figure 27 – Stockout probabilities per class baseline scenario

To check the effect of inventory policies, the baseline scenario is adjusted and a new scenario is created by assuming that all items use the same inventory policy (R, s, S) based on the items respective parameters like for example lead time. The (R, s, S) policy is chosen since it is the only policy that in reality can works somewhat practical for all demand characteristics. Just-in-time for example is not practical for low-cost C-items like screws. It is too expensive to create a tightly controlled, very reliable supply chain for such cheap items.

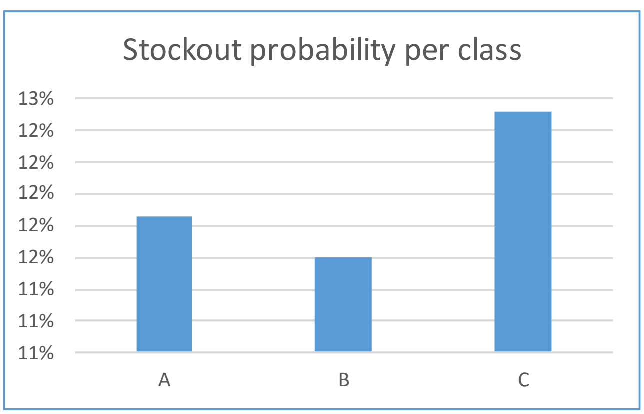


Figure 28 – Stockout per class with all items using (R, s, S)

In the adjusted baseline scenario, a lot of things change by implementing the (R, s, S) policy for all items. First, the total stock cost increase with 12% to €83 million. However, the average stockout probability drops to only 12%, which is a 42% decrease. This is logical since the (R, s, S) policy increases the amount of safety stock to account for the variability of demand during the lead time. Additionally, figure 28 shows that the difference in stockout probability between classes is very small. This can intuitively be explained by the fact that all items use the same inventory policy and safety stock calculations. The small difference between classes can be explained by the different configurations within the class regarding fast, slow and intermittent demand. For example, the C class has the biggest percentage of items which are intermittent items with less predictable demand and on average have higher stockout probabilities.

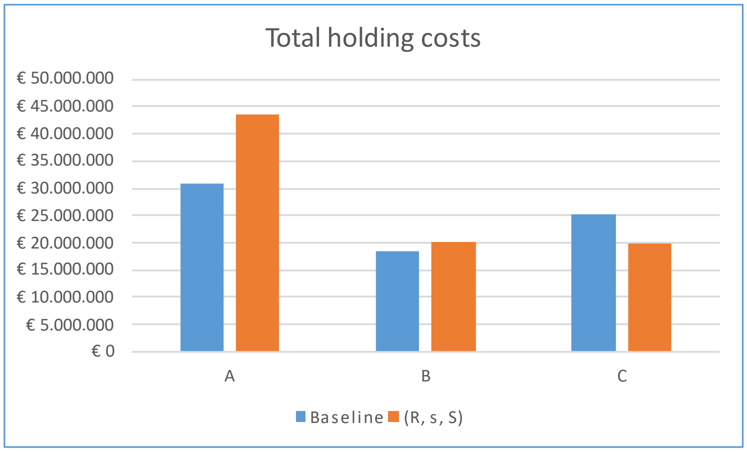


Figure 29 – Holding costs per class

Looking at figure 29, overall holding costs increase due to the more holistic approach which accounts for variability and replenishments cycles. While the baseline is mere a snapshot, void of the order pipeline which deflates the average stock over all items, still a cost reduction is observed within the C-Class despite the variability considerations and the inclusive approach towards replenishment cycles. This indicates that overall, Thales C-class stock levels high.

As Thales has a wide range of items with different characteristics in demand, one can imagine that the same policy for all items might be suboptimal. In the next section the different classification methods, inventory policies and configurations are explored.

5.1.1 – Inventory method Performance

Starting from the adjusted scenario with only (R, s, S), several changes can be implemented. The periodic review policy is suitable for constant high demand. For items with low or intermittent demand base stock might be more suited. The advantage of using base stock instead of (R, s, S) is that the average stock decreases without a reduction in stockout probability. In figure 30, the results of adding the base stock policy for all slow and intermittent items to the model is shown.

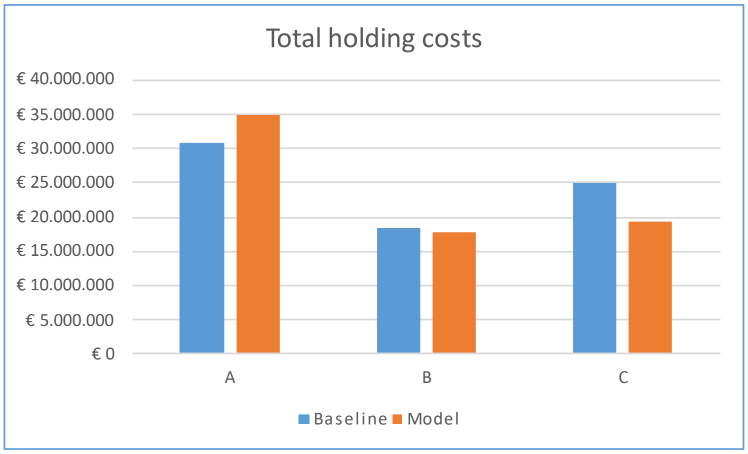


Figure 30 – Holding cost per class with (R, s, S) and Base stock

Figure 30 reveals that the transition to these inventory policies results in a significant reduction in holding costs compared to the previous scenario. While holding costs decrease the same level of stockout probability is maintained. This model results in a total holding cost of approximately €72 million. It offers a cost improvement of €2.4 million, which is a 11% enhancement.

The transition to a Just-In-Time or a Lot-for-Lot policy is suitable for tightly controlled A items, especially when these items are slow movers, or their demand follows intermittent behavior. Due to the intensity of resources required for a JIT/L4L management, it is mostly only practical for solely A class items.

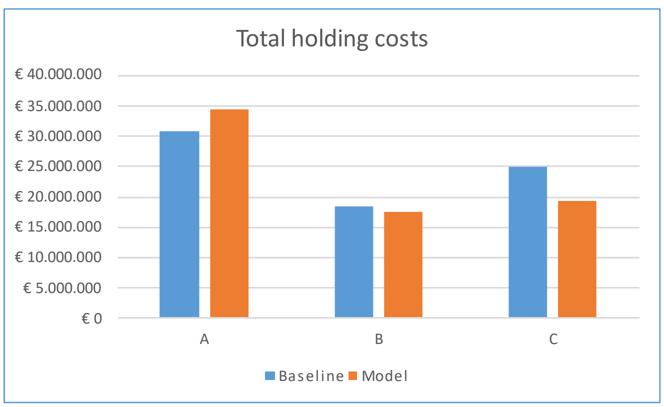


Figure 31 – Holding cost per class with (R, s, S), Base stock and JIT

Figure 31 highlights a total improvement of €2.9 million, which is an increase compared to the previous scenario with a total improvement of €2.4 million. However, in this scenario the stockout probability rises to 11.3%. For situations where JIT proves too demanding, L4L is a feasible alternative. L4L does potentially result in an increase of stock levels due to the inclusion of multiple planned horizons. Choosing for L4L results in a total cost improvement of €2.7 million. It becomes clear that the biggest cost reductions are achievable by managing fast-moving A class items more efficiently. If Thales can fortify its suppliers' relationships for these items, less stock can be achieved.

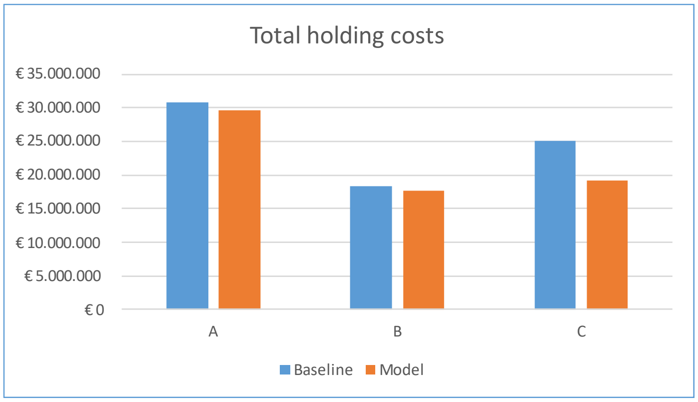


Figure 32 – Holding cost per class with (R, s, S), Base stock, JIT and L4L

Utilizing the L4L inventory policy for the fast-moving A class, in contrast to only implementing L4L for slow and intermittent items, yields substantial cost reductions in stock value. A total of cost reduction of €7.8 million is observed. The breakdown of the improvements is shown in table 9.

Table 9 – Improvement per class and demand type

CLASS	FAST MOVERS	SLOW MOVERS	INTERMITTENT
A	€ -446.593	€ 1.523.653	€ 57.500
B	€ -566.317	€ 1.326.492	€ 18.753
C	€ 4.632.431	€ 1.163.267	€ 56.167

The data shows that the most significant gains can be obtained in the C-class. This suggests that Thales' current stock levels are excessively high, which underscores the observation made in chapter 2. In contrast to lowering inventory for C-class, the model indicates an increase in stock levels for fast moving A and B items to attain for the stockout probability.

5.1.2 – Classification Performance

The classification method can have a big impact on the total inventory costs. Currently Thales creates its classes solely based on item price. The last configuration of inventory policies from the previous chapter is used to compare the effects of classification.

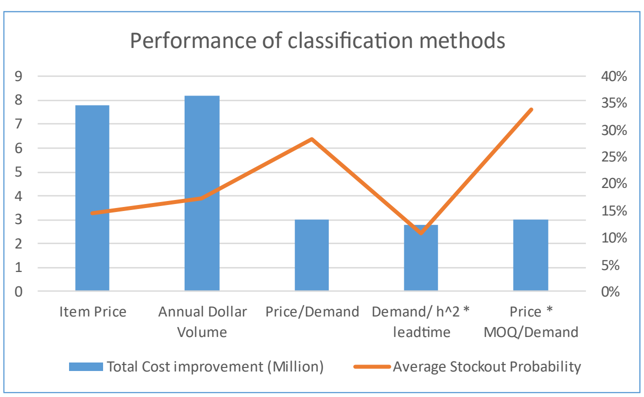


Figure 33 – Performance of classification methods, cost versus stockout probability

As illustrated in figure 33, using item price as the main classification method does not necessarily maximize cost improvements. Annual dollar volume shows the biggest improvements in cost. However, this comes with contrast that stockout probability marginally elevates when this metric is chosen. The other classification methods show less desirable outcomes in costs. Interestingly however the fourth classification shows a decrease in stockout probability which can indicate that this is an interesting choice if Thales wants to aim for less scheduling.

MCIC

7 different criteria have been created. To check their individual performance, the criteria are compared. Figure 34 shows the performance of the individual criteria given the MCIC calculations.

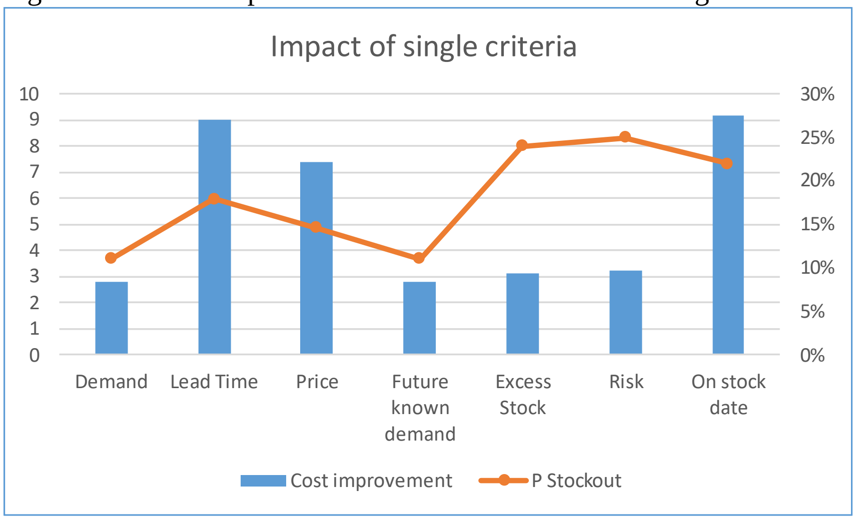


Figure 34 – Performance of MCIC with only one criterion

The effect of classification criteria in MCIC can substantially affect cost behavior. Given these Thales specific criteria, both lead time and on-stock date show to be very influential determinants. Their performance separately shows the biggest cost improvements. While the correlation between different criteria and its effect on cost is complicated, looking at these findings, it suggests that these criteria can be beneficial to a possible MCIC configuration. Note that leveraging these criteria an impressive holding cost reduction of €9 million can be realized. However, both these criteria show a significant increase of stockout probabilities. A deeper dive into the results of this classification shows another weakness of using only one criterion. In both these cases the A class is disproportionately big as it contains over 60% of all items. Such a classification is not practically viable for Thales's operations as the whole goal of the classification is to divide the intensity of inventory management effectively. After some experimentation adding the price criterion a more nuanced outcome is realized. Its inclusion not only refines cost and stockout probabilities it also ensures that the distribution of items over the item classes are practically represented.

After experimenting table 10 shows three promising configurations of the MCIC algorithm.

Table 10 - configuration of MCIC

Configuration	1	2	3
On stock date	x	x	x
Risk			x
Excess stock			
Future known demand			
Price	x	x	x
Lead Time	x	x	x
Demand		x	x
P-Stockout	15%	14%	19%
Cost improvement (Million)	€8,3	€5,1	€7,2

The 'on stock date' has shown to be an important criterion to differentiate between inventory classes. It is evident that items which have remained in stock for a long time often are C-class items, irrespective of their high costs. Meanwhile, the demand criterion leads to a decline in stockout probability. This can logically be explained since this criterion ensures that more stock is reserved for items with higher demand. A comparison between configurations 1 and 2 from table 10 shows this trend. A 1%-point reduction in stockout probability is achieved by an additional expenditure of €3.2 million. Furthermore, a focus on the "risk" criterion, which considers depreciation, enhances stock cost improvements. The advantage of configuration 3 is offset by a big increase in stockout probability. While the MCIC algorithm allows for more strategic inventory decisions, looking at the previous section its effectiveness is somewhat less than the traditional classification method annual dollar volume.

5.2 Item analysis

In the previous section it is shown that stock cost improvements can be realized while at the same time stockout probabilities can decrease. Combining the most promising classification (ADV) and inventory methods of the previous scenario the following tables gives the result.

Table 11 – Cost improvement per class and Inventory policy

CLASS	A		B		C	
(R, S, S)	€	-	€	772.640	€	3.301.995
JIT	€	1.342.927	€	-	€	-
L4L	€	-4.414.214	€	-	€	-
BASE STOCK	€	-	€	1.535.112	€	3.163.439
DEAD	€	43.133	€	1.198.657	€	1.394.578

To attain the stockout probability, the model adds more stock to the fast-moving A class. Which in this scenario incorporates the L4L policy. As mentioned above, the C-class includes a lot of excessive stock as the model suggests. Hence, the most substantial cost improvements are visible in the C-class. This observation aligns with earlier sections. Note that in chapter 2 it is shown that a substantial amount of stock is within the category dead stock. The model assumes to eradicate all non-strategic dead stock, (not obsolete). Even while this category was to be thought of as substantial, even bigger improvements are made in the active stock categories, the latter illustrates the model's effectiveness.

5.3 – KPI Impact

Looking at the main KPI's from chapter 2. If the improved baseline situation based on section 5.1.1 and 5.1.2 (see Appendix E) is used, the KPI's are improved as seen in figures 35 and 36.

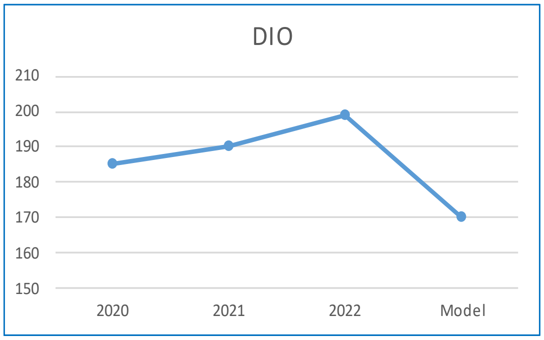


Figure 35 – Days inventory Outstanding

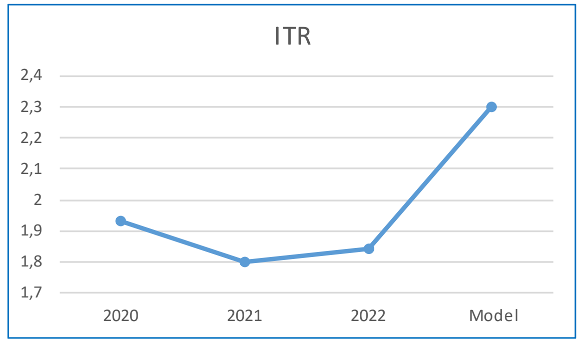


Figure 36 – Inventory turnover ratio

When looking at the KPI's mentioned in chapter 2, and adopting the refined baseline situation, improvements are shown in the figures above. A significant increase is shown in both figures. It is worth noting that part of the improvement stems from the model's strategy to erase all non-strategic 'dead' items. Which could mean that this is the sole reason both KPI's improve. However, when this category of stock is set aside and not factored into the KPI evaluation, the metrics for DIO and ITR are 192 and 2 respectively. This indicates that even when dead inventory is excluded, the models strategy yields improved KPI's.

5.4 – Sensitivity Analysis

Besides the configuration of the classification and inventory policies, other input parameters exist. These parameters can be changed by decision makers. However, to get insight into the effects of these parameters a sensitivity analysis is done.

Table 12 - sensitivity analysis of input values

SAFETY FACTOR	ORDERING COST	HOLDING COST	DISCOUNT FACTOR	DATA POINTS	CV	STOCK VALUE REDUCTION	CHANGE %
1,5	**10**	**0,2**	**0,5**	**10**	**5**	**€ 11.133.880,20**	**0%**
1,5	10	0,2	0,5	100	5	€ 8.225.662,26	-26%
1,5	10	0,2	0,5	1	5	-€ 1.076.270,26	-110%
0	10	0,2	0,5	10	5	€ 12.310.199,50	11%
3	10	0,2	0,5	10	5	€ 8.114.559,78	-27%
1,5	0,01	0,2	0,5	10	5	€ 9.833.256,15	-12%
1,5	100	0,2	0,5	10	5	€ 5.975.704,77	-46%
1,5	10	0,2	0,01	10	5	€ 8.689.084,76	-22%
1,5	10	0,2	100	10	5	€ 8.692.776,24	-22%
1,5	10	0,2	0,5	10	10	€ 11.205.570,32	1%
1,5	10	0,2	0,5	10	1	€ 8.223.282,02	-26%
1,5	10	0,5	0,5	10	5	€ 11.531.869,71	4%
1,5	10	1	0,5	10	5	€ 13.738.846,83	23%

To identify the most significant factors and to determine how changes in these factors impact the inventory performance a sensitivity analysis is done. Note the stock value reduction mentioned in table 12 is the reduction of the amount of stock compared to a situation with and without inventory policies. Hence, the difference between Thales' current situation and the situation when the model is used.

The sensitivity analysis shows that the safety factor has a significant impact on profitability. When there is no safety factor, the profit increases by 11%, which makes sense since a lower safety factor implies less safety stock. However, increasing the safety factor from 1.5 to 3 results in a big decrease in profit due to the purchase of more safety stock. Increasing the holding cost ensures less stock and thus a bigger stock value reduction. Increasing holding costs means Q decreases and ultimately results in less stock. The discount does not have much effect on profit, although increasing the discount factor by a factor of 100 leads to a decrease in profit due to the higher value given to historical data and thus resulting in more stock. Moreover, the number of data points has a significant impact on the results, as items with only one data point can lead to high deviations and very high safety stocks, which decreases the profit. Finally, the CV exclusion increase does not have a significant impact, probably because not many items have a CV exclusion of higher than 5 in the starting experiment. However, reducing the CV exclusion actually leads to a relative negative result. This might be because many "profitable" items are excluded and thus less reduction is realized for these stocks.

5.5 Results Conclusion

This chapter illustrates the results of the model regarding its configuration of inputs and in comparison, to Thales's baseline scenario. This chapter identified that holding costs could be reduced by using different classifications and inventory policies. A significant 11% improvement in costs are realized when specific inventory policies are implemented. In this scenario, an emphasis is placed on the benefits of utilizing JIT and L4L for A-class items. Still, it must be acknowledged that both these methods require significant organizational effort and to choose which is a matter of practical tradeoffs within Thales.

Furthermore, different classification methods can significantly impact the inventory costs, stockout probability and class sizes. Thales current method of solely looking at item price, it is shown that other methods are more fruitful. Moreover, an alternative to traditional methods like annual dollar volume is explored. The MCIC shows a potential more nuanced approach to the classification problem. Alternative metrics like 'on stock date' and 'risk' are incorporated into the classification method and more strategic results are possible. While multi criteria inventory classification offers strategic flexibility, the traditional method ADV still outperforms it. By understanding and optimizing these elements, Thales can realize substantial cost savings, improve stockout probabilities.

Chapter 6 – Conclusion & Recomendations

This section discusses the conclusion of this Thesis in the first section, 6.1. It continues with the recommendations the author gives to Thales in section 6.2. Furthermore, the evaluation and discussion is stated in section 6.3 and lastly in the sections 6.4 and 6.5 the contribution to theory, practice and future research are discussed.

6.1 – Conclusion

This thesis shows solutions to the inventory challenges faced by Thales. As Thales inventory increases the urgency to create a more balanced and efficient inventory system increases as well, as the capacity of the warehouse is not infinite. During the high times of business, the implications of increasing inventory costs might seem trivial, but in tight business circumstances, they can escalate into substantial pains for management. Hence, affecting the financial stability and health of the whole organization.
Within Thales inventory, multiple critical findings are present indicating improvements are possible. Among these critical findings were the substantial amount of dead stock and excess stock. In addition, this Thesis showed that Thales inventory management policies are barely present.

This thesis addresses these problems by introducing a pragmatic model that incorporates Thales diverse roster of products in stock. The practical model incorporates multiple theoretical inventory policies and classifications. By doing so it showed considerable reductions in stock levels, especially within the C-class. These reductions are possible without compromising on stockout probabilities. In addition, the model shows that by with implementing these theoretical methods, significant yields can be realized within the items which demand is categorized as slow-moving and intermittent demand. Hence, the model shows that these classification and inventory methods foster balanced and efficient inventory management.

Besides the improvements shown in Chapter 5, the developed model serves as a potential tool for inventory managers and decision makers. It increases the visibility of existing inventory problems and by tweaking its configuration, strategies and solutions can be found. The model hints at improvements that should be made to further enhance the current inventory situation. It does this by showing that over €8 million can be saved in stock value without reducing stockout probabilities. It also showed that the two main KPIs improve, and this thesis indicates how these improvements can be realized. If used well, Thales can take a step towards a more organized inventory structure, and possibly ensuring a healthier bottom line. Thus, this thesis shows the way towards less inventory costs and a more resilient management system.

6.2 – Recommendations

Excessive Stock

The inventory model reveals in every configuration that the C-class is overstocked. Despite their low cost and stocking them in large quantities without incurring significant expenses, the current strategy seems suboptimal. While a single type of item in the C-class is insignificant in costs, looking at the whole class a lot of excessive stock does become a problem. The model outcomes consistently suggest substantial savings through the reduction of these items in stock. These savings can be made reality without a reduction of stockout probabilities. This implies that Thales could maintain service levels while reducing holding costs, thereby optimizing the inventory resource efficiency. While this counts for the other classes as well as the C-class, implementing inventory policies to this class would be beneficial to creating a more balanced and cost-effective inventory system.

Financial Risk

The current presence of items with 100% risk, signifies that these items are already undergone depreciation. Hence, Thales has already absorbed the costs associated with these parts. Often, these parts are within the dead inventory class. Hence, these items serve no active role in production or supply chain. A policy that eliminates these fully depreciated items could be beneficial to inventory costs. There is simply no benefit in retaining these items in stock, where they perpetually incur additional holding costs. In addition, most of the time these items are not obsolete and readily available on the market. Scrapping these items won't hinder Thales' ability to procure them when demand increases. Hence, this proposed policy could increase warehouse effectiveness and reduce overall stock costs.

Dead inventory

In Thales' current inventory system, dead inventory, which are defined as items which have no demand in the past 5 years, consumes warehouse resources and negatively impacts KPIs. Furthermore, it has been observed that the demand probability for stock that has been on the shelf for at least 3 years is the same as 5-year-old inventory. Hence, it is recommended that the criteria for categorizing inventory as "dead" should be revised to 3 from 5 years. This change statistically does not impact future demand prospects and it increases the visibility of the issue. Given that the dead inventory class would increase by comparison and could pave the way for further optimization strategies. Given the analysis of this thesis, it is recommended that dead inventory is erased as much as possible. A lot of costs can be eradicated by removing dead inventory as these items only cost warehouse recourses, do not contribute to turnover and since they are not obsolete if Thales requires these items after they are scrapped, one can simply procure them from the market. It would also be advised that Thales looks to sell these parts, while they do not add value for Thales, they can still be a value to other companies. It would be interesting to look for ways to sell dead inventory.

6.3 – Evaluation & Discussion

Due to the poor quality of Thales data, it was necessary to make assumptions. Due to the absence of real-time data on inventory positions, only demand data was recorded, the utilization of a snapshot of current inventory positions became the pragmatic approach. While being a practical solution, it does mark a limitation in the study. The snapshot approach ensures that the analysis of inventory is based on an arbitrary point within the order replenishment cycle, potentially influencing the accuracy of the findings. The baseline scenario, resulting from the snapshot approach, enables the comparison of model outcomes to the real-world scenario. Hence, improvements identified by the model can be translated into the real-world scenario. Using methodologies like a simulation study or real-time forecasting in the real world, would increase the reliability of the result. However, these methodologies only work if data quality is enhanced, and more data is available to train/compare the outcomes of these methodologies with.

Moreover, the evaluation in the thesis predominantly centered on only two dimensions: holding costs and stockout probabilities. Hence, offering a somewhat simplified perspective of the complex reality. In a real-world scenario, inventory management incorporates a broader spectrum of costs. Due to the lack of data, these costs were not available. For example, Thales does reschedule when a stockout occurs. The financial repercussions of these stockouts or replanning is unknown and additionally, there is no data if these stockouts have occurred at all. Given the lack of data a more simplistic analytical view is chosen to avoid over-complication and excessive assumption building.

It is important to note that even without comprehensive data, the chosen KPIs over the two dimensions remain central to formulating inventory management strategies. A well-balanced inventory management system makes the tradeoff between stocking costs and stockout probabilities and in turn service levels. While this thesis shows potential improvements and increases the visibility of some current problems, it does not delve deeper into the potential effects of these cost reductions. Especially when regarding inventory policies like JIT. The cost reduction from less stock is not compared to the increase in inventory management costs due to the requirement of a lot more organizational effort to allow for the JIT inventory policy. Thus, while this thesis paves the way for substantial advancements in inventory costs, this thesis alone does not pretend to solve all problems as it does not fully incorporate the complex real-world situation of Thales. A more expansive study is required to fully grasp the multifaceted dynamic inventory of Thales.

6.4 – Contribution to Theory and Practice

This thesis contributes to both theoretical and practical applications in the realm of inventory management. It shows the integration of diverse inventory policies and classification methods can create substantial enhancements in managing inventories in the context of high mix low volume businesses.

On the theoretical front, this thesis shows how various theoretical models can create fruitful outcomes, adding to the understanding and broadening of the inventory management theories. Furthermore, this thesis shows that traditional methods like annual dollar volume retain their efficacy. More complex methods like MCIC do not outperform traditional methods in few key performance indicators. However, this thesis also shows that MCIC does not lag far behind in terms of performance and in fact, it introduces a pragmatic dimension to classification. The latter potentially facilitates more nuance in classification and creates strategic levers for decision makers.

In practice, the model functions as a versatile tool. It enables decision makers to strategize through their inventory cost saving journey. This Thesis shows that even within a complex and dynamic business environment, utilizing a combination of strategies and classes, one can create a more balanced and cost-effective inventory environment. The thesis shows the effectiveness of traditional methods but to a greater extent, also shows the effectiveness of more nuanced inventory control through MCIC. This dual contribution to theory and practice indicates an interesting trajectory for both the scientific and practical fields of inventory management.

6.5 – Future Research

While the current findings offer valuable insights into Thales' inventory management, future research can provide more insights or improvements can be added to the model to enhance its performance. One promising avenue could involve adding algorithms like Nearest Neighbor to navigate through all the possible configurations of the model to optimize the outcome. Another advanced technique worth considering is goal programming. As the model shows improvements among multiple dimensions, goal programming provides a solution into multi-objective optimization. Furthermore, expanding on the inventory and classification policies might also yield better model performance. For example, one can study the effects of increasing the number of classes as Thales's inventory is very complex. Or more tailored inventory strategies can be included to incorporate this complex environment.

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Appendix A – Thales Safety Stock Calculations

Safety Stocks are calculated using an 8-step plan.

1. Calculate weighted year demand using usage	$$weigted\ year\ demand = \frac{2 * jvb^{huidig-1} + 2 * jvb^{huidig-2} + jvb^{huidig-3}}{5}$$
2. Calculate stdev	$stdev = \frac{2 * (jvb^{huidig-1} - gewjvb)^2 + 2 * (jvb^{huidig-2} - gewjvb)^2 + (jvb^{huidig-3} - ge}{5}$
3. Variance calculation	$Variance = \frac{std}{Weighted\ year\ demand}$, if DIV/0 then 0
4. Calculate InputOSG	$InputOSG - low = weighted\ year\ demand$ $InputOSG - medium = jvb^{huidig-1}$ $InputOSG - high = Demand_O$
5. Choose InputOSG	Variance < 0,3 = InputOSG – low Variance 0,3 < 1 = InputOSG – medium Variance > 1 = InputOSG – high
6. Calculate safety stock	$$SS = \frac{InputOSG * LeadTime(days)}{260}$$ if LT = 0: $SS = 0{,}2 * InputOSG$
7. SS → 0	In some cases SS needs to be 0 1. If demand O = 0 2. If current IP > demand O+T
8. Round safety stock	Based on the depreciated price ranges given by suppliers, safetystock needs to be round upwards.

Appendix B – Inventory policies as modelled in the system

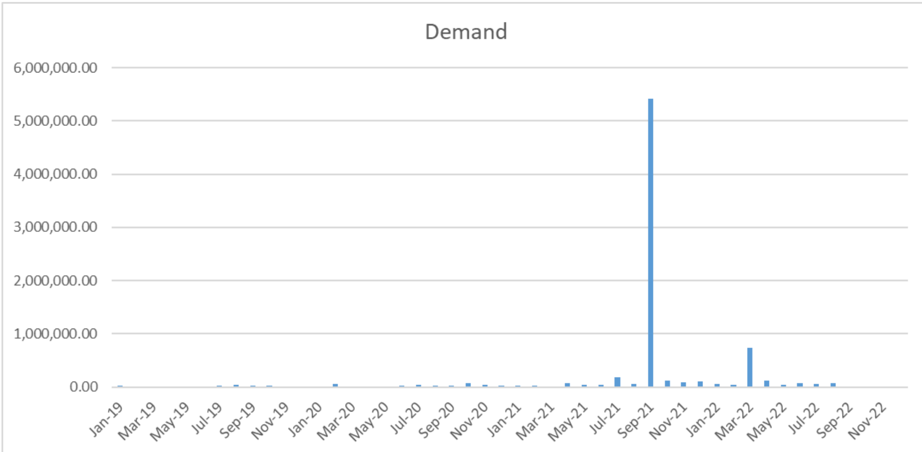
The inventory policies discussed in chapter 3 are implemented in the inventory model. Note that the inventory policies are only implemented for items with existing demand data. For example, dead items have no demand data and as such their mean and variance cannot be calculated.

Since base stock is only used for low demand items like intermittent demand or slow movers. The behavior of base stock is very particular as single items are ordered when item stock mutations happen, thus item stocks for this policy range from [Base stock, Base stock + MOQ] in case of MOQ's, otherwise [Base stock, Base stock + 1].

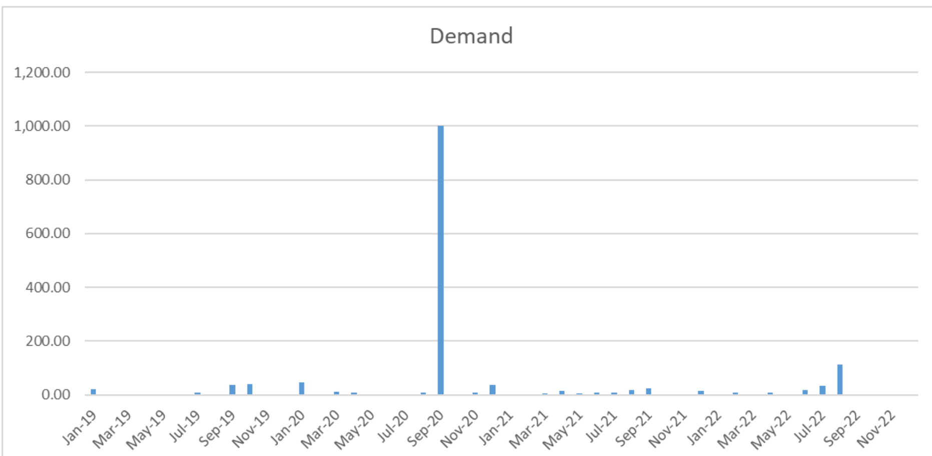
Lot for lot is modelled like JIT. Due to the tightly controlled environment safety stock is assumed to be zero. Furthermore, the minimum stock is equal to lead time demand. However, in contrast to JIT, L4L orders up to a multiple of a planned forecast horizon. The default is set to 100 days, as this is roughly one average lead time demand. Lot sizes are higher for L4L than JIT, so the L4L stock ranges are given by:

- [D_L, D_L + MOQ], in case MOQ > 2 * D_L,
- [D_L, 2*D_L].

Appendix C – Examples of Highly irregular demand



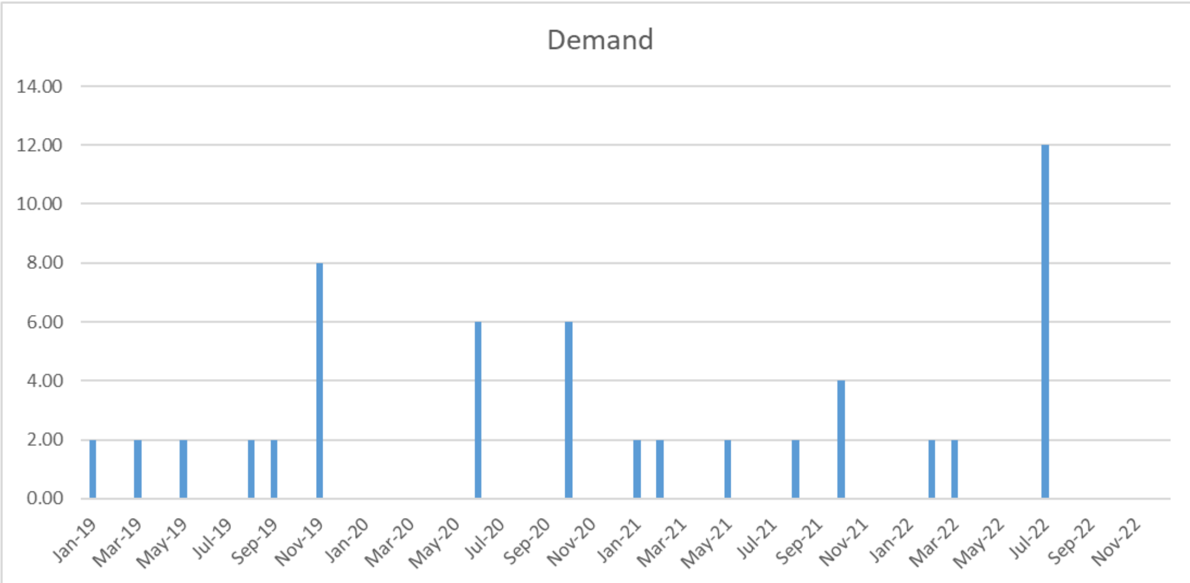
Demand of Item 032204203031..



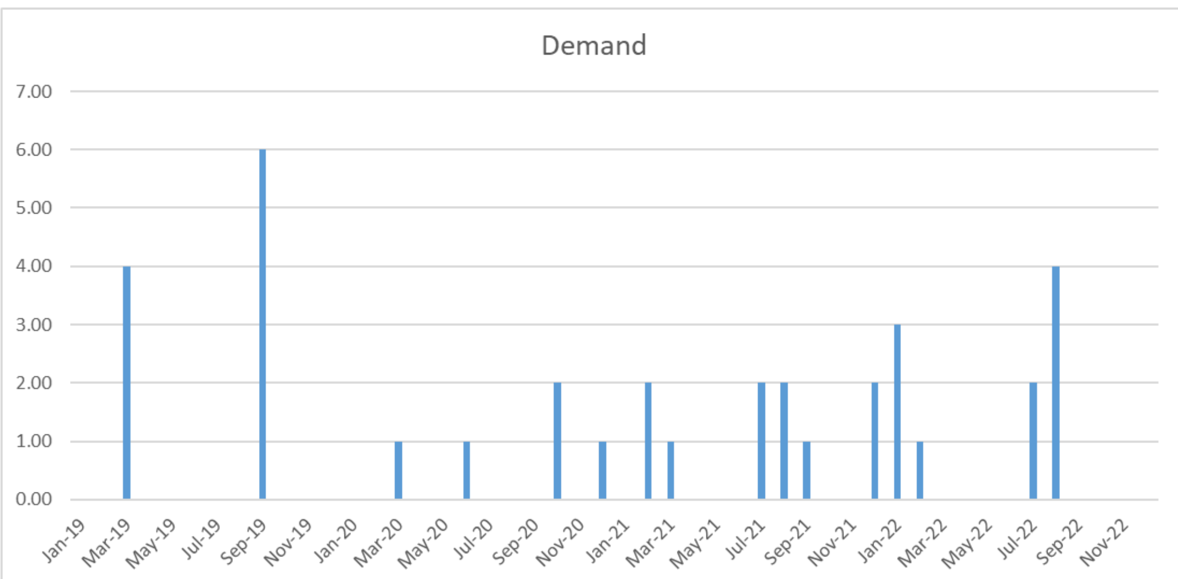
Demand of item 352250041176..

Demand of item 122210398256..

Appendix D – Examples of Intermittent Demand



Demand of item 352259902881..



Demand of item 352250054694..

Appendix E – Improved Baseline configuration of the model

Exclusion Criteria	
Data points	10
CV	5
Inventory	Common stock
Discount Factor (p	1

Classification Method	Select
Item Price	
Annual Dollar volume	x
Price/Demand	
Demand /h ^2 Lead time	
Price *MOQ/Demand	
MCIC	

Choose Inventory Method 01/10/2022

List of Methods
(R, s, S)
JIT
L4L
Base Stock

Class	Fast Movers	Slow Movers	Intermittent Demand
A	L4L	JIT	JIT
B	(R, s, S)	Base Stock	Base Stock
C	(R, s, S)	Base Stock	Base Stock

MCIC Criteria	Select
On stock date	
Risk	
Excess stock	
Future known demand	
Price	
Lead Time	
Demand	

Safety Factor	1,5
Holding Cost	0,2
Ordering cost	10

Figure 35 – A snapshot of the configuration of the improved baseline

Appendix G – Model explanation

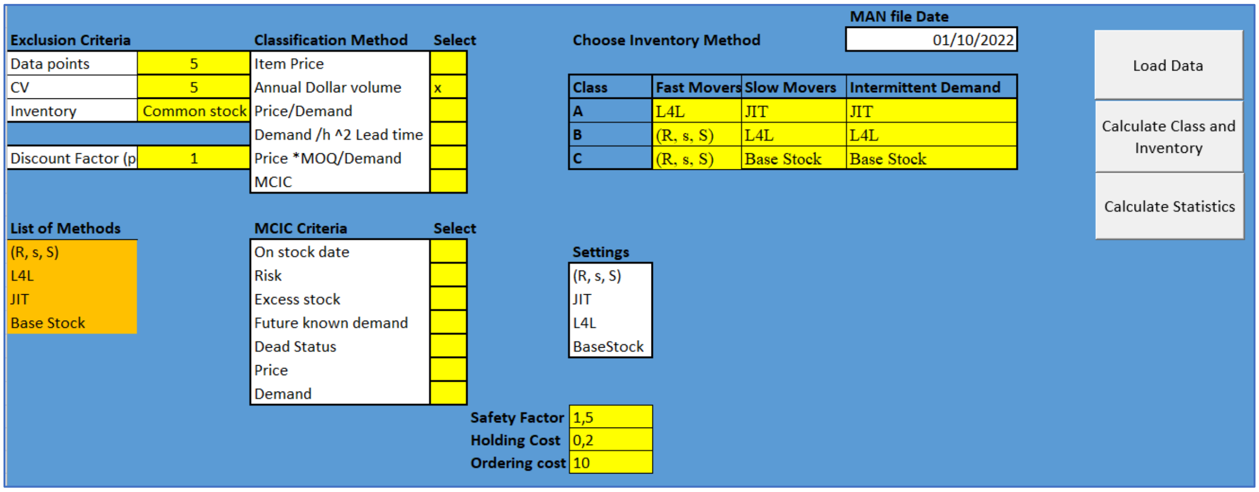


Figure 36 – settings dashboard of model

The model works in 4 steps.

Step 1: Set input parameters. It is important all the yellow cells (except the cells from the Classification method or MCIC criteria) are filled in. For the classification yellow cells only one yellow cell must be filled with an x. This indicates that this specific classification method is used. If MCIC is chosen then the end user must fill in what criteria should be taken into account by the MCIC, this is done below the first set of "x" selected cells.

Step 2: when all input variables are set, the button Load data should be clicked. 2 popups will come up. Since the data is combined from several sheets, first the system asks the end user to select the MAN65 excel sheet. Secondly the demand characteristics sheet needs to be selected after the second popup.

Step 3: After the data is combined and filled it is time to calculate inventory performance. This is done through the second button called "Calculate Class and Inventory". Make sure a classification method is selected as mentioned in step 1.

Step 4: After all calculations for all items are done, the final step is to calculate the performance. This can be done with the last button called "Calculate Statistics". This button will update all performance indicators in the sheet "Results". If the end user wants to check the performance with a different setup, change the yellow cells and go back to step 2.

Appendix H – Chi Squared code

```
Sub Chi_Square(observed() As Double, PDF As String, mean As Double, stdev As Double, prob As Double, cv As Double)
'Take the demand data and calculate the viability of the PDF
Dim p As Double, count As Long, i As Long, expected() As Double, min As Double, max As Double, j As Long
Dim crit_prob As Double, alfa As Double, buckets As Long, bucketi() As Double, bucketj() As Double, step As Double, bucketO()
Dim BucketE(), chi As Double, a As Double, b As Double, r As Long, prob_gamma As Double, niet As Long

count = UBound(observed)
ReDim expected(1 To count)
buckets = 9
ReDim bucketi(1 To buckets)
ReDim bucketj(1 To buckets)
ReDim bucket(1 To buckets)
ReDim bucketO(1 To buckets)
ReDim BucketE(1 To buckets)
If cv > 5 Or stdev = 0 Then
   Exit Sub
End If
'create the observerd data
'initialize
min = Application.WorksheetFunction.min(observed())
max = Application.WorksheetFunction.max(observed())
alfa = 0.05
step = (max - min) / buckets
'Some distributions cant handle 0 as minimum
If min = 0 Then
   min = 0.001
End If

prob = 0
prob_gamma = 0

For i = 1 To buckets
   bucketi(i) = min + step * (i - 1)
   bucketj(i) = min + step * i
Next i

   For i = 1 To count
      For j = 1 To buckets
         If observed(i) >= bucketi(j) And observed(i) < bucketj(j) Then
            bucketO(j) = bucketO(j) + 1
         End If
      Next j
   Next i
```

```
    For i = 1 To buckets
        bucketO(i) = bucketO(i) / count 'set the data
    Next i


'Normal
If PDF = "Normal" Then
    'make observations according to statistical distribution
    For i = 1 To buckets
        BucketE(i) = Application.WorksheetFunction.Norm_Dist(bucketj(i), mean, stdev, True) -
Application.WorksheetFunction.Norm_Dist(bucketi(i), mean, stdev, True)
    Next i
End If

'Negative Binomial
If PDF = "Negative Binomial" Then
    r = (mean / stdev) ^ 2
    p = mean / (mean + (stdev ^ 2))
    If r = 0 Then
        r = 1
    End If
    'make observations according to statistical distribution
    For i = 1 To buckets
       BucketE(i) = Application.WorksheetFunction.NegBinom_Dist(bucketj(i), r, p, True) -
Application.WorksheetFunction.NegBinom_Dist(bucketi(i), r, p, True)
    Next i
End If

'Poisson
If PDF = "Poisson" Then
    'make observations according to statistical distribution
    For i = 1 To buckets
       BucketE(i) = Application.WorksheetFunction.Poisson_Dist(bucketj(i), mean, True) -
Application.WorksheetFunction.Poisson_Dist(bucketi(i), mean, True)
    Next i
End If

'Compound Poisson

'Gamma/Lognormal 'Wss gnw gamma doen
If PDF = "Gamma/LogNormal" Then
    'Gamma
    a = (mean ^ 2) / (stdev ^ 2)
    b = mean / (stdev ^ 2)
    'make observations according to statistical distribution
    For i = 1 To buckets
        BucketE(i) = Application.WorksheetFunction.Gamma_Dist(bucketj(i), a, b, True) -
Application.WorksheetFunction.Gamma_Dist(bucketi(i), a, b, True)
    Next i
niet = 0
```

```
chi = 0
'check how many expected buckets are 0
For i = 1 To buckets
    If BucketE(i) = 0 Then
        niet = niet + 1
    End If
Next i

'Chi squared for gamma
For i = 1 To buckets - niet
    If BucketE(i) <> 0 Then
        chi = chi + ((bucketO(i) - BucketE(i)) ^ 2) / BucketE(i)
    End If
Next i
If buckets - niet > 1 Then
    p = Application.WorksheetFunction.ChiSq_Inv_RT(alfa, buckets - 1 - niet)
    prob_gamma = Application.WorksheetFunction.ChiSq_Dist_RT(chi, buckets - 1 - niet) 'prob moet groter
zijn dan 0.05 oftewel alfa om te laten zien dat ze hetzelfde zijn
End If

    'Lognormal
    'make observations according to statistical distribution
    For i = 1 To buckets
        BucketE(i) = Application.WorksheetFunction.LogNorm_Dist(bucketj(i), mean, stdev, True) -
Application.WorksheetFunction.LogNorm_Dist(bucketi(i), mean, stdev, True)
    Next i
End If




'Goodness of fit test


    'Calculate

niet = 0
chi = 0
'check how many expected buckets are 0
For i = 1 To buckets
    If BucketE(i) = 0 Then
        niet = niet + 1
    End If
Next i

'Chi squared for gamma
For i = 1 To buckets - niet
    If BucketE(i) <> 0 Then
        chi = chi + ((bucketO(i) - BucketE(i)) ^ 2) / BucketE(i)
    End If
```

```
Next i
If buckets - niet > 1 Then
    p = Application.WorksheetFunction.ChiSq_Inv_RT(alfa, buckets - 1 - niet)
    prob = Application.WorksheetFunction.ChiSq_Dist_RT(chi, buckets - 1 - niet) 'prob moet groter zijn dan 0.05 oftewel alfa om te laten zien dat ze hetzelfde zijn
End If
If prob > prob_gamma Then
    prob = prob
Else
    prob = prob_gamma
End If

End Sub
```