Inventory Control of Finished Goods for the Aftermarket

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TITANX
Powertrain Cooling

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Preface

This master's thesis presents a degree project performed at TitanX Engine Cooling AB in the department of supply chain. This thesis has been performed by Sercan Eminoglu, a student in the master's program in Logistics and Supply Chain Management and Joan Esteve i Magrané, an exchange student in master's program in Industrial Engineering. This thesis has been our last step towards becoming Masters of Science in Industrial Engineering and Management and it has been a wonderful opportunity to put our theoretical knowledge gathered throughout our studies to practice in a real-world situation.

We would like to thank the company TitanX and especially our supervisors Hannu Kauppinen and Niklas Möller for giving us this chance and for guiding us throughout this journey. We would also like to thank our examiner Johan Marklund for his reflections willingness to collaborate with us, and finally we want to show our sincerest appreciation to our supervisor at Lund University, Peter Berling, for his continuous help and dedication towards ensuring the success of this project.

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Abstract

Title

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Background

TitanX Engine Cooling is a global supplier of powertrain cooling solutions to commercial vehicles, both for OEMs and the independent aftermarket. The company with annual sales of over 1.6 billion SEK (US$ 192 million) has some 800 employees worldwide. TitanX is headquartered in Gothenburg, Sweden and has manufacturing sites in Sweden, USA, Brazil, China and Mexico.

Its manufacturing facilities are designed and operated with a strong and continuous application of lean manufacturing principles, and they perceive themselves as a very flexible supplier. The production sites have a high level of vertical integration, including the manufacturing of key critical components to ensure the highest quality results. The production operations are continuously adjusted to meet variations in customer demand. The vision is to be the number one global supplier of powertrain cooling solutions to the commercial vehicle industry.

The facility in Sölvesborg consists of three zones; a raw material warehouse, a shop floor, and a finished goods warehouse. TitanX generally keeps high inventory levels of raw material and finished goods. An important reason for this is the marketing strategy to increase the current market share above 30% of the independent aftermarket for truck engine cooling systems. Therefore, high customer service levels and high efficiency are key performance measures that drive high capacity and stock levels.

Purpose

The purpose of the degree project is to analyze the finished goods inventory for independent aftermarket products to provide both more accurate forecasting methods and a scientific approach for controlling these inventories by finding the reorder points for a given service level and considering trade-offs between the production lead times and the safety stock needed for those.

Methods

Liebermann & Hillier (2001) described all the major phases of a typical operations research (OR) modeling approach used to conduct the research in this project.

Quality assurance was done by a process of validation and verification based on Banks, Carson II, Nelson, and Nicol, (2005)

Data collection was done using semi-structured interviews, direct observation, literature review and data provided by the company.

By using those, a new forecasting model and inventory control tool have been developed and the results have been compared to the older model provided by the company to observe the level of improvement obtained.

Conclusions

New forecasting model improves upon the results of the previous one by 21,2% in terms of forecasting accuracy for a specific available sample.

The implemented inventory control tool is a new advancement that the company previously did not possess and remarkably diminishes the required safety stock levels by 59% which accounts for 279.783,5 €/year.

Finally, the tools provided will save planning time and will allow for the comparison of different scenarios.

Keywords

Aftermarket products, forecasting, operations research, intermittent demand patterns, inventory control.

List of abbreviations, variables and parameters

List of variables and parameters

P	Average inter-demand interval
CV^2	Squared coefficient of variation of the demand size
CV^2_{DDTL}	squared coefficient of demand size variation during the lead time
L	Lead time
Λ	Mean number of arrivals per time unit
N	Number of periods with demand
t_i	Period i=1…T
Σ	Standard deviation of the historic demand data
μ	Mean of the historic demand data
μ_0	Initial value of the mean demand
μ_τ	Mean demand size of the periods where demand has occurred, only considering the first τ periods
T	Number of periods used for initialization
Q	Time until the next demand during the current iteration of the forecast iteration
T	Last period in the historic data
X_t or y_t	Real demand in period t
p_t	Expected inter-demand interval in period t
z_t	Expected demand size in period t if the demand is positive
F_t	Forecast in units/period
α_i	Smoothing constant for p
α_s	Smoothing constant for z
S_t	Simple Exponential Smoothing forecast in period t
A	Smoothing constant for Simple Exponential Smoothing
MAD	Mean Absolute Deviation
N	Number of periods used in the forecast
S_1	Probability of no stock out per order cycle
S_2	"fill rate"- Fraction of demand that can be satisfied immediately from stock on hand
S_3	"ready rate"- Fraction of time with positive stock on hand
R or s	Reorder point

Q	Batch size
S	Maximum inventory level
$P(k)$	Probability of having k customers in one period
f_j	Probability of demand size j
Var	Variance
D(t)	Demand of period t
P(D(t)=X)	Probability of the demand of a period being X
P	Success probability in each experiment
R	Number of failures until the experiment is stopped
μ'	Mean expected demand during the lead time
σ'	Standard deviation of the forecasts during the lead time
$g(x)$	Density function of the Gamma distribution
$\Gamma(r)$	Cumulative probability distribution of the Gamma distribution
r (gamma distr.)	Parameter from the gamma distribution
Φ	Probability distribution function of the standardized normal distribution
φ	Probability density function of the standardized normal distribution
G(x)	Loss function of the normal distribution
F(x)	Probability distribution function of demand size x
R_U	Upper bound of the reorder point used in the inventory control iterative process
R_L	Lower bound of the reorder point used in the inventory control iterative process

List of abbreviations

E	Expected
MAD	Mean Absolute Deviation
MSE	Mean Squared Error
OEM	Original Equipment Manufacturer
OES	Original Equipment Supplier
IAM	Independent AfterMarket
NBD	Negative Binomial Distribution
SBA	Syntetos and Boylan Approximation
SKU	Stock Keeping Unit
SES	Simple Exponential Smoothing
OR	Operations Research
L	Lead time
MPS	Master Production Schedule
SMA	Simple Moving Average

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1. Introduction

This chapter presents a degree project that is performed at TitanX Engine Cooling AB in production management. First the general background of the problem will be introduced, followed by the problem description, purpose of the project, company overview, research questions, research limitations, and potential contributions to knowledge will also be explained.

1.1. Background

TitanX manufacturing facilities are designed and operated with a strong and continuous application of lean manufacturing principles, and they perceive themselves as a very flexible supplier. The production sites have a high level of vertical integration, including the manufacturing of key critical components to ensure the highest quality results. The production operations are continuously adjusted to meet variations in customer demand. The vision is to be the number one global supplier of powertrain cooling solutions to the commercial vehicle industry.

The company has three distinct types of customers which are Original Equipment Manufacturer (OEM), Original Equipment Supplier (OES) and Independent AfterMarket (IAM).

- The OEM segment is the biggest in terms of demand, and it consists of finished cooling systems sold to a number of manufacturers to be used in their production of new trucks. The demand for these customers is high and repetitive and it is known well in advance. Orders from these customers can thus be made-to-order.
- The products in the OES segment are spare parts (mostly chargers and radiators) sold to the same customers as the previous segment (OEM). The demand in the OES have a lot of resemblance to the OEM segment and are thus easy to plan.
- Finally, the customers in the IAM segment also orders spare parts, but they are very different than the OES customers. IAM customers are independent distributors that sell the spare parts to smaller truck repair shops. Due to the smaller nature of the customers in this segment, order sizes are usually smaller and more unpredictable, making them harder to control.

The facility in Mjällby consists of three zones; a raw materials warehouse, a shop floor, and a finished goods warehouse. TitanX generally keeps high inventory levels of raw material and finished goods. An important reason for this is the marketing strategy to increase the current market share above 30% of the independent aftermarket for truck engine cooling systems. High customer service levels and good availability are key to achieve this.

1.2. Problem description

To figure out what are the challenges of the company that can be the focus of this project, the supervisors at the TitanX factory in Mjällby were approached, and the collected information is provided.

When a customer places its order, TitanX is committed to ship those products within 14 days. This time span is defined as an order to delivery lead time. However, the company is often able to supply the products before the requested time. In fact, most products can be sent immediately and in larger quantities than ordered, even though when an additional amount is shipped with the regular order, the sales department will need to offer a discount. On the other hand, if they cannot ship the items in 14 days, this might cause penalties and/or lost sales.

TitanX also measures dock to dock lead time, this refers to the time an item spends in the system from the time it enters as raw material until it is shipped as a finished good. Today, dock to dock lead time is much higher than the time for order to delivery. The average value for dock to dock lead time is 86 days in total, respectively; 52 days in the raw material warehouse, 19.6 hours of work-in-process, and 33 days in the finished goods warehouse. It is sensed that the total time in the system (86 days) quite long, and the total amount of stock is also pretty high. On the other hand, 19.6 hours work in process is often not sufficient. This since inventory buffers between operations provoke halting of the job and longer time as work in process. Those numbers represent the averages, however, TitanX keeps both OEM and aftermarket stocks. The demand for aftermarket products is rising, moreover, the company sells high variety of the aftermarket products to different distributors. Hence, TitanX would like to have a better understanding of appropriate inventory levels at the finished goods warehouse to meet for the increasing sales of aftermarket products.

The increasing interest of the company in its Independent Aftermarket (IAM) segment started during the 2008 crisis when a new source of income was needed in order to compensate for the decreasing demand tendencies at the time. A new sales team was created to launch this product segment to market and to make it grow. The sales team is making a good job and this segment is continuously growing. Currently, the company wants to increase the ratio of offered IAM products from 65% of their potential market to a goal of 80%, increasing their market share until stabilizing at a desired value of 35% of the global market. These ambitious goals will not come without growing pains in the supply chain of the company.

The Independent Aftermarket (IAM) segment, entail added difficulties compared to the original range of customers. Here are several of the issues that define this new market:

- Customers do not place their orders well in advance, but rather when they need the products.
- Customer orders are very unpredictable.

- The market has not stabilized yet. New customers are appearing and demand in general is still in a growing stage.
- Smaller customer orders.
- Quick response (14 days) is expected

Thus, demand needs to be forecasted and stock must always be at hand.

In terms of production, IAM orders introduce many challenges to the company. If one tries to match the customer orders with production orders, productivity issues will arise. This is due to an increase of the total number of setups which will also make production planning harder to optimize. Also, the fact that many products sold in the IAM segment are quite old means that older and more manual machines need to be used, resulting in extra time for the operators and, for the same reason, decreasing part standardization, making production even more complex.

Finally, in terms of inventory management, this relatively new branch of products is also introducing new challenges due to the need of forecasting methods, the space constraints caused by the consistent growth in demand and the inventory control difficulties created by the increasing number of offered products.

To comprehend the problems correctly a cause-effect diagram was drawn as seen in *Figure 1.1*.

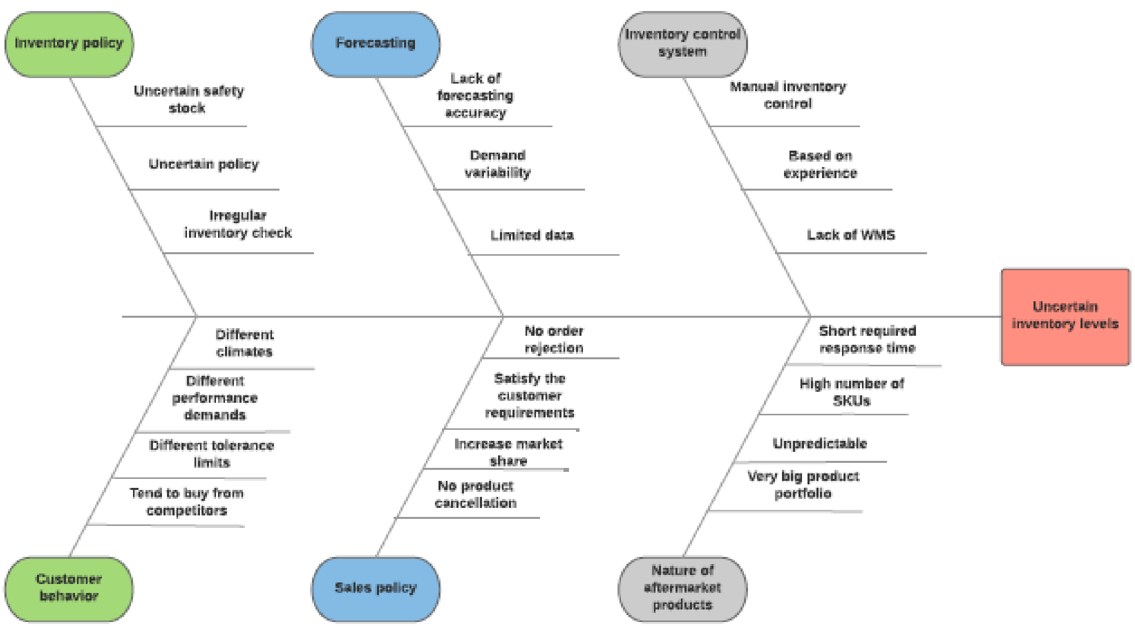

Figure 1. 1 - Cause and effect diagram for IAM products.

1.3. Purpose

The purpose of the degree project is to analyze the finished goods inventory for independent aftermarket products to provide both more accurate forecasting methods and a scientific approach for controlling these inventories by finding the reorder points for a given service level and considering trade-offs between the production lead times and the safety stock needed for those.

1.4. Research questions

The research questions of the thesis are the following:

- RQ 1. How to forecast the demand of the products sold in the independent aftermarket segment with sporadic patterns?
- RQ 2. How to control inventory levels of the same group of products?

1.5. Research limitations

As it can be inferred from the research questions, this project will limit its scope to what the company calls Independent Aftermarket products. This is because the spare parts sold to the IAM customers currently use very rudimentary and intuition based planning methods and their sporadic demand patterns make them especially hard for the company to control. Even though the focus market is challenging, TitanX is enriching the product portfolio to gain a bigger market share because of the profitable nature of the aftermarket products. Another limitation of this project is the consideration of only the (R, Q) inventory policy as well as the order quantities/batch sizes (Q) used by the company.

1.6. Contribution to knowledge

This degree project will have practical contributions by understanding how the company should set the reorder point for these products with very specific characteristics and high variation under fast growing market conditions. To do so, a new forecasting tool specific for this special kind of products will be the focus and contribution provided in this project.

It will also support a more theoretical contribution to the issue of spare part management, since this subject has a limited number of conducted studies, by providing guidance for the application in similar cases as the one being studied of categorization and forecasting methods for erratic and/or intermittent demand products, some of which may also be presenting seasonality.

Finally, on a personal level an improvement in problem-solving skills is expected, especially within mathematical modelling of inventory control problems, and will also acquire project management abilities.

2. Methodology

As the need for a systemic approach to help carry out and structure the project's efforts arises, the merits of a more deductive approach to research in contraposition to the more inductive one, become apparent. Deductive reasoning is the process of reasoning from one or more general statements regarding what is known to reach a logically certain conclusion (Johnson-Laird, 2000); (Rips, 1999); (Williams, 2000), and since the company is interested in finding applicable, empirical results that can improve the current forecast and inventory control systems for IAM products, taking advantage of the already existing literature seems the fastest and safest way to do that. Thus, the inductive task of reasoning from specific facts or observations to reach a likely conclusion that may explain the facts Johnson-Laird (2000) is not going to be the most prevalent in this thesis.

In the following lines, the different methods used during this project will be mentioned and explained. Qualitative approaches will have their representation in the use of interviews, and quantitative ones will have theirs in Mathematical Modeling.

For the reason cited in the first paragraph, this chapter also explains "Operations Research" as the approach used to discretize the project into a sequence of steps to reach the project's final goals. These steps will be covered in more detail in section 2.1.

Eventually, the methods used to gather the required data will be exposed and expanded upon, to better explain the particularities of their application in this project.

2.1. Research method

To study the illustrated case methodically, a quantitative model-driven empirical research method will be practiced.

Kotzab et al. (2005) explained that quantitative model-driven empirical research deals with real life data as well as situations and offers. The same authors noted that empirical model-driven quantitative research is crucial when more practically relevant problems are considered. It is also emphasized that this type of research can be used to validate operations research models in real-life supply chain processes. Thus, operations research approach will be applied to solve the real-life problem that was specified in the first chapter. Winston and Goldberg (2004) defined the operations research as simply a scientific approach to decision making that seeks to best design and operate a system, usually under conditions requiring the allocation of scarce resources. Liebermann & Hillier (2001) described all the major phases of a typical operations research (OR) modeling approach as the following:

1. *Define the problem of interest and gather relevant data.*
   In general, OR teams receive the description of encountered problems in an imprecise way. So, primarily it must be studied the relevant system and developed a well-defined statement of the problem. This involves specifying the appropriate objectives, constraints

on what can be done, interrelationships between the area to be studied and other areas of the organization, feasible alternative courses of action, and time limits for deciding. This effort enables the developers to find the relevant conclusions of the study.

The important thing to be aware of is that an OR team needs to work in an advisory capacity. This means that team members are considered not only as problem solvers but also as advisers of the company's management team. Therefore, the team should analyze the problem in detail and then present the recommendations. The report will determine the alternatives that are specifically attractive under different assumptions or over a different range of values of some policy parameters that are comprehensible only for managers. Management will make the final decision through evaluation of the study and the recommendations considering a variety of intangible factors. Thus, the OR team must agree on the same perspective with managers to build a support for the improvement.

Data collection can be considered as an initial phase to provide the mathematical model. Much of the needed data will not be available at the beginning of the study, since it is possible that required data never has been kept or data at hand is outdated or kept in the wrong form. Thus, it is recommended to install a new computer-based management information system to gather required data continuously and in the needed form. On the other hand, the OR team may face too much available data, so that it is measured in gigabytes or terabytes. Under this circumstance, a technique that is called data mining would be a solution to process the relevant data.

2. *Formulate a mathematical model to represent the problem.*

Once the decision maker defines the problem, the next phase will comprise the reformulation of the stated problem in a form that is convenient for analysis. Usually, the OR approach is to develop a mathematical model that reflects the essence of the problem. Mathematical models refer to idealized representations, including mathematical symbols and expressions like $F = ma$ in physics. The mathematical model for a business problem also describes the essence of the problem with the system of equations and related mathematical expressions.

Basically, mathematical models contain decision variables, an objective function, constraints and parameters. If there are *n* related quantifiable decisions to be made, decision variables (say, $x_1, x_2, \ldots, x_n$) are used to represent those values that need to be determined. The measure of performance will be expressed as a mathematical function of these decision variables (e.g. $P = x_1 + 3x_2 + \ldots + 5x_n$), and it is called objective function. If there is any restriction on the values that would relate to these decision variables they are mathematically expressed with inequalities or equations (e.g. $2x_1 + 4x_1x_2 + 6x_2 \leq 8$) and these kinds of expressions for the restrictions often are called constraints. The constants in the constraints and the objective function are named as the parameters of the model. The mathematical model might then indicate that the problem intents to choose the values of the decision variables to maximize the objective function subject to the specified constraints.

Model building can be started with a very simple version, and then it can be modified toward more elaborate models to reflect the complexity of the real problem. This process is called model enrichment and lasts if the model remains tractable.

3. *Develop a computer-based procedure for deriving solutions to the problem from the model.*

   In OR study, the model formulation phase will continue with developing a procedure (usually a computer-based procedure) for deriving solutions to the problem from the model. This step might be considered relatively simple, since a proper algorithm of OR is applied in one of the available software packages. The OR study investigates an optimal or best solution; however, it must be noted that the optimal solution is valid only with respect to the model being used just because the formulated model represents the idealized form of the problem. Therefore, it is not guaranteed that the optimal solution for the model will be the best possible solution to implement for the real problem. However, once the model is well formulated and tested, it will give a resulting solution that offers a good approximation to an ideal course of action.

   After finding an optimal solution, postoptimality analysis should be conducted. This process is sometimes verbalized as what-if analysis because it is an ongoing process based on the following question, what would happen to the optimal solution if different assumptions are made about future conditions. Moreover, sensitivity analysis is considered as part of the postoptimality analysis to determine which parameters of the model are most critical. Those sensitive parameters of the model require exceptional care to avoid distorting the output of the model.

4. *Test the model and refine it as needed.*

   When a large mathematical model is developed, it must be expected to develop a large computer program in some way. The initial version of the computer program naturally contains many bugs, so it must be tested successively to seek out and correct as many of them as possible. At the end of the continuous improvement process, the programmer needs to feel that the final program is giving reasonably valid results. Of course, some minor bugs may not be detected, however, the major bugs have been eliminated and hence the program can reliably perform.

   In addition to bugs, the initial version of the computer program typically contains many flaws that originate from relevant factors or interrelationships which have not been incorporated into the model. Furthermore, some parameters that are accounted inaccurately will also cause the flaws. Thus, before applying the model, it must be tested carefully to detect and eliminate as many flaws as possible. Once the model is improved sufficiently, the OR team can claim that the current model is now giving reasonably valid results. This testing and improvement process is commonly called model validation. The model validation process differs depending on the nature of the problem at hand and the formulated model. However, the OR team would start the model validation with an overall observation to check the model for obvious errors or oversights. It is recommended that the controlling group should include at least one individual who did not participate in the model building process. The definition of the problem might be reexamined and further it can be compared with the model to reveal the mistakes. It should also be considered whether all the mathematical expressions are dimensionally consistent in the units used. Lastly, the model can be validated through changing the values of the parameters and/or the decision variables while observing the model behavior.

5. *Prepare for the ongoing application of the model as prescribed by management.*
   When the testing phase has been completed with an acceptable model, it must be installed a well-documented system for applying the model as prescribed by the manager which helps to use the model repeatedly, which will consist of an instruction handbook with the steps for application as well as explanations of the components found in the input and output interfaces. The required system will consist of the model, solution procedure (including postoptimality analysis), and operating procedures for implementation. This system be computer-based. Indeed, several computer programs often need to be used in harmony, such as databases and management information systems may contribute up-to-date input to run the model each time. One another program is applicable to the model for generating the implementation of the results automatically. In other cases, a decision support system can be installed to help managers use data and models while supporting the decision-making process. It also exists a program to create managerial reports that interpret the output of the model and its implementations for the application.

6. *Implement.*
   When a system is developed for the model, the last phase of an OR study will be the implementation of the system as prescribed by management. The benefits of the study are only occurred here, so that the OR team should participate into the implementation phase to check how the model solutions are accurately translated to an operating procedure and to eliminate any flaws in the solutions that have not handled yet. To carry out this phase successfully, the OR team needs to gain the support of both top management and operating management. Therefore, the OR team should inform management and further encourage the management's active guidance throughout the course of study to ensure that the study matches with their requirements and they have a greater sense of ownership.

The following steps can be used for the implementation phase. First, the OR team explains to operating management how the new system will be adopted and how it relates to operating realities. Then, both parties need to collaborate to develop the procedures required to put this system into operation. After that, operating management monitors that a detailed indoctrination is given to the personnel involved, and the new course of action is initiated. If the new system works successfully, it may be used for years in the same form. Although the system works well the OR team must track the initial experience with the course of action taken to find required modifications that should be attained in the future.

2.2. Quality Assurance

In the previous section, it is explained how to test the model as part of the OR approach. Nevertheless, this assessment should be elaborated in detail having both a verification and validation plan.

2.2.1. Validation

Validation is executed when the developers need to compare the behaviors of the model and the real system. Thus, this process allows to make some adjustments through comparison of the real system and the model. Banks et al. (2005) emphasized a three-step approach for the validation process:

1. *Build a model that has high face validity*.
   In this study, the model will be developed in Excel environment, therefore it is possible to illustrate the input and output clearly.

2. *Validate model assumptions*.
   It will be done through observation of real scenarios and if time allows it, by statistical testing. Required assumptions will be specified in the following chapters.

3. *Compare the model input-output transformations to corresponding input-output transformations for the real system.*
   This approach will be applied for analyzing the results of the model.

2.2.2. Verification

Model verification enables the developers to assure if the conceptual model (representation of real system) is reflected accurately in the operational model (computerized representation). The conceptual model usually comprises some degree of abstraction regarding system operations or some amount of simplification of actual operations. Therefore, it should be investigated whether the conceptual model (assumptions about system components and system structure, parameter values, abstractions, and simplifications) is represented properly by the operational model. (Banks et al., 2005)

The same source provided the following considerations to verify the model that will be developed in this study. The only consideration that will not be used is *verifying that what is seen in the animation imitates the actual system*, due to the operational model not being animated.

1. *Have the operational model checked by someone other than its developer.*
   The model is going to be shown to the supervisors at the company throughout the project.

2. *Make a flow diagram that includes each logically possible action a system can take when an event occurs, and follow the model logic for each action for each event type.*
   A full decision making diagram of the inventory control model will be prepared.

3. *Closely examine the model output for reasonableness under a variety of settings of the input parameters. Have the implemented model display a wide variety of output statistics, and examine all of them closely.*
   Reasonableness will be examined by comparing the model outputs with current numbers together with the company expertise. Moreover, the model behavior will be observed multiple times with the applications of different adjustments over input data and coefficients.

4. *Have the operational model print the input parameters at the end of the simulation, to be sure that these parameter values have not been changed inadvertently.*
   The input parameters will be kept in an Excel worksheet (Appendix I).

5. *Make the operational model as self-documenting as possible. Give a precise definition of every variable used and a general description of the purpose of each submodel, procedure (or major section of code), component, or other model subdivision.*
   During the model building process each variable, submodel and procedure will be defined within the program.

6. *The Interactive Run Controller (IRC) or debugger is an essential component of successful simulation model building.*
   The debugging tool will be used to check if any errors exist. Besides the code can pause to check the status of the variables.

7. *Graphical interfaces are recommended for accomplishing verification and validation. The graphical representation of the model is essentially a form of self-documentation. It simplifies the task of understanding the model.*
   The interface is an Excel file that shows the input and output data as well as buttons to choose the confidence interval for the forecasted values, and to run the code.

2.3. Data collection

2.3.1. Interview

The semi-structured interview seeks to obtain descriptions of the interviewee's point of view with respect to interpreting the meaning of the described phenomenon; it will have a sequence of themes to be covered, as well as some suggested questions (Kvale, 2011). To understand the current forecasting and inventory control system of the case company, semi-structured interviews will be conducted together with the following departments: logistics and supply chain, production and sales.

The procedure by Kvale (2011), is the following:

1. *Setting the interview stage (briefing).*
   Creation of an environment in which the interviewee feels comfortable to explain their point of view. It is done by allowing them to have a grasp of the interviewer and the nature of the conversation, and by the interviewer showing respect and interest and listening actively.

2. *Scripting the interview.*
   Development of two lists of questions: one with the project's main research questions in academic language, and another with the research questions translated into interview questions that can be understood by the interviewee.

3. *Conducting the interview.*
   The interview must have a sequence of themes to be covered as well as some prepared questions, yet at the same time, there should be openness to changes of sequence and question forms to follow up the answers and stories given. At the same time the quality of the interview relies on the interviewer's ability to apply different techniques such as allowing a pause for the interviewee to continue an answer, probing for more information and attempting to verify the answers given.

4. *Analysis of results.*
   Finally, notes or other material obtained from the interview must be analyzed and relevant conclusions must be drawn.

The interviews conducted throughout the project with the purpose of data collection, will mainly be using a semi-structured style and sometimes unstructured. For the semi-structured case, the following steps will be used most often:

Preparation of the interview:

1) Scripting the interview by preparing which questions to ask and which language to use.
2) Prioritization of questions by putting first those questions with higher importance.
3) Setting up premises for the interviewee to know what type of answers are expected from him.

Development of the interview:

4) Actively listening and showing respect towards the interviewee.
5) Asking questions simultaneously between the two interviewers with room for improvisation.
6) Allowing the interviewee to lead the conversation towards other topics if deemed interesting.

Debriefing of the interview:

7) Further discussion between the interviewers to agree on conclusions.

2.3.2. Direct observation

Direct observation is a method of collecting evaluative information in which the evaluator watches the subject or activity unfold in its usual environment without altering it (Holmes, A. 2013), and will be carried out by visiting the TitanX production facilities in Mjällby.

The procedure is the following:

1. *Planning.*
   Preparation of an observational form, allowing the observer to record the occurrence of different activity categories. This must be done after a period of unstructured observation to have a good grasp of the situation.

2. *Observation.*
   During this step, the observer must write down or capture in some way all the relevant information for further analysis.

3. *Data analysis.*
   Treatment of the raw data from the direct observational studies, for example by counting frequencies or durations of different activities.

2.3.3. Literature review

A literature review is an account of what has been published on a topic by accredited scholars and researchers (Taylor, D., & Procter, M. 2008).

The procedure is explained by Liston, K. (2011) in the following lines:

1. *Find resources related to the topic of interest.*
   Sources of information must be obtained regardless of format impact or presentation of the information.

2. *Exploration.*
   During this step, the found resources must be read and relevant information must be outlined, structured and analyzed.

3. *Focus review.*
   Discussion of the scope of the research and contributions to the work.

4. *Refine review.*
   Documentation and organization of the information used, and explanation of how the review has affected the project's research.

2.3.4. Data provided by the company

For this type of data, the company will provide the information already collected and stored in their databases during the last two years (2015 and 2016). The processing of the information into understandable structures for further use will be carried out using different approaches.

One of them will be data mining from the company's main software to extract valuable data sets for further use in the project. This process will be carried out by the supervisors at TitanX.

Once this information has been extracted, another approach that will be used is the manual check of the data found in the excel files which will be further explained in the empirical data chapter. The purpose of this second approach is the elimination of errors and the adjustment for possible missing data.

Finally, another approach will be the use of Python programming language to prepare data for its later use in the forecasting tool.

3. Theory

The theory chapter is divided into two main groups; forecasting and inventory control. Particularly, forecasting has a focus on items with intermittent demand pattern, while inventory control covers the single echelon systems. Forecasting will be used to provide a better insight on the demand patterns that the different IAM products are expected to have as well as to feed the inventory control tool created in this project and inventory control will be used to know the different reorder points as well as to gain better insight on the leverage of lead times compared to the necessary safety stocks to meet the desired service levels.

3.1. Forecasting

For this project, several forecasting approaches have been taken into consideration, such as the use of Bootstrapping methods reviewed by Smith, M., & Babai, M. Z. (2011) or the use of neural networks (Kourentzes, N., 2013). These are not going to be explained because of their complexity and lack of relation to this project. A categorization procedure for forecasting purposes was chosen as it is an alternative that has been studied and reviewed by many authors. For instance, Bucher and Meissner (as cited in Altay and Litteral, 2011), provide a satisfactory performance for the group of items that is being studied and is accessible to the company in terms of its simplicity.

In this chapter, demand categorization schemes are explained first. The one used for this project is expanded and its parameters and their respective calculations are also shown. Next, a five-step process for the implementation of a demand categorization scheme is presented, the possibility of seasonal and trended demand patterns is considered and finally, the chosen forecasting methods are mentioned together with their procedures and formulas.

3.1.1. Demand patterns

The company was interested in analyzing the historical demand data of their products to find possible patterns that would give a better understanding of them as well as to improve the accuracy of the forecast and inventory control tools being developed. Mainly two types of patterns were expected by the supply chain team: seasonal effect and trend.

Seasonality is a repeated pattern of spikes or drops in a time series associated with certain times of the year (Bozarth and Handfield, 2008). Time-series plots, seasonal subseries plots, box plots and autocorrelation plots will also be used as they help visualize seasonal patterns (6.4.4.3. Seasonality, 2017).

Trend represents a long-term movement, up or down, in a time series. (Bozarth and Handfield, 2008). For this case, the same analysis as the one explained in the previous paragraph is carried out.

Aside from those items with the special demand patterns mentioned in the previous paragraphs and where alternative methods and more careful attention will be required, Bucher, D., & Meissner, J., (2011), authors of the five-step process for the implementation of a demand categorization scheme explained in the following paragraphs, noted a configuration of the forecasting categorization scheme which considers four different patterns based on the mean inter-demand interval (p) and squared coefficient of variation of the order sizes (CV^2), as seen in *Figure 3.1:*

Smooth: Short time between orders and low variance of the order sizes.
Slow: Long time between orders and low variance of the order sizes.
Erratic: Short time between orders and High variance of the order sizes.
Lumpy: Long time between orders and High variance of the order sizes.

As you can see in *Figure 3.1.* smooth and erratic categories have more demand points in historic data, conversely slow and lumpy ones have many periods with zero demand. In addition, the similar structure exists for demand variation where high variation occurs for erratic and lump categories as well as more consistent demand size for smooth and slow products.

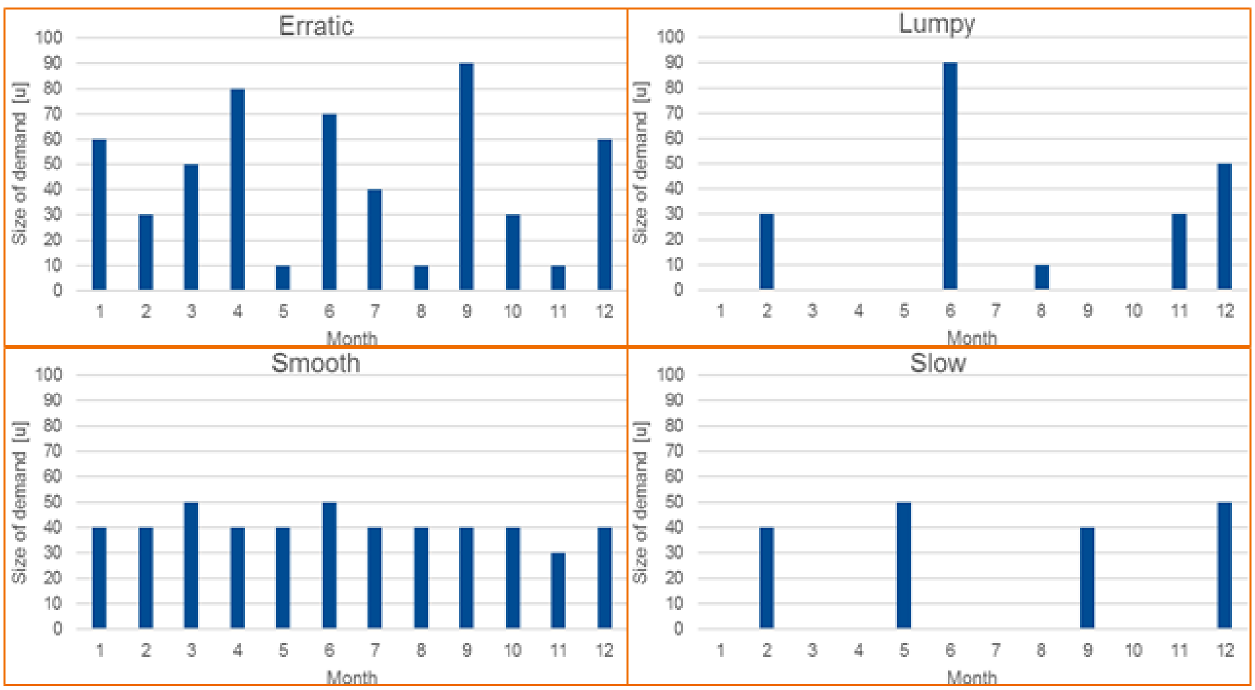

Figure 3. 1 - Graphic representation of different demand patterns.

3.1.2. Demand segmentation

The classification of the various products within the portfolio of a company is a topic that has attracted many studies in the past. The main objective here is to help identify the regions that differ in suitable method for forecasting in order to improve the forecasts which in turn should lead to cost reductions and/or service level improvements.

One of the first categorization schemes, and still to this day a very popular one, is the ABC-analysis (Dickie, 1951), that classifies products in one of three categories (A, B or C) in a decreasing fashion, according to the benefit they report to the company or the size of the demand. This analysis is currently being used in the company with the purpose of prioritizing the production of the different items and will also be used later in this project to obtain the production lead times of the various products as shown in the empirical data section of chapter 4. Even though ABC analysis is applicable for demand pattern categorization, it is not the main purpose of this method, since it does not consider any information regarding demand patterns, but it is mentioned as a precursor to other categorization schemes that appeared during the decades after.

Williams (1984) was the first author to examine intermittent demand patterns in his categorization by using the concept of variance partition. In his work, he calculates the squared coefficient of the variation of demand during the lead time as seen in *Equation 3.1*

$$CV^2{}_{DDTL} = \frac{1}{\lambda L} + \frac{CV^2}{\lambda L} \qquad (3.1)$$

where L: lead time; $CV^2{}_{DDTL}$: squared coefficient of demand size variation during the lead time; CV^2: the squared coefficient of variation of the distribution of the demand sizes; λ: Mean number of arrivals per time unit.

The first term represents the mean number of lead times between demands whereas the second term relates to the lumpiness of demand, and both parameters are later used to categorize a product sample.

Johnston and Boylan (1996) showed that the Croston forecasting method outperforms the exponentially weighted moving average (EWMA) method robustly over a wide range of parameter settings, when the average inter-demand interval is greater than 1.25 forecast revision periods. This study showed the importance of intermittence as a parameter to consider when setting up a categorization scheme for your products.

Eaves (2002) took the categorization made by Williams one step further, adding a parameter to consider lead time variability. Since then, lead time variability has remained as a topic for further research.

Finally, the categorization used in this project is the one by Syntetos et al. (2005), who were the first to create a categorization scheme close to achieving universal validity, using the inter-demand interval (p) and the coefficient of variation of the demand size (CV^2), which will be touched on later (not to be confused with $CV^2{}_{DDTL}$ from Williams (1984)).

Formulas of p and CV^2 can be seen in *Equation 3.2* and *Equation 3.3*. The calculation of p is an approximation used by the authors of this project based on the interpretation of the same article and is explained in the following lines (n: number of periods with demand; t_i: period i=1...T; σ: standard deviation; µ: mean).

$$p = \frac{\sum_{i=1}^{n-1} t_i}{n-1} = \frac{T}{n-1} \tag{3.2}$$

$$CV^2 = \frac{\sigma^2}{\mu^2} \tag{3.3}$$

Bucher, D., & Meissner, J., (2011) developed the basic steps for the implementation of a demand categorization scheme. This framework is especially interesting for organizations that keep a high number of SKUs and so desire to increase both the level of automated inventory management and the overview of their inventories, by grouping spare parts using factors in line with a single-echelon system configuration. The following five steps are defined to be a guide especially for the considerations of categorization. The framework for the implementation of a categorization scheme can be seen in *Figure 3.2*.

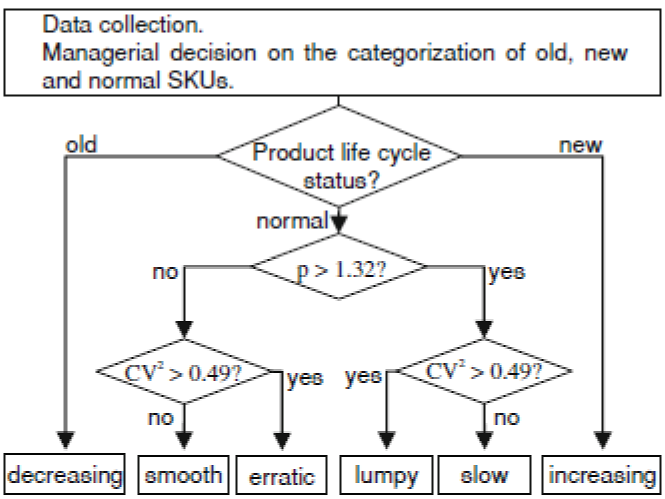

Figure 3. 2 - The framework for the implementation of a categorization scheme (Bucher, D., & Meissner, J., 2011).

1. In this step, the historic demand data should be collected for all SKUs of the spare parts inventory. Commonly, this information can be gathered from reports of the corporate ERP system.
2. The authors formed the first categorization factor by considering the status of an item in the product life cycle and those are normal, new and old SKUs. The reason is to differentiate new and old SKUs as they are usually very difficult to predict with parametric forecast. Then they would be managed either manually or with other best practice methods. On the other hand, distinguishing each SKU is a time consuming manual process. Thus, a factor can be assigned, such as the cumulative demand of the last 12 months might be compared to the cumulative demand of the last 36 months to detect either decreasing or increasing demand trend. Lack of historic demand records indicates that it might be a newly introduced item.

3. When the normal SKUs differentiated from new and old ones, the average inter-demand interval p and the squared coefficient of variation of demand size CV^2 can be determined from historic demand data for each item.
4. The values that are calculated in the previous step will be used to categorize the SKUs according to the illustrated scheme. Afterwards, the single-echelon inventory system can be configured for each SKU with respect to the assigned methods.
5. Eventually, it is recommended to re-group the products on a yearly or a more frequent basis. This process is important to keep the results as trustable especially when SKUs change over from new to normal and from normal to old.

3.1.3 Forecasting methods

The forecasting methods for a categorization scheme of intermittent demand products recommended by Bucher, D., & Meissner, J., (2011) are Croston and the Syntetos and Boylan Approximation (SBA). The methods chosen in this project will be motivated during the analysis chapter.

In the following lines, the theoretical iterative processes for the different forecasting methods used are explained.

Croston and SBA method:

Step 0: Initialization of the process using the first τ periods.

For initialization purposes, the initial value for the size of the estimated demand (z_0), is equal to the initial value of the mean demand (μ_0) which is calculated as the mean demand size of the periods where demand has occurred, only considering the first τ periods. The initial value of p (p_0) is also the one calculated for the first τ periods. Finally, q is the time until the next demand during the current iteration, and is initialized to zero. $\mu_0 = \mu_\tau$; $z_0 = \mu_0$; $p_0 = p_\tau$; $q = 0$. If there is no demand then $\mu_0 = 1$; $z_0 = 1$; $p_0 = \tau$; $q = 0$.

Step 1: Start of the iterative method at period τ +1 (until period T).

For period t = τ +1 to T:

If $y_t = 0$:

$$p_t = p_{t-1}$$
$$z_t = z_{t-1}$$
$$q = q + 1$$

Else:

$$p_t = p_{t-1} + \alpha_i(q - p_{t-1})$$
$$z_t = z_{t-1} + \alpha_s(X_t - z_{t-1})$$
$$q = 1$$

where p_τ and z_τ denote the estimates of inter-demand interval and demand size.

Step 2: Forecast.

Once z_T and p_T are obtained, the iteration ends. Finally, the forecast in units/period (F_t) is defined in *Equation 3.4* and *Equation 3.5* are calculated:

- Croston: $F_t = {z_T}/{p_T}$ *(3.4)*
- SBA: $F_t = \left(1 - \frac{\alpha_i}{2}\right) \cdot {z_T}/{p_T}$ *(3.5)*

where α: smoothing coefficient; F_t: forecast in demand/period.

Simple Exponential Smoothing (SES):

Step 0: Initialization (Using the first month)

The output of the first iteration of the SES algorithm (S_0) will be equal to the demand of the first period.

$S_0 = X_0$

Step 1: Iterative method.

The forecast for the following periods will be calculated with *Equation 3.6*:

$$S_t = \alpha \cdot x_t + (1 - \alpha) \cdot S_{t-1} \tag{3.6}$$

where S_t and X_t denote the forecast and the real demand in period t. Further, αagain refers to the smoothing coefficient.

Step 2: Forecast.

Once the iterative method ends, the demand forecast for the next period as well as variance (as seen in *Equation 3.7*) are calculated:

$$VAR = \frac{\sum_{t=1}^{T}(X_t - S_{t-1})^2}{T-2} \tag{3.7}$$

where T is the total number of periods.

On the other hand, the company believes that products with a certain increasing/decreasing trend as well as seasonality exist within the company's aftermarket portfolio. The *Holt-Winters* method is a promising option to forecast these products since it adapts to both additive and multiplicative seasonality and/or trend, all in one method. Additive seasonality or trend for monthly data assumes that the difference between the January and July demand values is approximately the same each year, while the multiplicative case implies that the July value is the same proportion higher than the January value in each year (Time series forecasting:

understanding trend and seasonality, 2014). The analysis conducted in chapter 5 proved that there is no perceivable seasonality and that there are a very limited number of products with a trend pattern. Therefore, the application of this method is not necessary for this project.

Aggregation level

In addition to the application of the methods, and to improve their performance, following recommendations by Nikolopoulos et al. (2011), for each data set there is a certain level of aggregation of the data into time buckets which may improve forecast accuracy. For example, the same authors recommend the review period plus the lead time as a promising alternative, since in a practical inventory setting, it would make sense to set this aggregation level, as cumulative forecasts over that time horizon are required for stock control decision making (Nikolopoulos et al., 2011).

To be able to compare errors for different aggregation levels, Axsäter (2006) suggested *Equation 3.8*. If the assumption of normal distribution of the forecasting errors is accepted, *Equation 3.9* is valid (Axsäter, 2006) and therefore *Equation 3.8* can be applied for the case of MAD resulting in *Equation 3.10*. Therefore, if the effects of auto-correlation are not taken into consideration, monthly MAD can be converted to weekly dividing by $\sqrt{4weeks}$.

$$\sigma(L) = \sigma_t \sqrt{L} \tag{3.8}$$

$$\sigma = \sqrt{\pi/2}\, MAD \approx 1{,}25 MAD \tag{3.9}$$

$$MAD(L) = MAD_t \sqrt{L} \tag{3.10}$$

Exponential smoothing coefficient (α)

Axsäter (2006), recommended the use of *Equation 3.11* to calculate the smoothing coefficient, which implies that α changes based on the aggregation period, as, for example, a data set of 12 months (N=12) will now have an N of 52 if the aggregation is changed from monthly to weekly.

$$\alpha = 2/(N+1) \tag{3.11}$$

Where N: number of periods used in the forecast.

By using *Equation 3.11* the average age of the used data is ensured to be the same for both SES and Simple Moving Average (SMA) forecasting procedures with a rolling horizon of N (Axsäter, 2006).

It is also important to note that a smaller α has the effect of putting relatively more emphasis on old values of demand.

Forecast accuracy

The most common way to describe variations around the mean is through the standard deviation (σ). In the case of forecast errors, the widespread practice by most of the forecasting software is to use the Mean Absolute Deviation (MAD), as seen in *Equation 3.12* calculated as the expected value of the absolute deviation from the mean. This tradition came from the fact that originally, MAD simplified the computations in comparison to other estimators like σ and σ^2. Nowadays, this is not the case anymore, but due to MAD and σ giving a very similar picture of the variations of the mean in most cases, a need for change has not appeared. (Axsäter, 2006).

$$MAD = E[|X - \mu|] \tag{3.12}$$

Aligning with the conventional procedures in this field, the measurement of forecasting error used will also be MAD.

3.2. Inventory control

According to Axsäter (2006), an inventory control system has a function to determine when and how much to order. It considers the stock situation, the anticipated demand and different cost factors. Therefore, this section will cover primarily different ordering systems, followed by the single echelon systems in terms of resolving the reorder points. It should be noted that this study does not cover determination of the batch size since a certain batch size has already been assigned to each product by TitanX.

A suitable safety stock or reorder point can be determined based on either a prescribed service constraint or a certain shortage or backorder cost. Service level can be defined differently: (Axsäter, 2006)

S_1= probability of no stock out per order cycle,

S_2= "fill rate"- fraction of demand that can be satisfied immediately from stock on hand,

S_3 = "ready rate"- fraction of time with positive stock on hand.

The first definition of service level (S_1) does not take the batch size into account. Therefore, it might not be able to represent the real service level or situation. Instead, in this study, a sufficient reorder point R is investigated to satisfy a given ready rate S_3 (which in the cases of Normal, Poisson and Gamma distributions will be equal to the fill rate S_2 according to Axsäter (2006)). It must be recalled that a continuous review (R, Q) policy is the concern in this study and further the batch quantity Q for each item is given by the case company.

3.2.1. Different ordering systems

According to the 5-steps framework for the categorization of intermittent demand patterns described in section 3.1.2, the periodic review system is recommended for all categories even though other systems are also applicable. Moreover, the dynamic (t, S)-policy will naturally be the choice considering the context of spare parts management, where the order-up-to level S needs to be recalculated in every order period (t) in which demand occurs. Meanwhile, in general the selection of the order-policy does not affect significantly to the inventory performance for intermittent demand. (Bucher, D., & Meissner, J., 2011)

In this section, different ordering policies in terms of continuous and periodic review will be explained. Specifically, continuous review and (R, nQ) policy will be elaborated more in detail, since that is the desire of the company.

Continuous or periodic review

An inventory control system can be designed based on either continuous or periodic review. Before emphasizing the difference between the two, it is necessary to describe the *inventory position* and the *inventory level*. Normally the stock situation implies stock on hand, however, when it comes to an ordering decision, it should also be regarded the outstanding orders that have not yet arrived, and backorders. This explains why the stock situation needs to be represented by the inventory position. (Axsäter, 2006)

It is illustrated as seen in the following expression:

$$inventory\ position = \ stock\ on\ hand\ + outstanding\ orders - \ backorders$$

A parenthesis can be opened here for the event that the customers can reserve units for later delivery. This reserved units should be subtracted from the inventory position unless delivery time is too distant. Inventory position is related to make ordering decisions, but instead the inventory level becomes applicable to reveal holding and shortage cost. (Axsäter, 2006)

It is formulated:

$$inventory\ level = \ stock\ on\ hand - backorders$$

For some cases, the holding costs should also include holding costs for outstanding orders. This would be easily obtained as the average lead time demand. (Axsäter, 2006)

After a brief explanation of the inventory position and the inventory level, we can return to the review systems. The continuous review system refers that the inventory position is monitored continuously and when it is sufficiently low an order is triggered. This order will be delivered after a lead-time which starts once the ordering decision has been made and finishes when the ordered amount is placed on a shelf. Along with the transit time from an external supplier or the production time for an internal order, the lead-time also contains order preparation time, transit time for the order, administrative time at the supplier, and time for inspection for the received order. (Axsäter, 2006)

Alternatively, the inventory position can be assessed only at certain given points in time. This approach is called as periodic review and it offers advantages, especially when it is needed to coordinate orders for different items. Besides, periodic review helps to reduce the costs for the inventory control system specifically for items with high demand. But since the case company evaluates the inventory level several times within a week, continuous review will prevail in this study. Furthermore, it is common to use continuous review for items with low demand in practice and it reduces the needed safety stock. (Axsäter, 2006)

Different ordering policies

Axsäter (2006), expressed the two most common ordering policies about inventory control, namely (R, nQ) and (s, S) policy. The case company prefers to use the (R, nQ) policy since it has been an exercised method until today. As a required alternative, this policy is chosen to build an inventory control solution.

The reorder point-R regulates the ordering decision, meaning that when the inventory position declines to or below the reorder point R, a batch quantity of size Q is ordered. In case that the inventory position is dramatically dropped, it may be necessary to order more than one batch to get above R. (Axsäter, 2006)

The second policy is also like the (R, nQ) policy. Now the reorder point is represented by s and when the inventory position decreases to or below this number, it is ordered up to the maximum level-S. If the reorder point is hit exactly (continuous review and continuous demand), the two policies can be considered as equivalent provided $s = R$ and $S = R + Q$. (Axsäter, 2006)

3.2.2. Single-echelon systems determining reorder points

The purpose of this study is developing a model to find the reorder points or safety stocks for a given service level, which helps to test the effect of different service conditions on safety stock. Furthermore, with an inventory control model, reorder points can be evaluated for lead-time changes easily. To formulate this problem, the demand distribution of the products must be shown. In forward part, inventory level distributions will also be described since it is needed in the service level calculation.

Demand distributions

Axsäter (2006) suggested the use of different theoretical demand distributions to model the real demand distributions seen for each of the products.

The demand during a certain time is a discrete stochastic variable as it is nearly always a nonnegative integer. If the demand is reasonably low, it is then natural to use a discrete demand model, which resembles the real demand. On the other hand, when the demand is relatively large, it is more practical to use a continuous demand model as an approximation. (Axsäter, 2006)

According to Bucher, D., & Meissner, J., (2011), different theoretical distributions are recommended to approximate the empirical demand distributions. It is expected that the normal distribution will bring a good description of the empirical distributions for the erratic and smooth categories. Furthermore, Boylan et al. (2008) used the Poisson distribution for the slow category and the negative binomial distribution for the lumpy category. Finally, the single-echelon configurations for each category can be seen in *Figure 3.3*.

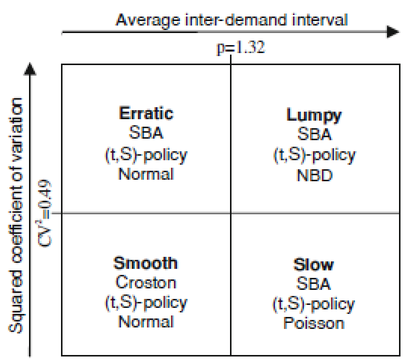

Figure 3. 3 - Categorization scheme for a single-echelon inventory configuration (Bucher, D., & Meissner, J., 2011).

For the discrete demand case, first the pure Poisson together with the compound Poisson demand will be described, and later it will be shown the logarithmic compounding distribution. In stochastic inventory models, it is commonly assumed that the cumulative demand can be modeled by a non-decreasing stochastic process with stationary and mutually independent increments. It is possible to represent this process as a limit of an appropriate sequence of compound Poisson processes. Consequently, the demand is often assumed that it follows a compound Poisson process. In depth, the customers arrive corresponding to a Poisson process with a certain intensity λ. Further the size of a customer demand is also a stochastic variable. (Axsäter, 2006)

Demand distribution formulas

The probability of having only one customer is expressed as $\lambda\Delta t$ for a brief time interval Δt,at the same time the probability for more than one customer can be disregarded. Eventually, the number of customers in a time interval of length *t* has a Poisson distribution and the probability for the k customers is represented with *Equation 3.13*. (Axsäter, 2006)

$$P(k) = \frac{(\lambda t)^k}{k!} e^{-\lambda t}, \quad k = 0, 1, 2, \dots \qquad (3.13)$$

The average and the variance of the number of customers are calculated through λt. Compound Poisson demand denotes that the size of a customer demand indicates also a stochastic variable which does not depend on the other customer demands and the distribution of the customer arrivals. The distribution of the demand size determines the compounding distribution. It can be assumed that each customer requires an integral number of units. Probability of demand size j is illustrated by f_j (for j = 1, 2, ...), when f_1= 1 the demand process degenerates to pure Poisson demand. In this case, the demand will equal to the number of customers and the demand distribution will be as shown by *Equation 3.13*. (Axsäter, 2006)

Another discrete distribution is the logarithmic compound distribution. When the demand size has a logarithmic distribution, the probability of the demand size *j* can be represented as seen in *Equation 3.14*.

$$f_j = -\frac{\alpha^j}{\ln(1-\alpha)j} \quad j = 1, 2, 3, \ldots \tag{3.14}$$

where $0 < \alpha < 1$. The mean and the variance of this distribution are respectively given in *Equation 3.15* and *Equation 3.16*. (Axsäter, 2006)

$$E(J) = \frac{\alpha}{(1-\alpha)\ln(1-\alpha)}, \tag{3.15}$$

$$Var(J) = -\frac{\alpha(\ln(1-\alpha)+\alpha)}{(1-\alpha)^2(\ln(1-\alpha))^2}. \tag{3.16}$$

The distribution of the demand *D(t)* during the time *t* can be determined with a simpler way compared with the compound Poisson process. Because now it is acceptable to show that *D(t)* has a negative binomial distribution. The initial probability is $P(D(t) = 0) = (1-p)^r p^k$, and the rest can be calculated with *Equation 3.17*. (Axsäter, 2006)

$$P(D(t) = k) = \frac{r(r+1)\ldots(r+k-1)}{k!}(1-p)^r p^k, \quad k = 1, 2, \ldots \tag{3.17}$$

The parameter *r* is any positive number while *p* is restricted between 0 and 1. The negative binomial distribution represents *E(D(t)) = rp/(1 - p)* and $Var\big(D(t)\big) = \frac{rp}{(1-p)^2}$,. Therefore, for the given mean and standard deviation during the lead time ($\mu' = \mu L$ and $\sigma' = \sigma L$), the unknown parameters can be figured as illustrated in *Equation 3.18* and *Equation 3.19*. (Axsäter, 2006)

$$p = 1 - \frac{\mu'}{(\sigma')^2} = \alpha, \tag{3.18}$$

$$r = \mu' \frac{(1-p)}{p}. \tag{3.19}$$

The Poisson distribution is computationally efficient in practice; however, it is valid only if $\frac{(\sigma')^2}{\mu'} = 1$. In theory, it is recommended to use the Poisson distribution for $0.9 \leq \frac{(\sigma')^2}{\mu'} \leq 1.1$. If

$\frac{(\sigma')^2}{\mu'} > 1.1$. then it is efficient to apply to the negative binomial distribution, which refers compound Poisson demand with a logarithmic compounding distribution. (Axsäter, 2006)

For continuous demand models, the normal and gamma distributions are applicable. The normal distribution is commonly used for many reasons. The central limit theorem shows that a sum of many independent random variables will have a distribution that is approximately normal which is convincing under very general conditions. (Axsäter, 2006)

The demand generally comes from several independent customers. That makes the normal distribution to be a reasonable representative. In addition, the discrete demand from a compound Poisson process will become approximately normally distributed when the considered period is long enough. Furthermore, because of its simplicity the normal distribution seems appealing, however it has also an issue since there is always at least a small probability for negative demand. Therefore, some results which are exact for compound Poisson demand will be only approximately true for normal demand. (Axsäter, 2006)

The gamma distribution does not include negative demand and its density function is expressed in *Equation 3.20* (Axsäter, 2006).

$$g(x) = \frac{\lambda(\lambda x)^{r-1} e^{-\lambda x}}{\Gamma(r)}\ , x \geq 0. \tag{3.20}$$

The two parameters r and λ can only take positive values, and $\Gamma(r)$-the gamma function is denoted in *Equation 3.21* (Axsäter, 2006).

$$\Gamma(r) = \int_0^\infty x^{r-1} e^{-x}\, dx\ . \tag{3.21}$$

Its mean and variance are respectively expressed as r/λ, r/λ^2. Moreover, when μ' and σ', are given, it can be easily calculated the corresponding unique parameters r and λ as seen in *Equation 3.22* and *Equation 3.23*. (Axsäter, 2006)

$$r = \left(\frac{\mu'}{\sigma'}\right)^2, \tag{3.22}$$

$$\lambda = \frac{\mu'}{\sigma'^2} \tag{3.23}$$

Distribution of the inventory level

The corresponding relationship is derived for normally distributed demand. The continuous inventory position is assumed uniformly distributed on the interval [R, R + Q] in case the probability of negative demand is negligible. Furthermore, $\mu' = \mu L$ and $\sigma' = \sigma L^{1/2}$are respectively gives the mean and the standard deviation of the lead time demand. It should also be noted *f(x)* and *F(x)* denote the density and the distribution function of the inventory level in steady state. The distribution function then is formulated in *Equation 3.24*. (Axsäter, 2006)

$$F(x) = P(IL \leq x) = \frac{1}{Q}\int_R^{R+Q}\left[1 - \Phi\left(\frac{u-x-\mu'}{\sigma'}\right)\right]\,du\,. \qquad (3.24)$$

If the inventory position *u* at time *t*, the inventory level at time $t + L$ is less or equal to *x* when the lead-time demand is at least *u* - *x*. From this point, the loss function G(x) is introduced as shown in *Equation 3.25.* (Axsäter, 2006)

$$G(x) = \int_x^{\infty}(v - x)\varphi(v)dv = \varphi(x) - x\big(1 - \Phi(x)\big)\,. \qquad (3.25)$$

Besides, the below *Equation 3.26* allows a modification on the distribution and density function (Axsäter, 2006).

$$G'(x) = \Phi(x) - 1 \;\leftrightarrow\; -G'(x) = 1 - \Phi(x)\,, \qquad (3.26)$$

By using the above expression in *Equation 3.24*, the distribution function is restructured as:

$$F(x) = \frac{1}{Q}\int_R^{R+Q}\left[-G'\left(\frac{u-x-\mu'}{\sigma'}\right)\right]\,du = \frac{\sigma'}{Q}\left[G\left(\frac{R-x-\mu'}{\sigma'}\right) - G\left(\frac{R+Q-x-\mu'}{\sigma'}\right)\right]. \qquad (3.27)$$

(Axsäter, 2006).

Lastly the density function is obtained from the same expression as given in *Equation 3.28*. (Axsäter, 2006)

$$f(x) = \frac{1}{Q}\int_R^{R+Q}\frac{1}{\sigma'}\varphi\left(\frac{u-x-\mu'}{\sigma'}\right)du = \frac{1}{Q}\left[\Phi\left(\frac{R+Q-x-\mu'}{\sigma'}\right) - \Phi\left(\frac{R-x-\mu'}{\sigma'}\right)\right] \qquad (3.28)$$

On the other hand, it can be explained the other set of formulas for discrete demand distributions. To generate inventory level distribution, it will be revised compound Poisson demand, which has the following *Equation 3.29*. (Axsäter, 2006)

$$P(IL = j) = \frac{1}{Q}\sum_{k=\max\{R+1,j\}}^{R+Q} P(D(L) = k - j) \qquad j \leq R + Q\,, \qquad (3.29)$$

It is proven that the inventory level at time $t + L$ can never exceed the inventory position at time *t*, in other words $k > j$(Axsäter, 2006).

For an individual item the probability of having a certain inventory level should be calculated associated with its defined demand distribution. That means $P(D(L) = k - j)$ will vary based on a demand distribution, e.g. it will provide a different result for the Poisson than negative binomial distribution.

Determining service level

For continuous normally distributed demand S_3 can be obtained through the probability of positive stock as shown in *Equation 3.30*. (Axsäter, 2006)

$$S_2 = S_3 = 1 - F(0) = 1 - \frac{\sigma'}{Q}\left[G\left(\frac{R-\mu'}{\sigma'}\right) - G\left(\frac{R+Q-\mu'}{\sigma'}\right)\right] \qquad (3.30)$$

For a fixed service level, it is introduced a simple bisection search to find the smallest R giving the required service level. In this method, R value will take lower and upper bound. First the lower bound should be set to $R_L = -Q$, and an upper bound R_U, which gives a service level that exceeds the target service level. After that it can be considered $R = (R_L + R_U)/2$. If the obtained service is too low, R can be replaced with R_L, otherwise R_U displaces R values instead. This step should be repeated until the gap between R_U and R_L is sufficiently small. (Axsäter, 2006)

Service level for compound Poisson demand is similarly the probability for positive inventory level, which denotes the ready rate $S_3 = P(IL > 0)$. Apart from that determining the ready rate, fill rate- S_2 is a little more complicated because of the varying demand size. Anyway, service level determination for compound Poisson demand is not the interest of this study, but instead the special case of Poisson demand where $f_1 = 1$, and $S_2 = S_3$. It is obvious that service levels will increase with an increment of the reorder point R. Furthermore, the following inequality can be always considered "$R > -Q$", otherwise the stock is never positive and both S_2 and S_3 are zero. To resolve the reorder point, R can be increased by one unit at a time starting from $R = -Q$ until calculated service level hits the target rate. It is also noted that for each value of R, the probabilities of having positive inventory level $P(IL = j)$ should be recalculated. For the case of discrete distributions, a bisection process is not performed since it is recommended for normal distributions. (Axsäter, 2006)

4. Empirical data

In this chapter, the case company will be briefly introduced. After that, the current system will be described in terms of inventory control processes together with the forecasting step. Lastly, the collected data will be exhibited and explained.

4.1. Company overview

TitanX Engine Cooling is a global supplier of powertrain cooling solutions to commercial vehicles, both for OEMs and the independent aftermarket. The company with annual sales of over 1.6 billion SEK (US$ 192 million) has 800 employees worldwide. TitanX is headquartered in Gothenburg, Sweden and keeps its manufacturing activities in Sweden, USA, Brazil, China and Mexico. (About TitanX, 2017)

4.2. System description

TitanX produces engine coolers that include both a radiator and a charger. The main components are side plates, header plates, tubes, and fins as it can be seen in *Figure 4.1*

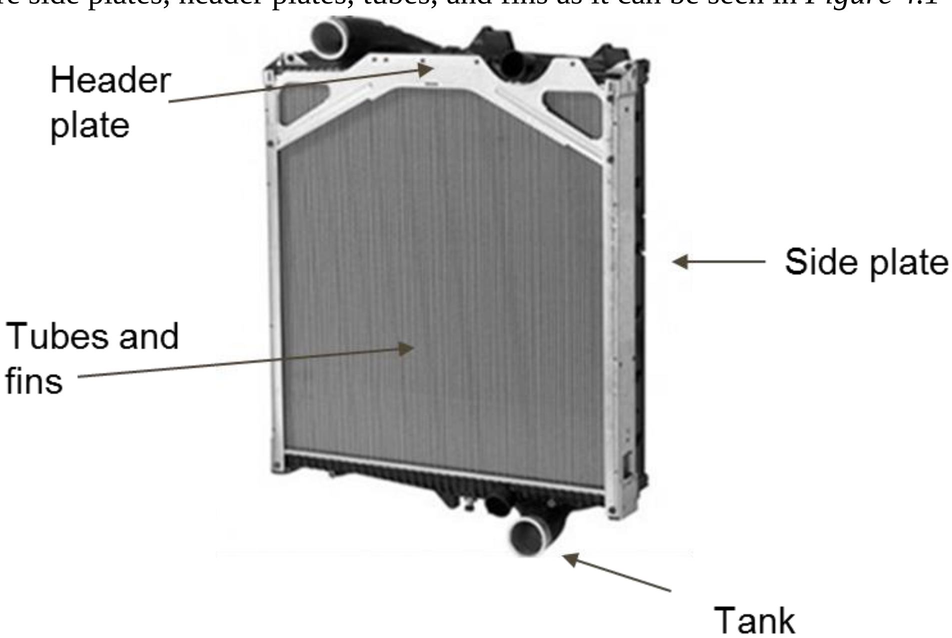

Figure 4. 1 - Engine cooling module.

The flow in the Mjällby facility can be seen in *Figure 4.2*. Everything begins with received items that are stocked in the raw material warehouse. First the quality check is carried out once a batch arrives, then operators put it away to a consigned area. In this step TitanX does not own the materials, but further each batch will be picked and distributed around the dedicated stock places so that the ownership will be switched. When an internal order is placed, the needed batch will be delivered to the buffer area where the replenishment of workstations takes place. The different components seen in *Figure 4.1*, except the tanks, are manufactured simultaneously by using press machines at different workstations as illustrated in *Figure 4.2*. Afterwards both the radiators and the chargers are formed in the building machine. The next step is the brazing process that takes place in the furnace to fasten the tubes and the fins. Then, the plastic tanks are assembled to the radiators through the crimping process, similarly the aluminum tanks are also assembled to the chargers in the welding machine, but additionally this process requires the leaking test to check tightness.

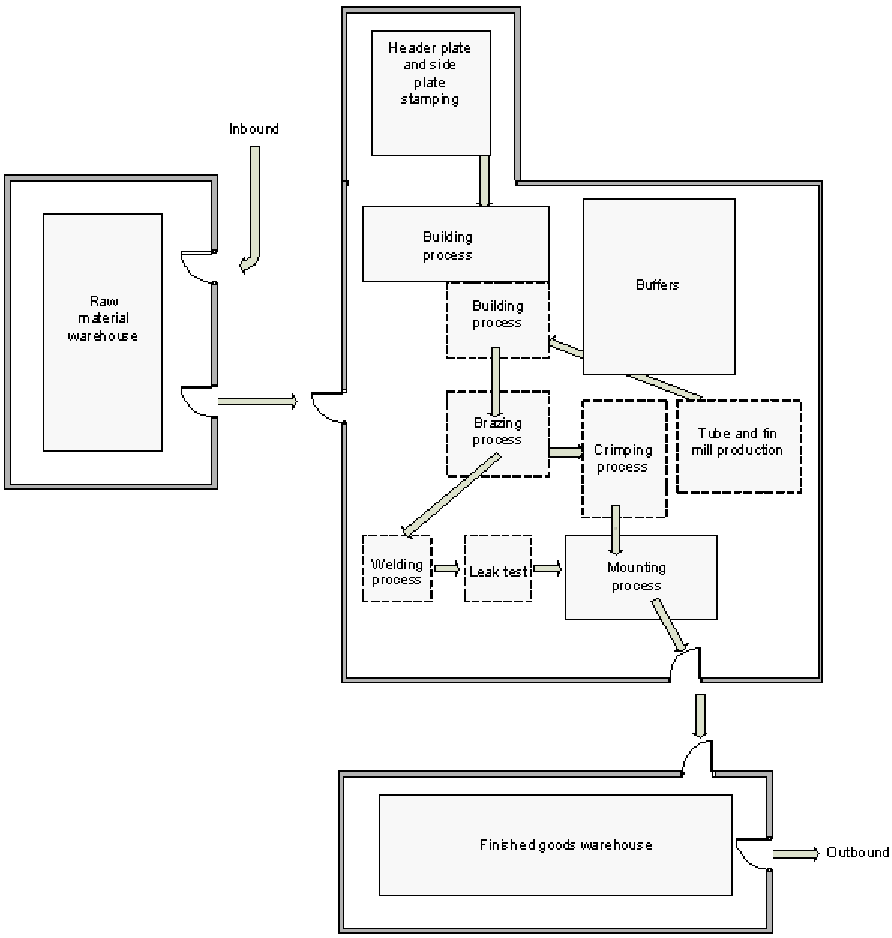

Figure 4. 2 - Internal flow.

Lastly, the mounting process is performed to link a charger and a radiator, distinctly the aftermarket products are demanded as independent parts either only a charger or a radiator. Therefore, the mounting process is skipped for the aftermarket products and those are directly sent to the finished goods warehouse.

To manage the production, a master production schedule (MPS) is prepared each Tuesday within the supply chain department by gathering input data from the customers via the MAC-PAC ERP system, paired with demand forecasting for those products without customer orders information. Then, once the schedule is attained, a production planner evaluates the security stock while comparing the current stock levels with the amounts that had been demanded to notice if the current safety stock needs an adjustment. At the end of MPS procedure, the ready schedule will be delivered to the production department through the same program (MAC-PAC). These processes can be seen in *Figure 4.3*.

It should be emphasized that the demand data does not exist for the independent aftermarket products. Therefore, TitanX should estimate the future demand for this market segment to generate input data for the planning process.

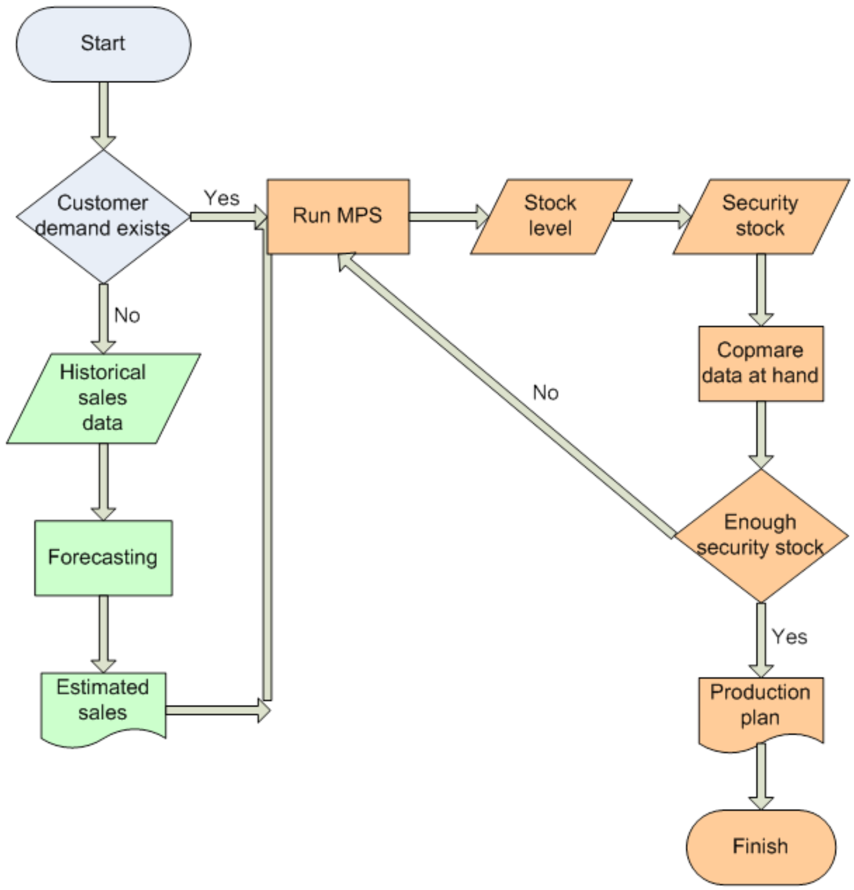

Figure 4. 3 - A flow chart for the MPS procedure.

4.3. Empirical data sets

In this section, the different data sets used for the project are explained together with the most relevant information found in them. To get a better understanding, head to Appendix II.

Shipments 15-16

This is the main file used during this project, which consists of a query from the MAC-PAC software at the company that contains all orders shipped in the years 2015 and 2016. The file gives the following key information about each of the shipments:

- Factory: 001 = Linköping; 002 = Mjällby.
- Order number
- Name of the part
- Customer name
- Market segment: IAM = Independent aftermarket…
- Shipping date
- Order quantity
- Invoice date

This file is not usable in its initial state for two main reasons:

1) There are some orders that provide a negative demand due to defective products, shipping of wrong items or excessive quantities that the customer does not agree to keep.
2) Item numbers can appear written with different endings due to the coding policy of the company, e.g., 100304410 (stocked in Mjällby), 100304410Z (stocked in Mjällby for customer Valeo service), 100304410AM (stocked in the warehouse in Krakow), 100304410KAM (same as AM but including a kit).

To solve the first problem, the data has been carefully cleared always making sure to compensate the elimination of the negative demand orders with the elimination of the positive demand quantities associated to those returns. For the second one, the item names have been standardized to only one name for each item, and the demand for each of the former codes has been aggregated to have a true representation of the total demand of each product.

1701_January_SIOP_IAM_takt_time

Another important Excel file that has been provided by the company is the one containing their previous forecasting procedure used for the IAM segment. The file gives the following key information about each of the products:

- Total demand of the product for each of the last three months prior to the forecast.
- The sales in SEK from the demand of each of the last three months.
- The kind of product: Radiator, Radiator w/o frame, Radiator core, Intercooler, Intercooler core, Oil cooler and Condenser.
- Field: Truck, Bus, both.
- Brand.
- Price
- ABC categorization based on two parameters (Volume and Easiness of production).

- A forecast of the demand as well as the sales in SEK in the format of next thirteen weeks and next three months which comprise the planning horizon. The calculation consists of a moving average of the last three months multiplied by a weekly or monthly seasonal coefficient.
- Monthly indexes are calculated as the index of that same month for the previous year divided by the average of the monthly indexes for the previous three months. The weekly indexes take the value of the monthly index for the month they are in.

The ABC categorization is of special importance here, since the company defines the production lead times of its IAM products following the logic in *Table 4.1*. It must be noted that the company does not have an ABC categorization for all the products, therefore, the forecast will still be available to all products, but some products will not be eligible for inventory control, and will be incorporated to the system as soon as the supply chain team at the company categorizes them.

It is also important to explain the forecasting method used due to its use in the forecasting section of the analysis chapter. The tool forecasts demand based on a simple moving average procedure with a three-month rolling horizon and monthly seasonal weights. This should not be confused with a weighted moving average procedure which dedicates a specific weight to each period within the average to account for their relative importance to the forecast. The three-month rolling horizon means that products which have not experienced any demand for the past three months will not be available for forecasting calculations. Finally, the seasonal coefficients are calculated as the seasonal index of the same month in the previous year divided over the mean of the seasonal indexes for the previous three months.

Table 4. 1 - Lead time of products based on ABC categorization.

Category	Lead Time
A	13 days
B	18 days
C	28 days

Batchqty IAM

This file contains the following information for most IAM items:

- Initial batch quantity: The minimum number of units in a row to produce of a certain item to minimize order and setup costs.
- Minimum quantity increase after the initial batch: the minimum number of units by which you can increase your production amount once the initial batch quantity has been covered. This information has not been considered in this project since the company would like to always increase the produced quantity by a multiple of the initial batch quantity.

It is important to mention that not all products have the information of their batch sizes available. To solve this issue, Boylan et al. (2008) recommends determining it as the cumulative forecast over the lead time using the SBA method. Due to the specific nature of the IAM products at TitanX, the use of such a broad assumption could lead to an error during the analysis phase making the rendered results be less than optimal. For this reason, the decision has been made to keep the analysis to only those products with a defined batch size.

IAM history

This file shows the IAM products aggregated sales of all months for years 2011 to 2016 and the expected demand during 2017.

LDPM - Mar week 1609 - 1613 (service levels company)

This last data set provides information for the service level based on customer and market segment. In this case, the only data of interest is the service level of the company for this random week and only for IAM products, since it is used as a benchmark of the service level that the company is working at.

5. Analysis

This chapter shows the analysis that has been conducted with the data collected throughout the project to provide an improved forecasting system and a new tool for automatic inventory control which was previously lacking for the products in the IAM segment at TitanX. To do so, a code was written in Visual Basic for Applications (VBA) environment for Microsoft Office Excel 2007. Moreover, the developed program was run in a personal computer which has Intel® Core™ i5-3210M CPU @ 2.50GHz (4 CPUs) feature.

5.1. Forecast

In this section, the different decisions made in this project to implement an adapted version of the 5-step guideline for the categorization of the demand mentioned in section 3.1.1. (Demand segmentation) are exposed as well as the analysis applied to reach the conclusions.

5.1.1. Seasonality and trend

The company feels that depending on the time of the year, demand increases or decreases, to the point where their previous forecasting tool includes seasonal coefficients for every month. As mentioned during chapter 3, before the categorization of the demand patterns, it is important to detect if the historic demand data of the products object of the analysis may have any underlying patterns that, if left untreated, can suppose a decreased performance of the different forecasting methods used. The most common of these patterns is trend, which is the effect seen in the demand pattern of a product during the beginning (growing trend) or the end (declining trend) of its life cycle. Another one would be seasonality, which is described as the correlation between certain periods of time repeating with a defined frequency (usually one year) and the volume demanded of a product.

An initial test is conducted by aggregating the demand during one year for all the IAM products, by product and year, as well as the aggregated trend throughout the years. This can be seen in *Figures 5.1, 5.2 and 5.3*. Further analysis is still required since the demand of each product is masked, and the application of the same seasonal indexes for the entire range of IAM products done in the company's previous forecasting tool could decrease the forecast performance in many cases.

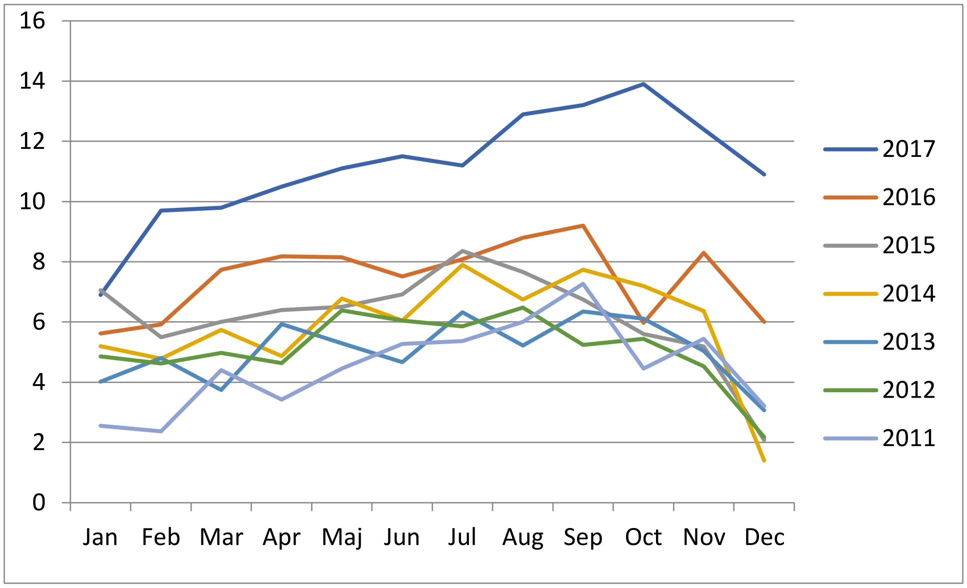

Figure 5. 1 - Yearly demand (Units) aggregated for all products.

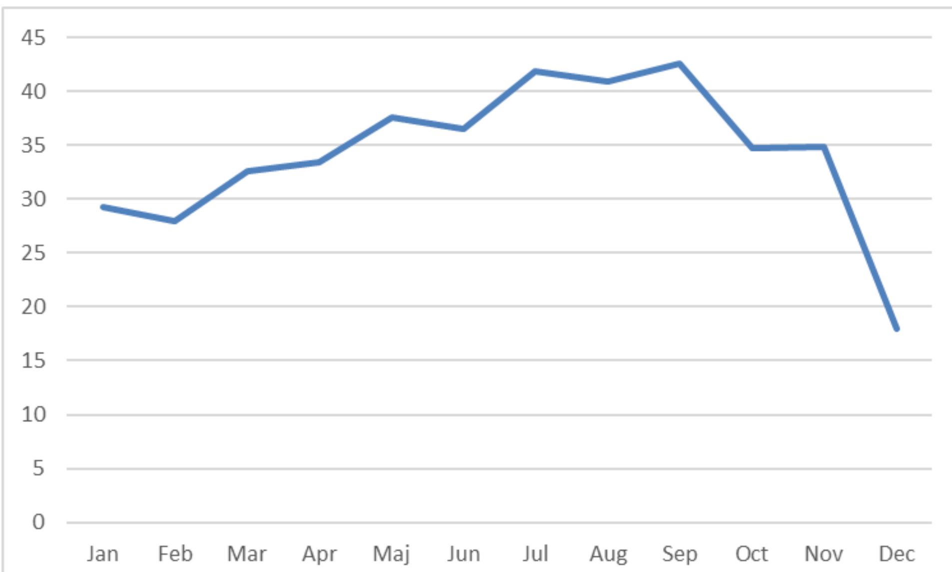

Figure 5. 2 - Yearly demand (Units) aggregated for all products and years.

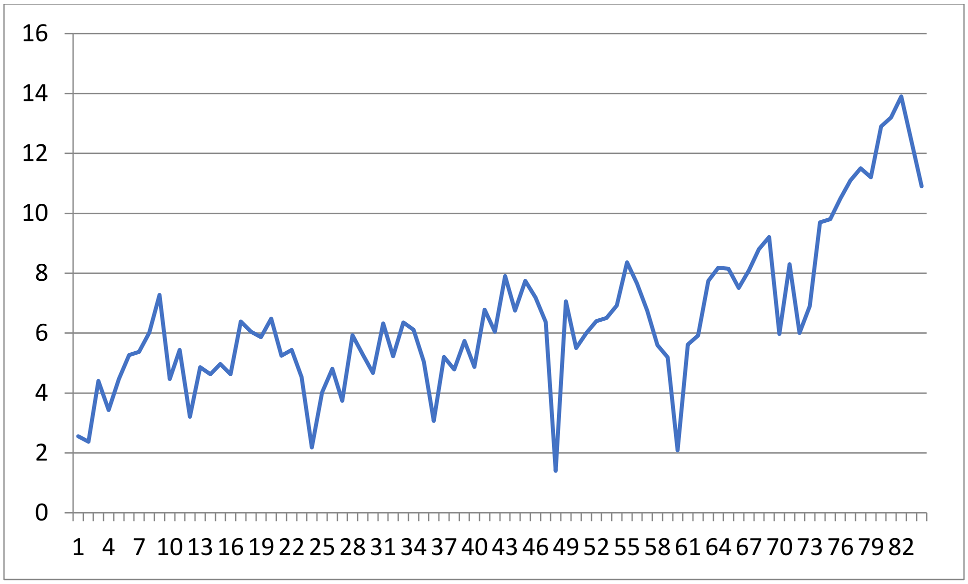

Figure 5. 3 - Aggregated trend (Units) aggregated for all products throughout the years.

On *Figure 5.2*, a clear increase in the demand during the months of July, August and September can be appreciated, which makes the possibility of seasonal data a real consideration. On the other hand, *Figures 5.1 and 5.3* show a gradual increase in demand throughout the years that seems to indicate an undeniable upward trend in demand as the company also suggests, although the reason could be the gradual increase of the width of the product portfolio, which is completely disguised in this data set.

To conduct a more in-depth analysis, the Forecast library from R software is utilized to test for additive and multiplicative seasonality assumptions from the Holt-Winters method on every single IAM product. The data sets used (Appendix II) are two:

1) The same data set used to forecast the future demand, which consists of the historic order quantities shipped in the years 2015 and 2016.

2) Due to the need of having multiple years of data to be able to dismiss the possibility of the results obtained being merely a momentary coincidence, and instead a real case of seasonality or trend, a new data set is used providing data from 2014 until 2016. In this case, the data provided are also the shipped quantities instead of the actual demand orders.

The program provides, between many other parameters, information about the type of trend and seasonality (N: None, A: Additive, Ad: Additive damped, M: Multiplicative) that better fits the historic demand of a certain product. In *Table 5.1*, the results for both data sets can be seen.

Table 5. 1 - Items with observed seasonality and/or trend patterns.

	ITEM	TREND	SEASONALITY
1st data set (15-16)	100315133AM	A	N
	100315135KAM	A	N
	100315553AM	A	N
	21209725KAM	A	N
	755843Z	A	N
2nd data set (14-16)	100308873	A	N
	100314736AM	A	N
	100314871AM	A	N
	100315508AM	A	N
	21209725KAM	A	N
	50177340	Ad	N
	851697AM	Ad	N

From *Table 5.1*, it can be observed that a total of 323 items, five of them on the first data set and seven on the second, have some type of additive trend, while none of the products present any seasonality.

After this first analysis, a graphical analysis consisting of a time-series plot, seasonal subseries plot, box plot and autocorrelation and partial autocorrelation plots for each product in *Table 5.1* is done to verify the previous findings visually, which has helped to confirm the negligible existence of trend (Appendix III).

5.1.2. Demand segmentation

Since p-value in many occasions cannot be calculated due to not having the first demand point at the time when the data horizon starts, a simplification is applied which says that the time between the last demand point before the beginning of the horizon and the first demand point equals to the time between the beginning of the horizon and the first demand point plus the time between the last demand point and the end of the horizon as seen in *Figure 5.4.*

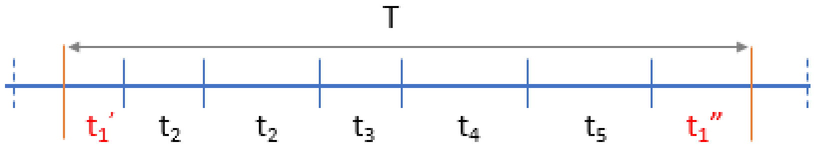

Figure 5. 4 - Graphic representation of the mean inter-demand interval (p).

As shown in the theory part, the recommended forecasting methods are Croston and the Syntetos and Boylan Approximation (SBA) for those products with observable intermittence in their demand (p>1). For products that historically have had demand every month (p=1), Simple Exponential Smoothing (SES) is going to be used as a natural alternative. The reasons why these methods are the ones that have been finally chosen are the following:

- SBA and Croston are used for intermittent demand patterns such as the ones that appear on the aftermarket products being studied.

- On the topic of service parts management Bucher and Meissner (as cited in Altay and Litteral, 2011) provide a thorough review of most literature relating to demand forecasting methods for the spare part categories mentioned in the previous section and recommends the use of SBA and Croston in the same way as Syntetos et al. (2005), as seen in the 5-step process for the implementation of a categorization scheme suggested in that chapter and explained in later paragraphs of this document. Their claim is that these methods are almost universally validated as the ones performing best in the given circumstances.

- SBA and Croston consider both the CV^2 and p values. These factors represent demand size variability and demand arrival variability, which the company specifically asked to be considered when applying the new forecasting method.

- SES is chosen because it is the fundamental method underlying both the SBA and Croston forecasts, but also because SES is one of the simplest and at the same time best performing methods to forecast continuous demand patterns.

As mentioned previously, the two main parameters used to create the different forecasting categories are the mean inter-demand interval (p) and the squared coefficient of variation of demand size (CV^2). On the other hand, a variation of the Mean Absolute Deviation (MAD) error measurement defined in *Equation 3.12*, has been introduced in *Equation 5.1* to measure the effect of changes on the cut-offs of the parameters with respect to forecast accuracy.

$$MAD = \sum_{h=1}^{H} \frac{X_{h+1}/q_{h+1} - Y_h}{H-1} \qquad (5.1)$$

H: Number of periods with demand without counting those during the initialization process.
X_{h+1}: Real demand of period t+1.

q_{h+1}: Number of periods between t+1 and the previous demand occurrence.
Y_h: Production forecast of units per month to satisfy the next order (X_{h+1}).

To produce a demand pattern categorization for forecasting purposes, the exponential smoothing parameter (α), the cut-off points p and CV^2, the forecasting methods used in each region, and the aggregation level of the demand (weekly or monthly) must be decided. The conducted analysis to evaluate the different choices is shown below.

Exponential smoothing parameter (α)

To choose α, different possibilities are tested by calculating the MAD for each product. The calculation is done considering the forecasting method (SBA or Croston) that provides the lowest error to each specific product.

The results of this analysis, shown in *Table 5.2* indicate that all products have errors of comparable size, and the chosen alpha is not really going to have much of an impact. Therefore, the chosen alpha was calculated with *Equation 3.11*. When N=54 weeks, the obtained result is α≈0,04.

Table 5. 2 - Sensitivity analysis of alpha value for weekly demand.

α	Sum of MAD (SBA & Croston)	Mean MAD SBA	Mean MAD Croston
$\alpha = 0{,}02$	1765,63	5,45	5,89
$\alpha = 0{,}03$	1765,95	6,72	5,16
$\alpha = 0{,}04$	1766,79	6,84	5,08
$\alpha = 0{,}05$	1767,71	6,8	5,08

For the case of Simple Exponential Smoothing, α is not improved, analyzed since in the case of weekly demand aggregation the probability of having demand in every period for the group of IAM products is extremely low.

Forecasting methods used in each region

To decide which forecasting method to use for each of the categories, comparisons between the number of products that have SBA or Croston as their optimal forecast has been done for multiple cut-off points. The cut-offs have been chosen based on *Figure 5.5* and the results (Appendix III) have proven unanimously that SBA should be used for erratic products, but instead, Smooth, Slow and Lumpy products give better results using Croston.

Cut-off points (p and CV^2)

To choose the right and for this project, an initial choice was made (p and CV^2) based on theoretical evidence provided by Syntetos et al. (2005). Further cut-off points are chosen by looking at *Figure 5.5*, that shows each product in terms of its p and CV^2 and it also says which forecasting method works best for it based on the given color scheme.

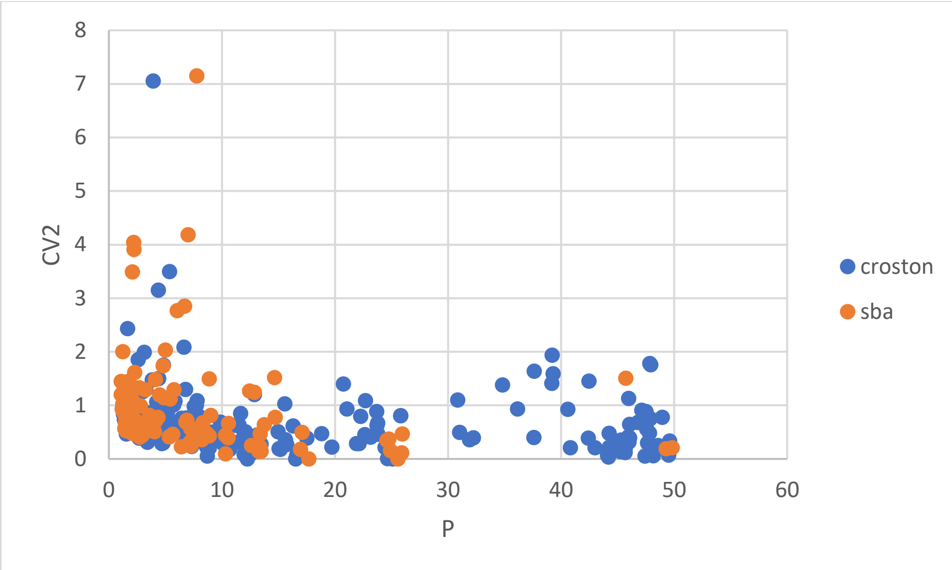

Figure 5. 5 - Representation of products based on (p, CV2) and optimal forecasting method.

An iterative procedure that compares the number of products that are going to be forecasted with their optimal forecasting method based on the given cut-offs is implemented, and since the optimal forecasting method is found by comparing the MAD obtained by the different forecasts, the products with a difference between MADs of the forecasts lower than 0,01 have been excluded from the analysis to give more importance to those products that can suffer the most from a sub-optimal categorization. Finally, close to optimal cut-offs have been found at p=2,9 and CV^2=0,7. These results are appreciably different from the ones by Syntetos et al. (2005). This may be due to the change of the error formula from a theoretical Mean Squared Error or MSE, which is calculated through an assumption of the demand occurring as a Bernoulli process therefore having a geometrically distributed inter-demand interval to an empirical calculation of MAD. Another reason may be the change from a monthly aggregation level to a weekly one which in turn has repercussion on the calculation of the smoothing coefficient and the error calculation as will be seen in the time aggregation portion of this section. Finally, one last reason may be the use of a small sample (323 items) from a very specific industry, in comparison to the more than 3000 items used in the mentioned article. With these values, the number of products contained in each category is shown in *Table 5.3*.

Table 5. 3 - Number of items categorized in each region.

Category	Smooth	Slow	Erratic	Lumpy
N. of prodts. [u]	25	161	49	88

Time aggregation level (Weekly or Monthly)

As referred to in section 3.1.3. Nikolopoulos et al. (2011) talk about using specifically the review period plus lead time as a promising option, but due to the specifications made by TitanX and the important effort in terms of time required to do an analysis of this kind, the chosen options are reduced to a total of two (weekly and monthly demand). All the analysis in this section is done for the weekly demand case, but it has been repeated for the case of monthly demand as well, ending up with a different optimal α value, different methods used in each category, and different cut-off points. To see the results obtained for the monthly case, go to Appendix III.

The MADs obtained using the optimal configurations for the weekly and monthly with the cut-off points forecasting methods and α values found in the previous analysis have been compared, transforming the MAD calculated for the monthly case by using *Equation 3.10* as $MAD_{weekly} = \frac{MAD_{monthly}}{\sqrt{4}}$.

Finally, *Table 5.4* shows how the MAD calculation is smaller for the case of weekly demand, and for that reason, it is chosen before the monthly one.

Table 5. 4 - Sum and mean of errors for weekly and monthly aggregation levels.

Aggregation	$\sum MAD$	μ_{MAD}
Weekly	1768,71	5,48
Monthly	$4330{,}62/\sqrt{4} = 2165{,}31$	$13{,}4/\sqrt{4} = 6{,}7$

The reason for this result may lay in the fact that greater aggregation levels imply a loss of precision in the calculation of p, since having a demand occurrence every 4 weeks would imply p=4 for a weekly aggregation, while it would seem like there is continuous demand (p=1) for the monthly case. Another reason that could explain this is the fact that using a smaller aggregation period, the probability of having two customers in one period is lower, therefore the variation of the demand of each period will be generally lower.

5.1.3. Comparing with the previous forecast

Now that the final forecasting model has been revealed, it is the time to test the results of this one compared to the tool that the company is currently using to produce their forecasts, to then see if one of the two main purposes of this project has been reached. (For reference, the forecasting model from the company is explained in section 4.3).

To do this test, the followed procedure is the calculation of the MAD error indicator explained previously for both the current forecasting software of the company as well as the one developed throughout this project.

Due to restrictions with information availability from the forecasting tool the company is using coming from their forecast being done using monthly seasonal coefficients and information of these coefficients for each of the months being missing, the historic data sample chosen is comprised only by the months of November and December of 2016, for which all the data is already available. The MAD for the new forecasting method will be calculated as the mean of the absolute value of the difference between the real order sizes divided by the time interval since the last demand occurrence and the value of the forecast for that period (expected demand per week Y_t), taking only the last nine weeks (months of November and December) into consideration for this calculation. For the current forecast, MAD will be calculated as the absolute value of the difference of the real demand of each of the last nine weeks minus the expected demand calculated by the forecasting tool. The results of this analysis are provided in *Table 5.5*.

Table 5. 5 - Sum of errors and number of optimal items for each forecasting tool.

Forecasting tool	$\sum MAD$	No. items opt. forecast
3-month moving avg. (old)	1654,486186	68
New forecasting tool	1303,514604	174

The first and most obvious conclusion to take from *Table 5.5* is that the new forecasting tool provides better results compared to the previous one, for most of the products as well as an overall decrease in MAD of 21,2% for this specific sample. This value is not going to be the same for all error calculations but it is still useful as an indicator of the superior performance of the new method.

The first thing to be observed is the short rolling horizon used by the current forecast. As mentioned previously, this implies that it will not be possible to obtain a forecast for those products that have not experienced any demand in the past three months. This issue has been shored up by the new forecasting procedure based on exponential smoothing that in theory has an arbitrarily long horizon even though most weight are put on the most recently observed demand. In practice, a horizon of 106 weeks is used (equivalent to two years of data). The first 52 weeks where used to initiate the forecast and for the remaining weeks the forecast was updated as described in section 3.1.3. Having a low N on their rolling horizon (three months), the company aims to have a high capacity of quickly adapting to significant fluctuations in the demand pattern from one period to the next one. Nevertheless, this implies that the forecast is more vulnerable to the influence of random variations that should not be considered. On the other hand, the choice of a higher N value will cause that even though, random effects are going to be filtered, the forecasts present a slow adaptation in front of significant fluctuations of the more recent data, since such prediction will take into consideration the value of older data points as well. An efficient way to solve that is to use exponential smoothing as done in the new method, since this method will also consider all previous observations, but with a greater emphasis on the newer data. By adjusting the smoothing coefficient α, the importance of the newer data in comparison to the older one can be changed to obtain a smoother or more responsive forecast.

Another factor that may be causing worse results for the old model is the use of seasonal indexes, since traces of a possible seasonality pattern can only be found if the demand of all products is aggregated, as mentioned in section 4.3, while evidence of it in a product basis has been found to be lacking, thanks to the seasonality and trend tests already explained in the same chapter. Instead, the old forecast applies seasonal indexes to all its products, which means that most products are being treated as seasonal when they are not.

Finally, to end the comparative analysis of both models, it is important to mention that the new forecast lets the user know when is the next demand expected to occur thanks to the introduction of p as another forecast. Meanwhile, the old forecast only provides information for the demand during the month and then disaggregates that amount equally through its constituent weeks, making it harder for the planning team at TitanX to anticipate the weeks in which the orders should arrive.

Finally, the new forecast provides a new feature, in comparison to the previous one, that calculates the confidence intervals of the forecasts p_t and z_t based on the level of confidence chosen by the user. The normal distribution has been used as an approximation of the real distributions of the aforementioned parameters, so the bounds obtained will have a certain margin for that reason. The results for the different confidence intervals available are portrayed in *Table 5.6.*

Table 5. 6 - Upper & lower bounds for different conf. intervals as well as distance to the expected value.

C.I.	$p_t[weeks]$ $z_t[units]$	Mean lower bound	Mean expected value	Mean upper bound	$\mu_E - \mu_L$	$\mu_U - \mu_E$
C.I. = 0,85	p_t	4,66	14,32	23,98	9,66	9,66
	z_t	28,12	32,92	37,73	4,8	4,8
C.I. = 0,90	p_t	3,29	14,32	25,36	11,04	11,04
	z_t	27,43	32,92	38,42	5,5	5,5
C.I. = 0,95	p_t	1,17	14,32º	27,47	13,15	13,15
	z_t	26,38	32,92	39,47	6,55	6,55
C.I. = 0,99	p_t	-2,95	14,32	31,6	17,28	17,28
	z_t	24,33	32,92	41,52	8,59	8,59

Analyzing *Table 5.6.*, the upper and lower bounds increase their distance from the expected value as the confidence intervals demanded grow, while the expected value will of course remain the same for all cases. Another thing to be observed is that each time the confidence interval is increased the bounds increase by a bigger margin, since the shape of the normal distribution has a tail at each end which gets thinner towards the edges, going towards a probability of zero asymptotically. The lower and upper bounds are separated equally from the expected value due to the symmetrical shape of the normal distribution. It can also be seen how the bounds required for the same confidence interval are bigger for p_t in absolute terms, and even bigger relative to their expected values, which indicates that p_t is a parameter with a higher variability for TitanX, and therefore the most problematic out of the two.

5.2. Inventory control

In this section, an alternative inventory control model, the purpose of which is to provide accurate calculations of the reorder points and safety stock of the IAM items, for a given service level. Further, a comparison to the company's current calculations of service level and safety stock will be introduced.

5.2.1. Inventory control model

The essential motivation for developing a better forecasting model is due to supporting the inventory model with more accurate data. In the previous section the findings of the developed forecasting model were shown. Namely, this model produces the forecasted values for the future demand containing also its variance. The prior describes the expected mean of the order size while the further denotes the standard deviation. It should be perceived a variance/standard deviation is obtained based on a comparison between the observed demand and the obtained prediction at a time. Since the developed model is iterative and has an estimate for each demand occurrence, variances can be easily calculated as seen in *Equation 5.2*

$$VAR = \sum_{I=1}^{n} \frac{(D_i - F_i)^2}{n-1} \qquad (5.2)$$

where D_i and F_i refer respectively to the demand and the forecast value in time i. The variance can be translated to the standard deviation by taking the square root of its value. After capturing the standard deviation and the average demand, those values should be expressed in lead-time doing simple multiplication ($\sigma' = \sigma \cdot \sqrt{L}$ and $\mu' = \mu \cdot L$). It is worthy to mention that a lead-time must have the same time dimension with a mean and its standard deviation, for instance in this study all are described weekly. Another parameter in the developed inventory model is called as a batch size and this data was collected from the company and placed in the interface like the other inputs. As mentioned before the batch size optimization is not considered in the inventory model, instead given values are directly used. The definition process is an ongoing project in the company, therefore some items do not have a specified batch size. As a result, those items were evacuated from the product list. The last parameter is the target fill rate which might be given by a customer or alternatively figured by the case company.

A crucial point to notice is that the order sizes should be rescaled owing to the discrete nature of Poisson and negative binomial distribution. In fact, a variance and a mean must be determined by the normalized order sizes for only distinguishing the distribution type. This transaction can be conducted with a certain method that finds first the average order size then rescales each demand point dividing its certain value by the mean. The introduced process is called normalization and it can be assimilated through the following example in *Table 5.7*.

Table 5. 7 - Weekly demand for an artificial item.

Time/Week	1	2	3	4	5	6	7	8	9	10	11	12
Demand/Unit	0	20	0	0	30	0	0	0	25	10	0	35

The average order size for this given sample is calculated as $\mu = \frac{20+30+25+10+35}{5} = 24\ units.$ As it was explained this number is used to normalize the order size. Finally, the demand points are rescaled as seen in following *Table 5.8*.

Table 5. 8 - Resized weekly demand for an artificial item.

Time/Week	1	2	3	4	5	6	7	8	9	10	11	12
Demand/Unit	0	0.8	0	0	1.3	0	0	0	1	0.4	0	1.5

This normalization is needed to obtain a new variable equivalent to the average order size (the new unit can be called a box for a more visual interpretation). When the order sizes are rescaled, the demand values will characterize how many multiples of the average box size has the customer ordered in a period. If it is always one (or close to it) the demand can be considered as Poisson with the re-scaled unit size (box) being equal to the average number of units, that means the customer always (or almost always) orders a box of μ.

In *Figure 5.6* the statistical distribution of each product based on these conditions can be seen and a clear pattern shows up, where the items with a Poisson distribution tend to be below those with NBD, which seems to have little to do with the categorization parameters (p and CV^2).

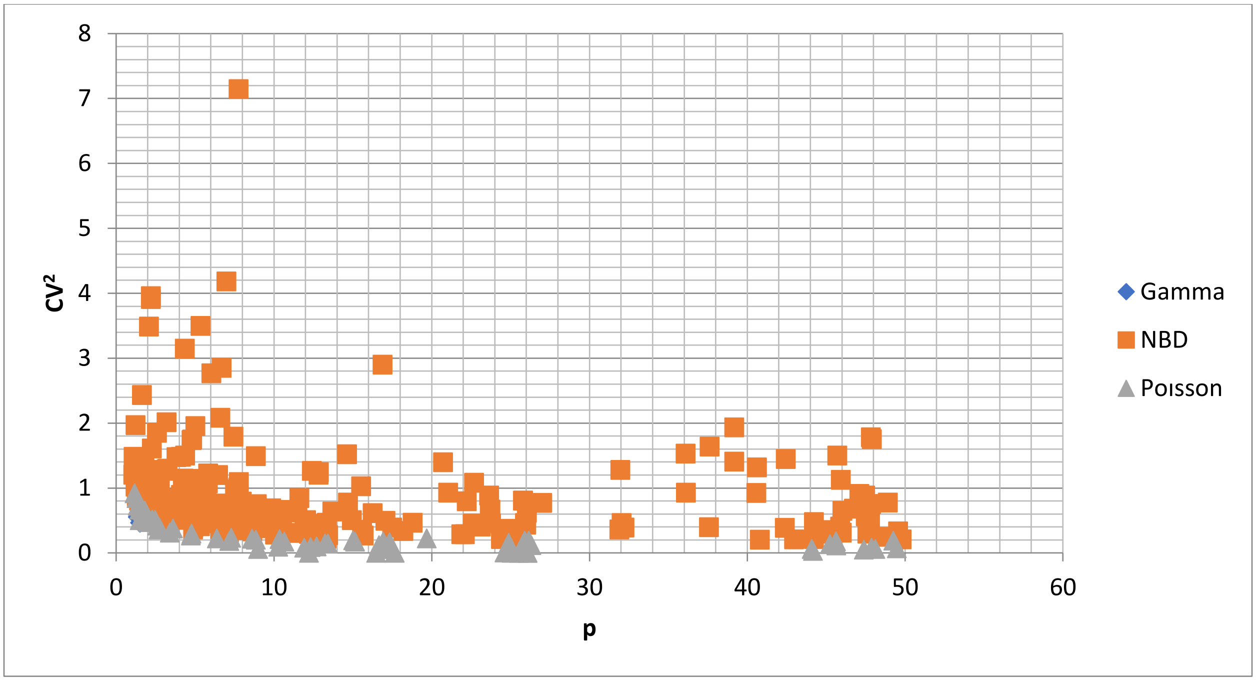

Figure 5. 6 - Representation of products based on (p, CV2) and optimal inventory distribution.

As explained in the categorization scheme in Altay, N., & Literal, L., (2011), normal demand distribution suits both erratic and smooth products, on the other hand Poisson and negative binomial demand distribution fit slow and lumpy items respectively. However, it is obvious that not all products might have the same distribution in a specific category. In other words, a specified demand distribution may not represent all items, e.g., in the smooth product category some items might have a demand distribution different than the normal one. To eliminate that weakness the demand distribution of each item can be defined individually, in this manner each item will be represented by its real distribution. This will improve the performance of the inventory model, but of course the problem will be harder to manage in most cases due to the high number of products.

Now it will be introduced how the inventory model is considering input data and which decision points it contains.

Step 0: First, the batch size and lead time of the products are checked. In the case the value of one of these parameters is missing, that item will not be considered.

Step1: Each item has a certain distribution as seen in *Figure 5.6*. In this step, all items should be treated individually, this approach enables the model to use true distributions. An item might have the following distributions:

Normal if: : $\frac{mean}{standard\ deviation} \geq 3$

As normal distribution has a chance of having negative demand, if mean is much greater than standard deviation, this chance will be sufficiently small to consider this distribution for this problem (no negative demand is observed).

For those products not meeting the previous condition, the next logic can be used:
If: $0.9 \leq variance/mean \leq 1.1$ >>**Poisson**
Else if: $variance/mean > 1.1$ >> **Negative binomial**
Else: $variance/mean < 0.9$ >> **Gamma** (Gamma is capable to fit many cases so that it is assigned to the remaining cases, ratio < 0.9)

Step 2: Once the demand distribution is shown, then the reorder point can be optimized for a given service level. The reorder point definition procedure was introduced in the theory chapter. This iterative process is translated into a computer program in Visual Basic for Applications (VBA) and its algorithm can be illustrated by *Figure 5.7* (the algorithm for the Poisson distribution will use all parameters in the resized variable and will change back to the original variable after the result is obtained). For the first iteration, the reorder point is assigned to the negative of the batch size "R= -Q". After that, the code reads all input data from the interface, they are a lead time, a standard deviation, a mean order size, a batch size and a target fill rate. In the third step the probability of inventory level j *(1,2, …, R+Q)* is iteratively calculated. For each positive inventory level the code calls a function that includes one of the probability distribution to compute demand during the lead time. Such as initially the probability of inventory level at j = *1* is determined by using the related demand distribution. The sum of all iterations illustrates a service level for the current reorder point. This number will be compared with the target fill rate in the next step to decide whether the current R is sufficient to achieve the target fill rate. If the calculated service level, e.g. *P(IL=1 to 10, where R=-5)* is lower, then the procedure should be repeated for the new R value which was increased 1 unit e.g. *R= -4*. Once the service level reaches the target level the program will be stopped and the last reorder point is defined as the optimal. After all, the code can perform to write this result into the defined Excel worksheet. This illustrated process is valid and quite similar for the service level calculation of a normal distribution, but as explained in section 3.2.2., it needs a simple bisection search as a difference.

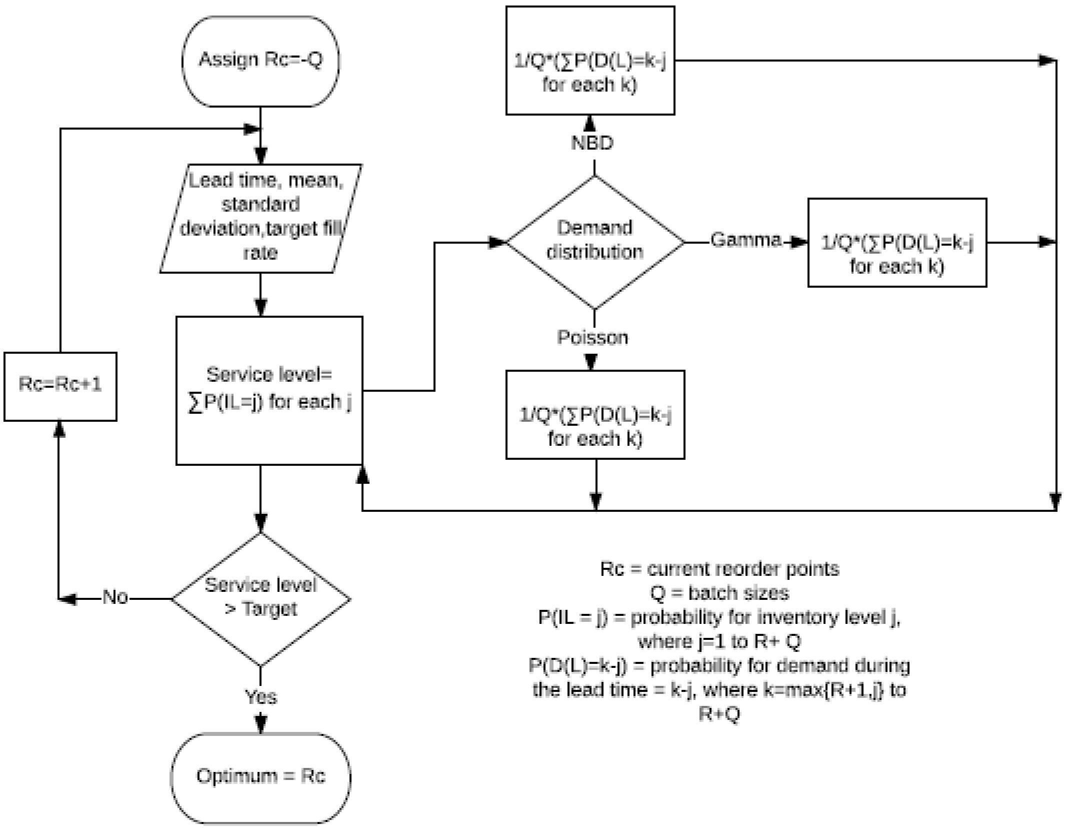

Figure 5. 7 - Algorithm to find the reorder point.

The developed program was run for only 226 unique items, since the remaining items do not have either the batch size and/or the lead time defined. It is apparent that before running the inventory model first the forecasting model was performed to extract the mean and standard deviation. Then after that the inventory model was tested for different service level target: 80%, 85%, 90%, and 95%. It should be expected that run time will be longer in the case of higher service level. The underlying reason is the system needs to keep more inventory under a strict condition. This means that the model will be working for more iterations. The results demonstrate computational times, the total number of items that entails positive reorder point, furthermore, it shows the total amount of safety stock as seen in *Table 5.9*.

Table 5. 9 - Analysis of reorder points for each service level.

	Developed model				Case company
Service level (%)	80	85	90	95	80-85
Computation time (sec)	517.36	635	1449.24	3293.39	28,800
Total number of items with positive R	97	136	150	170	155
Safety stock	1041	1682	2778	5008	3333

Finally, another investigation was conducted to analyze the effect of the lead time changes. The given lead times was used for the initial solution, later they were increased by half and its current values as shown in *Table 5.10*. The considerations are the same with the previous analysis.

Table 5. 10 - Analysis of reorder points for different lead times.

Lead time (week)	current	1.5*current	2*current
Service level (%)	80	80	80
Computation time (sec)	517.36	2009.59	4485.14
Total number of items with positive R	97	142	150
Safety stock	1041	2497	3978

The increase of the lead time of the products will suppose an increment in safety stock to be able to satisfy the same demand patterns with a longer lead time until the products are finished. Something else to mention is that even though the total number of items with positive R increases less for each increment of lead time ($\Delta r^{+}{}_{1} = 45, \Delta r^{+}{}_{2} = 8$), the total number of SKUs to keep as safety stock increases more ($\Delta ss_1 = 1456, \Delta ss_2 = 1481$).

5.2.2. Comparison to previous model

The new model gives quick results when compared to the current method of specifying safety stocks, even though its computation time tends to rise when high service levels are forced. That means the company will be available to test and analyze different scenarios quickly. Moreover, the outputs from the model are based on a scientific method which provides the best solution, while the current system is running intuitively depending on the employee's expertise. As well as time advantage, the developed model offers lower safety stocks while promising to reach the same target service level. Numerically it is around 1362 units for 80-85% target rate while it is 3333 units in the current system. That indicates if the company reduces the current safety stocks, they can still satisfy their customers with less inventory as seen in the following *Figure 5.8*. The products have an average price around 1670 €, if it is assumed that TitanX has a 15% profit margin, then the production cost can be calculated as 1419,5 €. Moreover, 10% of the production cost is estimated as a good representative of yearly inventory holding cost, so it is roughly equal to 141,95 €/year. Therefore, the company might save 279.783,5 €/year when using the new tool.

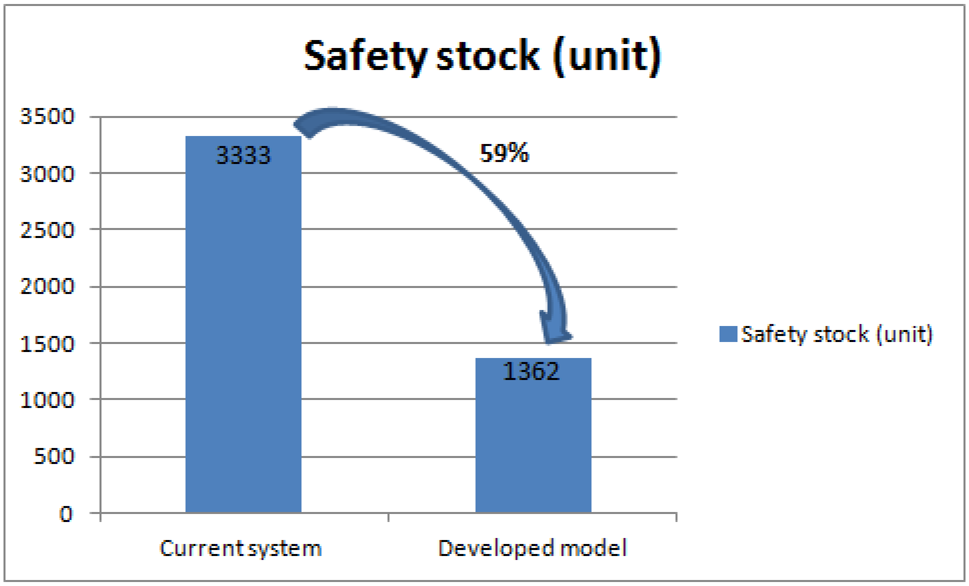

Figure 5. 8 - Comparison of safety stock for the old and new forecasting models.

It should be mentioned that the safety stock of 1362 units found for the developed model in *Figure 5.8* is calculated as the mean of the safety stocks for service levels of 80% and 85%.

6. Discussion

In this chapter, this project is going to be compared to the rest of work done in the fields of spare part forecasting and inventory control to observe in what way it has built upon the existing theory and on the other hand, what have been the contributions made from a theoretical and practical standpoint. Future work that can be done within the context of the company to improve upon the work done in this project is motivated and personal opinions and recommendations from the authors are also shared.

In the field of forecasting, the work has been based mainly on the theoretical background built up by Syntetos, Boylan and Croston, but due to the empirical nature of this project, many additional changes have been made to better adapt to the reality at TitanX. From a theoretical standpoint, the project looks to broaden the available literature in the field of intermittent demand forecast and inventory control. Moreover, it provides another empirical case with a set of products for the independent aftermarket segment of a truck provider company in which to test and evaluate the study by Syntetos et al. (2005) on the optimal categorization of demand patterns and their association with certain forecasting methods. From a practical standpoint, the provided contribution is an easy to use forecasting tool with higher accuracy rates for the company's IAM items as well as two additional forecasts in the form of p_t and z_t that allow to present the forecast as its different components (time until the next order and size of the order), as well as the calculation of the lower and upper bounds of their desired confidence intervals.

In terms of inventory control, Bucher, D., & Meissner, J. (2011) already warn the reader that the categorization scheme suggested by them does not constitute an approach of universal validity in a technical sense. Nevertheless, the application of best practices for the choice of both the statistical distributions of the items as well as the inventory control policies should lead to adequately configured inventory systems in many industrial settings. This case has not been different, since the plotting of the items in the (p, CV^2) *Figure 5.5* shows a very specific pattern, and seeing how it cannot seem to be categorized by the demand categories defined for the forecasting categorization, the decision has been made to base the categorization on another parameter which is the variance over the mean (as explained in section 5.2). Therefore, a theoretical contribution to inventory control made by this project is the confirmation that if there is an intention of obtaining more accurate reorder points and service level calculations from your inventory control tool, the categorization scheme used during the forecasting stage, and in particular the use of the same cut-off points for forecasting and inventory control which does not have any base in the theory, should generally not be used to fit the inventory control categorization. On the other hand, a practical contribution of this project in terms of inventory control is an automatic inventory control tool based on scientific on assigning the inventory level of each item to the statistical distribution that suits it best and then calculates the reorder point based on the desired batch size and Service level using the formulas by Axsäter (2006).

Another potential obstacle, when implementing this approach is that it might create a black box of how every SKU is managed. Therefore, it is important for the inventory management personnel to understand the applied forecast and inventory methods and to question their appropriate application in the company's inventory system. Another study by Syntetos et al. (2009) shows that the combination of parametric forecast methods with managerial judgement often leads to a considerable improvement of the inventory performance. Therefore, it is worth mentioning that manual managerial judgements are often important in the context of spare parts management, as a wide range of information may be very important.

Parting from the findings of this project, further investigation could be done to improve even more the performance of the management of items in the finished goods warehouse. One possibility could be the use of p_t and z_t in the inventory control tool to more fully utilize the advantages of having a forecast that is able to provide information about the time of arrival of the next demand, as well as the size of such demand, which due to the time constraint for this project, as well as the request for an (R, Q) policy coming from the company, has not been implemented. Another possibility would be to study more in depth what is the optimal temporal aggregation level of the data set as recommended by Nikolopoulos et al. (2011) by comparing the results obtained by the different forecasting methods when many different aggregation levels are used, starting by the recommended lead time plus review period, and so on. Another way to further improve upon this project's research would be to optimize the smoothing coefficients (α). In this project, the smoothing coefficients are chosen to be equal for the mean inter-demand interval (p_t) and mean demand size (z_t), and only a sensitivity analysis is performed by checking the performance of the forecasting methods by a given range of α values. Instead, it could be of interest to try the separate optimization of both smoothing coefficients ($\alpha_i$and α_s) and to also use a better optimization procedure; both of those things explained in Syntetos (2009). Another improvement could be the addition of a bisection search for the reorder point calculation of the discrete distributions, as is already used in the normal one, always taking into consideration the integer constraint. On a different note, there are still many challenges to tackle throughout the supply chain at TitanX Mjällby, as mentioned in the introductory chapter of this project. Therefore, the improvement of the planning, sequencing and machine assignment processes within the production lines as well as the optimization of inventory levels and stock keeping times at the raw materials warehouse possibly by adapting the inventory model used maybe taking advantage of the already created inventory model for the finished goods warehouse.

Finally, some tips learnt throughout the project are shared for future research in this field to be conducted more efficiently:

Plan what is going to be the required data and collect it, since scarcity of information is a very widespread problem in real world cases, and therefore, the sooner this is known, the more time there is to solve the potential issues.

Another recommendation is to look for possibilities of extrapolating conclusions from smaller data samples. Data sets can be quite big in size, making an analysis of every specific product very time consuming. Looking for similarities in the products allows for the possibility of extracting conclusions without having to test certain assumptions on all of them. For the case of trend and seasonality, a program had to be created to run an analysis for all products which ended up being very time consuming. Instead, due to the glaring similarities of the various products, a proper sampling process could have saved a significant amount of time.

Trust the findings until evidence against them arises. A critical point of view is always important, but too much skepticism on the findings may have a paralyzing effect which will not allow for the project to move forward.

Finally, the use of the software created in this project is recommended for further improvement, since it contains a scientific base, it is thoroughly explained throughout this document and it will save a lot of time compared to a clean start of the problem (Appendix III).

7. Conclusion

TitanX is a prime truck engine cooler supplier with a growing independent aftermarket segment. The demand of IAM products is known with little advance due to customers being smaller independent suppliers that do not have the same level of integration to the supply chain at TitanX as the big truck producers and the demand of these products has an intermittent and erratic nature. For these reasons, a forecasting and inventory control tool for IAM products has been developed to be implemented at the Mjällby production facility and the Krakow central warehouse respectively.

The two research questions,

- RQ 1. How to forecast the demand of independent aftermarket products with sporadic patterns?
- RQ 2. How to control inventory levels of the same group of products?

have been answered throughout this project, and the obtained results will be commented.

The new forecasting tool provided in this project is showing better results for the tests conducted with the historical data at hand. It is also important to note that for several products, the old forecast seems to still perform better. The reason is the stochastic nature of the demand, which implies that there is not one single forecasting approach that is going to perform better in every single iteration of the forecast. In the case where the assumptions of the old forecast are met by the empirical evidence of the real data, then the old forecast will inevitably outperform the new one. Nevertheless, the assumptions taken by the new model are generally better when referring to this set of items, as seen in the analysis chapter, meaning that its application will provide better results when looking at the set of products.

The new inventory control tool provided in this project is a clear improvement over previous practices by the company, since an inventory control tool that provides automatic reorder points/safety stocks by considering the desired service level and batch size and reading the output coming from the forecasting tool. However, this solution had not yet been implemented at TitanX.

As a summary, the purpose of this project was the analysis of the finished goods inventory for the IAM segment to provide a more accurate forecast and an inventory control approach that shows how various levels of safety stock affect the balance between holding, ordering and backordering costs. Looking back, the goals of the project have been met for the most part. On the other hand, due to the lack of accurate calculations of the inventory keeping, ordering and backordering costs, an alternative inventory control tool has been created using a service level calculation (calculated as the ready rate/fill rate) to determine safety stock and reorder point, and an additional feature has been added which allows to see the relations between the inventory level to be kept of each item and the lead time in which TitanX can afford to produce them.

Finally, this project has been very enriching at an educational level. From knowledge into the general techniques in the theory of forecasting and inventory control, to those more specific to intermittent demand products or greater familiarization with the common practices and procedures used in the field of spare parts management. From a professional standpoint, very valuable experience has been obtained in the industry of large vehicle suppliers by being able to see the inside of the TitanX production plant in Mjällby as well as working on it and having contact with the supply chain management team. Finally, from a personal point of view, this project has helped abilities such as planning, communication and the interpersonal skills necessary to work efficiently in a group setting.

8. Bibliography

6.4.4.3. Seasonality. (2017). Retrieved from http://www.itl.nist.gov/div898/handbook/pmc/section4/pmc443.htm

About Titanx. (2017). Retrieved from http://titanx.com/about/

Altay, N., & Literal, L. (2011). *Service Parts Management, Demand Forecasting and Inventory Control*.

Axsäter, S. (2006). Inventory control (international series in operations research & management science). *Springer, Berlin*.

Banks, J., CARSON II, J. S., & Barry, L. (2005). *Discrete-event system simulation.* 4th ed. Pearson.

Boylan, J. E., Syntetos, A. A., Karakostas, G. C., Boylan, J., Syntetos2, A., & Karakostas3, G. (2008). Classification for Forecasting and Stock Control: A Case Study. Source: The Journal of the Operational Research Society Journal of the Operational Research Society Journal of the Operational Research Society, 59(59), 473–481.

Bozarth, C. C., Handfield, R. B., & Weiss, H. J. (2008). *Introduction to operations and supply chain management*. Upper Saddle River, NJ: Pearson Prentice Hall.

Bucher, D., & Meissner, J. (2011). Configuring Single-Echelon systems using demand categorization. In *Service Parts Management* (pp. 203-219). Springer London.

Dickie, H. F. (1951). ABC inventory analysis shoots for dollars not pennies. *Factory Management and Maintenance, 109(7),* 92-94.

Eaves AHC (2002) Forecasting for the ordering and stock holding of consumable spare parts. Unpublished PhD thesis, Lancaster University

Holmes, A. (2013). Direct Observation. In F. R. Volkmar (Ed.), *Encyclopedia of Autism Spectrum Disorders* (pp. 980–981). New York, NY: Springer New York.

Johnson-Laird, P. N. (2000). Thinking: Reasoning. In A. Kazdin (Ed.), Encyclopedia of psychology (Vol. 8, pp. 75–79). Washington, DC: American Psychological Association.

Johnston FR, Boylan JE (1996) Forecasting for items with intermittent demand. J Oper Res Soc 47:113–121

Kotzab, H., Seuring, S., Müller, M., & Reiner, G. (Eds.). (2006). *Research methodologies in supply chain management.* Springer Science & Business Media.

Kourentzes, N. (2013). Intermittent demand forecasts with neural networks. *International Journal of Production Economics*, *143*(1), 198-206.

Kvale, S. (2008). *Doing interviews.* Sage.

Lieberman & Hiller (2001), introduction to operations research, 7th edition, New York: The McGraw-Hill Companies

Liston, K. (2011). Literature Review Methods: Point of Departure.

Nikolopoulos, K., Syntetos, A. A., Boylan, J. E., Petropoulos, F., & Assimakopoulos, V. (2011). An aggregate – disaggregate intermittent demand approach (ADIDA) to forecasting: an empirical proposition and analysis. Journal of the Operational Research Society, 62(3), 544–554.

Rips, L. J. (1999). Deductive reasoning. In R. A. Wilson & F. C. Keil (Eds.), The MIT Encyclopedia of the cognitive sciences (pp. 225–226). Cambridge, MA: MIT Press.

Smith, M., & Babai, M. Z. (2011). A review of bootstrapping for spare parts forecasting. In *Service Parts Management* (pp. 125-141). Springer London.

Syntetos, A. A. A., Boylan, J. E., Croston, J. D. (2005). On the categorization of demand patterns, 56(5), 495–503

Syntetos, A. A., Babai, M. Z., Dallery, Y., & Teunter, R. (2009). Periodic control of intermittent demand items: theory and empirical analysis. *Journal of the Operational Research Society*, *60*(5), 611-618.

Taylor, D., & Procter, M. (2008). The literature review: a few tips on conducting it. *Writing Support, University of Toronto*

Williams, R. N. (2000). Epistemology. In A. E. Kazdin (Ed.), Encyclopedia of psychology (Vol. 3, pp. 225–232). Washington, DC: American Psychological Association.

Williams, T. M. (1984). Stock control with sporadic and slow-moving demand. *Journal of the Operational Research Society, 35(10),* 939-948.

Winston, W. L., & Goldberg, J. B. (2004). *Operations research: applications and algorithms* (Vol. 3). Belmont, CA: Duxbury press.