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Analysis & optimization of inventory policies for global supply chain management at Ampleon

a case study in inventory management

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Analysis & Optimization of Inventory Policies for Global Supply Chain Management at Ampleon
- A Case Study in Inventory Management

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Analysis & Optimization of Inventory Policies for Global Supply Chain Management at Ampleon - A Case Study in Inventory Management

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Abstract

This project provides an insight into the inventory management policies at Ampleon, its shortcomings and ways to improve the same. The project is focused around the optimization of safety stock settings at the company and suggesting an improved, robust and reliable method to calculate the same backed by appropriate theory, data analysis and modelling. Additionally, the project also looks into supplier reliability assessment and its integration, along with certain other factors into the safety stock policy. The objective here is to reduce inventory and maintain high levels of service, essentially making the inventory management more efficient. The work done over the past 9 months has shown that this objective is fairly achievable while there still remains a lot of scope for future research. The work done as apart of this project has a high degree of scientific relevance and industrial applicability. The results are positive and show promise. This report summarizes the findings, outcomes and recommendations based of the work done during the project.

Management Summary

This project describes the analysis and optimization of inventory policies at Ampleon Semiconductors, Nijmegen.

Introduction

Ampleon is a global semiconductor manufacturer spun off from NXP Semiconductors in May 2015 headquartered in Nijmegen, Netherlands. The company was founded in December 2015 and since then has grown leaps and bounds in terms of capacities, supplier links, customers and profitability. Ampleon primarily deals in the manufacturing of radio frequency chips which serve a variety of purposes and focuses on mobile broadband, multi-market, and RF energy electronic products. Currently, Ampleon is the leading global partner in RF power and has around 30% market share.

Ampleon's supply chain extends across Europe and Asia in countries including the Netherlands, Germany, Taiwan, China, Honk Kong, Japan, Korea and Philippines. The company's main manufacturing facility is in Cabuyao, Philippines this site, referred to as AMP also serves as the primary inventory holding location in the supply chain. The inventory location includes a Die Bank and a raw material inventory, which together serve as the customer order decoupling point. AMP is the main assembly site and although most of the product stages before AMP are outsourced or subcontracted, most of the processes including assembly and packaging are carried out here. Apart from AMP, inventory is also held at certain vendor managed inventory locations which fall under the company's indirect control.

Problem Statement

Ampleon classifies its inventory as critical and non-critical. The critical items are managed using the IBP module in SAP that takes into accounts all kinds of parameters and constraints. The focus of this project has been on these critical items including the pre-tested dies (CEPT) stored at the Die Bank along with other raw materials including headers and flanges. At the moment, Ampleon uses a one-size fits all approach for managing its inventory, a policy inherited from NXP. The main idea behind the inventory management is to maintain stocks at an inventory target level throughout. The inventory target level, also referred to as safety stocks is meant to cover fluctuations in demand over lead time. The inventory targets are calculated as 'x' weeks of safety stock based on an average demand over 13 weeks (1 quarter). The x is dependent on the lead time of the product and the specific lead time of each SKU, also depending on the supplier involved. The issue on hand here is that this 'x' has no calculated background which makes it difficult to assess the efficiency and reliability of the same. The policy does not include any considerations of demand variabilities, forecasting inaccuracy, supplier variabilities or service levels. With this project, the aim has been to change that and come up with a modified inventory management policy.

The management problem is defined as follows:

"Ampleon experiences difficulties in matching supply with demand with the current inventory management approach."

Consequently, it was established that there's a need for a new inventory policy which takes into account several parameters that influence demand and supply planning, has a theoretical background for calculation and can be product specific in calculation while being generic in approach. Hence, the main question is defined as follows:

"How should Ampleon calculate its inventory target so as to incorporate demand and supply variabilities while maintaining a requisite service level."

The approach of this project has been to answer this main research question, with the the main research topics being demand and supply uncertainties, safety stocks and supplier reliability. The primary deliverable in this project was to develop a new model for calculating inventory targets. When achieved, that would gave answered the research question mentioned above in sufficient capacity.

Methodology

As a first step, in order to get a good hold of Ampleon's inventory management, it was important to understand each and every aspect of it and represent the policy using a mathematical model. Once an in-depth understanding was laid down, the problem areas were be identified and in accordance with the main research question, existing literature was explored and studied to get an idea about the kind of work that had already been done in a similar context. The next step was to choose the correct approach, backed by existing theory and scientific literature. Since the considerations for Ampleon's inventory control are very subjective, a culmination of concepts was used to formulate the necessary inventory target model.

For the quantitative analysis, the scope of the project was limited to the two main categories of pre-tested dies stored at the Die Bank. The assumption here was that the policy developed for these dies would be consistent for all critical items while the subjectivity of the same would be achieved through parameters. The demand planning data for the aforementioned die types was obtained using the dependent demand generated from the end-product demand and the bill of materials on each SKU. The data was then categorized into LDMOS and MOSCAP based on the product description and then aggregated on a weekly basis for further analysis. This was done to accelerate the analysis process since the governing policies were only dependent on this level of classification but were applicable to all sub-categories. For MOSCAP dies, a standard lead time of 16 weeks was considered (including a review period of 1 week) while for LDMOS dies, a combined measure of lead time and review period equalled 21 weeks. A common safety lead time of 4 weeks was assumed for both die types. These numbers were obtained after discussions with the master planning team and were checked to be in accordance with the ordering policies.

The processed data for CEPT dies was then analyzed from week 1, 2018 till week 26, 2019, spanning over 6 quarters or 1.5 years. The cumulative demand forecast was hence calculated for a total of 52 weeks for both die types. This data was analyzed to understand the probability distribution in order to establish an underlying probability density function fur further analysis. The data was found to be most accurately following a lognormal distribution while it could be fit to a gamma or normal distribution with a reliable goodness of fit. For final calculations however, gamma distribution was preferred due to its non-negative nature and higher robustness. The next step was to analyze the forecast error by pitting the cumulative forecasted demand against the cumulative actual demand, observed as an equivalent to the actual consumption of dies in assembly. The forecast error would reflect the inaccuracy of forecast over the order lead time, expressed as a sum of the actual lead time, the review period and the safety lead time. The standard deviation of forecast error was calculated over FT periods for both die types, where FT is the order Flow Time, decided based on a norm for supply lead time.

To get an understanding of supplier reliability and to quantify its impact, the supplier/subcontractor performance data was analyzed for the same time period as the demand analysis. The delivery time uncertainty was expressed using the RLIP performance measure and the delivery quantity or yield uncertainty was expressed using a new measure, described as PCO which represents the percentage of complete orders delivered. The supplier reliability was then expressed as a product of these two quantities. For the inventory target model, the delivery time variability was taken into account in the form of lead time uncertainty. The yield uncertainty however had to be ignored due lack of information and the complexity of quantitative analysis. As a final step a safety stock correction factor was introduced, based on the work done by Teunter & Syntetos [31]. This correction factor, expressed as CF was meant to inflate the safety stocks in order to compensate for the co-relation in forecast errors. As evident, this correction factor would depend on the type of forecasting method used and additional parameters including lead time and forecast period. In Ampleon's case the forecast method was found to be very close to the traditional simple moving average method with minor manual tweaks to account for known future demands. The manual intervention however, was difficult to quantify and was less significant in generating dependent demand for CEPT dies. Hence, it was ignored and the final correction factor would only vary as a function of the lead time.

Conclusion

Based on the quantitative analysis and exiting literature, the final formula for inventory target setting was expressed as a function of three variables: the quantity z, representing the target inventory, the mean periodic demand, μ_t and the safety stock correction factor, CF (which is dependent on the forecasting method, the forecast period and the lead time). To account for supplier reliability, FT for suppliers with low supplier reliability ($SR < 90\%$), is decided based on a norm for delivery lead time. The following formula describes this calculation and also serves as the primary deliverable for this project:

$$\boxed{SS = CF * (z_t - \mu_t)}$$

$$CF = \textit{Correction Factor for Forecasting, obtained from Table F.2}$$

$$z_t = \psi^{-1}(P, \alpha_t, \beta_t), \textit{ where } \psi \textit{ is the Cumulative Gamma Distribution Function}$$

$$\alpha_t, \beta_t = f(\mu_t, \sigma_{FE});\ \alpha_t\ \&\ \beta_t \text{ are the Shape \& Scale Parameters of the Gamma Distribution}$$

$$\mu_t = \textit{Mean Demand over L+R};\ \sigma_{FE} = \textit{Std. Dev. of Forecast Error over Flow Time (FT)}$$

As mentioned earlier, the equation described above answers the main research question in sufficient capacity, which was the main objective of this project. Comparing this to the existing inventory target model, the new model offers higher robustness, includes more parameters so is more subjective and can be modified for each SKU on the basis of multiple considerations. We can conclude that the new model is an overall improvement over the current model for calculating inventory targets. Hence, the research objectives of this project can be considered achieved. Additionally, this project laid laid the groundwork for future research in context of Ampleon to fill in the research gaps observed in this project and also to deal with demand and supply uncertainties and make the inventory management process even more robust and efficient. The rest of this report describes the work in various stages of this project in detail.

Preface

This thesis is written as a part of the masters program Operations Management & Logistics (special track: Manufacturing Systems Engineering) at Eindhoven University of Technology. The thesis project phase started in January 2019 and lasted till October 2019. The project was carried out at Ampleon, Nijmegen and acted as a follow-up to my internship at the same company which extended from September to December, 2019. I was able to identify the research areas during my internship after which i worked on a research plan for the thesis itself. The research questions were in-line with the company's requirements and expectations out of the project.

The primary topics of research include inventory management, safety stock policies, inventory modelling, operations planning and supplier management. The project revolves around finding the most appropriate methods for managing inventory at Ampleon, primarily focused on more efficient and robust safety stock settings while also dealing with issues such as efficient supplier reliability assessment, demand-supply mismatch, adaptability of policies, etc. This thesis consists of a systematic, step-by-step description of the project. Starting with an introduction to the entire supply chain of Ampleon and the inventory policies implemented by the company. Further, it also describes the problem definition and scoping of the project, followed by the pre-requisites and literature study regarding the same. Post that, the approach and methodology used for research and analysis are described in detail after which the modelling and results are described. The analysis of the results are then elaborated and inferences discussed, eventually ending with a solid conclusion. The ultimate objective was to find appropriate answers to the research questions and come up with work which has high scientific relevance as well has a sense of practicality and applicability in an industry like Ampleon. I hope to have achieved all of that through this thesis. Even if the outcomes of this thesis cannot be realized fully, the least it has done is pave the way for future research in a similar context, both in a scientific circle and in context of Ampleon's supply chain management.

The motivation to take up a project like this came from my aim to have a career in operations and supply chain management. I can safely say that throughout the course of this project, I've hand invaluable experiences, conversations and learning which will help me realize this goal in the future. I have gained a lot of knowledge about some of the practices and problems associated with supply chain management and have simultaneously developed an insight to try and find solutions to these problems. Additionally, I've learnt things that are beyond the scope of traditional textbooks. I've become more efficient with my work, developed better time management skills and in general grown a lot on a personal and professional level. The mix of academia and industry has been a boon for me as i conclude this phase of my life feeling more enriched overall.

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I'd also like to express my gratitude towards the European Supply Chain Forum (eSCF), Eindhoven University of Technology and Ampleon for this opportunity. I have had a wonderful experience during the past year, pursuing my internship first and then my master's thesis. I've learned a lot over this course and have grown tremendously as a professional and also as a person. I'd like to thank my friends and colleagues at TU/e and Ampleon who've helped me pull through this crucial phase of my life with a fair amount of ease. They've always been there for me and were always ready to support and help me every time I was in a spot of bother or just needed some company. Lastly, I would like to thank my parents for their constant support and encouragement. I owe everything to them and I hope to have made them proud.

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Chapter 1

Company Introduction

1.1 About the Company: Ampleon B.V.

Ampleon was founded in December 2015 after being sold by NXP Semiconductors as a result of their takeover of Freescale. The company is built on a base of over 50 years of leadership and innovation in the RF sector, with products facilitating a wide range of applications, such as cellular base stations, radio/TV/broadcasting, radar, air traffic control, cooking, lighting, industrial lasers and medical devices. Currently, Ampleon is the leading global partner in RF power and has around 30% market share. It is a company that believes in moving forward with every step and aims to exploit the full potential of data and energy transfer in RF.

The company's headquarters are located in Nijmegen, Netherlands. The primary manufacturing and assembly facility is located in Cabuyao, Philippines while there are R&D centers in Nijmegen, Toulouse and Shanghai. Additionally, there are 14 other sites spread across 3 continents for application support and sales. More than 1300 people work for the company and it has a supplier base of more than 500 to support its manufacturing operations and services. The company has partnered with a number of leading external manufacturers in order to establish a solid and secure industrial base for its differentiating technologies. These include the likes of Vanguard International(VIS), ASE Korea, EPSON, etc.

Figure 1.1: Ampleon's Major Manufacturing Partners

In the mobile broadband sector, Ampleon ranks no. 2 in terms of wireless infrastructure. The company has few of the top companies associated with mobile communication and broadband as their customers, including Nokia, Samsung, Huawei, Ericsson and ZTE among several others. In the broadcast sector, the company ranks no. 1 in the world with customers like Hitachi, Rohde & Schwarz, NEC, etc.

Apart from the aforementioned industries, Ampleon has a remarkable contribution in sectors like Aerospace & Defence, RF Energy and Industrial, Scientific & Medical applications. The company offers a broad LDMOS and GaN technology portfolio and a widespread yet consistent package lineup to facilitate these industries. More than 5000 shipments move from and to 22 countries worldwide on an annual basis.

Figure 1.2: Ampleon's Major Customers - Mobile Broadband

Figure 1.3: Ampleon's Major Customers - Broadcast

1.2 Product Classification

Ampleon has a wide range of products [2] to offer including transistors and other RF power chips. It is a leading company in the segments of Mobile Broadband; Broadcast; Industrial, Scientific & Medical, Air Traffic Control and Aerospace & Defense. It leverages leading edge process technologies for higher performance (GaN, LDMOS) and cost-efficiency to deliver a leading portfolio of options for RF Power.

1.2.1 RF Applications

Radio frequency applications span across a lot of industries and sectors, requiring a variety of products including RF chips, pellets, etc. The following sectors are the primary ones which Ampleon caters through its customers:

- Mobile Broadband

  One of the major product packages of Ampleon is RF power transistors for base stations. Ampleon is the fastest growing supplier of LDMOS transistors for cellular infrastructure, leading the WCDMA and LTE markets while the 5G scenario is looking very promising for the company. It also manufactures Single-Package Asymmetric Doherty (PAD) Transistors and MMICs, Integrated Doherty Amplifiers. Additionally, Ampleon is the first supplier providing both, high-performance GaN HFET and Si LDMOS technology to its customers. The product portfolio is extended with the Air-Cavity Plastic (ACP) packages, which combine high performance with low cost and also make up a considerable percentage of the revenue generated. Other products include Repeaters and Small Cells.

- Broadcast

  Ampleon provides LDMOS solutions for all segments of the broadcast market. The solutions offered include chips for FM/HDR/DAB Radio, UHF/D-TV and VHF/D-TV. Solutions based on narrowband and ultra-wideband Doherty power amplifiers deliver increased efficiency of 50 % and above. thye company's broadcast offering has been enhanced recently with a full range of extremely Rugged (XR) products in our Overmoulded Plastic (OMP) package platform.

- Industrial, Scientific and Medical (ISM)

  The ISM frequency bands feature a diverse range of applications including chemical processing, magnetic resonance imaging (MRI), etc. However, the basic requirements across all these are similar and Ampleon caters to each one of them. High power transistors (for ISM up to 1600 MHz and for the ISM 2.45 GHz Band) are offered along with Low Power Transistors (ranging from 2 to 100 Watts).

- RF Energy

  Solid state RF Energy represents a radical approach to powering many different types of applications. Ampleon is a founding member of the RF Energy Alliance whose members share the vision of building a fast-growing and innovative marketplace and ecosystem around the use of solid state RF Energy as a highly efficient and controllable source of heat and power. naturally, Ampleon offers products to cater to this industry facilitating solutions like RF cooking, RF lighting, RF heating, etc.

- Aerospace & Defence

  For aircraft systems, Size, Weight and Power (SWaP) have long been the key requirements. Ampleon is able to satisfy to those exact needs and more with a broad portfolio for the strategic aerospace & defense market. Ampleon offers RF components, MMICs and complete RF pallets to help in applications like Radar, Electronic Counter Measures (ECM), Military Communication Systems (Milcom), etc.

1.2.2 Technologies

In terms of semiconductor technologies, Ampleon deals in two types of semiconductor technologies at a primary level of classification - LDMOS, and GaN. Both of these have a variety of applications and offer different characteristics to the final product. The following subsections discuss these technologies in detail:

- LDMOS - Laterally Diffused Metal Oxide Semiconductor

  LDMOS is the mainstream device technology used in high-power RF amplifiers for frequencies ranging from 10 MHz to 3.8 GHz. LDMOS offers significant performance advantages, including very high ruggedness and efficiency, high gain, and compatibility with low-cost packaging platforms. LDMOS also offers a strong cost advantage combined with a large industrial base versus other technologies, such as GaN. Ampleons LDMOS technology platforms are designed for devices that run from supply voltages in the range of 28 to 50 V, with outstanding efficiency, power, and ruggedness. It has applications in High Power Doherty Processes and Architectures, Broadband MMICs and Drivers, Markets requiring Higher Power Densities and Ruggedness, Aerospace & Defense Applications, and Aerospace & Defense Applications.

- GaN - Gallium Nitride Semiconductor

  Ampleon leads the industry in offering GaN RF power devices through a secure and reliable mainstream supply chain for wireless infrastructure, industrial, scientific and medical (ISM), and aerospace and defense applications. They find specific uses in areas where there's a need of high frequency performance as they offer high electron mobility and can be used effectively for applications with a demand for high efficiency, high temperature operation, high power, low memory effects, etc. like the creation of High Efficiency Doherty Architectures. They are used heavily in Commercial wireless infrastructure (base stations), Radar systems and jammers, Broadband and narrow band general-purpose amplifiers, Public mobile radios and ISM applications: test instrumentation and EMC testing.

1.2.3 RF Power Transistor Packages

Packaging is an important element in RF power transistors, influencing both the cost-efficiency and performance of a given device. Since peak powers can vary widely, from as low as 5 W to more than 1 kW, a range of packages is needed to cover every application. The choice of package format, often depends on the design requirements, and any trade-offs to be made between performance and cost. The following are the primary types of packages offered by the company:

- ACC - Air-Cavity Ceramic Packages

  The traditional package for RF power transistors is the air-cavity package with a ceramic lid.The package is made of three parts: flange, ringframe and lid. The flange (or heat sink) is brazed with the ringframe at high temperature and the resulting component is known as a header. Active and passive dies are then soldered to the flange and wire bonds are used to create the matching circuits and the connections with the leads. The transistor is then closed by gluing the lid on top. The final step consists of testing the product for compliance to specification.

- ACP - Air-Cavity Plastic Packages

  In order to overcome the limitations of the ACC package while keeping its performance advantages, Ampleon has introduced a new family of packages known as Air-Cavity Plastic (ACP2). Their structure is similar to ACC but the lid and the ringframe are made of polymers instead of ceramic. This enables the ringframe to be glued to the flange rather than brazed, and reduces the stress and distortions of the flange. This in turn allows the use of thinner matching capacitors, reducing RF losses both at the gate and the drain.

  The improved ACP3 package has a further key enhancement by replacing the traditional CPC flange with a Cu flange which gives a 30 % improvement in thermal performance as well as simplifying the board level assembly to provide a highly effective cost-efficient RF package solution.

- OMP - Overmolded Plastic Packages

  A third transistor package family is overmolded plastic (OMP). The package structure is similar to that of an integrated circuit, with a copper flange and a molded body, but discrete wire bonds are used in the matching network for improved RF performance. OMP packages have a number of outlines, from the HVQFN package for low power drivers, to PQFN package for higher power drivers, and the SOT502 format of packages for dual path MMICs, and discretes. OMP is an ideal package for low frequency and low power applications.

1.3 Supply Chain Flows

Ampleon products go through a specific set of stages before they are stored in the global distribution warehouse in Philippines. These processes are common for most products and only a few that need extra processing steps are exceptions. Table 1.1 shows the various stages of manufacturing that a product goes through (top to bottom flow). The figure on the following page describes the entire product-process flow with stages and locations. The locations are described in Appendix A.1.

SLSI	Slice Silicon (Raw) Wafer
SLDI	Slice Diffused Wafer
SLGR	Slice Grinded Wafer
CEPT	Electrical Circuit - Pre-Tested (Die)
CESF	Electrical Circuit - Sawn & Formed
CEGP	Electrical Circuit - Gel-Packed
ICAM	Integrated Circuit - Assembled & Mounted
PEP	Packed End Product (Final Tested)

Table 1.1: Product Stages

1.3.1 Generic Overview - Product Stages

Front & Mid End

The raw wafer (SLSI) is obtained through Nexperia, a supplier in Nijmegen (Vanguard International, Taiwan in the future). Thereafter, the raw wafer undergoes diffusion. This is done in ICN8, which is NXP's manufacturing facility in Nijmegen. More recently, the raw wafer is outsourced to Vanguard for some packages, which also is the long term plan for all packages. For the next stage, the diffused wafer (SLDI) goes to Nexperia's manufacturing facility in Hamburg, Germany or PSI in Taiwan (only in PSI from Q2'19 onwards). The raw wafer is grinded here and finished before being shipped out to AMP - Ampleon's manufacturing and testing facility in Cabuyao, Philippines. The incoming dies are tested (or pre-tested) and then stored in the inventory. These pre-tested dies (CEPT) are stored in the die bank here along with headers, flanges, leadframes, ringframes, etc. which are stored in the raw materials inventory. The die bank, along with raw material inventory serves as the effective decoupling point for the supply chain. The incoming orders govern the release of material from this stage for further processing.

Back End

In the back-end stage, the dies are sawed and/or gel-packed. This process is carried out at AMP for all packages except one, for which it is carried out by ASE, a supplier in Korea.

For the next stage, which is assembly, the dies are shipped to one of AMP, Huashan or ASE Korea, depending on the package and processing requirements. The assembly involves the die, header, flange and other integrated devices as the primary components. Post assembly, the final product is then tested for the final time at AMP (or Sigurd in one case) before they are packed and stocked.

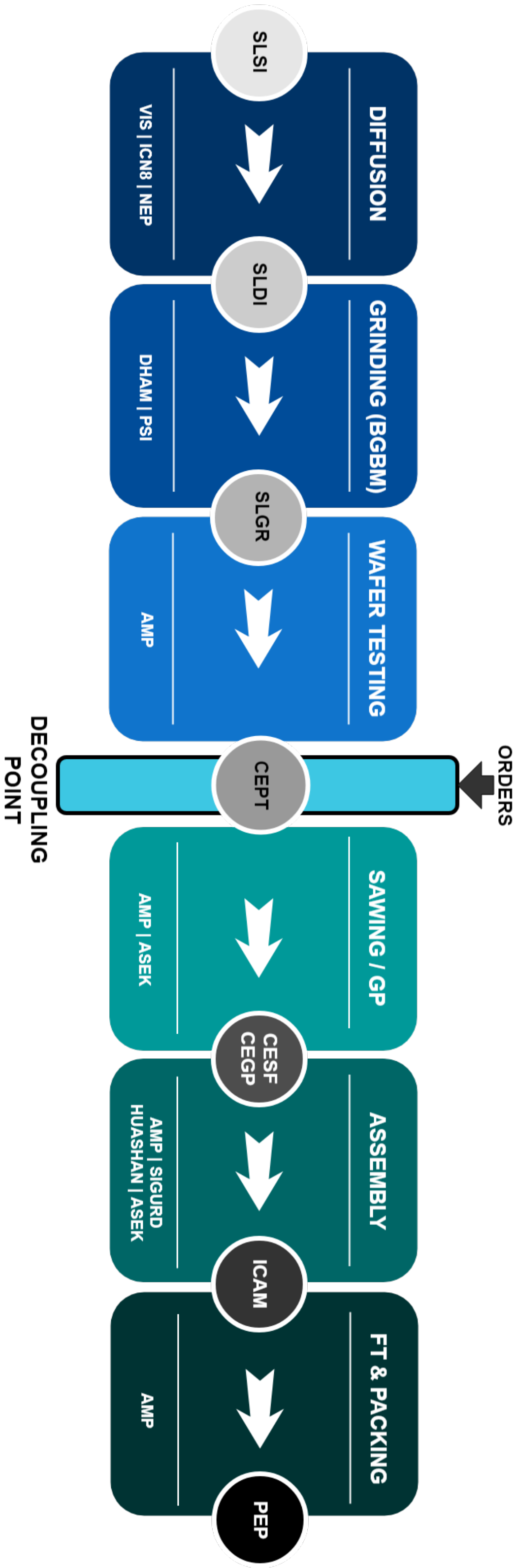

Figure 1.4: Product-Process Flow

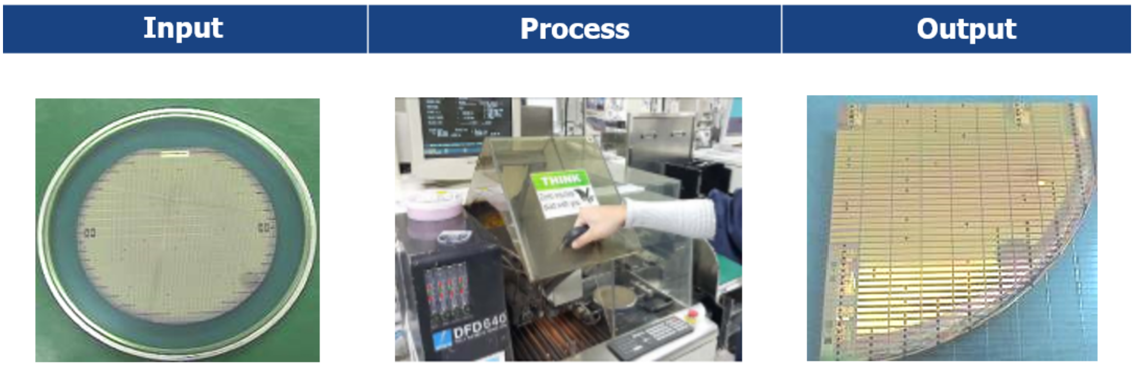

Figure 1.5: Sawing

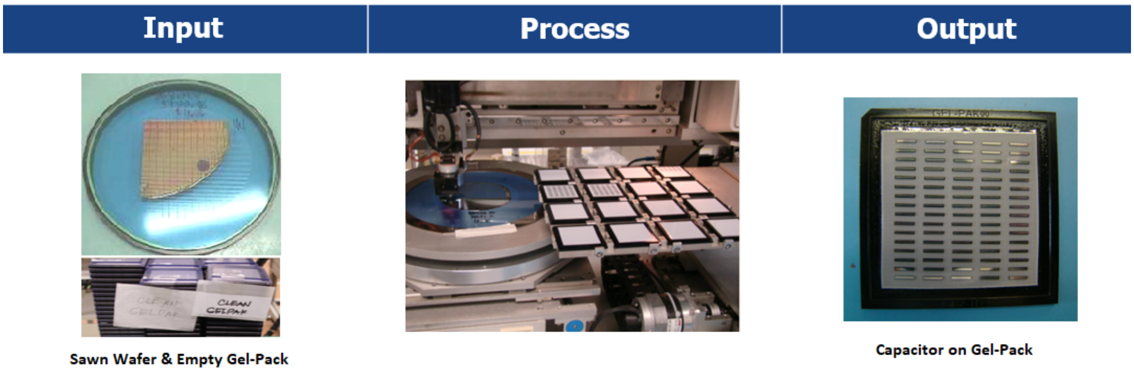

Figure 1.6: Gel Packing

The following steps describe the in-house back-end processing including assembly and testing at AMP:

- Diebond : Process of attaching die (crystal/capacitor) to the header.

Figure 1.7: Die Bond

- Plasma Clean : Process of cleaning the contaminants from the headers and components.

- Wirebonding with Argon : Process of connecting wire from the bonding pad of the die to the metallization.

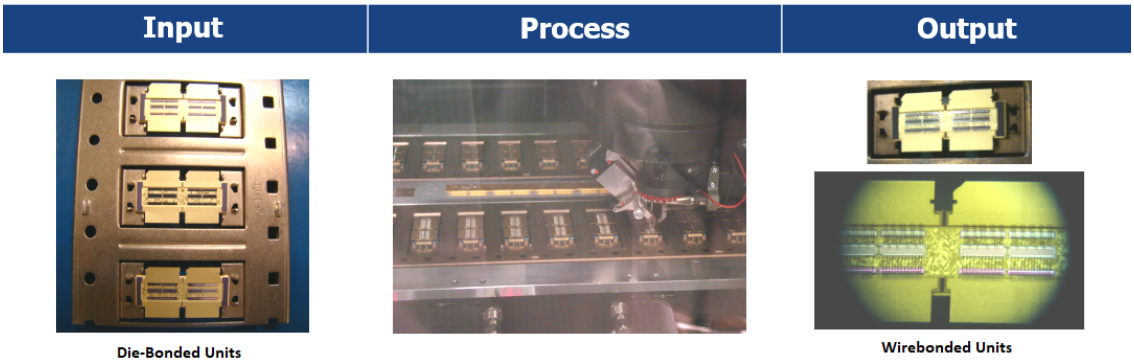

Figure 1.8: Wirebonding

- Low Power Inspection: Process of sorting rejects according to visual criteria.
- Sealing: Process of encapsulating the device using pre glued caps and glue preform.
- Marking: Process of marking the units with device name, code or other requirement.
- Curing: Process of curing uncured mark for marking permanency.
- Bubble Test: Process of submerging encapsulated/cured units in warm Chemical (FC-40) for possible leakage.
- DC1 Test: Process of characterizing the product according to it DC (direct current) electrical specification.
- Chroma Test: Process of determining the scattering parameter response, characterizing the product according to its Radio Frequency specifications and can perform Laser Marking.
- Spar Test: Process of determining the scattering parameter response at Resonance Frequency of the device.
- RF Test: Process of characterizing the product according to its Radio Frequency specifications.
- DC2 Test: Process of checking the open and short + DC (direct current) characteristics.
- Final Visual Inspection: 100% visual inspection done by FVI operator to check the quality of the product and labels.
- Packing: Process of packaging units to the box with appropriate label and exact quantity.
- Outgoing Quality Check: Process where the OQA draw samples to check the integrity of the product prior shipment.

1.3.2 Package Specific Overview

Ampleon's supply chain expands across 6 countries, considering the major manufacturing partners and suppliers. The specifics of these supply chains however, differ minutely from each other based on the packages, their processing requirements and the ease of transport.

In terms of packages, 7 specific packages contribute to 94% of the company's revenue. The processes involved in their manufacturing and the associated supply chain stages and locations of each one of these packages and their individual components can be understood from the following flowchart table. As mentioned earlier, there are 3 primary components for assembly, as described below:

- Dies:
  LDMOS - Laterally Diffused (Multi-Layer) Metal Oxide Semiconductor
  MOSCAP - Metal Oxide Semiconductor Capacitor
- IPD - Integrated Passive Devices
- Headers & Flanges

The Table 1.2 contains a flowchart that denotes the presence of these components with a colour-code (no colour means component absent). For each component in a package, reading from top to bottom as downstream, the supply chain flow can be understood with the column on the left depicting the stage with location and/or process and the column on the right depicting the vendor or location. The assembly location of the package is specified with the package name and that affects the processing locations directly.

For example, if we consider the **ACP2** package in the flowchart, we can understand that it is assembled at AMP. The package contains all 4 components listed - LDMOS, MOSCAP, IPD and a Flange. For LDMOS, the raw wafer undergoes the diffusion and then the grinding processes at ICN8, Nijmegen and Nexperia, Hamburg respectively with Nexperia being the acting supplier. Further, the dies are tested at AMP and stored in the Die Bank. The pre-assembly steps for LDMOS including Gel packing, etc. also take place at AMP for this product package. The MOSCAP and IPDs for ACP2 go through a similar fate and the same processing steps as LDMOS at the exact same locations. The basic flanges are supplied by Plansee and NGK and the gritblasted flanges are supplied by Orapma. Finally, the processed components are assembled and packed at AMP, as mentioned earlier.

Similarly, if we consider the package **OMP**, we can understand that it primarily contains only two components - LDMOS and IPD, which are assembled at AMP or outsourced to HUASHAN for the same. The LDMOS has a similar supply chain flow as described above for ACP2. The IPD for OMP however, is supplied by Vanguard where the diffusion and grinding is carried out before it's sent to AMP for storage and further processing.

NOTE : The described supply chain flow is the current in-practice scenario. Future plans and implementations have not been included.

AMPLEON Product-Process Supply Chain Flowchart (Assembly Components)

Product Package	LDMOS Stage	LDMOS Vendor	MOSCAP Stage	MOSCAP Vendor	IPD/IPD2 Stage	IPD/IPD2 Vendor	Flange/Header Type	Flange/Header Vendor
ACC Assy: AMP	SLDI (ICN8)	Nexperia	SLDI (VIS)	Nexperia			Basic Headers	NGK
	SLGR (DHAM)	Nexperia	SLGR (DHAM)	Nexperia				Materion
	CEPT (WT)	AMP	CEPT (WT)	AMP				Kyocera
	CEGP (WS/PnP)	AMP	CESF (WS/PnP)	AMP				
ACP2 Assy: AMP	SLDI (ICN8)	Nexperia	SLDI (VIS)	Nexperia	SLDI (ICN8)	Nexperia	Basic Flanges	Plansee
	SLGR (DHAM)	Nexperia	SLGR (DHAM)	Nexperia	SLGR (DHAM)	Nexperia		NGK
	CEPT (WT)	AMP	CEPT (WT)	AMP	CEPT (WT)	AMP	Gritblasted	Orapma
	CEGP (WS/PnP)	AMP	CESF (WS/PnP)	AMP	CESF (WS/PnP)	AMP		
ACP3 Assy: AMP	SLDI (ICN8)	Nexperia	SLDI (VIS)	Nexperia	SLDI (ICN8)	Nexperia	Copper Flanges	Possehl
	SLGR (DHAM)	Nexperia	SLGR (DHAM)	Nexperia	SLGR (DHAM)	Nexperia		
	SLCW (Plating)	EPSON	CEPT (WT)	AMP	CEPT (WT)	AMP	Gritblasted Flanges (SOT27X)	Orapma
	CEPT (WT)	AMP	CESF (WS)	AMP	CESF (WS)	AMP		
	CEGP (WS/PnP)	AMP						
HVSON Assy: ASEK	SLDI (ICN8)	Nexperia						
	SLGR (PSI)	Nexperia						
	CEPT (WT)	AMP						
	CESF (Sawing)	ASEK						
PQFN Assy: ASEK/AMP	SLDI (ICN8)	Nexperia						
	SLGR (PSI)	Nexperia						
	CEPT (WT)	AMP						
	CESF (Sawing)	AMP						
OMP Assy: AMP/Huashan	SLDI (ICN8)	Nexperia			SLDI (ICN8)	VIS		
	SLGR (PSI)	Nexperia			SLGR (DHAM)	VIS		
	CEPT (WT)	AMP			CEPT (WT)	AMP		
	CESF (Sawing)	AMP			CESF (WS)	AMP		
TO270 Assy: Huashan	SLDI (ICN8)	Nexperia						
	SLGR (PSI)	Nexperia						
	CEPT (WT)	AMP						
	CESF (Sawing)	AMP						

Table 1.2: Supply Chain Overview for Packages

1.4 Supply Chain Management

The company's manufacturing supply chain extends across Europe and Asia starting from Netherlands or Taiwan and ending in Philippines through the likes of Germany, China and Korea. Organized in two locations (Nijmegen-NL and Cabuyao-Philippines) with many nationalities, the supply chain management focuses on global order fulfillment & planning, manufacturing & subcontractor planning, product life cycle management, volume ramp-up and global distribution & warehousing. The following table describes the typical supply chain flow and expanse in brief along with the lead times.

Front End	Wafer Diffusion	Outsourced	4-16 Weeks
Mid End	Grinding of Wafer	Outsourced	2-4 Weeks
Decoupling Point after Wafer Test (WT) in AMP Philippines			
Back End	Assembly & Final Test	AMP + Subcontracted	4-7 Weeks

Table 1.3: Ampleon Supply Chain Flow

The location and positioning of the decoupling point is justified for a variety of reasons. The pre-tested dies have the maximum shelf life and they allow some flexibility in terms of usability in the assembly for multiple end-products. Additionally, the storage location in Philippines is also the main assembly site, allowing seamless flow of pre-tested dies into assembly. The total lead times from start to finish can extend up to 27 weeks. Apart from the in-house manufacturing and assembly facility, the entire process also involves a number of external manufacturing partners, suppliers and service providers. As a result, it is very important to have a structured inventory policy that enables the company to keep the inventories in check and also keep the customers satisfied.

Ampleon used to be part of NXP with only internal manufacturing locations. In its journey to become independent and to support the increasing variety of technology offerings, Ampleon is relying more on external parties. At the moment, Ampleon has an increasing number of links in the supply chain with multi-tier suppliers. So far, the company has inherited a one size fits all approach in defining the inventory targets. This is currently defined in the so called "Die Bank" (roughly after 2/3 of leadtime) with a fixed number of pieces to cover for an average demand of 'x' weeks. Although the lead times are huge and can vary based on a variety of factors, the variation due to distribution variabilities are negligible since all of the transportation for Ampleon is done by air freight or express deliveries.

1.4.1 Inventory Policy Brief

At Ampleon, inventory is held in three forms (or locations) - the die bank in Philippines which holds the pre-tested dies, the raw material inventory (also located in Philippines) which holds the headers, flanges, etc. and other vendor managed locations. The die bank and raw material inventory together are the physical interpretation of the decoupling point in the supply chain, placed just before assembly. The vendor managed inventory (VMI) locations hold the packed end products (PEP) in stock. The inventory control policies for all these three units are defined separately. For dies and headers, the inventory management and replenishment policies are governed by preset inventory targets. They are dependent on several factors such as lead time, supplier reliability, etc. This inventory target inherently incorporates the following elements:

1. Strategic stock (to cover for opportunity demand)
2. Supplier variation (to cover for supplier delivery reliability)
3. Demand variation (to cover for customer demand swings)
4. Operational stock (to always have some stock to cover production and production variation)

Although these factors are taken into account, their exclusive contribution is difficult to analyze and they do not contribute directly to the numerical calculation of the inventory target. The inventory management at Ampleon has been discussed in detail in the chapter 3.

Chapter 2

Relevant Concepts

Inventory management is widely considered as the basis of good performance in a supply chain. Before diving into the details about Ampleon's inventory management, it's important to lay out the relevant concepts of Inventory Management. This will allow us to draw a parallel between theory and practice and understand how similar or different they are from one another. Further, this will also enable us to look into the right places to improve the existing inventory management practices.

2.1 The Role of Inventory

In today's date, it's a pretty well known fact that better management of inventories throughout the supply chain represents a huge opportunity for businesses. The ultimate challenge for any business is the management of costs along with customer satisfaction. The critical nature of inventory management can be understood by the fact that inventory directly affects both costs and service. Hence, it's important to find the right balance between inventory and customer service levels. Figure 2.1 depicts this balance between inventory and customer service, as described by Neale et al. [20].

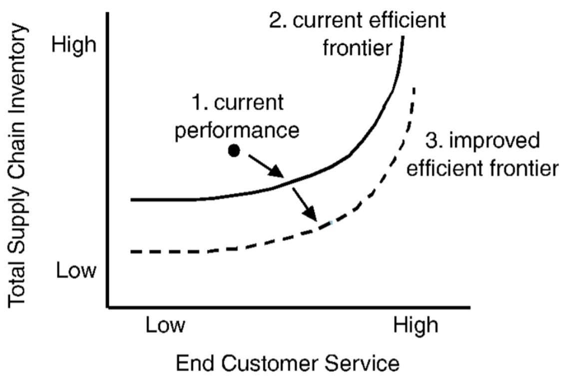

Figure 2.1: Inventory v/s Customer Service [20]

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The efficient frontier in the figure represents the general approach towards inventory management which is the reduction of inventory (costs) while maximizing customer service and satisfaction. For each possible end customer service level, the efficient frontier plots the minimum amount of supply chain inventory required to achieve that service level. Ideally, having more inventory would result in better service levels. However, holding larger inventories results in higher costs too. Hence, the objective within any supply chain should be to move as close to the efficient frontier as possible.

2.2 Decision Variables

The decision making process associated with inventory management as a whole is quite complex and includes the consideration of several parameters. These parameters vary based on the nature of product, the supply chain expanse, locations, costs, etc. The table 2.1 gives a brief idea of the key decision variables in inventory management, as described in the book Inventory Management and Production Planning and Scheduling by Silver et al. [27].

Service requirements • Customer expectations • Competitive practices • Customer promise time required • Order completeness required • Ability to influence and control customers • Special requirements for large customers	*Customer-ordering characteristics* • Order timing • Order size • Advanced information for large orders • Extent of open or standing orders • Delay in order processing
Demand patterns • Variability • Seasonality • Extent of deals and promotions • Ability to forecast • Any dependent demand? • Any substitutable products?	*Supply situation* • Lead times • Reliability • Flexibility • Ability to expedite • Minimum orders • Discounts (volume, freight) • Availability • Production versus nonproduction
Cost factors • Stockout (pipeline vs. customer) • Carrying costs • Expediting • Write-offs • Space • Spoilage, etc.	*Nature of the product* • Consumable • Perishable • Recoverable/repairable
	Other issues • A–B–C pattern • Timing and quality of information • Number of stocking locations • Who bears the cost of inventory?

Table 2.1: Inventory Planning Decision Variables
[27]

In this project, the focus is on the aspects of demand variation, supply variation and service requirements to assess the existing inventory management practices at Ampleon and formulate safety stock policies with theoretical justification. Depending on the requirement and necessity, these decision variables will be used and referred to in later parts of this report.

2.3 Classical Inventory Models

Silver, Pyke & Peterson [27] describe four classic inventory models which form the basis of inventory management. These models have been defined using certain parameters which drive the decision making. The driving factors or parameters include the reorder point (s), the order-upto level (S), the order quantity (Q) and the review period (R). Based on these parameters, the classical inventory models are described as follows:

- **(s,Q) Model**
  In this model, the critical parameters are the reorder point and the order quantity. In simple terms, an order of size Q is placed every time the inventory level is equal to or less than the reorder level.

- **(s,S) Model**
  In this model, the critical parameters are the reorder point and the order-upto level. Every time the inventory level is equal to or less than the reorder point, an order is placed which increases the inventory position (defined as the total inventory on stock and in the pipeline) to the order-upto level.

- **(R,S) or the Base-Stock Model**
  In this system, the inventory level is checked every R periods. An order is placed to increase the inventory position upto the order-upto or the base-stock level after every R periods, regardless of the inventory level at the end of the period.

- **(R,s,S) Model**
  Similar to the (R,S) system, the inventory level in this system is checked every R periods. At the end of R periods, if the inventory level is equal to or below the reorder point, an order is placed to increase the inventory position upto the order-upto level.

2.4 Service Measurements

In order to judge and analyze the performance of a system, certain performance measurement metrics are defined. In inventory management, the service levels provide as this performance metric. The service level can be described as the ability to satisfy a customer demand within a certain time. This reflects how good or bad is the inventory management & supply chain management as a whole. In theory [27, 22], three basic service level definitions exist while a few more are used in the industry for a more robust assessment of service.

2.4.1 Theoretical Service Level Definitions

- **P_1, Cycle Service Level**
  It is defined as the Probability of no stock out in a replenishment cycle. In other words, P_1 is the fraction of cycles in which a stockout does not occur.

- **P_2, Fill Rate**
  It is the fraction of customer demand that is met routinely from available inventory.

- **P_3, Ready Rate**
  It is defined as the fraction of time during which the net stock is positive; that is, the fraction of periods when there are no backlogs.

2.4.2 Industrial Service Level Definitions

- **LAP** - Line Acceptance Performance
  It is defined as the fraction of customer order lines that are confirmed at the customer requested date.

- **CLIP** - Confirmed Line Item Performance
  It is defined as the fraction of orders delivered on or before the pre-decided norm for supply, based on the first confirmed date for an order. RLIP can also be expressed as a product of LAP and CLIP.

- **RLIP** - Requested Line Item Performance
  It is defined as the fraction of orders delivered according to a pre-decided norm for supply (the period in which an early or late delivery can be considered as okay), based on the customer requested date for an order.

$$RLIP = LAP * CLIP$$

2.5 Safety Stock

Safety stock is defined as inventory that is carried to prevent stock out and back order situations. Safety stocks provide protection against various variabilities and uncertainties, such as demand fluctuation, delivery date variances (when the replenishment lead time varies), requirement variances (when the forecast is inaccurate) delivery quantity variances (when the vendor does not deliver enough materials or the quality of delivered materials is poor) and inventory variances (when inventory recognizes a deviation between the plan and actual inventory) [22].

Safety stock policies can be formulated in order to minimize costs, achieve a certain service level or other aggregate considerations. In most cases, safety stock policies are governed by a service level definition and is often expressed as a product of two parameters, a safety factor and standard deviation of demand (or forecast). Figure 2.2 shows the standard approach for setting safety stock policies, as described by Silver et al [27].

$$SS = k * \sigma_L \tag{2.1}$$

$$k = \phi^{-1}(\alpha) \tag{2.2}$$

$$s = \hat{x}_L + SS \tag{2.3}$$

Here, k is the safety factor decided based on the target service level α. It is given by the inverse of the standard normal cumulative distribution (ϕ) where the desired probability is equal to the cycle service level (α) or the probability of no stock outs when the replenishment order arrives. The underlying assumption is that the demand is normally distributed.

σ_L is given as the standard deviation of forecast error during the lead time. The standard deviation of demand can also be used but in cases where a forecasting model is in place, the safety stocks are meant to cover the inaccuracy in forecast and not the demand fluctuation since that is already taken care of by the forecasting model.

x_L is the mean demand during lead time L, obtained from the forecasting model. In other words, it is the mean demand forecast during the lead time. Other factors such as supplier reliability, lead time variation, etc. can also be taken into account depending on the existing inventory model and the critical nature of these parameters in inventory planning.

s is the base-stock level or the order-upto level. For a [R,s] system, s is expressed as the sum of safety stock and the mean demand during the lead time L.

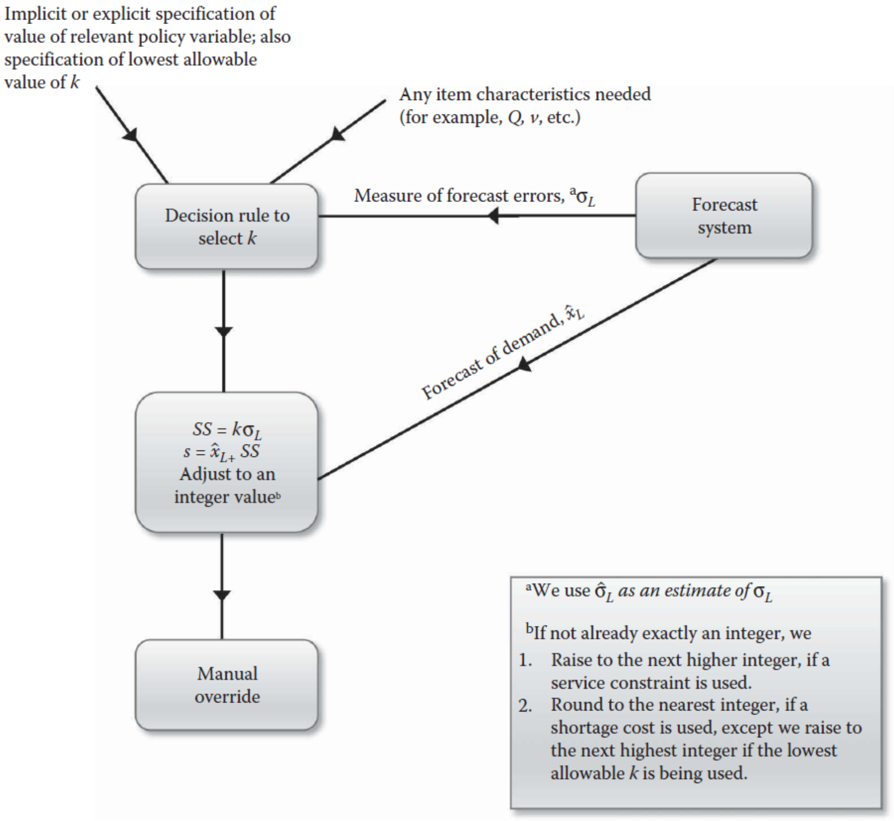

Figure 2.2: Decision Rule for Calculating Safety Stock & Reorder Level [27]

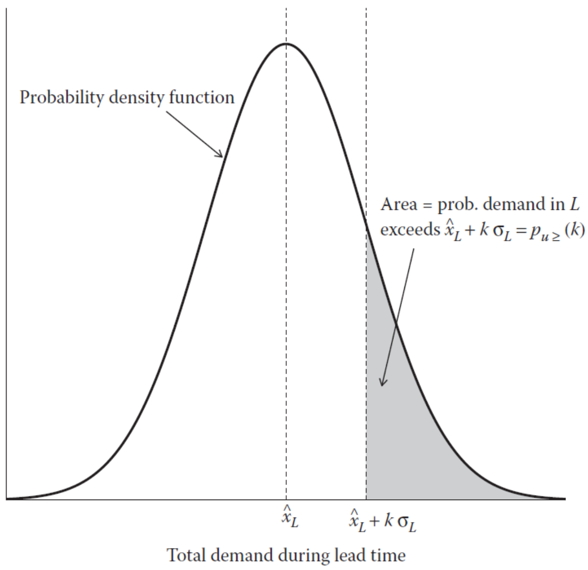

Figure 2.3: Probability Density Function of Normally Distributed Demand

Chapter 3

Ampleon's Inventory Management

Ampleon, as a company has been operational for around 3 and a half years now. In terms of supply chain management, most of the policies have been inherited from NXP. However, based on the changes in requirements of products, processes and the global semiconductor market, there have been modifications, additions and omissions to the original set of policies over time. Ampleon's supply chain is pretty vast and has multiple flows for various product categories. We already have an overview of the supply chain and the lead times involved. As discussed in Chapter 1, Ampleon has one major inventory holding location in the Philippines, called the Die Bank which holds all the pre-tested dies (referred as CEPT). A raw material stock is also available at the same location which holds inventory for other components required for assembly. These raw materials, for example headers, are ordered via external suppliers and only the inventory levels are controlled by Ampleon. Additionally, Ampleon has certain Vendor Managed Inventories (VMIs) which are not under direct control of the company but the policies for these locations are set by Ampleon.

3.1 Inventory Classification

On a basic level, the company deploys two types of inventory policies depending on the type of products:

1. **Critical Items**
   These need to be taken into account in supply planning and are managed via a SAP based Advance Planning System (APS) called IBP - Integrated Business Planning. The basis of this planning, however, is defined my the company. The critical items include the dies, stored in the Die Bank and Headers/Flanges, stored in the raw material inventory.

2. **Non-Critical Items**
   These are planned using a reorder level in SAP, mostly applicable to standard bulk materials. The non-critical items include the likes of packages, tubes, reels, lids, etc.

Ampleon uses a one size fits all approach, inherited from NXP in defining the inventory targets for critical items. This is currently defined for the Die Bank with a fixed number of pieces to cover for an average demand of 'x' weeks. This is the safety stock, stored and maintained to deal with demand fluctuations and supply variabilities. The objective is to maintain inventory at the target level while satisfying weekly demand using the scheduled receipts of supplies. The 'x' here is essentially a time equivalent of the safety stock level. In other words, the inventory target or the safety stock equals x weeks of stock based on an average demand across a certain number of weeks. The inventory control model utilized by the system is applicable to only these items.

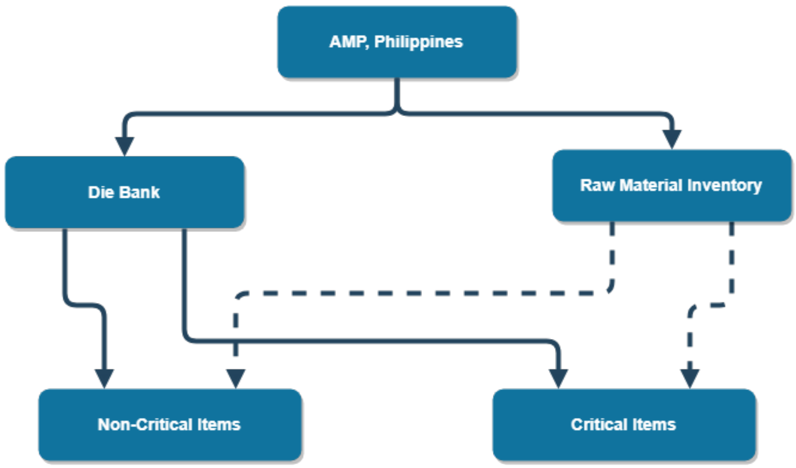

Figure 3.1: Inventory Classification

3.2 Operational Inventory Model

Ampleon's inventory management is driven by an inventory target setting for the dies and headers which underlines the approach towards holding inventory. It's essentially a reactive approach towards dealing with incoming (forecasted) demand while holding enough inventory to see-out any kind of lapses in manufacturing or supply. As mentioned before, the basic idea is to keep the net inventory at the inventory target at all times, regardless of the variation in demand.

The dies are ordered based on a supply metric, derived from the demand forecast for the dies for the period post lead time (obtained using the bill-of-materials and the end-product demand forecast). In other words, to fulfil demand in period $w+L$, dies are ordered in period w. When the order arrives, it's supposed to add to the existing inventory and this total inventory would be used for supply in that period. The projected inventory at the beginning of period $w+L$ is analyzed to calculate the order quantity for orders placed in period w. Orders are placed such that the total inventory (shelf + pipeline inventory) is sufficient to meet the expected demand in period w and maintain the inventory level post supply equal to the safety stocks, $SS_w + L$. This total inventory is given by the Target Inventory Level, TIL_w. This cycle of ordering, replenishment and consumption continues and the net stock for all the dies and headers is expected to fluctuate around the inventory target level as the demand is fulfilled. The net stock at the end of a period is the inventory at the beginning of the next period. The actual inventory at the beginning of every period is used to assess the service level. This process is carried out every week, essentially meaning that the review period is 1 week. As a result, orders are placed every week.

While ordering in week w, the following parameters are taken into account:

Lead Time = L

Review Period = R = 1 Week

Demand forecast for week w (based on demand forecast) = F_w

Hence, supply data for week $w + L = F_{w+L}$

Actual demand for week $w = D_w$

The scheduled receipts (arriving replenishment orders) in week $w = SR_w$

Projected Inventory at the beginning of an arbitrary week $w = PI_w$

Actual Inventory at the beginning of an arbitrary week $w = AI_w$

Projected Inventory at the beginning of week $w + t$ in the future $= PI_{w+t}$

$$PI_{w+t} = PI_{w+t-1} + SR_{w+t-1} - F_{w+t-1} \tag{3.1}$$

Actual Inventory at the beginning of week $w + t$ in the future $= AI_{w+t}$

$$AI_{w+t} = AI_{w+t-1} + SR_{w+t-1} - D_{w+t-1} \tag{3.2}$$

Looking L periods ahead of a specific period, W:

Projected Inventory at the beginning of week $W + L = PI_{W+L}$

Now, Actual Inventory at the beginning of the current period $= AI_W$

Also, Projected Inventory at the beginning of the current period $= PI_W = AI_W$

Hence, Projected Inventory at the beginning of next week $= PI_{W+1}$

$$PI_{W+1} = AI_W + SR_W - F_W \tag{3.3}$$

Using equation (3.1), we have:

$$PI_{W+L} = PI_{W+L-1} + SR_{W+t-1} - F_{W+t-1} \tag{3.4}$$

Hence, using equations (3.1), (3.3) and (3.4), **for any arbitrary week w:**

$$PI_{w+L} = AI_w + \sum_{t=0}^{L-1} SR_{w+t} - \sum_{t=0}^{L-1} F_{w+t} \tag{3.5}$$

Similarly,

$$AI_{w+L} = AI_w + \sum_{t=0}^{L-1} SR_{w+t} - \sum_{t=0}^{L-1} D_{w+t} \tag{3.6}$$

3.2.1 Replenishment Policy

The current Safety Stock Policy is described in Section 3.3. A production order is generated every week (w) which is aimed at restoring the inventory level for the period $w + L$ upto the safety stocks, after the demand is fulfilled. Hence, this accounts for the demand forecast for the period $w + L$ and the expected shortage in inventory in period $w + L$ with respect to the safety stock. If no shortage is expected, i.e. the projected inventory post supply is equal to the safety stocks, then the order is equal to the demand forecast for the period in which the order arrives. Currently, lead time variabilities are assumed to be negligible for ordering purposes.

At the beginning of week w, the projected inventory at the beginning of week $w+L$ can be given by PI_{w+L}, given by equation (3.5). Hence, projected inventory at the end of week $w+L$ can be given by:

$$PI_{(w+L)^+} = PI_{w+L} - F(w+L)$$

Hence,

$$PI_{(w+L)^+} = AI_w + \sum_{t=0}^{L-1} SR_{w+t} - \sum_{t=0}^{L} F_{w+t} \tag{3.7}$$

The objective here is to keep the net stock at the end of week $w+L$ equal to the Safety Stock for that week, that is SS_{w+L}. Hence, the order quantity necessary to restore the net inventory upto the safety stock level in week $w+L$ can be given by Q_w, for an order placed in week w.

$$Q_w = SS_{w+L} - PI_{(w+L)^+}$$

Hence,

$$Q_w = SS_{w+L} + \sum_{t=0}^{L} F_{w+t} - \sum_{t=0}^{L-1} SR_{w+t} - AI_w \tag{3.8}$$

The orders placed in week w are expected to arrive in week $w+L$, for planning purposes. Hence, the expression for Scheduled Receipts is given by:

$$SR_{w+L} = \begin{cases} Q_w, & \text{if } Q_w > 0. \\ 0, & \text{if } Q_w \leq 0. \end{cases} \tag{3.9}$$

The same expression contributes to the calculation of the projected inventory for period beyond $w+L$, as described in equation (3.5) and so on. This completes the cycle for inventory management, which is indeed a recursive operation of maintaining optimal and sufficient inventories.

Target Inventory Level

The equation (3.8) can be understood as Q_w is the order quantity necessary to take the inventory level post replenishment in week $w+L$ upto a Target Inventory Level TIL_w, which is sufficient to cover the demand for that week and restore the inventory level to the safety stock. Hence,

$$Q_w = TIL_w - PI_{w+L} \tag{3.10}$$

Therefore, using equations (3.5), (3.8) & (3.10), the Target Inventory Level, TIL_w can be expressed as the sum of Safety Stock for week $w+L$ and the Demand Forecast for week $w+L$, as observed in week w. The expression for Target Inventory Level is:

$$TIL_w = SS_{w+L} + F_{w+L} \tag{3.11}$$

3.3 Safety Stock Policy

As stated before, Ampleon uses a one-size fits all approach for inventory management. Essentially, the inventory policy in place for a particular die type remains the same across all product variants that use that die type. The same logic applies to the raw materials too, such as headers, flanges etc. The inventory is controlled based on an inventory target setting, also referred to as the safety stocks. The inventory target is primarily dependent on three factors:

1. Lead Time
2. Average Demand (based on forecast, looking ahead)

3. Supplier Reliability

However, the exclusive effect of each of these factors is difficult to analyze and they do not contribute to the numerical calculation. The inventory target set as a time equivalent for inventories, is set for different categories as follows:

- CEPT - Pre-Tested Dies
  Average demand per week over 2 quarters (26 weeks)
  × 6 Weeks (MOSCAP)
  × 12 Weeks (LDMOS through ICN8)
  × 16 Weeks (LDMOS through VIS)
  × 20 Weeks (LDMOS, 1 product category, through EPSON)
- Headers
  Average demand per week over 1 quarter (13 weeks)
  × 8 Weeks (Average LT for Headers)
- VMI
  Average demand per week over 12 weeks
  × 4 Weeks

At the moment, the inventory targets are set for the entire horizon. However, the planning is carried out on a monthly basis which essentially sees the targets modified every month or in some cases, every week. This allows relatively more flexibility in terms of being able to incorporate external factors which might affect the inventory planning such as demand hikes & drops or other manufacturing variabilities. However, since the lead times of components involved are really high at times, this also increases risks associated to the inventory management.

3.4 Demand & Supply Planning

The demand and supply planning is carried out almost entirely using SAP-IBP. The following parameters define the operational characteristics of the module:

- **Input Parameters**
  1. Consensus Demand Forecast (from Forecasting Model)
  2. Inventory Target
  3. Stock On Hand
  4. Capacity Constraints
- **Output Key Figures**
  - Demand-Side Output Figures
    1. Dependent Demand (Based on Consensus Demand Forecast & BOM)
    2. Capacity Demand
  - Supply-Side Output Figures
    1. Supply
    2. Customer Receipts
    3. Production Receipts
    4. Transport Receipts
    5. Projected Stock

The inventory target settings are manually adjusted by demand planners based on their experience and expertise. Depending on requirement and necessity, the target is modified and fed into the optimizer. The optimizer returns the dependent demand forecast and other key figures which govern the ordering and demand fulfilment at the company.

Each supply run in the optimizer returns a set of the aforementioned output figures. A supply run is carried out once every week. In other words, the review period for inventory control is 1 Week. A single run returns the upstream results which are then adjusted based on capacities other constraints for the downstream results. The downstream results are used for supply planning. The Figures 3.2 & 3.3 describe the upstream and downstream results obtained from a single run in the SAP-IBP optimizer.

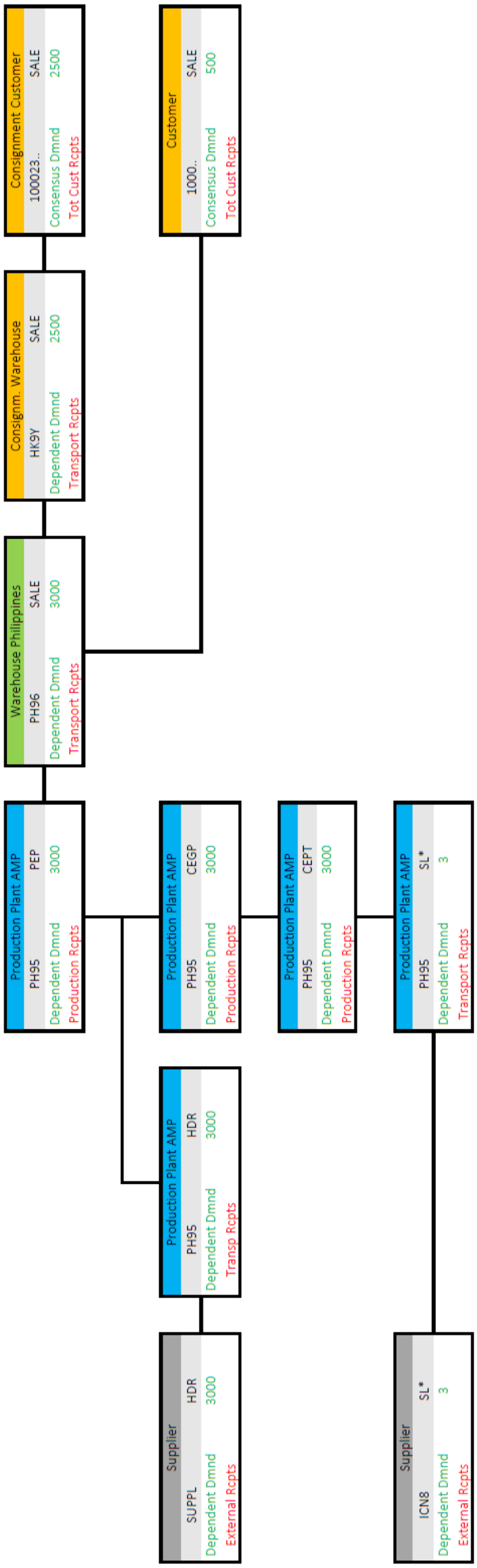

Figure 3.2: Upstream Results - SAP-IBP Supply Run

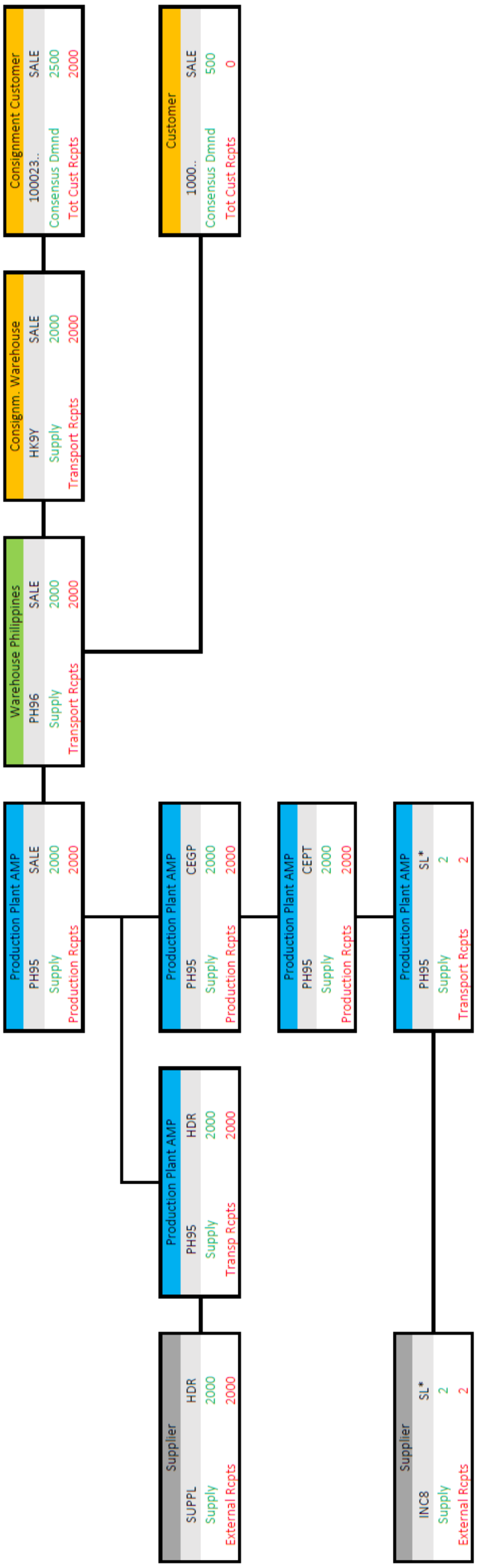

Figure 3.3: Downstream Results - SAP-IBP Supply Run

Chapter 4

Problem Definition

4.1 Problem Context

Now that we have established an in-depth understanding of Ampleon's supply chain flows and inventory policies, it's possible to dive into the relevant aspects which need to be assessed and could be improved. Based on previous chapters and feedback from the supply chain management team at Ampleon, the following problem areas were identified:

1. The 'x' in 'x' weeks of safety stocks
   The safety stock policies Ampleon sets for the dies and headers which serve as the inventory targets for demand and supply planning do not have a rigorous definition. Although the dependencies have been defined, they are not taken fully into consideration while setting inventory targets. As a result, the authenticity of the inventory targets is unchecked and at times it results in very high inventories. The following points highlight the issues:
   - The relation between x and the lead times of the respective die types is unclear.
   - Supplier reliability is not taken into account.
   - Demand fluctuation or deviation from forecast is not taken into account.
   - The mean demand considered is across a longer time period which normalizes any sudden fluctuations during the actual lead time.
2. Demand Forecasting
   Ampleon uses a forecasting module to generate a demand forecast for the upcoming weeks. This forecast is used for demand and supply planning and also for setting the inventory targets. The following points highlight the issues:
   - The dependencies of forecasts are not clear.
   - Forecast accuracy is not considered while using the data for inventory planning.
3. Supplier Reliability
   Ampleon uses Confirmed Line Item Performance as a metric to judge supplier performance. The following points highlight the issues with supplier reliability assessment:
   - Although reliable, in some cases CLIP does not represent the accurate picture. RLIP should be preferred since it's based on the initial requirement date.
   - The company only focuses on the compliance of agreed date of delivery and not the agreed quantity.
   - Supplier reliability is considered in a very crude manner but not numerically involved in the safety stock settings.

4.2 Cause-Effect Diagram

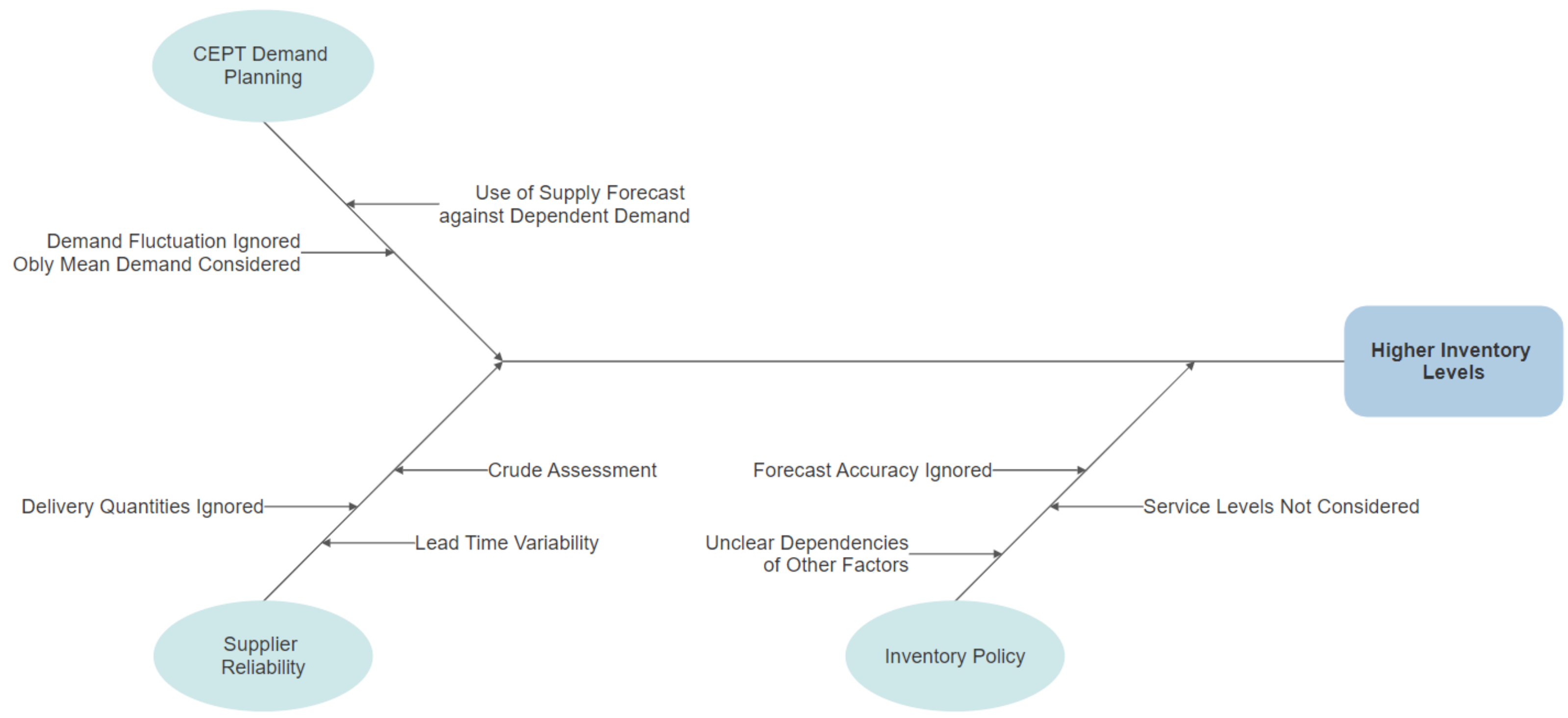

Figure 4.1: Cause-Effect Diagram

4.3 Research Questions

Based on the aforementioned points and the cause-effect diagram described in Figure 4.1, it's clear which aspects must be looked into. The following research questions were drafted for the thesis and obtaining answers to these are the primary objectives for this project:

1. **How accurate is the demand planning at Ampleon? How can the forecast accuracy be assessed and taken into account for inventory management?**
2. **What is the suggested method to calculate the safety stocks and inventory targets?**
3. **Devise a way to measure supplier reliability and its integration into the calculation of safety stocks.**

4.4 Project Scope

The scope of this project is limited to the critical items, as classified by Ampleon for inventory management. The primary agenda is to have well-defined inventory policies in place for specific product categories which are handled at the Die Bank in Philippines. All processes happening beyond the die-bank stage in the company's supply chain have been considered out of scope. However, it's important to understand that the inventory policies for handling products at the die bank have an impact on the customer service levels of the respective end products and the company's overall service level. This fact has been taken into account while analyzing the data since the demand for raw materials and dies at the die bank are dependent on the demand for the end products. Although the company handles end product inventories differently, the fulfilment is based on the supply of dies and raw materials. Hence, inventory management of the end products (PEPs) is also considered out of scope. Lastly, for supplier assessment, only the direct suppliers for dies and raw materials have been taken into consideration for this project. No second-tier suppliers have been assessed and any performance issues at bay will not be a representative of the reliability of these suppliers.

4.5 Research Areas

4.5.1 Safety Stocks

Ampleon offers a wide variety of products to its customers. Although the composition of each product is different, it can be generalized in categories, as described in chapter 1. In each product category, there are a variety of components and die variants that are used. The two main categories are LDMOS & MOSCAP. The other die categories include dies used in Integrated Passive Devices (IPD) and several other non-critical dies. If we dive deeper into the specific end product categories, each of these die types are further classified into sub categories which are associated with a set of end products. However, the control strategy is defined at the primary classification level, as depicted in the figure 4.2.

These dies are stored after pre-testing them at the Die Bank. The inventories of these dies are handled separately and have well-defined policies for inventory management. As discussed in chapter 3, the inventories of dies and headers are governed by setting 'x' weeks of safety stocks. In this project, the focus has been on LDMOS & MOSCAP dies at the CEPT(pre-tested) stage. This is because these are considered the most crucial in terms of inventory management and their flows and lead times are well known. Understandably, the dependencies can be identified easily in the case of these dies. The objective here was to analyze the demand, supply and inventory data to understand the inventory control, demand and supply planning for these dies and find a method to optimize their safety stock settings.

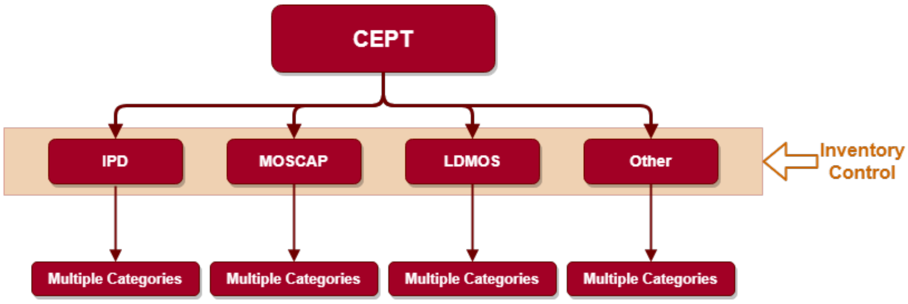

Figure 4.2: CEPT Categories & Inventory Control

4.5.2 Supplier Reliability

The 'x' in 'x' weeks of safety stocks is dependent on the leadtime of the product and the supplier reliability which is judged crudely on the basis of order history but does not entirely contribute to the calculation of x. In order to understand this dependency better, a consolidated method for supplier reliability assessment was necessary. The primary analysis was done only for those suppliers for whom sufficient data was available. The assumption here is that a standard method of assessing supplier performance should be applicable to the entire supplier database.

Chapter 5

Literature Study & Methodology

5.1 Literature Review

Over the years, inventory management and safety stock optimization in particular has been a well studied and researched topic. The importance of efficient inventory management policies is no secret and multiple approaches have been used by various people & companies in various contexts to find the best ways to manage their inventory. Most of the research involved complex objective functions which are difficult to analyze and implement. On a basic level, the approach has varied only slightly over the years with contextual references being able to refine the methods as the time went by. Most researchers have opted to start with a basic single-stage system and explore the possibilities and application to more complex ones.

In [4], W. C. Benton acknowledged that safety stock is a requirement for purchased items in a manufacturing system to protect against supply uncertainty. He identified the need to maintain a specific safety stock level in order to achieve a certain service level and stressed that if this was followed for a long time, the service level would eventually saturate at the desired level assuming minimal changes in influencing factors. This has been the basic idea behind most of the research on safety stocks and service levels. The ultimate question is: How much safety stock should be held. James [17] applied classical statistics theory to safety stock and was able to express safety stocks as a function of mean absolute demand, MAD and the Lead Time, LT:

$$SS = k * MAD * \sqrt{LT} \tag{5.1}$$

The k here is the safety factor multiplier which represents the desired service level. Although fair and accurate, a fundamental flaw became apparent: the fixed safety stock could not respond proportionately to seasonal and/or trend variations in future demand. To address this, he used time based deviation in absolute demand and was able to achieve impressive results in terms of ways to calculate safety stocks and suppress them in case of overoptimistic forecasting.

Silver et al. [27] suggested a very straight-forward but efficient way to calculate safety stocks. They incorporated the inaccuracy in forecasting and suggested that that safety stocks be planned against the deviation of forecast from the actual demand over lead time, based on the following formula:

$$SS = k * \sigma_{FE} \tag{5.2}$$

$$k = \phi^{-1}(\alpha) \tag{5.3}$$

Here, FE is the forecast error; σ is the standard deviation of forecast error calculated over the lead time of the product under consideration and k is the safety factor which is expressed as the inverse cumulative normal distribution for the desired service level, α. The Table E.1 shows how the safety factor k varies with change in desired service level. The approach used by Silver et al.

has been and still is the most common basis for research in systems where the demand is forecasted.

Safety stocks are held to hedge against uncertainties in demand and supply and are held at and before (upstream) the customer order decoupling point (Heijden et al. [32]). The calculation of safety stocks in different production and inventory systems has been explored by several researchers. In most cases, service level is used as decision variables to identify safety factor, the actual calculation of which varies based on the type of service level considered. Assuming demand is normally distributed, the safety factor is calculated as the inverse of the normal distribution for percentile of required coverage, when the no-stockout probability is used. When the fill rate is used as the service level, then the safety factor is determined by the standard loss function $G(k)$, which expresses the expected amount of shortage per cycle (De Kok A [11]).

Brander and Forsberg [7] presented safety stock levels based on estimation of the standard deviation in total demand during a replenishment lead time. They considered the problem of inventory and production scheduling of multiple items with random demand, on a single facility and presented a model for determination of safety stocks, order-up-to levels and an estimation method for the variance in demand. Neale et al. [21] explored inventory management in supply chains facing stochastic, non-stationary demand. Beutel & Minner [5] presented a procedure for safety stock planning in systems where there is causal demand forecasting. Alin Radasanu [22] discusses the balance between service levels and safety stocks for inventory management. He stresses that the objective for inventory management should be to determine the value and the mix of inventory that support a high service level for customers as well as one that maximizes the companies financial performance. Youssef Boulaksil [8] describes an approach to develop an approach to determine the safety stock levels in supply chain systems that face demand uncertainty. The customer demand is forecasted and is assumed to be following the Martingale Model of Forecast Evolution.

One very recent research literature about safety stocks formulation which was of particular interest was published by Syntetos, Teunter & Prak [31], on the calculation of safety stocks when the demand is forecasted. Teunter & Syntetos explore the safety stock assessment based on existing literature and suggest methods to refine the calculation. The refinement comes through the application of a correction factor which primarily depends on the forecasting method utilized and is a function of the lead time and a forecast parameter. This is based on the logic that the forecast errors for different periods are correlated and that the safety factor k is not entirely independent of the forecast error deviation. The paper provides corrected lead time demand variance expressions and reorder levels for inventory systems with a constant lead time where demand fluctuates around a constant level. The ideas and outcomes of this paper have been discussed in more detail with a better sense of application and relevance in Chapter 7.

Most of the research regarding safety stocks has been with an underlying assumption that the demand is distributed normally. However, in some cases it has been observed that a gamma distribution fits real-life deterministic demand distributions better than a normal distribution. Hence, the suggestion by Silver cannot be considered to be correct in all cases. Moreover, since gamma distribution is always non-negative, it should be preferred over normal distribution since it is applicable in most scenarios. Strijbosch et al. [29] explored the use to gamma distribution for safety stock settings. A paper by Strijbosch & Moors [30] described the calculation of safety factors when the demand follows a gamma distribution. However, this was limited to situations where the lead time was comparable to the review period. Chaturvedi and Martnez−deAlbniz [9] also explored the safety stocks and capacity trade-offs under gamma distributed demand.

Apart from the literature mentioned above, there have been multiple research papers and books in relation to inventory management and safety stock policies in the semiconductor manufacturing industry that have touched upon issues of interest of this project but are not entirely relevant. Hung et al. [16] researched the optimal method for safety stocks assessment for production planning in uncertain manufacturing industries, specifically semiconductor wafer manufacturing. Bezemer &

Akkermans [6] explored the delays in semiconductor supply chains, highlighting that such delays are caused more my minor issues than the major ones. This paper presents research that explains these delays by means of a system dynamics simulation model. The model, based on pre-existing and well-tested generic models is able to capture both, the major and minor aspects in semiconductor supply chain dynamics. Schwartz et al. [26] explored a simulation-based optimization of process control policies for inventory management in supply chains with high demand fluctuation.

With regards to supplier reliability, a handful of research paper and scientific literature was found to be relevant to one of the research questions of this project. The paper by Bezemer & Akkermans [6] was able to r elaborately explain the industrial service measurement metrics of LAP, CLIP and RLIP, as discussed in chapter 2. These terms are nothing new for the semi-conductor or the manufacturing industry in general. They have been used extensively over the years and are used in this project too for analysis of supplier reliability. Hydari et al. [15] identified supplier lead times as a crucial parameter. They described the impact of lead time variability on supply chain performance. So & Zheng [28] analyzed the impact of variation in supplier lead times and forecasted demand on order quantity variability. A paper by Henig & Gerchak (1989) discusses the inventory models that can be utilized in a periodic system with random supplier yield. It helps us understand the qualitative implications of yield randomness for lot sizing in fairly general periodic review systems. Although relevant, the concepts and formulae involved were considered too complex for this project but could be utilized in a future research.

Furthermore, few thesis projects have been done in the near past in which the research topics are directly or indirectly related to the research topics of this thesis project. The dissertations of these projects were found to be helpful in understanding the crux of the problem at hand and finding relevant solutions to the same. The documentation for these past projects [1, 3, 13, 18, 19, 24] have been referred for structural and contextual help in mild yet varying degrees of reference.

5.2 Approach

The ultimate aim of this project was to find answers to the research questions described in Chapter 4. As a first step towards obtaining these answers, regardless of the qualitative and quantitative nature of the questions, it was important to establish an in-depth understanding of how Ampleon handles its inventory. After establishing a firm base and an in-depth understanding of Ampleon's supply chain and inventory policies, the next step was to analyze how efficient this setup was and obtain insights about the same. Certain objectives were defined to channelize this analysis using data from past orders and some forecast for the future. The next step was to collect sufficient relevant data with minimal anomalies and ensure that a large-enough data set was available for any kind of analysis to make sense. It was crucial that this data set was both robust and reliable at the same time. The data was then analyzed aimed at achieving the pre-defined objectives and a few important metrics were obtained. The underlying formulae and concepts used for analysis were limited to the concepts introduced by Silver et al. [27] with contextual references to other literature mentioned in the previous section as and when required. The concepts introduced by Teunter & Syntetos [31] were used to refine the results and create a robust model for safety stock setting. The metrics obtained from data analysis and post processing of the same are expected to help answer the research questions directly or indirectly.

5.3 Project Outline

The project was carried out in three phases:

1. **Data Analysis**
   Objectives:

- To obtain sufficient data in order to build a data set which takes into account all possible variabilities in demand including seasonality.
- To identify the appropriate demand distribution function for the cumulative demand forecast data.
- To obtain the forecast accuracy while comparing cumulative forecasted demand against cumulative actual demand based on weekly consumption of dies.
- To understand the effect of change in service levels on inventory targets.
- To establish an understanding of parameters used to judge supplier & subcontractor performance.

2. **Model Development**
   Objectives:
   - To analyze results of data analysis establish links between theory and practice.
   - To develop an improved method for setting inventory target based on theories on safety stock and service levels.
   - To establish an understanding of supplier reliability and suggest an improved method for estimating supplier reliability.
   - To comprehend the incorporation of supplier reliability in the calculation of inventory targets.
   - To describe the new model, its dependencies and operation.

3. **Formulating Final Results and Recommendations**
   Objective:
   - To obtain answers to the research questions defined in chapter 4.
   - To identify potential areas of refinement and suggest future research topics.

The pre-project phase, described elaborately in chapter 3 establishes the understanding of Ampleon's Inventory Management in detail. Based on this understanding, the project phases 1 and 2 were carried out and described in chapter 6 and chapter 7 respectively. Phase 3 has been covered in chapters 7 and 9. The chapter 8 gives the concluding points of the project.

5.4 Expected Outcomes

The understanding of Ampleon's Inventory Management is crucial to pave the way for any study or analysis in reference to this project. The data analysis will give us important metrics to be able to have a numerical estimation of demand variation, forecast accuracy, supplier reliability and will then enable the formulation of new policies based on the same. The objective here is to see how the modified policies are different from the existing operational ones and would it be a good choice to switch to them.

Once the results are formulated, the research questions will have been answered sufficiently. In an event where a research question isn't answered completely or with enough authenticity, the work done here will help channelize the future research in order to achieve the necessary insights and answers. Change and improvement are ongoing processes. This project should prove to be the first stepping stone in the way to revamp of the entire inventory management at Ampleon.

Chapter 6

Data Analysis

6.1 Data Collection

In order to build a large enough data set, the demand forecast data was considered from Week 1, 2018 till Week 30, 2019. In total, a little over one and a half year's worth of data spanning across SKUs, product types and dies used for demand and supply planning activities was taken into consideration. Each file (showing demand data for the week and looking almost a year forward for planning) was thoroughly analyzed to observe any discrepancies and the ones found were eliminated. Some weeks had to be ignored due to difficulties in obtaining data (due to linked cloud storage) or the absence of it altogether. The effective analysis involved demand planning for 1 year, the considered weeks varying based on the lead times of the specific die types.

Order details involving the dies was also obtained for the same time period. This provided the data for actual consumption of the pre-tested dies at Die-Bank which would in-turn represent the actual demand for the respective die types. This data was cross-verified to comply with end-product demand using the bill of materials. A sufficient level of accuracy and compliance was observed as a result of which the end-product demand wasn't exclusively required for analysis.

Furthermore, the supplier/subcontractor performance file maintained by Ampleon at AMP was used in order to assess supplier reliability while exploring multiple options to effectively calculate the same. In total, over 10000 orders were taken into account from all the suppliers, spanning from January, 2018 till June, 2019. However, since supplier data wasn't available for all the listed suppliers, only the ones that were present in the file have been taken into account for analysis. The final results in terms of new assessment method for supplier reliability should be applicable for all suppliers though since they all operate in a similar manner.

6.2 Pre-processing

As discussed in chapter 4, the inventory control for pre-tested dies (CEPT) is done based on the die type and the lead times. The demand and supply planning, however, is done on an SKU level which goes one level deeper in terms of the classification showed in Figure 4.2. The primary classification for die types still exists but it's not fed in the system, hence not available in the reports. Therefore, as a first step towards getting the right data set, a filter was created to classify the dies based on primary classification into the following categories:

1. LDMOS
2. MOSCAP
3. IPD

4. Others

This enabled focusing the analysis on the critical dies - LDMOS and MOSCAP. From here on, the weekly demand for these die types were aggregated to obtain the aggregated dependent demand forecast. Since the inventory policies are defined on the basis of these categories, it was then possible to separate the data into two distinct datasets for LDMOS and MOSCAP. The collected data was then filtered to account for exactly one year's worth of demand data including lead times, safety lead times and review periods.

6.2.1 Assumptions

- The safety lead time for both product categories was set as 4 weeks after discussion with the supply chain management team at Ampleon.
- The forecasting method used by the company is assumed to be reliable. As a result, the standard deviation of forecast error over lead time for specific product categories is expected to reflect the shortcomings in demand planning more accurately, in comparison to the standard deviation of forecasted demand.
- However, if the previous assumption is not reflected in the results and the standard deviation of forecast error is observed to be extremely high, then the standard deviation of forecasted demand would be used for analysis.
- Stationary demand has been assumed for analysis and calculation for both die types.
- The safety stock is meant to cover the uncertainties in demand over $L + R + SL$ for both categories of dies. Hence, cumulative demand has been considered for forecast accuracy analysis. In reality, replenishment orders are generated every week to cover for weekly demand post lead time.
- A generic assumption is that unmet demand is backlogged.
- For supplier reliability assessment, it's assumed the data available is the same for all suppliers and any outcome derived based on analysis of a subset of suppliers is applicable to all suppliers.

6.2.2 Parameters

Product Category: **MOSCAP**

- Standard Lead Time, $L = 15$ Weeks
- Review Period, $R = 1$ Week
- Safety Lead Time, $SL = 4$ Weeks
- Uncertainty Period, $L + R + SL = 20$ Weeks

Product Category: **LDMOS**

- Standard Lead Time, $L = 20$ Weeks
- Review Period, $R = 1$ Week
- Safety Lead Time, $SL = 4$ Weeks
- Uncertainty Period, $L + R + SL = 25$ Weeks

6.2.3 Service Norms

The company does not deploy any pre-defined service level to assess the efficiency of demand and supply planning of dies in the Die Bank. The only effective service level is the a metric that compares existing stock to projected demand. For safety stock calculations, the time equivalent of inventory is used and the number of weeks are set based on lead times but are independent of any service level.

At the moment the company uses CLIP as the primary performance measurement metric for assessment of customer satisfaction as well as the supplier and subcontractor performance. The norm for suppliers is that all orders that are delivered at most 1 day post the first confirmed date are considered to be on-time. The first confirmed date in this case is the same as the first requested date by the company. So, in technical terms, the CLIP data can also be judged as RLIP data with a norm that orders delivered with at most 1 day of delay are considered on time. This has been described in the Figure 6.1. As can be seen, orders arriving with a delay of less than or equal to a day are considered on time, expressed as the OK region in the figure. Orders arriving later than a day after the first requested date are considered late.

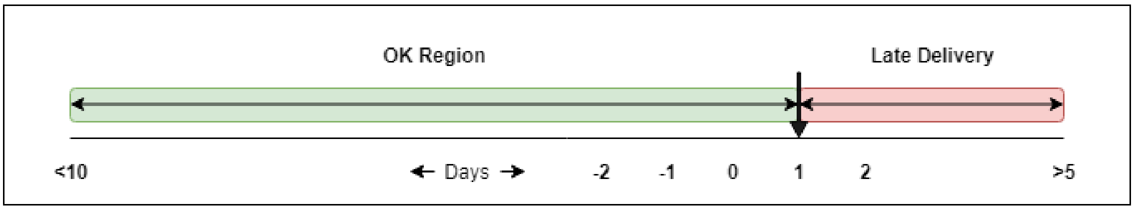

Figure 6.1: RLIP Norm

6.3 Demand Analysis

In order to generate the demand forecast dataset from the available data, the cumulative demand across the uncertainty period was considered. The uncertainty period is the sum of the lead time, the review period and a safety (buffer) lead time for orders which is fixed as 4 weeks. For LDMOS dies, the demand planning data was used from week 2, 2018 to week 1, 2019. Effectively, for an uncertainty period of 25 weeks as described earlier, the assessment was for the forecast from week 27, 2018 till week 26, 2019. For MOSCAP dies, similar to LDMOS, the demand planning data was used from week 2, 2018 to week 1, 2019. However, since the uncertainty period for MOSCAP is 20 weeks, the effective assessment was for the forecast from week 22, 2018 till week 21, 2019. The following equations describe the cumulative demand forecast analysis based on available data:

T_U = *Uncertainty Period* = *L* + *R* + *SL*
D(w) = *Demand Forecast for week w*
FD(w) = *Cumulative Forecasted Demand for week w over* T_U

$$FD(w + T_U) = \sum_{i=1}^{T_U} D(w + i) \tag{6.1}$$

As mentioned before, the demand planning data was considered for a little over a year and a half to generate cumulative demand forecast dataset for LDMOS and MOSCAP, both spanning across 52 weeks (1 year). The first step in the analysis after establishing this dataset was to analyze the behaviour of the data and find the best fitting probability distribution function for the forecasted and actual demand. For this purpose, the data was analyzed in MS Excel to provide relevant descriptive statistics about both data sets. The idea was to get an estimate about the quality of data and the ability to fit it to a probability distribution function. The Table 6.1 shows the results of the descriptive statistical analysis of the two data sets.

	LDMOS Forecast	**MOSCAP Forecast**
Mean	28649226.29	29085006.51
Standard Error	424204.941	822478.5959
Median	28957730.37	28529042.42
Mode	#N/A	#N/A
Standard Deviation	3058985.332	5930977.501
Sample Variance	9.35739E+12	3.51765E+13
Kurtosis	-0.356374509	-0.165101656
Skewness	0.219249004	0.014498998
Range	12756296.9	25212297.67
Minimum	22912267.07	15852371.58
Maximum	35668563.96	41064669.25
Sum	1489759767	1512420338
Count	52	52

Table 6.1: Descriptive Statistics - Demand Forecast

Kurtosis and Skewness are statistical measures that are used to describe a distribution. As a rule of thumb, a range of -2.0 to +2.0 is considered a good measure for Kurtosis and Skewness. In order to be considered acceptable to prove normal distribution (which has been traditionally used for most of the scientific research about safety stocks and other studies in inventory management), the range is somewhat around -0.5 to +0.5. As seen in Table 6.1, the Kurtosis and Skewness values were found to be very close to 0 for both datasets. This showed that the chances of the datasets following a probability distribution function is good. The next logical step was to find out the best fitting probability distribution function for the demand.

Using curve fitting procedure, both datasets were fit against standard probability distribution functions to identify the best fitting distribution function. The P-value and chi-squared value were used as metrics to analyze the goodness of fit for different distributions. A P-value greater than 0.5 (significance level) represents an OK fit in the sense that it shows that the data considered is significantly consistent with respect to a specific distribution. Higher P-values are considered better and ideally, higher P-values imply a better fitting distribution. Based on a similar logic, lower chi-squared value show a better fit as they signify the statistical deviation from the distribution considered. Based on the results obtained, it was observed that both datasets closely followed a lognormal distribution with highest P-values and lowest chi-squared values resulting in case of both datasets. Apart from the lognormal distribution, the normal and gamma distributions were also found to be a good fit. The results of the curve-fitting procedure are shown in Appendix C. With respectable values of P-factor, it was implied that the assessment of demand data for the next steps was possible while assuming any of the aforementioned distributions, in the order of preference described in Tables 6.2 & 6.3.

Distribution	**Chi-sq**	**P-Value**	**Fit**
Lognormal	4.339	0.740	OK
Gamma	4.364	0.737	OK
Normal	4.970	0.664	OK

Table 6.2: Curve Fitting - LDMOS Forecast

Distribution	**Chi-sq**	**P-Value**	**Fit**
Lognormal	5.390	0.613	OK
Gamma	5.716	0.573	OK
Normal	6.442	0.489	OK

Table 6.3: Curve Fitting - MOSCAP Forecast

6.4 Forecast Accuracy Assessment

To get an idea about the forecast accuracy, it is important to analyze the actual cumulative demand across the uncertainty period and see how it differed in comparison to the cumulative forecasted demand obtained according to the equation (6.1). The demand forecast analysis has already been described in the previous section. The actual weekly demand was obtained from the weekly consumption of dies by the company, as described earlier. For both LDMOS and MOSCAP, the cumulative actual demand would represent the actual demand during the same weeks considered for demand forecast. For week w, it would be the sum of actual consumption of dies across the uncertainty period before and including week w. The following equations describe how the cumulative actual demand was analyzed.

C(w) = Actual consumption of dies in week w

AD(w) = Cumulative Actual Demand for week W over T_U

$$AD(w + T_U) = \sum_{i=1}^{T_U} C(w + i) \tag{6.2}$$

After obtaining individual data sets for cumulative forecasted demand and cumulative actual demand for the two product categories, the next step was to compare the two in order to get an estimate about the forecast error. The weekly forecast error depicted the deviation of the cumulative demand forecast from the cumulative actual demand as a difference of the two. The following equations describe the forecast error analysis for both, LDMOS and MOSCAP:

$$FE(w) = AD(w) - FD(w) \tag{6.3}$$

Mean Forecast Error for week w, calculated over L+R Periods, denoted by $\mu_{FE}(w)$

$$\mu_{FE}(w) = \frac{1}{L+R} * \sum_{i=1}^{L+R} FE(w - (L+R) + i) \tag{6.4}$$

Standard Deviation of Forecast Error over L+R Periods, denoted by $\sigma_{FE}(w)$

$$\sigma_{FE}(w) = \sqrt{\frac{\sum_{i=1}^{L+R} (FE(w - (L+R) + i) - \mu_{FE}(w))^2}{L+R}} \tag{6.5}$$

The standard deviation of the forecast error is an important parameter in the calculation of the safety stocks and has been used extensively over the years as an accurate reflection of forecast accuracy. The safety stock level is set in an attempt to hedge against the inaccuracy in forecast. As described in the equations (2.1) & (5.2) in previous chapters, the standard deviation of forecast error across a certain number of periods (in this case $L + R$ periods) is used as an estimate for forecast inaccuracy. This is then multiplied by a safety factor, depending upon the type of demand distribution under consideration to get the safety stocks. The results of demand analysis and the forecast error assessment are given in Appendix E and the safety factor and safety stock calculations are discussed in the next chapter.

6.5 Supplier Reliability Assessment

For supplier reliability assessment, the subcontractor/supplier performance data was considered for all internal orders placed between and including Week 1, 2018 and Week 26, 2019. As mentioned earlier, Ampleon uses CLIP as the primary service measure to assess supplier performance. As described in Subsection 6.2.3 of Section 6.2 in this chapter, the CLIP data can also be judged as RLIP data according to the norm described in Figure 6.1, based on the first requested date. The expression of RLIP for each individual supplier is shown in the equation (6.6).

$$RLIP = \frac{No.\ of\ Orders\ Delivered\ According\ to\ the\ Service\ Norm}{Total\ No.\ of\ Orders\ Placed\ at\ the\ Supplier} \tag{6.6}$$

Apart from assessing the 'on-time delivery', represented in the form of RLIP, another metric considered is the percentage of order quantity delivered on time. In some cases, it was observed that the delivery was considered on-time even when the delivery quantity was lower than the ordered quantity. This aspect would not be reflected in the RLIP measurement and needed to be addressed separately. A metric PCO was used to reflect the percentage of complete orders. It was expressed for individual suppliers as the percentage of number of orders that were delivered completely by the supplier as compared to the total no. of orders placed (equation (6.7)). The variation in the delivered order quantity was not considered for this analysis.

$$PCO = \frac{No.\ of\ Orders\ where\ (Delivered\ Quantity\ is\ equal\ to\ Ordered\ Quantity)}{Total\ No.\ of\ Orders\ Placed\ at\ the\ Supplier} \tag{6.7}$$

Since RLIP is a representation of the flow time uncertainty and PCO is a representation of the delivery quantity or the yield uncertainty, these two variables can be assumed to be mutually independent. The supplier reliability will hence be measured as a product of these two quantities since they are both contributing equally to the uncertainty in supply and and are independent of each other.

$$SR = PCO * RLIP \tag{6.8}$$

Using the expression described in equation (6.8), the supplier reliability was calculated for all the suppliers for whom the necessary data was available. It is assumed that this calculation can be standardized and applied to all existing suppliers since the information utilized for this assessment should ideally be available for all suppliers. The final results for supplier reliability assessment can be found in Appendix D. The results have been discussed in the next chapter along with the integration of supplier reliability into the the calculation of safety stocks.

Chapter 7

Results & Model Development

7.1 Results of Data Analysis

7.1.1 Demand Distribution

From the demand analysis carried out according to the description in chapter 6, it was established that the cumulative demand data can be fit into a lognormal, gamma or normal distribution function in the exact same order of goodness of fit. Based on existing literature and ease of analysis, gamma and normal distributions were considered for further analysis. A normal distribution can be used with high a high degree of confidence for cases where the coefficient of variation C_v, expressed as the ratio of the standard deviation of forecast error (σ_{FE}) and the mean of demand forecast (μ_F) in the same period(s), is less than 0.5.

$$C_v = \frac{\sigma_{FE}}{\mu_F}$$

The data analysis showed that the C_v values for all categories were in the range [0.2,0.32], suggesting that using normal distribution would be a good option. However, for such low values of C_v, both normal and gamma distributions behave similarly. Using a gamma distribution has it perks since it's ensured that the demand is always non-negative, irrespective of C_v values and in general brings more robustness to the model due to higher dependencies. The results of demand analysis for MOSCAP and LDMOS demand can be found in Appendix B.

7.1.2 Forecast Accuracy

The derivation of forecast accuracy was discussed in Section 6.4 of Chapter 6. The final dataset and results of forecast accuracy assessment can be found in Appendix C. On an average, the standard deviation of forecast error was found to be lower than the standard deviation of demand during the same period for both die types. This is a reflection that the second assumption described in Chapter 6 holds true. Hence, the standard deviation of forecast error, calculated over $L + R$ periods would contribute towards the calculation of safety stocks.

$$\sigma_{FE} = \textit{Std. Dev. of Forecast Error over } (L + R) \textit{ periods}$$

7.1.3 Supplier Reliability

With regards to supplier reliability, the information available was limited to a subset of suppliers. As discussed in the previous chapter, uncertainties were observed on both, the timing and the quantity of delivery. The delivery time uncertainty was recorded using RLIP and the delivery order quantity uncertainty was recorded using the measure PCO, also described in the previous chapter. The results of this analysis are enclosed in Appendix D. As described in equation (6.8), the Supplier Reliability is given by the product of RLIP and PCO:

$$SR = PCO * RLIP$$

This formula can be assumed to be applicable for all suppliers alike.

7.2 Model for Inventory Target Setting

7.2.1 Safety Stocks

The assessment of optimal safety stock settings is done under the assumption of stationary demand. The safety stock represents an inventory quantity that is sufficient to maintain the desired service level for demand fulfilment. This quantity accounts for the additional stock that must be kept beyond the mean demand to cover for fluctuations and forecast inaccuracies. The representation of this is given by a quantity z, expressed as a sum of mean demand and the safety stock.

$$z = \mu + SS \tag{7.1}$$

The service level mentioned above represents the non-stockout probability during a replenishment cycle, explained in Chapter 2. Essentially, a target service level of P would mean that of all possible points of stockout, $P\%$ of them should be able to avoid a stockout. In the context of this project, all possible points of stockout are the moments just before a replenishment order arrives. This is because the review period is 1 week and replenishment orders are placed every week.

For demand that is normally distributed (described in figure 2.3), the safety stock is given by the product of a safety factor, k and the standard deviation of forecast error σ_{FE} across $L+R$ periods. k given by the inverse of the cumulative distribution function (ϕ) with the desired service level P as the operational parameter.

$$k = \phi^{-1}(P) \tag{7.2}$$

The calculation table for k can be found in the Appendix E in Table E.1.

$$SS = k * \sigma_{FE} \tag{7.3}$$

For demand that is gamma distributed, the quantity z is directly given by the inverse of the cumulative gamma distribution function (ψ), with the desired service level (P) and the shape & scale parameters of gamma distribution (α, β) being the operational parameters. α and β are in turn dependent on the mean of demand forecast and the standard deviation of forecast error during a fixed timed period.

$$z = \psi^{-1}(P, \alpha, \beta) \tag{7.4}$$

Hence, using equations (7.1) and (7.4), safety stock for gamma distribution can be expressed as:

$$SS = z - \mu \tag{7.5}$$

Strijbosch & Moors [30] described the safety stock calculations for a special case where the demand is gamma distributed and the lead time is less than or equal to the review period. In such cases, safety stock is given as the product of a safety factor and the standard deviation of forecast error. The safety factor, (c) is given by a complex function with three parameters - the desired service level (P), the coefficient of variation(ν) and the ratio (K) of the lead time expressed as a multiple of the review period.

$$K = \frac{L}{R} \tag{7.6}$$

$$c = f(\nu, K, P) \tag{7.7}$$

The calculation table for c can be found in the Appendix E in Table E.2.

$$SS = c * \sigma_{FE} \tag{7.8}$$

Since this is only valid for situations where $K \leq 1$, it will not be taken into account for this project.

In Ampleon's case, the demand distribution can be assumed as gamma or normal with a more than decent measure of goodness of fit. However, gamma distribution is preferred due to its non-negative nature (hence, also applicable for higher values of coefficient of variation) and higher robustness. As stated in Subsection 7.1.1, the C_v is very low for all categories of products under consideration. For such low values, the behavior of normal and gamma functions are very similar. This similarity can be judged by looking at the figures shown in Appendix B. Figures B.3 & B.4 show the demand distribution and curve fitting for LDMOS and Figures B.7 & B.8 show the demand distribution and curve fitting for MOSCAP. However, when the analysis is done on an SKU level, the C_v values are expected to go higher in which case gamma distribution will be the only option.

Considering all factors involved, **gamma distribution was preferred** for safety stock settings. Hence, equation (7.5) is used for calculating the safety stock. To get a better understanding of the situation, both gamma and normal distribution-based models were simulated and the performance was compared. This has been discussed in more detail in Section 7.4.

7.2.2 Integration of Supplier Reliability

Yield Uncertainty

Despite their being a considerable variation in the quantity delivered on-time by the suppliers, this variation in yield could not be explained entirely since for several orders where the delivery quantity was less than the ordered quantity, the delivery was reported complete. A possible explanation is that a minimum sufficient quantity was delivered in all such cases which allowed the company to go ahead with the normal production schedules while the rest of the order arrived soon after. Henig & Gerchak [14] elaborately discussed periodic review policies in the presence of random yield. However, the equations involved are partially relevant in this case and too complex in comparison to rest of the modelling implemented. In any case, since the terms were unclear and the reports did not explain this variability in yield, the yield or delivery quantity uncertainty was not taken into consideration for safety stocks calculation.

Flow Time Uncertainty

The condition for hedging against lead time uncertainty, can be adapted based on flow time (FT) of the orders, which is the expected time a supplier takes to deliver an order. FT should therefore be used as a norm and can be assessed for every individual supplier using RLIP as follows:

For suppliers with high supplier reliability ($RLIP \geq 90\%$),

$$FT = \textit{Standard Flow Time} = L + R \tag{7.9}$$

For suppliers with low supplier reliability ($RLIP < 90\%$),

$$FT = \textit{Delivery Lead Time Norm for which } 98\% \textit{ of orders are delivered on time} \tag{7.10}$$

Let us consider a supplier with a standard flow time of $L + R$ weeks but the actual flow times for which range between a and b weeks. Let the RLIP be lower than 90%. For such a case, FT would be the delivery lead time norm for which 98% of the orders would be delivered on time, that is before FT. For the suppliers the standard $L + R$ weeks would serve as the norm for delivery and supplier reliability measurement. But for planning, the order will have to be considered arriving FT periods after the order is placed. Figure 7.1 shows the graphical interpretation of the instance described above. Assuming the demand follows the distribution curve shown, FT would be the value of delivery lead time for which 98% of all orders are delivered with delivery times in the shaded area.

From this point onward, σ_{FE} will represent the standard deviation of forecast error over FT, which is constant for every supplier but depends on the norm described above. This standard deviation would then be used to calculate the safety stock using the equation (7.3), if the demand is normally distributed or the shape and scale parameters in equation (7.4) if the demand is gamma distributed.

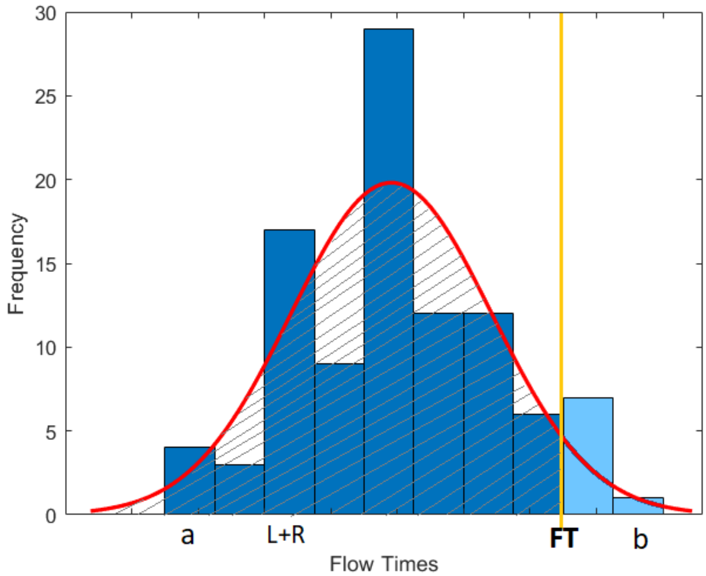

Figure 7.1: Delivery Lead Time Norm for SS Assessment

$$\sigma_{FE} = \text{Std. Dev. of Forecast Error over } FT \tag{7.11}$$

7.2.3 Safety Stocks Correction Factor

When considering cumulative demand forecasts, the safety factor and the standard deviation of forecast error are considered independent parameters. However, depending on the forecast method, an additional correction factor maybe included. If the forecasts are adapted time and again, a certain inflation factor seems necessary on most occasions to inflate the safety stock level. Teunter & Syntetos [31] argue that in calculating the standard deviation of forecast errors, the fact that forecast errors are correlated over time are often ignored since the demands are not. As a result, a correction factor must be used to compensate for the correlation which will inflate the safety stocks calculated using the traditional approach. The literature provides correction factors for two of the most widely applied forecasting techniques (Single Exponential Smoothing and Simple Moving Average) on the basis of some typical control parameters.

For this project, we'll call this correction factor CF for calculation purposes. CF can be expressed as the percentage increase in safety stocks calculated by the traditional approach (using equations

(7.3) or (7.5)). The correction factors, as concluded by Teunter & Syntetos [31], can be found in Appendix F. Hence, the effective formula for safety stock or inventory target calculation (when the demand follows a gamma distribution) becomes:

$$SS = CF * (z - \mu) \tag{7.12}$$

Ampleon uses a forecasting method that is very similar to the traditional Simple Moving Average method, carried out over a year (52 weeks or periods). Manual interventions are made to ensure that the inventory targets are in compliance with known past end-product demand trends and in some cases, known future end-product demands. However, the manual intervention in forecast can be ignored for dependent demand generated for the CEPT dies. Hence, the CF values suggested for SMA with N=52 should be used for Ampleon. The table used to identify the correct CF as a function of the Lead Time is showed in Table F.2 in Appendix F.

7.3 New Inventory Model

The modified inventory model uses the same control policy as the currently operational model, described in the Section 3.2 of Chapter 3 along with a new method for calculating safety stocks, as described in the equation (7.12). However, in order to make the SS calculation more dynamic, a time-dependant approach was used with safety stocks being calculated for every period t.

$$\boldsymbol{z_t = \psi^{-1}(P, \alpha_t, \beta_t)} \tag{7.13}$$

$$\boldsymbol{SS = CF * (z_t - \mu_t)} \tag{7.14}$$

In the expression (7.14), z_t is obtained using the equation (7.13) for every week, where ψ is the cumulative gamma distribution function. The calculation of z_t and μ_t is time dependant with a total of $L + R$ periods considered for each week's calculations. Hence, the safety stock primarily depends on the target service level P, the mean demand μ_t and the standard deviation of forecast error σ_{FE}, which is obtained over FT which depends on the lead time norm described in expressions (7.9) & (7.10). As a result, the safety stock settings are dynamic in nature. The sum of safety stocks and the demand forecast for week $w + L$, as observed in week w, give the Target Inventory Level in week w, denoted by TIL_w. The expression for TIL_w is given in equation (3.11).

Apart from the SS policy, the remaining parameters and control equations for the model described in Chapter 3 remain unchanged. The model can be understood as a dynamic base-stock model where the base-stock level changes on a weekly basis and is equal to the Target Inventory Level.

7.4 Model Simulation and Validation

The proposed inventory model was simulated using discrete event simulation in order to understand the behaviour of the same in 2 scenarios. Further, the current model was also simulated in the same scenarios and results were compared to understand the improvements, shortcomings and a general comparison of the two models. This was done on an aggregate level for both die types, LDMOS and MOSCAP. The two scenarios considered are explained as under:

1. Stationary Demand - Gamma (preferred) & Normal Distribution
   The demand data (both forecast and actual demand) was generated with the same mean and standard deviation as the available demand data when fit into a gamma distribution with relevant shape and scaling parameters α and β. Additionally, a simulation was also run to observe the performance when the demand was normally distributed. The simulation was carried out using MATLAB for $52 + 2L$ periods and the performance was analyzed for

a total of 52 weeks, excluding the first L periods and the last L periods in the timeline for simulation. An evident drawback in this approach was that since the forecasted and actual demand were generated randomly, even though they were similar to the real world scenario, they were not co-related. As a result, a considerable drop in the observed service levels was expected. On the contrary, if the model performed well in this scenario, it would most definitely perform better when there was a definite co-relation between the forecast and actual demand while factors such as seasonality kicked in too.

2. Non-Stationary Demand - Real World Data
The demand data available was limited to a total of 78 weeks. Additional data was pulled in (in-line with the pre-existing data) to compensate for the extra periods, wherever necessary. Similar to the simulation for stationary demand, simulation was carried out using MATLAB for $52 + 2L$ periods and the performance was analyzed for a total of 52 weeks. An expected drawback was that due to the limited availability of data and the fact that the analysis of forecast error was based on this data itself, the service levels observed during the simulation were expected to be very high by default.

7.4.1 Simulation Results

Table 7.1 describes the simulation results for the existing and the proposed inventory model for both the aforementioned scenarios. The results provide the averaged values over 1000 iterations for each scenario where the incoming orders for the first L periods have been randomized to bring authenticity and dynamism to the data.

Parameter	**LDMOS**	**MOSCAP**
Old Model (Based on 'x' weeks of SS)		
Stationary Demand - Randomly Generated, Gamma Distributed		
Avg Inventory on-Hand per week	19.70 mil.	9.1 mil.
P_1	99.99%	99.70%
P_3	100%	99.96%
Non-Stationary Demand - Real World Demand Data		
Avg Inventory on-Hand per week	20.7 mil.	10.4 mil.
P_1	100%	100%
P_3	100%	100%
NEW Model (Based on Expression (7.12) for SS)		
Stationary Demand - Randomly Generated, Gamma Distributed		
Avg Inventory on-Hand per week	12.74 mil.	10.30 mil.
P_1	99.97%	99.70%
P_3	99.99%	99.96%
Non-Stationary Demand - Real World Demand Data		
Avg Inventory on-Hand per week	10.15 mil.	9.00 mil.
P_1	99.99%	99.99%
P_3	100%	100%

Table 7.1: Simulation Results for Stationary & Non-Stationary Demand comparing Old and New Model Performances

As far as the performance is concerned, the stationary demand models based on normal and gamma distributions were pitted against each other. Figures 7.2 and 7.3 show how the performance (average inventory v/s service level) varies in both cases for LDMOS and MOSCAP respectively. The individual performance characteristics of both models for different categories can be found in Appendix G.

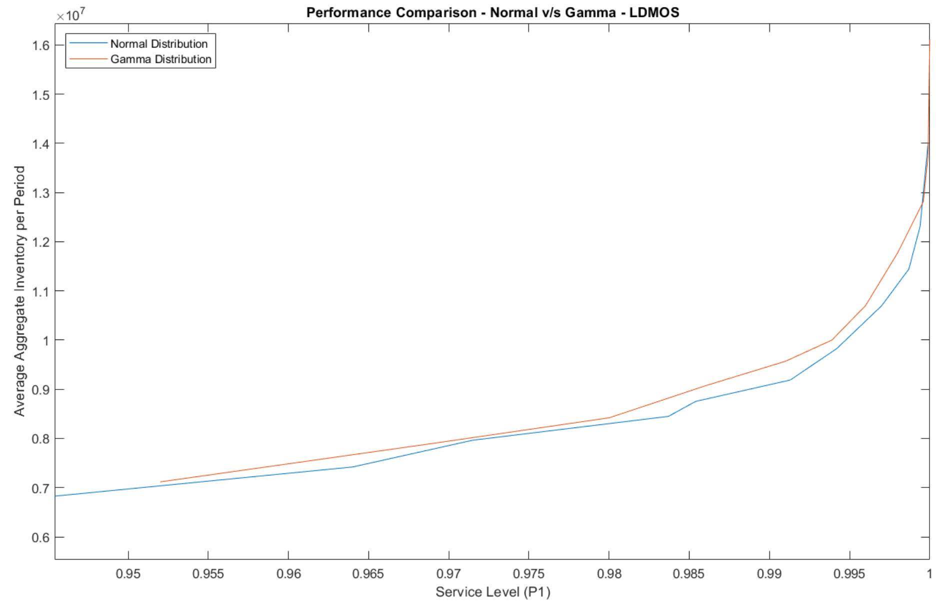

Figure 7.2: Performance Comparison - Gamma v/s Normal Distribution - LDMOS

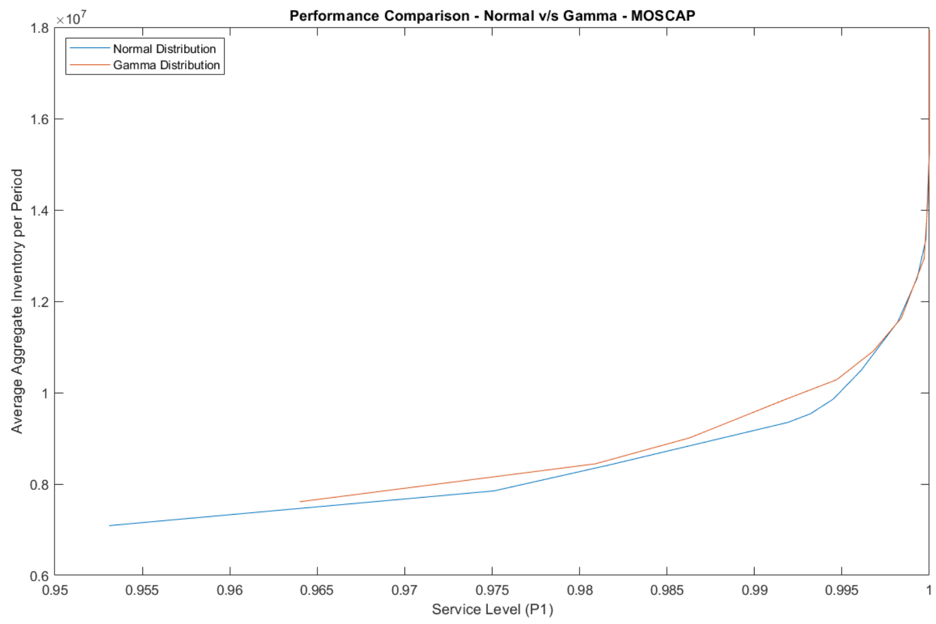

Figure 7.3: Performance Comparison - Gamma v/s Normal Distribution - MOSCAP

The ultimate aim of this project was to have a better inventory control model in place. These figures describe the effect of tuning the target service level on the average inventory per week for the two die categories. It's evident that the performances aren't too dissimilar when the demand follows a normal distribution to that when it follows a gamma distribution. The normal distribution shows slightly better performance but this was expected since the C_v values involved are very low. However, as mentioned before, gamma distribution is preferred over normal distribution for a variety of other reasons, including goodness of fit, non-negative nature and higher robustness.

7.4.2 Inference

Based on the results of the simulation, it's observed that for real world data (non-stationary) demand, the service levels are extremely high when planning is carried out using either of the models explained, as expected. However, it's important to note that there is a significant reduction in average weekly inventory for both die types when the new model is used, while maintaining high service levels.

For stationary demand for which data is generated randomly based on a gamma distribution similar to the real world data, the average weekly inventory required when using the new model in order to match the service levels offered by the old model is either very close (for MOSCAP) or much lower (for LDMOS) in comparison to the average weekly inventory required when using the old model. The performance takes a decline for lower inventory values but that again, is expected. There is a considerable difference in the expected and actual performance for both models but this gap reduces to almost 0 for higher service levels. This can be judged from the figures presented in Appendix G. However, this can be traced back to the fact that the demand for both these cases is generated randomly without any seasonality or correlation between the demand forecast and actual demand per week. Moreover, this shortcoming can easily be overcome by tuning the safety factors.

Even if the factors affecting the performance negatively are ignored, the new model as suggested in this chapter shows promise. It already has better adaptability, is resulting in lower inventories in most cases with high levels of service and still has a lot of room for improvement in terms of the service levels. Additionally, in most cases the service levels are observed to be 100%. Model instances of these cases are provided in Appendix G.

7.5 Qualitative Comparison with Existing Model

Ampleon's existing model for calculating inventory targets is based on average demand across $L + R$ periods for specific products and the x weeks of safety stock, which is decided based on the supplier lead time. The model is consistent over all sub-categories and works on a one-size fits all approach, as described in Chapter 1.

In contrast, the new model is based on multiple parameters: the mean demand, the standard deviation of forecast error over flow time or FT periods of product demand (Standard Flow Time $= L + R$), the target service level (non-stockout probability during a replenishment cycle) and a safety stock correction factor to incorporate the necessary inflation caused due to correlation of forecast errors based on the forecasting method. Since the new model has more parameters and even more dependencies, it can be evidently considered to be more robust. The model would remain consistent across all categories but will be very different for each SKU since factors like demand forecast, forecast error, lead time, supplier performance and service level can be very different for different SKUs. The model is also more adaptable since slow moving or less important SKUs with low priority can be handled with a lower service level and so on.

The Table 7.2 shows the comparison of the new introduced model described in the previous sections for setting inventory targets with the currently existing model.

	Existing Model	**New Model**
Operational Formula	$SS = \mu_{(L+R)} * x$	$SS = CF * (z_t - \mu_t)$
Parameters	$\mu_{(L+R)} =$ Average Demand across $L + R$ periods	$CF =$ Safety Stock Correction Factor
	$x =$ No. of SS Weeks	$z_t = \psi^{-1}(P, \alpha_t, \beta_t)$
		$\mu_t =$ Mean Periodic Demand
Parameter Dependencies	$\mu_{(L+R)}$: LT	z_t: LT, Service Level (P), Demand PDF Parameters. Supplier RLIP
	x: Product Category, Total LT	α_t, β_t: Mean Period Demand (μ_t), Std. Dev. of Forecast Error (σ_{FE})
		CF: forecasting method, no. of periods for forecast
Objective	To maintain enough stock to deal with variation in demand	To hedge against inaccuracy in forecast & lead time uncertainty
Robustness	Low	High
Adaptability	Low	High

Table 7.2: Existing Inventory Target Model v/s New Inventory Target Model

7.6 Improvements

The following points describe the expected improvements with the new model, as compared to the existing model:

- The new model is more robust and adaptable.
- The new model takes into account the aspect of supplier reliability and uncertainty in delivery lead time.
- The new model should reduce the net inventory levels, hence reducing the costs since the idea is to hold enough inventory to see off any lapses in forecast.
- The new model is dependent on more parameters which makes it easy to tune based on category, importance and other requirements while keeping the operational idea consistent.
- The new model can also be applied to other critical items including Headers and Flange with minor tweaks in the parameters.

Chapter 8

Conclusions

During the course of this project, multiple aspects were studied, understood and analyzed. Some of them were helpful in the formulation of results while others helped in better understanding of the company, the industry as well as the domain of inventory management.

Based on the analysis of the existing inventory policies, areas of improvement were identified with a focus on devising an improved inventory model with a robust and reliable method for calculating safety stocks. The new model takes points from the existing model, described in detail in Chapter 3 coupled with a new safety stock policy, described in Chapter 7. A simulation-based approach was used to analyze the performance of the new model and understand how it is better than the existing ones. The results were promising and it can safely be claimed that the new model is a considerable improvement over the current one, with all factors considered. For cases where there is negligible improvement, reasons were identified and can easily be worked around. Judging by the simulation results, the new model contributes in reducing the required weekly inventory to a great without any compromise in the service levels. This essentially means that the policy tends to move the performance characteristics towards the efficient frontier shown in Figure 2.1. Furthermore, the analysis was carried out for dies on an aggregate level. However, the applicability of the model introduced is not limited and can be easily expanded to the SKU level. This allows for a more robust approach, well-catered to the needs of Ampleon.

Hence, considering all findings and results, it can be concluded that the research questions described in chapter 4 have now been answered with a sufficient degree of certainty. A new safety stock policy was the main deliverable of this project and it has been described in detail. Additionally, a framework for supplier reliability assessment was also described. Even though this project has successfully accomplished most of the objectives set at the beginning, the progress and detailing was hampered by several factors including time, availability of data etc. As a result, there is still a lot of scope for improvement. Recommendations for the same and channelization of future research have been mentioned in the Chapter 9. The idea to to keep improving and moving forward.

Chapter 9

Recommendations

Most aspects covered as a part of this report were explained using relevant information obtained from the company. However, there are certain areas where work needs to be done to get a good hold of information. The following points should be considered possible areas of refinement which will pave the way for better information sharing and future research:

- The company should define a set of service measurements such as fill rate and stock-outs at the die level that will help identify and understand the operational the service levels at the die bank. Such service level definitions will also help in better implementation of the new inventory target model described in chapter 7.
- The company should clearly define subcontractor performance assessment criteria to account for both, delivery time and delivery quantity.

9.1 Future Research

This project should prove to be a starting point for further improvements in inventory management and supply chain management as a whole. The following points describe the possible topics that can be undertaken for future research:

1. Incorporation of yield uncertainty of suppliers into the calculation of safety stocks.
2. Further improvement and simplification of the proposed model for safety stock setting.
3. Application and extension of the proposed model to other critical items. and SKUs.
4. Analysis of a possibility for multiple inventory holding locations across the supply chain to reduce lead time uncertainty.
5. Analysis of the impact of a suggested Wafer Bank at the primary wafer supplier on inventory policies and service levels.

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Appendix A

Locations

VIS	Vanguard International Semiconductor Corporation, Hsinchu City, Taiwan
ICN8	NXP Semiconductors Manufacturing Facility, Nijmegen, Netherlands
NEP	Nexperia, Nijmegen, Netherlands
DHAM	Nexperia Germany GmBH, Hamburg
PSI	Phoenix Silicon International Corporation, Hsinchu City, Taiwan
AMP	Ampleon Manufacturing Plant, Cabuyao, Philipines
ASEK	ASE Korea, South Korea
SIGURD	Sigurd Microelectronics Co., Hsinchu City, Taiwan
HUASHAN	Shantou Huashan Electronic Devices Co., Guangdong, China

Table A.1: Manufacturing Locations

Appendix B

Demand Analysis - Distribution Identification

B.1 LDMOS

Input Summary			
Data Type		Continuous	
Method		Moments	
Fit		Auto	
Confidence Level		95%	
Worksheet Rows		52	
Analysis Results			
Distribution	**Chi-Sq**	**P**	**Fit**
Beta	6.196	0.517	OK
Cauchy	10.576	0.158	OK
Erlang	4.424	0.73	OK
Extreme Value	8.338	0.304	OK
Exponential	19.419	0.007	
Gamma	4.364	0.737	OK
Laplace	11.56	0.116	OK
Log Normal	4.339	0.74	OK
Logistic	6.48	0.485	OK
Log Logistic	6.008	0.539	OK
Normal	4.97	0.664	OK
Pareto	30.439	< 0.001	
Power	12.288	0.091	OK
Rayleigh	18.404	0.01	
Triangular	18.713	0.009	
Uniform	5.97	0.543	OK
Weibull	15.914	0.026	

Figure B.1: Distribution Identification: LDMOS Demand

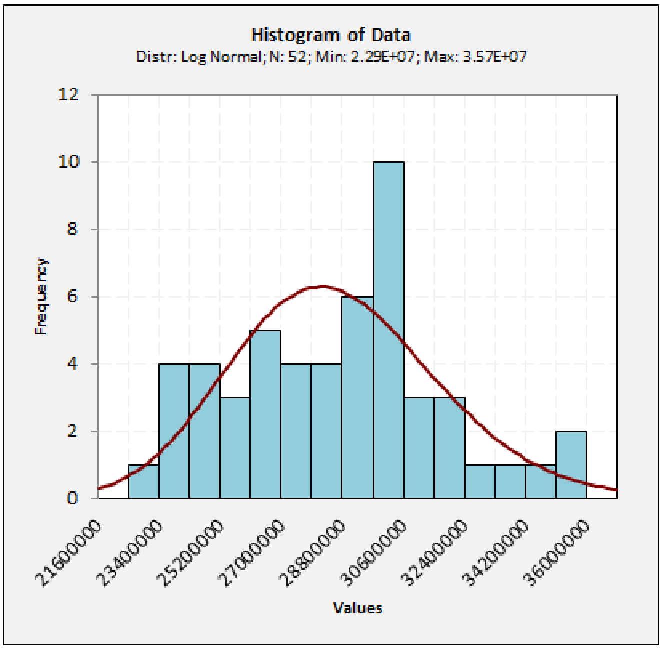

Figure B.2: LDMOS Demand Frequency Histogram v/s Lognormal Distribution

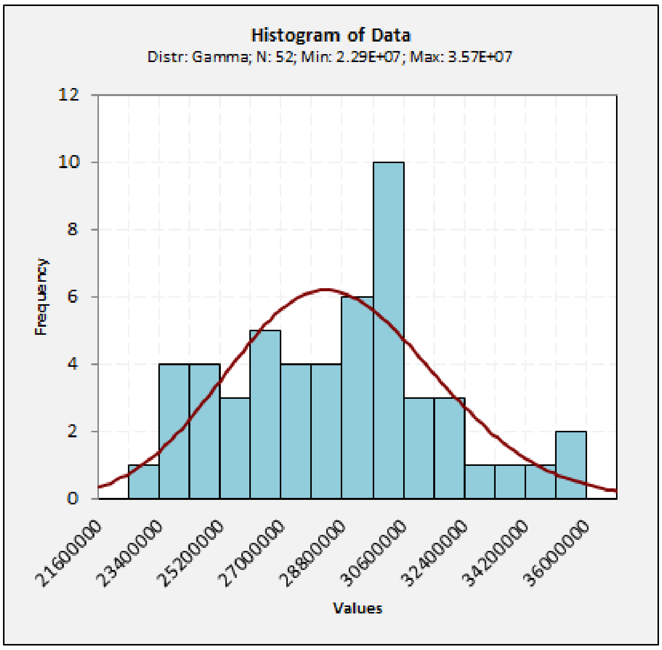

Figure B.3: LDMOS Demand Frequency Histogram v/s Gamma Distribution

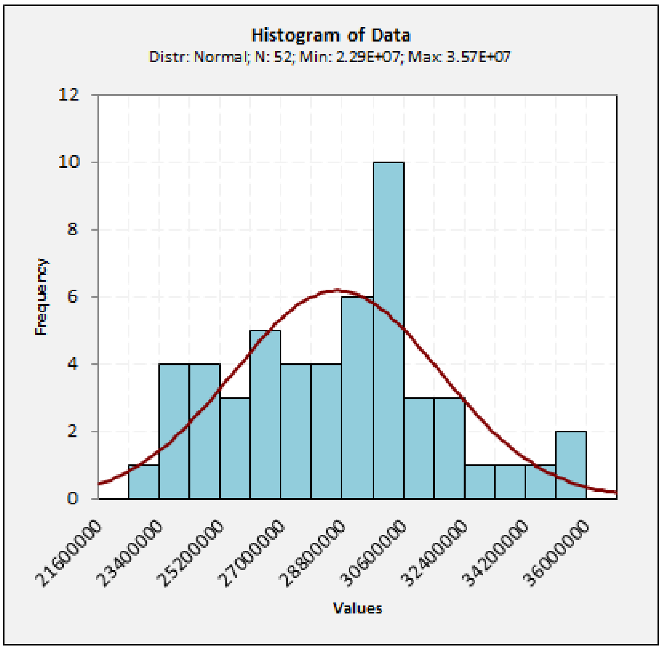

Figure B.4: LDMOS Demand Frequency Histogram v/s Normal Distribution

B.2 MOSCAP

Input Summary			
Data Type		Continuous	
Method		Moments	
Fit		Auto	
Confidence Level		95%	
Worksheet Rows		52	
Analysis Results			
Distribution	**Chi-Sq**	**P**	**Fit**
Beta	10.628	0.156	OK
Cauchy	9.061	0.248	OK
Erlang	5.766	0.567	OK
Extreme Value	21.5	0.003	
Exponential	27.093	< 0.001	
Gamma	5.716	0.573	OK
Laplace	10.564	0.159	OK
Log Normal	5.39	0.613	OK
Logistic	7.759	0.354	OK
Log Logistic	7.104	0.418	OK
Normal	6.442	0.489	OK
Pareto	65.89	< 0.001	
Power	11.77	0.108	OK
Rayleigh	18.461	0.01	
Triangular	28.407	< 0.001	
Uniform	70.023	< 0.001	
Weibull	9.467	0.221	OK

Figure B.5: Distribution Identification: MOSCAP Demand

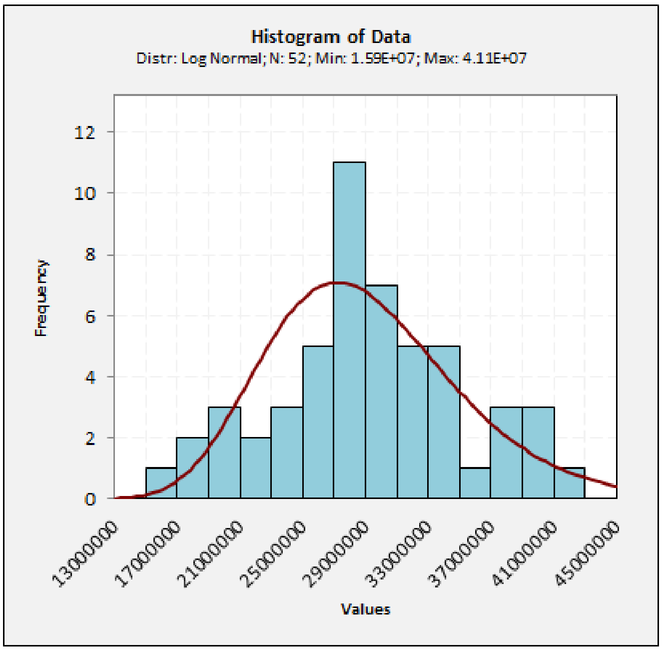

Figure B.6: MOSCAP Demand Frequency Histogram v/s Lognormal Distribution

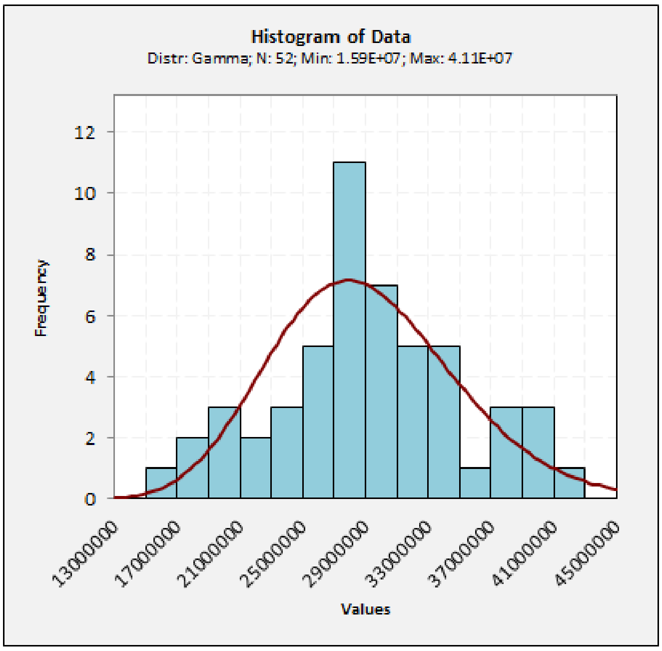

Figure B.7: MOSCAP Demand Frequency Histogram v/s Gamma Distribution

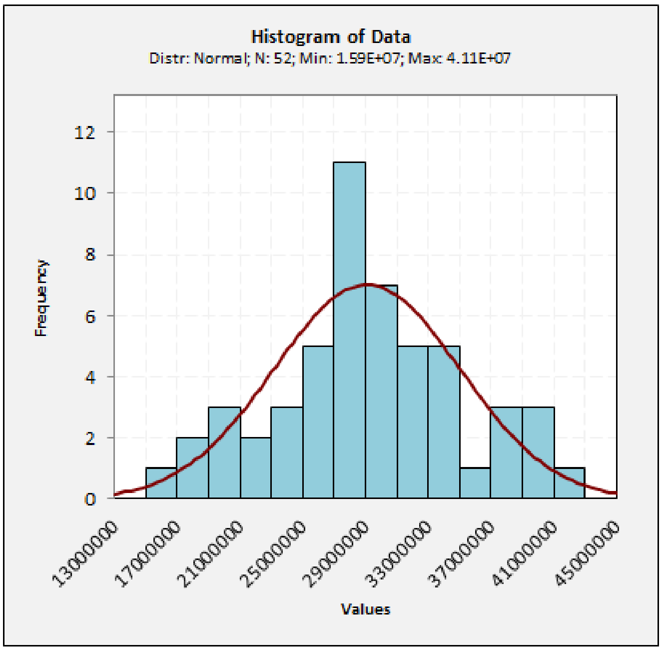

Figure B.8: MOSCAP Demand Frequency Histogram v/s Normal Distribution

Appendix C

Forecast Accuracy

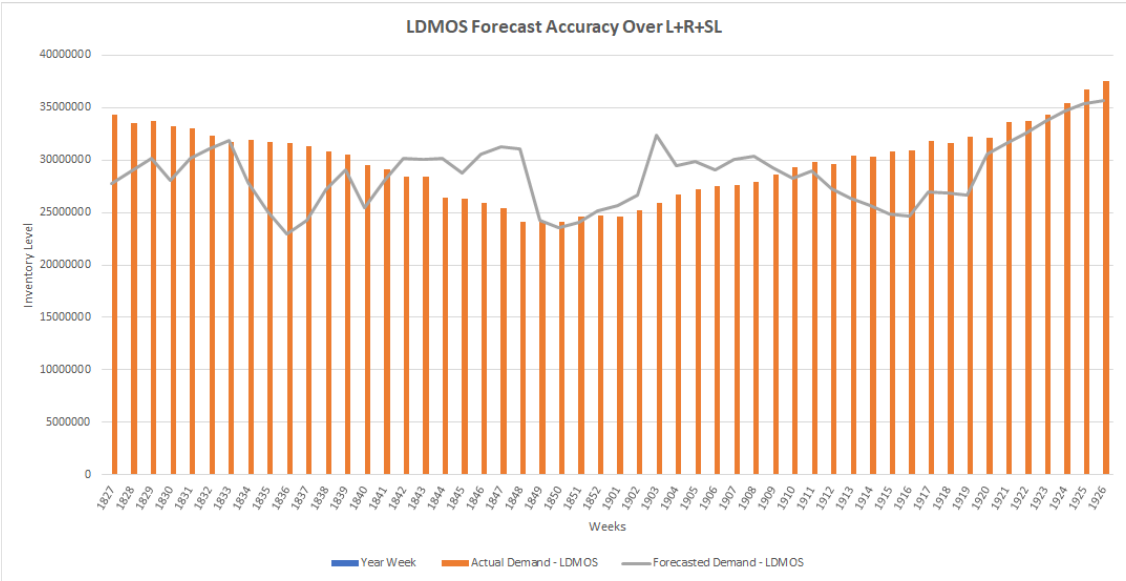

Figure C.1: Forecast Accuracy - LDMOS

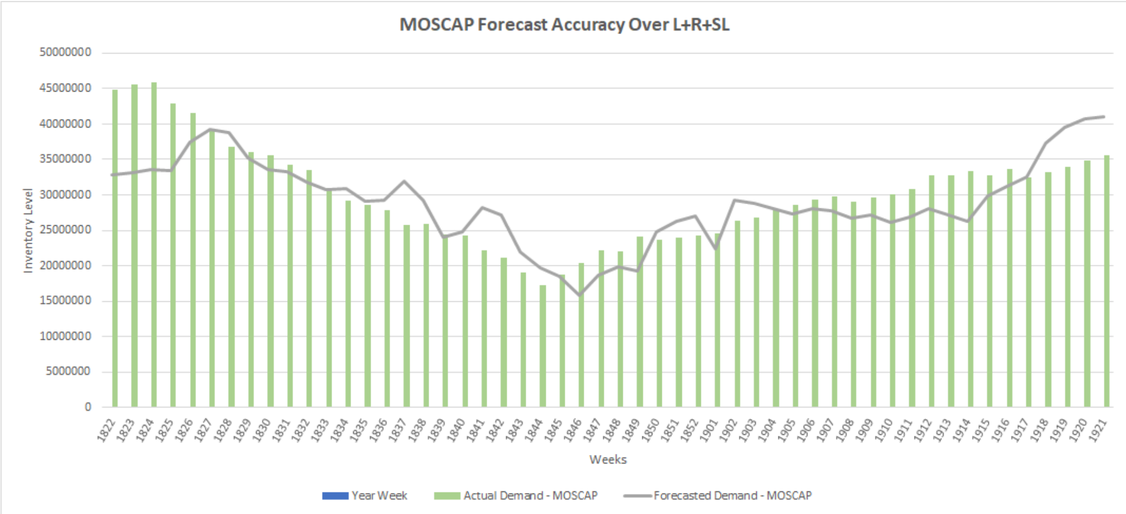

Figure C.2: Forecast Accuracy - MOSCAP

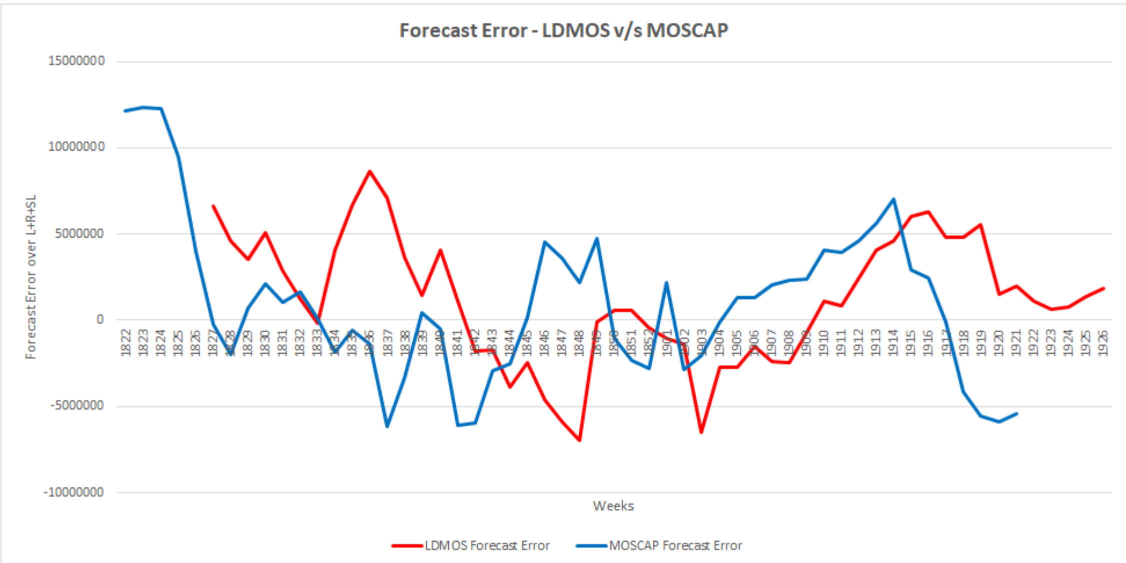

Figure C.3: Forecast Error Comparison - 52 Weeks

Appendix D

Supplier Reliability

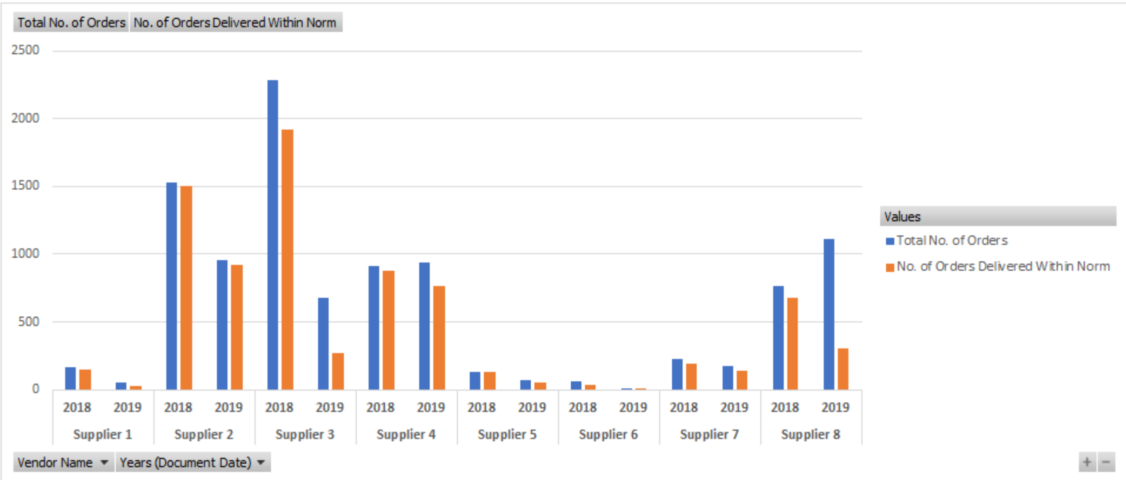

Figure D.1: RLIP Comparison

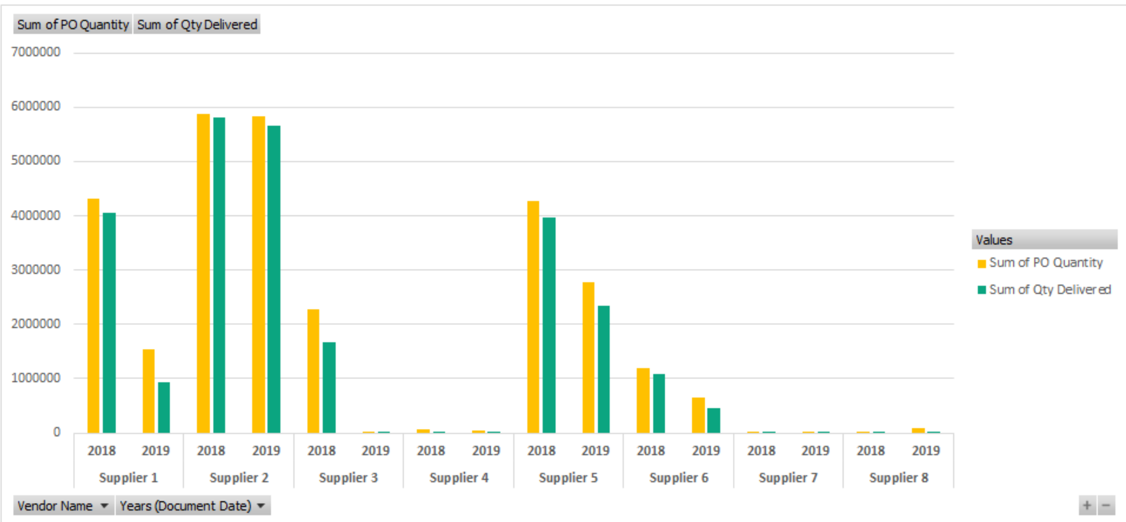

Figure D.2: PCO Comparison

Suppliers/Subcontactors	Sum of PO Quantity	Sum of Qty Delivered	Sum of No. of Orders Delivered Within Norm	Sum of Total No. of Orders	Delivery Reliability (PCO)	RLIP	Supplier Reliability	Best Case Scenario
Supplier 1	**5857189**	**4981525**	**173**	**219**	**85.05%**	**79.00%**	0.67	
2018	4309550	4047431	148	169	93.92%	87.57%	0.82	**0.82**
2019	1547639	934094	25	50	60.36%	50.00%	0.30	
Supplier 2	**11719676**	**11463226**	**2429**	**2486**	**97.81%**	**97.71%**	0.96	
2018	5879645	5798415	1504	1527	98.62%	98.49%	0.97	**0.97**
2019	5840031	5664811	925	959	97.00%	96.45%	0.94	
Supplier 3	**2286597**	**1687107**	**2192**	**2955**	**73.78%**	**74.18%**	0.55	
2018	2269430	1679874	1918	2280	74.02%	84.12%	0.62	**0.62**
2019	17167	7233	274	675	42.13%	40.59%	0.17	
Supplier 4	**109792**	**48356**	**1644**	**1855**	**44.04%**	**88.63%**	0.39	
2018	74664	22630	879	913	30.31%	96.28%	0.29	**0.59**
2019	35128	25726	765	942	73.24%	81.21%	0.59	
Supplier 5	**7057262.61**	**6308250**	**178**	**203**	**89.39%**	**87.68%**	0.78	
2018	4278862.61	3963268	128	132	92.62%	96.97%	0.90	**0.90**
2019	2778400	2344982	50	71	84.40%	70.42%	0.59	
Supplier 6	**1843569**	**1545017**	**50**	**75**	**83.81%**	**66.67%**	0.56	
2018	1188081	1082260	41	62	91.09%	66.13%	0.60	**0.60**
2019	655488	462757	9	13	70.60%	69.23%	0.49	
Supplier 7	**9739**	**8533**	**334**	**407**	**87.62%**	**82.06%**	0.72	
2018	5457	5249	195	228	96.19%	85.53%	0.82	**0.82**
2019	4282	3284	139	179	76.69%	77.65%	0.60	
Supplier 8	**101839**	**35274**	**987**	**1872**	**34.64%**	**52.72%**	0.18	
2018	25174	21311	681	763	84.65%	89.25%	0.76	**0.76**
2019	76665	13963	306	1109	18.21%	27.59%	0.05	

Table D.1: Supplier Reliability Assessment

Appendix E

Safety Factor Calculation

E.1 Safety Factor for Normally Distributed Demand

Service Level v/s k-Factor: k $= \phi^{-1}(P)$ for Probabilities (P) ≥ 0.75

Service Level (P)	**k-Factor**
0.7500	0.67
0.7750	0.76
0.8000	0.84
0.8250	0.93
0.8500	1.04
0.8750	1.15
0.9000	1.28
0.9100	1.34
0.9200	1.41
0.9300	1.48
0.9400	1.55
0.9500	1.64
0.9550	1.70
0.9600	1.75
0.9650	1.81
0.9700	1.88
0.9750	1.96
0.9800	2.05
0.9850	2.17
0.9900	2.33
0.9910	2.37
0.9920	2.41
0.9930	2.46
0.9940	2.51
0.9950	2.58
0.9960	2.65
0.9970	2.75
0.9980	2.88
0.9985	2.97
0.9990	3.09
0.9995	3.29
0.9996	3.35

Service Level (P)	k-Factor
0.9997	3.43
0.9998	3.54
0.9999	3.72

Table E.1: Inverse Cumulative Normal Distribution Table

E.2 Safety Factor for Gamma Distributed Demand

Service Level(P) v/s c-Factor: c $= f(\nu, k, P)$

	k	0				0.2			
	P	0.9	0.925	0.95	0.975	0.9	0.925	0.95	0.975
ν	0.5	1.340	1.567	1.877	2.384	1.337	1.559	1.860	2.350
	0.7	1.337	1.589	1.938	2.521	1.324	1.571	1.911	2.473
	0.9	1.318	1.594	1.981	2.638	1.284	1.556	1.934	2.568
	1.1	1.284	1.583	2.006	2.735	1.227	1.521	1.934	2.637
	1.3	1.238	1.556	2.013	2.811	1.159	1.472	1.918	2.686
	1.5	1.180	1.516	2.003	2.867	1.085	1.414	1.888	2.718
	1.7	1.113	1.464	1.980	2.906	1.006	1.348	1.848	2.734
	1.9	1.040	1.402	1.943	2.928	0.925	1.277	1.798	2.738
	k	0.4				0.6			
ν	0.5	1.332	1.550	1.845	2.323	1.326	1.541	1.831	2.300
	0.7	1.308	1.552	1.884	2.432	1.291	1.532	1.860	2.396
	0.9	1.252	1.521	1.892	2.509	1.222	1.489	1.854	2.458
	1.1	1.178	1.469	1.875	2.558	1.135	1.424	1.824	2.492
	1.3	1.094	1.405	1.841	2.587	1.039	1.347	1.778	2.506
	1.5	1.007	1.333	1.797	2.601	0.941	1.265	1.722	2.506
	1.7	0.919	1.257	1.744	2.601	0.845	1.180	1.660	2.494
	1.9	0.831	1.178	1.685	2.592	0.752	1.095	1.593	2.474
	k	0.8				1			
ν	0.5	1.320	1.533	1.819	2.280	1.312	1.524	1.807	2.262
	0.7	1.274	1.514	1.838	2.364	1.258	1.496	1.817	2.336
	0.9	1.194	1.460	1.821	2.413	1.168	1.432	1.790	2.374
	1.1	1.096	1.384	1.780	2.435	1.060	1.348	1.740	2.386
	1.3	0.990	1.298	1.723	2.438	0.946	1.254	1.676	2.379
	1.5	0.884	1.207	1.659	2.426	0.833	1.156	1.604	2.358
	1.7	0.781	1.115	1.589	2.405	0.724	1.058	1.528	2.329
	1.9	0.684	1.025	1.516	2.376	0.622	0.963	1.450	2.293

Table E.2: Safety Factor Calculation Table for Gamma Distribution

Appendix F

Safety Stock Correction Factor

	Increase in safety stock for			
Lead time	N = 1 (Naïve)	N = 4	N = 12	N = 52
1	0%	0%	0%	0%
2	22%	10%	4%	1%
3	41%	18%	7%	2%
4	58%	26%	11%	3%
5	73%	34%	14%	4%
6	87%	41%	18%	5%

Table F.1: Safety Factors for SMA Forecast as a function of Lead Time and Forecast Periods

Lead Time (L)	**SS Correction Factor**	**CF**
1	0%	1
2	1%	1.01
3	2%	1.02
4	3%	1.03
5	4%	1.04
6	5%	1.05
7	6%	1.06
8	7%	1.07
9	8%	1.08
10	9%	1.09
11	10%	1.1
12	11%	1.11
13	12%	1.12
14	13%	1.13
15	14%	1.14
16	15%	1.15
17	16%	1.16
18	17%	1.17
19	18%	1.18
20	19%	1.19
21	20%	1.2
22	21%	1.21
23	22%	1.22
24	23%	1.23
25	24%	1.24

Table F.2: CF Values for N=52, Based on Table F.1

Appendix G

Model Simulation Results

G.1 Performance Comparison - Actual v/s Expected

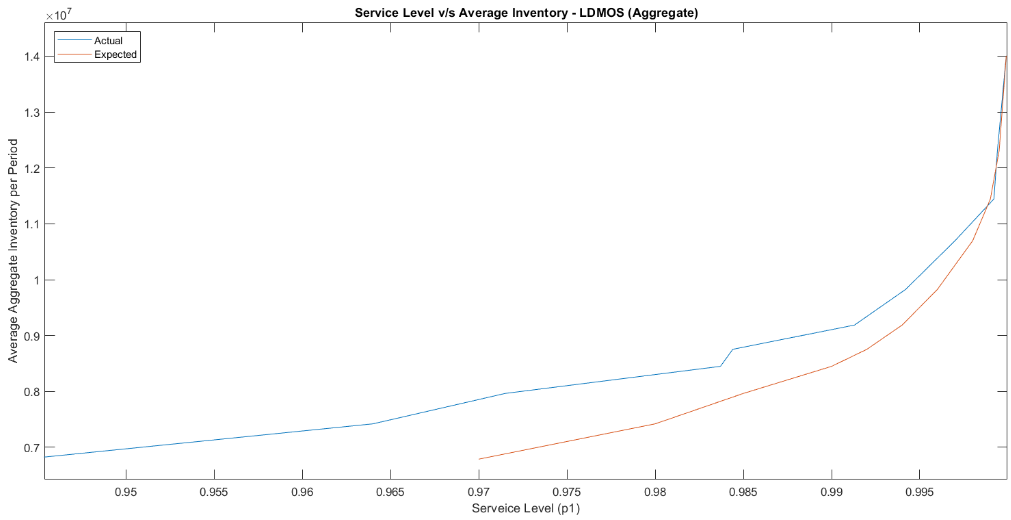

Figure G.1: Average v/s Expected Performance - Normal Distribution - LDMOS

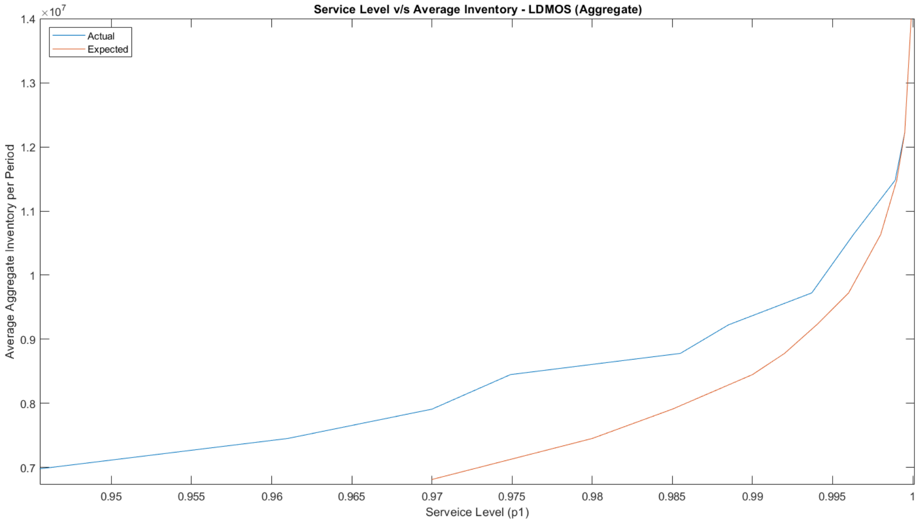

Figure G.2: Average v/s Expected Performance - Gamma Distribution - LDMOS

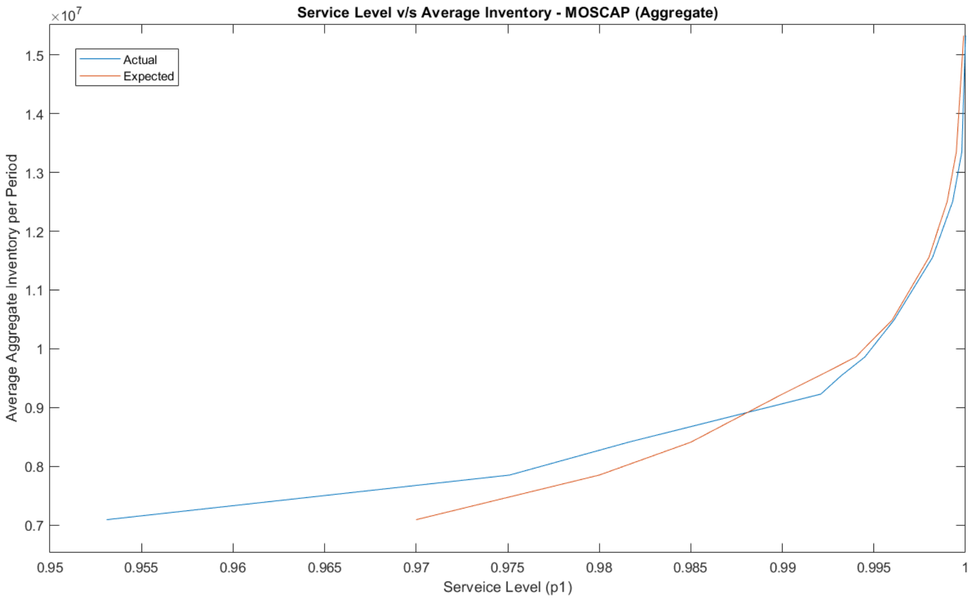

Figure G.3: Average v/s Expected Performance - Normal Distribution - MOSCAP

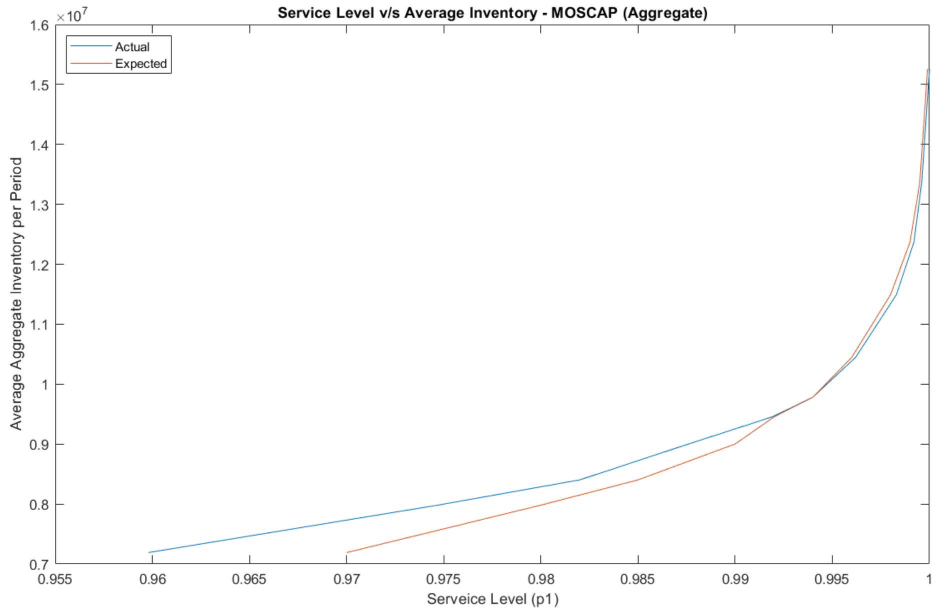

Figure G.4: Average v/s Expected Performance - Gamma Distribution - MOSCAP

G.2 Model Instances

The following figures present the most common instances based on the new (proposed) model, run on gamma and normal demand distributions. Evidently, the inventory stays positive throughout the timeline considered, rendering a 100% service level. Figure G.5 shows the variation in safety stock level, inventory target level (planned inventory position based on the safety stocks and forecast for the period beyond the average flow time, 21 weeks). Similarly, Figure G.6 shows the variation in safety stock level, the actual inventory-on hand inventory target level (planned inventory position based on the safety stocks and forecast for the period beyond the average flow time, 16 weeks). Both figures show the weekly variation in the aforementioned parameters, based on a single simulation of the model described in chapter 7.

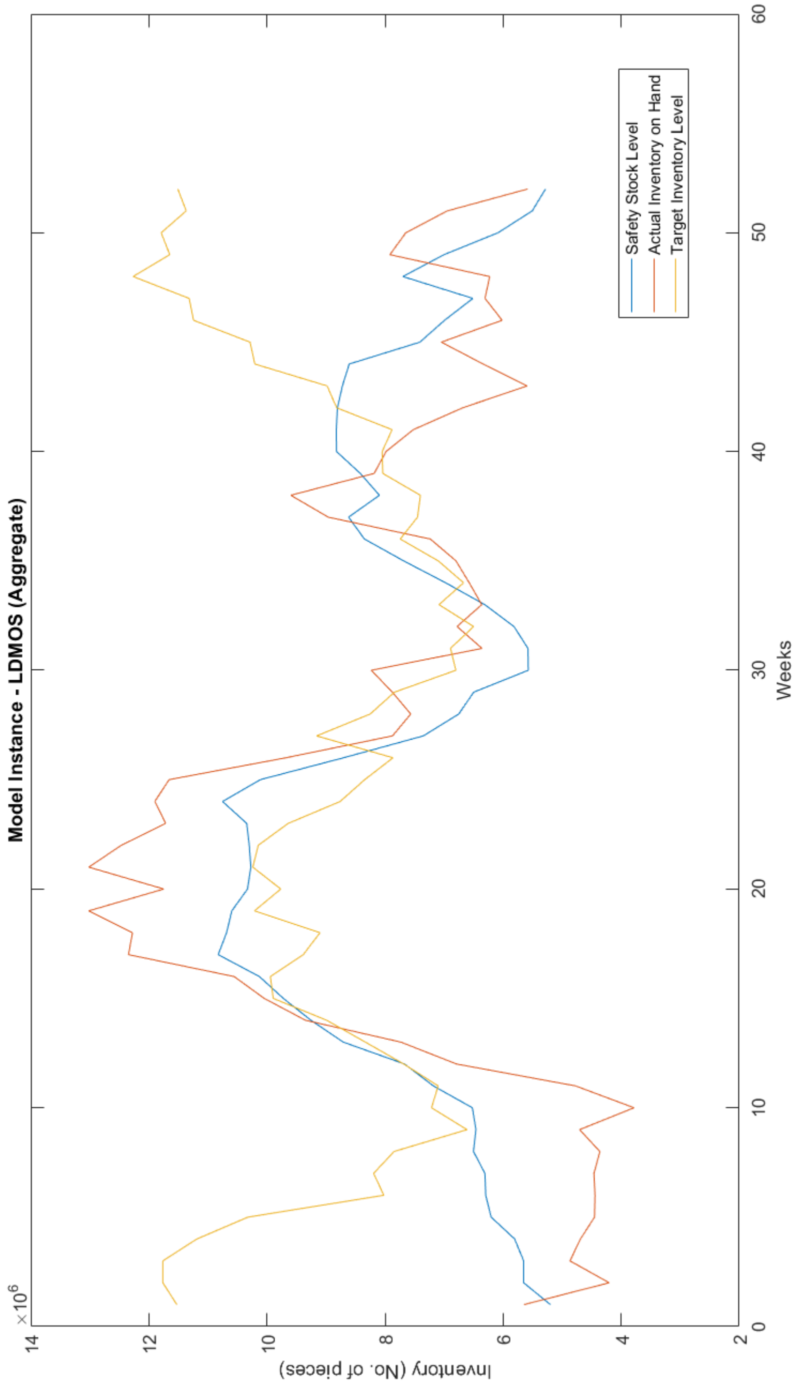

Figure G.5: Model Instance - LDMOS

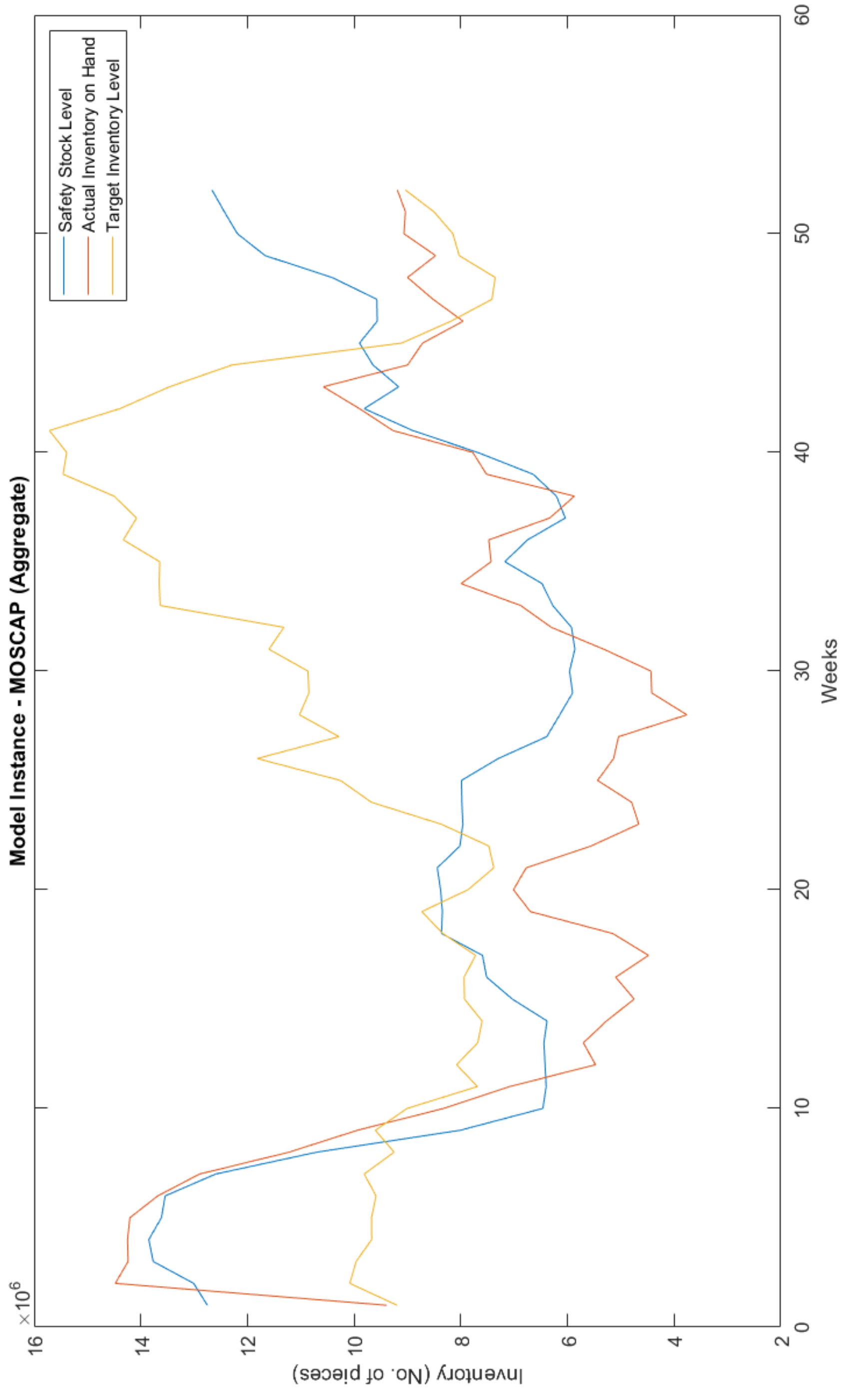

Figure G.6: Model Instance - MOSCAP

Appendix H

List of Abbreviations (Ampleon)

BGBM	Backside Grinding and Backside Metalization
DAB	Digital Audio Broadcasting
EMC	Electromagnetic Compatibility
FM	Frequency Modulation
GaN HFET	Gallium Nitride based High Electron Mobility Transistor
HDR	High Dynamic Range
HVQFN	Heatsink, Very Thin Quad Flat Package, No-leads
HVSON	Heatsink, Very Thin Quad Small Outline Package, No-leads
LTE	4G Communication - Long Term Evolution
MMIC	Monolithic Microwave Integrated Circuit
MRI	Magnetic Resonance Imaging
PAD	Package Asymmetric Doherty
PnP	Positive-Negative-Positive Configuration Transistor
PQFN	Power Quad Flat Package, No Leads
RF	Radio Frequency
Si LDMOS	Silicon based Laterally Diffused Metal Oxide Semiconductor
SWaP	Size, Weight and Power
UHF/D TV	Ultra High Frequency/Definition Television
VHF/D-TV	Very High Frequency/Definition Television
WCDMA	Wideband Code Division Multiple Acess

Table H.1: Abbreviations