A SYSTEM DYNAMICS SIMULATION FOR STRATEGIC INVENTORY MANAGEMENT IN THE SOUTH AFRICAN AUTOMOTIVE INDUSTRY

by

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Submitted in accordance with the requirements for the degree of

PHILOSOPHIAE DOCTOR

(INDUSTRIAL ENGINEERING)

At the

FACULTY OF ENGINEERING, BUILT ENVIRONMENT AND INFORMATION TECHNOLOGY

DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

UNIVERSITY OF PRETORIA

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December 2017

This thesis is dedicated to my wife Rouxné and daughters Rolandi and Sherize who supported me throughout the many hours of work.

I would also like to express my thanks to my parents, company and colleagues who stayed patient and kept motivating me through my journey.

A wise man (Professor Gideon de Wet) once told me: "Andries, if you want to do a PhD, let us do 80% of the work and then you enrol and do the other 80%." He also told me that people do not learn from other people's mistakes. If this journey taught me one thing it was: Professor Gideon de Wet was correct.

DECLARATION

This dissertation is the result of my own work and includes nothing, which is the outcome of work done in collaboration except where specifically indicated in the text. It has not been previously submitted, in part or whole, to any university of institution for any degree, diploma, or other qualification.

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ABSTRACT

The automotive parts supply chain is characterised by expectations of high levels of parts availability, as vehicles are designed to be maintained throughout their life cycles. There is, however, a significant level of unpredictability in demand, requiring suppliers to store sufficient inventory to service demand associated with planned maintenance and unplanned repair events. In this thesis, a supply chain characterisation framework is proposed and confirmed with a series of case studies. The automotive supply chain is characterised as a Class III-P supply chain. This type of supply chain has products with high complexity and long life expectancies, which is augmented through the design of maintenance and repair schedules, requiring a supporting parts distribution supply chain. Automotive part supply continues for 15 years after production of a model ceases, requiring a wide array of items to be available for a significant period of time after the end of vehicle production. The need for parts availability for such a long period results in space constraints within the supply chain. Just-In-Time (JIT) manufacturing results in lean supply chains, but it is shown that the cost for post vehicle production can be high as the volumes required can decrease significantly. To implement JIT in the automotive parts supply chain a MAX/MAX inventory strategy is most commonly followed. The MAX/MAX inventory strategy is implemented with the Maximum Inventory Position (MIP) inventory management method. Deriving the method theoretically and comparing it with the practical implementation shows clear concerns regarding the dimensional consistency of the practical implementation. Using a System Dynamics Simulation Model (SDSM), it is shown that while the theoretical version of the method (MIP_{Theory}) may minimise inventory, it does not maximise parts availability, as measured by allocation fill rate (AFR). The actual implementation (MIP_{Actual}) improves the AFR, but increases average inventory levels significantly (as much as 100 times in some cases).

While it is accepted that stock-on-hand inventory management policies are inherently unstable, a stock-on-hand policy, Stock Target Setting (STS) was developed and redesigned to be stable. The SDSM showed that the STS method could result in stable behaviour, using the supply chain lead time as a damping factor. Comparison between the three methods in a theoretical set of demand, demand variance, lead time and lead time variance scenarios showed that the STS method improves the AFR above that of MIP_{Theory} and requires significantly less inventory than the MIP_{Actual} method. Analysis of the STS method indicates there are some areas for improving the stock target equation,

but this has to be performed with sufficient care. Extending the SDSM to use vehicle sales to generate service parts demand, it is possible to evaluate the inventory management methods under non-stationary demand conditions. The STS method is shown to be the preferred method for domestic supplied parts when there is no start-up inventory. For imported parts, the STS method performs better in the long term. The MIP_{Actual} method also results in high levels of parts availability. The MIP_{Actual} method, however, requires significantly more inventory. In the case of start-up inventory, the STS method is less effective in the short term, but in the long term requires less inventory to maintain an AFR of 100. A practical analysis using actual data show that there are cases where the STS method outperforms the MIP methods, but this is dependent on the demand and lead time behaviour.

The study clearly shows that stock-on-hand inventory management policies, such as the STS method developed in this study, have the potential to improve the performance of the automotive parts supply chain. With the STS method, inventory levels can be reduced, reducing the pressure on storage space requirements resulting from the MIP_{Actual} results. At the same time, the AFR levels can be maintained. The practical problem in the automotive parts supply chain has clearly been addressed and solved.

Significant achievements in the study include the development of a practical supply chain characterisation framework that provides guidance on the supply chain design for specific product classes. The SDSM is a powerful generic tool that can be adjusted for alternative inventory management methods. It can be expanded to evaluate any alternative inventory management method. The STS method showed that the assumption that stock-on-hand inventory management methods are inherently stable is incorrect, opening up the potential to initiate a new research direction towards effective stock-on-hand inventory management methods. The STS method was shown to be a viable alternative for the automotive service parts supply chain.

ACKNOWLEDGEMENTS

I would like to thank all my supervisors at the Department of Industrial and Systems Engineering at the University of Pretoria who supported me in this journey:

- Professor Paul Kruger
- Professor Chris van Schoor
- Professor Sarma Yadavalli
- Dr. Jacomine Grobler

My thanks also go to Ms Cora Bezuidenhout at the University of Pretoria Library Services for her support in my literature searches.

Dr. Lizelle Fletcher and Jaqui Sommerville of the UP Department of Statistics provided invaluable help with the required statistical analysis.

Mrs Esme Bluff, who helped her brother with key statistical insights.

Thank you to Kayla Friedman and Malcolm Morgan of the Centre for Sustainable Development, University of Cambridge, UK for producing the Microsoft Word thesis template used to produce this document.

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LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviation	**Explanation**
AFR	Allocation Fill Rate
APDP	Automotive Production Development Programme
APICS	American Production and Inventory Control Society
CBU	Completely Built Up Unit – fully imported vehicles
CKD	Completely Knocked Down Kit – components imported to combine with local parts for car manufacturing
DAD	Daily Average Demand
GS	Guaranteed Service
GSCF	Global Supply Chain Forum
JIT	Just-In-Time
MAD	Monthly Average Demand
MAX/MAX	Inventory management method that orders to a maximum point every time the inventory falls below the maximum
MIDP	Motor Industry Development Programme
MIN/MAX	Inventory management method that orders to a maximum point when inventory reaches a given minimum
MIP	Maximum Inventory Position
MIP_{Actual}	Equations used to implement the MIP model
MIP_{Theory}	Theoretical derivation of the MIP method equations
OEM	Original Equipment Manufacturer
SCOR	Supply Chain Operations Reference
SDSM	System Dynamics Simulation Model
SKD	Semi Knocked Down Kit – all components stripped and boxed for reassembly
STS	Stock Target Setting Method

LIST OF APPENDICES

1 INTRODUCTION AND OVERVIEW

Supply chains have existed since the dawn of humanity. Joseph oversaw a supply chain that harvested grain all through Egypt, stored it in centralized warehouses and distributed it to citizens during the time of drought. In modern times, supply chains span the globe, with sophisticated management and information systems keeping track of product movements, warehousing and sales. Raw materials and products are sourced globally, consolidated in warehouses and distributed globally, when required.

The purpose of supply chain management is to ensure that products are available to users when and where required. This primary objective of availability results in a need to keep sufficient stock at appropriate locations and the need for effective distribution. At the same time, to control costs, it is necessary to minimise the amount of stock carried at any point in time. A key problem in supply chains is the so-called bullwhip effect, where small changes in demand results in amplification, which eventually leads to a system that oscillates between overstocking and understocking (Forrester, 1958).

The specific supply chain under study in this thesis is the South African automotive parts supply chain. However, the results are also applicable to other countries, as discussed in Chapter 2. The automotive industry is a basic life cycle management supply chain (Blanchard, 2004). Vehicles are assembled and distributed using a network of dealerships. This part of the business is usually, referred to as the OE (Original Equipment) part of the business. Once the vehicle leaves the dealers' showroom, life cycle management commences. As part of the design process, regular service intervals are stipulated with specific service parts to be replaced at each interval. Service centres also inspect specific wear and tear parts to determine if they are still within specification or need to be replaced. In addition, components can fail for a variety of reasons and need to be replaced or repaired. The final aspect of the life cycle support is the repair and replacement of parts due to accidents. In addition to the standard life cycle elements, there is also the use of recall campaigns to correct design problems identified once the vehicles enters the market.

The automotive parts supply chain includes a variety of demand patterns, such as: fast moving service parts, medium moving wear and tear parts and slow and erratic moving repair parts. Each of the groupings has its own specific average demand and demand variance. In the case of fast moving parts, demand is predictable, yet it still includes demand variance. In the case of erratic demand, both the incidence and quantity of items required at any point in time is unpredictable.

1.1 Research Question

Practical experience shows that the South African automotive parts supply chain sometime suffers from stock-outs. Dealers do not have parts to service or repair vehicles, negatively affecting customer experience. Within the supply chain, the original equipment suppliers experience the bullwhip effect with overstocking as well as stock-outs. Overstocking places strain on warehouse space, while stock-outs result in client dissatisfaction. To address the problem of the bullwhip effect in the South African automotive parts supply chain, the following research questions are addressed:

- Can a framework based on product characteristics be developed to simply the selection of a supply chain design?
- Is the existing inventory management method, based on a MAX/MAX strategy sufficient to manage the bullwhip effect?
- Can an alternative stock-on-hand inventory management method, be developed to manage the bullwhip effect and provide high levels of availability at lower average inventory levels?

1.2 Objectives

The objectives of this study are:

- To develop a conceptual supply chain characterisation framework which addresses supply chain design from a product and life expectancy point of view.
- To conduct a theoretical analysis of the current inventory management methods (including the ordering algorithms).
- To confirm that Just-In-Time (JIT) is a feasible solution for the automotive parts industry.

- To develop an alternative stock-on-hand based inventory management method that will not result in the bullwhip effect.
- To evaluate and compare three inventory management methods (best practice practical, best practice theory and new theoretical method) within a theoretical domain, using various statistical demand patterns.
- To evaluate and compare the performance of the three inventory management methods against a practical demand dataset that includes a variety of demand patterns.
- To determine appropriate parameters for the recommended inventory management methods to obtain the best possible results.

1.3 Contributions

The thesis provides a number of key contributions to the field of strategic inventory management and optimisation. The contributions include:

- A conceptual supply chain characterisation framework that simplifies the task of practitioners when decisions are to be made regarding the structure and design of supply chains. The framework simplifies the decisions regarding supply chain structure.
- The implications of Just In Time or Lean Supply Chain on parts cost target setting are analysed and a standardised strategy for setting cost targets is proposed.
- Historically the MIP ordering aproach has been treated as a "black box" development by consultants and embedded in software for planners to use. In this thesis, the theoretical principles are analysed, allowing inventory controllers to better understand why the software provides the results that it does.
- The Stock Target Setting (STS) method is developed and it is shown that this stock-on-hand inventory management method can be adapted to be stable and not induce the bullwhip effect. The development of a stable stock-on-hand method opens up a new domain for academics and practitioners to develop stock-on-hand inventory management methods. These methods were previously not pursued due to historical assumptions that have now been shown to be invalid under certain conditions.

- A System Dynamics Simulation Model (SDSM) is developed, that can be used to test alternative inventory management methods, for both local and imported parts supply. The model is sufficiently generic, that it can be adapted to any inventory management method. The model can also be adjusted to address any other supply chain and is, therefore, not limited to the automotive spare parts supply chain, allowing academics and practitioners to explore the effectiveness of alternative inventory management methods. While the practical analysis was performed on South African automotive parts distribution scenarios, the SDSM can be applied to scenarios from any country.
- The SDSM also allows for analysis using simulated stationary and non-stationary demand and real data.
- The most effective inventory management method (from the three methods analysed) for achieving effective supply chain performance under various demand patterns and supply chain structures, is identified. The analysis is performed in both a theoretical domain, as well as with a specific dataset that reflects the various demand patterns experienced in a real automotive parts supply chain. These practical results can provide practitioners with a better understanding of a more appropriate inventory management method to apply to the specific case of automotive parts supply.

1.4 Document Structure

The thesis structure is as follows:

Chapter 2 focuses on a review of relevant literature. Areas that are covered in the review include the basic definitions of a supply chain, a selection of supply chain frameworks, the different methods for analysing supply chains, inventory theory, tools to test supply chains and simulation techniques in supply chain analysis.

Chapter 3 describes the development of a supply chain characterisation framework. The proposed supply chain characterisation framework provides a practical method to simplify the design of supply chains based on two key characteristics of the supply chain. The framework is evaluated against case studies to confirm its applicability.

Chapter 4 focuses on the South African automotive parts supply chain. The concept of Just-In-Time (JIT) in the supply chain is also discussed and the economic order quantity theory is used to derive a JIT unit cost. A model for cost target management of automotive parts is developed and discussed in detail. Finally, a case study is presented to demonstrate the practical implications of JIT on parts manufacturing set up costs.

In Chapter 5 the focus is on the basic elements of the lean supply chain. The MIP inventory management model is derived from basic principles leading to the MIP_{Theory} equations. The implementation of the MIP method in practice is described, providing the MIP_{Actual} equations. Finally, the STS inventory management method is derived and the appropriate equations developed.

In Chapter 6 system dynamics modelling concepts are discussed. The basic methodology of SDSM development and testing is presented, including a review of the use of SDSM in the supply chain environment. The development of the specific SDSM used in the thesis is discussed. The SDSM is set up to allow different inventory management methods to be tested. In addition to being able to compare the inventory management methods, the SDSM is also used to evaluate the design of the proposed STS method and to ensure that the parameters used are such that the method does not lead to the bullwhip effect.

Chapter 7 provides the results of the various simulation runs. Firstly, the development and refinement of the STS method is discussed. An overview of the proposed theoretical framework for analysing the various inventory management methods is provided. A comprehensive theoretical analysis of each of the three methods is presented including both stationary and non-stationary demand environments. The datasets and results for the practical comparison of the inventory management methods are also discussed in detail. Finally, the STS method is subjected to a sensitivity analysis to determine if it is possible to improve the ordering algorithm. An analysis using real data is presented and discussed.

Chapter 8 summarises the results and provides conclusions on the study. It also highlights further research opportunities that were identified.

2 LITERATURE REVIEW – SUPPLY CHAIN MANAGEMENT AND INVENTORY OPTIMISATION

In this chapter, basic supply chain management concepts and frameworks are discussed and inventory management and the bullwhip effect is introduced. The bullwhip results in excessive oscillations in inventory, with the subsequent cost implications of over stocking or opportunity cost of being out of stock. As this thesis focuses on inventory management models it is also critical to understand the impact of inventory management on supply chain behaviour and the stability of the supply chain, these concepts are reviewed. Finally, the various approaches to supply chain modelling and simulation are discussed.

2.1 Supply Chain Definition

According to the American Production and Inventory Control Society (APICS) Dictionary, 11th edition (APICS, 2005) a supply chain is a “global network used to supply products and services from raw materials to end customers through an engineered flow of information, physical distribution, and cash.”

Gattorna (2010) applies a much broader definition to supply chains: “... any combination of processes, functions, activities, relationships and pathways along which products, services, information and financial transactions move in and between enterprises, in both directions.” Gattorna (2010) focuses on understanding client buying behaviour and designing supply chains that meet the client demands.

The Global Supply Chain Forum (GSCF) is a group of non-competing firms and academics who meet regularly to improve the theory and practice of Supply Chain Management (GSCF, 2017). The definition that the GSCF uses is the broadest. It explicitly states that supply chain management should not been seen as logistics only, but permeates all processes within the company

2.2 Challenges in Supply Chain Management

The most fundamental concern in supply chain management is service to the customer. Gattorna (2010) and Holweg and Pil (2001) both state that service to the customer is critical. Holweg and Pil (2001) support build-to-order supply chains, while Gattorna

(2010) uses segmentation to identify alternative supply chain designs. With this segmentation in mind, the work of Humair and Willems (2006) on the Guaranteed Service (GS) model is of critical importance. The GS model and its implications are discussed in Section 2.6.1.

The need to effectively provide a service to customers is fundamental in the processes of supply chain design and supply chain operations. To achieve this, a number of issues need to be addressed, including location of warehouses, location of inventory, transport modes (land, sea or air), daily transport plans and inventory management. Inventory management focuses on how much inventory to hold, when to order and how much to order (Winston, 1994). The details of inventory management are discussed in Section 2.6. For the purposes of this study, the focus is on the question of inventory management, however, for the sake of completeness, a broad overview of supply chain challenges is provided.

The bullwhip effect in supply chains was identified by Jay Forrester (1958) and has been studied extensively. Despite the research, customer demand variation still causes the bullwhip effect as shown in a number of studies (Morán & Barrar, 2006), as well as personal experience gained in the automotive vehicle and parts industry. \

2.3 Contemporary Supply Chain Frameworks

The purpose of this section is to explore various supply chain management frameworks. All the frameworks discussed share a number of fundamental elements. Each framework has certain strengths and weaknesses and was developed with specific needs in mind. The frameworks are compared and gaps are identified as basis for the development of the practical supply chain planning and management framework proposed in Chapter 3. This discussion focuses on four contemporary frameworks, as proposed by APICS, The Supply Chain Council, Gattorna (2010) and the Global Supply Chain Forum. These frameworks provide a good overview of the current state of the art.

2.3.1 APICS Supply Chain Framework

According to APICS (2008), most supply chains consist of a manufacturing entity (service supply chains also exist), with a supplier of raw materials or components on the one side and a customer on the other side. While these elements are sufficient for a supply chain to exist, they are not sufficient to describe typical global supply chains.

The APICS supply chain model suggests that the basic supply chain has three entities and four flows. The entities are:

- Supplier – "..provides material, energy, services, or components for use in producing a product or service."
- Producer – "..receives services, materials, supplies, energy, and components to use in creating finished products, .."
- Retailer – "..receives shipments of finished products to deliver to its customers.."

The flows are:

- Physical Material and Services – "...flowing from suppliers through the intermediate entities that transform them into consumable items for distribution to the final customers."
- Money – "..from the customer back towards the raw material supplier."
- Information - "..back and forth along the chain (also back and forth within the entities and between the chain and external entities) .."
- Reverse Flow of Products – "..returned for repairs, recycling, or disposal."

These simple entities and flows can be combined to demonstrate complex supply chains, as shown in Figure 2-1, where a manufacturing supply chain is shown with distribution and two tiers of suppliers.

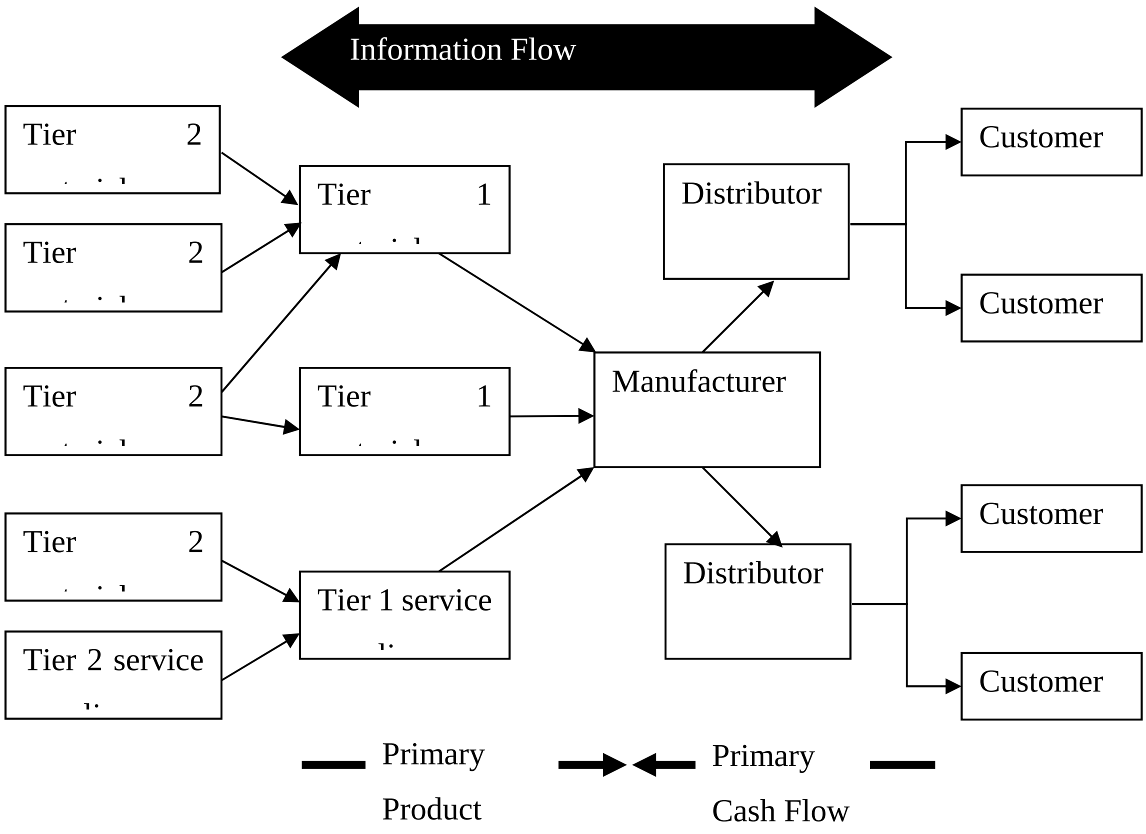


Figure 2-1: Manufacturing Supply Chain Model (APICS, 2008).

The APICS framework is simple and flexible and is useful as an introductory training aid. The framework does not, however, provide any additional information or utility than would be expected from a standard logical approach to supply chains. From a logistics point of view, it is simply flows of goods, information and money. The framework does not provide any insight in terms of operations design, warehouse location and/or inventory management methodology.

2.3.2 Supply Chain Operations Reference (SCOR) Framework

The Supply Chain Council ("a non-profit organization with the aim of being the cross-industry standard for supply chain management") developed and endorsed the Supply-Chain Operations Reference (SCOR) framework as a process reference framework for supply chain management (Supply Chain Council, 2009).

The SCOR framework provides a standardized description of the five process types that the Supply Chain Council has defined as core to supply chains. The framework is clearly defined, both in its scope, as well as in its application. The five processes contained in the SCOR framework are:

- Plan
- Source
- Make
- Deliver
- Return

In its standard application, SCOR takes into account the processes in a company, as well as the same five processes in two tiers of suppliers and two tiers of clients. Figure 2-2 shows a schematic description of the SCOR framework.

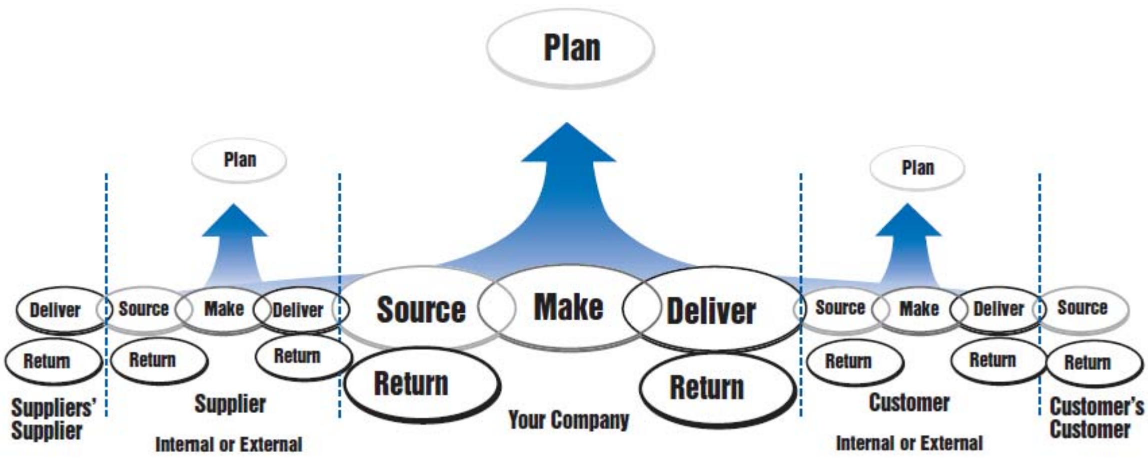


Figure 2-2: Supply Chain Overview as Defined in the SCOR Framework (Supply Chain Council, 2009).

Three levels of process detail are contained in the SCOR framework. At the highest level, process types are identified. At the configuration level, process categories are identified. At the third level, the process element level, processes are decomposed. The implementation level and lower, at which process elements are decomposed, is organization specific and not included in the SCOR framework. Figure 2-3 shows the levels of detail as contained in the SCOR framework.

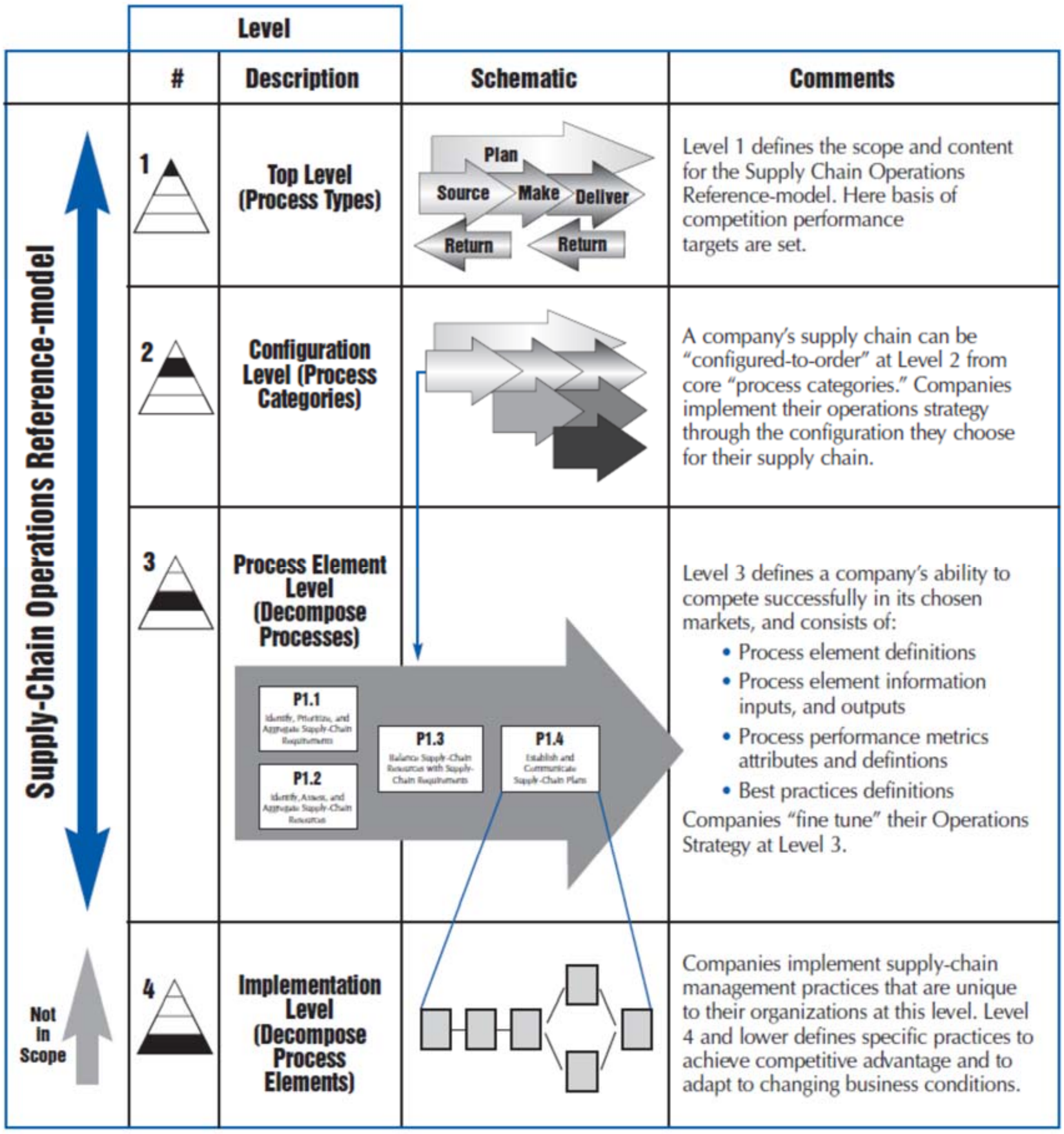


Figure 2-3: Levels of the SCOR Framework (Supply Chain Council, 2009).

The fundamental purpose of the SCOR framework is to be a reference model that can be used to design standard processes and benchmark performance. Level 2 in Figure 2-3 suggests that a company's supply chain can be "configured-to-order". Level 3 in the model mentions performance metrics and "best practice definitions". Both of these assume that supply chains have standardized processes that can be selected "off the shelf" to meet the requirement. It does not adequately address the complexity of real supply chains where non-standard processes may be critical to operations or provide a competitive edge.

Where the APICS framework does consider that extended reverse supply chains exist, such as, for example, an iron ore mine using trucks that are constructed using steel made from ore from the mine, SCOR focuses only on two levels of suppliers and two levels of customers and does not take into account the total span of the supply chain. In his original work on the bullwhip effect, Forrester (1958, 1961) indicated that every inventory point in the supply chain plays a role in how the supply chain behaves overall and not just two tiers of suppliers and customers. As a retailer, lack of awareness of the impact of order decisions on the manufacturer shows clearly in the results of playing the "Beer Game" (Sterman J. , 1989). To classify supply chains based on their structure, it is necessary to focus on the number of players in the complete supply chain.

SCOR also provide users with a "check sheet" to manage supply chain activities, indicative of a strong mechanistic based approach to supply chain management. Another advantage of SCOR is actual performance data made available from different companies that can be used for benchmarking purposes. SCOR, however, does not consider all functional areas such as, for example, marketing.

2.3.3 Behavioural Based Supply Chain Framework

Gattorna (2009, 2010) defined four generic aligned supply chain types. The premise is that by understanding customer buying behaviour, a supply chain management approach can be developed to address the customer requirements. This focus ignores the impact of the supply chain scope or production process complexity. It does, however, challenge the user to ensure that the customer remains the focus of the supply chain. The proposed framework is based on four forces that drive behaviour:

- Feeling
- Intuition
- Sensing
- Thinking

Each buyer is affected by the resultant of these forces when making buying decisions. Gattorna (2010) proceeds to identify 16 possible dominant behavioural segments as shown in Figure 2-4.

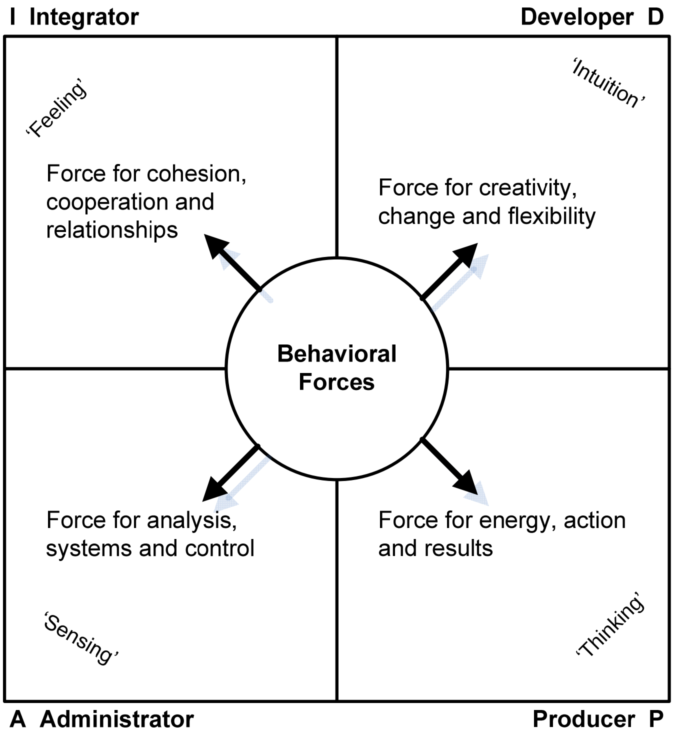


Figure 2-4: General Characteristics of the Four Dominant Behavioural Forces or Logics (Gattorna, 2010).

The 16 dominant behavioural segments can be reduced to four commonly observed buying patterns as shown in Figure 2-5. The figure shows how specific elements in the buying environment affect the dominant buying behaviour. It also identifies four main potential supply chain design requirements, namely:

- Collaborative
- Efficient
- Dynamic
- Innovative Solutions

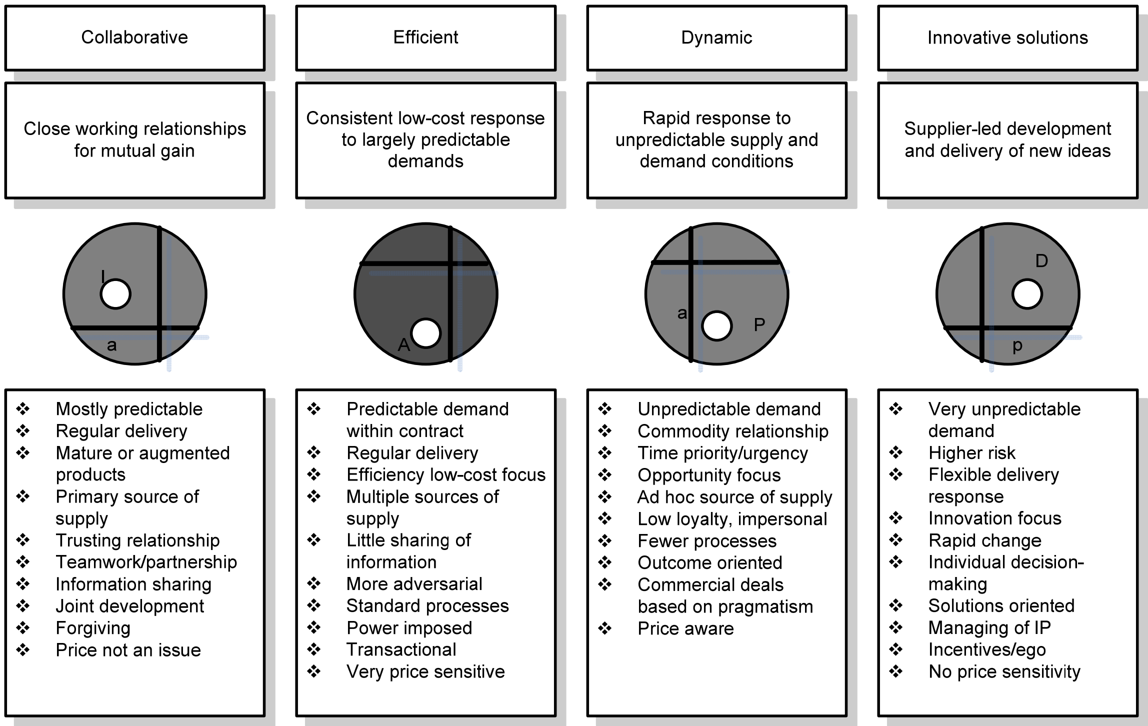


Figure 2-5: The Four Most Commonly Observed Dominant Buying Behaviours (Gattorna, 2010).

Four types of supply chains are required to address the buying behaviours, as shown in Figure 2-6 (Gattorna, 2010).

Continuous Replenishment Supply Chain – customers and suppliers collaborate to keep products flowing as fast as they are consumed.

Lean Supply Chain – Gattorna (2010) describes lean as a "… push into the marketplace and a focus on efficiency by removing waste ..." The author's understanding of lean is that it focuses on manufacturing only what is needed, when it is needed (Shingo, 1981). While this focus requires high efficiency and strives to reduce waste, it requires significant collaboration and trust between supplier and customer. Suppliers and customers must collaborate to resolve problems and improve efficiency.

Agile Supply Chain – a supply chain that "responds to customers in unpredictable demand situations..."

Fully Flexible Supply Chain – this is an extreme example of an agile supply chain and it could be argued that it is a required capability to respond to extreme situations.

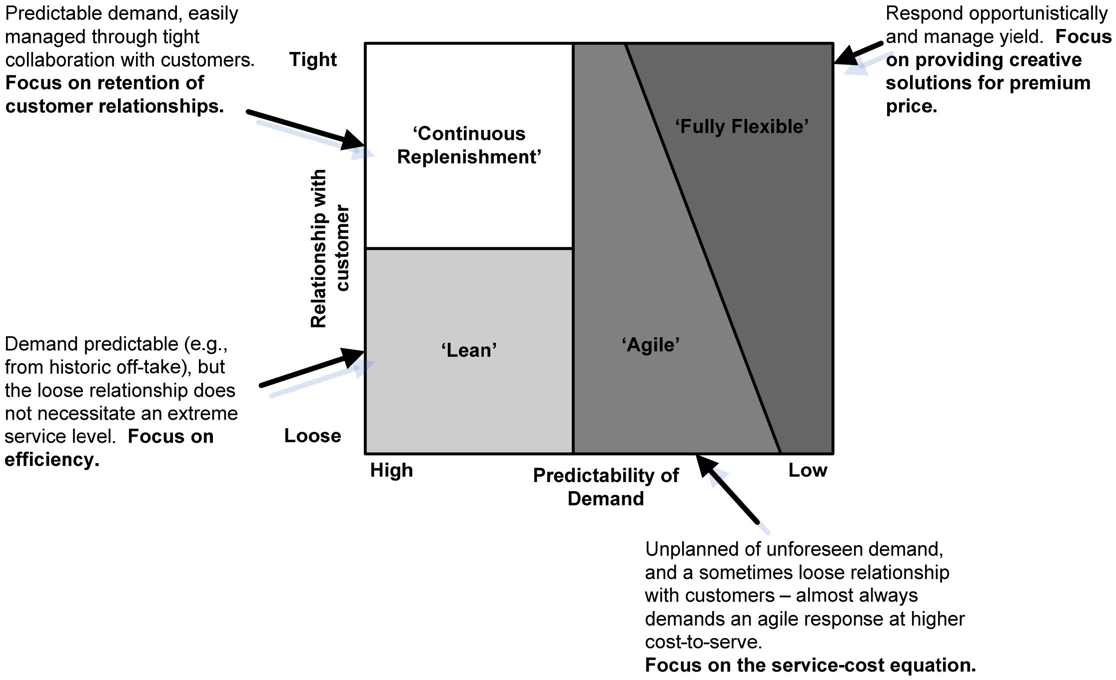


Figure 2-6: The Four Generic Supply Chain Types – Demand-Side (Gattorna, 2010).

The most useful evolution of the Gattorna model is found in Figure 2-7, where Flow Types (demand patterns), Types of Supply Chains and Customer Segments are linked. The important contribution lies in the identification of different demand patterns requiring different supply chain designs.

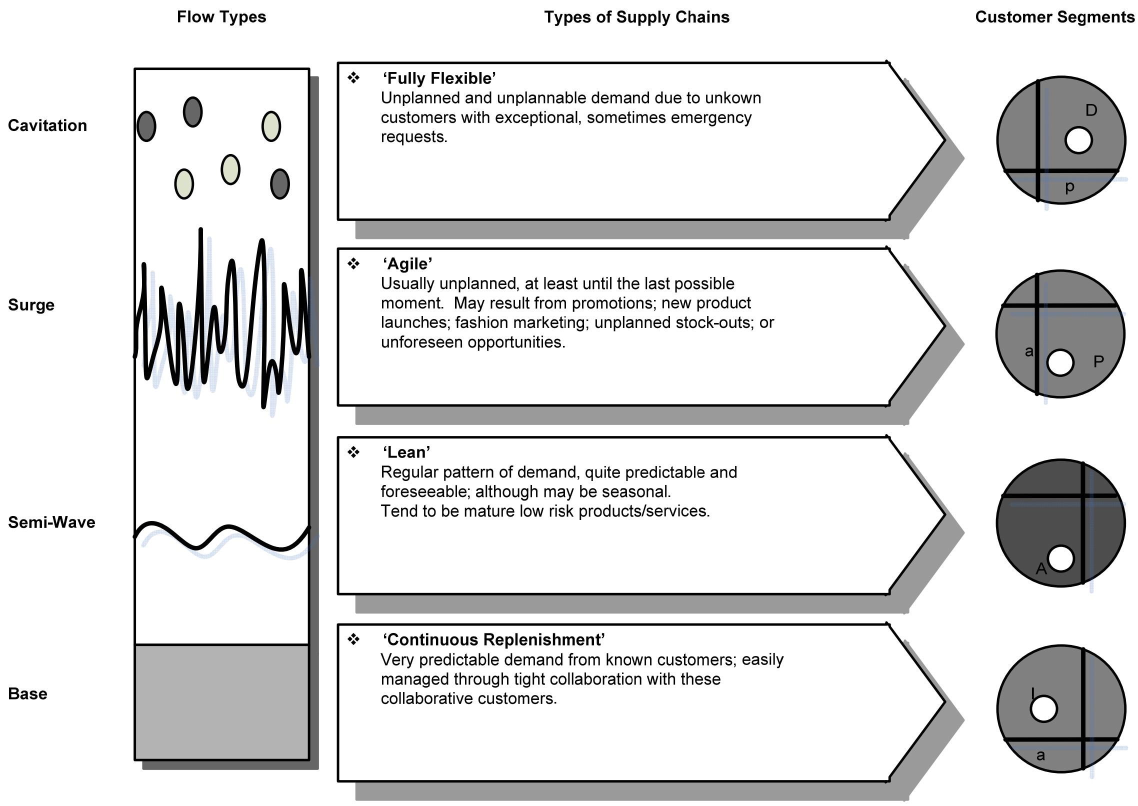


Figure 2-7: Flow Types and Matching Supply Chain Types (Gattorna, 2010).

If the Gattorna (2010) model is applied in an alternative manner, not focusing on the buying behaviour, but rather the needs or demand drivers, an important application to the automotive parts environment exists. Four different supply chain designs, determined by the demand patterns, are required for each of the four types of after-market parts:

Service Parts – regular and planned, based on number of kilometres driven (flow type: base).

Maintenance or Wear and Tear Parts – regular, but less predictable as it depends not only on kilometres driven, but also individual driving style (flow type: semi-wave).

Accident Repair Parts – unplanned events, but the type of parts involved are usually standard (flow type: agile).

Repair Parts – unplanned breakage of components due to age, operating conditions or other unpredictable events (flow type: cavitation).

2.3.4 Global Supply Chain Forum Framework

The Global Supply Chain Forum (GSCF) framework is the most comprehensive view of supply chain management. The framework includes the network view proposed by

APICS, as well as the process view of SCOR. GSCF proposes that the total organisation and especially customer related functions need to be aligned as part of the supply chain perspective. Supply chain management is thus elevated to the core of the organisation.

The GSCF framework focuses on identifying the role players in the company's specific network as well as the structural dimensions of the network. The structural dimension considers both horizontal and vertical elements. The horizontal structure describes the number of tiers across the supply chain and the vertical structure the number of suppliers or customers in each tier. The structure for each company is unique and a good understanding is required to plan processes that span company boundaries. The key business processes identified by the GSCF are indicated in Figure 2.8.

The extent of management between the supply chain partners varies from supply chain to supply chain: Managed Process Links – links that the focal company consider important to manage.

- Monitored Process Links – links that are less important, but need to be monitored or audited.
- Non-managed Process Links – links that the focal company does not consider sufficiently important to manage or monitor. The focal company trusts other members to manage these links effectively.
- Non-member Process Links – links where other players' decisions can affect the focal company's behaviour. An example includes suppliers who produce components for a company as well as its competitors.

It is notable that the framework does not focus on the traditional elements of transport, logistics, warehousing, distribution and technology, but is more global and focuses on relationship building and long-term stakeholder value.

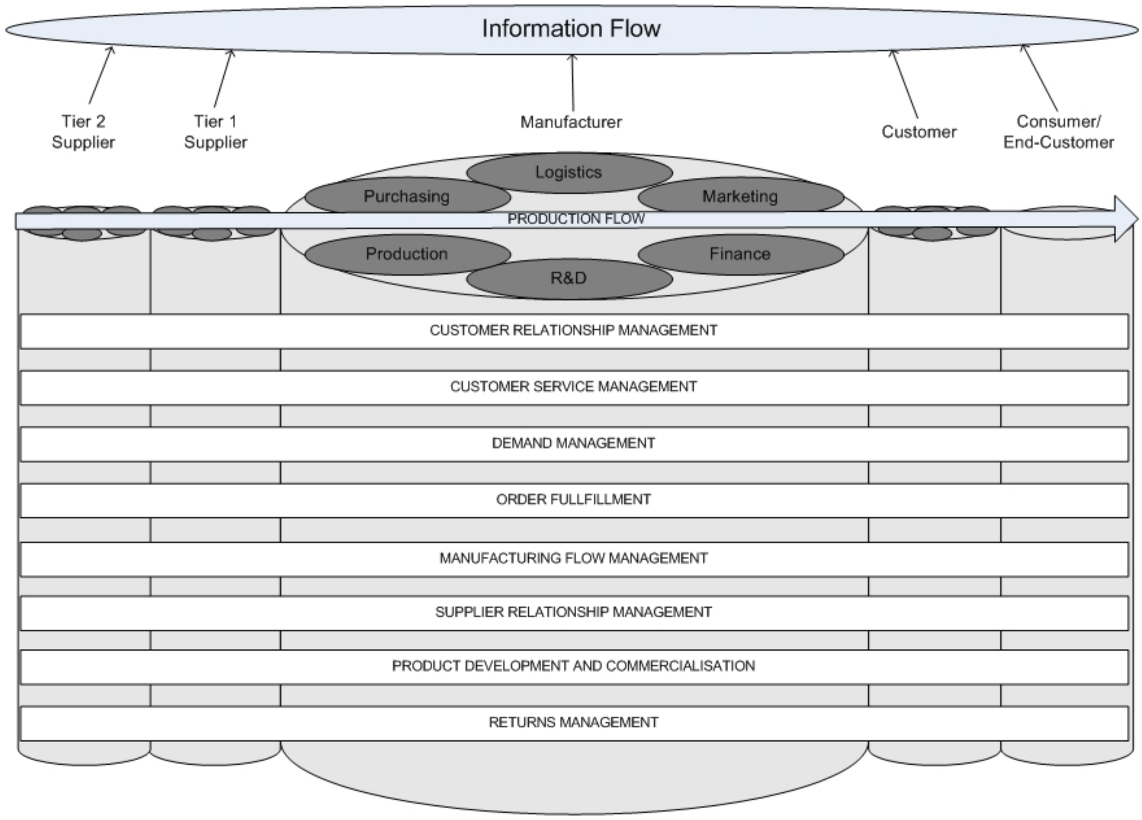


Figure 2-8: Supply Chain Management: Integrating and Managing Business Processes Across the Supply Chain (Lambert D. M., 2017).

2.3.5 Fischer's Two-Axes Framework

None of the frameworks specifically focuses on the detail impact the product characteristics may have on the design elements or effectiveness of the supply chain. Fisher (1997) proposed a framework based on two axes. The first axis categorizes products into either Functional Products or Innovative Products. The second axis categorizes either Efficient Supply Chains or Responsive Supply Chains. The framework proposes that Functional Products require Efficient Supply Chains and Innovative Products require Responsive Supply Chains. The analysis of mini-case studies in companies by Kaipia and Holmstrom (2007) results in a significantly more complex framework extended to include Uncertainty of Demand, Life-Cycle Phase, Capacity Utilisation Rate and Flexibility. This four axis framework, however, seems to be only applicable to the specific case studies, rather than focusing on fundamental design elements.

To address these gaps, a supply chain characterisation framework is proposed in Chapter 3.

2.4 Dynamic Behaviour of Supply Chains

Arguably, the most widely disseminated study on evaluating supply chain performance was published by Jay Forrester in 1958, followed by "Industrial Dynamics" in 1961, which is still a popular textbook today. Forrester (1961) addresses two key concepts:

- System Dynamics Simulation Modelling (SDSM) as a tool to analyse complex dynamic problems with feedback loops.
- Assessing the dynamics of supply chain performance, focusing on lead time and inventory behaviour.

Forrester (1958) used the term "demand amplification" to describe the result of the over compensation by decision makers in supply chains, leading to large oscillations, that result in excess inventory or stock-out conditions. As ordering information travels up the supply chain, each additional tier experiences an exaggeration of this effect. In other words, small changes in end-user demand results in highly exaggerated oscillations in ordering and inventory availability throughout the supply chain (Forrester, 1958).

Lee, Padmanabhan and Wang (1979) first used the term "bullwhip effect" after studying the behaviour of disposable diapers in Proctor and Gamble.

A number of teaching tools were developed to teach supply chain concepts (Torres & Morán, 2006), including the Beer Game and other board games and computer based games.

Torres and Morán (2006) consolidate the work of a number of authors on the subject of the bullwhip effect. These cover three main areas:

- Causes of the bullwhip effect
- Controlling the bullwhip effect
- Measuring the bullwhip effect

2.4.1 Causes of the Bullwhip Effect

Lee, Padmanabhan and Wang (1979) identified four forces that contribute to the bullwhip effect, namely:

- Demand Forecast Updating
- Order Batching
- Price Fluctuations
- Rationing

Bhattacharya and Bandyopadhyay (2011) also review the various causes of the bullwhip effect and include items such as lead time and inventory ordering policy. Sterman (2006)suggest that there are both operational and behavioural causes. Instability in the supply chain arises from the failure to account for feedback, time delays and unfilled orders in the system. Lee and Whang (2006) agree that the bullwhip effect is prevalent in many supply chains, but focused their studies on the Beer Game. Using case studies, Lee and Whang (2006) concluded that different solutions addressing different drivers are required for different supply chains. This conclusion is in line with the design proposals of Gattorna (2010).

Morán and Barrar (2006) identify various structural causes for the bullwhip effect. They evaluate the impact of alternative supply chain management strategies using system dynamics simulation modelling. The Advanced Forecast-sharing Coordination Model, which takes into account, expected future market conditions to place orders, showed the most promise. Further investigation of “agile” and “lean” supply chains was also recommended.

In the stock target method developed in this thesis, one of the key assessments is to confirm that the inventory management method will not be the cause of the bullwhip effect.

2.4.2 Controlling the Bullwhip Effect

. Wikner, Towill and Naim (1991) discuss a number of possible solutions for reducing the bullwhip effect. These include among others:

- Vendor Managed Inventory
- Co-Managed Inventory or Jointly Managed Inventory
- Collaborative Planning, Forecasting and Replenishment
- Collaborative Transport Management

Disney and Towill (2006) focus on improving replenishment policies to control the bullwhip effect. Their conclusion is that a unique ordering policy should be set for each SKU, depending on its demand pattern. This conclusion is also similar to the proposal by Gattorna (2010) which recommended supply chains designed for particular buying patterns.

Towill, Naim and McCullen (2006) studied a supply chain that spans across multiple countries to study the impact of elements such as: Time Compression, Information

Transparency, Echelon Elimination and Control System Design as means to control the bullwhip effect. Botha (2007) shows with electronic versions of a custom developed game, similar to the Beer Game, Echelon Elimination has the biggest impact, followed by Time Compression and Control System Design. The complexity of time delays and feedback loops cannot be solved manually. The propensity of inventory controllers to intervene and apply “expertise” to override control system decisions by adjusting orders also results in Control System Design being difficult to implement.

Ouyang, Lago and Daganzo (2006) focus on alternative ordering strategies. Using a Root Mean Square Error calculation, they demonstrate that “order-up-to” (ordering to a target) and “generalized kanban” will result in the bullwhip effect. A simple “order-based” (sell-one-buy-one) policy will not result in the bullwhip effect for “any realization of demand and for chains with any number of stages.” While this assertion suggests that sell-one-buy-one is an ideal ordering policy, the analysis does not take into account the levels of service provided, does not assess stock-outs and would only be valid for very specific cases. In addition, the analysis method relies on a static calculation of a set of variables, rather than the dynamic behaviour of a supply chain.

Machua and Barajas (2006) discuss the impact of information technology and specifically Electronic Data Interchange, on controlling the bullwhip effect. This approach has the benefit that data is transferred faster and more accurately. The key is that all players must be integrated into the data transfer system and there should be no manual interference with the data.

This thesis does not focus on improvements to the supply chain design, but rather focuses on the decision algorithms associated with inventory management.

2.4.3 Measuring the Bullwhip Effect

The general conclusion is that the extent of the bullwhip effect is unique to each supply chain and its circumstances. No dynamic analysis of supply chain performance is complete without taking into account the effect of demand amplification. Supply chains react to disturbances in ways that result in oversupply and undersupply. In the worst case, during out of stock conditions, customers place orders with competitors and the supplier may end up needing to do a significant inventory write-off as described in the CISCO case study (Torres & Morán, 2006).

The key drivers for the bullwhip effect, Time Compression and Echelon Reduction, ties back into the premises of the Toyota Production System (TPS) or Lean Manufacturing paradigm. TPS focus on the removal of waste and stable production driven by customer demand or pull (Shingo, 1981). Extending this approach to supply chains, the characteristics of a lean supply chain is:

- Short lead times → Time Compression
- Removing non value adding steps → Echelon Removal
- Buy-One-Sell-One (Demand Pull) → Order-up-to

Demeter and Zsoltmatyusz (2011) found a significant correlation between lean management practices and inventory turnover. Singh, Singh, Mand and Sing (2013) provide a broad overview of lean methodologies and their application in supply chain management. As with the introduction of lean principles into manufacturing, introducing lean principles into supply chain management will require a long-term commitment and a step-by-step approach.

2.5 Inventory Theory

Inventory theory is widely taught as part of operations research or purchasing management, using textbooks such as Hillier and Liberman (2005), Winston (1994) and Benton (2007). This section discusses inventory placement, forecasting and lean supply chains.

Placing inventory in the supply chain is a critical financial question, which affects cost and profitability, but even more importantly, service delivery to the client (Willems, 2011). Willems (2011) also states, “not all inventory is of equal consequence.” Thus, not all inventory items have the same priority and that not all inventory levels can be adjusted at the same time. Inventory levels cannot be reduced in an instant. Inventory optimization is, therefore, a continuous process.

Graves and Willems (2000) evolve a model they call the Guaranteed Service (GS) model. The model requires that each node in the supply chain network promise 100% delivery to the customer within the promised lead time. The placement of safety stock throughout the supply chain network can then be calculated, using a multi-echelon approach. Bossert and Willems (2007) evaluate the GS model for periodic review supply chains. They extend the methodology to address acyclic networks, stochastic lead time and time phased demand. They also highlight that the models are becoming ever more complex, affecting the solvability of these models. Neale and Willems (2009) investigate the implications of the GS model to supply chains with non-stationary demand. Non-stationary demand is defined as demand for a product that will change over the product life cycle. They identify a number of counter intuitive results. Firstly, safety stock should be a function of backward looking demand. Secondly, demand forecast accuracy and demand uncertainty propagate differently through the supply chain.

Humair and Willems (2006), Graves and Willems (2008) and Humair and Willems (2011) developed improvements in solving the GS model to optimize the location of safety stock throughout the network. Case studies of this work are provided by Billington et al. (2004), Farasyn et al. (2011), Wieland, Mastrantonio, Willems and Kempf (2012) and Manary and Willems (2008). In all cases benefits were derived. Key learning includes:

- Keep models and processes simple.
- Make “things” better now.
- Implement in a phased manner.
- Be clear about what success is.

2.5.1 Forecasting to Determine Inventory Levels

Forecasting forms a standard component of any operations research, supply chain management and/or statistical textbook. Forecasting uses historical information to project the future. In supply chain management, the application is usually focused on the demand side. Demand is not necessarily smooth and simple to forecast. According to Choy and Cheong (2012) three types of demand functions exist, namely:

- A generic cyclical model with standard demand following a trend, which could include seasonal behavior.
- Stochastic demand with variability.
- Lumpy demand which is highly irregular.

If these demand patterns are linked to the buying behaviour identified by Gattorna (2010), base demand and semi-wave demand would be covered by the generic cyclical demand function. The surge demand pattern would be a stochastic demand function and cavitation would be equivalent to the lumpy demand function.

2.5.2 Lean Supply Chain Management

Lean manufacturing has had a positive impact on many firms. By reducing waste, costs are reduced and profitability increased. Lambert (2008) provides an overview of lean thinking in supply chain management. The concept of "waste" is extended to include waste specific to the supply chain, such as ineffective coordination and misalignment across functions. Supply chain management is seen as a tool that can operate side by side with lean thinking. Benton (2007) provides a superficial overview of JIT in purchasing and while suggesting it may have benefits, suggests that the time frames to fully implement JIT is such that results are still far in the future.

One of the key wastes identified in the Toyota Production System is the waste of over production (Shingo, 1981). Extending the concept to inventory management would suggest that large amounts of inventory are over production. Inventory management; on the other hand, dictate that an economic order quantity, *Q*, be ordered. On arrival, the inventory results in a Maximum Inventory Position (MIP) equal to *Q*, as shown in Figure 2-9.

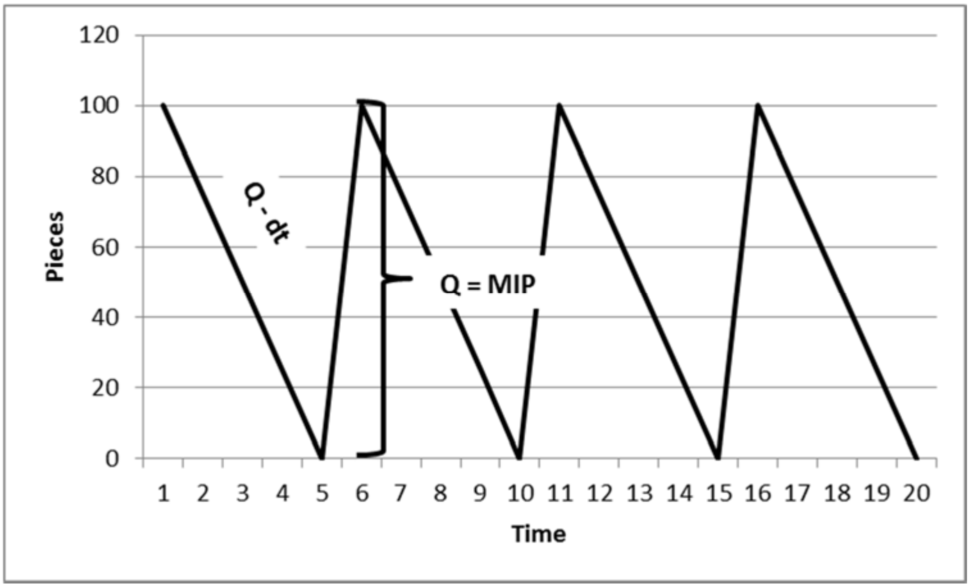


Figure 2-9: Inventory Ordering- Economic Order Quantity.

JIT or lean thinking in the supply chain would suggest that *Q* is reduced and the order frequency increased. Ultimately, the increase in order frequency translates into a system that allows orders to be placed on a continuous basis with an order quantity equal to substitution. If a supplier can deliver every day, the order quantity should be equal to the daily demand. Figure 2-10 demonstrates the suggested concept.

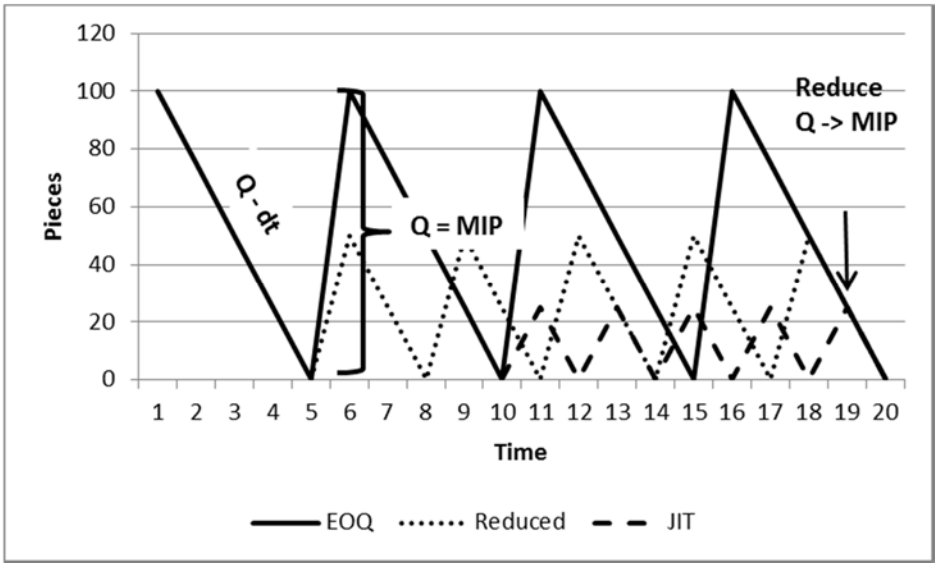


Figure 2-10: Object of JIT/Lean Supply Chain – Daily Order, Daily Delivery.

Following a JIT strategy will affect the total cost. The impact of the total cost is discussed in Section 5.1.

2.6 Supply Chain Management Concepts Summary

This chapter provided a literature review addressing various introductory supply chain management concepts. A number of popular supply chain management frameworks are reviewed and the dynamic behaviour of supply chains and inventory theory is covered in detail.

In summary, the four models all provide useful management tools, applicable at specific levels, but not necessarily addressing the detail of the supply chain design or management of the dynamic nature of supply chains. Opportunities exist in extending the body of knowledge in the development of improved inventory management approaches and supply chain frameworks based on product characteristics. Chapter 3 focuses on the development of such a framework for designing supply chains.

3 SUPPLY CHAIN CHARACTERISATION FRAMEWORK

In this chapter an alternative framework to characterise supply chains is proposed. The framework forms an extension of the simplistic framework model proposed by APICS (2008), by developing a specific structure to classify supply chains by the characteristics of the product involved.

Such a framework makes it possible to identify the complexity, nodes, operations strategy and supply chain infrastructure that is required to design and operate different types of supply chains. With this information available, the supply chain manager can design a supply chain appropriate for that specific class of supply chains.

The main purpose of this research is to develop a bridge between the academic and practitioner's view of supply chain frameworks by developing a supply chain management framework that will address the needs of the practitioner when designing a supply chain. Designing a supply chain will inter alia include the design of:

- Physical Flow and Location of Product.
- Process and Logistics Elements

3.1 Framework Model Development Background

For the purpose of this study, a two-dimensional matrix is proposed. This matrix is used to identify generic supply chain classes. The framework is then applied to a series of generic supply chains to confirm that the framework sufficiently describes the various types of supply chains that can be identified. The effectiveness of the framework is evaluated against the following criteria:

- Does the framework model support the fundamental design approach for an effective supply chain? This criterion is achieved when the framework can be used to derive the fundamental network structure, identify basic process steps and identify handling and storage requirements (APICS, 2008).
- Does the framework model provide guidance for an acceptable management strategy? This criterion is achieved when the framework can be used to identify the specific market related supply chain design required (Gattorna, 2010).

3.2 Supply Chain Characterisation Framework Development

Supply chains have many functions, but always include some form of a physical flow of a product or service. This product or service dictates the key parameters for the infrastructure that is required. The infrastructure includes, handling equipment, processing equipment, transport equipment, storage requirements, operating environment requirements (such as temperature control) and more.

The characteristics proposed for the supply chain framework are:

- Product Complexity – A measure of the complexity of the product delivered to the user. Basic raw materials (such as iron ore and fruit) are simple (least complex), with products consisting of a variety of components and raw materials (such as automobiles and fridges) are complex.
- Product Life Expectancy – A measure of the length of time a product can be in use. This time can range from a matter of days to years.

Product complexity is selected as it provides a clear indication of the level of processing and manufacturing steps required to produce the product. Increased complexity affects the structure and scope of the supply chain network, the infrastructure required as well as the need for supplementary supply chains. As complexity increases, cost and value of products also increase. Increased product value affects the market positioning and expectations of the end-user. This characteristic meets the criteria in Section 3.1 by providing insight into the network design.

Life expectancy is selected as it provides an indication of longevity and identifies the potential for maintenance and repair as part of the life cycle management. Life cycle management will indicate the need for supporting supply chains that exist to ensure functional maintenance during the use cycle. The longer a product is expected to last, the bigger the need for maintenance facilities and parts provision as part of the overall supply chain. Shorter life expectancy will drive designs to ensure speed to market and environment management during the stages of the supply chain. This criterion will have a direct impact on the operational strategy selected for the supply chain. The proposed supply chain framework is depicted in Figure 3-1.

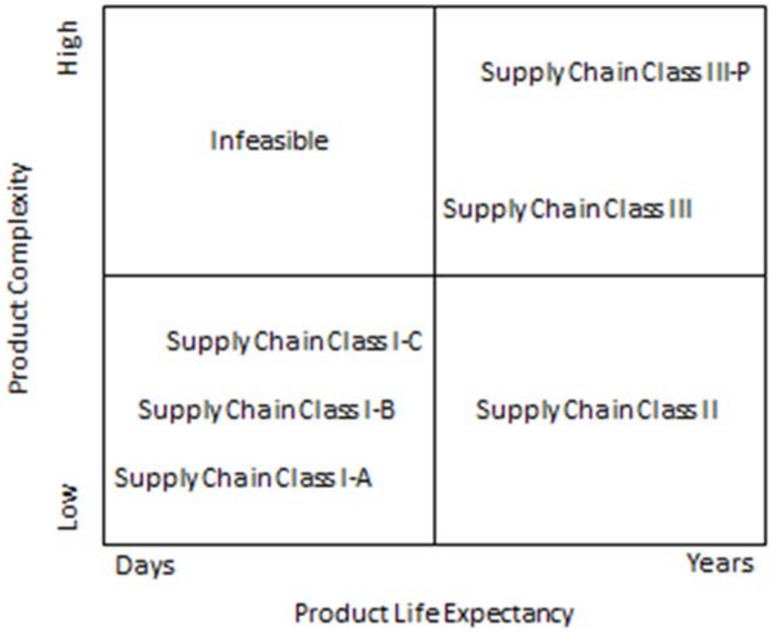


Figure 3-1: Proposed Supply Chain Framework.

Based on the matrix, it is possible to develop the framework by developing a series of generic supply chains for each quadrant.

3.2.1 Quadrant 1 Overview

In Quadrant 1 the product complexity is low and the product life expectancy is measured in days. The products in this quadrant move directly from the primary producer to the consumer. Supply chains in this quadrant are called Class I supply chains.

Class I: Primary Producer ➔ Consumer

These are mostly agriculture based supply chains where "products" are produced and consumed with no additional processing. This type of supply chain can also include mineral "crops" such as salt.

Class I supply chains can be divided into three distinct sub-classes.

Class I-A: Harvest ➔ Pack ➔ Distribute ➔ Consume

This type of supply chain requires no further processing other than packaging into appropriate containers for transport and distribution. Examples would include fresh produce such as fruit and vegetables for direct consumption. In many cases, overflow product from these processes is treated as a Class I-B supply chain.

Class I-B: Harvest ➔ Process ➔ Pack ➔ Distribute ➔ Consume

This type of supply chain requires that the produce is processed prior to packing and distribution. Examples include the commercial production of fruit juice and jams. In this case, the fruit is not picked for direct consumption, but is picked, processed and then packed for distribution and consumption. Products such as meat, fish, poultry and dairy can be included in this class. Mineral harvesting can in some cases be included in this class. For example, salt is harvested, refined and packed for distribution and consumption.

Class I-C: Harvest ➔ Store ➔ Process ➔ Pack ➔ Distribute ➔ Consume

This particular class of supply chains allows the raw product to be stored for a period of time before processing and final consumption. This class of supply chain would include grain that is stored and milled only prior to final distribution and consumption.

The critical characteristic in Class I supply chains is that the production capacity is generally highly dependent on environmental factors. In general, the amount of land under cultivation is well known, but the biomass yield is difficult to predict. The quality and quantity of the crop available is unknown until the crop has finally been harvested. In contrast to most production processes, it is not possible to accurately set the upper or lower production limits on this type of production. In an exceptional year, production may far exceed a normal year. An unexpected environmental event can potentially wipe out a complete crop hours before harvesting. In general, these types of goods are also highly seasonal in production. Some exceptions (products with very broad seasonal harvesting periods) do exist. Of course, the seasonality can be counteracted by sourcing products globally, given the different seasonal conditions. Production capacity for the crops can also be affected by the availability of equipment and limits in the production processes. However, in general these types of supply chains are also characterised by their push nature. Once the crop is planted, every effort is made to harvest it and deliver it to the market.

3.2.2 Quadrant 2 Overview

In Quadrant 2 the product complexity is low and the product life expectancy is measured in years. The products in this quadrant move from the primary producer to a secondary producer and only then to the consumer. There may be significant waiting times in the supply chain. Supply chains in this quadrant are Class II supply chains.

Class II: Primary Producer ➔ Secondary Producer ➔ Consumer

These supply chains focus on processing a single commodity from ore to a pure substance to a final product. These supply chains include the production of steel beams from iron ore, refining of oil to petrol and other by-products for consumption and the processing of cotton crops to clothing. The raw materials may move through complex processes, but in general, the products constitute of a single base material. The raw materials, as well as the intermediary and final products, can be stored for long periods if suitably treated and protected from the elements.

In these supply chains the maximum production capacity is a design constraint. Production targets are usually at 80% to 90% of capacity to effectively utilise equipment and optimise returns. Not running at 100% of capacity allows the production process time for maintenance and ensures long-term utilisation of equipment.

3.2.3 Quadrant 3 Overview

In Quadrant 3 the product complexity is high and the product life expectancy is measured in years. The products in this quadrant move from the primary producer to a secondary producer, then through a combining process and only then to the consumer. There may be significant waiting times in the supply chain. Supply chains in this quadrant are called Class III supply chains.

Class III: Primary Producer ➔ Secondary Producer ➔ Combining ➔ Consumer

Class III supply chains are the most complicated supply chains from a production point of view. In these supply chains, raw materials come from different sources, are refined and converted to different product components, which are then combined to form a single product. Class III supply chains consists of complex production facilities.

Products include items such as white goods. In the manufacturing of these items, iron ore is converted to steel sheets and petro-chemicals are turned into plastic sheets. The steel and plastic sheets are then shaped and combined with a compressor and cooling system into a final product that is ready for distribution to the end user. Supply chains in this class usually require some form of life cycle product management. Life cycle product management requires the creation of a maintenance supply chain in parallel to the main supply chain. The parallel supply chain can be a simple supply of components to repair wear and tear items. It can also be as complicated as the parts and accessories supply chain in the automotive sector. In this case, the parallel supply chain supports maintenance, repair and replacement components, as well as components to enhance and expand the original product (Elhafsi & Hamouda, 2015, van der Heijden, van Harten, & de Smidt-Destombes, 2006 and Kennedy, Wayne Patterson, & Fredenhall, 2002).

Class III-P: Primary Producer → Secondary Producer

↓ ↓

Distributor → Consumer

Class III-P supply chains are the parallel supply chains set up to support the life cycle management of products in operation. Life cycle support will include components for maintenance, wear and tear, repairs and damage. A key characteristic of this supply chain is that it deals with components, as well as complete sub-assemblies. For example, a vehicle manufacturer, through its dealer network (supply chain Class III) sells a vehicle with a complete air-conditioner unit. When the air-conditioner fails, the dealer can place an order for a new air-conditioner, or any of the individual components that exist in the bill of materials. The components could include every O-ring, tube, sensor, compressor, radiator and more.

3.2.4 Quadrant 4 Overview

In Quadrant 4 the product complexity is high and the product life expectancy is measured in days. This combination is not feasible and no supply chain class can be defined for Quadrant 4, since the cost to develop and manufacture a complex product is not justified if the product has a limited life expectancy.

The supply chain framework incorporates a series of general supply chains, however, there may be specific cases that have evolved over time that may not be included. To ensure that the supply chain framework adds value to the practitioner who needs to design a new supply chain, the model is applied to review the impact on supply chain decision making.

3.3 Supply Chain Characterisation Framework Application

The evaluation of the model is conducted in two ways. Firstly, each supply chain type in each quadrant is expanded to describe basic product characteristics, production processes, demand patterns and supply chain characteristics. The product characteristics include complexity and life expectancy, while supply chain characteristics include the network structure, infrastructure and operating environment. Examples of products of each class are also provided. Secondly, specific case studies are used as verification of the validity of the framework.

3.3.1 Quadrant 1 Application

Table 3-1 provides a detailed overview of the Class I supply chain.

Table 3-1: Class I Supply Chain Characteristics.

Class I: Primary Producer ➔ Consumer	
Examples	Grown products of a wide range, including fresh produce such as vegetables and fruits, flowers, as well as products such as grain.
Product Complexity	Low to medium complexity, direct utilisation or consumption of basic or processed product.
Product Life Expectancy	Short life expectancy, measured in days and weeks, or months if processed.
Production Processes	Plant, harvest, supply.
Demand Patterns	Mostly seasonal, with exceptions where minerals are harvested. Products are utilised or consumed with no further processing.
Network Structure	Many producers linked to many consumers in a flat network structure.
Infrastructure	Land area for growing products. Farming and transport equipment.
Operating Environment	No special operating environment is required.

There are a number of case studies where supply chains of type Class I-A, I-B and I-C are considered. Ge, Yang, Proudlove, & Spring (2004) focus on a supermarket supply chain. Fresh produce confirms the need for Class I-A and processed foods confirm the need for Class I-B supply chains. Flour and other milled products represent the Class I-C supply chain structure. The overall class in the supermarket supply chain is a combination of all three supply chain types.

Table 3-2 provides a detailed description of the Class I-A supply chain characteristics.

Table 3-2: Class I-A Supply Chain Characteristics.

Class I-A: Harvest ➔ Pack ➔ Distribute ➔ Consume	
Examples	Fresh produce such as fruit, vegetables and flowers. Harvested minerals such as salts.
Product Complexity	Low complexity, direct utilisation or consumption of basic product. Packaging and distribution is included in the process of providing the product to the market.
Product Life Expectancy	Short life expectancy, measured in days and weeks. Life expectancy can be extended through selection of appropriate infrastructure and operating environment, such as cold storage and transport.
Production Processes	Plant, harvest, package and supply. Packaging may include a preparation steps such as cooling of fruit. The pack quantity will vary per end-user requirements.
Demand Patterns	Mostly seasonal, with exceptions where minerals are harvested. Products are packaged only and utilised or consumed with no further processing.
Network Structure	Many producers linked to many consumers in a flat network structure. Distribution usually through a retail chain. Branding can be specific to supplier or retail distributor.
Infrastructure	Land area for growing products or mining minerals. Farming and transport equipment. Some form of cooling for products coming from the land. A packing store where products are packed.
Operating Environment	Cooling and packing requires temperature controlled environment.

Georgiadis, Vlachos, & Iakovou (2005) provide a framework for modelling supply chain management of food chains. The selected case study is from the fast food industry, which confirms the need for speed and a direct supply chain for fresh produce.

Table 3-3 provides a detailed overview of the Class I-B supply chain.

Table 3-3: Class I-B Supply Chain Characteristics.

Class I-B: Harvest ➔ Process ➔ Pack ➔ Distribute ➔ Consume	
Examples	Fruit and vegetables processed for longer terms storage through freezing or cooking and tinning. Processing of fruit and vegetables by turning it into juice, sauces or concentrates.
Product Complexity	Low to medium complexity. Products go through basic processing before utilisation or consumption of the final product.

Class I-B: Harvest ➔ Process ➔ Pack ➔ Distribute ➔ Consume	
Product Life Expectancy	Short to medium life expectancy, measured in days, weeks and months.
Production Processes	Plant and harvest, followed by processing of the product to allow for consumption in the processed for, as well as extending the shelf life. If not processed immediately, the product will spoil.
Demand Patterns	Demand is all year round, despite the fact that harvesting is seasonal. Processed and packed products are stored in the distribution centre.
Network Structure	Many producers can be linked to a single processing plant. Processing plants can pack products for multiple or single brands. The network structure becomes more complex with multiple suppliers linked to a single or multiple processing plants. The processing plants can be linked to a single distributor with one or multiple brands, or multiple distributors with their own brands. A retail network links the product to the consumer.
Infrastructure	Land area for growing products or mining minerals. Farming and transport equipment. A processing plant, including a packaging facility.
Operating Environment	Food preparation and processing which require an operating environment that ensures high levels of hygiene.

Ge, Yang, Proudlove and Spring (2004) provide an extensive overview of the Class I-B supply chain for processed foods such as tinned food, jams and sauces. Farasyn et al. (2011) discuss the Procter & Gamble supply chain, a Class I-B supply chain that includes a wide variety of processed products with short life expectancies. Once processed, the products can be stored after being processed and distributed through an extensive retail network. Minegishi & Thiel (2000) provides a detail study of the generic poultry supply chain, a good example of the Class I-B supply chain. Once processed and frozen, the life expectancy of the product is extended, but now requires a tightly controlled cold chain to ensure the product is not damaged. Nallusamy, Rekha, Balakannan, Chakraaborty, & Majumdar (2015) also study the poultry supply chain, focusing on the specific case of India.

Table 3-4 provides a detailed description of the Class I-C supply chain.

Table 3-4: Class I-C Supply Chain Characteristics.

Class I-C: Harvest ➔ Store ➔ Process ➔ Pack ➔ Distribute ➔ Consume	
Examples	Grains stored after harvesting, until milled and packed for final distribution.
Product Complexity	Low to medium complexity. Raw materials can be stored in the unprocessed format. Once processed, distribution and consumption take place.
Product Life Expectancy	Medium life expectancy. Product life expectancy includes pre-processing and post processing. Proper storage facilities ensure raw material availability throughout the year and allows for buffering of seasonal variability in production.
Production Processes	Production processes are usually a simple process to convert the material from raw form to consumable form. Basic processes such as milling are required.
Demand Patterns	Demand is spread throughout the year, in contrast to potential seasonal harvesting seasons.
Network Structure	Many raw material producers are linked to a limited number of storage facilities. Producers can process for single or multiple brands, distributing to retail off set points. The retail network supplies the end product to the consumer.
Infrastructure	Land area for growing products or mining minerals. Farming and transport equipment. Silos for storage of raw materials. Production and packaging facility to process raw materials to be ready for consumption.
Operating Environment	Milling raw materials finely requires a zero spark, dust suppression environment. Storage requires dry aerated facilities.

Thakur & Hurburgh (2009) provides a detailed study of the bulk grain supply chain, including an overview of the network structure of bulk grain supply in the United States of America (USA). Mogale, Dolgui, Kandhway, Kumar, & Tiwari (2017) provides an analysis of the grain supply chain in India, proposing the use of centralised government controlled storage facilities for storing excess grain. Sachan, Sahay, & Sharma (2005) use a system dynamics approach to address the cost model in the Indian grain supply chain.

3.3.2 Quadrant 2 Application

Table 3-5 provides the detailed description of the Class II supply chain.

Table 3-5: Class II Supply Chain Characteristics.

Class II: Primary Producer ➔ Secondary Producer ➔ Consumer	
Examples	Primary ores that are processed to base metals that are then converted into products for direct use as specific metal based products. Specific products include inter alia, railroad tracks and roof sheeting.
Product Complexity	Low to medium complexity.
Product Life Expectancy	Life expectancy is measured in years.
Production Processes	Single source primary distributors extracting ores. Secondary producers may consolidate raw materials from various sources and convert them to final products.
Demand Patterns	There is continuous production of the raw materials. Specific end products can be required on a project basis or continuously.
Network Structure	A few global secondary producers are networked to a global market of many primary producers and many end users. Little branding of products happen and most demand is based on technical performance specifications.
Infrastructure	Mining equipment, heavy load distribution equipment and smelters for refining and final product manufacturing.
Operating Environment	Mining activities require high levels of focus on safety due to explosive use and other risks. Smelting activities are high temperature high risk operating environments. Storage does not require any specific operating environment, but protecting the environment from potential pollution is critical.

Liu, An, Xiao, Yang, Wang, & Wang (2017) provides a comprehensive overview of the iron and steel industry supply chain, including the various steps, processes and network structure. Beresford, Pettit, & Liu (2011) focuses on the transport infrastructure required to transport the bulk ore from mines to the processing plants.

3.3.3 Quadrant 3 Application

The third quadrant contains two supply chain classes.

Table **3-6** provides a detailed overview of a Class III supply chain.

Table 3-6: Class III Supply Chain Characteristics.

Class III: Primary Producer ➔ Secondary Producer ➔ Combining ➔ Consumer	
Examples	White goods, computing based products and other items with a life expectancy measured in years. These goods may have components for sale to repair and upgrade, but does not include specific maintenance plans that require the replacement of components at regular intervals.
Product Complexity	High complexity. Products combine various components manufactured with various raw materials.
Product Life Expectancy	Measured in years. In some cases product enhancements happen faster than the life expectancy of products and product replacement happens prior to the end of life cycle.
Production Processes	Production processes start with the production of raw material, refinement to material level and conversion into specific components. Components and sub-assemblies enter a final assembly process before distribution to the end-user. Products are usually uniquely branded by the manufacturer and distributed through a proprietary network.
Demand Patterns	Demand is continuous and usually affected directly by global economic factors.
Network Structure	Complex network structure with multiple raw materials such as plastics, metals and other components from various suppliers. Component suppliers may brand specific components that later forms part of products assembled and distributed by a variety of retail brands.
Infrastructure	Each supplier level in the supply chain requires appropriate manufacturing infrastructure. The final assembly and distribution is usually controlled by a leading brand.
Operating Environment	Some manufacturing processes require specific operating environments. Electronic component manufacturing requires dust and static free environments. Assembly of electronic based products also require static free operating environments.

Huang et al. (2007) describes the supply chain of lamp production where multiple raw materials are converted into a final product. Tian, Willems and Kempf (2011) describes the supply chain of a semiconductor, which, while a Class III product in its own right, forms a basic component of all electronic based products. Manary and Willems (2008) and Wieland, Mastrantonio, Willems and Kempf (2012) describe the detail of the Intel central processing unit supply chain, a complex product that is used in the assembly process for desktop and laptop computers. Graves and Willems (2000) discusess the complete supply chain for the manufacture of notebook computers, giving a good overview of how the supply chain network narrows down from supply side to assembly and widens at the final distribution point. Billington et al. (2004) discusses the network for digital cameras, a complex product with a relatively long life expectancy (two to five years) and no need for a parts supply chain as it is more cost effective to replace than to repair. Billington et al. (2004) and Graves and Willems (2000) describe the Hewlett-Packard printer supply chain. While printers have the basic characteristics of the Class III supply chains and service parts are not the norm, the consumables required for printing can be treated as a Class III-P supply chain.

Table 3-7 provides a detailed overview of the Class III-P supply chain. This supply chain focuses on products where the complex product is supplemented with a parts distribution supply chain. Parts are required to ensure that the product is effective over its planned life cycle.

Table 3-7: Class III-P Supply Chain Characteristics.

Class III-P: Primary Producer → Secondary Producer ↓ ↓ Distributor → Consumer	
Examples	Aircraft, automobiles, trains, etc.
Product Complexity	High complexity products designed specifically with maintenance as part of the life cycle management. Products combine various components manufactured with various raw materials.
Product Life Expectancy	Long life expectancy that is measured in multiples of years. Maintenance and refurbishment can extend the life expectancy.
Production Processes	Production processes start with the production of raw material, refinement to material level and conversion into specific components. Components and sub-assemblies are assembled into a final product before distribution to the end-user. Products are usually uniquely branded by the manufacturer and distributed through a proprietary network. An extensive spare parts operation is provided by the Original Equipment Manufacturer (OEM).

Class III-P: Primary Producer → Secondary Producer ↓ ↓ Distributor → Consumer	
Demand Patterns	Demand is continuous and usually affected directly by global economic factors. Spare parts for maintenance are continuously in demand. Demand for repair parts is less predictable.
Network Structure	Complex network structure with multiple raw materials such as plastics, metals and other components from various suppliers. Component suppliers may brand specific components that later forms part of products assembled and distributed by a variety of retail brands. OEM's consolidate parts and sub-assemblies and distribute them for maintenance and repairs through a branded retail network.
Infrastructure	Each supplier level in the supply chain requires appropriate manufacturing infrastructure. The final assembly and distribution is usually controlled by a leading brand. The retail network includes service centres with equipment and trained staff to perform maintenance and repairs.
Operating Environment	The supply chain does not require a specific operational environment.

El Dabee, Marian and Amer (2013) use the case of electric motor manufacturing, which is not only a supply chain on its own, but also includes repair and maintenance components to ensure effective life cycle performance. As previously mentioned, Billington et al. (2004) and Graves and Willems (2000) discuss printer supply chains. To operate a printer, ink, toner and drums are required. The manufacturer, therefore, needs to set up a Class III-P to distribute the consumables. In contrast to the traditional service centres, printers are designed specifically so that the user performs the consumable replacement. Graves and Willems (2000) describe both the primary supply chain as well as the parts distribution supply chain associated with bulldozers.

3.4 Summary and Discussion

This chapter proposes a supply chain framework based on product characteristics. A number of supply chain types were identified and categorized. Various case studies were used to show that it is possible to describe a wide range of practical supply chains using the developed framework. In Chapter 4 the South African automotive supply chain is discussed in detail.

4 AUTOMOTIVE SUPPLY CHAIN

The automotive supply chain has a number of unique characteristics. Firstly, it consists of a vehicle supply chain that is driven by the production cycle of a particular model of vehicle. In most cases, the model is actually a product platform, with a range of options. Options include body enhancements, drive trains and trim levels. The vehicle production generally follows a model life cycle, with a model staying in production for a number of years in which the tooling is amortised. Small changes (facelifts) and specification enhancements are made throughout the production cycle, which usually spans seven years. The changes and enhancements are aimed at ensuring competitiveness relative to new models from competitors.

Vehicles, however, need to be treated as life cycle products, with support provided for the vehicle's entire operational life. This support refers to all parts and services that are required to support the vehicle during its usage life. There is a distinction between the vehicle production period and the use. Owners may buy and drive the vehicles for any period. The life cycle of the vehicle does not end when the first owner does not require it anymore. The vehicle is sold as a second hand vehicle and continues its life cycle. Defining the maximum life expectancy of a vehicle in use is thus not possible. With sufficient care, a vehicle may easily spend 20 years or more on the roads. There is no regulatory requirement in South Africa, but most of the original manufacturers continue to supply parts for at least 15 years after the last date of vehicle model manufacture (industry norm).

Effectively, the automotive supply chain consists of three parallel, but interlinked, supply chains, as shown in Figure 4-1. Supply Chain 1 is the main “driver” supply chain, namely vehicle production and sales. This supply chain will include imported and local components and subassemblies. This supply chain includes completely-knocked-down (CKD) kits. The basic kit is packed at a global source and sent to the assembly plant.

The kit is supported with local content (parts made by the plant itself or local suppliers) and painted and assembled on a local production line. Semi-knocked-down (SKD) kits consist of a full vehicle disassembled and packed in units in a container for assembly, usually not even requiring further painting. The distinction between the two types of kits is that the former requires significant additional components, while the latter only requires assembly. The final source of vehicles is completely-built-up (CBU) vehicles. These are complete vehicles imported from a specific source. CBU vehicles are popular in the South African market for bringing in new models and brands through marketing and sales organisations that do not have the capacity to manufacture vehicles locally.

From the vehicles' manufacturer or distributor, the completed vehicles are distributed via a network of dealerships. Dealerships play the primary role of selling the vehicles to the end-user. This step completes the main vehicle supply chain. Subsequent sales of the vehicle through second-hand dealers, or via the owners, would technically form part of this supply chain.

The second supply chain focuses on parts. Parts supply focuses on ensuring that once a vehicle is sold, it remains on the road in an effective manner, for as long as the owner desires to drive it. Service parts supply forms part of the system life-cycle (Blanchard, 2004). While the design may have a target life-cycle in mind, the owner in this case does not agree to any specific life-cycle time period.

Parts required to support the use of a vehicle can be split into the following categories:

- Service parts: These are part of the regular maintenance cycle and include oil and air filters, as well as spark plugs. The replacement of these parts is driven by a specific service schedule developed by the designer of the vehicle. While service parts are usually supplied by the vehicle manufacturer during the vehicle maintenance period, there is a strong market for alternative suppliers especially on the higher value, high volume parts.

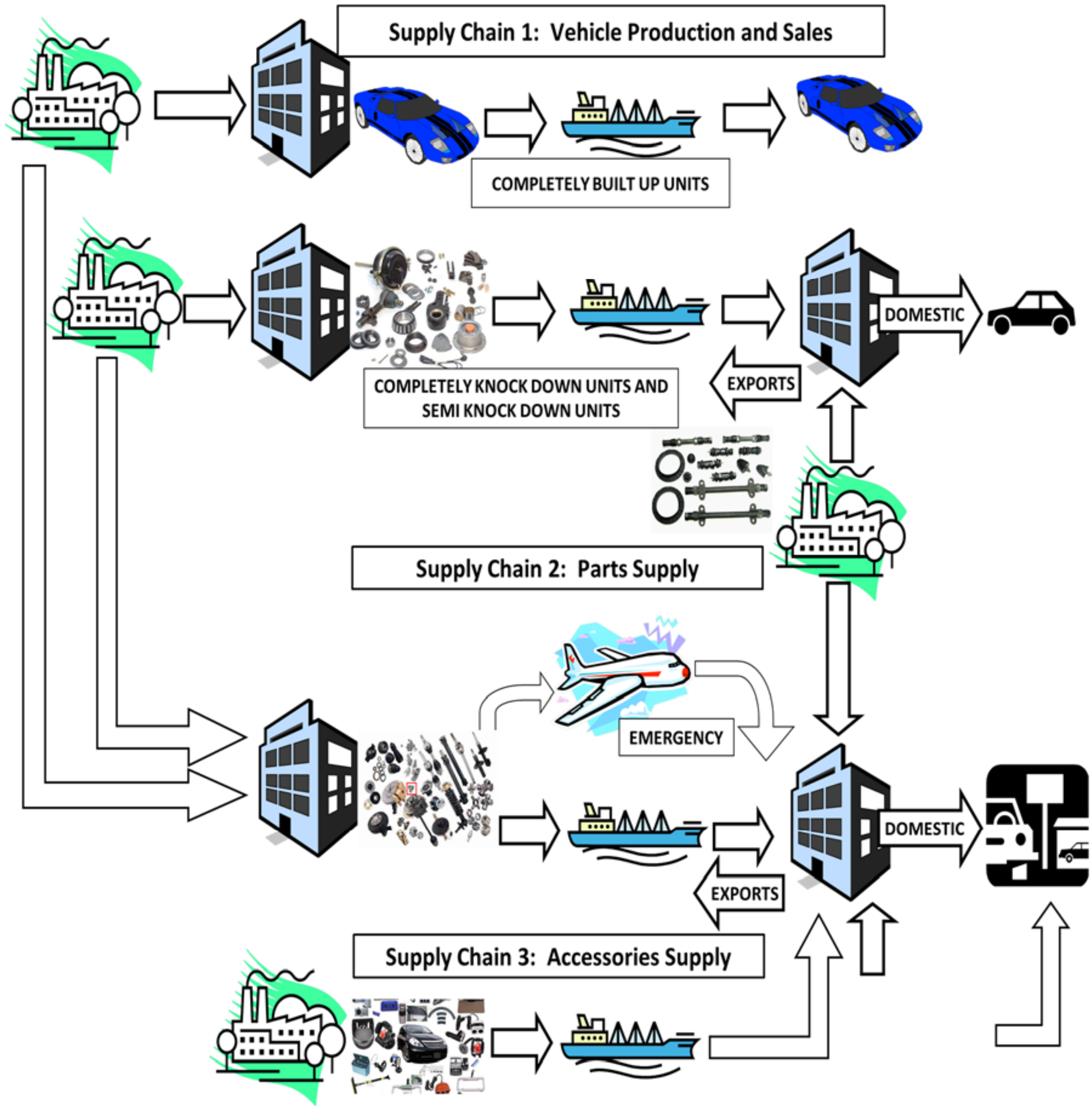


Figure 4-1: Overview of Three Supply Chains.

- Maintenance parts: Also known as wear and tear parts, these parts such as brake discs, clutch plates, brake pads and shoes, shock absorbers, will last for a specific period, depending on driving conditions and driving styles, but eventually wear out and need replacement. Unlike filters that have a set design life, these parts are only replaced once a certain threshold has been reached. The life of these parts varies from vehicle to vehicle and driver to driver. Brake pads on a small, high powered sports car are unlikely to last as long as the brake pads on a small, low powered entry level car. The demand on these parts is driven by user behavior and vehicle age. Parts supply can be through the original vehicle manufacturer or specialist suppliers.

- Crash parts: The demand on these parts depends on the occurrence of accidents or other unpredictable events such as hail storms. These events are highly unpredictable, their occurrence, but also the extent of damage and the parts to be replaced. In many cases, items such as body panels have original vehicle manufacturer design registrations and are difficult to replace. It is, however, possible to source secondhand parts from various sources.
- Repair parts: These parts need to be replaced due to specific failures or vehicle age. For example, a wiring harness might fail due to the aging of the insulating material and then needs to be replaced. Certain elements could be classified as wear and tear parts, but with a long operational life, such as pistons and gears inside the gear box or differential.

Parts demand can vary from very high to completely erratic. The objective of original vehicle suppliers is to provide a stable supply of service and maintenance parts. Crash and repair parts tend to be more complicated with huge demand variance, as discussed in Section 7.3. Where common vehicle platforms and similar models exist, parts can be shared. These common platforms allow for economies of scale and continuity of supply. The third supply chain focuses on customisation and accessories. This supply chain has an original equipment component that is directly linked to the automotive manufacturer and its dealer network. Accessories are developed and certified by the OEM. The OEM certifies that the accessories will not negatively affect vehicle performance. Certified accessories will not negatively affect the warranty provided by the OEM. Non-manufacturer approved accessories are often manufactured and sold to clients, without informing the client that installing these accessories would result in a voided warranty. Typical examples of customisation and accessory parts for vehicles are tow bars, nudge bars, raised suspension, off-road suspension, turbo chargers and sound systems (over and above normally offered with a vehicle). These accessories can be fitted at the factory as part of a special edition, at dealerships, or at specialist fitment centres. In general, accessory sales are closely related to vehicle sales. Customers tend to buy accessories when they buy new vehicles.

Patterson, Fredenhall and Kennedy (2002) focus on the spare parts supply chain, indicating that supply chain models should help the practitioner to decide: When to place the order, how much to order and the impact of cost versus availability. Van der Heijden, van Harten and Smidt-Destombes (2009) and van der Heijden, van Harten and de Smidt-

Destombes (2006) analyse the problem of spare parts supply in the defence systems environment where both spare parts supply and repairs are taken into account. In the automotive industry, parts supply for maintenance, repair and replacement is critical. As vehicles age, the need for repairs and replacement increases. Maintenance is a “designed-in” function. Vehicle aging is a reality, with the average age of the vehicles in the USA at 11.4 years (Office of the Assistant Secretary for Research and Technology, 2015).

In the automotive parts industry there are a number of models for inventory placement. These vary from single location distribution centres, multiple regional distribution centres to consignment inventory at the dealers. In each case, the decision is global rather than local. The lead time within these chains are affected by a variety of factors, including the local versus imported parts mix. If the problem is analysed from a pure logical perspective it would be expected that for very fast moving parts, distributed inventory at the dealership would provide the best coverage. Conversely, slow moving parts demand may be distributed throughout the network and it may be that certain dealers will not have any demand to service. Aggregating the demand by centralizing inventory in the supply chain will improve the availability, provided the service lead time promise can be maintained. Due to the mix of parts in the automotive supply chain, it is usually not possible to maintain a 100% guaranteed service rate. The industry standard target of 95.5% is set to allow for stocking and non-stocking parts, as well as parts with different demand functions.

For the purposes of this study, the focus is on a centralized inventory model, with limited use inventory at dealerships and all safety stock at the distribution centre. Investigating the distribution of inventory throughout the supply chain falls outside the scope of this thesis.

4.1 South African Automotive Market Structure

A small number of large international automotive manufacturers, who have production facilities located throughout the country, dominate the South African vehicle market. These manufacturers (OEMs) manufacture for local and export demand as well as import vehicles (CBUs) for local demand. The South African automotive market is representative of a number of countries with similar structures. Despite OEMs having global footprints, local policies often support the establishment of local manufacturing capacity. The South African automotive parts supply chain forms the base of the thesis, as demand data is available. The level of manufacturing and localisation vary. The extent of localisation results from industry support schemes, such as the Motor Industry Development Programme (MIDP) and the Automotive Production and Development Plan (APDP). Both these schemes are specific to South Africa.

The MIDP was introduced in 1995, providing OEMs with duty free allowances. The main features of the programme, according to Pitot (2011), are:

- A duty free allowance for OEMs to import components up to 27% of the vehicle selling price.
- A duty credit system for vehicle and component exports up to the value of 14% of the local content of the export.
- A productive asset allowance for OEM and related component investments equal to a duty credit of 20%.

The APDP was introduced in 2013 and is based on the following four pillars namely, import duty, vehicle assembly allowance, production incentive and an automotive investment scheme. The main features of the scheme are (Pitot, 2011):

- Import duties – 25% for CBUs (CBUs from Europe only 18%) and 20% for CKD components.
- Vehicle assembly allowance - will allow plants that manufacture more than 50,000 units per year to import components duty free. The basic allowance starts at 20%, and reduces on a sliding scale to 18% as production volumes increase.
- Production incentive – allowance for duty free import of vehicles and components equivalent to 55% of the South African supply chain value add, reducing to 50% over 5 years, with an additional 5% for vulnerable sub-sectors.
- Automotive incentive scheme – incentives based on investment and job creation in the local manufacturing and component sector.

The domestic market share of the major automotive suppliers in 2013 is shown in Figure 4-2. All other manufacturers had market shares equal to or below 1%.

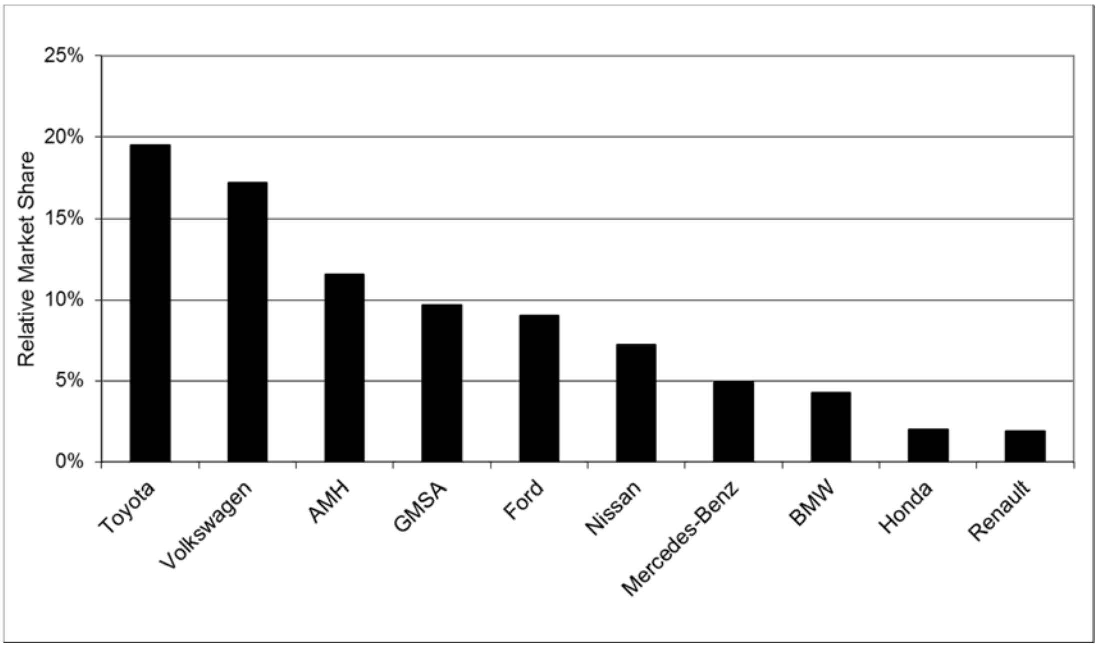


Figure 4-2: Domestic Market Share of Major Automotive Suppliers (NAAMSA, 2013).

Of these manufacturers, only AMH and Honda do not have manufacturing plants in South Africa. Manufacturing plants are distributed throughout the country as shown in Figure 4-3.

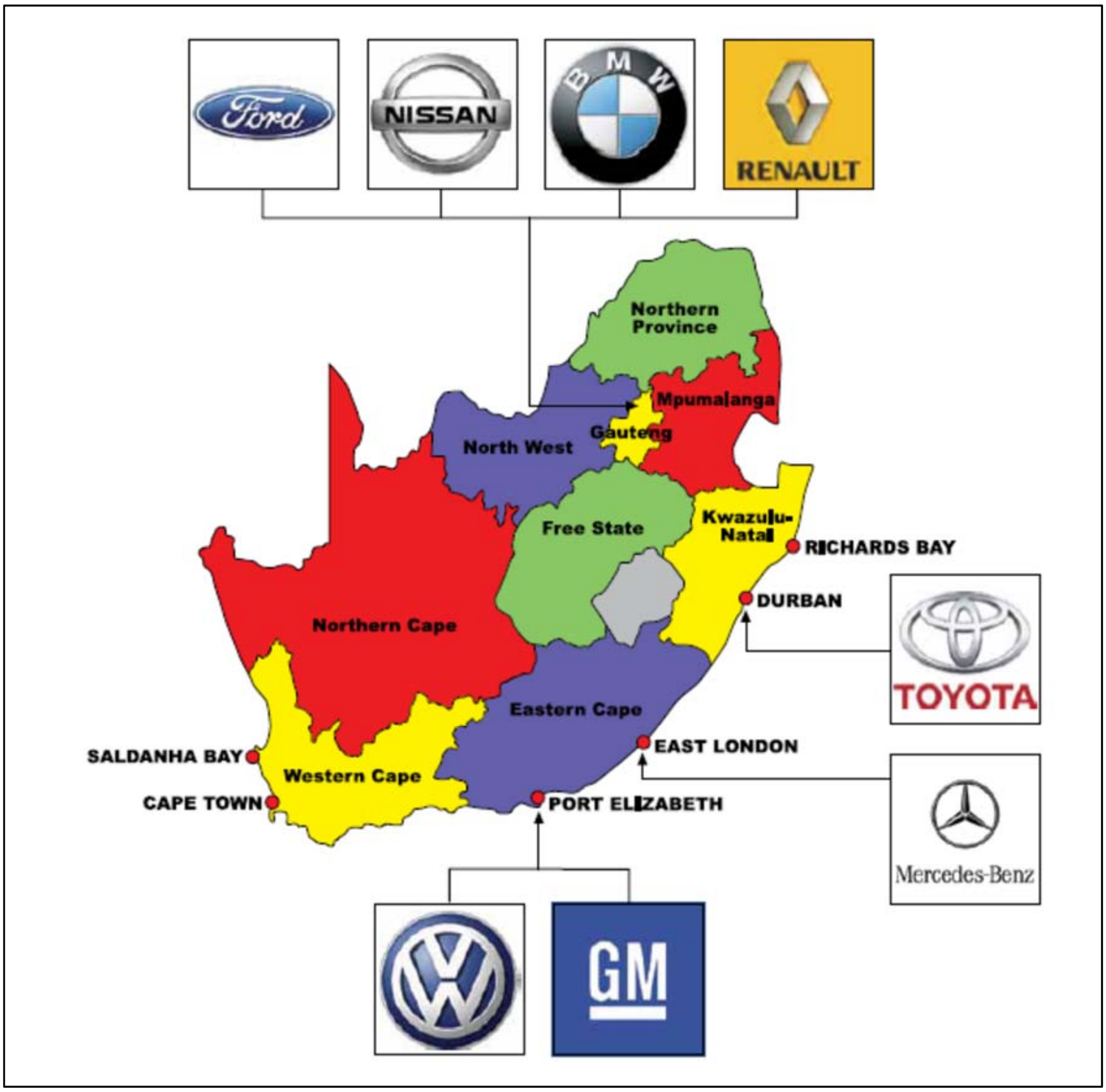


Figure 4-3: Location of Automotive Manufacturing Plants in SA (Pitot, 2011).

Vehicle distribution for importers only tends to consist of local sales, while manufacturers all have export programs. Figure 4-4 shows the market share the various manufacturers have of the export market.

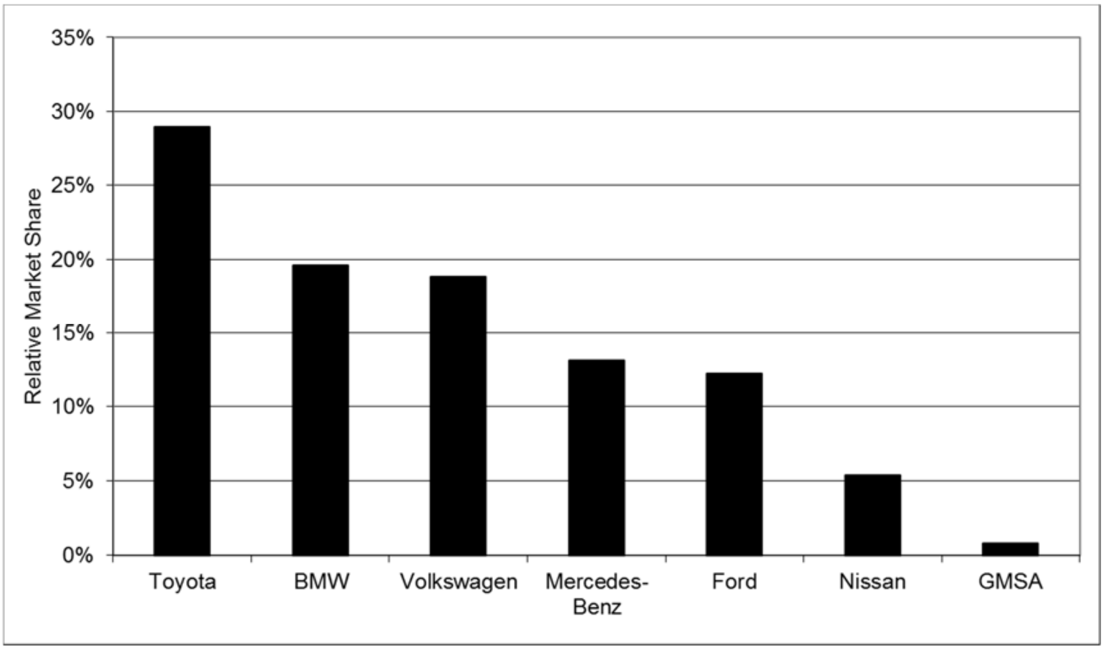


Figure 4-4: Export Market Share of SA Based Automotive Companies (NAAMSA, 2013).

None of the other manufacturers exports. Please note that the Common Customs Union Countries (Botswana, Lesotho, Namibia and Swaziland) are considered to be local sales and not exports.

Vehicle sales occur through dealer networks that are owned by the OE companies, individually owned franchises or direct imports to company owned facilities. An example of the latter would be AMH that imports and distributes a number of different brands through its dealership network.

Vehicle service, maintenance and repair are usually performed through dealerships. As vehicles age, the share serviced by independent and non-automotive brand franchise service centres increase. Crash repairs are usually performed by specialist panel-beaters who are authorised by the OE manufacturers. Parts supply to the various facilities originates either from the OE parts supply operation, or from non-OE manufacturers of components. Where possible, manufacturers patent or trademark components to protect their intellectual property. The parts sales from the various OE operations are driven by the vehicle park (total number of manufacturer vehicles registered) they service. Parts are sourced either locally (for locally manufactured vehicles) or imported (for imported vehicles, CBU, SKD and CKD kits), depending on the original part's source. In certain cases, localisation occurs where parts manufacturing for parts that may originally have been imported, have been localised. Conversely, if the local demand is too low, parts may be resourced to import sources where global demand results in manufacturing being more viable.

In South Africa, the commitment by vehicle manufacturers is to provide parts for vehicles for 15 years after the model production has stopped (industry norm). Each manufacturer provides parts given their own vehicle life expectancy as well as retention rate. Retention is a basic indication of vehicle owners that use OE parts rather than alternatives.

4.2 South African Automotive Parts Environment

Strydom provided the data of an unpublished benchmark study performed in 2013. The data reviewed the parts businesses of a number of OE suppliers including some of the large local manufacturers and import exclusive suppliers. The results are discussed below, with permission. Figure 4-5 shows the relative sales volume and inventory levels for the OEs.

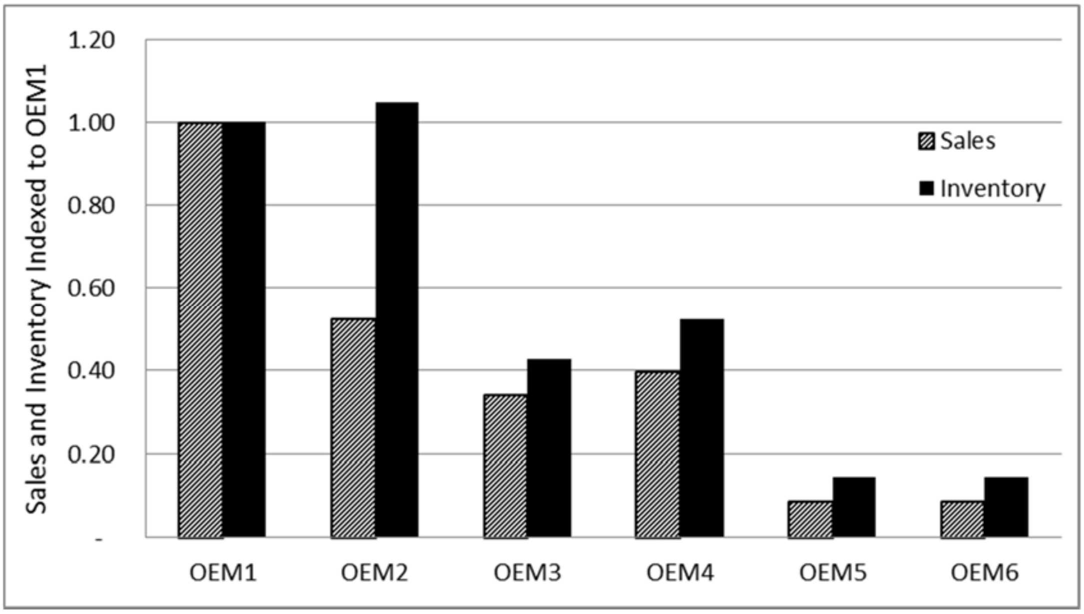


Figure 4-5: Relative Parts Sales and Inventory (Data from Strydom, 2013).

OEM2 carries the most inventory (1.05 times that of the base OEM1), but is only second in terms of sales (53% of that of OEM1). In all cases, except for OEM1, the OEMs have more inventory than sales. This result would suggest that OEM1 is running a lean supply chain for parts supply.

Figure 4-6 shows the frequency of lines in versus lines out (Lines = order lines rather than pieces). This result is an indicator of the orders placed by the OE companies relative to sales order lines they receive from their dealer networks. Higher lines out per lines in would indicate larger or bulk orders, indicative of an economic order quantity ordering approach. Fewer lines out per line in would indicate a lean sell one, buy one approach.

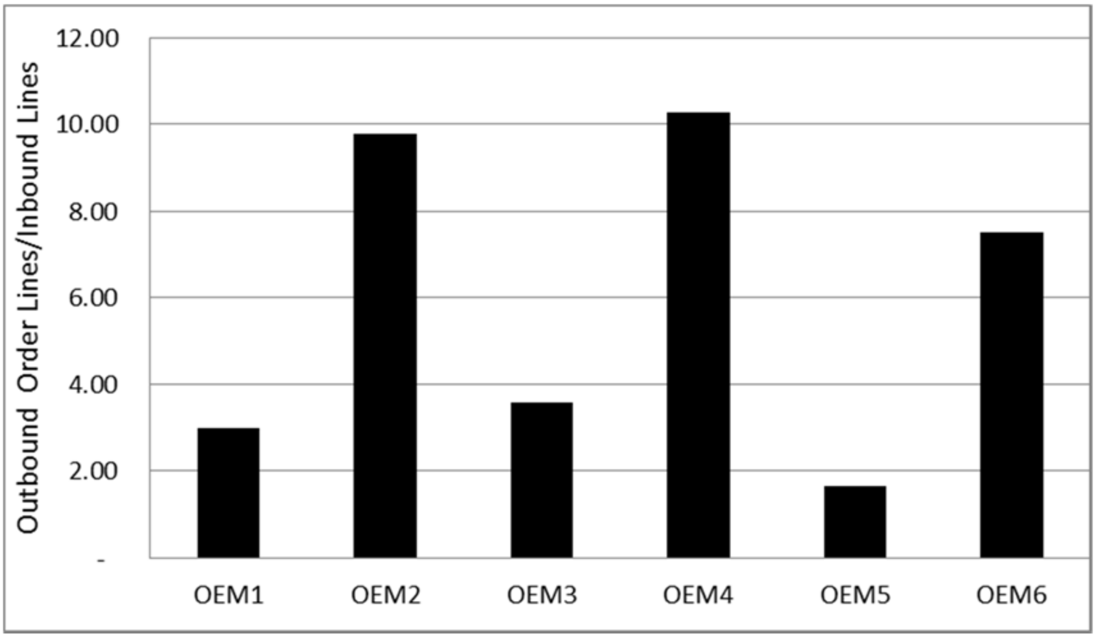


Figure 4-6: Outbound Order Lines versus Receiving Lines (Data from Strydom, 2013).

It can be seen that OEM1, OEM3 and especially OEM5, follow a lean strategy for ordering, in other words only order to replace what has been sold or items for which an order has been received.

Figure 4-7 shows the sales generated per inventory unit or inventory turns. Inventory turns are an indication of how efficient inventory is managed. Higher inventory turns show a high turnaround time and that inventory does not age significantly.

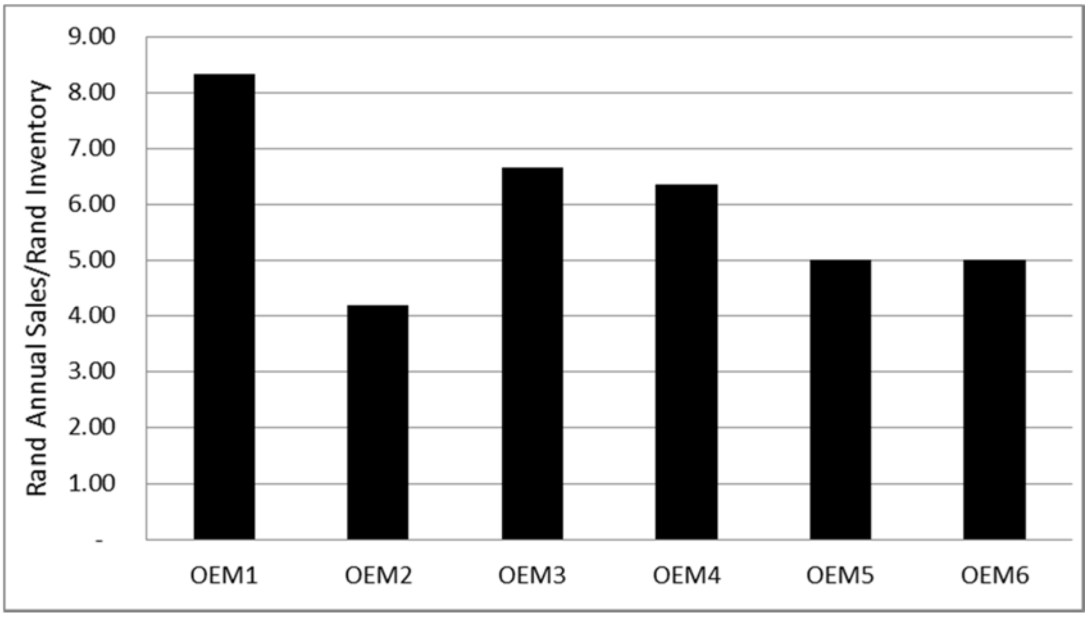


Figure 4-7: Rand Annual Sales/Rand Inventory or Inventory Turns (Data from Strydom, 2013).

As expected from Figure 4-5, OEM1 has the highest and OEM2, the lowest inventory turns. Figure 4-8 shows the inventory value held per order line. Again, this result is an indicator of inventory management efficiency.

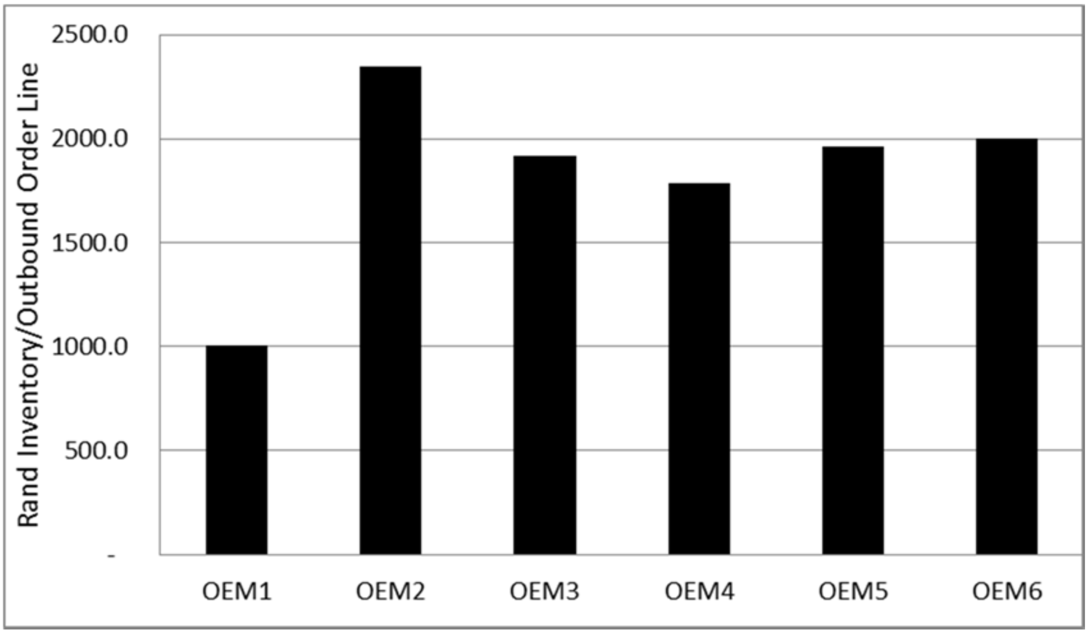


Figure 4-8: Inventory Value per Outbound Order Line (Data from Strydom, 2013).

Figure 4-9 shows the value of the inventory held per square meter of warehouse space. The value of inventory per square meter is an indication of the efficiency of storage.

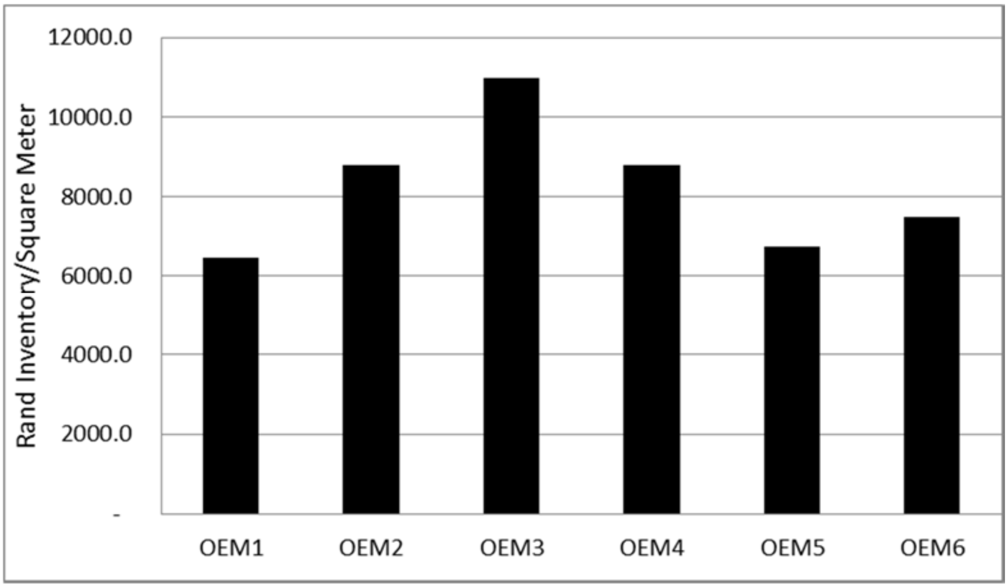


Figure 4-9: Inventory Density (Data from Strydom, 2013).

In contrast to all the other efficiencies, OEM1 ranks the lowest on inventory density. Figure 4-10 shows the throughput in terms of order lines per square meters of warehouse space. This throughput is an indication of operational efficiency.

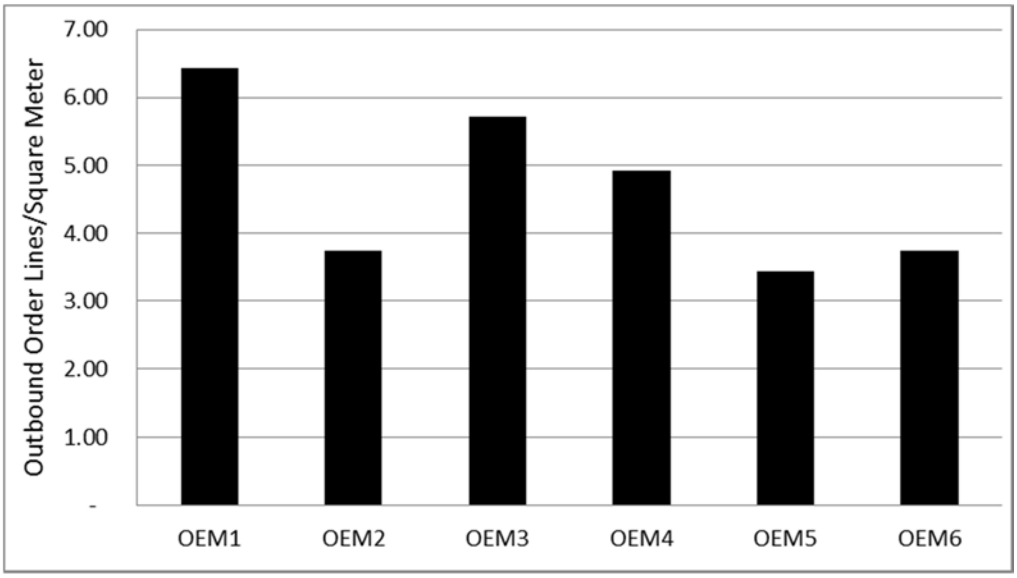


Figure 4-10: Throughput per Square Meter of Warehouse Space (Data from Strydom, 2013).

Despite its low inventory density, OEM1 has the highest throughput per square meter, while OEM2, OEM5 and OEM6 have the lowest warehouse productivity. While OEM1 has the lowest storage density, it has a high inventory turnover and high throughput. OEM2 with the highest storage density has poor inventory turnover and low throughput speed. OEM1, OEM3 and OEM5 seem to follow a sell-one-buy-one strategy, with supplier order line matching receiving order lines closely. OEM2 and OEM4 seem to import bulk quantities, supporting the many receiving order lines per supplier order.

This study gives an interesting insight in the supply chain management of the parts operations of six OEMs. Some of the factors seen are a result of strategic decisions regarding vehicle platforms, service level promises and approaches to managing inventory. All the OEMs seem to retain their clients adequately and the various strategies, as long as they are in line with service delivery promises, are effective.

4.3 Parts Market Structure – Supply Side

Part supply focuses predominantly on component parts, rather than assemblies or sub-assemblies. In general, these items would be specific components, which the plant would often only see as part of an assembly or subassembly. For example, engines may be imported with the oil filter already installed as part of the drive train assembly. In the parts supply chain, the oil filter is a key service part that is replaced at every service interval. Similarly, repair, crash and maintenance parts tend to be sold at the component level. Only with regard to customisation and accessory parts is it likely for a full assembly to be sold. A specific example would be air conditioners, which can be sold as an after-market fitment, in which case the full air conditioner unit with all components required for installation is sold as a single assembly. For repair and maintenance purposes, each single component of the air conditioner is sold separately. These components include the radiator, hoses, connectors, O-rings, compressors and sensors.

From a sourcing point of view, parts usually originate with the OE supplier. For past model parts, a process of re-sourcing may mean that an imported part is now produced locally (localisation), or a part, previously locally produced, is now imported.

In general, part sourcing will distinguish between stock and non-stock items, current and past model parts, as well as local and imported parts. The basic structure of the parts supply chain is shown in Figure 4-11. The exact design will vary from OEM to OEM at a detail level. For example, some OEMs do not have local content and all parts are imported. In addition, some OEMs use hubs for sub-distribution, some use dealers to carry consignment inventory and some supply directly to the dealers as shown. In cases of emergency, parts are imported by means of airfreight, but this action is a function of the part type (airbags are seen as hazardous and may, for example, not be air freighted) and the company policy.

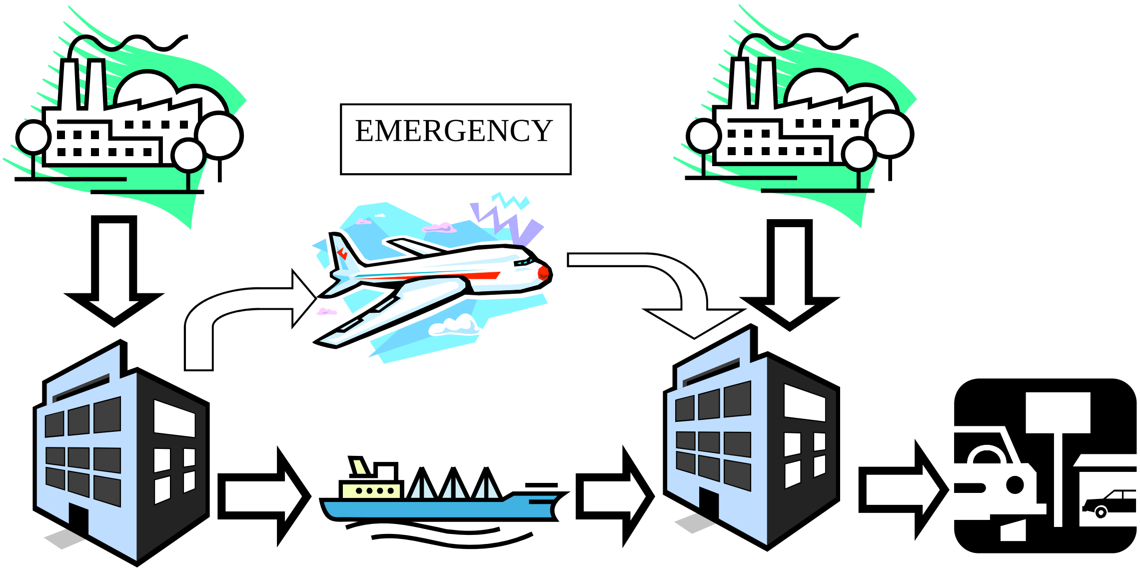


Figure 4-11: Parts Sourcing Supply Chain.

Lead time depends on distance and contractual arrangements. Imported parts lead time includes production lead time, processing lead time or picking lead time (if it is a stock item) shipping lead time, transport to the distribution centre and receiving lead time. The average lead time is approximately 63 days.

Domestic lead time consists of production lead time, transport to the distribution centre, and receiving lead time. Production lead time could be very short, but is usually determined by contractual arrangements. For current model parts, 7 days lead time is the norm and for past models 28 days is the norm. The latter allows the supplier to plan tool changes etc. for out of production part runs.

Supplier reliability forms a critical aspect of the performance of the automotive parts supply chain. OE suppliers are usually under significantly high pressure to produce parts for production lines. This pressure results in the priority for after-market parts being low. Any demand that is not in line with the forecast is treated as an abnormal request and may result in doubling of the lead time. Past model parts create problems of their own. The demand for older model parts seldom justifies continuous production. To interrupt the main production lines to perform a tool change for a short production run is not cost effective. In the case of, for example harnesses, past model parts have to be produced by hand. Components such as connectors, clips and connecting wire need to be sourced. This sourcing activity adds significantly to the production lead time.

4.4 Parts Market Structure – Demand Side

The demand side for parts supply in South Africa consists of both domestic demand and export demand for all categories of parts. Supply to the domestic market follows three distinct models. Firstly, there is supply via regional or wholesale operations. This approach allows a relatively small number of players to place consolidated orders. The parts are redistributed to the final retail/dealer for use and sales to end-users. Secondly, there is supply directly to dealers, using a vendor managed inventory model. In this case, parts are sent to dealerships on a consignment basis, as and where required. Special order parts are supplied when required. Thirdly, there is supplying to dealers based on dealer orders for dealer inventory or immediate consumption.

Demand from export destinations tend to be between distribution centre and distribution centre. The local distribution centre will receive an order from the distribution centre at the export destination and send the parts to the export destination.

End-user demand is driven directly by use or as a result of unplanned incidents. It would be reasonable to assume that service parts and maintenance (wear and tear) parts would have reasonably predictable demand patterns. During the launch of a new model, demand would increase in line with vehicles sold. As the vehicle park grows, demand should stabilise as vehicles exit the park and new vehicles enter. A stable vehicle park should be even more predictable for platform level parts where the same part is used in more than one vehicle generation. For low volume, short availability models, the demand pattern should follow sales and the life cycle of the product. The use of service parts are a result of vehicle usage and manufacturer design specifications. A vehicle will require an oil and an oil filter change every 10 000 km, an air filter every 20 000 km and new spark plugs and a fuel filter every 30 000 km, for example. The vehicle owner does not control the consumption of these parts. The only variable is the average distance covered in a certain period. If the vehicle park is sufficiently large, aggregate demand should be stable.

Wear and tear parts add additional degrees of freedom to the demand pattern. Factors that affect the variance include driver behaviour, terrain and other environmental factors. Dealers inspect brake pads at every service for wear. If the brake pad set is estimated to last to the next service, they are not replaced. Replacement is suggested on wear and the timing is not fixed by a service schedule. A vehicle travelling on freeways every day is likely to receive more mileage from a set of brake pads than a vehicle operating in a regular stop/start environment. A similar argument exists for suspension parts.

Mechanical failure requiring repairs can be a result of aging, design flaws, or driver behaviour. In general, when design flaws are identified, recall campaigns are launched to replace the defective components. It is, however, very difficult to accurately forecast the expected demand for repair parts. For some models, failure is more likely e.g. clutch systems on high performance vehicles may not last as long as expected when vehicles are abused during weekend racing.

The last and completely unpredictable demand, relates to incidental damages. Accidents tend to be individual events and while unpredictable, do not affect the system extensively. Significantly more difficult to process, would be the results of a hailstorm. Such a storm could damage a large number of similar vehicles at the same time, resulting in large demand volumes following the event. As an example, a supplier had 24 imported windscreens in inventory for a low volume new model. Following a single hailstorm, all 24 units were ordered and dispatched in 24 hours. When the next customer placed an order, he had to be informed that there was no inventory available and the lead time was 63 days as the weight of the windscreen made it too expensive to airfreight.

The automotive part supply chain contains examples of all of the different types of demand. With 80% of sales attributed to 3.5% of the parts and 5% of sales attributed to 80% of the parts, effectively managing this lumpy demand is vital.

4.5 Summary of the Automotive Parts Market

In summary, the automotive supply chain consists of three distinct supply chains, each with their own characteristics. For the purposes of this thesis, the focus is on the parts supply chain. The parts supply chain ensures that the vehicle is usable throughout its operational life. The South African automotive parts environment, as well as the supply and demand side of the supply chain was described in detail in this chapter. The next chapter explains why Just-In-Time (JIT) inventory management is a good fit for the automotive parts supply chain.

5 LEAN SUPPLY CHAIN AND INVENTORY MANAGEMENT

Bhattacharya & Bandyopadhyay (2011) explicitly state an "inventory on-hand policy is unstable in practical scenarios in terms of its effect on the order and the inventory variability, since small fluctuations in demand may result in uncontrollable order and inventory variability." In contrast, both base stock policies namely, installation stock policies and echelon stock policies, are accepted to result in a stable supply chain. In this chapter the case for JIT inventory management is presented. A case study is provided to demonstrate the impact a lean supply chain in the automotive industry has on setting cost targets. The base stock policy (Maximum Inventory Position – MIP) in the automotive parts supply industry is derived theoretically as a concept of lean manufacturing and then compared against the practical application of the method. This analysis highlights the changes that had to be made to the pure method to maximise supply chain performance while maintaining high levels of parts availability and low inventory levels. As an alternative, a stock-on-hand method, called the Stock Target Setting (STS), is developed. This policy includes a damping factor that suppresses the potential for the bullwhip effect to occur.

5.1 Economic Order Quantity to Just In Time (JIT) Cost

There are a number of fundamental assumptions associated with the economic order quantity model:

- A known and constant demand of *d* units per unit of time exists.
- The order quantity, *Q*, will replenish inventory when inventory levels reach zero. The full order quantity will arrive simultaneously and instantaneously.
- Delivery lead time is constant and the reorder point ensures that inventory arrives on time (Reorder Point = demand * lead time).
- A 100% availability is planned for, with no shortages allowed.

The total cost per unit time, *TC*, consists of the following components:

$$\boldsymbol{Production\ or\ Ordering\ Cost\ =\ K\ +c*Q} \quad \text{..}\textbf{(5-1)}$$

With:

$\boldsymbol{K\ =\ Setup\ Cost}$

$\boldsymbol{c\ =\ Unit\ Cost}$

$\boldsymbol{Q\ =\ Order\ Quantity}$

The average level of inventory is:

$$\boldsymbol{Average\ Inventory\ per\ Cycle\ = (Q - 0)/2 = Q/2} \quad \text{(5-2)}$$

Where:

$\boldsymbol{Cycle\ =\ Time\ to\ sell\ Q\ units\ at\ demand\ of\ d\ per\ unit\ time.}$

$\boldsymbol{Cycle\ Time\ = Q/D}$

Therefore:

$$\boldsymbol{Holding\ Cost\ per\ Cycle\ = hQ/2 * Q/D = hQ2/2D} \quad \text{(5-3)}$$

With:

$\boldsymbol{h\ =\ holding\ cost\ per\ unit\ per\ unit\ time.}$

Therefore:

$$\boldsymbol{Total\ Cost\ per\ Cycle\ =\ K\ +\ cQ\ + hQ2/2D} \quad \text{(5-4)}$$

The total cost per unit time is:

$$\boldsymbol{TC\ =\ (K\ +\ cQ\ +\ hQ2/2D)/(Q/D)\ =\ DK/Q\ +\ Dc\ +\ hQ/2} \quad \text{(5-5)}$$

The lowest cost occurs where the first derivative of *TC* to *Q* is equal to zero, resulting in:

$$\boldsymbol{DK/Q2\ +\ h/2\ =\ 0} \quad \text{(5-6)}$$

So that:

$$\boldsymbol{Qmin = (2DK/h)^{0.5}} \quad \text{(5-7)}$$

Equation 5-7 is the well-known EOQ formula.

The cycle time now becomes:

$$\boldsymbol{tmin\ =\ Qmin/D\ =\ (2K/Dh)^{0.5}} \quad \text{(5-8)}$$

Equation 5-8 provides the baseline to develop a method for calculating the requirements for base cost reduction for a JIT system. In the Toyota Production System, the elements contributing to the setup costs are normally targeted first (Shingo, 1981). Reducing set up time allows manufacturing in a *Heijunka* (even flow) manner. *Heijunka* manufacturing prescribes producing small quantities of every product on an on-going basis, rather than manufacturing significant quantities of one item. The ideal embodiment of JIT in supply chain management would be: Sell One – Buy One. This results in:

$$\boldsymbol{Q_{JIT}\ =\ 1} \quad \text{(5-9)}$$

Therefore:

$$\mathbf{1} = (\mathbf{2}\boldsymbol{DdK}/\boldsymbol{h})^{\mathbf{0.5}} \qquad \text{(5-10)}$$

And therefore the ideal setup cost for JIT must be:

$$\boldsymbol{K_{JIT}} = \boldsymbol{h}/\mathbf{2}\boldsymbol{D} \qquad \text{(5-11)}$$

An alternative JIT implementation strategy would be: Daily Order, Daily Delivery:

$$\boldsymbol{Q_{JITa}} = \boldsymbol{dD} \qquad \text{(5-12)}$$

Therefore:

$$\boldsymbol{D} = (\mathbf{2}\boldsymbol{dDK}/\boldsymbol{h})^{\mathbf{0.5}} \qquad \text{(5-13)}$$

Leading to:

$$\boldsymbol{D}^{\mathbf{2}} = \mathbf{2}\boldsymbol{DK}/\boldsymbol{h} \qquad \text{(5-14)}$$

Therefore, the ideal setup cost for this implementation of JIT must be:

$$\boldsymbol{K_{JITa}} = \boldsymbol{Dh}/\mathbf{2} \qquad \text{(5-15)}$$

In summary, to ensure that JIT is feasible in a supply chain, it is imperative that the setup costs are managed. In Section 5.2 a case is demonstrated to calculate the implications of JIT on the automotive supply chain for both current and past models. The example is also used to explain the cost implications on the automotive parts supply chain.

5.2 JIT Feasibility for Automotive Parts Supply Chain – Case Study

To demonstrate the JIT cost implications in the automotive parts distribution supply chain, a specific part, namely a fuel tank, is selected. A fuel tank is a repair part and the demand is inherently complex and difficult to predict.

The fuel tank was manufactured on an in-house production line, with a specific target cost. For the purpose of this study, the target cost is an index figure of 100. The line produces 200 pieces for an 8 hour shift of vehicle production. The production is planned according to a JIT system. It takes 20 minutes to set up the machine and 60 minutes to complete the production of 200 pieces. Material cost per unit is 80.

These assumptions suggest that based on the target cost of 100, the cost equation for an 8-hour shift, from Section 5.1, is:

$$\boldsymbol{Total\ Cost} = \boldsymbol{D} * \boldsymbol{K}/\boldsymbol{Q} + \boldsymbol{d} * \boldsymbol{c} + \boldsymbol{h} * \boldsymbol{Q}/\mathbf{2} \qquad \text{(5-16)}$$

With:

$\boldsymbol{D = Q}$

Then:

$$\boldsymbol{Total\ Cost = K + D * c + h * Q/2} \quad (5\text{-}17)$$

Therefore:

$$\boldsymbol{Total\ Cost = 100 * 200 = K + 200 * 80 + h * 200/2} \quad (5\text{-}18)$$

The holding cost on the line is difficult to estimate. If the product is fed to the production line at the line speed, then $\boldsymbol{h = 0}$. A line-side supply of two hours in the factory is seen to have negligible impact, with $\boldsymbol{h}$ approaching 0.

It is then possible to calculate $\boldsymbol{K_{JIT}}$ as follows:

$$\boldsymbol{Cost\ per\ 2\ hour\ cycle = 100 * 50 = K_{JIT} + 80 * 50} \quad (5\text{-}19)$$

Therefore:

$\boldsymbol{K_{JIT} = 2000}$

Thus to achieve the target cost, $\boldsymbol{K_{JIT}}$ must be 2000 or less.

During vehicle production, the aftermarket demand of one unit per month, which increased to one unit per day after five years of production, does not add to the cost. The normal production cycle could produce the required additional unit. After seven years of production, a new vehicle model was introduced. The new generation fuel tank became an imported part. The past model parts demand, however, remained only one per day.

With a sell one – buy one strategy in place:

$$\boldsymbol{D = Q = 1} \quad (5\text{-}20)$$

$$\boldsymbol{h = 0} \quad (5\text{-}21)$$

Therefore:

$$\boldsymbol{Total\ Cost = D * KJIT/Q + D * c + h * Q/2 = KJIT + D * c} \quad (5\text{-}22)$$

$$\boldsymbol{Total\ Cost = 2000 + 80 = 2080} \quad (5\text{-}23)$$

This cost is 20 times the previous target cost. If $\boldsymbol{D = Q = 5}$ (demand for 1 week), then:

$$\boldsymbol{Total\ Cost = 2000 + 80 * 5 = 2400} \quad (5\text{-}24)$$

Resulting in a unit cost of 480 or 4.8 times the previous target cost.

In a case like this, the revised target cost may be set at 1100, requiring K to be reduced to around 1000. This result affects two aftermarket dilemmas:

- The cost of low volume past model parts which are now significantly more expensive than when the vehicle was in production
- Suppliers are very reluctant to enter into past model contracts and be tied contractually for 15 years after the end of production supply, during the original OE contract negotiations.

In summary, it is feasible to apply just in time principles for the parts supply chain, but the end of production has significant price implications for low volume movers.

5.3 Inventory Management Models for Just In Time (JIT)

This section aims to analyse and evaluate the generally used inventory management method for JIT supply chains. Inventory management requires the setting of:

- Reorder point (RP) – at which inventory level is an order placed.
- Reorder quantity (RQ) – how many units should be ordered.

The first item to review is the concept of Guaranteed Service (GS) (Graves & Willems, 2000) in the automotive parts industry. A vehicle contains between 6 000 and 10 000 individual components. Many of these components are never replaced during the life cycle of the vehicle. Service parts are as few as five components per vehicle and wear and tear parts are 20 (with varying life expectancies). The rest of the parts are repair, accident damage or "never to be replaced" parts. While a customer expects 100% availability of parts, it is not economically feasible. It is, therefore, necessary to establish an overall GS target.

Once the service level targets have been defined, an inventory management strategy needs to be selected:

- MIN/MAX – A minimum inventory level triggers replenishment orders. This method requires a reorder point to be set, as well as a reorder quantity. Where there is an economic order quantity, MIN/MAX is the most effective method.
- MAX/MAX – Every time a sale is processed, a replenishment order is placed to replenish the inventory back to the maximum level. This method only requires the setting of the maximum inventory level.

MAX/MAX can be interpreted as a form of Just-In-Time ordering, with orders only placed to replenish actual demand.

The current approach to MAX/MAX is to set a Maximum Inventory Position (MIP). The MIP level reflects the demand over a period and accommodates inventory for order cycle, supplier lead time, as well as safety stock for lead time variance and safety stock for demand variance.

The basic inventory management model used for JIT parts supply is the Maximum Inventory Position (MIP) method. The MIP method is analysed and discussed in the next three sections. Starting with ideal theory, the theory under stochastic conditions and the practical implementation of the method is reviewed and discussed.

5.3.1 JIT Maximum Inventory Position Order Management Model - Theory

For a JIT supply chain, the inventory strategy is driven by: Daily Order – Daily Delivery. This strategy means that as soon as inventory is consumed, an order is placed for new inventory. The delivery for the next day may not be the order placed today, but an order offset by the lead time. If the supplier can maintain a same day delivery schedule, the parts sold today is replenished tomorrow.

Therefore:

$\boldsymbol{RP = 1}$

$\boldsymbol{RQ = D}$

With $\boldsymbol{D}$ the constant daily demand.

To take the order lead time into account, it is necessary to introduce the concept of pipeline inventory. Pipeline inventory includes all inventory that has been ordered and not yet sold. It consists of both inventory available to sell, as well as orders that have not yet been delivered. Two new variables are required, namely:

$\boldsymbol{S_{OH} = Stock\ on\ Hand}$ – Available inventory

$\boldsymbol{S_{OO} = Stock\ on\ Order}$ – Inventory ordered but not yet available to sell

Therefore:

$$\boldsymbol{Pipeline\ Stock = S_{OH} + S_{OO}} \quad \textbf{(5-25)}$$

The Pipeline Stock is the physical embodiment of the Maximum Inventory Position (MIP). If sales are set to zero, the inventory ordered using the MIP method will only build up to a maximum of the MIP level. Therefore:

$$\boldsymbol{MIP = Pipeline\,Stock = S_{OH} + S_{OO}} \text{ (5-26)}$$

Where:

$$\boldsymbol{S_{OH} = D * RP = D} \text{ (5-27)}$$

$$\boldsymbol{S_{OO} = \Sigma RQ = Lead\,Time * D} \text{ (5-28)}$$

$$\boldsymbol{RQ = Q = D} \text{ (5-29)}$$

Therefore:

$$\boldsymbol{MIP = D + Lead\,Time * D = D * (1 + Lead\,Time)} \text{ (5-30)}$$

Equation 5-30 describes the MIP calculation that is applicable under ideal conditions where demand is consistent with no variance in demand or lead time. In the next section, the equations are expanded to accommodate demand and lead time variances.

5.3.2 JIT Maximum Inventory Position Order Management Model Under Stochastic Conditions - Theory

Thus far, it was assumed that *d* is constant and that there would never be stock-outs. In a real environment, demand is random or stochastic. Therefore, it can be stated that:

$\boldsymbol{D}$ = a continuous random variable representing daily demand $\boldsymbol{\mu}$ = average value of $\boldsymbol{E}(\boldsymbol{D})$ with $\boldsymbol{\sigma}$ = standard deviation of $\boldsymbol{E}(\boldsymbol{D})$.

$\boldsymbol{D}$ has a probability density function, namely:

$$\boldsymbol{D} = \mathrm{f}(\boldsymbol{x}) \text{ (5-31)}$$

Lead time is also random, giving:

$\boldsymbol{H}$ = a continuous random variable representing lead time $\boldsymbol{\mu_2}$ = average value of $\boldsymbol{E}(\boldsymbol{H})$ with $\boldsymbol{\sigma_2}$ = standard deviation of $\boldsymbol{E}(\boldsymbol{H})$.

$\boldsymbol{H}$ has a probability density function, namely:

$$\boldsymbol{H} = \mathrm{f}(\boldsymbol{y}) \text{ (5-32)}$$

The equations in Section 5.3.1 can thus be expanded to:

$$\boldsymbol{S_{OH} = \mu * RP + SS_{DV} = \mu + SS_{DV}} \text{ (5-33)}$$

Where $\boldsymbol{SS_{DV} = Safety\,Stock\,for\,Demand\,Variance}$

$$\boldsymbol{S_{OO} = \Sigma RQ = (\mu_2 + SS_{LTV}) * \mu} \text{ (5-34)}$$

Where $\boldsymbol{SS_{LTV} = Safety\,Stock\,for\,Lead\,Time\,Variance}$

Therefore:

$$\boldsymbol{MIP = \mu * RP + SS_{DV} + (\mu_2 + SS_{LTV}) * \mu} \quad \text{(5-35)}$$

$$\boldsymbol{MIP = \mu * (RP + \mu_2 + SS_{LTV}) + SS_{DV}} \quad \text{(5-36)}$$

If $f(\boldsymbol{x})$ and $f(\boldsymbol{y})$ are normal distributions, the safety stock can be defined in terms of the service level to be achieved. For example, to achieve 95% service level, the safety stocks are:

$$\boldsymbol{SS_{DV} = 2 * \sigma} \quad \text{(5-37)}$$

$$\boldsymbol{SS_{LTV} = 2 * \sigma_2} \quad \text{(5-38)}$$

Therefore:

$$\boldsymbol{MIP = \mu * (RP + \mu_2 + 2 * \sigma_2) + 2 * \sigma} \quad \text{(5-39)}$$

This leads to:

$$\boldsymbol{Q = MIP - (S_{OH} + S_{OO}) + BO} \quad \text{(5-40)}$$

$$\boldsymbol{Q = \mu * (RP + \mu_2 + 2 * \sigma_2) + 2 * \sigma - (S_{OH} + S_{OO}) + BO} \quad \text{(5-41)}$$

With:

$\boldsymbol{BO = Backorders}$

This means that for stochastic demand, an order is placed daily. This order takes into account the Maximum Inventory Position, which is a function of order cycle, lead time, lead time variance, demand, demand variance and current inventory pipeline status. Backorders that have been created are added to the order.

Three issues arise, namely:

- How frequently $\boldsymbol{MIP}$ is adjusted
- What values of $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ is used
- What values of $\boldsymbol{\mu_2}$ and $\boldsymbol{\sigma_2}$ is used

5.3.3 JIT Maximum Inventory Position Order Management Model Under Stochastic Conditions - Practical Application

In practice, both of the calculations (safety stock and daily order) can be performed daily with a sufficiently capable computer system. Daily recalculation may, however, affect system stability, encouraging the bullwhip effect. It is therefore the norm to adjust MIP once a month. The value of $\boldsymbol{\mu}$ is calculated as a 6 month moving average demand (MAD) calculation. It is accepted that using a 6 month moving average will smooth day to day demand fluctuations and accommodate seasonal behaviour (Toyota, 2003). The value of $\boldsymbol{\mu_2}$ is less frequently updated and is treated as a manual intervention. The required safety stock is obtained as output from the system. Except for using the MAD and adjusting lead time when appropriate, the system is treated as a black box.

Toyota (2003) describes the implemented equation set in use as follows:

$$\boldsymbol{MIP = MAD * (OC + LT + SS\,for\,Lead\,time + SS\,for\,Demand)} \quad \textbf{(5-42)}$$

$$\boldsymbol{SOQ = MAD * (OC + LT + SS\,for\,Lead\,time + SS\,for\,Demand) - (OH + OO) + BO} \quad \textbf{(5-43)}$$

With:

$\boldsymbol{SOQ = Stock\ order\ quantity}$

$\boldsymbol{MAD = Monthly\ Average\ Demand\ *}$

$\boldsymbol{OC = Order\ Cycle}$

$\boldsymbol{LT = Lead\ Time}$

$\boldsymbol{SS\ for\ Lead\ Time = Safety\ Stock\ for\ Lead\ Time}$

$\boldsymbol{SS\ for\ Demand = Safety\ Stock\ for\ Demand}$

$\boldsymbol{OH = Stock\ on\ Hand}$

$\boldsymbol{OO = Stock\ on\ Order}$

$\boldsymbol{BO = Back\ Orders}$

*6 month moving average, adjusted to reflect daily demand.

A six months moving average demand (MAD) calculation is used to smooth day to day demand fluctuations and accommodate seasonal behaviour (Toyota, 2003). The value of lead time is less frequently updated and considered a manual intervention. The required safety stock is again obtained as output from the system. Except for using the MAD and adjusting lead time when appropriate, the system is treated as a black box.

The implementation of the MIP method raises a serious concern with regard to the calculation of MIP. If Equations 5-41 and 5-43 are compared, there is a distinct difference in the calculation of order quantity, *Q*, with regard to the calculation of safety stock for demand, *SSD*. In the theoretical derivation (Equation 5-41) the safety stock for demand considers the demand variance for the reorder period. Daily order placement suggests that the safety stock for demand is equal to the demand variance multiplied by the factor,

n, associated with a specific service level. This approach ensures that both the terms of the equation is consistent in its dimensions (pieces * time). In the practical application (Equation 5-43), the safety stock for demand is included in a single term with safety stock for lead time. Both the factors are multiplied by the demand, resulting in a term that does not have dimensional consistency (pieces * pieces + pieces * time). It is suspected that the practical solution is an attempt to improve the stock availability. The result of using Equation 5-43 would be an increase in service level, but it would also increase inventory levels significantly.
If the logic as shown in Equation 5-41 is used, the correct equation should be:

$$\boldsymbol{MIP} = (\boldsymbol{MAD} + \boldsymbol{SS\,for\,Demand}) * (\boldsymbol{OC} + \boldsymbol{LT} + \boldsymbol{SS\,for\,Leadtime}) \quad \textbf{(5-44)}$$

It is also suspected that the assumption that both lead time and demand have normal distributions may be the cause of the MIP method not providing adequate service levels. If lead time and demand have other distribution functions, such as log-normal or Gamma distributions, the theoretical MIP method will underestimate the amount of safety stock required. With the practical implementation, the inventory in the system is increased, allowing the AFR to remain high, even when the demand pattern does not follow a normal distribution.

5.3.4 JIT Stock Target Setting Order Management Model Under Stochastic Conditions - Theory

As an alternative to the MIP method, this thesis proposes a Stock Target Setting (STS) method. The MIP method focuses on inventory in the complete pipeline (stock-on-order and stock-on-hand), but does not specify location at which safety stock needs to be held. As long as the total inventory in the system is equal to the maximum inventory position, no additional action is taken. The proposed Stock Target Setting method focuses on stock-on-hand. It sets a target for the stock–on-hand, which includes safety stock for demand and lead time variance, and focuses on ensuring that this target inventory level is maintained.
In the Stock Target Setting Method two equations are required. Firstly, the order quantity to be placed needs to be calculated.

$$\boldsymbol{Order} = (\boldsymbol{Demand} - \boldsymbol{Back\,Orders}) + (\boldsymbol{Target} - \boldsymbol{Stock}) \quad \textbf{(5-45)}$$

Similar to the MIP method, back orders are h as having a secondary supply approach and they can, therefore, be subtracted from the demand. In the current format any correction from the $(Target - Stock)$ term should result in the bullwhip effect. It is, therefore, necessary to expand Equation 5-45 to introduce a damping factor for inventory level adjustment to overcome the statement by Bhattacharya and Bandyopadhyay (2011) that inventory-on-hand policies are inherently unstable. This adjustment results in:

$$\boldsymbol{Order = (Demand - Back\ Orders) + (Target - Stock)/(Damping\ Factor)} \quad \textbf{(5-46)}$$

The second equation focuses on how to set the target inventory level.

$$\boldsymbol{Target = (Delivery\ Cycle) * (Demand)} \quad \textbf{(5-47)}$$

As shown here, the equation assumes stable demand. The equation can once again be expanded to compensate for stochastic conditions, resulting in Equation 5-48:

$$\boldsymbol{Target = (Delivery\ Cycle + 2 * \sigma_2) * (Demand + 2 * \sigma)} \quad \textbf{(5-48)}$$

The STS method therefore consists of Equations 5-46 and 5-48.

5.4 Lean Supply Chain Inventory Management Models Summary

In this chapter the role of lean supply chain or JIT supply chain was explored. A cost comparison between the traditional EOQ and JIT costing methods was done. To confirm the feasibility of the lean supply chain approach, a cost target method was developed. This cost target method provides the practitioner an opportunity to calculate the potential cost increase to expect when an automotive model moves from current production to past production. A specific case in the automotive industry was analysed to confirm the cost model and cost breakpoint. The basic MIP model for JIT inventory management was described. Comparison of this model with the practical implementation shows that there is a fundamental difference in the theoretical derivation and the practical implementation. To address the resulting increase in inventory levels, the STS model was developed. This model aims to improve the AFR without a significant increase in inventory levels. In the next chapter, the development of a SDSM, which is used to evaluate the different methods, is described.

6 DEVELOPMENT OF A SYSTEM DYNAMICS SIMULATION MODEL FOR SUPPLY CHAIN BEHAVIOUR ANALYSIS

To effectively analyse the impact of an inventory management method, it is essential to evaluate the effectiveness of the method in a quantitative manner. The criteria against which to measure performance have been identified as allocation fill rate (AFR) and inventory levels. The automotive part supply chain is dynamic in nature with parts being sold and replenished on an on-going basis. Demand is variable and can move rapidly, or very slowly, as discussed in Chapter 4. Due to the stochastic nature of the demand, a dynamic simulation based approach was considered most suitable to evaluate the various inventory management approaches. For the purposes of this study, System Dynamics Simulation Modelling (SDSM) was selected.

In this chapter, the basic elements of decision support and system dynamics are discussed. The development of a SDSM to analyse various inventory management methods under various conditions is discussed. The SDSM accommodates the three supply chain structures: Local Current, Local Past and Imported Parts. Each of these models is set up to address the three inventory management methods: MIP_{Theory}, MIP_{Actual} and STS.

The detail of the statistical methods used to analyse the datasets are not discussed in this chapter, but provided in Appendix X. The basic elements of the statistical analysis are described in Section 7.3, given that these are standard methods.

6.1 Background

System Dynamics was developed by Jay Forrester. Starting with "pen and pencil models" Forrester expanded the methodology to include the use of computer simulation. The first problems addressed, focused on supply chain dynamics (Forrester, 1961), national problems (Forrester, 1969) and global problems (Forrester, 1973). Working with industrialists, politicians and economists, he developed a series of ground breaking solutions to short, medium and long-term problems.

As indicated, system dynamics focus on the dynamic domain where conditions continually change and the system adapts to changes. It also embraces non-linear behaviour through feedback loops. It does however, not attempt to develop a specific solution, but rather identify alternative policies (Forrester, 1958).

The system dynamics process is shown in Figure 6-1.

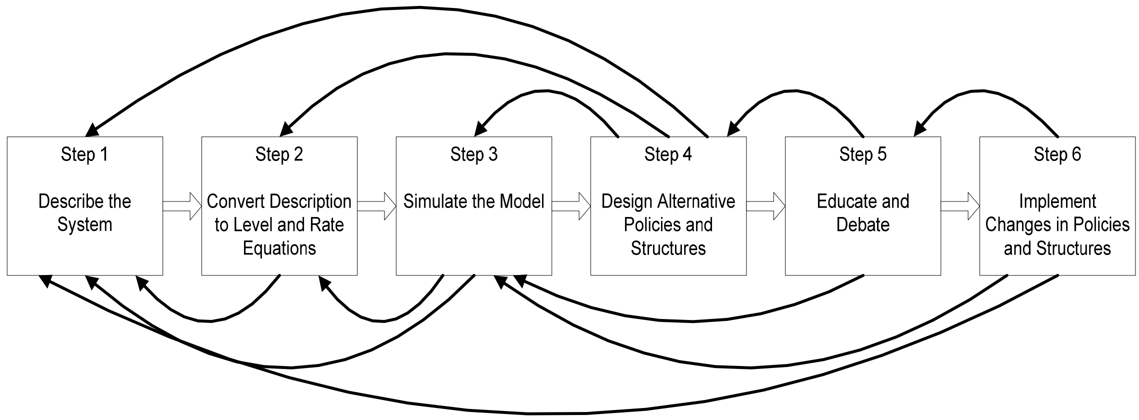


Figure 6-1: System Dynamics Process from Problem Symptoms to Improvement (Forrester, 1994).

Unlike operations research where there is a clear requirement to formulate the problem as a mathematical model, which suggests a certain level of rigor, system dynamics requires a description to be converted to level and rate equations. Sterman (2000) shows a stronger focus on the details of model development, while Forrester (1994) and Vennix (1996) focus on ensuring that the project results are implemented to resolve the problem and improve the system.

Kampmann (2012) expand on the lack of formal methodology for constructing system dynamics models: “formal methods have largely been restricted to simple classroom examples as guides to intuition”. He proposes that the method of system eigenvalues (Nathan Forrester (1982, 1983)) be introduced as a method to formally assess the important structures in system dynamics models. This method uses graph theory to analyse the feedback in system dynamics models and “may be a step towards a systematic analysis of feedback loops in system behaviour.” (Kampmann, 2012). Ford (1999) and Richardson (1995) also discuss the analysis of feedback dominance as a tool in system dynamics.

A number of authors propose the use of simulation to analyse and optimise supply chains. Sahay and Ierapetriou (2013) evaluate the interaction between simulation and optimisation requiring an active feedback loop between each solution. Umeda and Zhang (2008) apply a hybrid of discrete simulation, control models and system dynamics to solve supply chain problems. Tako and Robinson (2012) apply a combination of discrete event simulation and system dynamics to the supply chain.

Angerhofer and Angelides (2000) and Akkermans and Dellaert (2005) provide an extensive overview from the original industrial dynamics to more recent use of system dynamics to address supply chain issues. System dynamics has been applied in many industries to evaluate and solve supply chain issues. Vlachos, Georgiadis and Iakovou (2007) applied system dynamics for capacity planning in a closed-loop supply chain, Canella, et al. (2015) focus on a coordinated decentralised supply chain, while Minegishi and Thiel (2000) and Georgiadis, Vlachos and Iakovou (2005) focus on applying system dynamics in the food supply chain. Huang, et al. (2007) applied system dynamics to a so-called constant work in process controlled supply chain for lamps. The constant work in process system is a hybrid push-pull system.

As shown above, applying system dynamics to supply chain research is on-going. In this particular case the focus is on studying the performance of a specific inventory management method being used in the automotive parts supply chain. The objective of the study is to understand and improve on inventory management in an industry where parts move at highly differentiated demand patterns. It is also an industry where supply rate is critical. Additional complexity in the industry is that space is a constraint and the bullwhip effect is difficult to cope with in a practical manner.

6.2 iThink Constructs

The reality is that the basic constructs of system dynamics, namely, level and rate equations, are simply a way of describing the basic approach of using differential equations to describe a problem. Levels are commonly known as stocks and rates as flows. The simple mathematical version of the differential equation structure is given in Equation 6-1:

$$\boldsymbol{Stock(T) = Stock(T - dt) + (Flow_{In} - Flow_{Out})} \quad \text{.................................} \textbf{(6-1)}$$

More mathematically precise, an integral equation or a differential equation (Sterman J. , 2000) as shown in Equations 6-2 and 6.3, can be used:

$$\boldsymbol{Stock(t) = \int_{t_0}^{t} (Flow_{In}(s) - Flow_{Out}(s))\, ds + Stock(t_0)} \quad \text{......................} \textbf{(6-2)}$$

$$\boldsymbol{\frac{d(Stock)}{dt} = Net\ Change\ in\ Stock = \ Flow_{In} - Flow_{Out}} \quad \text{...........................} \textbf{(6-3)}$$

Solving the set of differential equations cycle by cycle, a dynamic picture of the model outputs is obtained. The advantage of SDSM is that it is designed to solve dynamic, time bounded problems and does not optimize under static or linear conditions. By connecting stocks and flows, it is possible to create higher order non-linear systems that are solved, even if there is no analytical solution. Changing boundary conditions can be included at any point in time during a simulation.

The tool used for developing the simulation model was iThink® 10.1.1, developed and owned by isee systems Inc.

The primary building block in system dynamics is the stock. Usually depicted as a rectangle (see Figure 6-2), stocks are used to "accumulate" the state of the system. It provides an indication of the level of a particular variable at a specific time. One of the most important attributes of a stock is that it always has an initial value. As an example, in a simple model of a dam, the dam itself is treated as a stock. It is possible to determine the amount of water in the dam, by observing the value of the dam stock.

Figure 6-2: A Stock as Implemented in iThink®

The second fundamental building block of system dynamics is the flow. Usually depicted as a pipe with a valve (refer to Figure 6-3), flows are used to adjust the level of stocks. The clouds at either end of the flow indicate that there is either an unlimited source (inflow side) or an unconstrained sink (outflow side). In the case of a dam system, the river or stream(s) feeding into the dam, as well as the overflow, are flows.

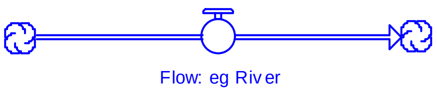


Figure 6-3: Flow as Implemented in iThink®

The value of a stock can only change if it receives an inflow or outflow. The dam can only fill up if water flows in and be emptied if water flows out. Figure 6-4 shows a simple inflow-outflow model of a dam. Stocks can have multiple inflows and outflows.

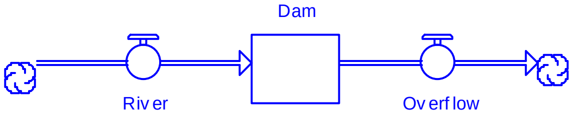


Figure 6-4: Simple Inflow and Outflow Model of a Dam

Please note that the inflow originates from an infinite source. The outflow is also a sump with infinite capacity.

Flows (in and out) can be defined as constants or functions. iThink® uses converters and connectors, as shown in Figure 6-5, for this purpose. Converters can be used to represent constants, variables or functions. Converters, stocks and flows can be connected by connectors. Figure 6-5 shows an inflow that is controlled by a function that includes both the value (level) of the stock over time, as well as the constant or function represented by the converter.

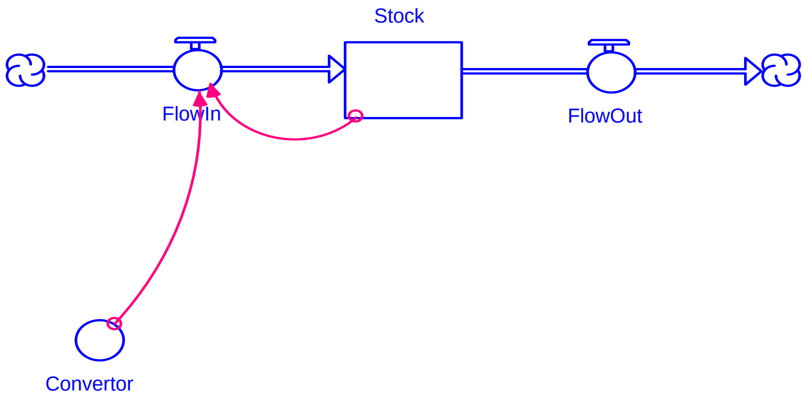


Figure 6-5: Converters and Connectors as Implemented in iThink®

A number of specialized stocks form part of the iThink® implementation. For the purpose of this study, a special stock called a conveyor is required. A conveyor acts as a time delay and is a good representation of lead time. It is possible to implement a variable time control that will speed up or slow down the conveyor. Figure 6-6 shows the same structure as in Figure 6-5, but with the stock changed to a conveyor.

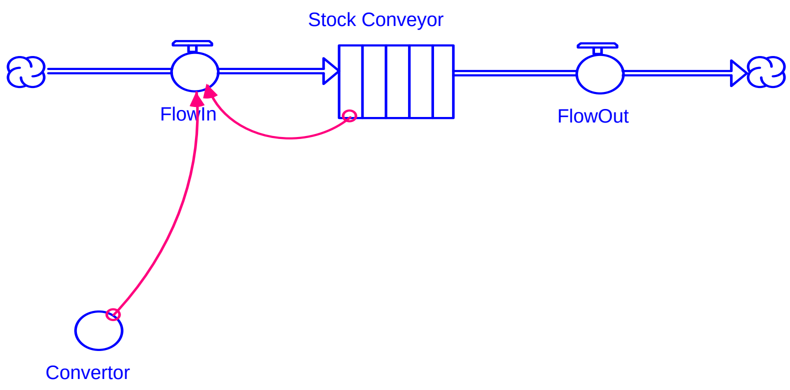


Figure 6-6: Conveyor as Implemented in iThink®.

The figure shows that the stock now is a conveyor with individual slats controlled by the time it takes for items to move through the conveyor. In this particular case, the conveyor implementation of the stock requires a transit time (constant or variable), capacity and inflow limit. The outflow is now controlled by the internal mathematics of the conveyor, which includes an externally set lead time.

6.3 Problem Description

Data from a large multi-national motor manufacturer was used to evaluate the performance of the inventory management methods. This company manufactures and sells vehicles in South Africa, as well as to a number of export destinations. These vehicles are provided with parts to support them throughout their life cycle.

Parts are imported from various international locations and local parts are received from various suppliers, including the manufacturing plant. All parts are received into a central distribution centre. Parts are stocked based on an inventory policy that identifies certain parts as stock and others as non-stock. Non-stock parts are processed through the facility when ordered, but not kept in inventory. Dealers and export distributors place orders on a daily basis. Dealer orders are classified as emergency orders, daily orders or stock orders. The latter orders are parts that dealers are expected to maintain some minimum level of inventory. Emergency orders and daily orders are supplied on a same day basis, while stock orders are shipped within two days. Orders are placed through an electronic portal and accumulated on a continuous basis. The system is available 24 hours per day and 7 days a week and allows for automated order loading as well as manually placed orders. In general, a small number of orders (10%) are placed over weekends. Export countries, as well as Botswana, Namibia, Lesotho and Swaziland (treated as local dealers) may place orders on South African Public Holidays.

Inventory management is currently based on a MAX/MAX principle. Orders are placed once a day. Import orders are assigned an estimated lead time and processed in the respective distribution centres and shipped in containers. Vessels usually depart once a week. Local orders are accepted by suppliers and are based on contractual lead times. Current model parts have a 7 day lead time, including delivery, and past model parts can be 7 days, if they are high volume, but in general past model parts have a 28 day lead time.

The maximum inventory position (MIP) is reviewed monthly and adjusted if required. A rolling three month demand forecast is provided to suppliers and a maximum order quantity of 20% higher than the forecast is acceptable. There is no minimum order quantity. The procurement team is measured by means of two key performance indicators:

- Allocation Fill Rate (AFR)
- Stock Months

The allocation fill rate is affected by the receiving operation. Local suppliers deliver daily and their deliveries are processed with a target lead time of 0.5 days from truck receiving to being confirmed into a storage location. Containers arrive when the ships dock and are received into the facility at a steady pace. Ship arrivals are usually on Sundays, and it takes a week to process the full shipment. From container receiving to being confirmed into a storage location takes one day. Parts are entered into the system during the receiving process. If a part is not available when an order is place, but arrives at the facility 10 minutes later, the AFR score remains zero. Given that some parts are not kept in inventory, the target allocation fill rate is set at 95.5%. This target implies that on any given day, a maximum of 4.5% of parts ordered can have zero availability.

To effectively manage the inventory, parts are classified by movement type and every effort is made to maintain 100% availability of the fast moving parts, which usually are service items. Two different classifications are used by the warehouse management system and the inventory forecasting systems. The results from the two systems are combined for order placement. Table 6-1 shows the classification system used by the warehouse management system and

Table **6-2** shows the classification used by the inventory management system.

Table 6-1: Parts Movement Classification Used by the Automotive Parts Warehouse Management System.

Movement Category	**Calculation**
New	Remains in this category for 18 months.
Fast	Greater or equal to 240 bin calls (orders) in last 12 months
Medium	60 to 239 bin calls in last 12 months
Slow	Between 7 and 59 bin calls per year **with**

Movement Category	**Calculation**
	Bin calls in at least 6 of the last 12 months
Erratic	1 to 6 bin calls in the last 12 months OR Between 7 and 59 bin calls in the last 12 months **with** Bin calls in less than 6 of the last 12 months
Dying	No bin calls in the last 12 months
Dead	No bin calls in the last 24 months
Superseded	Part replaced by new part number

Table 6-2: Parts Classification Used by the Automotive Parts Inventory Management System.

Pareto Category	**Calculation**
Pareto A (stocked)	Age <= 36 months and hits = 0 in 36 months Take off age <= 12 months
Pareto A (non-stocked)	Age <= 24 months, non-consecutive sales in past 3 months (less than 2 sales in 3 months)
Pareto B-F (stocked)	Take off age > 12 months and hits >= 4 in 24 months
Pareto B	80% unit contribution
Pareto C	10% unit contribution
Pareto D	5% unit contribution
Pareto E	3% unit contribution
Pareto F	2% unit contribution
Pareto M (stocked)	Take off age > 12 months and hits < 4 in 24 months
Pareto F (non-stocked)	Take on age > 36 months and hits = 0 in 36 months Part status in 1,3,4,5,6,7,10,13,15,16 All parts in dead and dying movement categories
Pareto X (non-stocked)	Age > 60 months and hits < 2 in 60 months

Inventory controllers' focus on Pareto B and C parts, as achieving a 100% AFR for these parts ensures a 90% AFR.

Stock month is the value of inventory divided by monthly turnover. This index is an indication of the amount of inventory in the system, relative to the monthly turnover. As this index is calculated using all inventory, it is also an indicator of inventory age. High inventory levels with a low AFR is unacceptable. At the same time, sufficient inventory must be available to ensure that the AFR remains high. Low inventory levels and high AFR is ideal. Considering the number of parts on the parts master relative to non-stocking parts, reasonable targets for AFR and stock months need to be set. The problem is to determine the ideal amount of inventory to hold for each part.

It should be noted that where possible, back orders are treated as emergencies and shipped via airfreight. They do therefore, not feature as part of the MIP calculation used to calculate the required inventory level for each part. Backorders, however, do form part of the MAD calculation and the demand variance.

6.4 Development of the System Dynamics Simulation Model

The rest of this section describes the feedback loop diagrams and actual construction of the SDSM. The model was deliberately designed to separate information and physical flows, which have in the past been simulated as single flows, resulting in outcomes that have to be questioned. Examples include Torres, O.A.C. and F.A.V Morán. (Editors) (2006) and Sterman (2000). Models developed without fully understanding the limitations in design and application domain often generate results that are incorrect.

6.4.1 Feedback Loop Diagrams

Feedback loop diagrams are used as a tool in systems thinking to understand not just the linear nature of situations, but also the feedback loops. Figure 6-7 shows the feedback loop of the supply chain under study.

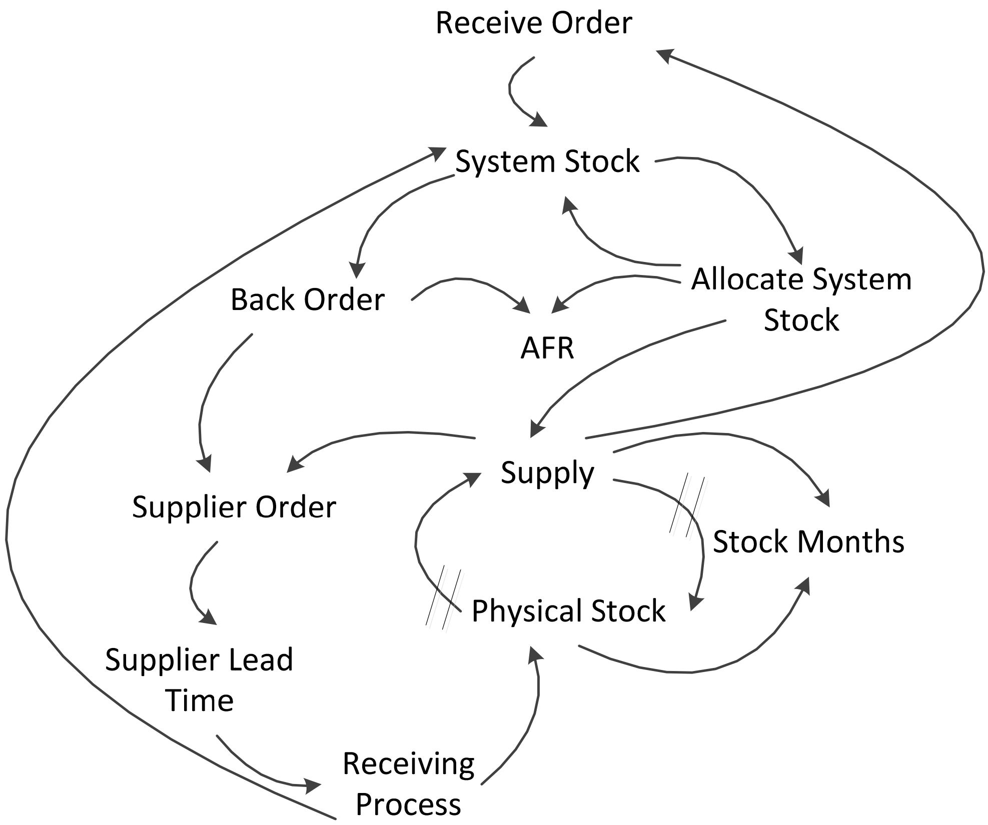


Figure 6-7: Feedback Loop Diagram of the Supply Chain.

In the diagram an order is received and validated against the system information. If no inventory is available on the system, a back order is generated. If the inventory is available according to the warehouse management system, the inventory is allocated on the system. The order is then supplied from the physical inventory, with a delay resulting from the process of supply. Supplier orders are created based on client orders supplied and back orders created. The supplier has a specific lead time after which the order reaches the receiving process. As orders are supplied from the physical inventory, the receiving process provides new physical inventory and updates the system inventory.

Once the order has been confirmed as supplied, the system inventory is adjusted. There are two reasons for differences between system inventory and physical inventory. The first is the time delays associated with the processing of the order or incomplete processes. While the system may have allocated the inventory to an order, the system will only be updated when the supply process is completed. (In most cases this action would take place on the generation of an invoice.) Secondly, there can be a discrepancy between the system inventory and physical inventory due to inventory having been misplaced or lost.

This gap is usually addressed through processes such as a cycle count (continuous process of counting inventory) and stock take activities. Secondly,

It should also be noted that this diagram reflects a continuous order system to the supplier. If the system has inventory to allocate, the AFR score is 1, otherwise it is zero. This calculation provides a cumulative score of how many orders can be satisfied from system inventory. For the purposes of this study, the focus is on the local distribution centre and, therefore, will only focus on supply from a single supplier at a time.

6.4.2 System Dynamics Model Construction

Six SDSMs were constructed; one for each each of the three inventory management methods for the imported parts suppliers and one for each of the three inventory management methods for the local parts suppliers. Each model was developed to simulate a just-in-time environment in which the demand equals the sales. The two sets of models are similar in nature, with the exception that the imported parts supply has an accumulation step to simulate weekly shipments.

The detail set of equations as used in each iThink® model are provided in Appendix II to VIII. Table 6-3 provides a summary of the key model variables, including the different algorithms used for each of the three methods.

Table 6-3: SDSM Variable Overview and Description.

Variable	Description
Exogenous Variables:	
Demand	Demand is the actual daily order inflow as received by the dealer network.
Average Demand and Demand Variance	Using historical data, average demand and the demand variance are calculated. These variables are a characteristic of a dataset over a period of time.
Lead-Time	Lead-Time is the contractual lead time agreed between the supplier and automotive parts supply company. This lead time would vary for import (63 days) and domestic suppliers (7 days for current production vehicles and 28 days for past production vehicles).
Average Lead-Time and Lead-Time Variance	Using historical data, average lead time and the lead time variance are calculated. These variables are characteristic of a dataset over a period of time.

Variable	Description
Endogenous Variables:	
Inventory	The inventory level at any point of time. The inventory level is calculated by means of a key differential equation.
Shipped	The number of units of inventory that can be shipped to clients based on the Accumulated Orders.
Accumulated Orders	Orders that have been placed on the supplier that have not yet been filled. The number of accumulated orders is a result of orders placed and shipped orders. These orders are calculated by means of another key differential equation.
Orders en Route	These are the orders that have been shipped by the supplier, but not yet received at the distribution centre. The level of orders en route is calculated by means of a key differential equation. The flow of these orders is managed so that the shipment sequence is maintained.
Back Orders	Dealer orders that cannot be supplied from available inventory are segregated as back orders. The back order process is treated as a separate flow as these orders will receive special treatment. Imported parts are shipped by air with lead times of 14 days, which is much lower than the contractual lead time.
Back Orders en Route	These backorders have been shipped and not supplied. The level of backorders is calculated by means of a differential equation. The backorder element has been included to allow an additional calibration element to balance order inflow and supply, but is not a focus of the study.
Total Allocation and AFR	The AFR is an indication of inventory availability at the time of order. It is calculated using the Total Allocation as a dummy stock to ensure accumulation over a full time interval is used, rather than an instantaneous calculation that would be susceptible to the calculation sequence. Total allocation is also calculated by means of a differential equation.
Algorithms: MIP_{Theory}	
Monthly Average Demand (MAD)	Monthly average demand, based on a 6 month moving average.
Maximum Inventory Position (MIP)	This algorithm calculates the total amount of inventory required in the supply chain as per the theoretical description, using Equation 5-39.
Supplier Order (Q)	This algorithm calculates the daily order, using Equation 5-41.
Algorithms: MIP_{Actual}	

Variable	Description
Monthly Average Demand (MAD)	Monthly average demand, based on a 6 month moving average.
Maximum Inventory Position (MIP)	This algorithm calculates the total amount of inventory required in the supply chain as per the theoretical description, using Equation 5-42.
Supplier Order (Q)	This algorithm calculates the daily order, using Equation 5-43.
Algorithms: STS	
Stock Target	This algorithm calculates the target level of the inventory required, using Equation 5-48.
Supplier Order (Q)	The algorithm calculates the daily order quantity, using Equation 5-46.

The SDSM solves a series of differential equations: Equations 6.4 to 6.9. The time interval $t = 1$ day and the integration interval $dt = 0.25$ days. The differential equations are solved sequentially using the Euler method as implemented in iThink® 10.1.1.

Key differential equations:

$$\boldsymbol{In\ Stock_t = In\ Stock_{t-dt} + (Arrive - Shipped)dt} \qquad \textbf{(6-4)}$$

With:

$In\ Stock = Number\ of\ pieces\ in\ the\ distribution\ centre$

$Arrive = Number\ of\ pieces\ arriving\ at\ the\ distribution\ centre$

$Shipped = Number\ of\ pieces\ sent\ to\ fulfill\ dealer\ orders$

$$\boldsymbol{Order\ Accum_t = Order\ Accum_{t-dt} + (Produced - Send\_to)dt} \qquad \textbf{(6-5)}$$

With:

$Order\ Accum$
$= Number\ of\ pieces\ ordered\ from\ the\ supplier\ waiting\ to\ be\ supplied$

$Produced = Number\ of\ pieces\ produced\ by\ the\ supplier$

$Send\_to = Number\ of\ pieces\ sent\ to\ fulfill\ orders$

$$\boldsymbol{Orders\_en\_Route_t = Orders\_en\_Route_{t-dt} + (Send\_to - Arrive)dt} \qquad \textbf{(6-6)}$$

With:

$Order\ en\ Route$
$= Number\ of\ pieces\ shipped\ from\ the\ supplier\ and\ not\ received$

$Send\_to = Number\ of\ pieces\ sent\ to\ fulfill\ orders$

$Arrive = Number\ of\ pieces\ that\ arrived\ at\ the\ distribution\ centre$

Secondary differential equations:

$$\boldsymbol{BO\ Accum_t = BO\ Accum_{t-dt} + (BO - BO\_Send\_to)dt} \quad \textbf{(6-7)}$$

With:

$BO\ Accum = Number\ of\ pieces\ that\ were\ not\ available\ at\ the\ time\ of\ order$

$BO = Number\ of\ pieces\ placed\ as\ back\ orders$

$BO\ Send\ to = Number\ of\ pieces\ that\ arrived\ to\ fill\ back\ orders$

$$\boldsymbol{BO\_en\_Route_t = BO\_en\_Route_{t-dt} + (BO\_Send\_to - BO\_Shipped)dt} \quad \textbf{(6-8)}$$

With:

$BO\ en\ Route$
$= Number\ of\ pieces\ shipped\ to\ fill\ backorders, but\ not\ yet\ arrived$

$BO\ Send\ to = Number\ of\ pieces\ that\ arrived\ to\ fill\ back\ orders$

$BO\ Shipped = Number\ of\ pieces\ shipped\ to\ dealers\ to\ fill\ back\ orders$

AFR calculation balancing differential equation:

$$\boldsymbol{Total\_Allocation_t = Total\_Allocation_{t-dt} + (Flow\_1 - Flow\_2)dt} \quad \textbf{(6-9)}$$

With:

$Total\ Allocation = Number\ of\ pieces\ that\ were\ available\ at\ the\ time\ of\ order$

$Flow\ 1 = Number\ of\ pieces\ dealers\ ordered$

$Flow\ 2 = Number\ of\ pieces\ dealers\ ordered\ delayed\ by\ 1\ day$

The difference between imported parts suppliers and local part suppliers are shown in Table 6-4.

Table 6-4: Differences to Account for in the Simulation Models.

Factor	**Local Parts Supplier**	**Imported Parts Supplier**
Supply Lead-Time	7 days for current model and high volume past model parts, 28 days for past model parts	63 days for all parts
Shipping Cycle	Daily shipping	Pick daily but consolidate weekly for shipping
B/O	Normal shipping	Can be sent by airfreight (7 to 14 days)

6.4.2.1 **Local Supplier Model**

Figure 6-8 shows the physical flow of parts from the supplier to the end user.

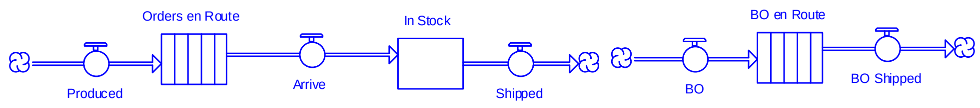


Figure 6-8: Physical Flow for Local Supplier.

The model contains a stock that reflects the physical parts in inventory. It also includes two conveyors. The two conveyors shown reflect the supplier lead time from order to receiving into inventory and the back order lead time from creation to fulfilment. For simplicity, it is assumed that backorders will not be binned, but rather supplied directly to the order in a cross-dock fashion. Key assumptions in this section are:

- Suppliers have sufficient capacity to cope with the orders placed
- Orders will be entered into the supplier system on a continuous basis, with daily deliveries
- Initial inventory in the physical system is allocated using lead time and demand

Figure 6-9 shows the information flow design for the MIP based model. Please note that both the theoretical and implemented MIP models have the same structure. The only difference is the method of calculating MIP.

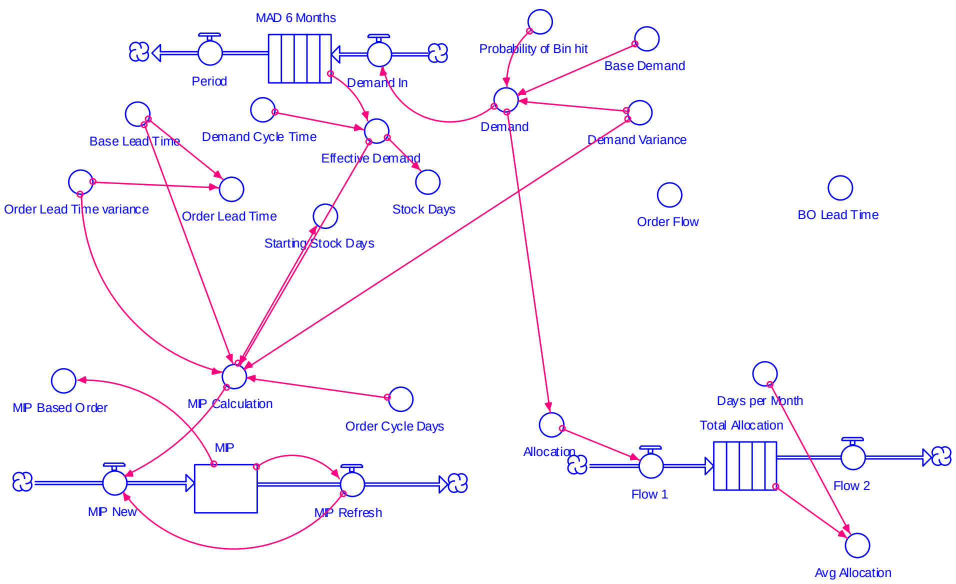


Figure 6-9: Information Flow Design for MIP Calculation.

The information flows have four key elements. Orders from clients can be simulated using a selected distribution, or if required, a specific data stream. Similarly, the lead time from suppliers has been treated as a variable, which can be simulated as a data stream or as a distribution. The calculation of the allocation fill rate requires a conveyor as a normal stock would calculate the average over the period of one month. The back order lead time has been set to a fixed time, as it does not affect the normal ordering process.

For the MIP calculation, two elements need to be added. Firstly, the Monthly Average Demand (MAD), a 6 month moving average, needs to be calculated. By using a conveyor, sales for each day of the last 6 months are combined, taking into account any day-to-day variance. The conveyor is initialized with 6 months' worth of average sales at the start of the simulation. The second element is the calculation of MIP, which is recalculated once a month with an initial value calculated based on the initial MAD.

Combining the information flow model (Figure 6-9) with the physical flow (Figure 6-8), results in an integrated model. Figure 6-10 shows the integrated model for the MIP based strategy.

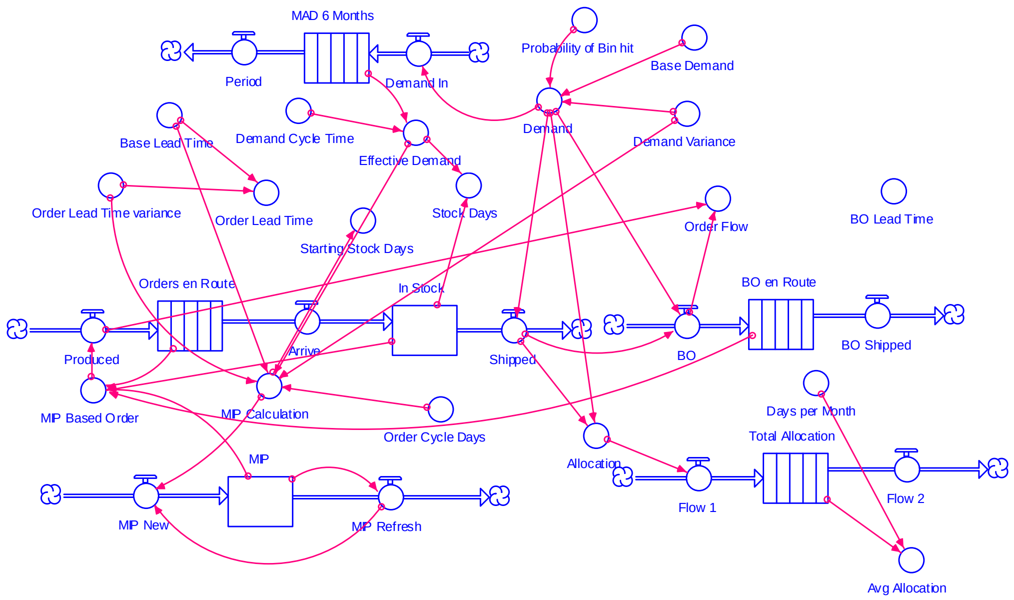


Figure 6-10: Comprehensive Model of MIP Based Strategy for Local Supplier.

As expected, the information system drives the physical flows. The two key links between the physical elements is the supply of parts that creates equivalent supplier orders and the orders not supplied that create equivalent back orders.

For the purposes of analysis, the current model parts and past model parts are identical, with the exception that the base lead time is set at 7 days for the current and 28 days for the past model.

6.4.2.2 **Imported Supplier Model**

The physical model for the imported suppliers differs from that of the local suppliers. The information models will in all cases be identical, as electronic portals are used. From an information point of view, transmission of information is immediate, accurate and continuous. The physical process does differ. When orders are received, there is no production lead time as the orders are placed on a distribution centre. Orders are processed and picked within one day, ready for shipment. Shipment does not happen immediately. Containers are filled and parts are shipped once a week. This shipping cycle is a function of the shipping line being used. The resultant model of the physical flow is shown in Figure 6-11.

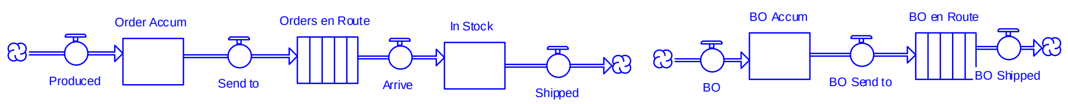


Figure 6-11: Physical Inventory Flow from Import Suppliers.

An additional stock has been added to hold the processed parts until shipment occurs. It is not necessary to show the information components of the model, as these are identical to that shown in Figure 6-9. Figure 6-12 shows the integrated model for the MIP strategy for an imported parts supplier.

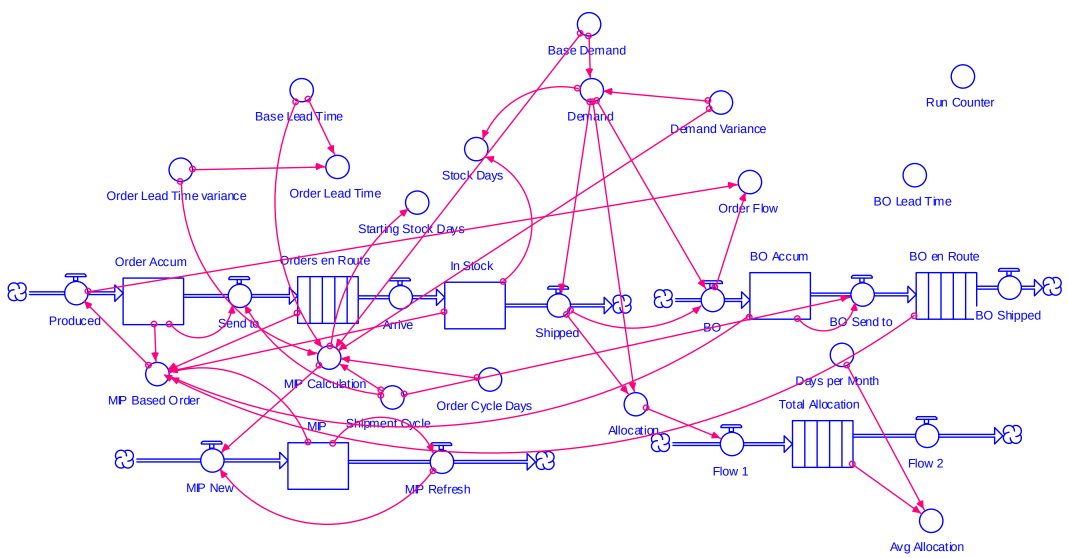


Figure 6-12: Integrated Model for Imported Suppliers with MIP Strategy.

The significant difference in these models is the shipment cycle that happens weekly, rather than on a daily basis. Please note that both the MIP_{Theory} and MIP_{Actual} models use the same structures for the import and local supplier supply chains. Only the order decision differs.

6.4.2.3 **Stock Target Setting (STS) Model**

The model for the Stock Target Setting (STS) method does not require the information flows required to calculate the MAD or MIP as it is an inventory-on-hand policy. The daily order calculation is based on demand, current inventory and the inventory target. Target setting is based on demand, delivery cycle and the damping factor. Similar to the MIP models, the local and import parts supplier model structures differ. The physical components of the model are identical to that used in the MIP method, apart from the STS order calculation model. Figure 6-13 shows the STS method for the import parts supplier.

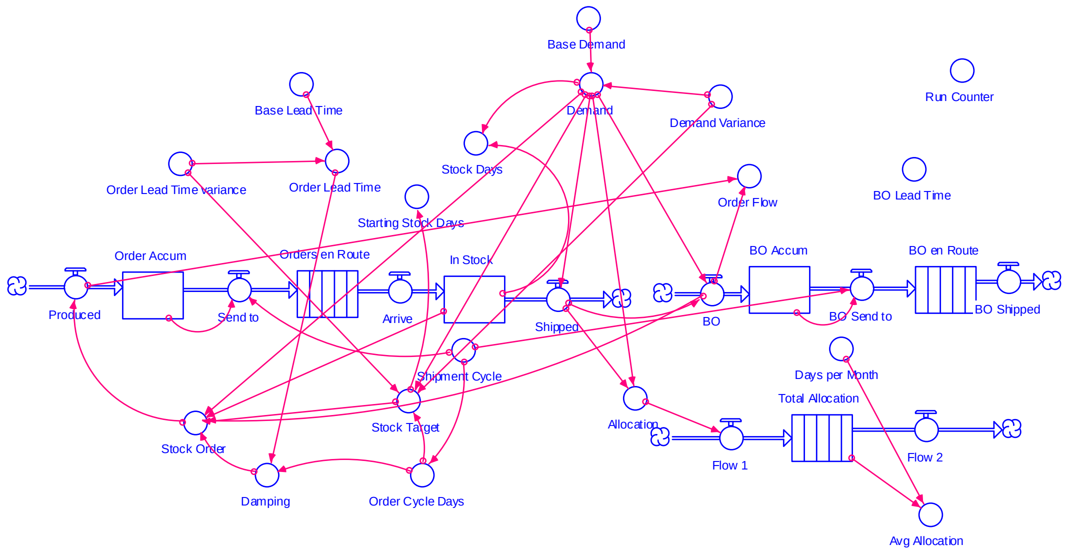


Figure 6-13: System Dynamics Model for the Import Parts Supply Chain Using the Stock Target Setting Method.

6.4.2.4 **SDSM Validation**

To validate and verify the SDSM for the three methods, an ideal environment was simulated. In the ideal environment, demand is constant and lead time shows no variance. Both the imported supplied parts and locally supplied parts are simulated as discrete delivery events and the results are shown in Figure 6-14. The status of the In-Stock variable is shown for a period of 30 days at every *dt* interval. These results confirm that the SDSM replicates the daily inventory behaviour properly, especially as daily deliveries are taken into account. In the ideal case, the inventory delivered at the start of the day is consumed during the same day until only the safety stock remains. Similarly, the weekly delivery from the imported supplier is consumed over the week. It is impossible to calibrate this level of detail, as the real life stock file is a dynamic file that is updated on a continuous basis. Historical data is not stored, as this will require large amounts of data storage space. In practice, a monthly snapshot is taken of the stock items at 24:00 on the last day of the month. This snapshot considers the inventory that is in the distribution centre at that specific time, but not safety stock or inventory that has just arrived or is at the end of its consumption period. For the purposes of analysis, this study will use an average inventory level over the period of study, rather than the daily detail.

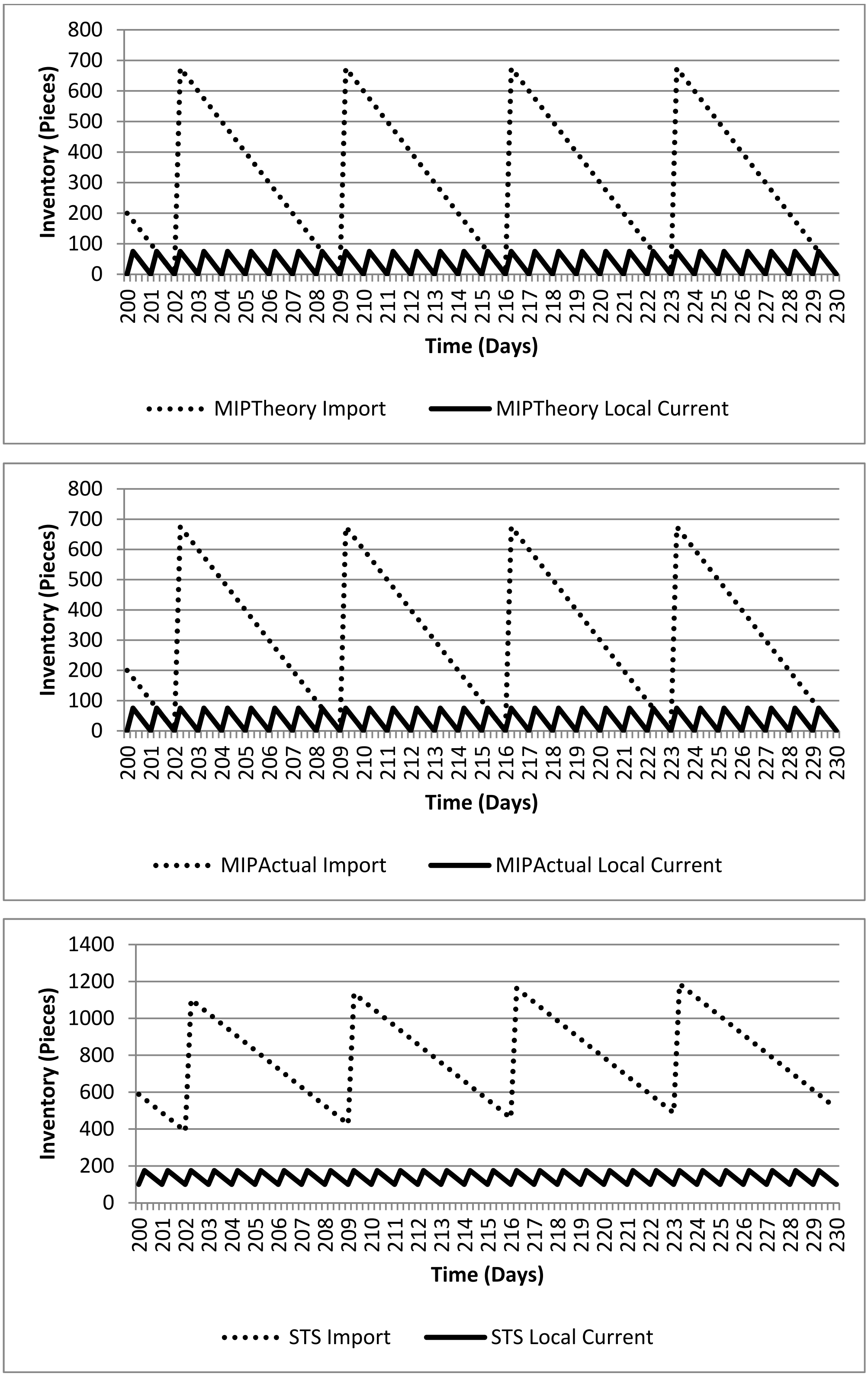


Figure 6-14: Calibration Results of the SDSM for the Three Inventory Management Methods.

6.4.2.5 **Service Parts Demand Forecast – Non-Stationary Demand**

To replicate the demand of a service part, a SDSM, shown in Figure 6-15 is used. At the time of vehicle model launch, the vehicle sales forecast is made available, based on production planning and market forecasts. This plan is translated into service parts demand, using the planned service interval in kilometres and the expected kilometres driven over time. The number of expected kilometres driven per time period is based on the market segment in which the vehicle operates. To simulate a realistic non-stationary demand environment, vehicle sales are generated using a normal, log-normal and gamma demand pattern, as discussed in Section 7.2.4.

Vehicles are serviced based on an average elapsed time, calculated using the expected time period between services. It is not guaranteed that all vehicles are serviced through the OE dealer network. However, the emergence of service plans as part of the vehicle purchase price ensures that most vehicles with service plans are serviced through the OE dealer network. The SDSM, therefore, uses the first five services as indicator of service parts demand. The MAD is again calculated as a six months moving average and converted to a daily demand (DAD).

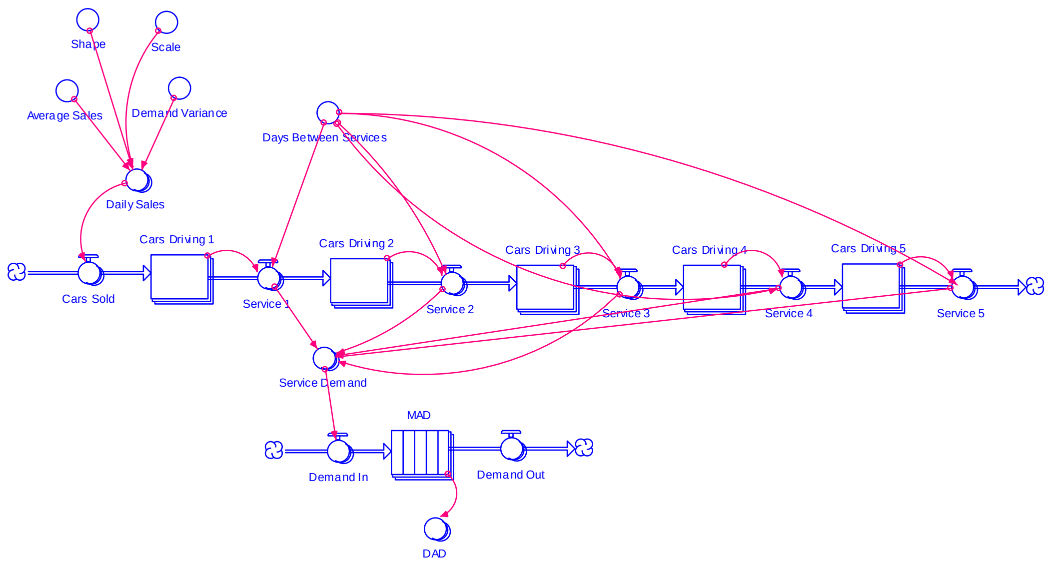


Figure 6-15: Service Parts Demand Generation SDSM.

The service parts demand SDSM is used to replace the demand distribution in each of the basic models to analyse the performance of the three inventory management models under various scenarios of non-stationary demand. The scenarios under study include three distributions, namely: Normal distribution, log-normal distribution and gamma distribution.

6.5 Model Development Summary

In this chapter, a series of seven SDSMs are described. These models focus on the characteristics of the automotive parts distribution system. The MIP_{Theory}, MIP_{Actual} and STS methods were described for two types of suppliers, namely local suppliers with daily shipping and imported suppliers with daily order processing, but weekly shipping. A service parts demand model was also developed to allow for the analysis of the three methods for a period of non-stationary demand. The model details are provided in the following appendices:

- Appendix II – MIP_{Theory} – Domestic
- Appendix III – MIP_{Theory} – Import
- Appendix IV – MIP_{Actual} – Domestic
- Appendix V - MIP_{Actual} – Import
- Appendix VI – STS – Domestic
- Appendix VII – STS – Import
- Appendix VIII – STS – Import Matrix (This version was later used for sensitivity analysis.)
- Appendix IX – Service Parts Demand

In Chapter 7 these models are applied to confirm the feasibility of the STS method, as well as the comparative performance of the three approaches – MIP_{Theory}, MIP_{Actual} and STS.

7 RESULTS AND DISCUSSION [1,2]

The purpose of this chapter is to review the results of the research described in the previous chapters. The chapter will focus on the following main areas:

- Calibration of the STS method to ensure that the bullwhip effect can be effectively controlled through the use of a damping factor.
- Theoretical and practical analysis of the two supply chain structures (imported and locally supplied), using three inventory management models, using the SDSM. The performance is compared by means of a SDSM using actual and statistical datasets for demand. The conditions during the launch of a new model were also replicated using statistical distributions.
- Detailed analysis of the structure of the STS method for both domestic and import suppliers to ensure the most effective design.

7.1 Simulation Analysis – Calibrating the STS Method

As described in paragraph 5.3.4 the STS method is a stock-on-hand policy, which according to Bhattacharya & Bandyopadhyay (2011), is inherently unstable and will result in the bullwhip effect. The purpose of this section is to confirm that the bullwhip effect does exist in this on-hand policy and to show that the damping factor proposed, controls the impact of the dynamic nature of the supply chain. An inherent design element of the supply chain, namely the lead time, provides an ideal level of damping.

1. **A modified version of this study was published in the Journal for Transport and Supply Chain Management.**
2. **A modified version of the work focusing on the analysis of the STS method was submitted to Management Dynamics.**

The first step in this process was to use the model in Figure 6-13 with no damping, namely $Damping\ Factor = 1$ in Equation 5-46. Once the expected bullwhip was demonstrated, a series of analyses were completed to confirm an effective value for the $Damping\ Factor$. The analysis domain, detailed for each of the supplier types, is described in

Table 7-1.

Table 7-1: Analysis Domain for Confirming STS Damping Factor.

Import Supplier					
Demand	100 per day	Variance	10 units		
Lead-Time	63 Days	Variance	0 Days		
Damping Factor	1 Day	15 Days	30 Days	63 Days (Lead-Time)	70 Days (Lead-Time + Shipping Cycle)
Domestic Supplier - Current					
Demand	100 per day	Variance	10 units		
Lead-Time	7 Days	Variance	0 Days		
Damping Factor	1 Day	3 Days	7 Days (Lead-Time)		
Domestic Supplier - Past					
Demand	100 per day	Variance	10 units		
Lead-Time	7 Days	Variance	0 Days		
Damping Factor	1 Day	3 Days	7 Days (Lead-Time)		

As the analysis includes only demand variance, only the first 100 time intervals were ignored to allow the model to stabilise. In each case, the model was run 50 times to allow for a statistically significant result.

The results for the inventory behaviour over time (average of 50 runs), with no damping, are shown in Figure 7-1, Figure 7-2 and Figure 7-3. Inventory is measured in pieces and time in days.

Figure 7-1: Results (Average for 50 Runs) for No Damping for Imported Parts Supply Chain.

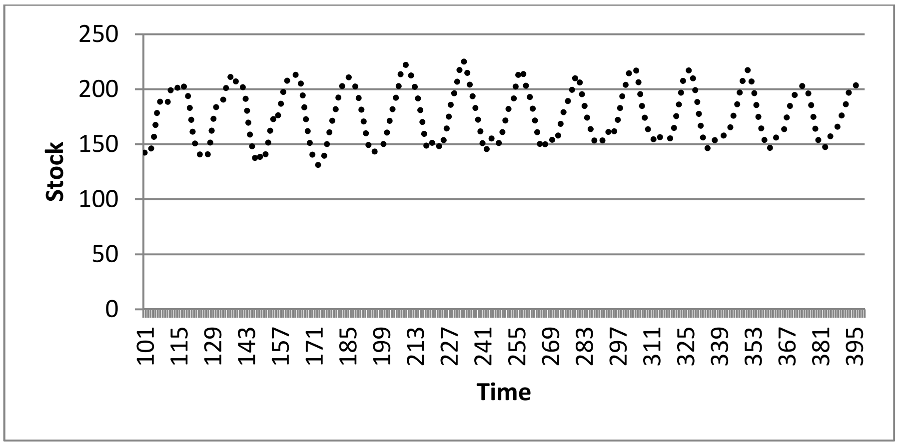


Figure 7-2: Result (Average for 50 Runs) for No Damping for Domestic Current Parts Supply.

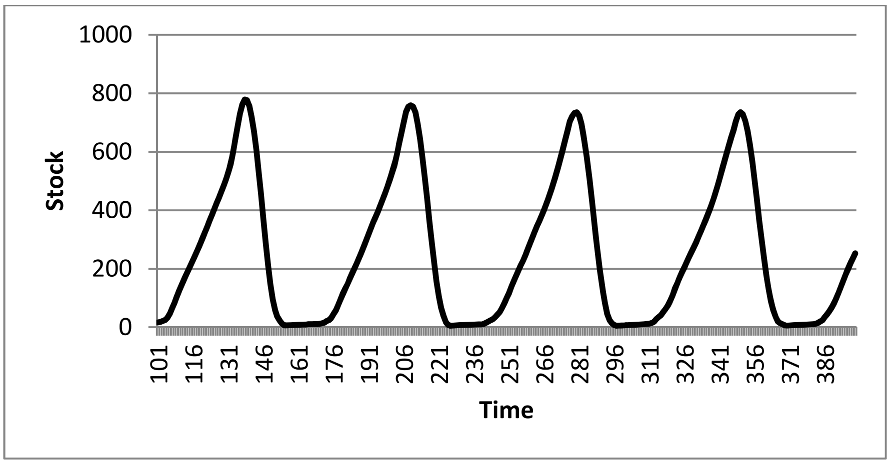


Figure 7-3: Results (Average for 50 Runs) for No Damping for Domestic Past Parts Supply.

The results show clearly that Bhattacharya & Bandyopadhyay (2011) is correct. A simple stock-on-hand policy will clearly result in the bullwhip effect for all three supply chain structures.

Throughout the rest of this section, the analyses of the impact of damping are shown for each of the three supply chain structures. Each result is compared using a scatter plot of inventory against AFR and also summarised in tables.

7.1.1 Damping Analysis – Imported Parts Supply Chain

The results in Figure 7-4 clearly indicates that by adding the damping factor, the significant overreaction characteristic of the bullwhip effect can be reduced. The inventory levels for the imported supply chain are shown over time, with the damping factor set to 1 (D1) (no damping), 15 (D15), 30 (D30) and 63 (D63) (lead time).

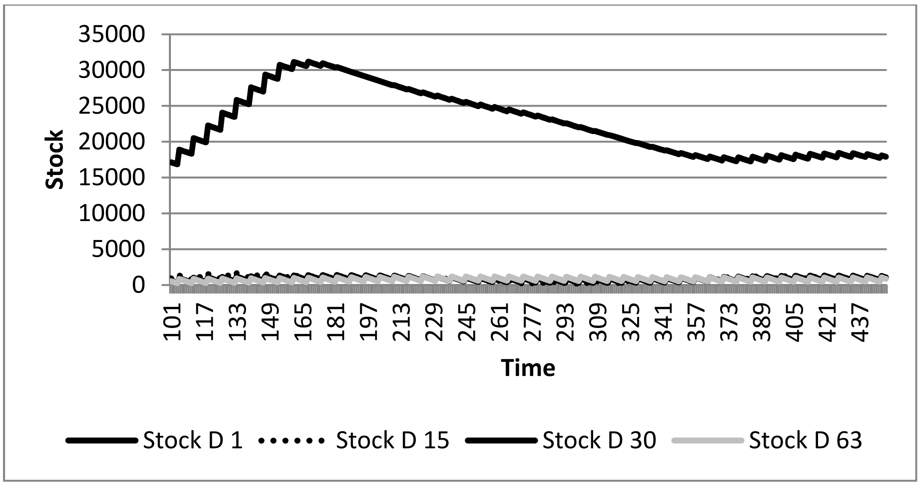


Figure 7-4: Effect of Damping Factor on Inventory for Import Parts Supply Chain.

When the results with no damping is removed, Figure 7-5 clearly shows how the simulation replicates the weekly inventory rundown and replenishment, as well as how increasing the damping factor reduces the overall variance, even with the demand variance introduced as part of the simulation.

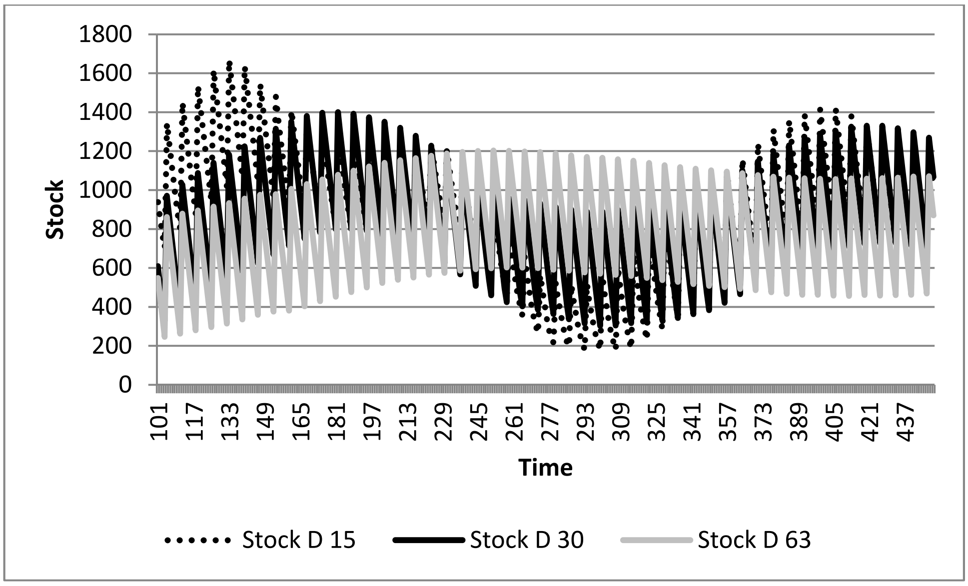


Figure 7-5: Imported Parts Supply Chain Inventory Levels, Excluding D=1.

In Figure 7-6 the impact on AFR and inventory levels is shown. The no damping (D1) situation has a better AFR than the D15 situation, but with significantly higher inventory.

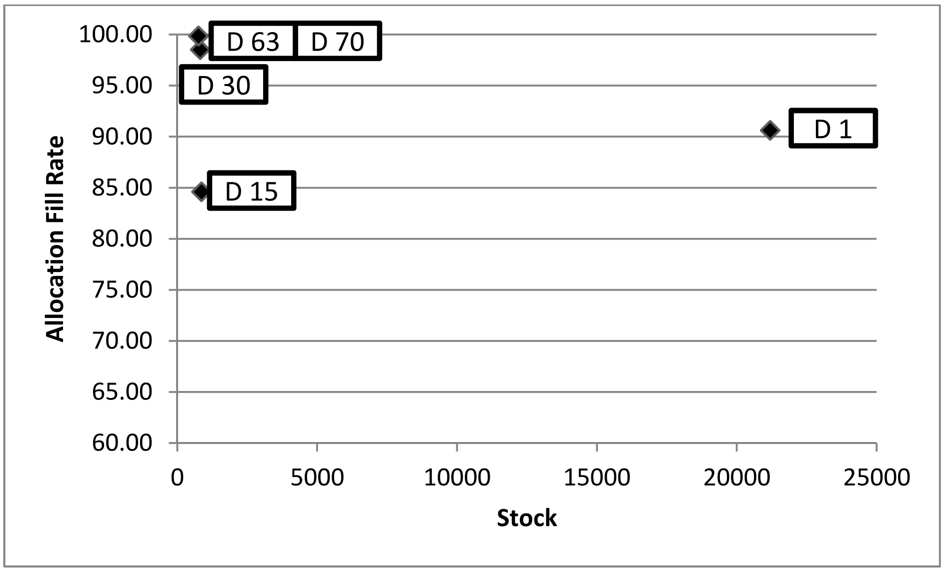


Figure 7-6: AFR versus Inventory Level for Imported Parts Supply Chain.

Once the no damping effect is removed, Figure 7-7 clearly demonstrates how the AFR improves and the inventory level reduces as the damping factor is increased.

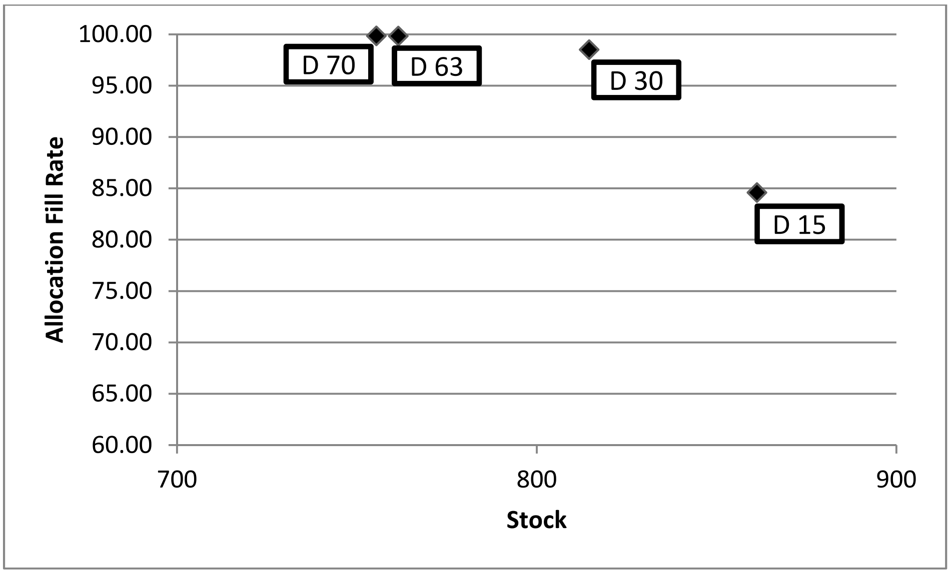


Figure 7-7: AFR versus Inventory Level for Imported Parts Supply With No Damping (D1) Removed.

The results clearly indicate that no damping (D1) results in high inventory, yet the average AFR is only 90.6. With D15 the inventory is significantly lower and the AFR is only 84.6. D30, D63 and D70 all show high AFR at low inventory levels. The results are summarised in Table 7-2.

Table 7-2: Results of Various Damping Factors for the Imported Parts Supply Chain.

Damping Factor	**1 Day**	**15 Days**	**30 Days**	**63 Days (Lead-Time)**	**70 Days (Lead-Time + Shipping Cycle)**
Average AFR	90.6	84.6	98.5	99.9	99.9
Average Inventory	21195	861	815	761	755

Based on the results, the benefit from using the lead time of 63 days provides a good solution for the damping factor for the imported parts supply chain. The addition of using 70 days gives the same AFR result for a saving of only 5 units.

7.1.2 Damping Analysis – Domestic Current Parts Supply Chain

The results in Figure 7-8 clearly show how the bullwhip effect affects inventory levels and how the alternative damping factors reduce the impact.

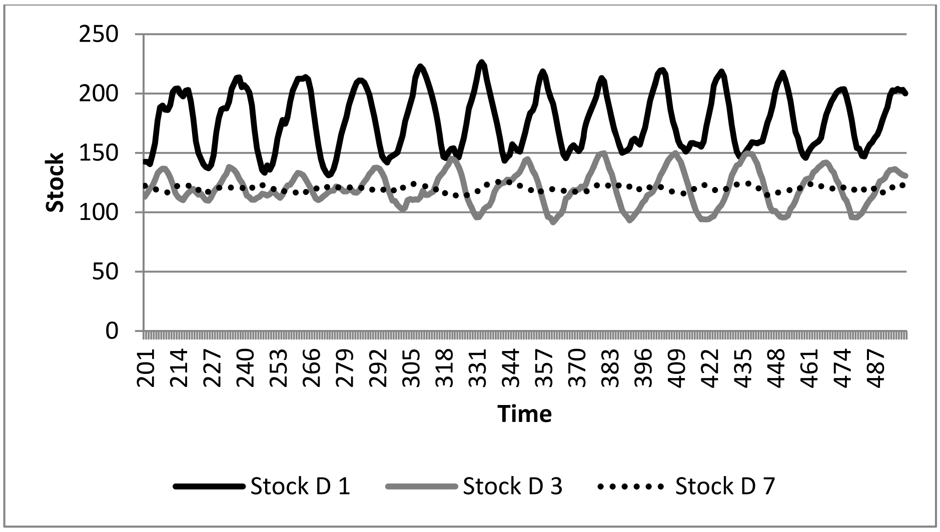


Figure 7-8: Effect of Damping Factor on Inventory for Domestic Current Parts Supply Chain.

Figure 7-9 clearly shows how the average inventory is reduced as the damping increases. The D7 and D3 situation have similar inventory levels, but the D7 case has an AFR equal to 100.

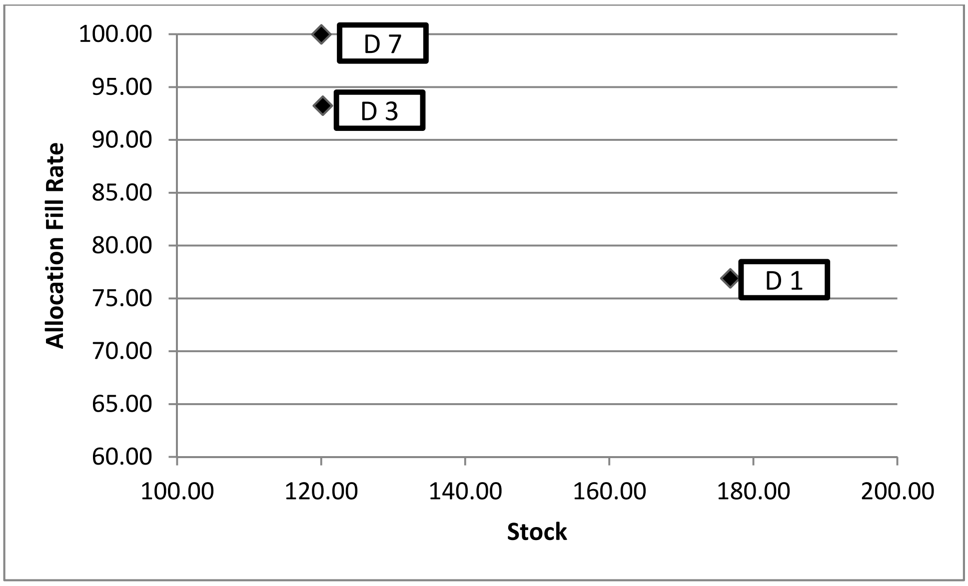


Figure 7-9: AFR versus Inventory for Domestic Current Parts Supply Chain.

Table 7-3 clearly shows the progression of AFR and the reduction in the inventory required to maintain the AFR.

Table 7-3: Results of Various Damping Factors for the Domestic Current Parts Supply Chain.

Damping Factor	**1 Day**	**3 Days**	**7 Days (Lead-Time)**
Average AFR	76.9	93.2	100.0
Average Inventory	177	120	120

Again, the best case is found where the damping factor is equal to the lead time.

7.1.3 Damping Analysis – Domestic Past Parts Supply Chain

The results in Figure 7-10 clearly indicates that by adding the damping factor, the significant overreaction characteristic of the bullwhip effect can be reduced. The increased lead time (28 days versus 7 days for current parts) increases the size of the bullwhip effect as can be seen in the D1 result.

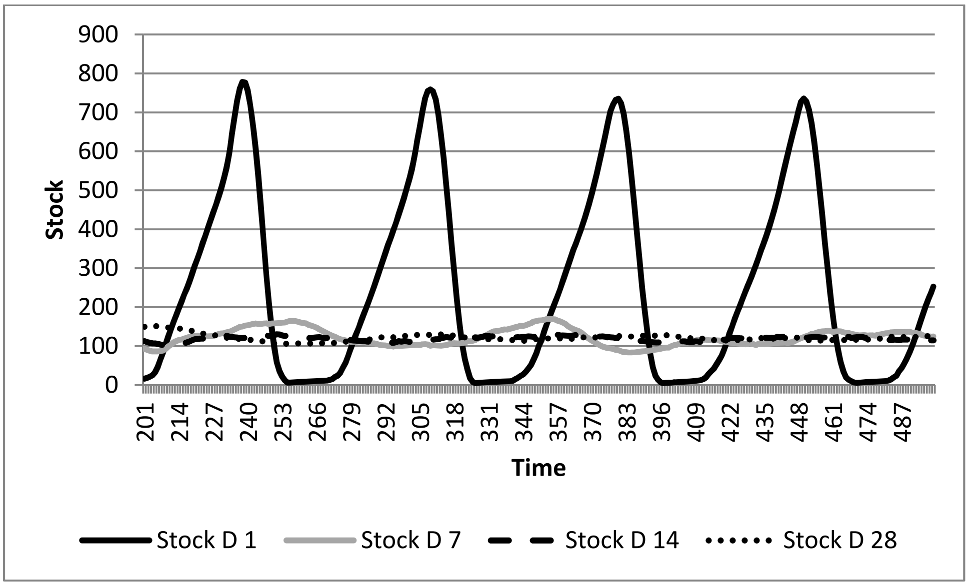


Figure 7-10: Effect of Damping Factor on Inventory for Domestic Past Parts Supply Chain.

Similarly to the imported parts supply chain structure, removing the no damping (D1) results is required to clearly show the damping options. The past model parts supply chain with D1 removed is shown in Figure 7-11. Again, it is clear that as the damping factor is increased towards the lead time, the bullwhip effect is eliminated.

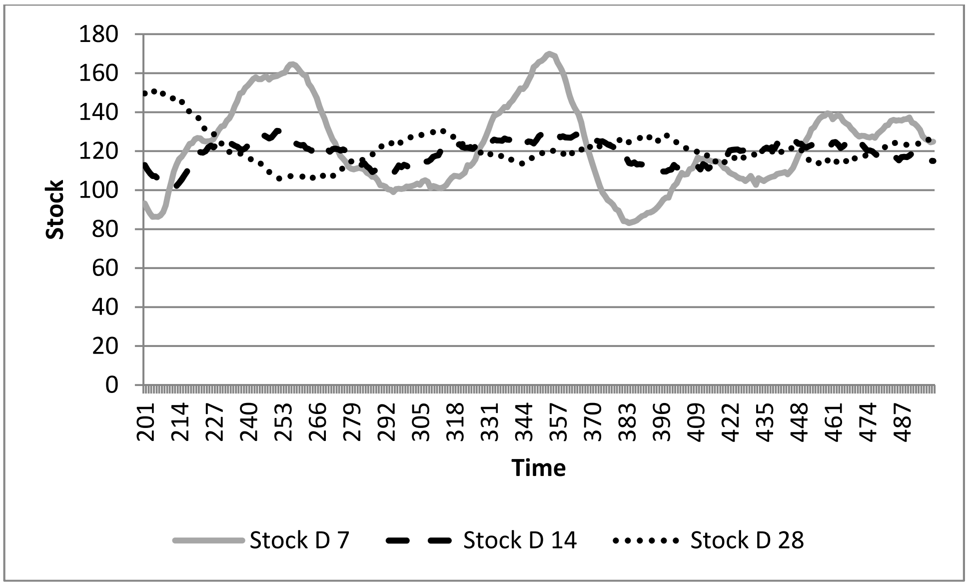


Figure 7-11: Domestic Past Parts Supply Chain Inventory Results, Excluding D=1.

Figure 7-12 shows the AFR versus inventory and it is clear that the situation with no damping requires significantly more inventory, yet does not achieve the same level of supply, measured as AFR.

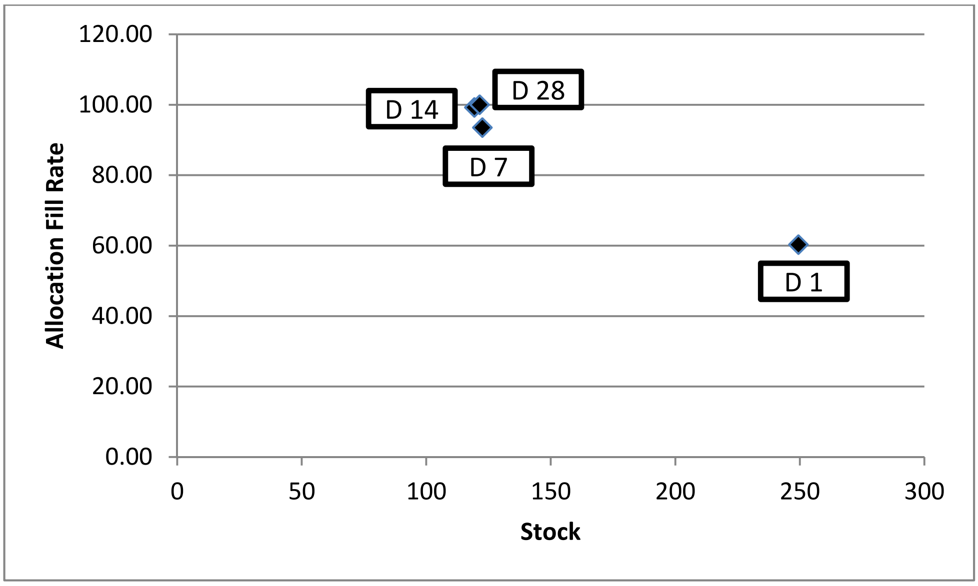


Figure 7-12: AFR versus Inventory for Domestic Past Parts Supply Chain.

When D1 is removed, Figure 7-13 shows that while D14 has the lowest average inventory, D14 does not have the same level of AFR as D21 and D28.

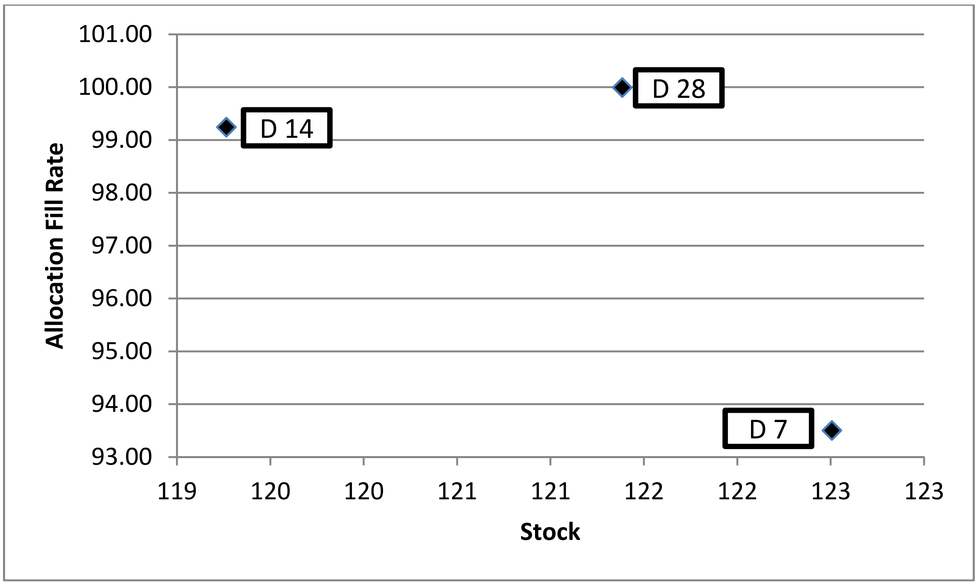


Figure 7-13: AFR versus Inventory for Domestic Past Parts Supply With No Damping (D1) Removed.

Table 7-4 clearly shows the progression of AFR and the reduction in the inventory required to maintain the AFR.

Table 7-4: Results of Various Damping Factors for the Domestic Past Parts Supply Chain.

Damping Factor	1 Day	7 Days	14 Days	28 Days (Lead-Time)
Average AFR	60.3	93.5	99.2	100.0
Average Inventory	249	123	119	121

While using 14 as the damping factor results in lower average inventory, using the lead time of 28 days, gives both a low average inventory and high AFR.

7.1.4 Damping Analysis – Conclusion

The damping analysis highlighted two points that hold for all three supply chain structures:

1. The STS method, while a stock-on-hand policy, can be made stable (avoiding the bullwhip effect) by the introduction of a damping factor.

2. A supply chain characteristic, namely the lead time, can be used effectively as the damping factor.

Any further analysis discussed in this document, using the STS method, uses the appropriate lead time value as the damping factor.

7.2 Simulation Analysis – Theoretical Environment

Following the confirmation of the efficacy of the STS method, further simulation analysis was conducted on all three inventory management methods. The objective of this analysis was threefold:

1. Firstly, a theoretical analysis and comparison between the three inventory management methods was completed, using three theoretical distributions (normal, log-normal and gamma) for demand and lead time. MIP_{Actual} and MIP_{Theory} were compared to show that the adaptation from the theoretical model (Equation 5.33) to the practical model (Equation 5.35) was performed to improve the AFR. It was shown that the unintended consequence of the adaptation was that the inventory levels were increased significantly.
2. Secondly, the three methods (MIP_{Actual}, MIP_{Theory} and STS) were compared to show that the properly damped STS method provides a high level of AFR with lower inventory than the implemented MIP method.
3. Thirdly, the theoretical analysis was concluded by stress testing the STS ordering algorithm to determine if it is possible to reduce inventory further, without reducing the AFR.

The first analysis answers five questions:

1. Does the simulation model work correctly? Logically it is expected that the implemented MIP_{Actual} approach will require more inventory than the MIP_{Theory} approach.
2. Do both methods provide adequate levels of service when applied to parts with different distributions?
3. Does the MIP_{Actual} implementation outperform the MIP_{Theory} implementation for inventory availability?
4. Does the MIP_{Actual} implementation result in significant overstocking?

The second analysis answers the question of whether the STS method provides an improvement over the MIP methods. The third analysis provides insight into the potential for improving the fundamental design of the STS method.

7.2.1 Theoretical Analysis – Scenario Setup

For the theoretical analysis, a scenario with a fast moving part selling 100 pieces per day, every working day of the year, is used. This hypothetical part is analysed in detail using the following approach:

1. The MIP_{Theory} calculation.
2. The MIP_{Actual} calculation.
3. The STS calculation.

The three methods are used to calculate the daily order quantity. In each case the safety stock is calculated using the assumption of a normal distribution. The safety stock for demand and lead time are both set to two standard deviations.

Three sources of parts are analysed for each MIP calculation, namely:

1. Imported Parts Supplier with a lead time of 63 days, daily order processing, but weekly shipment;
2. Local Current Parts Supplier with a lead time of 7 days, daily order processing and daily shipment; and
3. Local Past Model Parts Supplier with a lead time of 28 days, daily order processing and daily shipment

It is assumed that lead time follows a normal distribution as found in the statistical analysis. The lead time for imported parts has a standard deviation of 0, 7 and 14 days. The local suppliers have a lead time variance of 0, 1 and 2 days. Each of these cases was tested for a demand variance of 0, 5 and 10.

For the baseline analysis all distributions were treated as normal distributions. The demand was also subsequently represented as log-normal and gamma distributions. Choy & Cheong (2012) provides a summary of the demand analysis scenarios.

Table 7-5: Scenario Setup for Theoretical Analysis.

<table>
<tr><td colspan="6">Demand = 100 per day</td></tr>
<tr><td rowspan="5">Imported Lead-Time = 63 Days</td><td colspan="2"></td><td colspan="3">Demand Variance</td></tr>
<tr><td></td><td>Days</td><td>0</td><td>5</td><td>10</td></tr>
<tr><td rowspan="3">Lead-Time Variance</td><td>0</td><td></td><td></td><td></td></tr>
<tr><td>7</td><td></td><td></td><td></td></tr>
<tr><td>14</td><td></td><td></td><td></td></tr>
<tr><td rowspan="5">Domestic Current Lead-Time = 7 Days</td><td colspan="2"></td><td colspan="3">Demand Variance</td></tr>
<tr><td></td><td>Days</td><td>0</td><td>5</td><td>10</td></tr>
<tr><td rowspan="3">Lead-Time Variance</td><td>0</td><td></td><td></td><td></td></tr>
<tr><td>1</td><td></td><td></td><td></td></tr>
<tr><td>2</td><td></td><td></td><td></td></tr>
<tr><td rowspan="5">Domestic Past Lead-Time = 28 Days</td><td colspan="2"></td><td colspan="3">Demand Variance</td></tr>
<tr><td></td><td>Days</td><td>0</td><td>5</td><td>10</td></tr>
<tr><td rowspan="3">Lead-Time Variance</td><td>0</td><td></td><td></td><td></td></tr>
<tr><td>1</td><td></td><td></td><td></td></tr>
<tr><td>2</td><td></td><td></td><td></td></tr>
</table>

Please note that the simulation for a demand variance of 0 is identical in all cases. Three distribution functions are used, namely: 1. Normal, 2. Log Normal and 3. Gamma.

7.2.2 Theoretical Analysis - Results

All simulations were set to run for 500 days. The first 100 days' data was ignored, allowing the model to stabilise. Each simulation run was repeated 50 times to obtain a statistically representative dataset. All results were reported as the average of 50 runs. While all variables in the SDSM can be accessed, the focus was on availability of parts (AFR) and average inventory levels. The inventory level is measured at the end of each day and reported. As inventory is not a constant, the average inventory levels will provide an indicator of the amount of inventory that results due to the application of the ordering algorithm. The initial inventory was set to the Maximum Inventory Position or Stock Target at the start of each simulation.

The results for each inventory management method (MIP_{Theory}, MIP_{Actual} and STS), by scenario (normal distribution, log-normal distribution and gamma distribution), for each of the three supply chain structures, are shown.

7.2.2.1 **Simulation Results – MIP_{Theory} Method**

Figure 7-14 shows the results for MIP_{Theory}, in the normally distributed environment of the imported parts supply chain. The results show that for the imported parts supply chain, under a normal distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls. As lead time variance increases, the average inventory increases. With a lead time variance of 7 days, the AFR is below 100 for all cases. It is only at a 14 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

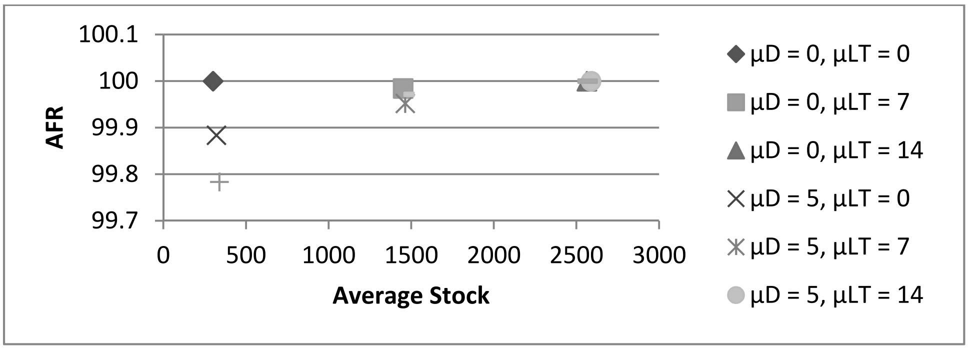


Figure 7-14: Results MIP_{Theory} Normal Distribution - Imported Parts Supply Chain.

Figure 7-15 shows the results for MIP_{Theory}, in the normally distributed environment of the domestic current parts supply chain. The results are similar to that of the imported parts under the same conditions, although the average inventory is significantly lower. The results show that for the domestic current parts supply chain, under a normal distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increase, the AFR falls, although not as much as for the imported parts supply chain. As lead time variance increases, the average inventory increases. With a lead time variance of 1 day, the AFR is below 100 for all cases. It is only at a 2 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

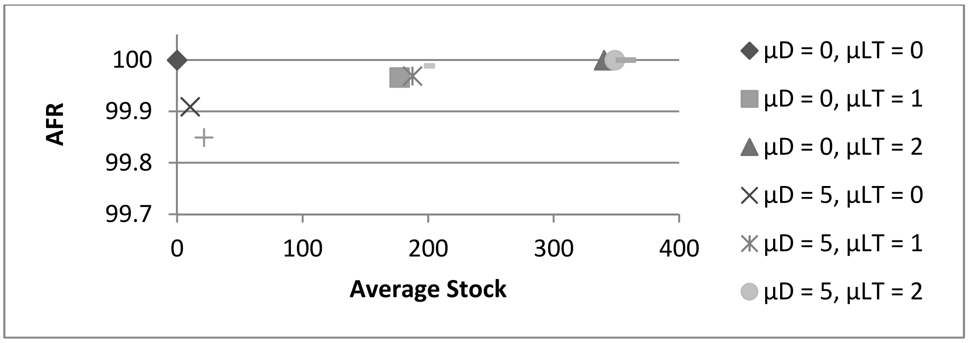


Figure 7-15: Results MIP$_{\text{Theory}}$ Normal Distribution - Domestic Current Parts Supply Chain.

Figure 7-16 shows the results for MIP$_{\text{Theory}}$, in the normally distributed environment of the domestic past parts supply chain. The results are similar to that of the imported and domestic parts under the same conditions, with similar inventory levels when compared to the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a normal distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls, although not as much as for the imported parts supply chain. As lead time variance increases, the average inventory increases. With a lead time variance of 1 day, the AFR is below 100 for all cases. It is only at a 2 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

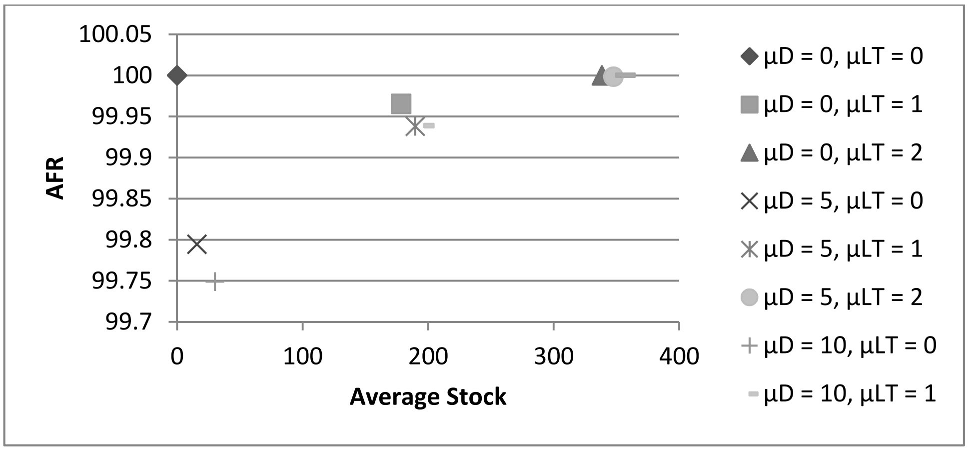


Figure 7-16: Results MIP$_{\text{Theory}}$ Normal Distribution - Domestic Past Parts Supply Chain.

Figure 7-17 shows the results for MIP$_{\text{Theory}}$, in the log-normally distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a log-normal distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increase, the AFR falls. As lead time variance increases, the average inventory increases. With a lead time variance of 7 days, the AFR is below 100 for all cases. It is only at a 14 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

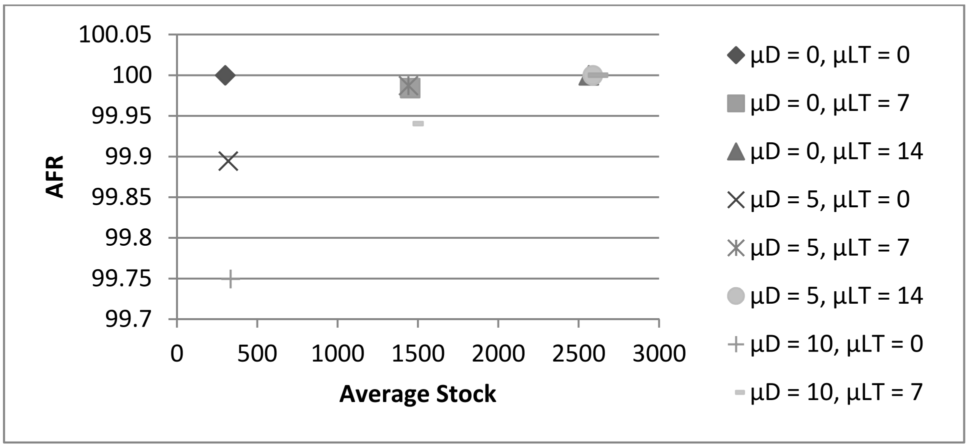


Figure 7-17: Results MIP_{Theory} Log Normal Distribution - Imported Parts Supply Chain.

Figure 7-18 shows the results for MIP_{Theory}, in the log-normally distributed environment for the domestic current parts supply chain. The results are similar to that of the imported parts under the same conditions, although the average inventory is significantly lower. The results show that for the domestic current parts supply chain, under a log-normal distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls, although not as much as for the imported parts supply chain. As lead time variance increases, the average inventory increases. With a lead time variance of 1 day, the AFR is below 100 for all cases. It is only at a 2 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

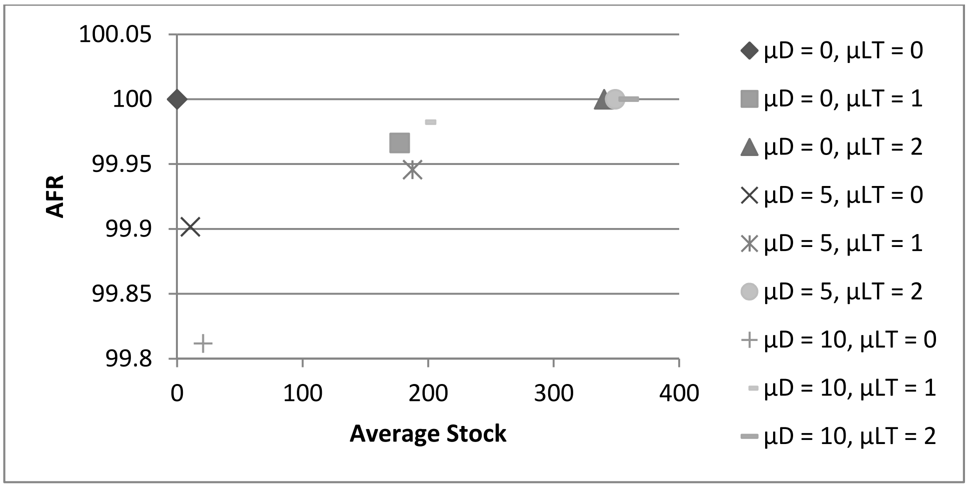


Figure 7-18: Results MIP_{Theory} Log Normal Distribution - Domestic Current Parts Supply Chain.

Figure 7-19 shows the results for MIP_{Theory}, in the log-normally distributed environment for the domestic past parts supply chain. The results are similar to that of the imported and domestic parts under the same conditions, with similar inventory levels to the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a log-normal distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls, although not as much as for the imported parts supply chain. As lead time variance increases, the average inventory increases. With a lead time variance of 1 day, the AFR is below 100 for all cases. It is only at a 2 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

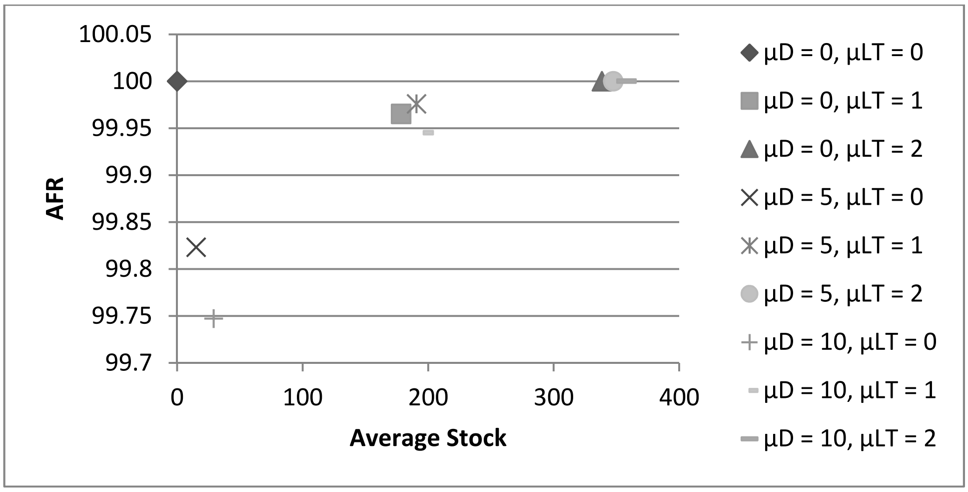


Figure 7-19: Results MIP_{Theory} Log Normal Distribution - Domestic Past Parts Supply Chain.

Figure 7-20 shows the results for MIP_{Theory}, in the gamma distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a gamma distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls. As lead time variance increases, the average inventory increases. With a lead time variance of 7 days, the AFR is below 100 for all cases. It is only at a 14 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

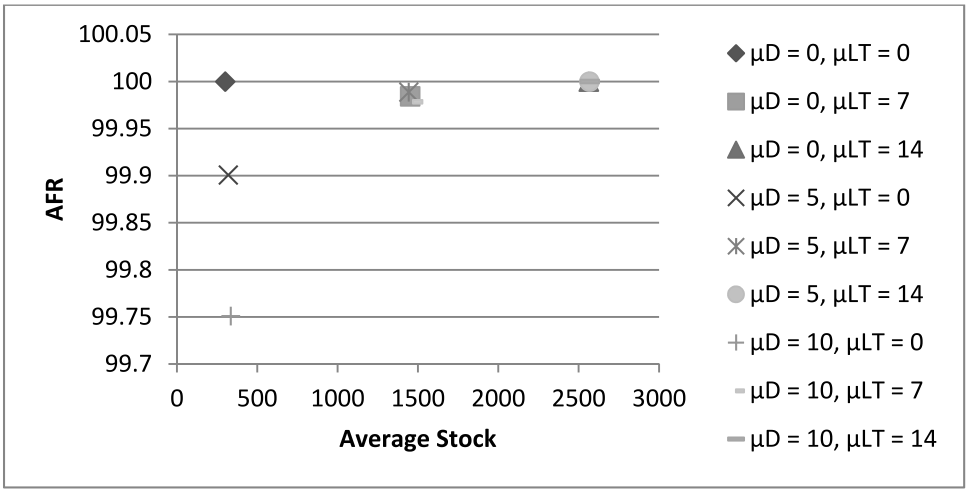


Figure 7-20: Results MIP_{Theory} Gamma Distribution - Imported Parts Supply Chain.

Figure 7-21 shows the results for MIP_{Theory}, in the gamma distributed environment for the domestic current parts supply chain. The results are similar to that of the imported parts under the same conditions, although the average inventory is significantly lower. The results show that for the domestic current parts supply chain, under a gamma distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls, although not as much as for the imported parts supply chain. As lead time variance increases, the average inventory increases. With a lead time variance of 1 day, the AFR is below 100 for all cases. It is only at a 2 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

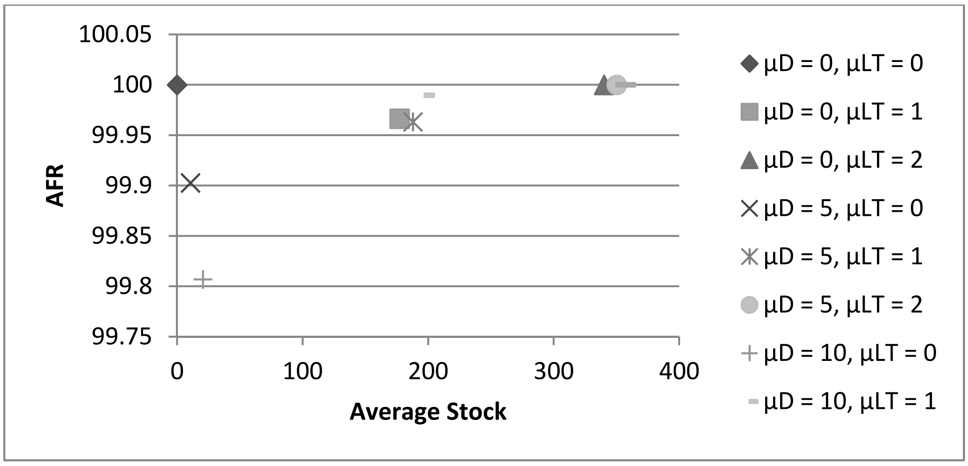


Figure 7-21: Results $\text{MIP}_{\text{Theory}}$ Gamma Distribution - Domestic Current Parts Supply Chain.

Figure 7-22 shows the results for $\text{MIP}_{\text{Theory}}$, in the gamma distribution environment for the domestic past parts supply chain. The results are similar to that of the imported and domestic parts under the same conditions, with similar inventory levels to the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a gamma distribution, the theoretical MIP method is ideal for the zero variance case. As demand variance increases, the AFR falls, although not as much as for the imported parts supply chain. As lead time variance increases, the average inventory increases. With a lead time variance of 1 day, the AFR is below 100 for all cases. It is only at a 2 day lead time variance, that the AFR returns to 100, but with a significant amount of inventory to cover the lead time variance.

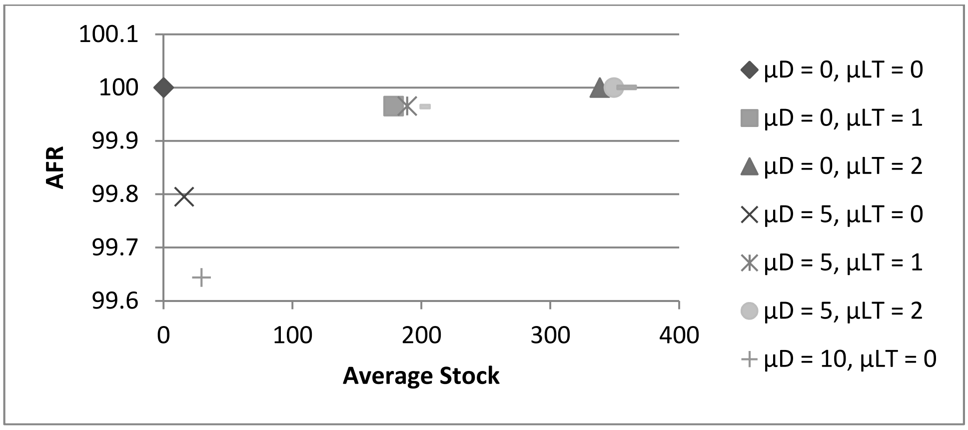


Figure 7-22: Results $\text{MIP}_{\text{Theory}}$ Gamma Distribution - Domestic Past Parts Supply Chain.

The $\text{MIP}_{\text{Theory}}$ inventory management method performed similarly in all cases. While adequate when there was no variance or high lead time variance, the method does not provide an AFR of 100. The lack of 100% availability of inventory, in all likelihood, leads to the adaptations that were made to the basic equation to create the MIP_{Actual} method. The MIP_{Actual} inventory management method is discussed in the next section.

7.2.2.2 **Simulation Results – MIP_{Actual} Method**

In the case of the MIPActual method, similar results are seen for all distributions (normal, log-normal and gamma) and all supply chains (imported, domestic current and domestic past). In each case, the no variance scenario has the lowest inventory level. In all cases an AFR of 100 is obtained, except for the case where $\mu_D = 0$ and $\mu_{LT} = 1\ or\ 7$. The results are shown in Figure 7-23 toFigure 7-31.

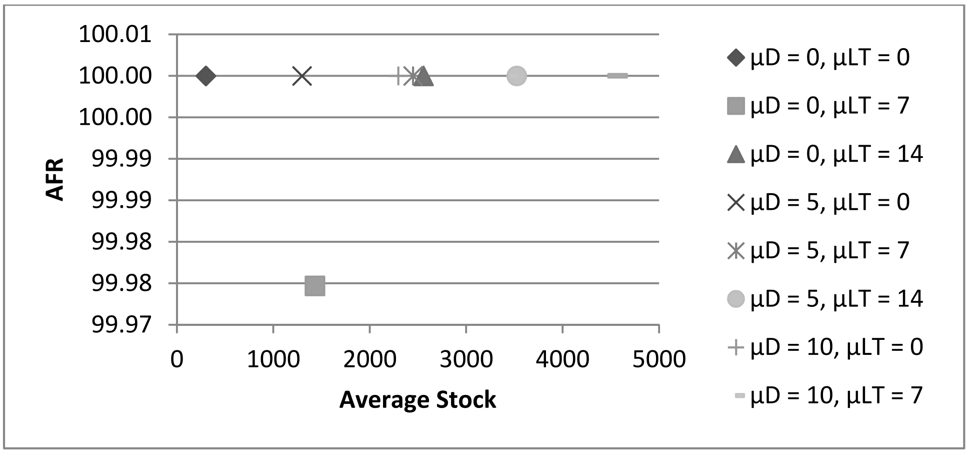


Figure 7-23: Results MIP_{Actual} Normal Distribution - Imported Parts Supply Chain.

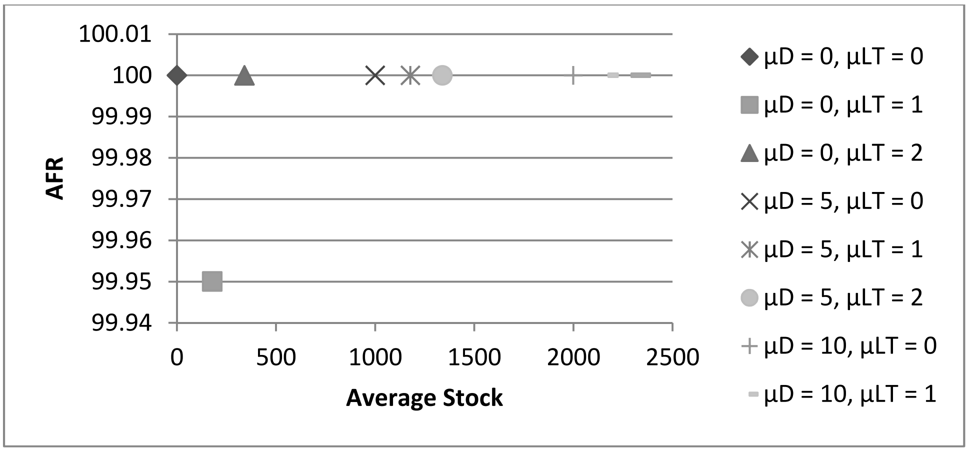


Figure 7-24: Results MIP_{Actual} Normal Distribution - Domestic Current Parts Supply Chain.

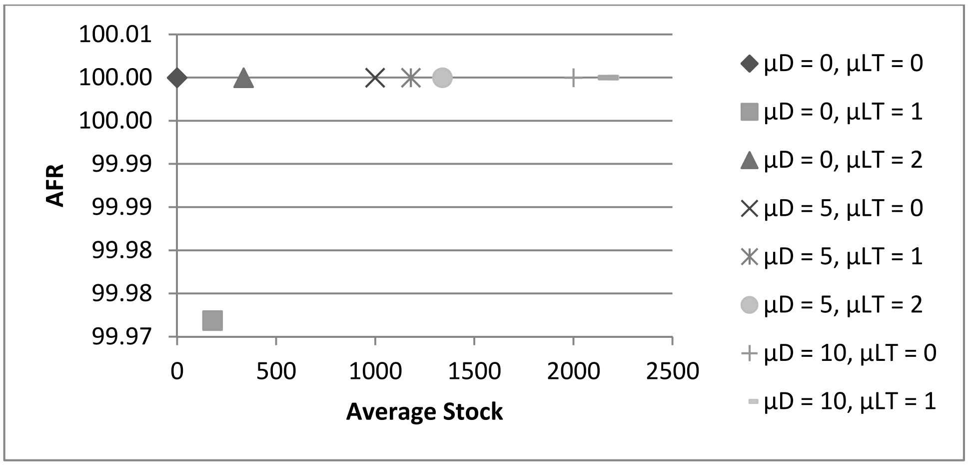


Figure 7-25: Results MIP$_{Actual}$ Normal Distribution - Domestic Past Parts Supply Chain.

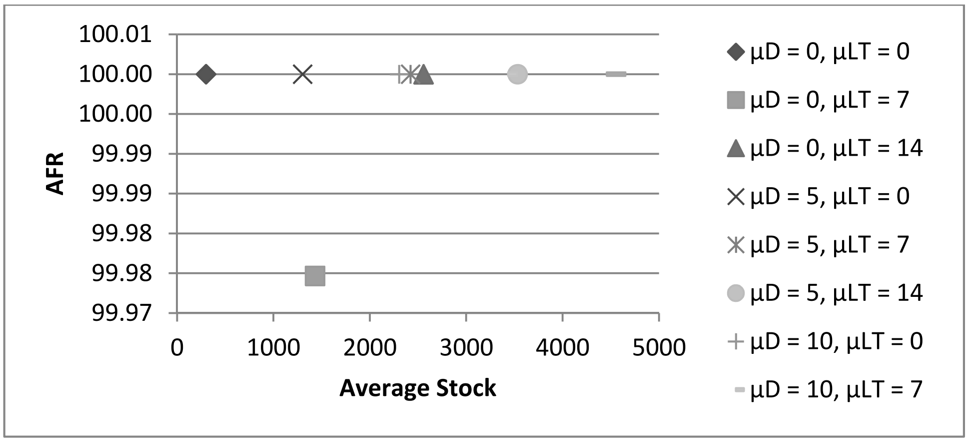


Figure 7-26: Results MIP$_{Actual}$ Log Normal Distribution - Imported Parts Supply Chain.

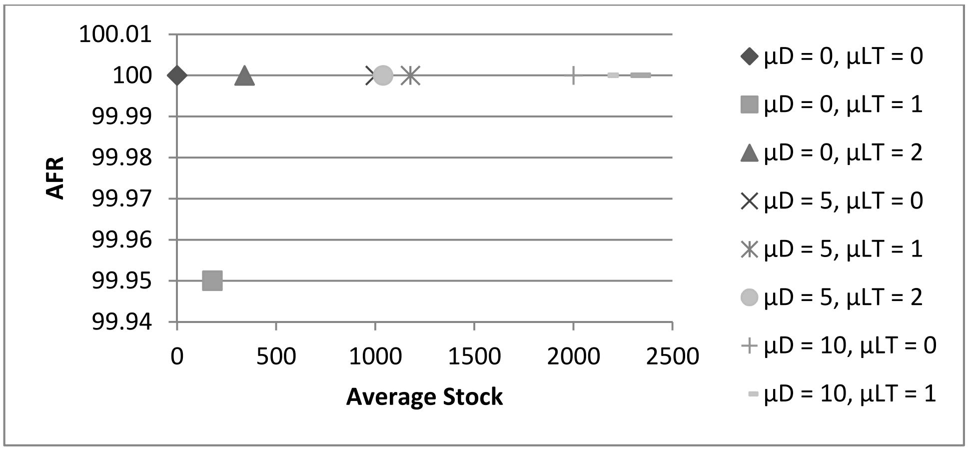


Figure 7-27: Results MIP$_{Actual}$ Log Normal Distribution - Domestic Current Parts Supply Chain.

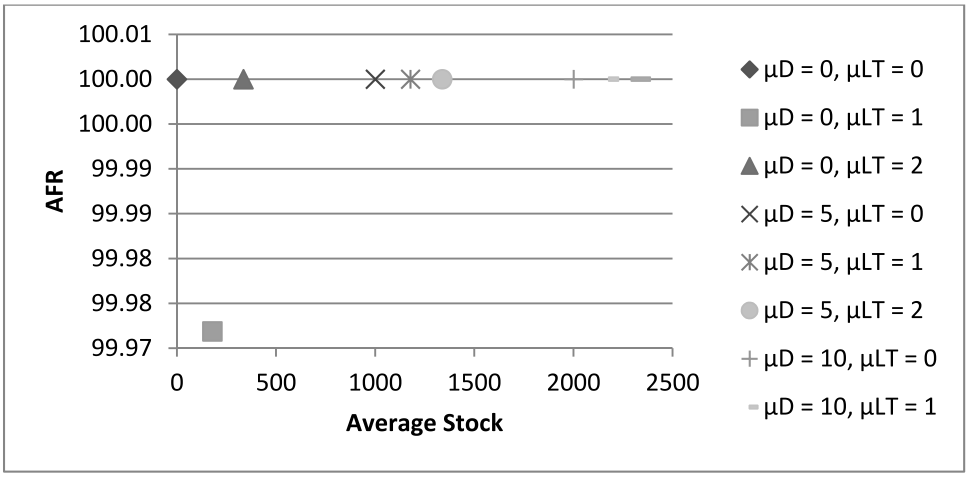


Figure 7-28: Results MIP_{Actual} Log Normal Distribution - Domestic Past Parts Supply Chain.

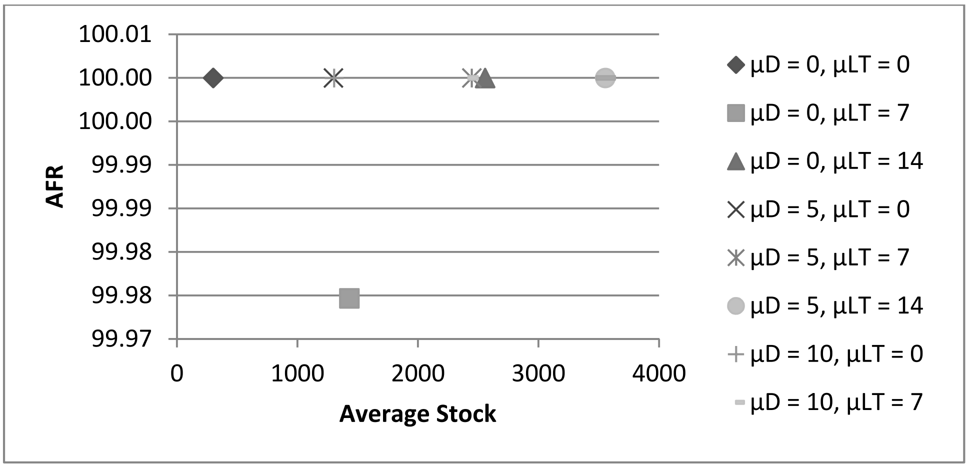


Figure 7-29: Results MIP_{Actual} Gamma Distribution - Imported Parts Supply Chain.

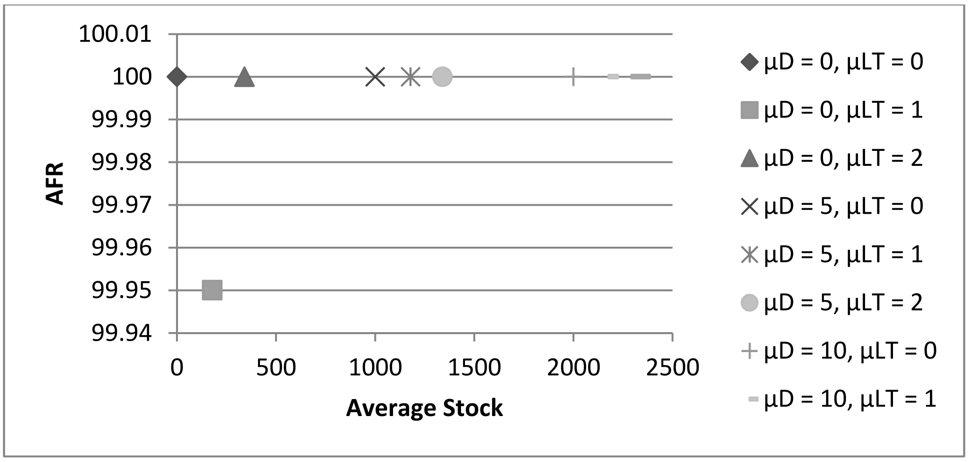


Figure 7-30: Results MIP_{Actual} Gamma Distribution - Domestic Current Parts Supply Chain.

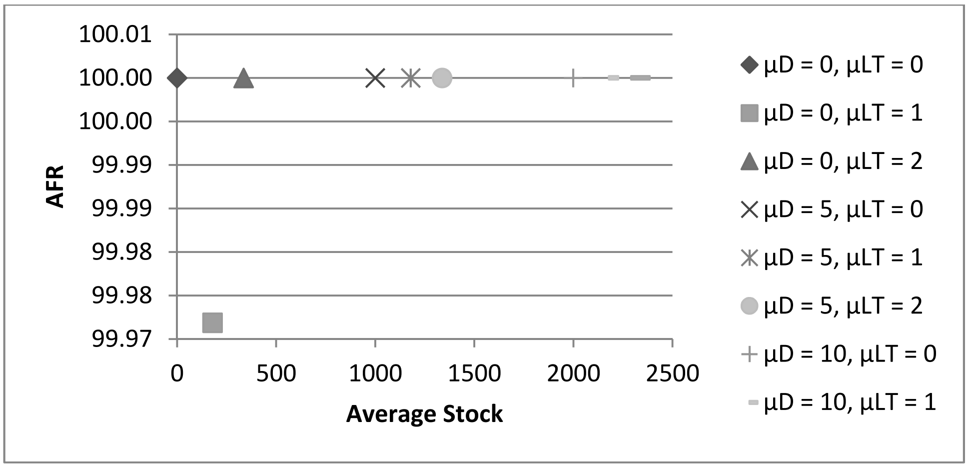


Figure 7-31: Results MIP_{Actual} Gamma Distribution - Domestic Past Parts Supply Chain.

The results for the MIP_{Actual} inventory management method are similar in all cases. Except for the instance with medium lead time variance, all cases have an AFR of 100. This result is an improvement over the MIP_{Theory} method and is explored later.

7.2.2.3 **Simulation Results – STS Method**

Figure 7-32 shows the results for the STS in the normally distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a normal distribution, the STS method is ideal for the zero variance case. With no lead time variance, the AFR is lower than 100. The case with a lead time variance of 7 and a demand variance of 10, the AFR is also less than 100.

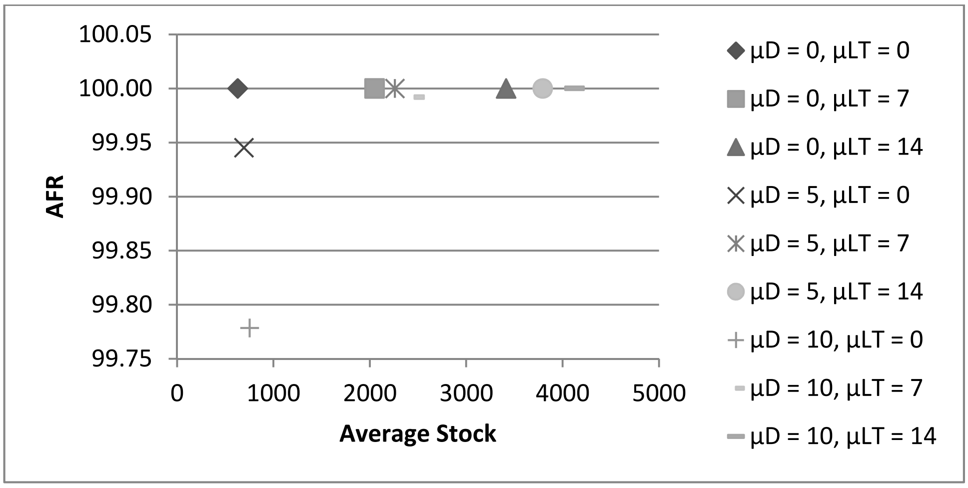


Figure 7-32: Results STS Normal Distribution - Imported Parts Supply Chain.

Figure 7-33 shows the results for the STS in the normally distributed environment for the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a normal distribution, the STS method results in an AFR of 100 for all cases.

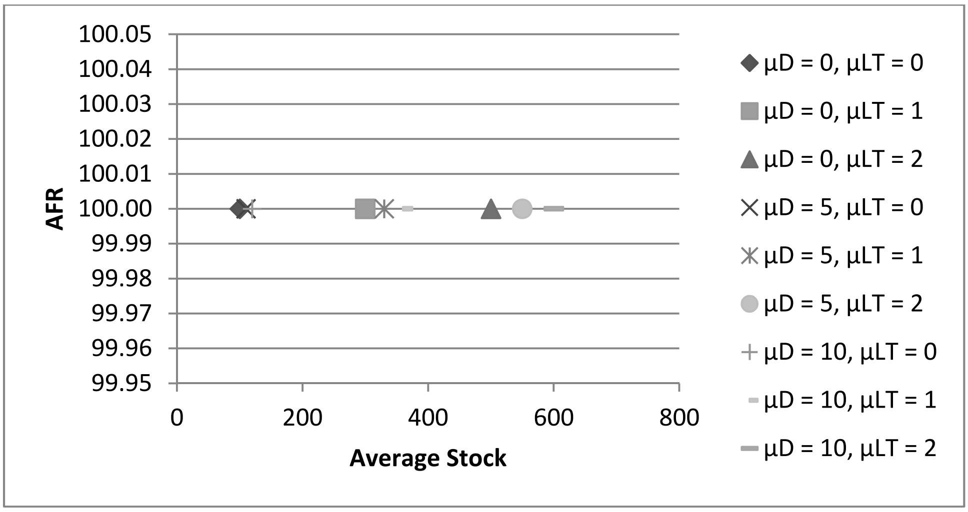


Figure 7-33: Results STS Normal Distribution - Domestic Current Parts Supply Chain.

Figure 7-34 shows the results for the STS in the normally distributed environment for the domestic past supply chain. The results show that for the domestic past parts supply chain, under a normal distribution, the STS method is ideal for the zero variance case. With no lead time variance, the AFR is lower than 100. For the case with a lead time variance of 7 and a demand variance of 10, the AFR is also less than 100.

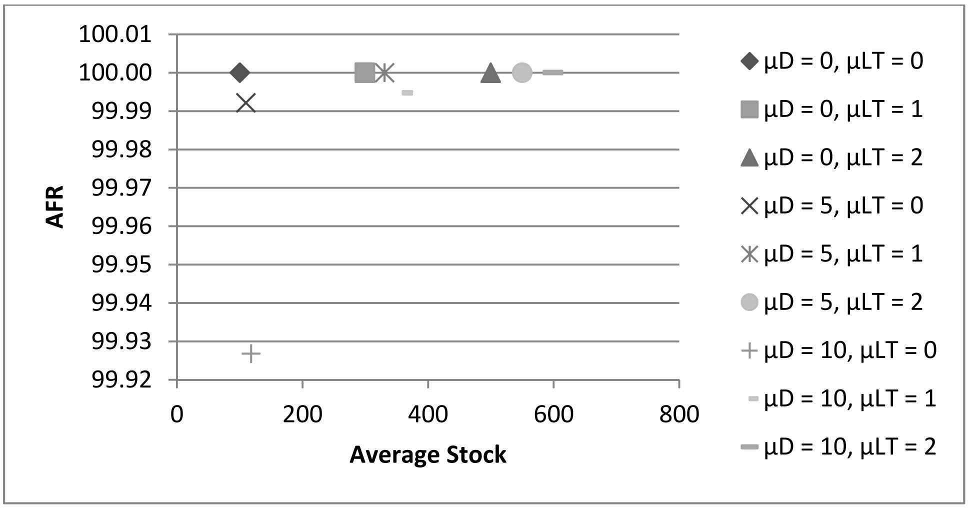


Figure 7-34: Results STS Normal Distribution - Domestic Past Parts Supply Chain.

Figure 7-35 shows the results for the STS in the log-normally distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a log-normal distribution, the STS method is ideal for the zero variance case. With no lead time variance, the AFR is lower than 100. For the case with a lead time variance of 7 and a demand variance of 10, the AFR is also less than 100.

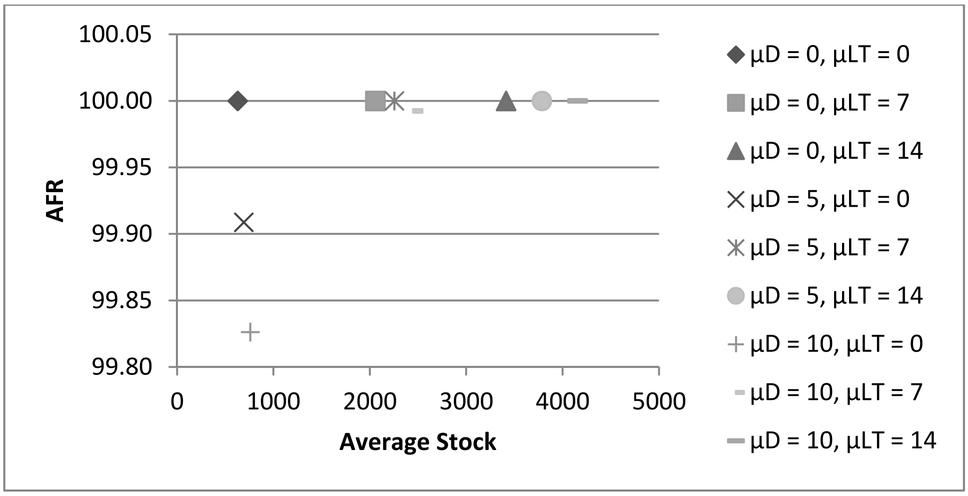


Figure 7-35: Results STS Log Normal Distribution - Imported Parts Supply Chain.

Figure 7-36 shows the results for the STS in the log-normally distributed environment for the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a log-normal distribution, the STS method results in an AFR of 100 for all cases.

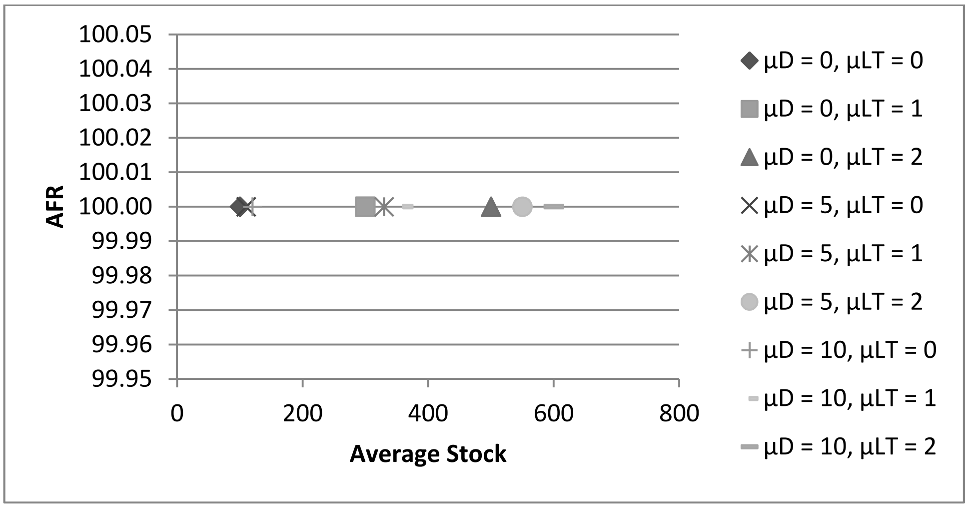


Figure 7-36: Results STS Log Normal Distribution - Domestic Current Parts Supply Chain.

Figure 7-37 shows the results for the STS in the log-normally distributed environment for the domestic past supply chain. The results show that for the domestic past parts supply chain, under a log-normal distribution, the STS method is ideal for the zero variance case. With no lead time variance, the AFR is lower than 100. All other cases show an AFR of 100.

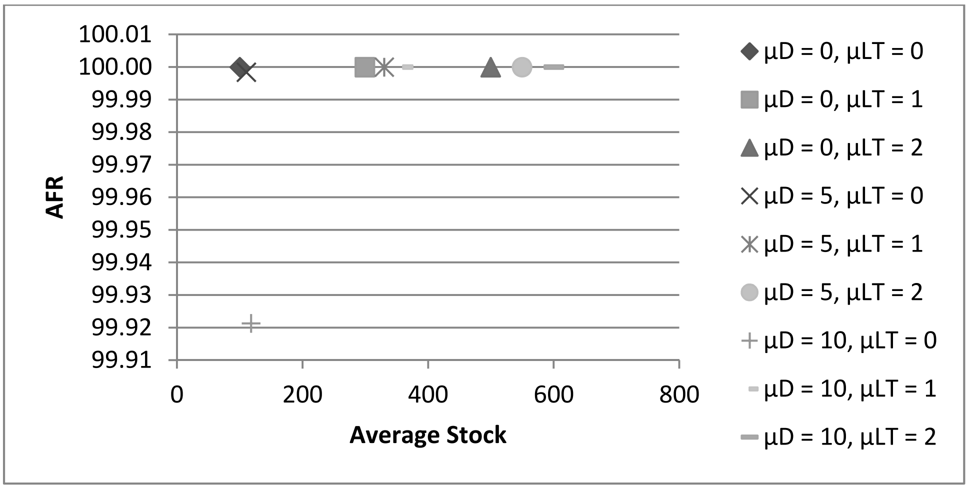


Figure 7-37: Results STS Log Normal Distribution - Domestic Past Parts Supply Chain.

Figure 7-38 shows the results for the STS in the gamma distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a gamma distribution, the STS method is ideal for the zero variance case. With no lead time variance, the AFR is lower than 100. With a lead time variance of 7 and a demand variance of 5 and 10, the AFR is also less than 100. With a lead time variance of 14 and demand variance 10, the AFR is also less than 100.

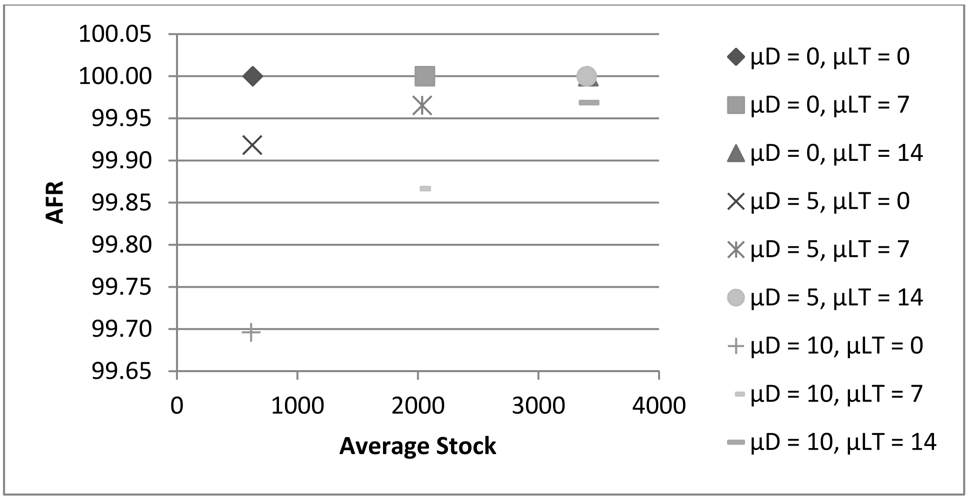


Figure 7-38: Results STS Gamma Distribution - Imported Parts Supply Chain.

Figure 7-39 shows the results for the STS in the gamma distributed environment for the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a gamma distribution, the STS method results in an AFR of 100 for all cases.

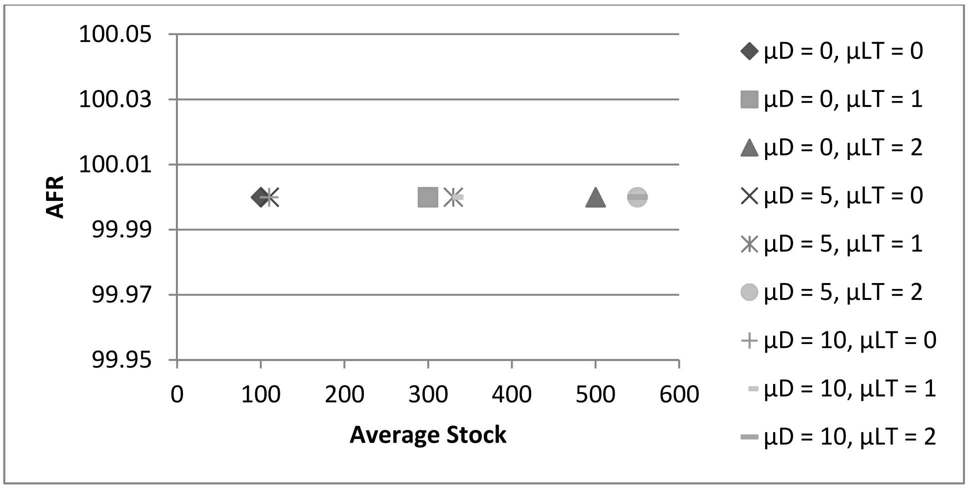


Figure 7-39: Results STS Gamma Distribution - Domestic Current Parts Supply Chain.

Figure 7-40 shows the results for the STS in the gamma distributed environment for the domestic past parts supply chain. The results show that for the domestic past parts supply chain, under a gamma distribution, the STS method is ideal for the zero variance case. With no lead time variance, the AFR is lower than 100. For the case with a lead time variance of 7 and a demand variance of 10, the AFR is also less than 100.

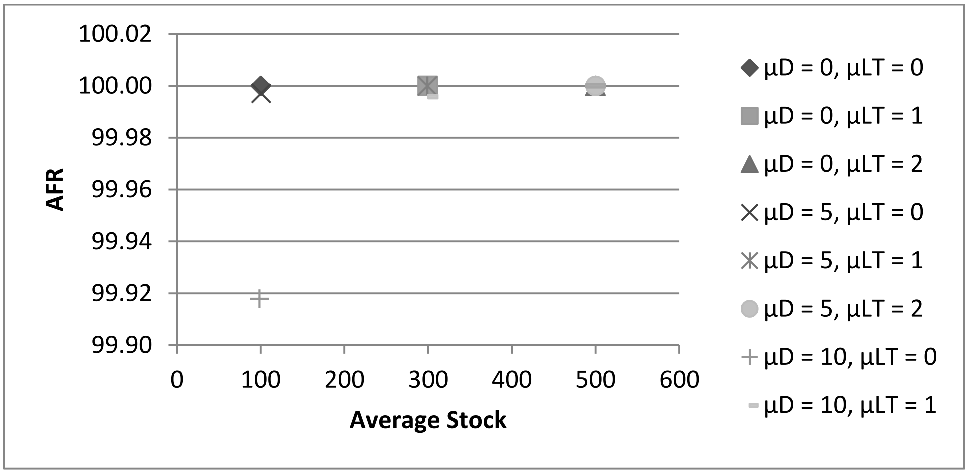


Figure 7-40: Results STS Gamma Distribution - Domestic Past Parts Supply Chain.

The STS inventory management method shows interesting results. For all scenarios, all the cases for the domestic current supply chain results in an AFR of 100. The imported parts supply chain shows the biggest variance from an AFR of 100 and specifically for the gamma distribution. The results indicate that the STS method is a valid solution, with particular benefit to the domestic current supply chain. The method is compared to the two base inventory policies in Section 7.2.2.5.

7.2.2.4 **Comparative Simulation Results – MIP$_{Theory}$ vs. MIP$_{Actual}$**

There is no need to discuss each result individually as the same trend is visible in all cases. For Figure 7-41 to Figure 7-49 the MIP$_{Actual}$ method shows higher AFR values than the MIP$_{Theory}$ method. This result, however, is associated with significantly higher average inventory values in all cases.

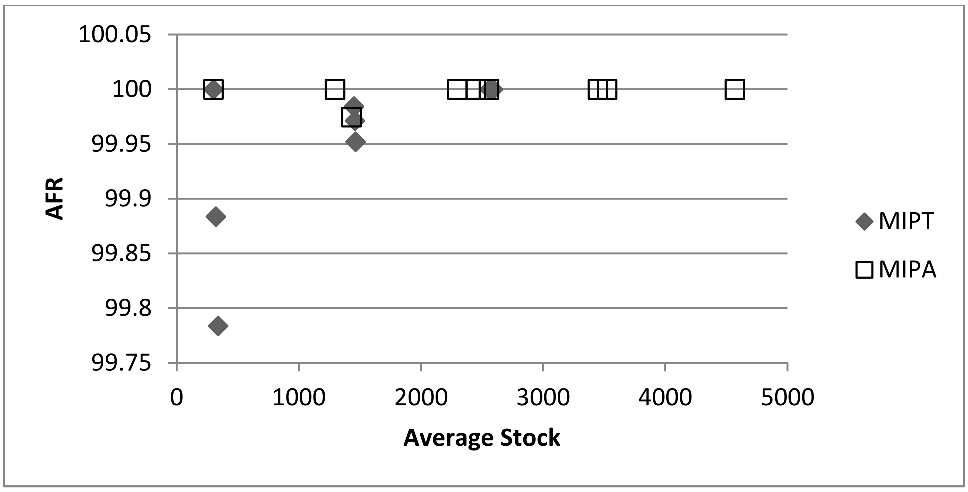


Figure 7-41: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Normal Distribution - Imported Parts Supply Chain.

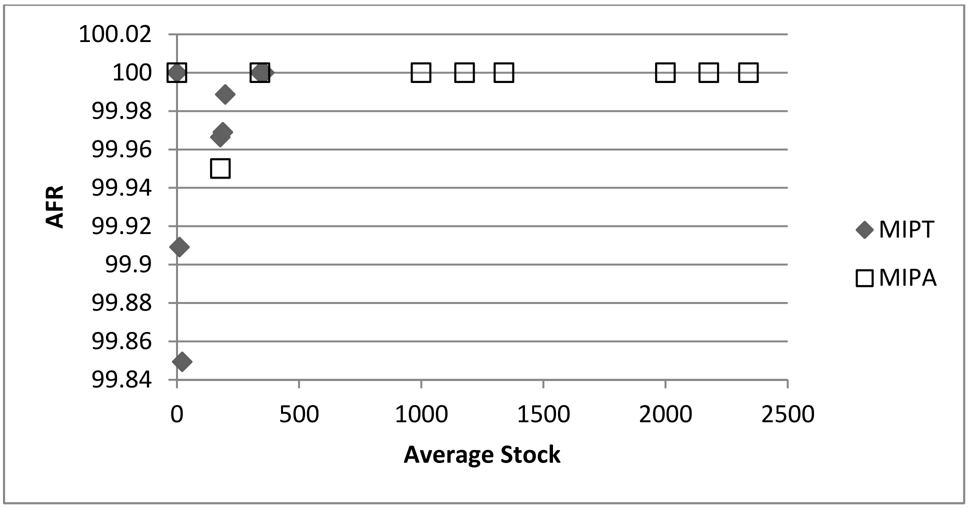


Figure 7-42: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Normal Distribution - Domestic Current Parts Supply Chain.

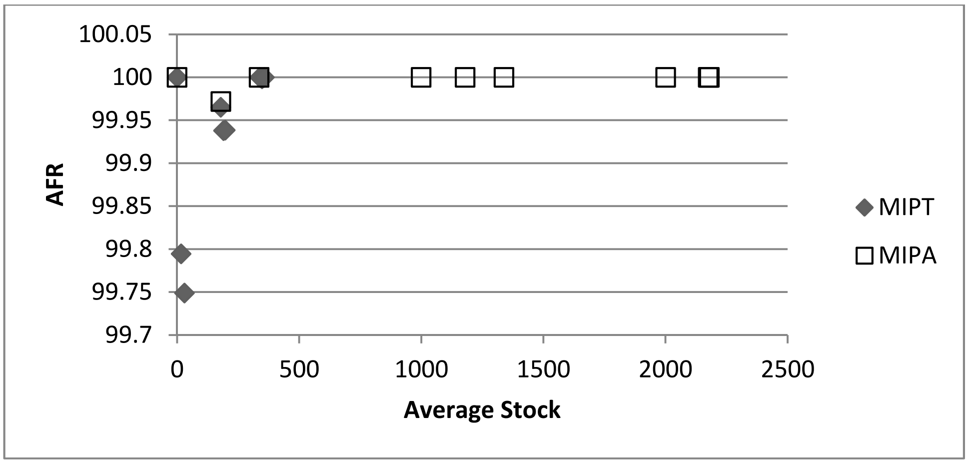


Figure 7-43: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Normal Distribution - Domestic Past Parts Supply Chain.

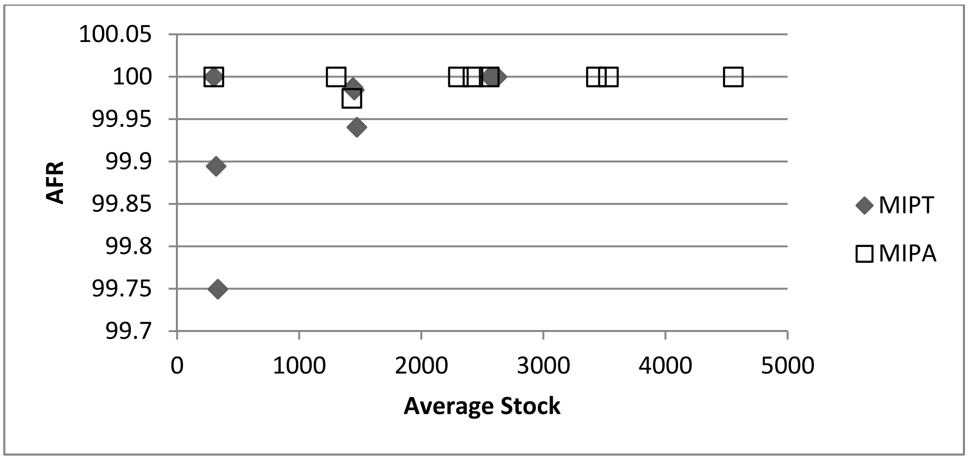


Figure 7-44: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Log Normal Distribution - Imported Parts Supply Chain.

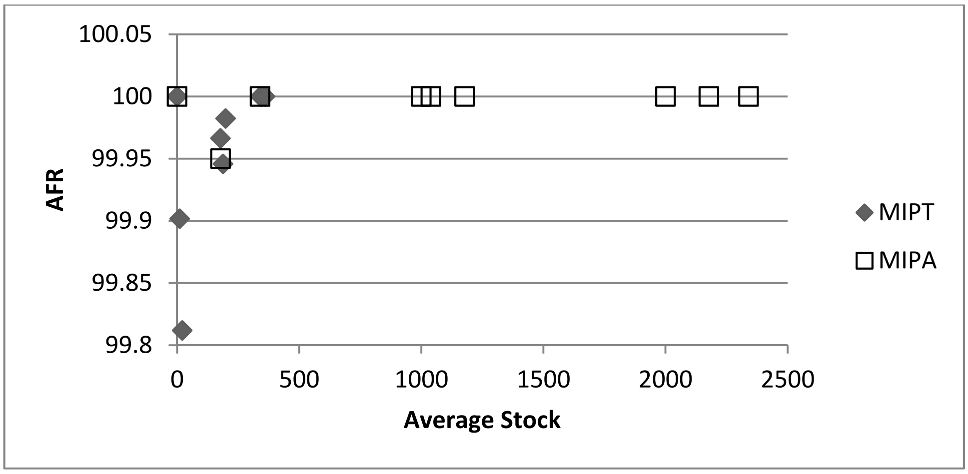


Figure 7-45: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Log Normal Distribution - Domestic Current Parts Supply Chain.

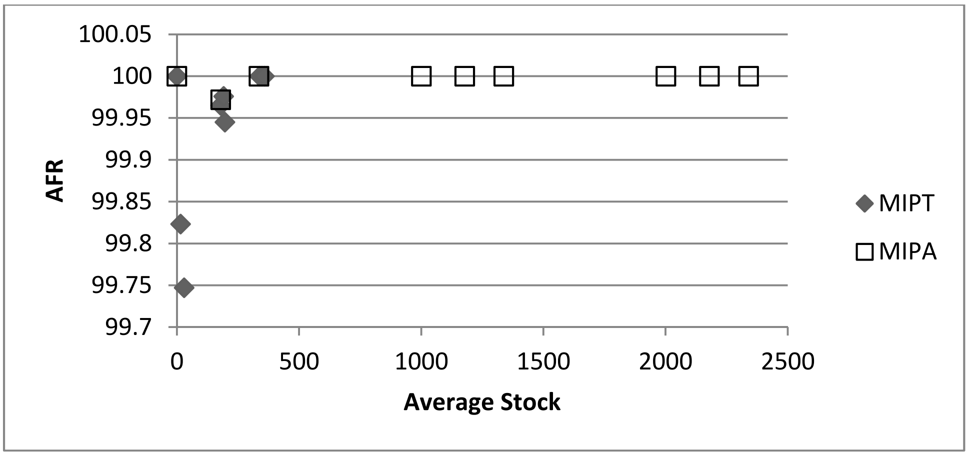


Figure 7-46: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Log Normal Distribution - Domestic Past Parts Supply Chain.

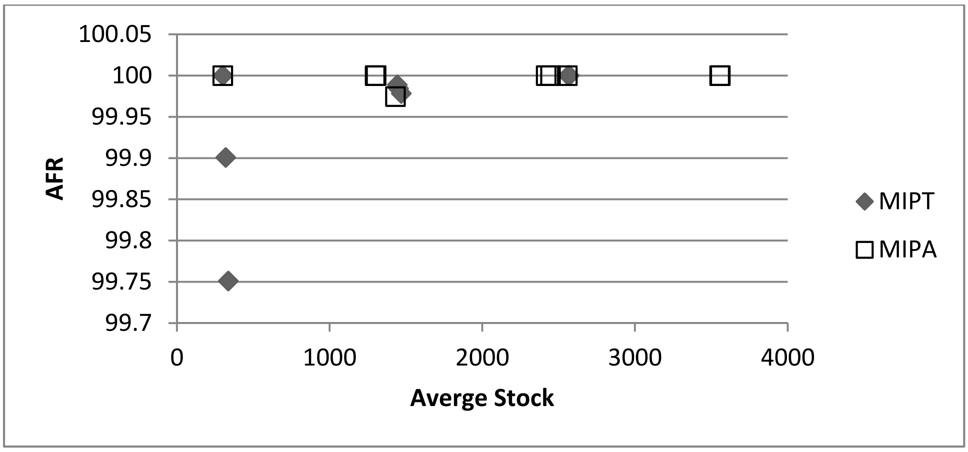


Figure 7-47: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Gamma Distribution - Imported Parts Supply Chain.

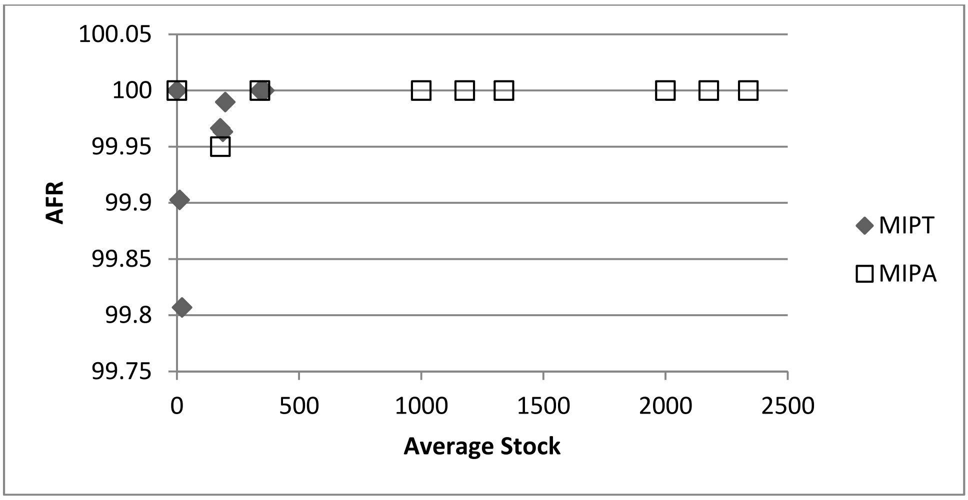


Figure 7-48: Results MIP$_{Theory}$ vs. MIP$_{Actual}$ Gamma Distribution - Domestic Current Parts Supply Chain.

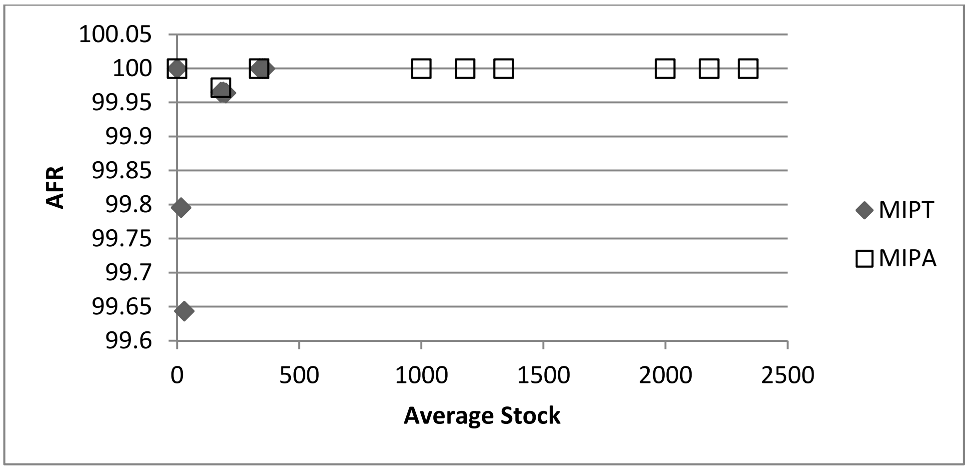


Figure 7-49: Results $\text{MIP}_{\text{Theory}}$ vs. $\text{MIP}_{\text{Actual}}$ Gamma Distribution - Domestic Past Parts Supply Chain.

These results show beyond any doubt that the $\text{MIP}_{\text{Actual}}$ method requires significantly higher average inventory values than the $\text{MIP}_{\text{Theory}}$ method. The reason for its development is also clear as it does bring a significant improvement in the AFR values, achieving 100 in almost all cases.

7.2.2.5 **Comparative Results – $\text{MIP}_{\text{Theory}}$ vs. $\text{MIP}_{\text{Actual}}$ vs. STS**

Figure 7-50 shows the results for the comparison between the $\text{MIP}_{\text{Theory}}$, $\text{MIP}_{\text{Actual}}$ and STS inventory management methods in the normally distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a normal distribution, the $\text{MIP}_{\text{Theory}}$ and $\text{MIP}_{\text{Actual}}$ methods are ideal for the zero variance case. The STS method required more inventory for the same case. As the lead time variance increases, the STS method has a consistently high AFR, with less inventory than the $\text{MIP}_{\text{Actual}}$ method. The $\text{MIP}_{\text{Theory}}$ method requires less inventory, but does not achieve the same level of AFR.

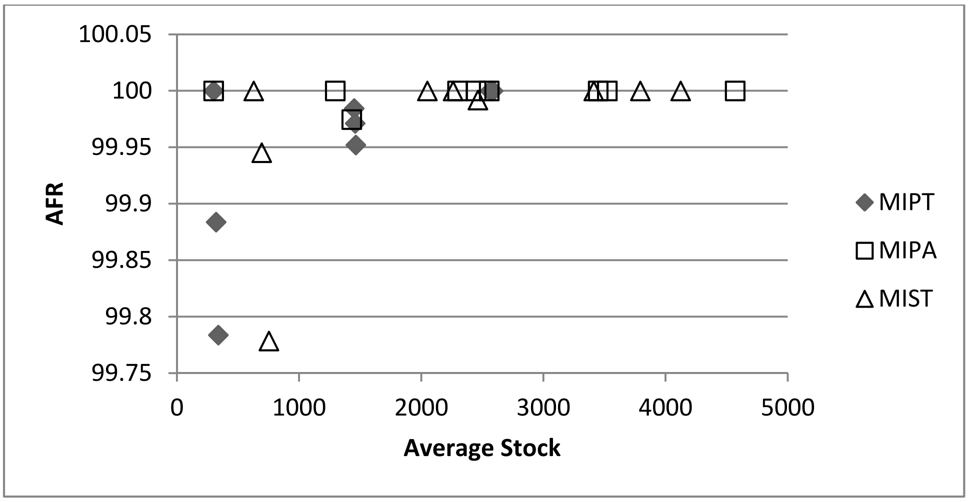


Figure 7-50: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Normal Distribution - Imported Parts Supply Chain.

Figure 7-51 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the normally distributed environment for the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a normal distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. However, the STS method obtained an AFR of 100 for all cases, with less inventory than the MIP_{Actual} method. The AFR results for the STS method are higher than the results of the MIP_{Theory} method.

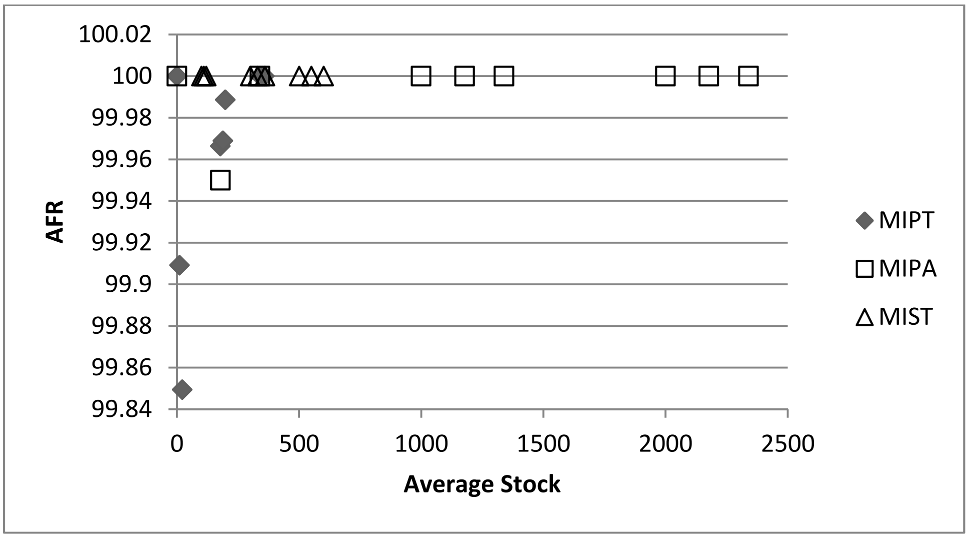


Figure 7-51: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Normal Distribution - Domestic Current Parts Supply Chain.

Figure 7-52 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the normally distributed environment for the domestic past parts supply chain. The results show that for the domestic past parts supply chain, under a normal distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. However, the STS method results in an AFR of 100 for all cases, with less inventory than the MIP_{Actual} method. The AFR results for the STS method are higher than the results for the MIP_{Theory} method

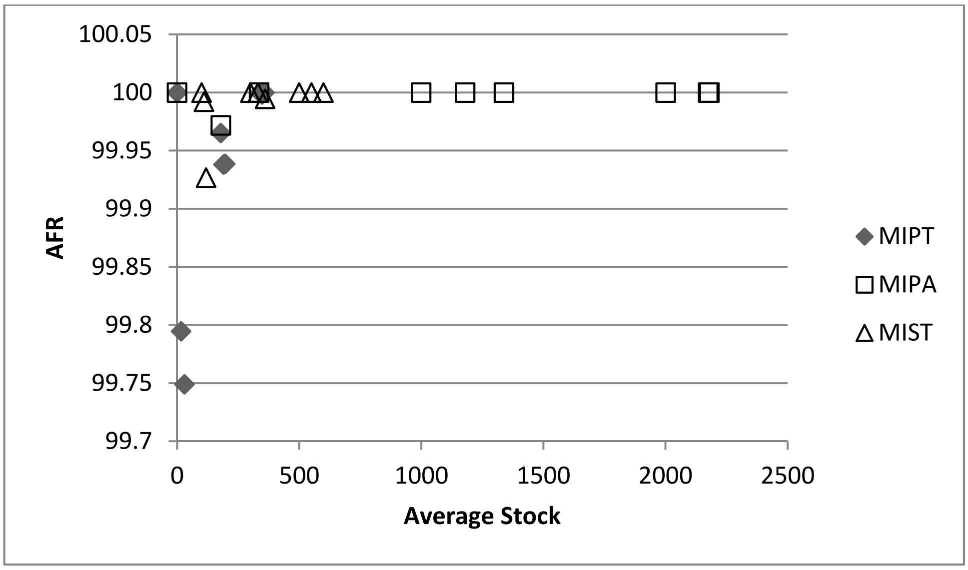


Figure 7-52: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Normal Distribution - Domestic Past Parts Supply Chain.

Figure 7-53 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the log-normally distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a log-normal distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. As the lead time variance increases, the STS method has a consistently high AFR, with less inventory than the MIP_{Actual} method. The MIP_{Theory} method requires less inventory, but does not achieve the same level of AFR.

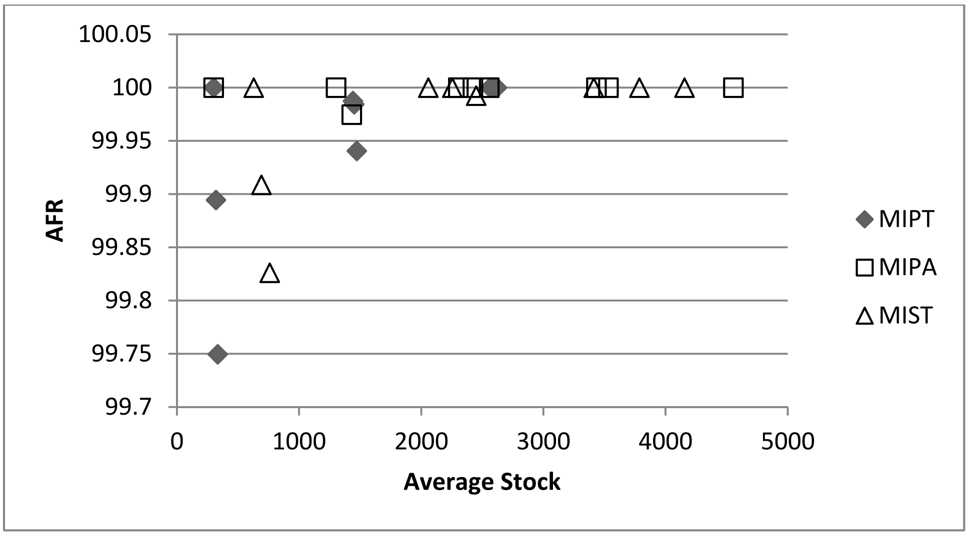


Figure 7-53: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Log Normal Distribution - Imported Parts Supply Chain.

Figure 7-54 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the log-normally distributed environment for the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a log-normal distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. However, the STS method results in an AFR of 100 for all cases, with less inventory than the MIP_{Actual} method. The AFR results for the STS method are higher than the results for the MIP_{Theory} method.

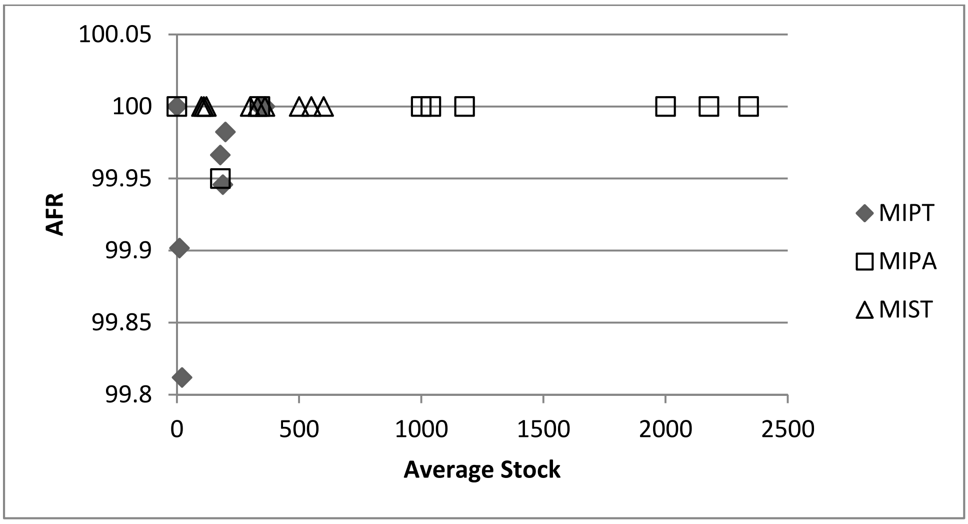


Figure 7-54: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Log Normal Distribution - Domestic Current Parts Supply Chain.

Figure 7-55 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the log-normally distributed environment for the domestic past parts supply chain. The results show that for the domestic past parts supply chain, under a log-normal distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. However, the STS method results in an AFR of 100 for all cases, with less inventory than the MIP_{Actual} method. The AFR results for the STS method are higher than the results for the MIP_{Theory} method.

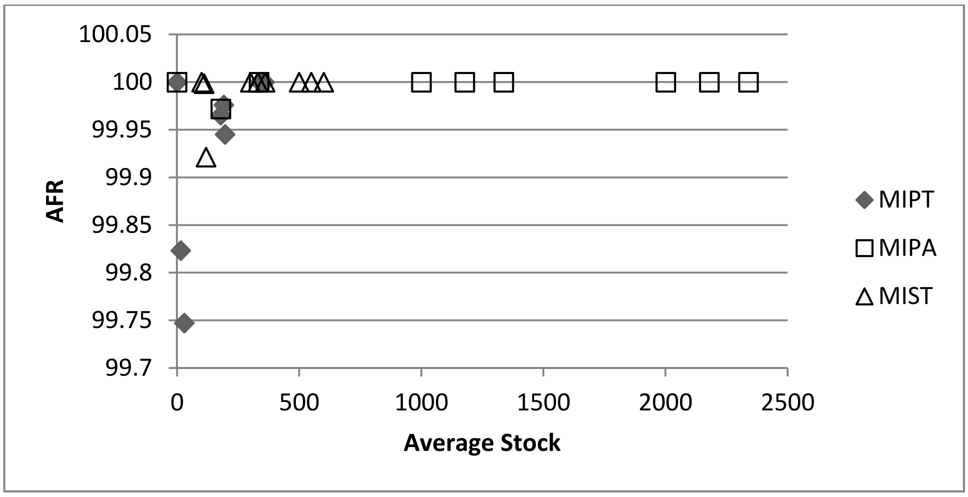


Figure 7-55: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Log Normal Distribution - Domestic Past Parts Supply Chain.

Figure 7-56 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the gamma distributed environment for the imported parts supply chain. The results show that for the imported parts supply chain, under a gamma distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. As the lead time variance increases, the STS method has a consistently high AFR, with less inventory than the MIP_{Actual} method. The MIP_{Theory} method requires less inventory, but does not achieve the same level of AFR.

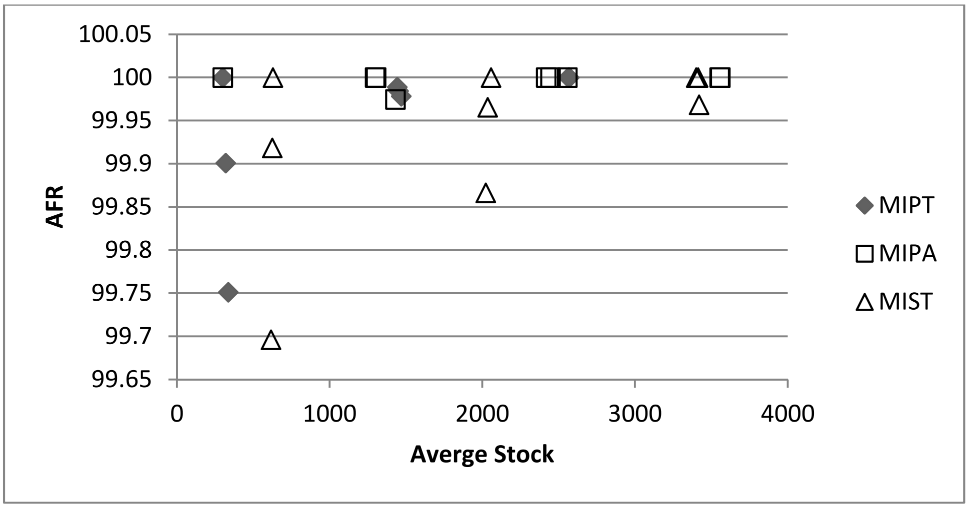


Figure 7-56: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Gamma Distribution - Imported Parts Supply Chain.

Figure 7-57 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the gamma distributed environment for the domestic current parts supply chain. The results show that for the domestic current parts supply chain, under a gamma distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. However, the STS method results in an AFR of 100 for all cases, with less inventory than the MIP_{Actual} method. The AFR results for the STS method are higher than the results for the MIP_{Theory} method.

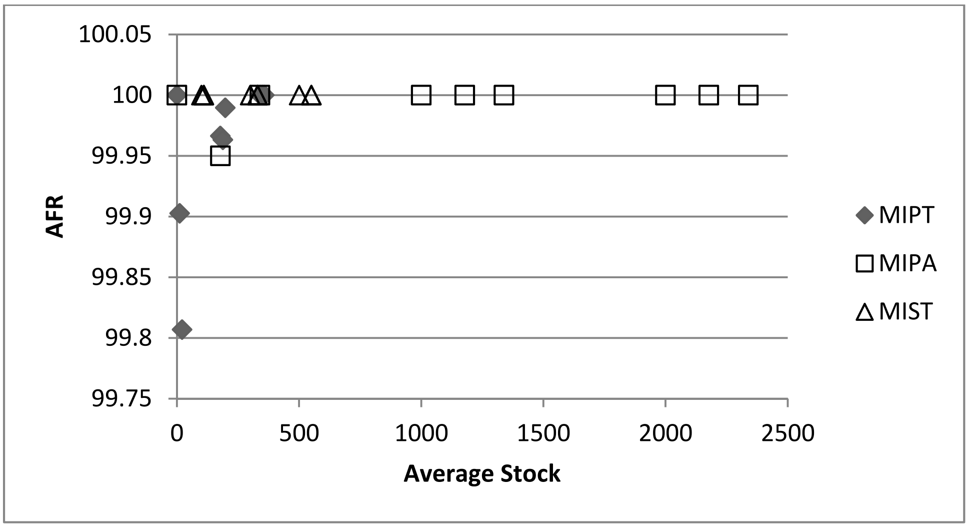


Figure 7-57: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Gamma Distribution - Domestic Current Parts Supply Chain.

Figure 7-58 shows the results for the comparison between the MIP_{Theory}, MIP_{Actual} and STS inventory management methods in the gamma distributed environment for the domestic past parts supply chain. The results show that for the domestic past parts supply chain, under a gamma distribution, the MIP_{Theory} and MIP_{Actual} methods are ideal for the zero variance case. The STS method required more inventory for the same case. However, the STS method results in an AFR of 100 for all cases, with less inventory than the MIP_{Actual} method. The AFR results for the STS method are higher than the results for the MIP_{Theory} method.

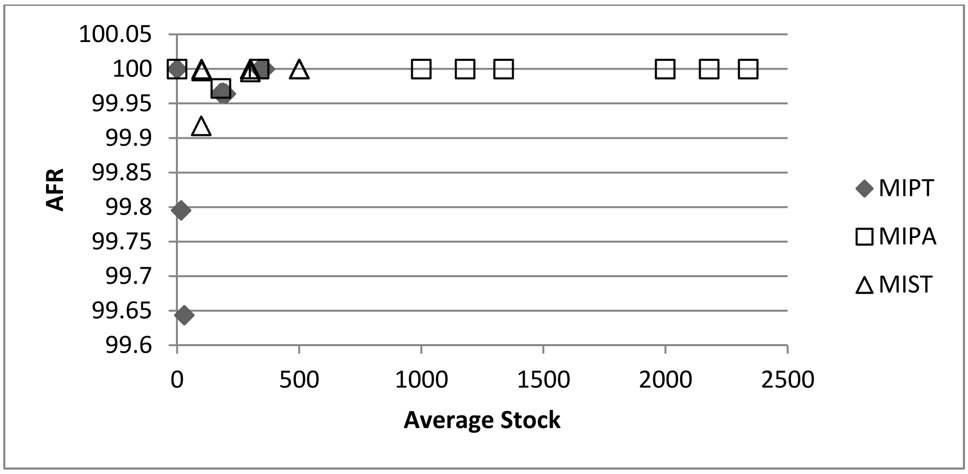


Figure 7-58: Results MIP_{Theory} vs. MIP_{Actual} vs. STS Gamma Distribution - Domestic Past Parts Supply Chain.

The STS method's performance lies in between the MIP_{Theory} and MIP_{Actual} in terms of AFR and average inventory. It is interesting to note that the best performance shown by the STS method is the domestic current and past cases. These are the supply chain structures that most closely represent the Just In Time case, with daily deliveries.

7.2.3 Sensitivity Analysis – STS Inventory Management Method

The difference between the MIP_{Theory} and MIP_{Actual} methods is driven by the need for effective management of the supply chain. Given that the automotive parts supply chain is based on the Guaranteed Service model, the concerns with lower than required AFR levels, led to the adaptation that resulted in the MIP_{Actual} inventory management model. The unintended consequence of high inventory levels is considered a cost of operating at the required service level. The STS method results in high AFR, but also increases the inventory required over the MIP_{Theory} method, but not as high as that of the MIP_{Actual} model, suggesting that as-is, it is an improvement.

However, given space constraints, reducing the inventory further would be highly advantageous. The difference in average inventory between MIP_{Theory} and the STS methods is the fact that the base inventory approach to inventory management does not consider the inventory location. It allows the daily inventory to run down to zero at the end of the day when the data sampling takes place. As long as the inventory arrives in time for the next day, there is no problem with running the inventory down. In contrast, the STS method aims to have at least the target inventory amount in stock at the end of each day. To optimise the inventory target that the STS method uses, two approaches are investigated, namely:

1. Analysis of the stock target equation structure. This analysis addresses the assumptions within the equation, for example reducing the adjustment for demand variance etc. This analysis is applicable to all the supply chain structures.
2. Analysis of the impact of the delivery cycle on the stock target. The question is if there is a need to adjust for the full week at the end of the week, or if the target can be adjusted dynamically.

The two different experimental setups are discussed and the results provided and discussed below. Each set of experiments is tested using the testing environment scenarios (Normal Distribution, Log Normal Distribution and Gamma Distribution) for each supply chain structure (Imported, Domestic Current and Domestic Past).

7.2.3.1 **Stock Target Equation Structure Analysis**

The stock target equation is given in Equation 5-40. The first set of experiments focuses on changes to the structure of the stock target equation. A base case and 6 alternative cases are compared. Each case is given a name for reference, details are explained and the appropriate stock target equation is given below.

Base – standard stock target equation.

$$\boldsymbol{Stock\,Target_{T0} = (\mu_{LT} + 2\sigma_{Lt}) * (\mu_D + 2\sigma_D)} \quad \textbf{(7-1)}$$

Option 1 - No safety stock – stock target equation with zero variance allowed.

$$\boldsymbol{Stock\,Target_{T1} = (\mu_{LT} + 0\sigma_{Lt}) * (\mu_D + 0\sigma_D)} \quad \textbf{(7-2)}$$

Option 2 - 1 sigma safety stock – stock target equation with only 1 standard deviation for demand and lead time allowed.

$$\boldsymbol{Stock\,Target_{T2} = (\mu_{LT} + 1\sigma_{Lt}) * (\mu_D + 1\sigma_D)} \quad \textbf{(7-3)}$$

Option 3 - No lead time safety stock – stock target equation with zero variance for lead time allowed.

$$\boldsymbol{Stock\ Target_{T3}} = (\boldsymbol{\mu_{LT}} + \boldsymbol{0\sigma_{Lt}}) * (\boldsymbol{\mu_D} + \boldsymbol{2\sigma_D}) \quad \text{(7-4)}$$

Option 4 - No demand safety stock – stock target equation with zero variance for demand allowed.

$$\boldsymbol{Stock\ Target_{T4}} = (\boldsymbol{\mu_{LT}} + \boldsymbol{2\sigma_{Lt}}) * (\boldsymbol{\mu_D} + \boldsymbol{0\sigma_D}) \quad \text{(7-5)}$$

Option 5 - Half lead time – stock target equation with the average lead time term divided by 2.

$$\boldsymbol{Stock\ Target_{T5}} = \left(\frac{\boldsymbol{\mu_{LT}}}{\boldsymbol{2}} + \boldsymbol{2\sigma_{Lt}}\right) * (\boldsymbol{\mu_D} + \boldsymbol{2\sigma_D}) \quad \text{(7-6)}$$

Option 6 - Half target – stock target equation divided by 2.

$$\boldsymbol{Stock\ Target_{T6}} = \frac{(\boldsymbol{\mu_{LT}}+\boldsymbol{2\sigma_{Lt}})*(\boldsymbol{\mu_D}+\boldsymbol{2\sigma_D})}{\boldsymbol{2}} \quad \text{(7-7)}$$

Figure 7-59 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the normally distributed environment for the imported parts supply chain. The results show that all options reduce the average inventory, but in most cases result in a lower AFR. The exception is option 2, which suggests that as long as sufficient safety stock is provided for two standard deviations of lead time inventory, the AFR is protected.

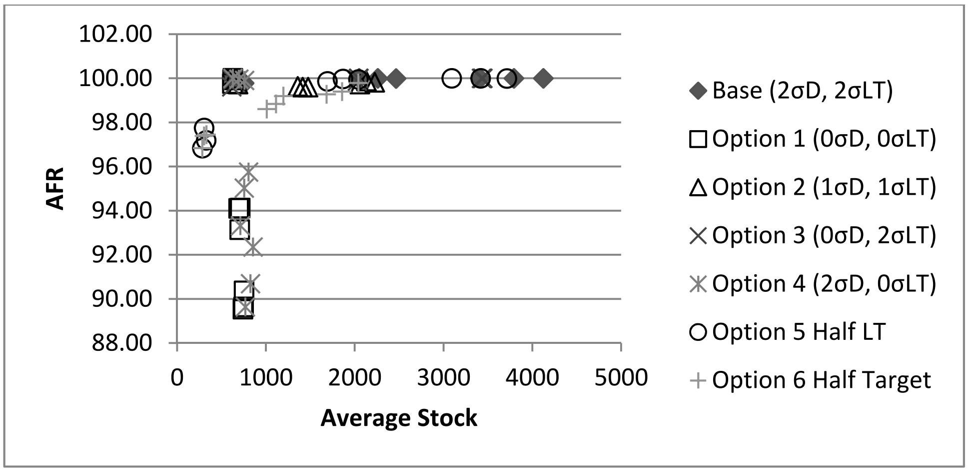


Figure 7-59: Stock Target Equation Structural Analysis Results for Imported Parts Supply Using a Normal Distribution.

Figure 7-60 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the normally distributed environment for the domestic current parts supply chain. The results show that all options reduce the average inventory. Only option 1 and option 4 results in lower AFR values.

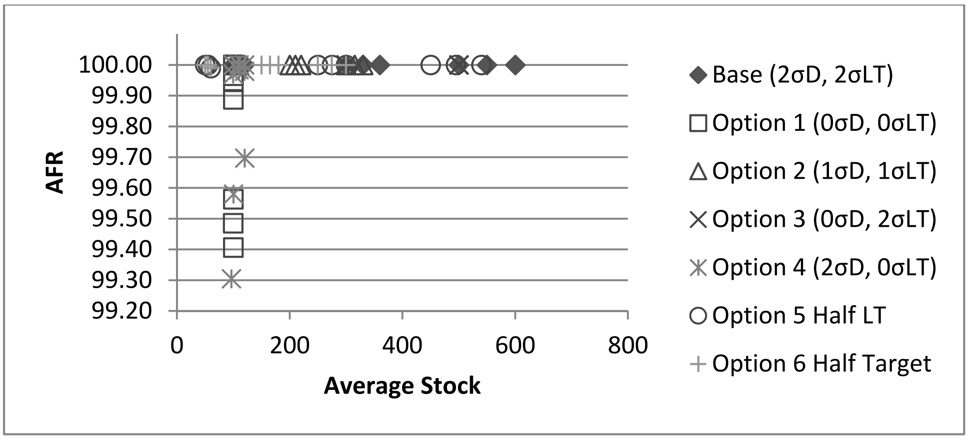


Figure 7-60: Stock Target Equation Structural Analysis Results for Domestic Current Parts Supply Using a Normal Distribution.

Figure 7-61 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the normally distributed environment for the domestic past parts supply chain. The results show that all options reduce the average inventory, but in most cases result in a lower AFR. The exception is option 2, which suggests that as long as sufficient safety stock is provided for two standard deviations of lead time inventory, the AFR is protected and option 3, which suggests one standard deviation of demand and lead time safety stock is sufficient.

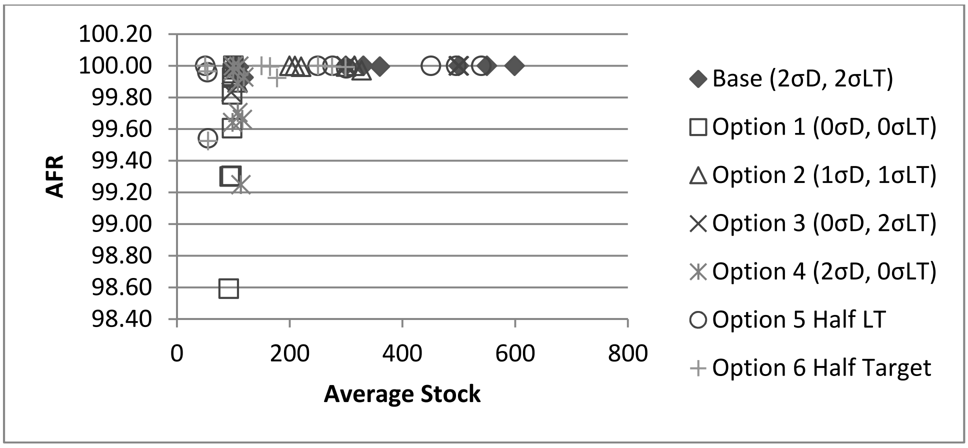


Figure 7-61: Stock Target Equation Structural Analysis Results for Domestic Past Parts Supply Using a Normal Distribution.

Figure 7-62 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the log-normally distributed environment for the imported parts supply chain. The results show that all options reduce the average inventory, but in most cases result in a lower AFR. The exception is option 2, which suggests that as long as sufficient safety stock is provided for two standard deviations of lead time inventory, the AFR is protected.

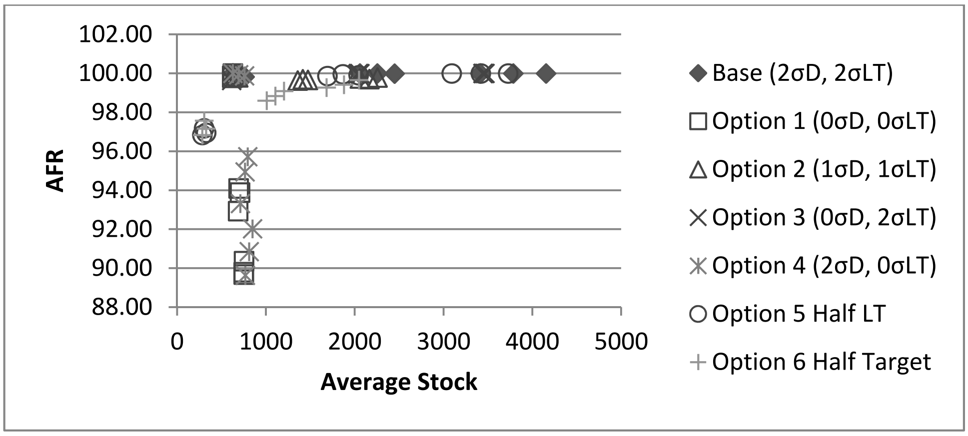


Figure 7-62: Stock Target Equation Structural Analysis Results for Imported Parts Supply Using a Log-Normal Distribution.

Figure 7-63 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the log-normally distributed environment for the domestic current parts supply chain. The results show that all options reduce the average inventory. Only option 1 and option 4 results in lower AFR values.

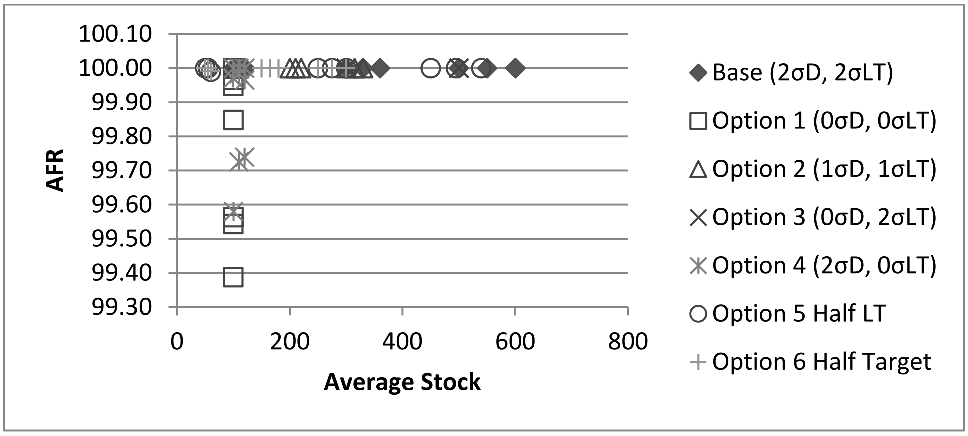


Figure 7-63: Stock Target Equation Structural Analysis Results for Domestic Current Parts Supply Using a Log-Normal Distribution.

Figure 7-64 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the log-normally distributed environment for the domestic past parts supply chain. The results show that all options reduce the average inventory, but in most cases result in a lower AFR. The exception is option 2, which suggests that as long as sufficient safety stock is provided for two standard deviations of lead time inventory, the AFR is protected and option 3, which suggests one standard deviation of demand and lead time safety stock is sufficient.

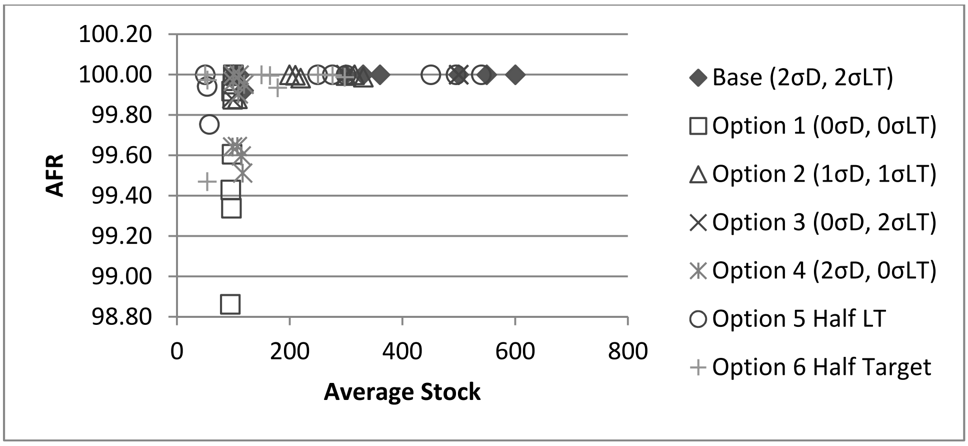


Figure 7-64: Stock Target Equation Structural Analysis Results for Domestic Past Parts Supply Using a Log-Normal Distribution.

Figure 7-65 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the gamma distributed environment for the imported parts supply chain. The results show that all options reduce the average inventory, but in most cases result in a lower AFR. The exception is option 2, which suggests that as long as sufficient safety stock is provided for two standard deviations of lead time stock, the AFR is protected.

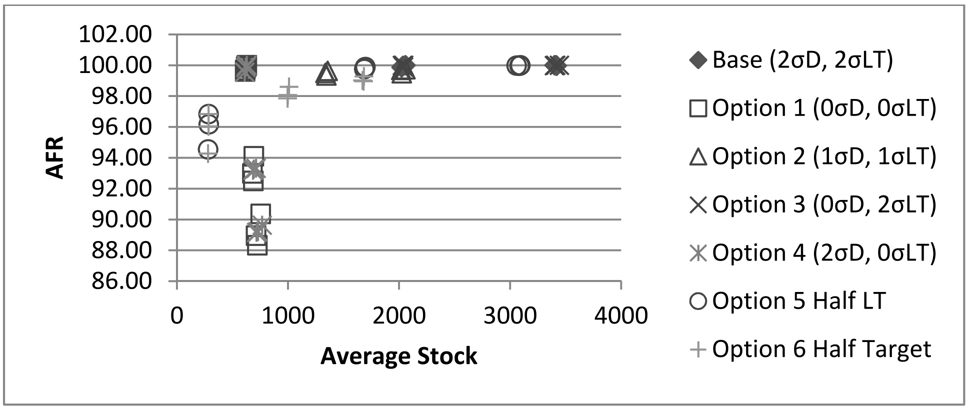


Figure 7-65: Stock Target Equation Structural Analysis Results for Imported Parts Supply Using a Gamma Distribution.

Figure 7-66 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the gamma distributed environment for the domestic current parts supply chain. The results show that all options reduce the average inventory. Only option 1, option 4 and option 5 results in lower AFR values.

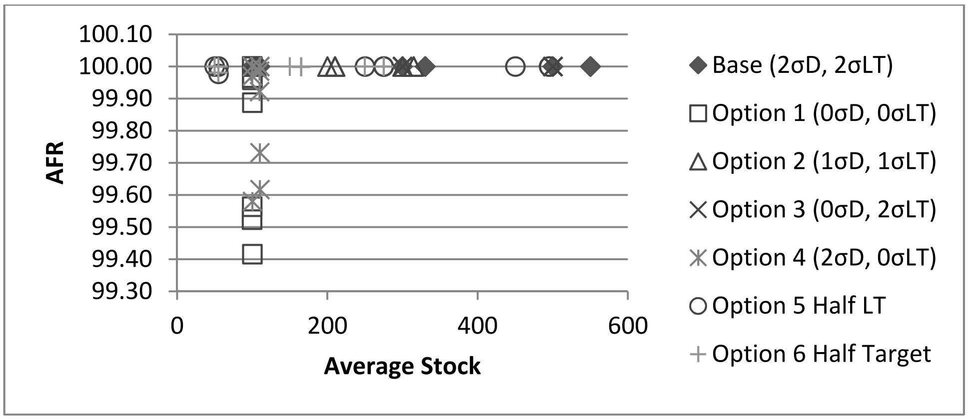


Figure 7-66: Stock Target Equation Structural Analysis Results for Domestic Current Parts Supply Using a Gamma Distribution.

Figure 7-67 shows the results for the comparison between the various possible improvement options for the stock target setting equation in the gamma distributed environment for the domestic past parts supply chain. The results show that all options reduce the average inventory, but in most cases result in a lower AFR. The exception is option 2, which suggests that as long as sufficient safety stock is provided for two standard deviations of lead time inventory, the AFR is protected and option 3, which suggests one standard deviation of demand and lead time safety stock is sufficient.

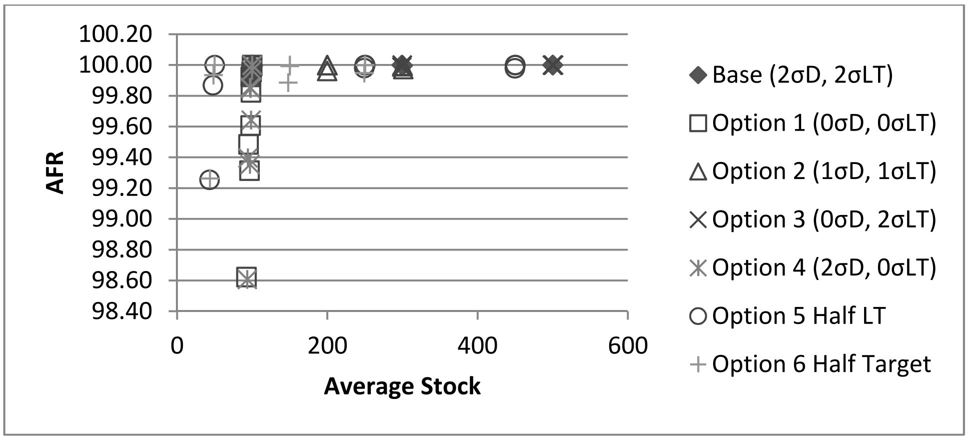


Figure 7-67: Stock Target Equation Structural Analysis Results for Domestic Past Parts Supply Using a Gamma Distribution.

The analysis of the various improvement options show that it is possible to address the need to reduce inventory while maintaining AFR. It is however critical to ensure that the solution is adapted to the environment. As long as the lead time variance is compensated for, the AFR should be sufficient. It will however be necessary to test the detailed solution before implementation, using the SDSM developed in this thesis.

7.2.3.2 **Stock Target Setting Equation for Imported Parts Delivery Cycle Sensitivity Analysis**

The second set of sensitivity analysis experiments focuses on the unique element of the imported parts supply chain, namely the weekly shipping cycle. With daily shipments, the stock target setting incorporates one day of shipping, while the imported parts supply chain has a seven day delivery cycle. This delivery cycle suggests that the stock target method, as per Equation 5-40, will kick off at seven days of inventory. The order equation will keep filling to the set point that reflects the inventory required at the start of the week. However, if the stock target is adjusted throughout the weekly shipment cycle, it may be possible to maintain the AFR with reduced inventory levels.

To achieve this objective, time counter i needs to be introduced, with:

$$\boldsymbol{i = counter(0, 7)} \qquad \textbf{(7-8)}$$

i is reset to zero every time it reaches 7 throughout the simulation time period.

Two structures of the stock target equation are analysed, namely:

1. Start the cycle with $\mu_{LT} = 7$ and reduce μ_{LT} linearly to a desired minimum, *N*, as shown in Equation 7-9.
2. Start the cycle with $\mu_{LT} = M$ and reduce μ_{LT} linearly to a 1, as shown in Equation 7-10.

$$\boldsymbol{\mu_{LTn} = \mu_{LT} - \left(\frac{\mu_{LT} - N}{\mu_{LT}}\right) * i} \qquad \textbf{(7-9)}$$

With:

$$\boldsymbol{n = (1, 2, 3, 4, 5, 6, 7, 8)}$$

$$\boldsymbol{N = (7, 6, 5, 4, 3, 2, 1, 0)}$$

$$\boldsymbol{\mu_{LTm} = M - \left(\frac{M-1}{\mu_{LT}}\right) * i} \qquad \textbf{(7-10)}$$

With:

$$\boldsymbol{m = (1, 2, 3, 4, 5, 6)}$$

$$\boldsymbol{M = (6, 5, 4, 3, 2, 1)}$$

Figure 7-68 graphically demonstrates the values of μ_{LT} for both sets of experiments.

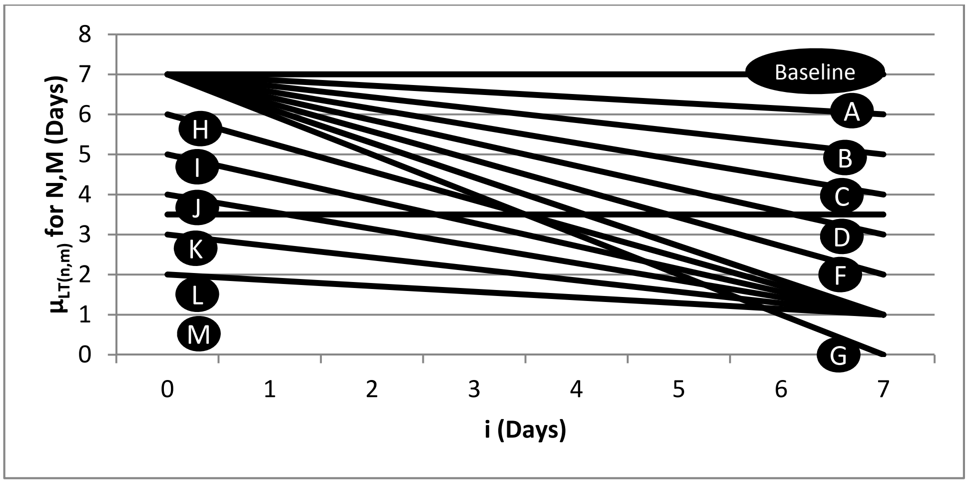


Figure 7-68: Summary of Scenarios for Import Parts Target Setting Analysis Domains.

The analysis is split into two sets of graphs. Set 1 includes Option A to Option G, while set 2 contains Option H to Option M. This split is implemented to simplify the review process. All results show that when a lead time variance is included, the adjustments will maintain the AFR and reduce the inventory. If there is only demand variance to accommodate for, the inventory is at a minimum, but the AFR falls far below 100, as can be seen in Figure 7-69 toFigure 7-74.

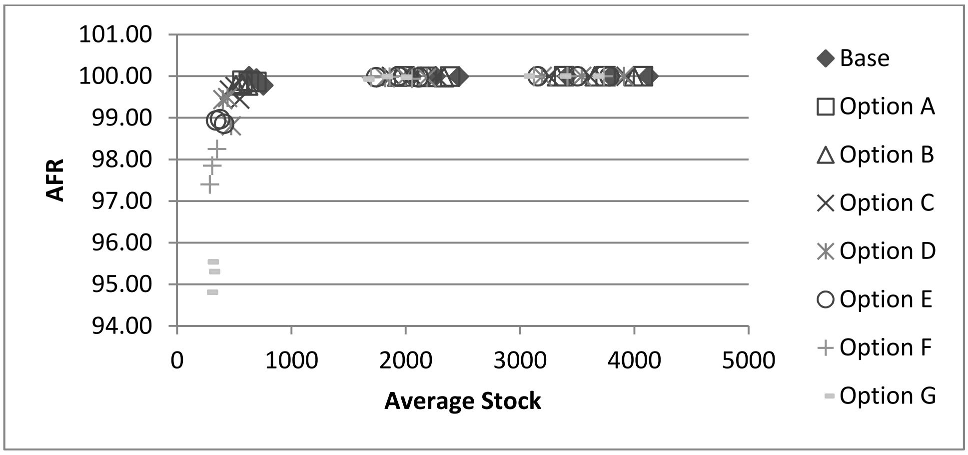


Figure 7-69: Sensitivity Analysis of Stock Target Equation to Delivery Cycle Under Normal Distribution – Set 1.

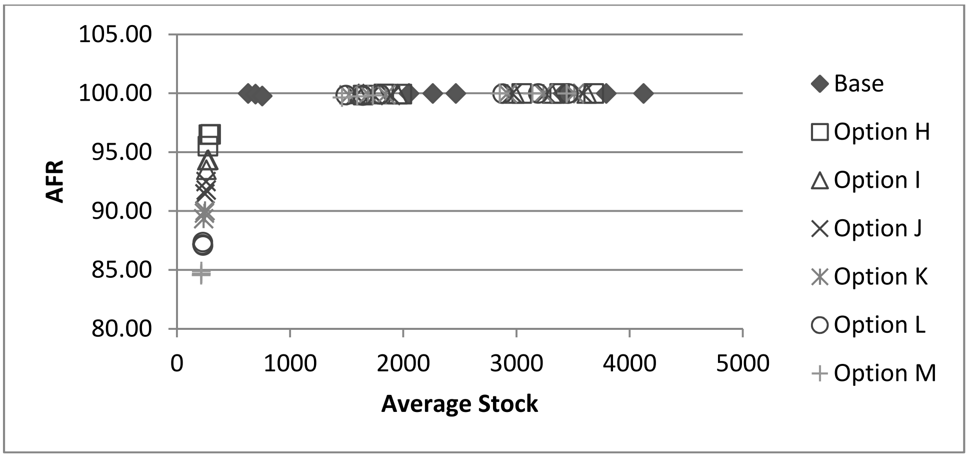


Figure 7-70: Sensitivity Analysis of Stock Target Equation to Delivery Cycle Under Normal Distribution – Set 2.

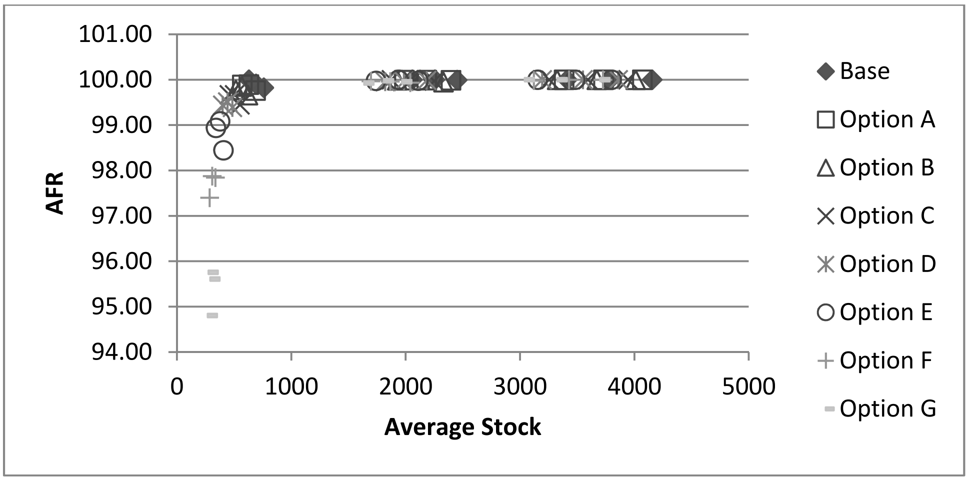


Figure 7-71: Sensitivity Analysis of Stock Target Equation to Delivery Cycle Under Log-Normal Distribution – Set 1.

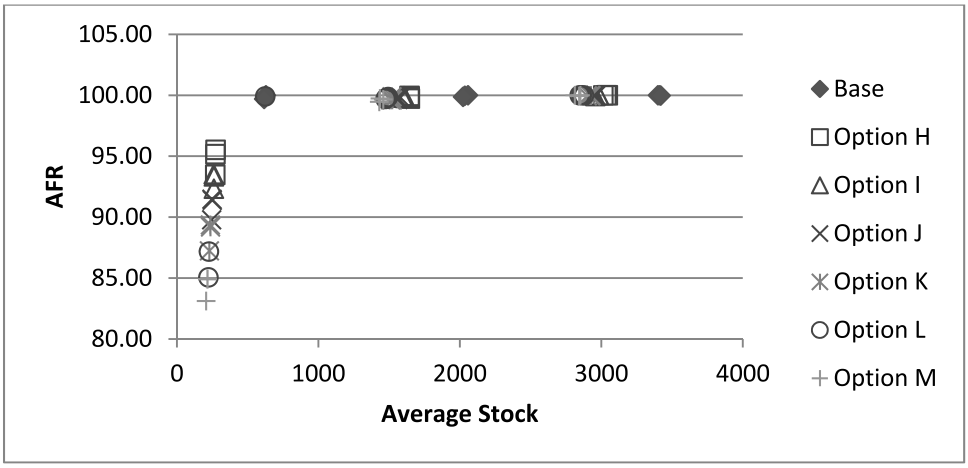


Figure 7-72: Sensitivity Analysis of Stock Target Equation to Delivery Cycle Under Log-Normal Distribution – Set 2.

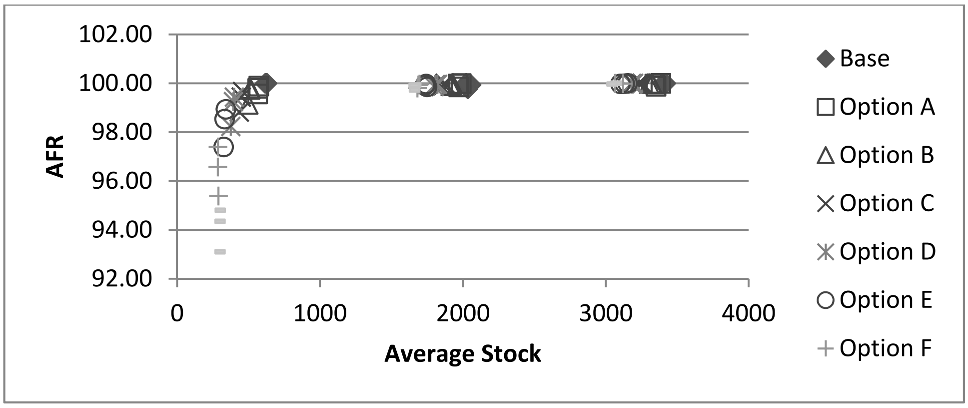


Figure 7-73: Sensitivity Analysis of Stock Target Equation to Delivery Cycle Under Gamma Distribution – Set 1.

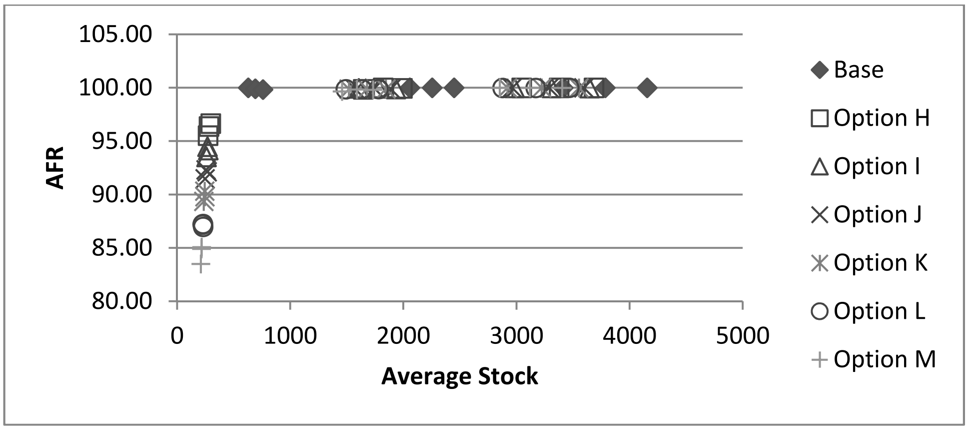


Figure 7-74: Sensitivity Analysis of Stock Target Equation to Delivery Cycle Under Gamma Distribution – Set 2.

In summary, the sensitivity analysis shows that it may be possible to reduce the inventory in cases where lead time variance is planned for. If no lead time variance is planned, the base stock target equation is the preferred method.

7.2.4 Theoretical Analysis – Non-Stationary Demand

In this section the performance of the three inventory management methods are compared in non-stationary demand conditions. Non-stationary demand is of particular interest in the automotive parts industry following the launch of a new vehicle model or new vehicle platform. In the period immediately following the launch, there is no demand information available for inventory management purposes. At best, demand can be estimated and extra inventory ordered to cover the launch period. The analysis of non-stationary demand is performed for each of the methods, in each of the theoretical demand scenarios (normal, log-normal and gamma) for two cases. The scenario setup is shown in Table

7-6. Local parts with 28 day lead time are not included as the focus is on newly introduced parts only, which by definition, are used in current models.

Table 7-6: Demand Scenarios for Non-Stationary Demand Analysis.

Vehicle Sales Demand = 20 - Results in Service Parts Demand = 100			
	Demand Variance		
Imported Lead-Time = 63 Days	0	5	10
Domestic Current Lead-Time = 7 Days	0	5	10

The non-stationary demand simulation runs for 3 600 days. This simulation duration ensures that the service parts demand stabilises and considers the first 5 services. Using vehicle sales of 20 per day and using 5 service intervals, the parts demand stabilises at 100.

In the first set of experiments, the new model production is kicked off with no initial inventory available. The purpose of this scenario is to establish the amount of time required for the supply chain to reach sufficient levels of inventory to maintain the service rate. The three methods are compared to determine which method achieves the required service rate first and how much inventory is required to achieve this.

In the second set of experiments, an initial amount of inventory is available. The methods are again compared as to the service rate achieved and the average inventory required to maintain the service levels. The initial inventory value is set to the expected demand for the first six months of vehicle sales. This is an arbitrary value used by automotive manufacturers.

7.2.4.1 **Comparative Results for Domestic Supplier Parts Under Non-Stationary Demand – MIP$_{\textbf{Theory}}$ vs. MIP$_{\textbf{Actual}}$ vs. STS - No Starting Inventory**

The zero demand variance case is the same for the various demand patterns. As shown in Table 7-7 and Figure 7-75 the STS method has the highest average AFR overall. The STS method is the first method to achieve an AFR of 100 and does so after 360 days. The MIP$_{\text{Actual}}$ method achieves an AFR of 100 after 2880 days. The STS method is, however, also the method with the highest average inventory level. This result is as expected, given that the MIP methods will allow inventory to reach zero before the next delivery cycle, while the STS method maintains sufficient inventory to cover the next cycle given the target setting equation.

Table 7-7: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - No Demand Variance.

	No Variance					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	85.77	89.10	96.18	28	3	73
1 to 180	29.29	27.38	28.14	1	0	0
181 to 360	55.50	55.05	95.49	4	2	8
361 to 720	76.70	77.17	100.00	9	4	27
721 to 1080	87.32	86.91	100.00	10	8	53
1081 to 1440	91.15	92.61	100.00	21	8	73
1441 to 1800	92.37	96.07	100.00	31	5	87
1801 to 2160	93.09	98.11	100.00	38	2	94
2161 to 2520	93.46	99.18	100.00	41	1	98
2521 to 2880	93.67	99.75	100.00	43	0	100
2881 to 3240	93.77	100.00	100.00	44	0	100
3241 to 3600	93.77	100.00	100.00	44	0	100

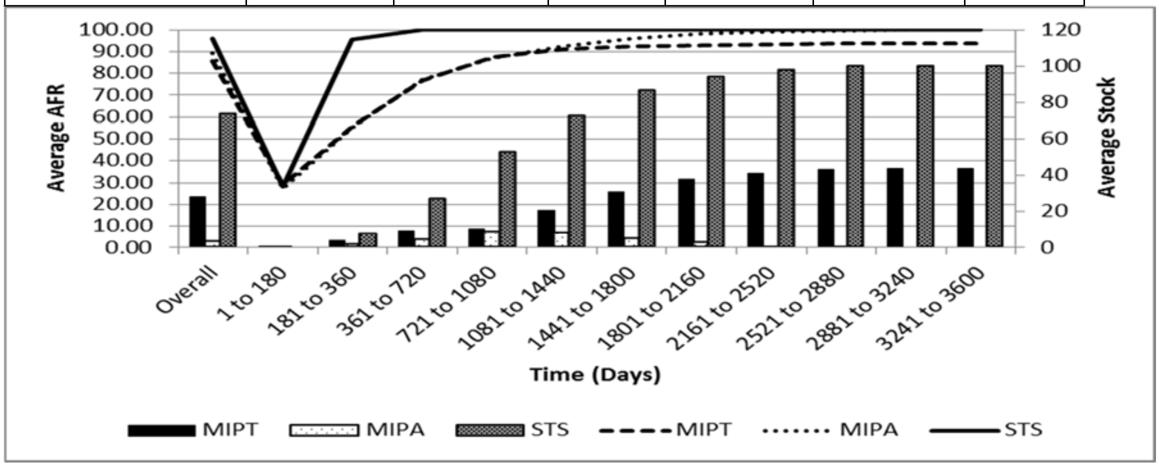


Figure 7-75: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - No Demand Variance.

When a normal distribution with a variance of 5 is used to simulate demand all three methods achieve an AFR of 100. Table 7-8 and Figure 7-76 show that the STS method achieves an AFR of 100 after 180 days, MIP_{Actual} after 360 days and MIP_{Theory} after 3240. While the STS method has an inventory level 11 times higher than MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a normal distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-8: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 5.

	Normal Distribution - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	91.08	98.64	99.22	15	726	83
1 to 180	58.14	72.76	84.36	1	1	9
181 to 360	63.32	99.99	100.00	4	62	18
361 to 720	80.12	100.00	100.00	9	252	37
721 to 1080	89.52	100.00	100.00	12	506	63
1081 to 1440	91.98	100.00	100.00	25	715	83
1441 to 1800	93.19	100.00	100.00	34	854	96
1801 to 2160	95.58	100.00	100.00	29	936	104
2161 to 2520	99.79	100.00	100.00	7	976	108
2521 to 2880	99.93	100.00	100.00	9	994	110
2881 to 3240	99.96	100.00	100.00	10	999	110
3241 to 3600	100.00	100.00	100.00	10	999	110

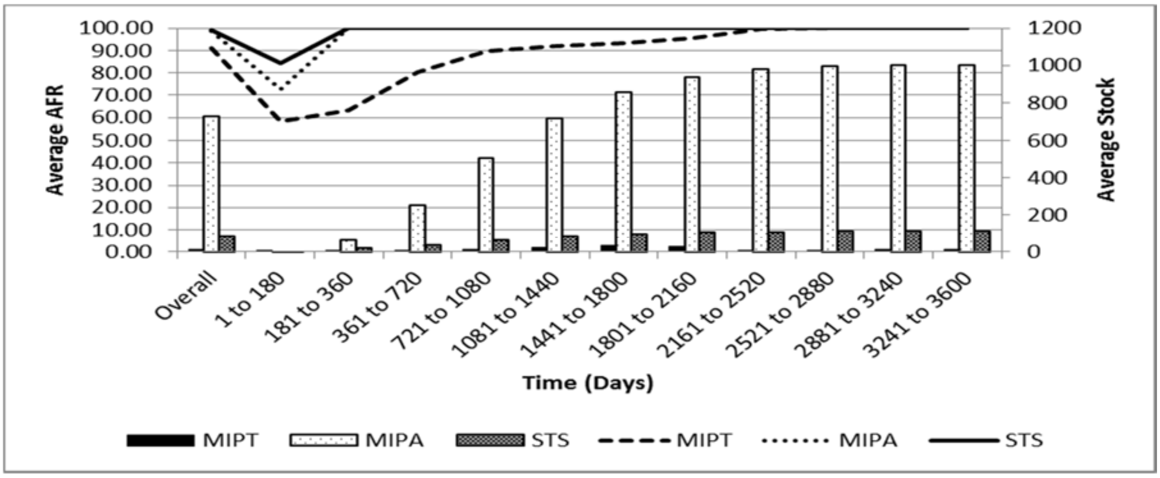


Figure 7-76: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 5.

When a normal distribution with a variance of 10 is used to simulate demand, all three methods achieve an AFR of 100. Table 7-9 and Figure 7-77 show that both the MIP_{Actual} and STS methods achieve an AFR of 100 after 180 days. The MIP_{Theory} method only achieves an AFR of 100 after 2 160 days. The STS method only results in 6 times the inventory of the MIP_{Theory} method while the MIP_{Actual} method results in 100 times the amount of inventory. This result indicates that in the case of a normal demand pattern with a variance of 10, the STS method is the most effective method when taking both AFR and inventory required into account.

Table 7-9: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 10.

	Normal Distribution - Variance = 10					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	93.55	98.97	99.22	17	1476	93
1 to 180	72.35	79.31	84.35	4	23	19
181 to 360	71.46	100.00	100.00	4	177	28
361 to 720	84.00	100.00	100.00	9	560	47
721 to 1080	90.50	100.00	100.00	16	1062	73
1081 to 1440	92.85	100.00	100.00	29	1465	93
1441 to 1800	96.25	100.00	100.00	23	1730	107
1801 to 2160	99.97	100.00	100.00	10	1884	114
2161 to 2520	100.00	100.00	100.00	16	1962	118
2521 to 2880	100.00	100.00	100.00	19	1995	120
2881 to 3240	100.00	100.00	100.00	20	2001	120
3241 to 3600	100.00	100.00	100.00	20	2000	120

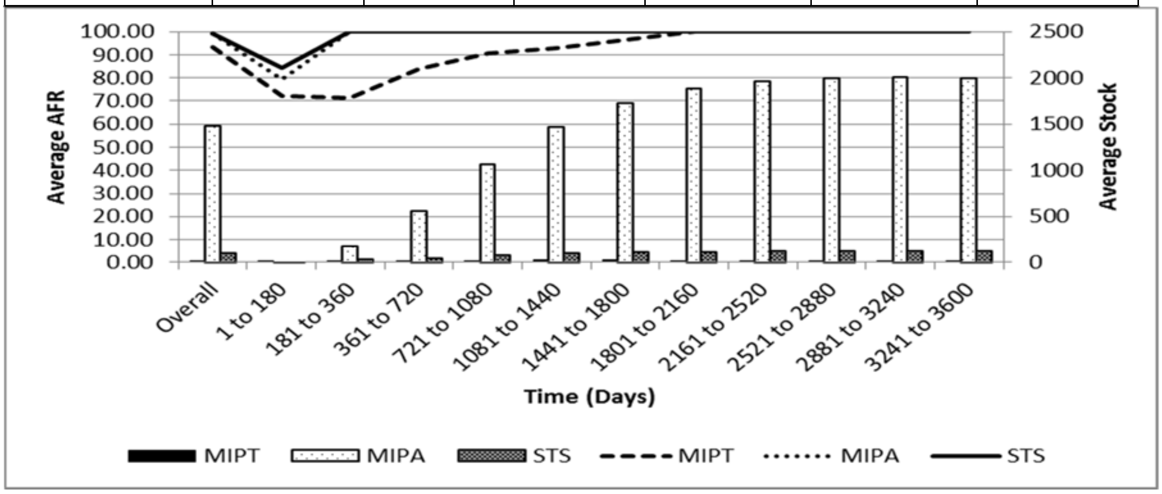


Figure 7-77: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 10.

When a log-normal distribution with a variance of 5 is used to simulate demand only the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-10 and Figure 7-78 show that the STS method achieves an AFR of 100 after 180 days while the MIP_{Actual} method achieves an AFR of 100 after 360 days. While the STS method requires 11 times the inventory of the MIP$_{Theory}$ method, the MIP$_{Actual}$ method requires nearly 100 times the inventory. This result indicates that in the case of a log-normal demand pattern with a variance of 5, the STS method is the most effective method when taking both AFR and inventory required into account.

Table 7-10: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 5.

	Log Normal Distribution - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP$_{Theory}$	MIP$_{Actual}$	STS	MIP$_{Theory}$	MIP$_{Actual}$	STS
Overall	91.09	98.64	99.22	15	727	83
1 to 180	58.12	72.86	84.39	1	1	9
181 to 360	63.26	99.99	100.00	4	62	18
361 to 720	80.14	100.00	100.00	9	252	37
721 to 1080	89.73	100.00	100.00	11	506	63
1081 to 1440	91.97	100.00	100.00	25	716	83
1441 to 1800	93.14	100.00	100.00	35	854	96
1801 to 2160	95.54	100.00	100.00	29	936	104
2161 to 2520	99.81	100.00	100.00	7	978	108
2521 to 2880	99.98	100.00	100.00	9	995	110
2881 to 3240	99.92	100.00	100.00	10	999	110
3241 to 3600	99.99	100.00	100.00	10	999	110

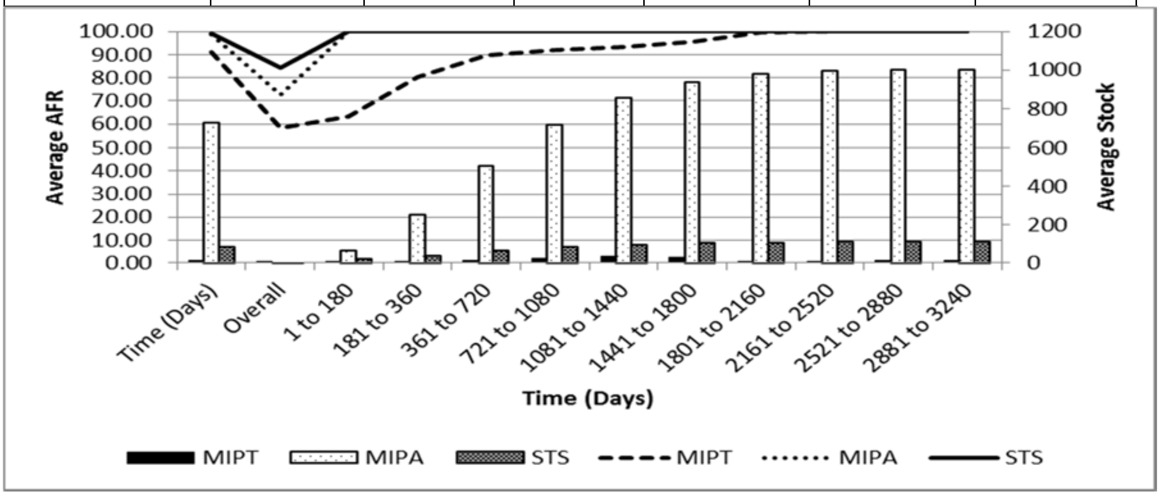


Figure 7-78: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 5.

When a log-normal distribution with a variance of 10 is used to simulate demand only the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-11 and Figure 7-79 show that both the STS and MIP_{Actual} methods achieves an AFR of 100 after 180 days. While the STS method requires 6 times the inventory of the MIP_{Theory} method, the MIP_{Actual} method requires nearly 100 times the inventory. This result indicates that in the case of a log-normal demand pattern with a variance of 10, the STS method is the most effective method when taking both AFR and inventory required into account.

Table 7-11: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 10.

	Log Normal Distribution - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	93.49	98.97	99.22	17	1472	93
1 to 180	72.45	79.49	84.49	4	24	19
181 to 360	71.61	100.00	100.00	4	177	28
361 to 720	83.83	100.00	100.00	9	560	47
721 to 1080	90.36	100.00	100.00	17	1061	73
1081 to 1440	92.80	100.00	100.00	29	1462	93
1441 to 1800	96.07	100.00	100.00	24	1727	106
1801 to 2160	99.92	100.00	100.00	11	1877	114
2161 to 2520	99.96	100.00	100.00	16	1955	118
2521 to 2880	99.97	100.00	100.00	18	1987	119
2881 to 3240	99.99	100.00	100.00	20	1996	120
3241 to 3600	99.97	100.00	100.00	20	1995	120

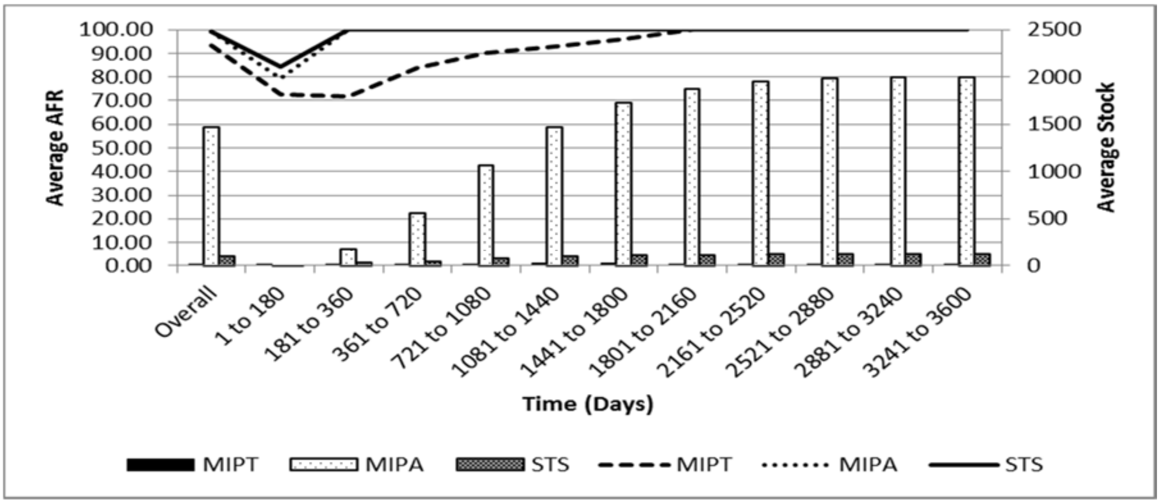


Figure 7-79: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 10.

When a gamma distribution with a variance of 5 is used to simulate demand all three methods achieve an AFR of 100. Table 7-12 and Figure 7-80 show that both the STS achieves an AFR of 100 after 180 days, the MIP_{Actual} method achieves an AFR of 100 after 360 days and the MIP_{Actual} method achieves and AFR of 100 after 2 520 days. While the STS method requires 11 times the inventory of the MIP_{Theory} method, the MIP_{Actual} method requires nearly 100 times the inventory. This result indicates that in the case of a gamma demand pattern with a variance of 5, the STS method is the most effective method when taking both AFR and inventory required into account.

Table 7-12: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 5.

	Gamma Distribution (80;0.25) - Variance = 5					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	91.08	98.64	99.22	15	727	83
1 to 180	58.05	72.77	84.40	1	1	9
181 to 360	63.31	99.99	100.00	4	62	18
361 to 720	80.21	100.00	100.00	9	252	37
721 to 1080	89.37	100.00	100.00	12	506	63
1081 to 1440	91.97	100.00	100.00	25	716	83
1441 to 1800	93.11	100.00	100.00	35	856	96
1801 to 2160	95.60	100.00	100.00	28	937	104

	Gamma Distribution (80;0.25) - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
2161 to 2520	99.92	100.00	100.00	6	978	108
2521 to 2880	100.00	100.00	100.00	8	996	110
2881 to 3240	100.00	100.00	100.00	10	999	110
3241 to 3600	100.00	100.00	100.00	10	1000	110

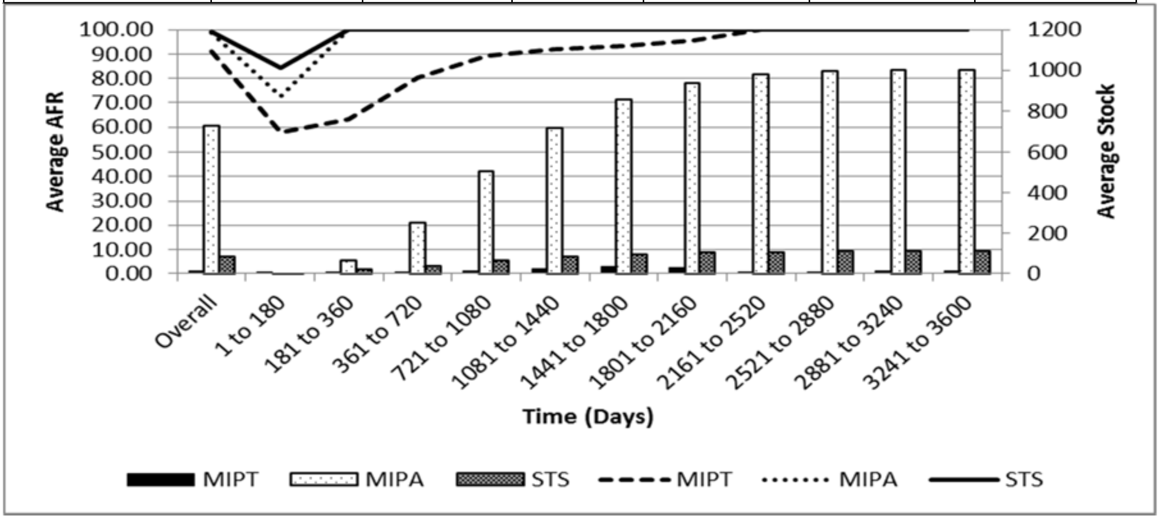


Figure 7-80: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 5.

When a gamma distribution with a variance of 10 is used to simulate demand all three methods achieve an AFR of 100. Table 7-13 and Figure 7-81 show that both the STS achieves an AFR of 100 after 180 days, the MIP_{Actual} method achieves an AFR of 100 after 180 days and the MIP_{Actual} method achieves and AFR of 100 after 2 160 days. While the STS method requires 6 times the inventory of the MIP_{Theory} method, the MIP_{Actual} method requires nearly 50 times the inventory. This result indicates that in the case of a gamma demand pattern with a variance of 10, the STS method is the most effective method when taking both AFR and inventory required into account.

Table 7-13: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 10.

	Gamma Distribution (20;1) - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	93.56	98.53	99.22	17	736	93
1 to 180	72.28	70.70	84.35	4	9	19
181 to 360	71.40	100.00	100.00	4	80	28
361 to 720	84.30	100.00	100.00	8	265	47
721 to 1080	90.53	100.00	100.00	16	515	73
1081 to 1440	92.82	100.00	100.00	29	727	93
1441 to 1800	96.10	100.00	100.00	24	871	106
1801 to 2160	99.99	100.00	100.00	10	952	114
2161 to 2520	100.00	100.00	100.00	16	988	118
2521 to 2880	100.00	100.00	100.00	19	999	120
2881 to 3240	100.00	100.00	100.00	20	999	120
3241 to 3600	100.00	100.00	100.00	20	998	120

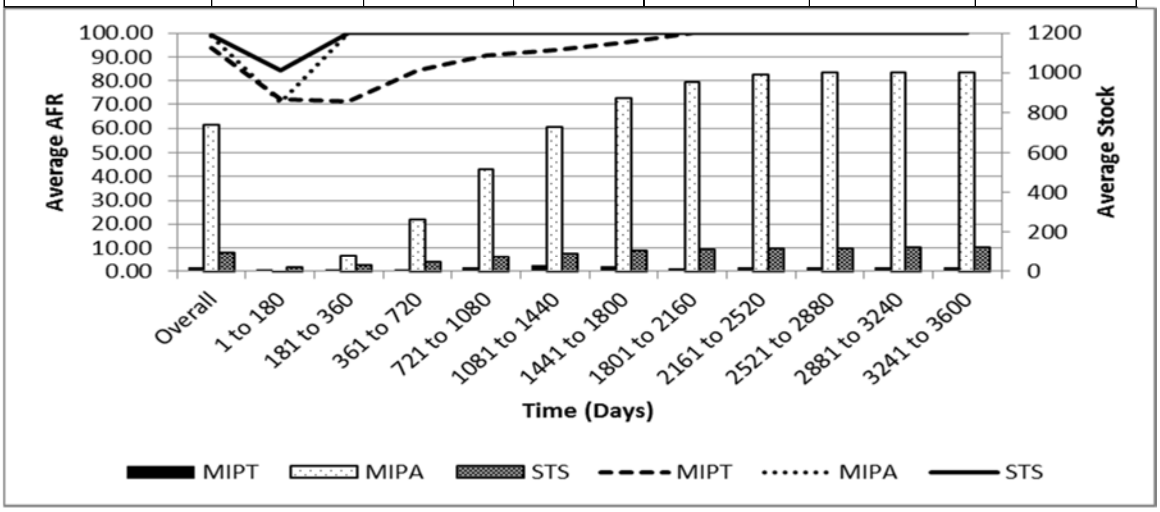


Figure 7-81: Comparative Results Local Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 10.

In summary, all cases of locally supplied parts under non-stationary demand with zero starting inventory show that the STS method not only consistently achieves an AFR of 100, but also achieves it in the shortest possible time. The MIP_{Actual} method also achieves an AFR of 100, but it takes longer than the STS method. The MIP_{Theory} method performs the worst in terms of achieving an AFR of 100. The MIP_{Theory} has the lowest inventory requirements and the MIP_{Actual} method requires significantly higher inventory. The STS method has the best AFR performance with an inventory increase, that is, however, much lower than that of the MIP_{Actual} method. For locally supplied parts, the STS method is the most effective with the highest AFR and the least amount of inventory, except for the ideal case with no demand variance.

7.2.4.2 **Comparative Results for Import Supplier Parts Under Non-Stationary Demand – MIP_{Theory} vs. MIP_{Actual} vs. STS - No Starting Inventory**

The zero demand variance case is the same for the various demand distributions. As shown in Table 7-14 and Figure 7-82 the STS method has the lowest average AFR overall. The STS method is, however, the only method to achieve an AFR of 100 and does so after 1800 days. The MIP_{Actual} and MIP_{Theory} methods do not achieve an AFR of 100. The STS method is, however, also the method with the highest average inventory level. This result is as expected, given that the MIP methods will allow inventory to reach zero before the next delivery cycle, while the STS method maintains sufficient inventory to cover the next cycle given the target setting equation. The MIP methods however have higher inventory levels that the STS method for the first 1440 days. In this case the STS method is the worst when taking AFR and inventory into account.

Table 7-14: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - No Demand Variance.

	No Variance					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	87.93	87.93	75.06	215	215	371
1 to 180	14.61	14.61	0.92	1	1	0
181 to 360	47.37	47.37	7.38	13	13	0
361 to 720	74.29	74.29	24.46	65	65	5
721 to 1080	86.92	86.92	50.02	140	140	44
1081 to 1440	93.32	93.32	75.61	206	206	136
1441 to 1800	96.50	96.50	96.34	253	253	345
1801 to 2160	98.35	98.35	100.00	281	281	581
2161 to 2520	99.23	99.23	100.00	294	294	627
2521 to 2880	99.73	99.73	100.00	301	301	648
2881 to 3240	100.00	100.00	100.00	298	298	660
3241 to 3600	100.00	100.00	100.00	302	302	665

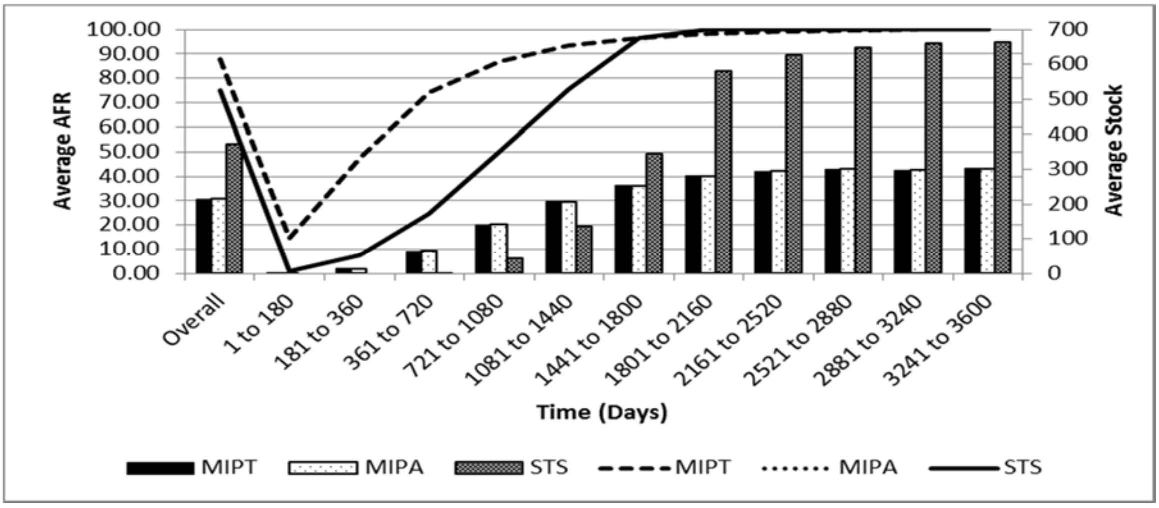


Figure 7-82: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - No Demand Variance.

When a normal distribution with a variance of 5 is used to simulate demand the $\text{MIP}_{\text{Actual}}$ and STS methods achieve an AFR of 100. Table 7-15 and Figure 7-83 show that the STS method achieves an AFR of 100 after 1440 days and $\text{MIP}_{\text{Actual}}$ after 1080 days. While the STS method has an inventory level two times higher than the $\text{MIP}_{\text{Theory}}$ method, the inventory level for the $\text{MIP}_{\text{Actual}}$ method is four times higher. The results indicate that in the shorter term the $\text{MIP}_{\text{Theory}}$ is the better method, while after 1440 days the STS method is better when comparing AFR and inventory.

Table 7-15: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 5.

	Normal Distribution - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	88.07	91.87	82.22	223	794	438
1 to 180	16.57	16.63	11.41	1	2	0
181 to 360	48.16	54.27	27.28	15	18	3
361 to 720	74.39	84.90	44.21	71	85	21
721 to 1080	86.88	98.32	67.75	152	213	85
1081 to 1440	93.12	100.00	90.92	217	559	203
1441 to 1800	96.63	100.00	100.00	256	884	547
1801 to 2160	98.46	100.00	100.00	283	1097	643
2161 to 2520	99.31	100.00	100.00	298	1216	699
2521 to 2880	99.71	100.00	100.00	311	1272	717
2881 to 3240	99.90	100.00	100.00	315	1297	727
3241 to 3600	99.92	100.00	100.00	316	1303	734

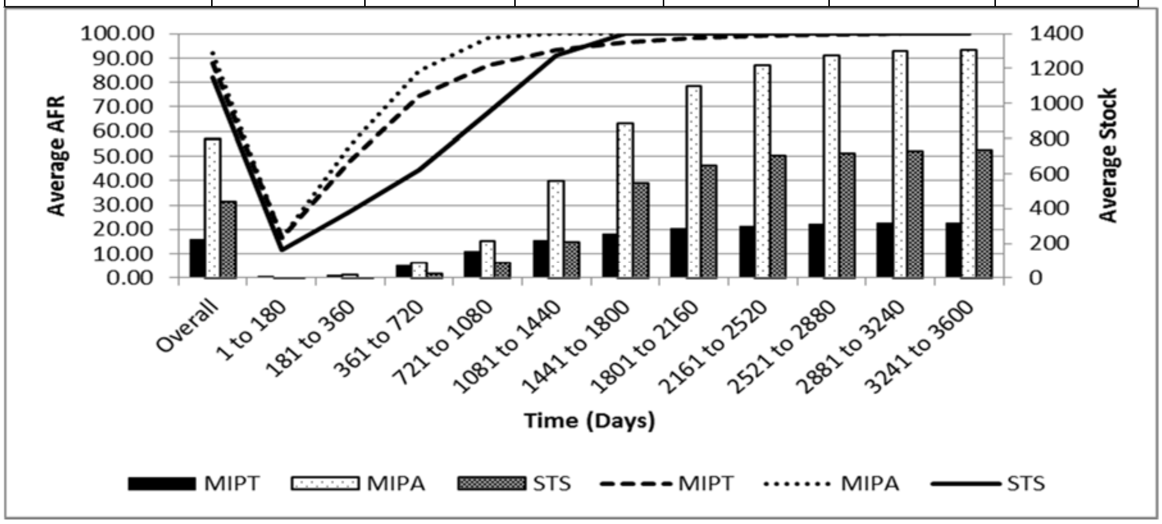


Figure 7-83: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 5.

When a normal distribution with a variance of 10 is used to simulate demand the MIP_{Actual} and STS methods achieve an AFR of 100. Table 7-16 and Figure 7-84 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days. While the STS method has an inventory level two times higher than the MIP_{Theory} method, the inventory level for the MIP_{Actual} method is four times higher. The results indicate that in the shorter term the MIP$_{Theory}$ is the better method, while after 1440 days the STS method is better when comparing AFR and inventory.

Table 7-16: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 10.

	Normal Distribution - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP$_{Theory}$	MIP$_{Actual}$	STS	MIP$_{Theory}$	MIP$_{Actual}$	STS
Overall	88.38	93.42	87.92	225	1495	506
1 to 180	18.49	18.96	21.46	2	2	2
181 to 360	49.03	61.02	46.40	17	24	11
361 to 720	74.83	94.21	62.61	71	133	44
721 to 1080	87.22	100.00	83.50	150	655	132
1081 to 1440	93.45	100.00	99.17	214	1287	407
1441 to 1800	96.84	100.00	100.00	256	1745	603
1801 to 2160	98.59	100.00	100.00	284	2038	709
2161 to 2520	99.39	100.00	100.00	301	2198	767
2521 to 2880	99.78	100.00	100.00	315	2275	791
2881 to 3240	99.95	100.00	100.00	321	2299	798
3241 to 3600	99.96	100.00	100.00	325	2304	804

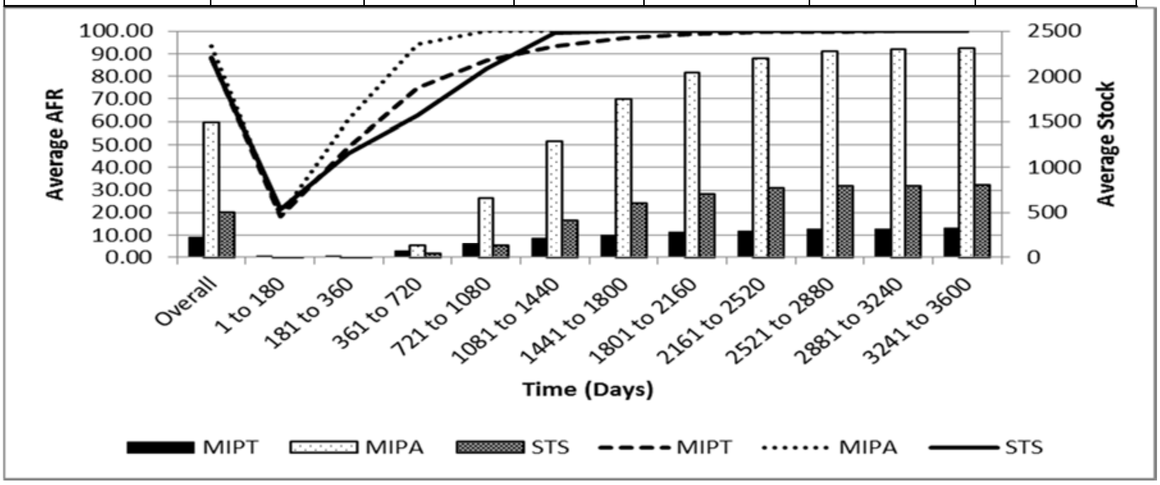


Figure 7-84: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Normal Demand With Variance = 10.

When a log-normal distribution with a variance of 5 is used to simulate demand the MIP$_{Actual}$ and STS methods achieve an AFR of 100. Table 7-17 and Figure 7-85 show that the STS method achieves an AFR of 100 after 1440 days and MIP$_{Actual}$ after 1080 days. While the STS method has an inventory level two times higher than the MIP$_{Theory}$ method, the inventory level for the MIP$_{Actual}$ method is four times higher. The results indicate that in the shorter term MIP_{Actual} is the better method, while after 1440 days the STS method is better when comparing AFR and inventory.

Table 7-17: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 5.

	Log Normal Distribution - Variance = 5					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	88.08	91.88	82.22	222	794	438
1 to 180	16.60	16.81	11.37	1	2	0
181 to 360	48.20	54.36	27.27	15	18	3
361 to 720	74.39	84.89	44.21	71	86	21
721 to 1080	86.85	98.36	67.76	152	211	85
1081 to 1440	93.16	100.00	90.95	218	563	204
1441 to 1800	96.64	100.00	100.00	256	884	545
1801 to 2160	98.47	100.00	100.00	283	1097	644
2161 to 2520	99.32	100.00	100.00	297	1217	699
2521 to 2880	99.71	100.00	100.00	309	1274	718
2881 to 3240	99.92	100.00	100.00	311	1298	727
3241 to 3600	99.96	100.00	100.00	314	1300	734

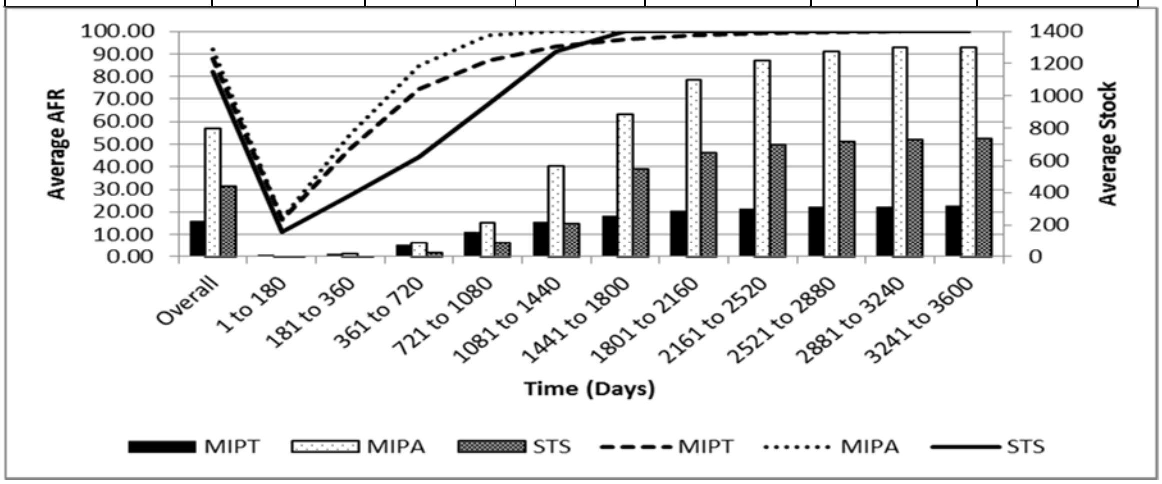


Figure 7-85: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 5.

When a log-normal distribution with a variance of 10 is used to simulate demand the MIP_{Actual} and STS methods achieve an AFR of 100. Table 7-18 and Figure 7-86 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days.

While the STS method has an inventory level two times higher than the MIP_{Theory} method, the inventory level for the MIP_{Actual} method is four times higher. The results indicate that in the shorter term the MIP_{Theory} is the better method, while after 1440 days the STS method is better when comparing AFR and inventory.

Table 7-18: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 10.

	Log Normal Distribution - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	88.35	93.42	87.96	226	1488	505
1 to 180	18.47	18.84	21.72	2	2	2
181 to 360	49.00	61.09	46.64	17	24	11
361 to 720	74.80	94.21	62.60	71	132	43
721 to 1080	87.20	100.00	83.60	150	652	132
1081 to 1440	93.42	100.00	99.25	214	1279	406
1441 to 1800	96.85	100.00	100.00	256	1736	600
1801 to 2160	98.56	100.00	100.00	285	2027	710
2161 to 2520	99.36	100.00	100.00	302	2188	764
2521 to 2880	99.73	100.00	100.00	318	2261	785
2881 to 3240	99.89	100.00	100.00	322	2285	800
3241 to 3600	99.92	100.00	100.00	331	2303	803

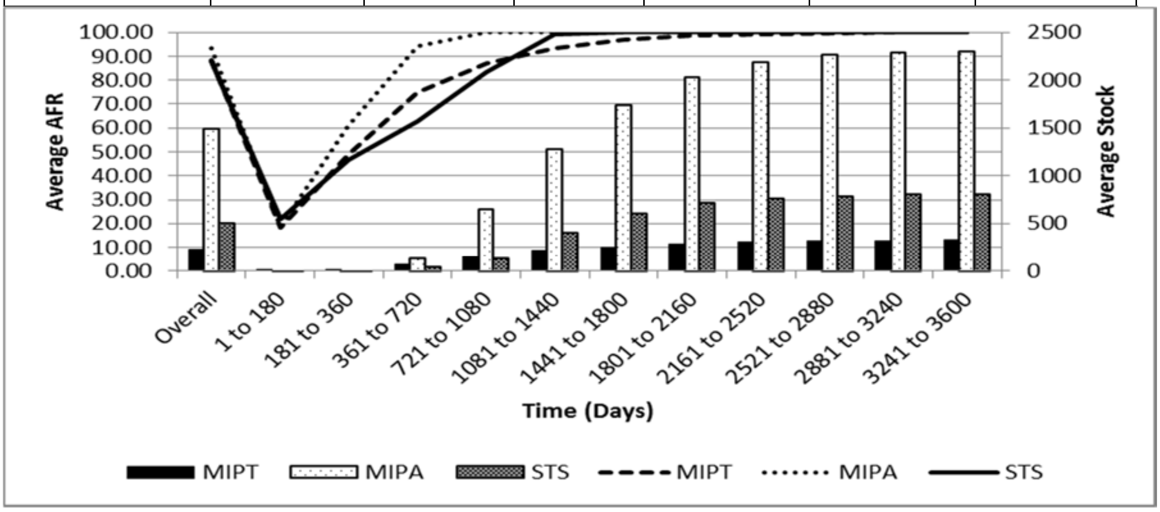


Figure 7-86: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Log Normal Demand With Variance = 10.

When a gamma distribution with a variance of 5 is used to simulate demand the MIP_{Actual} and STS methods achieve an AFR of 100. Table 7-19 and Figure 7-87 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 1080 days. While the STS method has an inventory level two times higher than the MIP_{Theory} method, the inventory level for the MIP_{Actual} method is four times higher. The results indicate that in the shorter term the MIP_{Theory} is the better method, while after 1440 days the STS method is better when comparing AFR and inventory.

Table 7-19: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 5.

	Gamma Distribution (80,0.25) - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	88.09	91.87	82.22	222	794	438
1 to 180	16.64	16.75	11.40	1	2	0
181 to 360	48.14	54.26	27.23	15	18	3
361 to 720	74.40	84.91	44.22	72	85	21
721 to 1080	86.82	98.30	67.75	153	212	85
1081 to 1440	93.10	100.00	90.89	219	560	203
1441 to 1800	96.63	100.00	100.00	257	884	547
1801 to 2160	98.48	100.00	100.00	283	1098	645
2161 to 2520	99.33	100.00	100.00	297	1218	699
2521 to 2880	99.74	100.00	100.00	306	1274	718
2881 to 3240	99.99	100.00	100.00	309	1298	728
3241 to 3600	99.98	100.00	100.00	313	1301	734

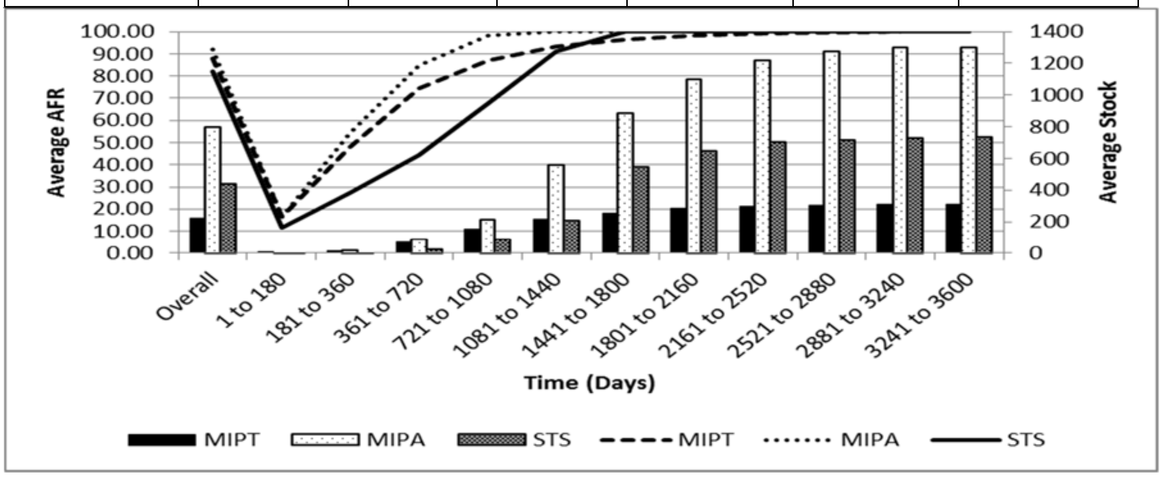


Figure 7-87: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 5.

When a gamma distribution with a variance of 10 is used to simulate demand the MIP_{Actual} and STS methods achieve an AFR of 100. Table 7-20 and Figure 7-88 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days. While the STS method has an inventory level two times higher than the MIP_{Theory} method, the inventory level for the MIP_{Actual} method is four times higher. The results indicate that in the shorter term the MIP_{Theory} is the better method, while after 1440 days the STS method is better when comparing AFR and inventory.

Table 7-20: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 10.

	Gamma Distribution (20,1) - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	88.37	93.43	87.95	224	1491	506
1 to 180	18.55	18.89	21.56	2	2	2
181 to 360	48.97	61.22	46.59	17	24	11
361 to 720	74.88	94.25	62.67	71	132	44
721 to 1080	87.17	100.00	83.60	150	653	132
1081 to 1440	93.40	100.00	99.20	214	1277	407
1441 to 1800	96.80	100.00	100.00	256	1738	600
1801 to 2160	98.59	100.00	100.00	285	2034	709
2161 to 2520	99.42	100.00	100.00	300	2195	769
2521 to 2880	99.78	100.00	100.00	313	2268	787
2881 to 3240	99.96	100.00	100.00	321	2297	800
3241 to 3600	99.97	100.00	100.00	323	2301	803

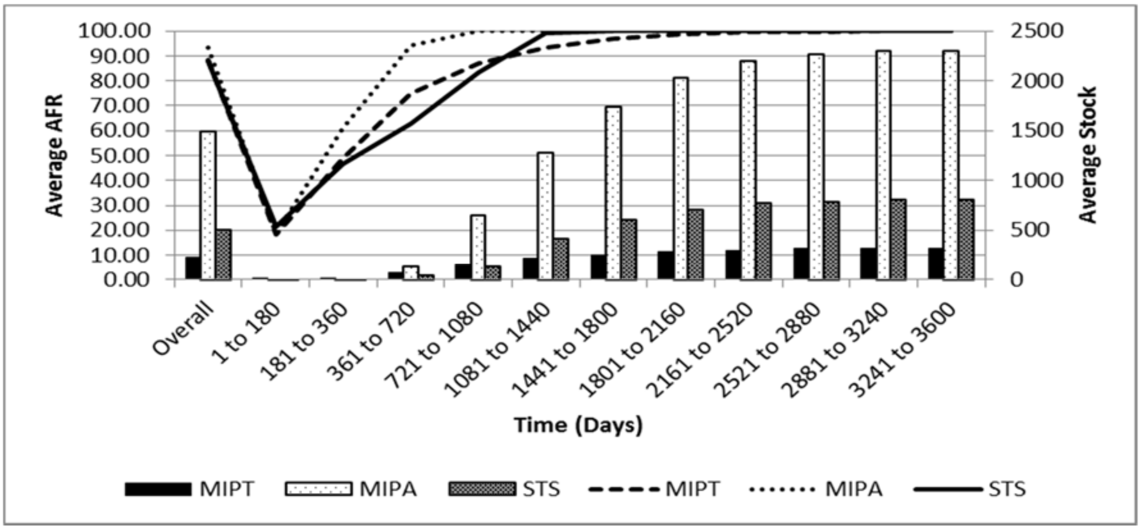


Figure 7-88: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, No Starting Inventory - Gamma Demand With Variance = 10.

In summary, under non-stationary demand conditions for imported parts supplied, the $\mathrm{MIP_{Actual}}$ method is the best in the short term. While it requires the most inventory, it also achieves an AFR of 100 sooner than the other methods. In the long term, the STS method also achieves an AFR of 100 with half the amount of inventory. This result indicates that in the longer term the STS method is the better method, except for the ideal case with no variance

7.2.4.3 **Comparative Results for Domestic Supplier Parts Under Non-Stationary Demand – $\mathbf{MIP_{Theory}}$ vs. $\mathbf{MIP_{Actual}}$ vs. STS - With Starting Inventory**

To compensate for new model launch demand, it is standard industry practice to establish an initial baseline of inventory of 6 months demand. Using the results from the no variance case described in Section 7.2.4.1, the value of the required starting inventory is calculated as 1060. For Sections 7.2.4.3 and 7.2.4.4 the initial inventory on hand is set to 1060.

The zero demand variance case is the same for the various demand patterns. As shown in Table 7-21 and Figure 7-89 the STS method has the highest average AFR overall. The STS method is the first method to achieve an AFR of 100 and does so after 360 days. The $\mathrm{MIP_{Actual}}$ method achieves an AFR of 100 after 2880 years. The STS method is, however, also the method with the highest average inventory level. This result is as expected, given that the MIP methods will allow inventory to reach zero before the next delivery cycle, while the STS method maintains sufficient inventory to cover the next cycle given the target setting equation. It is interesting to note that even when starting with initial inventory, all methods manage to run to an out of stock condition, before recovering and achieving stability.

Table 7-21: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - No Demand Variance.

	No Variance					
	AFR			Inventory		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	88.82	92.22	98.67	65	39	110
1 to 180	84.44	84.44	84.44	728	728	728
181 to 360	61.30	60.36	89.01	3	2	7
361 to 720	76.58	77.17	100.00	9	4	27
721 to 1080	87.48	86.90	100.00	10	8	53
1081 to 1440	91.15	92.61	100.00	21	8	73
1441 to 1800	92.37	96.07	100.00	31	5	87
1801 to 2160	93.10	98.11	100.00	38	2	94
2161 to 2520	93.46	99.18	100.00	41	1	98
2521 to 2880	93.67	99.75	100.00	43	0	100
2881 to 3240	93.77	100.00	100.00	44	0	100
3241 to 3600	93.77	100.00	100.00	44	0	100

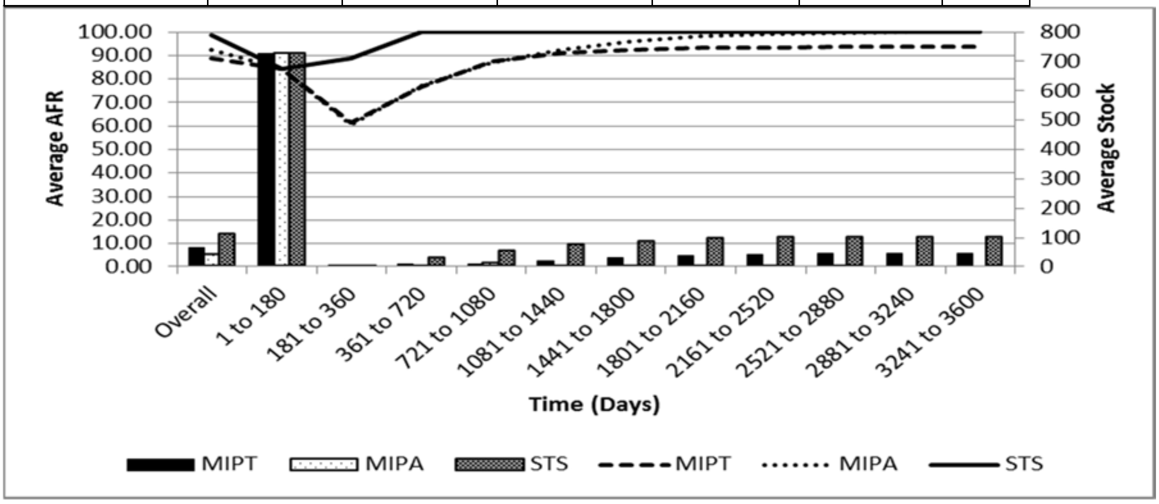


Figure 7-89: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, Six Months Initial Inventory - With No Variance.

When a normal distribution with a variance of 5 is used to simulate demand all three methods achieve an AFR of 100. Table 7-22 and Figure 7-90 show that the STS method achieves an AFR of 100 after 360 days, MIP_{Actual} after 180 days and MIP_{Theory} after 3240. While the STS method has an inventory level 11 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a normal distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-22: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 5.

	Normal Distribution - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	92.68	99.22	99.07	51	763	119
1 to 180	84.42	84.35	84.35	729	728	728
181 to 360	67.48	100.00	96.99	4	62	17
361 to 720	80.48	100.00	100.00	9	253	37
721 to 1080	89.82	100.00	100.00	11	507	63
1081 to 1440	91.98	100.00	100.00	25	716	83
1441 to 1800	93.19	100.00	100.00	35	855	96
1801 to 2160	95.59	100.00	100.00	28	936	104
2161 to 2520	99.87	100.00	100.00	6	977	108
2521 to 2880	99.94	100.00	100.00	9	995	110
2881 to 3240	99.98	100.00	100.00	10	999	110
3241 to 3600	100.00	100.00	100.00	10	999	110

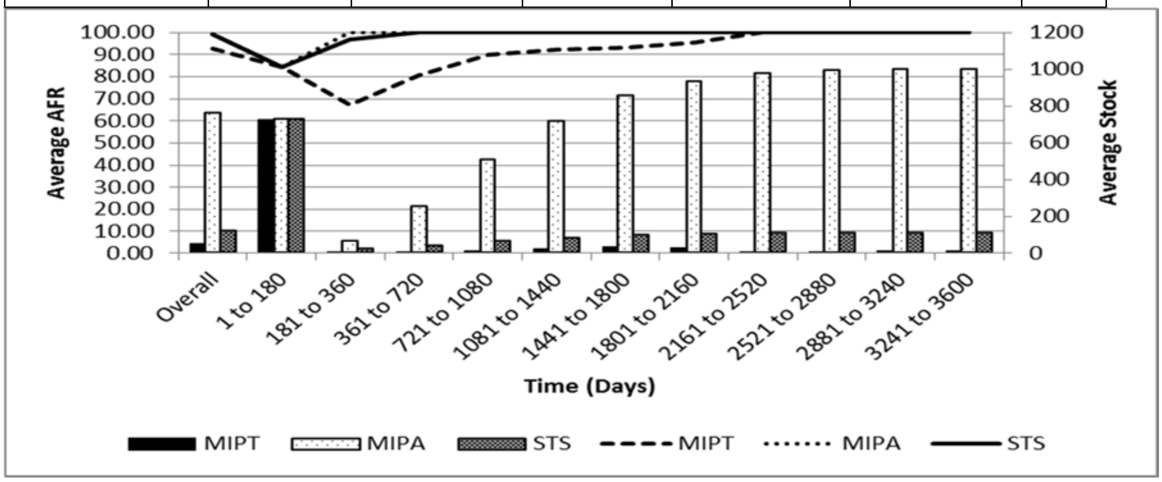


Figure 7-90: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 5.

When a normal distribution with a variance of 10 is used to simulate demand all three methods achieve an AFR of 100. Table 7-23 and Figure 7-91 show that the STS method achieves an AFR of 100 after 360 days, MIP_{Actual} after 180 days and MIP_{Theory} after 2160, although the AFR drops again after 2880 days. While the STS method has an inventory level 6 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a normal distribution with a variance of 10, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-23: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 10.

	Normal Distribution - Variance = 10					
	AFR			**Inventory**		
	MIP_{Theory}	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	94.41	99.22	99.15	52	1513	129
1 to 180	84.43	84.46	84.45	728	725	726
181 to 360	74.24	100.00	98.61	4	178	27
361 to 720	84.85	100.00	100.00	7	561	47
721 to 1080	90.93	100.00	100.00	15	1065	73
1081 to 1440	92.83	100.00	100.00	29	1468	93
1441 to 1800	96.20	100.00	100.00	23	1733	107
1801 to 2160	99.98	100.00	100.00	10	1887	114
2161 to 2520	100.00	100.00	100.00	15	1963	118
2521 to 2880	100.00	100.00	100.00	19	1996	120
2881 to 3240	99.98	100.00	100.00	20	2001	120
3241 to 3600	99.98	100.00	100.00	20	2000	120

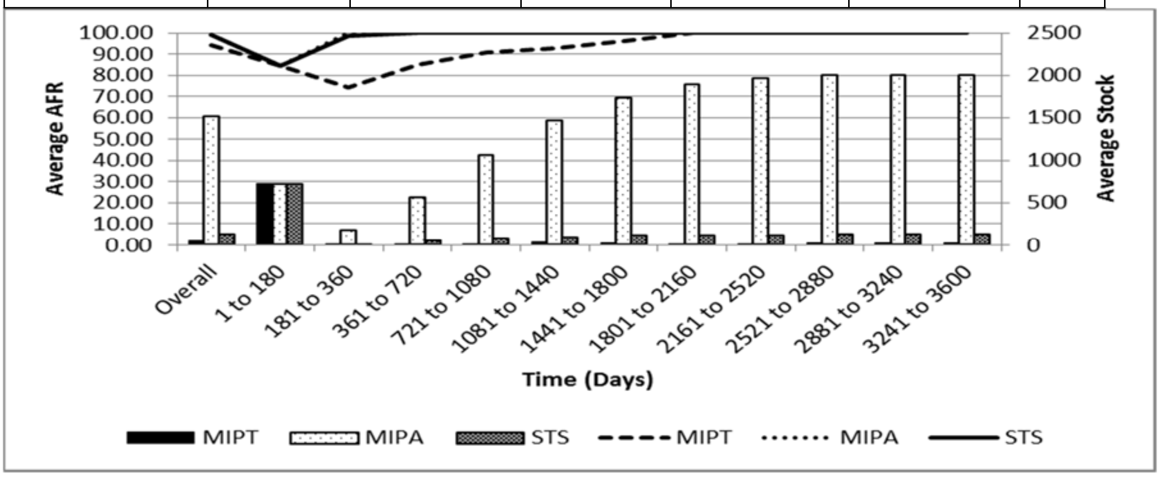


Figure 7-91: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 10.

When a log-normal distribution with a variance of 5 is used to simulate demand all three methods achieve an AFR of 100. Table 7-24 and Figure 7-92 show that the STS method achieves an AFR of 100 after 360 days, MIP_{Actual} after 180 days and MIP_{Theory} after 3240. While the STS method has an inventory level 11 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a log-normal distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-24: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 5.

	Log Normal Distribution - Variance = 5					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	92.67	99.22	99.07	51	763	119
1 to 180	84.37	84.37	84.32	729	728	729
181 to 360	67.59	100.00	96.99	4	62	17
361 to 720	80.44	100.00	100.00	9	253	37
721 to 1080	89.83	100.00	100.00	11	506	63
1081 to 1440	91.97	100.00	100.00	25	715	83
1441 to 1800	93.17	100.00	100.00	35	854	96
1801 to 2160	95.50	100.00	100.00	29	936	104
2161 to 2520	99.86	100.00	100.00	6	977	108
2521 to 2880	100.00	100.00	100.00	8	996	110
2881 to 3240	100.00	100.00	100.00	10	999	110
3241 to 3600	99.98	100.00	100.00	10	998	110

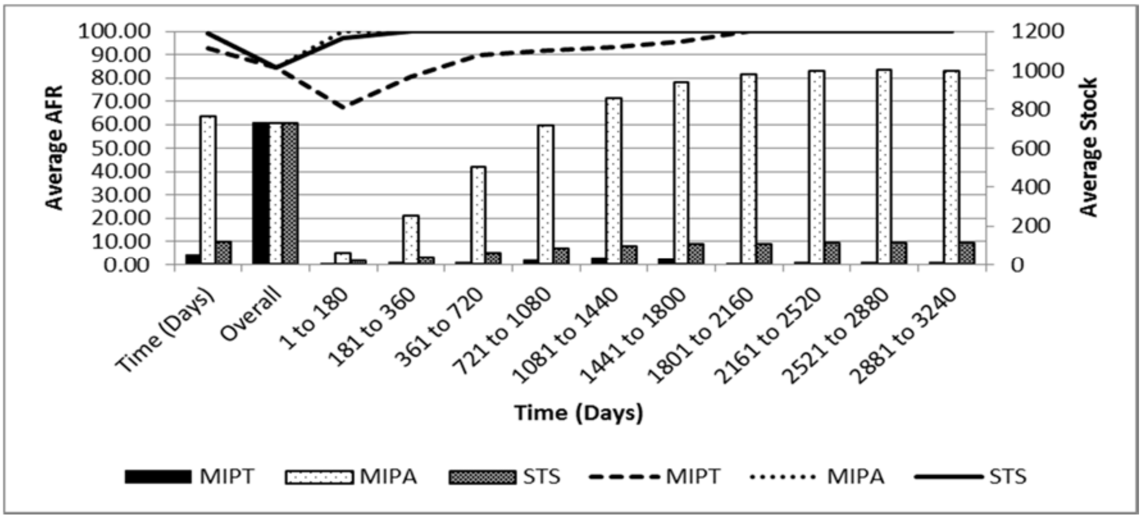


Figure 7-92: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 5.

When a log-normal distribution with a variance of 10 is used to simulate demand all three methods achieve an AFR of 100. Table 7-25 and Figure 7-93 show that the STS method achieves an AFR of 100 after 360 days, MIP_{Actual} after 180 days and MIP_{Theory} after 2520. While the STS method has an inventory level 6 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a log-normal distribution with a variance of 10, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-25: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 10.

	Log Normal Distribution - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	94.42	99.21	99.16	52	1506	129
1 to 180	84.43	84.29	84.49	728	727	726
181 to 360	74.30	100.00	98.62	4	177	27
361 to 720	84.94	100.00	100.00	6	557	47
721 to 1080	90.92	100.00	100.00	15	1056	73
1081 to 1440	92.84	100.00	100.00	29	1458	93
1441 to 1800	96.30	100.00	100.00	23	1720	106
1801 to 2160	99.94	100.00	100.00	11	1876	114
2161 to 2520	99.99	100.00	100.00	16	1954	118
2521 to 2880	100.00	100.00	100.00	19	1989	119
2881 to 3240	99.94	100.00	100.00	20	1998	120
3241 to 3600	99.99	100.00	100.00	20	1996	120

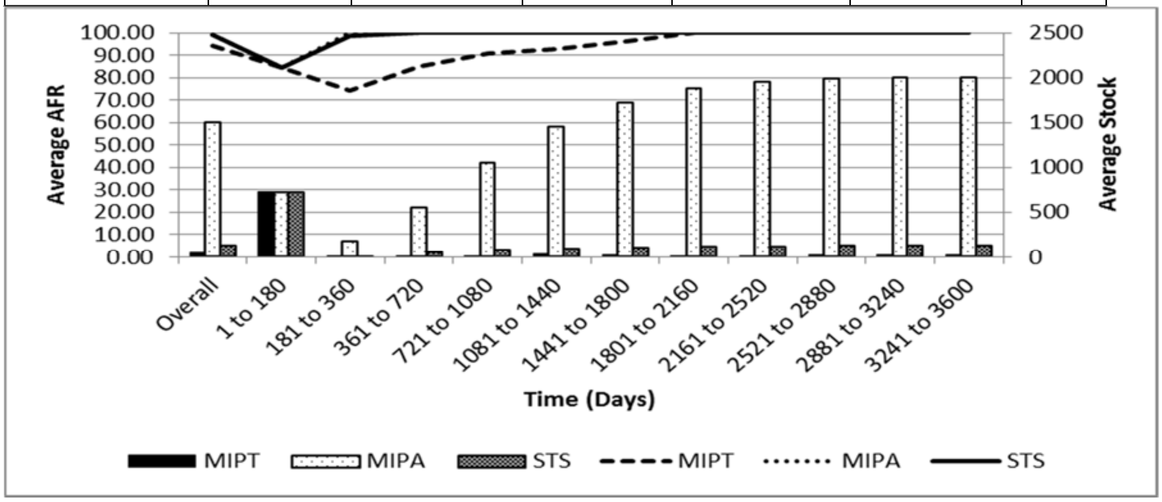


Figure 7-93: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 10.

When a gamma distribution with a variance of 5 is used to simulate demand all three methods achieve an AFR of 100. Table 7-26 and Figure 7-94 show that the STS method achieves an AFR of 100 after 360 days, MIP_{Actual} after 180 days and MIP_{Theory} after 3240. While the STS method has an inventory level 11 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a gamma distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-26: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 5.

	Gamma Distribution (80,0.25) - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	92.70	99.22	99.16	51	764	119
1 to 180	84.36	84.37	84.49	729	729	729
181 to 360	67.62	100.00	98.62	4	62	17
361 to 720	80.46	100.00	100.00	9	252	37
721 to 1080	89.81	100.00	100.00	11	506	63
1081 to 1440	91.98	100.00	100.00	25	716	83
1441 to 1800	93.09	100.00	100.00	35	855	96
1801 to 2160	95.72	100.00	100.00	28	937	104
2161 to 2520	99.92	100.00	100.00	6	978	108
2521 to 2880	100.00	100.00	100.00	9	996	110
2881 to 3240	100.00	100.00	100.00	10	1000	110
3241 to 3600	100.00	100.00	100.00	10	1000	110

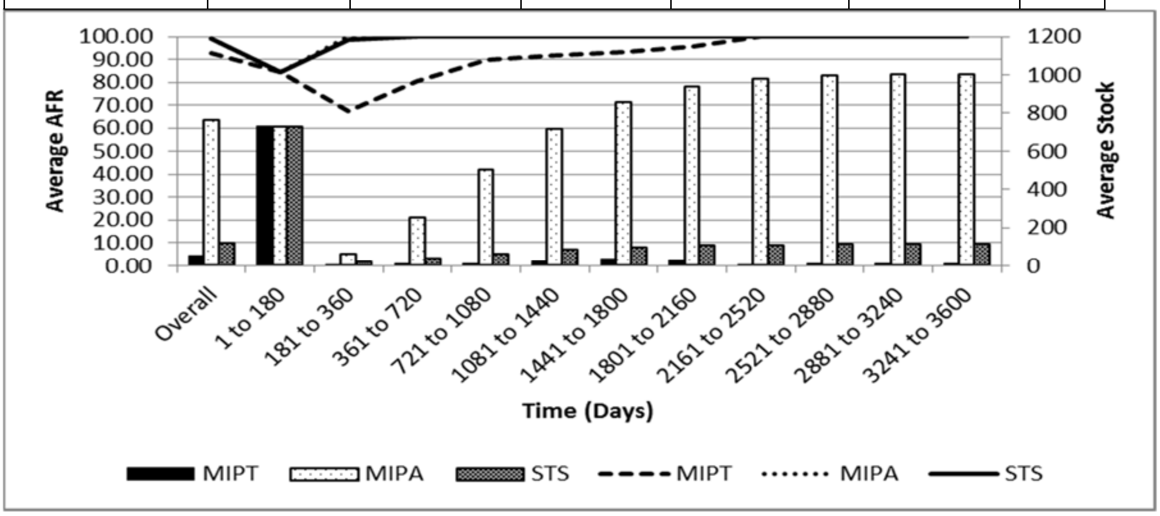


Figure 7-94: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 5.

When a gamma distribution with a variance of 10 is used to simulate demand all three methods achieve an AFR of 100. Table 7-27 and Figure 7-95 show that the STS method achieves an AFR of 100 after 360 days, MIP_{Actual} after 180 days and MIP_{Theory} after 3240. While the STS method has an inventory level 6 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 100 times higher. For a gamma distribution with a variance of 10, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-27: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 10.

	Gamma Distribution (20,1) - Variance = 10					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	94.40	99.22	99.15	53	1509	129
1 to 180	84.37	84.34	84.39	729	729	728
181 to 360	74.41	100.00	98.57	4	177	27
361 to 720	84.86	100.00	100.00	7	559	47
721 to 1080	90.90	100.00	100.00	15	1059	73
1081 to 1440	92.81	100.00	100.00	29	1464	93
1441 to 1800	96.08	100.00	100.00	24	1730	106
1801 to 2160	99.99	100.00	100.00	10	1883	114
2161 to 2520	100.00	100.00	100.00	15	1960	118
2521 to 2880	100.00	100.00	100.00	18	1991	120
2881 to 3240	100.00	100.00	100.00	20	1998	120
3241 to 3600	100.00	100.00	100.00	20	1998	120

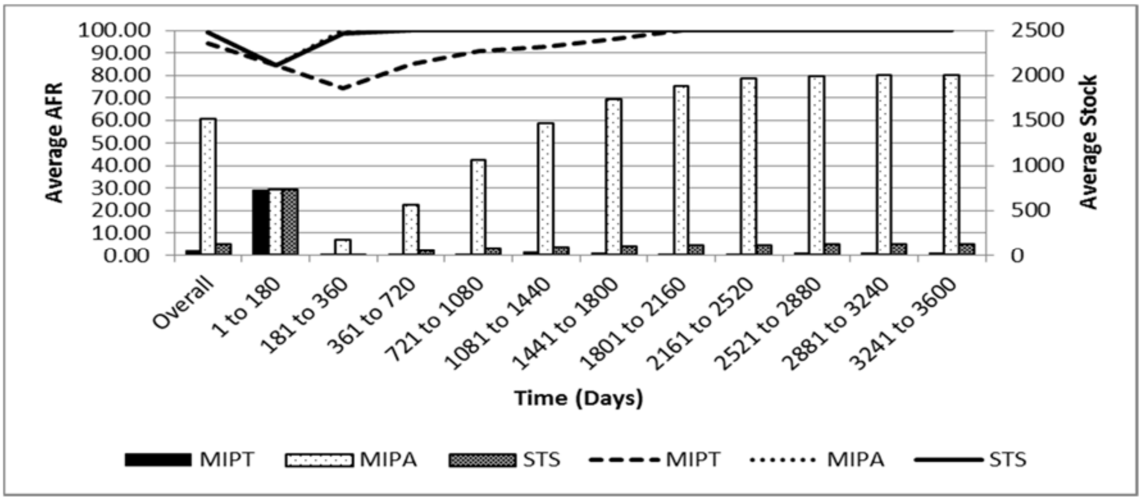


Figure 7-95: Comparative Results Domestic Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 10.

In summary, all cases of locally supplied parts under non-stationary demand with 6 months initial inventory show that the STS method is the only method that consistently achieves an AFR of 100. The MIP_{Actual} method also achieves an AFR of 100 and does so in the shortest time period. The MIP_{Theory} method performs the worst in terms of achieving an AFR of 100. The MIP_{Theory} has the lowest inventory requirements and the MIP_{Actual} method requires significantly higher inventory. The STS method has the best AFR performance with an inventory increase, that is, however, much lower than that of the MIP_{Actual} method. For locally supplied parts, the STS method is the most effective with the highest AFR and the least amount of inventory, except for the ideal case with no demand variance.

7.2.4.4 **Comparative Results for Import Supplier Parts Under Non-Stationary Demand – MIP_{Theory} vs. MIP_{Actual} vs. STS - With Starting Inventory**

The zero demand variance case is the same for the various demand distributions. As shown in Table 7-28 and Figure 7-96 the STS method has the lowest average AFR overall. The STS method is the first method to achieve an AFR of 100 and does so after 1800 days. The MIP_{Actual} and MIP_{Theory} methods achieve an AFR of 100 only after 2880 days. The STS method is however also the method with the highest average inventory. This result is as expected, given that the MIP methods will allow inventory to reach zero before the next delivery cycle, while the STS method maintains sufficient inventory to cover the next cycle given the target setting equation. The MIP methods however have higher inventory levels that the STS method for the first 1440 days. In this case the STS method is the worst when taking AFR and inventory into account.

Table 7-28: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Demand With No Variance.

	No Variance					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	91.41	91.41	82.35	253	253	412
1 to 180	84.44	84.44	84.44	728	728	728
181 to 360	47.85	47.85	33.40	17	17	4
361 to 720	74.01	74.01	34.52	72	72	12
721 to 1080	86.86	86.86	54.75	145	145	54
1081 to 1440	93.28	93.28	78.15	207	207	145
1441 to 1800	96.47	96.47	97.14	252	252	367
1801 to 2160	98.34	98.34	100.00	281	281	575
2161 to 2520	99.23	99.23	100.00	295	295	627
2521 to 2880	99.73	99.73	100.00	301	301	649
2881 to 3240	100.00	100.00	100.00	298	298	660
3241 to 3600	100.00	100.00	100.00	302	302	665

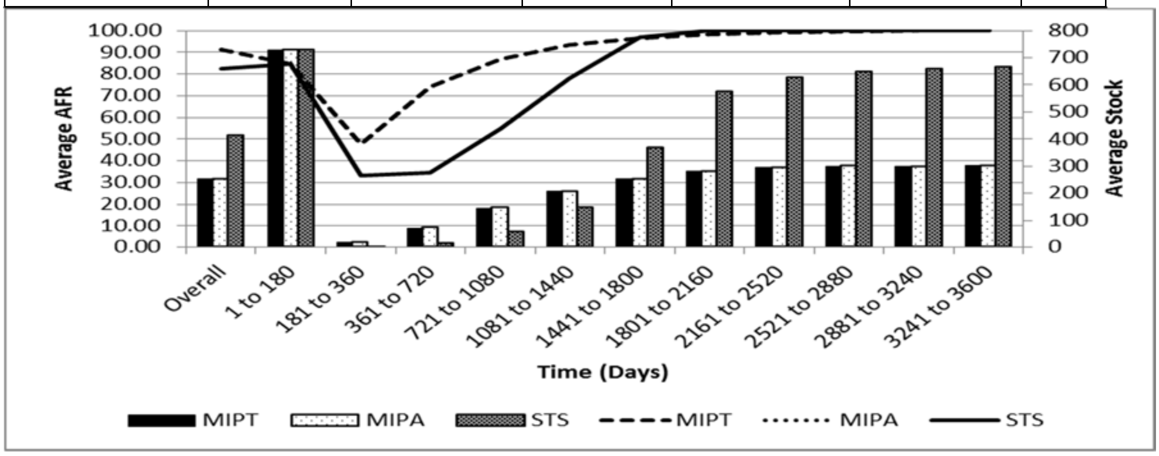


Figure 7-96: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory – With No Variance.

When a normal distribution with a variance of 5 is used to simulate demand the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-29 and Figure 7-97 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 1080 days. While the STS method has an inventory level 2.3 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 4 times higher. For a normal distribution with a variance of

5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-29: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 5.

	Normal Distribution - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	91.53	95.20	87.31	258	831	477
1 to 180	84.36	84.39	84.36	729	728	730
181 to 360	48.59	53.85	41.23	17	22	8
361 to 720	74.46	84.65	48.75	74	97	26
721 to 1080	87.17	98.22	69.70	151	219	90
1081 to 1440	93.35	100.00	91.82	211	559	209
1441 to 1800	96.53	100.00	100.00	254	882	551
1801 to 2160	98.43	100.00	100.00	282	1097	643
2161 to 2520	99.33	100.00	100.00	298	1215	700
2521 to 2880	99.72	100.00	100.00	310	1273	717
2881 to 3240	99.88	100.00	100.00	315	1297	728
3241 to 3600	99.93	100.00	100.00	316	1300	735

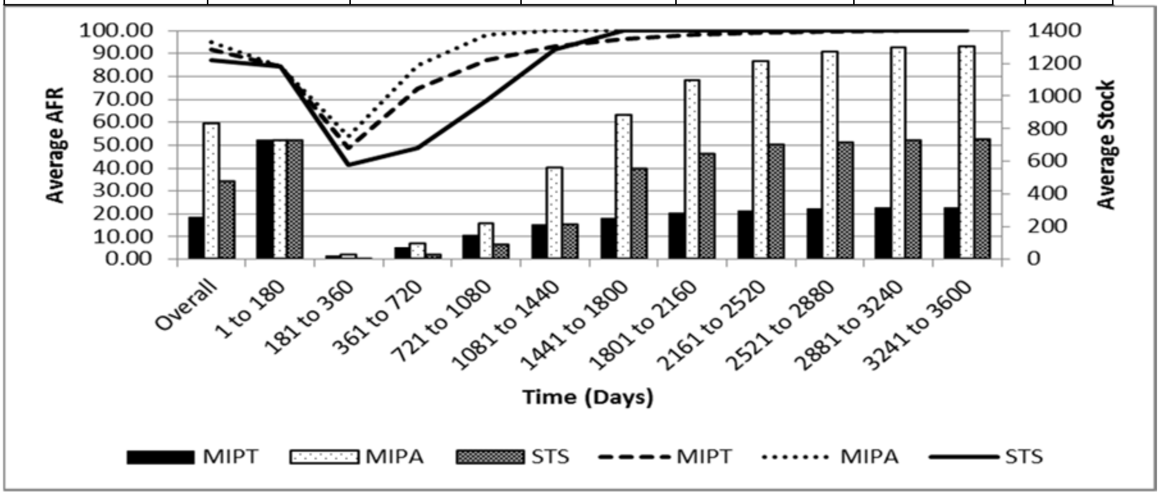


Figure 7-97: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 5.

When a normal distribution with a variance of 10 is used to simulate demand, the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-30 and Figure 7-98 show that the

STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days. While the STS method has an inventory level 2.5 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 7 times higher. For a normal distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-30: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 10.

	Normal Distribution - Variance = 10					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	91.70	96.60	91.24	262	1531	543
1 to 180	84.51	84.26	84.31	729	729	730
181 to 360	49.28	59.71	49.70	18	32	12
361 to 720	74.86	93.98	62.61	75	146	44
721 to 1080	87.43	100.00	83.56	153	653	133
1081 to 1440	93.53	100.00	99.25	213	1286	408
1441 to 1800	96.67	100.00	100.00	256	1744	602
1801 to 2160	98.56	100.00	100.00	284	2035	710
2161 to 2520	99.41	100.00	100.00	302	2198	769
2521 to 2880	99.74	100.00	100.00	317	2267	788
2881 to 3240	99.93	100.00	100.00	325	2297	798
3241 to 3600	99.92	100.00	100.00	325	2303	805

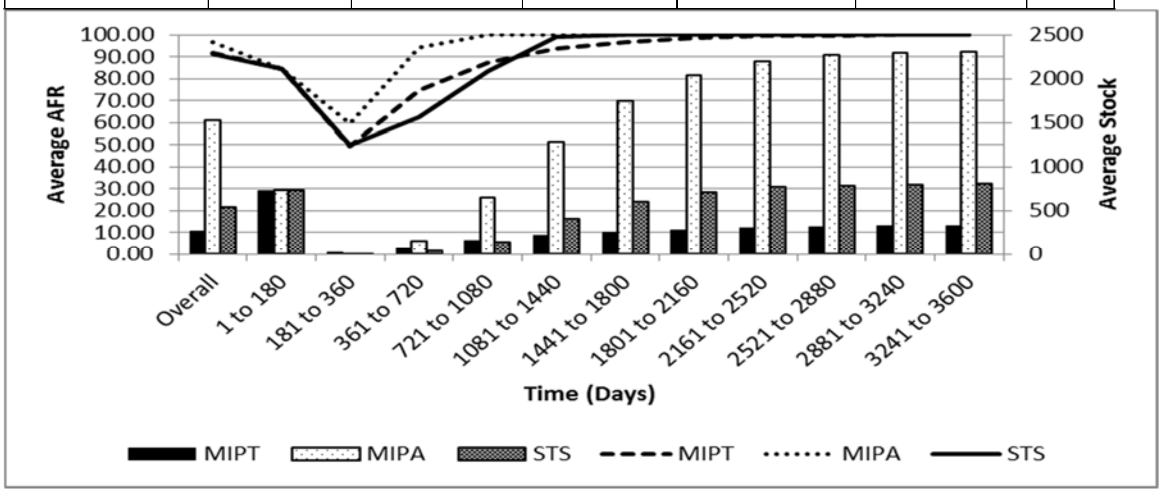


Figure 7-98: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Normal Demand With Variance = 10.

When a log-normal distribution with a variance of 5 is used to simulate demand, the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-31 and Figure 7-99 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 1080 days. While the STS method has an inventory level 2.3 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 4 times higher. For a log-normal distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-31: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 5.

	Log-Normal Distribution - Variance = 5					
	AFR			Inventory		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	91.55	95.20	87.30	257	832	476
1 to 180	84.38	84.44	84.34	728	727	731
181 to 360	48.57	53.82	41.38	17	22	8
361 to 720	74.49	84.64	48.75	73	97	26
721 to 1080	87.17	98.24	69.64	149	219	90
1081 to 1440	93.40	100.00	91.79	210	560	209
1441 to 1800	96.58	100.00	100.00	254	885	549
1801 to 2160	98.43	100.00	100.00	282	1097	643
2161 to 2520	99.32	100.00	100.00	299	1216	698
2521 to 2880	99.72	100.00	100.00	307	1275	717
2881 to 3240	99.95	100.00	100.00	312	1296	729
3241 to 3600	99.96	100.00	100.00	314	1298	734

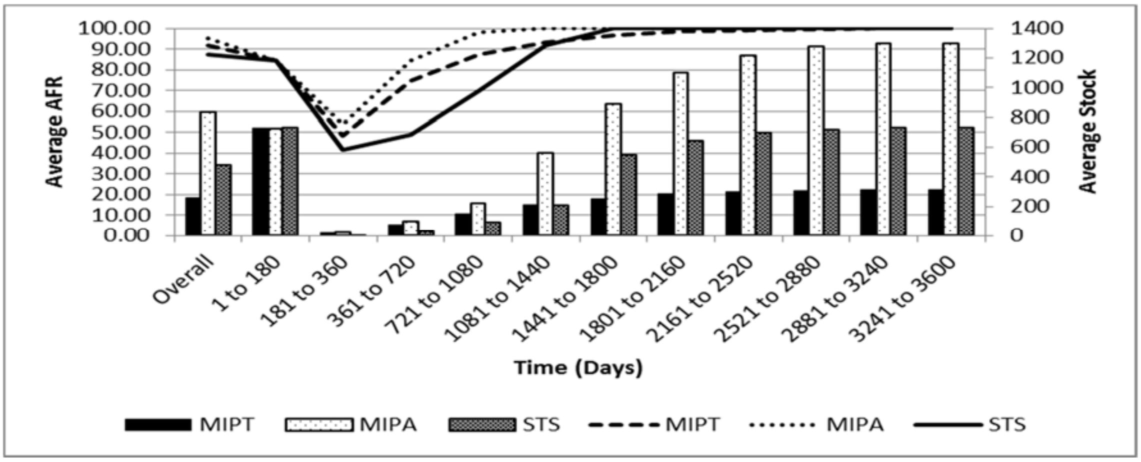


Figure 7-99: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 5.

When a log-normal distribution with a variance of 10 is used to simulate demand, the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-32 and Figure 7-100 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days. While the STS method has an inventory level 2.5 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 7 times higher. For a log-normal distribution with a variance of 10, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-32: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance = 10.

	Log Normal Distribution - Variance = 10					
	AFR			Inventory		
Time (Days)	MIP_{Theory}	MIP_{Actual}	STS	MIP_{Theory}	MIP_{Actual}	STS
Overall	91.73	96.59	91.31	260	1526	541
1 to 180	84.37	84.19	84.39	728	730	728
181 to 360	49.25	59.91	49.94	18	31	12
361 to 720	74.99	93.83	62.89	73	145	45
721 to 1080	87.45	100.00	83.79	149	654	133
1081 to 1440	93.57	100.00	99.27	211	1282	406
1441 to 1800	96.72	100.00	100.00	254	1739	598
1801 to 2160	98.58	100.00	100.00	284	2030	707
2161 to 2520	99.42	100.00	100.00	299	2189	763
2521 to 2880	99.78	100.00	100.00	313	2252	789
2881 to 3240	99.97	100.00	100.00	319	2292	798
3241 to 3600	99.98	100.00	100.00	324	2299	803

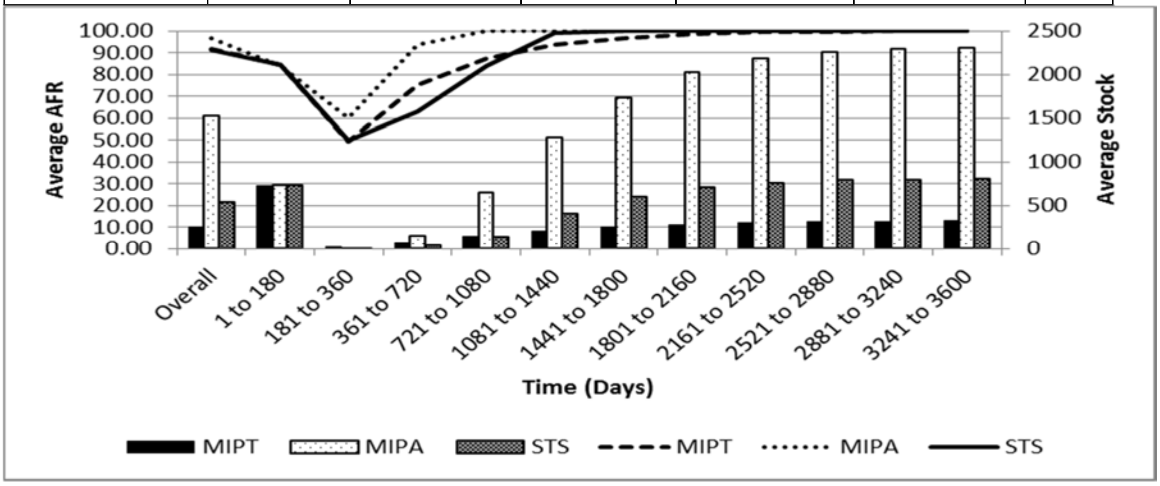


Figure 7-100: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Log Normal Demand With Variance =10.

When a gamma distribution with a variance of 5 is used to simulate demand, the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-33 and Figure 7-101 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days. While the STS method has an inventory level 2.5 times higher than the MIP_{Theory}, the inventory level for the MIP$_{Actual}$ method is 7 times higher. For a gamma distribution with a variance of 5, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-33: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 5.

	Gamma Distribution (80,0.25) - Variance = 5					
	AFR			Inventory		
Time (Days)	MIP$_{Theory}$	MIP$_{Actual}$	STS	MIP$_{Theory}$	MIP$_{Actual}$	STS
Overall	91.56	95.20	87.31	256	832	477
1 to 180	84.39	84.36	84.39	729	729	728
181 to 360	48.58	53.90	41.16	17	22	7
361 to 720	74.48	84.65	48.79	72	97	26
721 to 1080	87.16	98.19	69.70	147	218	90
1081 to 1440	93.41	100.00	91.80	209	560	208
1441 to 1800	96.57	100.00	100.00	254	884	551
1801 to 2160	98.47	100.00	100.00	283	1098	645
2161 to 2520	99.34	100.00	100.00	297	1219	699
2521 to 2880	99.76	100.00	100.00	307	1273	718
2881 to 3240	99.98	100.00	100.00	309	1297	729
3241 to 3600	99.99	100.00	100.00	313	1301	734

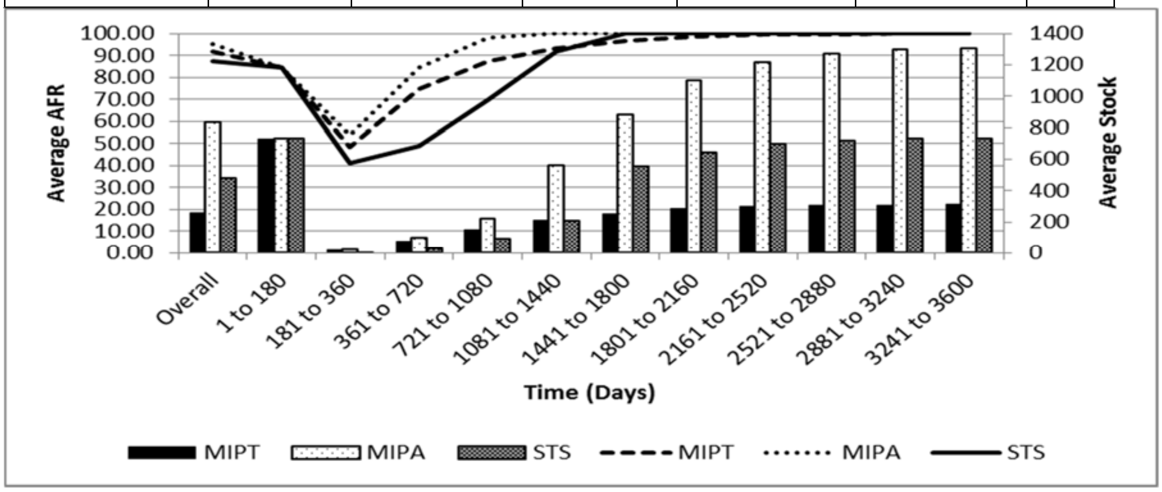


Figure 7-101: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 5.

When a gamma distribution with a variance of 10 is used to simulate demand, the STS and MIP_{Actual} methods achieve an AFR of 100. Table 7-30 and Figure 7-98 show that the STS method achieves an AFR of 100 after 1440 days and MIP_{Actual} after 720 days. While the STS method has an inventory level 2.5 times higher than the MIP_{Theory}, the inventory level for the MIP_{Actual} method is 7 times higher. For a gamma distribution with a variance of 10, the STS method is the most effective method if both AFR and inventory are taken into account.

Table 7-34: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 10.

	Gamma Distribution (20,1) - Variance = 10					
	AFR			**Inventory**		
Time (Days)	**MIP_{Theory}**	**MIP_{Actual}**	**STS**	**MIP_{Theory}**	**MIP_{Actual}**	**STS**
Overall	88.37	96.60	91.28	224	1529	542
1 to 180	18.55	84.38	84.34	2	729	730
181 to 360	48.97	59.80	49.81	17	33	12
361 to 720	74.88	93.92	62.89	71	145	45
721 to 1080	87.17	100.00	83.66	150	650	133
1081 to 1440	93.40	100.00	99.22	214	1279	408
1441 to 1800	96.80	100.00	100.00	256	1741	600
1801 to 2160	98.59	100.00	100.00	285	2035	709
2161 to 2520	99.42	100.00	100.00	300	2195	769
2521 to 2880	99.78	100.00	100.00	313	2270	788
2881 to 3240	99.96	100.00	100.00	321	2295	798
3241 to 3600	99.97	100.00	100.00	323	2301	802

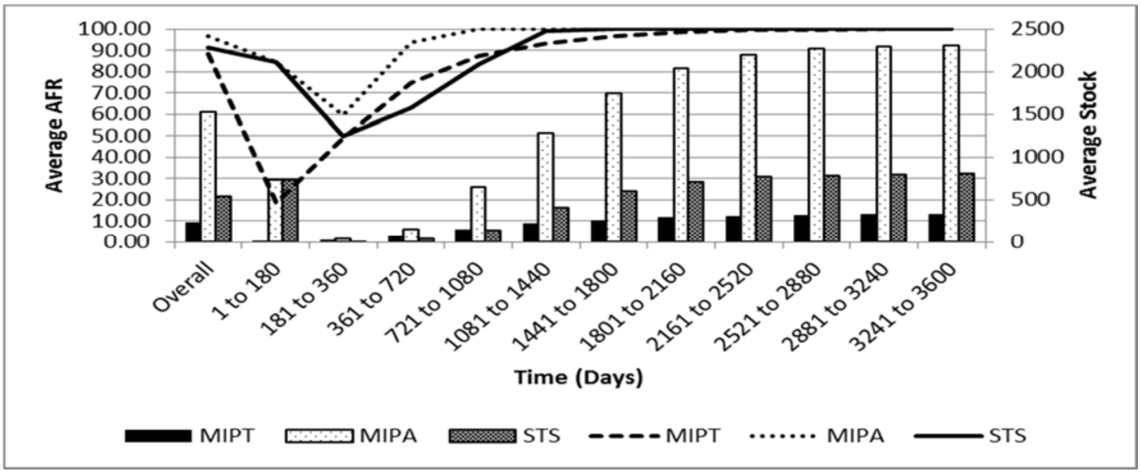


Figure 7-102: Comparative Results Import Supplied Parts Under Non-Stationary Demand Conditions, 6 Months Initial Inventory - Gamma Demand With Variance = 10.

In summary, all cases of import supplied parts under non-stationary demand with 6 months initial inventory show that the STS method is the only method that consistently achieves an AFR of 100. The MIP_{Actual} method also achieves an AFR of 100 and does so in the shortest time period. The MIP_{Theory} method performs the worst in terms of achieving an AFR of 100. The MIP_{Theory} has the lowest inventory requirements and the MIP_{Actual} method requires significantly higher inventory. The STS method has the best AFR performance with an inventory increase, that is however much lower than that of the MIP_{Actual} method. For locally supplied parts, the STS method is the most effective with the highest AFR and the least amount of inventory, except for the ideal case with no demand variance.

Finally, the STS and MIP_{Actual} methods consistently achieve an AFR of 100. The STS method does so with the least amount of inventory, as compared to the MIP_{Actual} method. While the MIP_{Theory} method has the lowest inventory level, it performs worst in terms of achieving an AFR of 100. Based on both the AFR and inventory criteria, the STS method is more effective.

7.3 Statistical Analysis of Historical Data

The statistical analysis will focus on determining the shape of the two distributions highlighted in Chapter 3, namely:

- Lead-Time
- Demand

In the next section each of these are reviewed, based on 2013 data obtained from one of the original equipment manufacturers in South Africa. The objective of this part of the study is to determine the best-fit distribution types for each of the datasets. The MIP method described in Chapter 3 is based on a safety stock calculation. The safety stock calculation is based on a service level. Given the stochastic nature of real supply chains, it is necessary to assume that some distribution is used. In general, it is assumed that a normal distribution is sufficient and that the requisite number of standard deviations can be used to ensure a certain service level. In this section the data is compared to a number of distributions to identify the best fit. The three probability distributions used most frequently are: Normal distribution, log-normal distribution and gamma Distribution.

For the purposes of this work, a dataset of lead times and a dataset of customer orders (demand) are analysed. The initial focus is on establishing which distribution represents the dataset best. Once the most likely distributions have been identified, it is possible to simulate the two MIP and STS methods in a theoretical environment, applying and evaluating the impact of the two MIP and STS methods on optimizing inventory and achieving the required service levels. After the completion of the experiments, the focus will turn to analysing the real data within the simulation environment.

7.3.1 Lead-Time Distribution Fit

Lead time for local suppliers is contractually set. For current model parts the lead time is 7 days and for past model parts it is 28 days. The logic behind this assumption is that current model parts are part of current production and the 7 day lead time will allow sufficient time to add additional volumes to the daily production and to deliver the parts as per schedule. For past model parts there is a need for more comprehensive production planning, as it may require tooling to be changed and machines to be set up. The 28 day target makes it possible to also include it in overtime planning if required. Intervention on the local supplier lead time is very quick. As soon as a supplier foresees a problem, the parts division is informed and alternative arrangements are made. The lead time data for local suppliers was not available for this study. It was, therefore, necessary to focus on the imported parts dataset that was available.

In contrast to the local lead time, it is very difficult to intervene with the import process. The lead time is made up of the following components:

- Order Processing (Receive Order to Pick Order)

- Container Consolidation
- Shipment Cycle – This cycle depends on the frequency of ships that will dock at the import site and in South Africa. The shipment cycle for the available data was weekly.
- Shipping
- Docking, Offloading and Customs Clearance
- Dispatch and Arrival at the Distribution Centre
- Unloading, Unpacking of Cases and Binning of Parts

Internal variances in process times can offset or expand the cycle time. The focus will therefore be on the total lead time, which is defined as:

Date Parts Are Binned minus Date of Order Placement.

This approach will provide an overall picture of the lead time (days) that affects the inventory and safety stock requirements.

The dataset that was obtained covered a 9 month period in 2013. It differentiates the parts in four groups:

- Key Parts from Source A
- General Parts from Source A
- All Parts from Source B
- All Parts from Source C

Each dataset is analysed separately to determine if there are significant differences regarding import source and part classification. (Key parts are fast moving, service parts.) The lead time for each part is calculated. It is important to distinguish between orders and parts. An order to the supplier will contain many parts. Parts in the same order may have different lead times, depending on part availability and process capacity. The lead time for each order for a particular part is then calculated individually. The result is a series of lead times

When combined in the four groups identified above, this information provides a series of lead times that describe the behaviour for a group.

Table 7-35 provides a summary of the basic statistical measures for the four groups of lead times being studied.

Table 7-35: Basic Statistical Measures of Lead-Time Data.

Basic Statistical Measures				
	Key Parts Source A	General Parts Source A	Source B	Source C
Observations	61588	1232	9120	661
Location				
Mean	63.60	64.63	57.32	57.00
Median	62	62	55	54
Mode	58	50	51	50
Variability				
Std Deviation	11.07	13.28	14.52	12.23
Variance	122.48	176.30	210.70	149.54
Range	138	83	172	79

The bulk of the observation points (61588 out of 7260 or 85%) are from the Key Parts from Source A. While the median lead time for key parts and general parts are the same, the general parts have a slightly higher average lead time, as well as a higher standard deviation. This statistic would indicate that key parts are more likely to be immediately ready for shipment, while general parts may sometimes require additional time to obtain. The difference is, however, not significant. The lead time results for Source B and Source C are quite interesting. Unlike the key parts and general parts for Source A, Source B and Source C are not geographically connected. Source B shows a slightly higher standard deviation.

With this data available, it is necessary to determine which standard distribution can be used to simulate the lead time behaviour of the particular supply chain. The data was analysed by the Statistics Department of the University of Pretoria, using SPSS.

Three goodness-of-fit tests were performed, namely:

- Kolmogorov-Smirnov
- Cramer-von Mises
- Anderson-Darling

The results of this analysis are discussed below.

7.3.1.1 **Lead-Time Analysis – Key Parts, Source A**

Key parts represent fast moving, high volume parts and will in general be typical service parts for vehicles with high numbers in use. Key parts include oil filters, air filters, spark plugs, fuel filters and other items that have a planned replacement cycle on the vehicle design life cycle.

Figure 7-103 provides a frequency distribution of the lead times (days) observed for the key parts from source A.

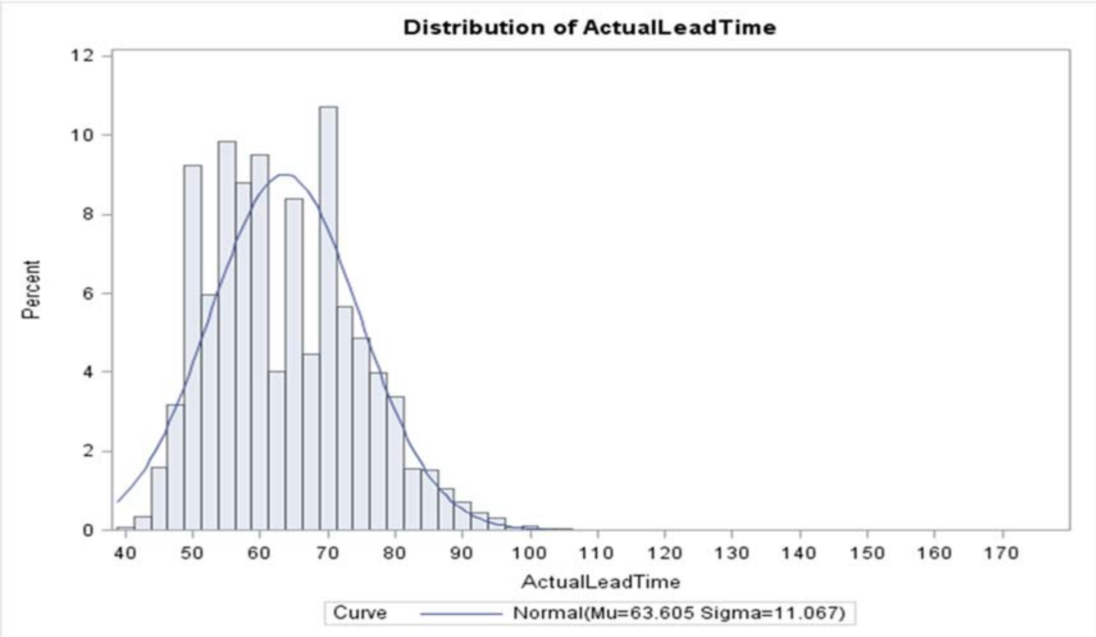


Figure 7-103: Frequency Distribution of Lead-Time for Key Parts from Source A.

The detailed statistical analysis for the key parts from Source A is given in Appendix IX. The basic statistics for 61588 observations is shown in Table 7-36. Each observation is a part order that was placed, shipped and received. The lead time was calculated from the day on which the order was placed, until the day it was received at the warehouse and is measured in days.

Table 7-36: Basic Statistics for Key Parts from Source A.

Basic Statistical Measures			
Observations		61588	
Location		Variability	
Mean	63.60	Std Deviation	11.07
Median	62	Variance	122.48
Mode	58	Range	138

Table 7-37 summarises the results of the goodness-of-fit testing for key parts from Source A. The results for the three most promising distributions are shown. In each case the three goodness-of-fit tests shows an acceptable value of *p*, which indicate that there is a fit. The parameters of the best fit curve were determined, depending on the distribution being tested. Using these parameters, values for the various quintiles were estimated. The differences between the observed and estimated values were squared and added to provide a method to decide which method had the best fit. This result, combined with the *p* values for the goodness-of-fit tests provides a simple method to select an appropriate distribution.

Table 7-37: Goodness-of-Fit Testing Results – Key Parts, Source A.

Goodness-of-Fit Tests for:	**Weibull Distribution**			**Gamma Distribution**			**Normal Distribution**		
Parameters for Distribution	Sym-bol	Estimate		Symbol	Estimate		Sym-bol	Estimate	
Threshold	Theta	0		Theta	0				
Scale	Sigma	68.27		Sigma	1.86				
Shape	C	5.57		Alpha	34.23				
Mean		63.07			63.60		Mu	63.60	
StdDev		13.09			10.87		Sigma	11.07	
Test	Statistic	p Value		Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	N/A			0.07	Pr > D	<0.001	0.09	Pr> D	<0.010
Cramer-von Mises (W-Sq)	105.91	Pr > W-Sq	<0.010	50.87	Pr > W-Sq	<0.001	70.61	Pr> W-Sq	<0.005

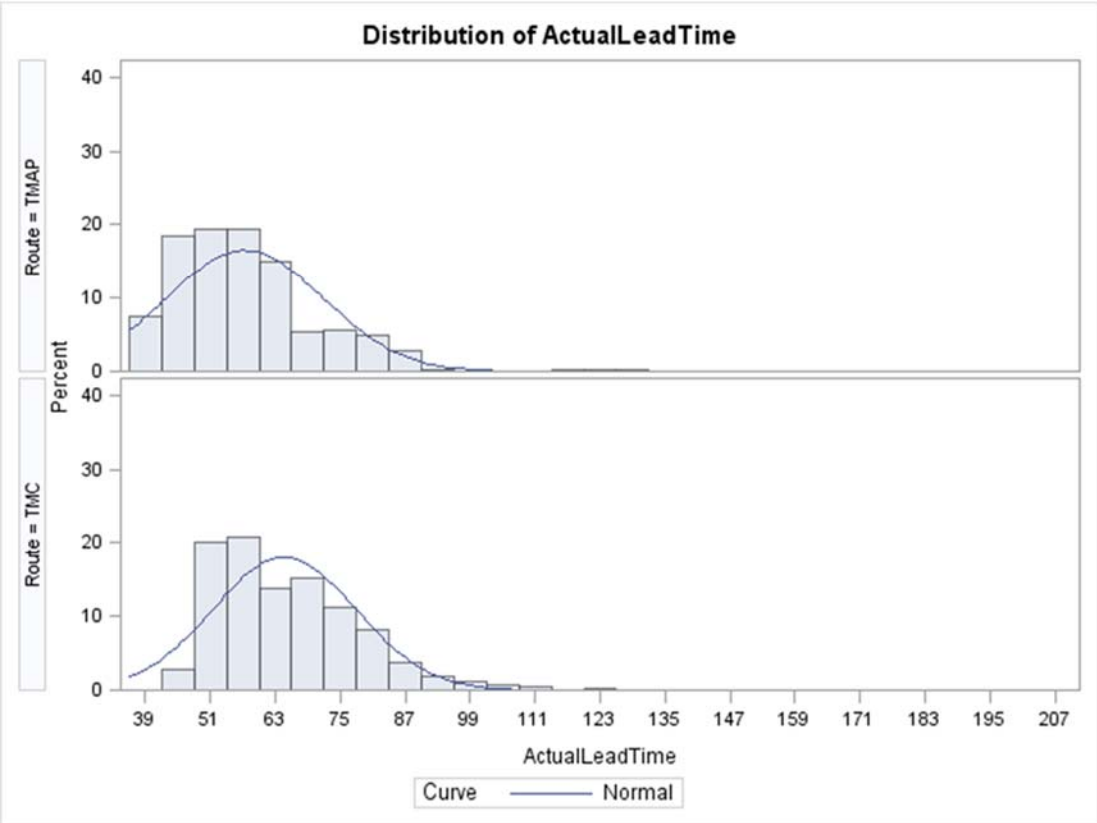
Goodness-of-Fit Tests for:		**Weibull Distribution**		**Gamma Distribution**		**Normal Distribution**	
Anderson-Darling (A-Sq)		857.72	Pr > A-Sq <0.010	295.85	Pr > A-Sq <0.001	437.30	Pr> A-Sq <0.005
Quintile		Quintiles for Weibull Distribution		Quintiles for Gamma Distribution		Quintiles for Normal Distribution	
%	Ob-served	Esti-mated	Differences Squared	Esti-mated	Differences Squared	Esti-mated	Differ-ences Squared
1	45	29.88	228.72	41.07	15.44	37.86	51.00
5	48	40.04	63.36	46.84	1.35	45.40	6.76
10	50	45.57	19.65	50.13	0.02	49.42	0.33
25	55	54.58	0.18	55.97	0.95	56.14	1.30
50	62	63.92	3.68	62.99	0.97	63.60	2.57
75	71	72.39	1.94	70.56	0.19	71.07	0.00
90	78	79.30	1.69	77.87	0.02	77.79	0.05
95	83	83.14	0.02	82.48	0.27	81.81	1.42
99	92	89.82	4.77	91.59	0.17	89.35	7.02
		Sum	324.01	Sum	19.38	Sum	70.45

The results indicate that the estimated values for all three distributions are adequate to describe the upper quintiles. The biggest discrepancies lie with the lower 5% for the gamma and normal distributions and the lower 10% for the Weibull distribution. Given the goodness-of-fit results and the squared differences calculated, the gamma distribution provides the best fit. Despite the normal distribution showing a worse fit, it is proposed that either a normal or a gamma distribution provides an acceptable distribution to use for the key parts from Source A. Using a normal distribution requires less computation and will ease further research.

7.3.1.2 **Lead-Time Analysis – General Parts, Source A, Source B and Source C**

General parts are basically all parts that do not have a specified replacement cycle. These parts include wear and tear parts, repair parts and crash parts. Orders are placed when client orders are received. Anomalies can appear following region specific events such as hail storms, fog and first rain of the season (oil that seeped into the roadway is washed out resulting in slippery roads). All of these factors affect the demand for crash parts. Other localized elements could be heavy dust and mining dust environments that add to wear and tear. In many cases the main driver for requiring these parts is time in use and driver behaviour.

Figure 7-104 provides a frequency distribution of the lead times (days) observed for the general parts from Source A, Source B and Source C.



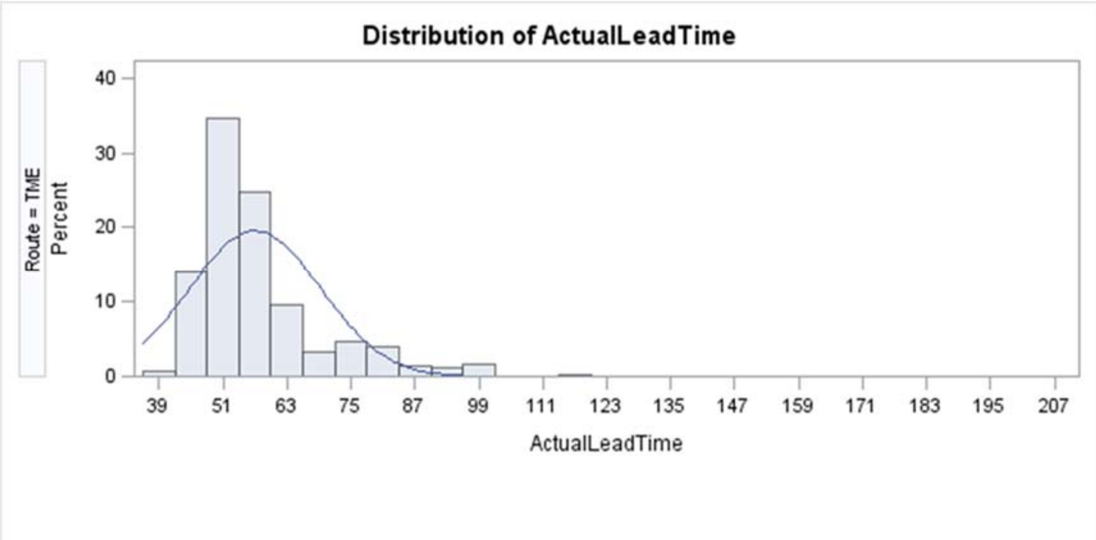


Figure 7-104: Frequency Distribution of Lead-Time for General Parts from Source A, Source B and Source C.

The detailed statistical analysis for the general parts from Source A, Source B and Source C is given in Appendix IX. The data from the three sources were analysed together, based on the assumption that the focus on general parts will provide similar results. The general parts are expected to have different demand patterns which may influence the availability of inventory and hence the lead time.

The basic statistics for general parts from Source A, 1232 observations, is shown in Table 7-38. Each observation is an order that was placed, shipped and received. The lead time was calculated from the day on which the order was placed, until the day it was received at the warehouse.

Table 7-38: Basic Statistics for General Parts from Source A.

Basic Statistical Measures			
Observations		1232	
Location		Variability	
Mean	64.63	Std Deviation	13.28
Median	62	Variance	176.30
Mode	50	Range	83

The number of observations is significantly lower than those for key parts. This results in not all parts being ordered every time. In contrast to key parts of which most are ordered on a daily basis, the general parts may not necessarily be ordered every day. In addition, quantities may be significantly smaller. Even though the parts demand is significantly different, the lead time is not significantly different.

Table 7-39 shows the data for the goodness-of-fit testing on the general parts from Source A. The results for the three most promising distributions are shown for this case as well. In each case the three goodness-of-fit tests shows an acceptable value of *p*, which indicates that there is a fit. In this particular case, the test results are slightly less positive, but still within acceptable parameters. The parameters of the best fit curve were determined, depending on the distribution being tested. Using these parameters, values for the various quintiles were estimated. The differences between the observed and estimated values were squared and added up to provide a method to decide which method had the best fit. This result, combined with the *p* values for the goodness-of-fit tests will provide a simple method to select an appropriate distribution.

Table 7-39: Goodness-of-Fit Testing Results – General Parts, Source A.

Goodness-of-Fit Tests for:	**Weibull Distribution**			**Gamma Distribution**			**Normal Distribution**		
Parameters for Distribution	Sym-bol	Estimate		Sym-bol	Estimate		Sym-bol	Estimate	
Threshold	Theta	0		Theta	0				
Scale	Sigma	70.13		Sigma	2.51				
Shape	C	4.73		Alpha	25.78				
Mean		64.18			64.63		Mu	64.63	
StdDev		15.46			12.73		Sigma	13.28	
Test	Statis-tic	p Value		Statis-tic	p Value		Statis-tic	p Value	
Kolmogorov-Smirnov (D)	N/A			0.09	Pr> D	<0.001	0.11	Pr> D	<0.010
Cramer-von Mises (W-Sq)	4.11	Pr> W-Sq	<0.010	1.85	Pr> W-Sq	<0.001	2.89	Pr> W-Sq	<0.005

Goodness-of-Fit Tests for:	**Weibull Distribution**			**Gamma Distribution**			**Normal Distribution**		
Anderson-Darling (A-Sq)	29.59	Pr> A-Sq	<0.010	12.14	Pr> A-Sq	<0.001	19.03	Pr> A-Sq	<0.005

Quintile		Quintiles for Weibull Distribution		Quintiles for Gamma Distribution		Quintiles for Normal Distribution	
%	Ob-served	Esti-mated	Diffe-rences Squared	Esti-mated	Diffe-rences Squared	Esti-mated	Diffe-rences Squared
1	46.00	26.52	379.49	38.74	52.72	33.74	150.28
5	49.00	37.43	133.89	45.21	14.36	42.79	38.57
10	50.00	43.58	41.20	48.95	1.11	47.61	5.69
25	54.00	53.89	0.01	55.65	2.72	55.67	2.80
50	62.00	64.90	8.42	63.80	3.23	64.63	6.92
75	73.00	75.14	4.59	72.70	0.09	73.59	0.34
90	81.00	83.65	7.03	81.39	0.15	81.65	0.42
95	89.00	88.44	0.32	86.89	4.43	86.47	6.40
99	106.00	96.85	83.68	97.87	66.12	95.52	109.86
		Sum	658.63	Sum	144.93	Sum	321.28

The results indicate that the estimated values for all three distributions are adequate to describe the quintiles between 25% and 95%. The biggest discrepancies lie with the lower 10% for the gamma and normal distributions and the lower 25% for the Weibull distribution. In all cases the 99% quintile shows a significant difference. Given the goodness-of-fit results and the squared differences calculated, the gamma distribution provides the best fit. Despite the normal distribution showing a worse fit, it is proposed that either a normal or a gamma distribution provides an acceptable distribution to use for the general parts from Source A. Using a normal distribution requires less computation and will simplify further research.

The basic statistics for general parts from Source B, 9120 observations, is shown in Table 7-40. Each observation is an order that was placed, shipped and received. The lead time was calculated from the day on which the order was placed, until the day it was received at the warehouse.

Table 7-40: Basic Statistics for General Parts from Source B.

Basic Statistical Measures			
Observations		9120	
Location		Variability	
Mean	57.32	Std Deviation	14.52
Median	55	Variance	210.70
Mode	51	Range	172

The number of observations is significantly lower than those for key parts, but significantly higher than that of the other two sources of general parts. This particular source provides a significant number of crash parts in the parts mix it supplies. Similar to other general parts, not all parts are being ordered every time. In contrast to key parts of which most are ordered on a daily basis, the general parts may not necessarily be ordered every day. In addition, quantities may be significantly smaller. The lead time from Source B differ significantly from Source A and this difference is expected due to their geographic location.

Table 7-41 shows the data for the goodness-of-fit testing on the general parts from Source B.

Table 7-41: Goodness-of-Fit Testing Results – General Parts, Source B.

Goodness-of-Fit Tests for:	**Weibull Distribution**		**Gamma Distribution**		**Normal Distribution**	
Parameters for Distribution	Sym-bol	Estimate	Sym-bol	Estimate	Sym-bol	Estimate
Threshold	Theta	0	Theta	0		
Scale	Sigma	62.83	Sigma	3.06		
Shape	C	3.54	Alpha	18.75		
Mean		56.56		57.32	Mu	57.32
StdDev		17.72		13.24	Sigma	14.52

Goodness-of-Fit Tests for:	**Weibull Distribution**			**Gamma Distribution**			**Normal Distribution**		
Test	Statistic	p Value		Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	N/A			0.08	Pr> D	<0.001	0.11	Pr> D	<0.010
Cramer-von Mises (W-Sq)	55.50	Pr> W-Sq	<0.010	13.62	Pr> W-Sq	<0.001	32.23	Pr> W-Sq	<0.005
Anderson-Darling (A-Sq)	366.64	Pr> A-Sq	<0.010	91.13	Pr> A-Sq	<0.001	198.67	Pr> A-Sq	<0.005

Quintile		Quintiles for Weibull Distribution		Quintiles for Gamma Distribution		Quintiles for Normal Distribution	
%	Observed	Estimated	Differences Squared	Estimated	Differences Squared	Estimated	Differences Squared
1	39	17.13	478.19	31.07	62.92	23.55	238.79
5	41	27.15	191.81	37.42	12.85	33.44	57.16
10	42	33.27	76.17	41.14	0.74	38.71	10.80
25	47	44.19	7.91	47.92	0.85	47.53	0.28
50	55	56.65	2.72	56.30	1.69	57.32	5.36
75	63	68.90	34.81	65.60	6.78	67.11	16.86
90	76	79.52	12.38	74.80	1.45	75.92	0.01
95	82	85.65	13.35	80.68	1.74	81.19	0.65
99	110	96.72	176.46	92.51	305.97	91.08	357.81
		Sum	993.79	Sum	394.98	Sum	687.72

The results indicate that while the test for goodness of fit are acceptable, the estimated values for all three distributions differ from the observed values. The gamma distribution shows the best fit, but shows especially large differences at the 99% quintile. Similarly, the normal distribution shows large differences for the 1 to 5% quintiles, as well as the 99% quintile. Given the observed fit for both general parts and key parts from Source A, Source B has significant worse performance. Using either a normal or a gamma distribution for calculating safety stock will provide inadequate results.

The basic statistics for general parts from Source C, 661 observations, is shown in Table 7-42. Each observation is an order that was placed, shipped and received. The lead time was calculated from the day or order, until the day it was received at the warehouse.

Table 7-42: Basic Statistics for General Parts from Source C.

Basic Statistical Measures			
Observations		661	
Location		Variability	
Mean	57.00	Std Deviation	12.23
Median	54	Variance	149.54
Mode	50	Range	79

The number of observations is the lowest from Source C. This particular source provides parts for some of the lower volume models in the South African market. Even key parts for these vehicles are unlikely to be ordered every day, or in large quantities. Even though the lead times for Source B and Source C are identical, it is not a significant finding, as the two sources are not geographically linked at all. The travel distances are similar and the only element to read into this similarity is that the process component of the lead time is similar. Given that this is part of a global supply chain, it is a likely outcome. Table 7-43 shows the data for the goodness-of-fit testing on the general parts from Source B.

Table 7-43: Goodness-of-Fit Testing Results – General Parts, Source C.

Goodness-of-Fit Tests for:	**Weibull Distribution**		**Gamma Distribution**		**Normal Distribution**	
Parameters for Distribution	Symbol	Estimate	Symbol	Estimate	Symbol	Estimate
Threshold	Theta	0	Theta	0		

Goodness-of-Fit Tests for:	Weibull Distribution			Gamma Distribution			Normal Distribution		
Scale	Sigma	62.05		Sigma	2.21				
Shape	C	4.28		Alpha	25.81				
Mean		56.46			57.00		Mu	57.00	
StdDev		14.89			11.22		Sigma	12.23	
Test	Statis-tic	p Value		Statis-tic	p Value		Statis-tic	p Value	
Kolmogorov-Smirnov (D)	N/A			0.16	Pr> D	<0.001	0.19	Pr> D	<0.010
Cramer-von Mises (W-Sq)	4.11	Pr> W-Sq	<0.010	4.15	Pr> W-Sq	<0.001	6.15	Pr> W-Sq	<0.005
Anderson-Darling (A-Sq)	29.59	Pr> A-Sq	<0.010	23.47	Pr> A-Sq	<0.001	34.02	Pr> A-Sq	<0.005

Quintile		Quintiles for Weibull Distribution		Quintiles for Gamma Distribution		Quintiles for Normal Distribution	
%	Observed	Esti-mated	Diff-erences Squared	Esti-mated	Diffe-rences Squared	Esti-mated	Diffe-rences Squared
1	42	21.19	432.96	34.18	61.15	28.56	180.76
5	44	31.01	168.77	39.88	16.93	36.89	50.57
10	45	36.69	69.14	43.18	3.32	41.33	13.46
25	49	46.38	6.85	49.09	0.01	48.76	0.06
50	54	56.96	8.75	56.27	5.15	57.00	9.02
75	60	66.97	48.52	64.12	16.96	65.25	27.57
90	76	75.39	0.37	71.77	17.87	72.67	11.06
95	82	80.17	3.36	76.63	28.87	77.12	23.84
99	99	88.64	107.40	86.30	161.32	85.45	183.58
		Sum	846.11	Sum	311.57	Sum	499.92

The results indicate that while the test for goodness of fit are acceptable, the estimated values for all three distributions differ significantly from the observed values. The gamma distribution shows the best fit, but shows especially large differences at the 99% quintile. Similarly, the normal distribution shows large differences for the 1 to 5% quintiles, as well as the 99% quintile. Given the observed fit for both general parts and key parts from Source A, Source C has significant worse performance. Using either a normal or gamma distribution for calculating safety stock provided inadequate results.

The goodness-of-fit testing for the import lead times clearly shows that the gamma distribution is the better fit in all cases. The normal distribution is the second best fit in all cases. The best fit between observed and estimated values was for the key parts from Source A. This result was followed by the results from general parts from Source A. The biggest discrepancy was shown between the observed values and estimated values of the general parts from Source B. Even with significant fewer data points, both the general parts from Source A and the general parts from Source C show smaller differences.

Based on these results it can be concluded that Source A and Source C have better control over the process component of their lead time. The local process lead times are identical (parts from all sources are processed on a first-in-first-out basis) and the shipping lead times for Source B and Source C are similar. The lead time from Source B has lower predictability.

In order to perform simulation analysis, it is necessary to select a set of appropriate parameters. Given that the bulk of the observations come from Source A, it was decided to focus on Source A to establish the basic parameters. It was decided to use a normal distribution for the simulation analysis as this is the computationally least complex method.

For the analysis of imported supplier parts, source A is used as a basis with the lead time set at 63 days and a normal distribution used in all simulations.

7.3.2 Demand Distribution Fit

In order to effectively calculate the safety stock requirements, it is necessary to understand the demand pattern effectively. If the base assumption is that the demand pattern is normal, the proposed safety stock calculation in the theoretical calculation described in Chapter 5 is acceptable. If the demand pattern differs significantly from this assumption, it may explain why the non-optimal implemented method is being used. This assumption does not suggest that the implemented method is correct, but make it possible to propose an alternative solution that may achieve both objectives of minimizing average inventory and providing the required levels of service.

A dataset describing demand data for 31 parts was obtained. The dataset cover approximately one year's actual daily order pattern. The data includes all orders received from local and export clients. Table 7-44 provides the basic statistic for the 31 parts. These parts were selected as they were perceived to be parts that required special attention to achieve the levels of client service required. The group was selected as they covered parts from all movement categories.

Table 7-44: Basic Demand Statistics for Selected Parts.

Part	Obser-vations	Mean	Median	Mode	Std Deviation	Variance	Range
Part 01	160	25.47	23	17	13.74	188.85	78.00
Part 02	160	1.99	2	1	1.24	1.53	6.00
Part 03	55	33.44	13	2	48.72	2374.00	213.00
Part 04	226	62.40	57	57	30.64	938.84	252.00
Part 05	69	20.54	5	4	34.95	1221.00	199.00
Part 06	71	3.13	2	4	2.14	4.60	11.00
Part 07	223	19.03	16	12	10.89	118.52	55.00
Part 08	224	19.43	18	14	11.03	121.70	64.00
Part 09	51	29.49	20	10	27.64	763.77	98.00
Part 10	23	4.09	3	1	3.37	11.36	12.00
Part 11	37	21.49	10	2	26.66	710.53	110.00
Part 12	93	24.58	10	1	32.30	1043.00	160.00
Part 13	226	8.54	8	7	4.59	21.03	27.00
Part 14	230	965.04	936	1069	301.90	91147.00	2383.00
Part 15	226	42.94	40.5	41	23.22	539.37	194.00
Part 16	221	5.93	5	4	3.61	13.01	23.00
Part 17	225	5.16	5	3	2.76	7.60	13.00
Part 18	210	3.73	3	3	2.12	4.50	15.00
Part 19	219	5.16	5	3	2.92	8.54	19.00

Part	Obser-vations	Mean	Median	Mode	Std Deviation	Variance	Range
Part 20	222	5.62	5	6	2.75	7.58	12.00
Part 21	170	2.01	2	1	1.08	1.16	4.00
Part 22	89	10.17	8	10	8.91	79.30	57.00
Part 23	203	3.14	2	2	2.49	6.20	21.00
Part 24	107	9.21	6	2	9.97	99.45	62.00
Part 25	227	350.37	320	260	181.64	32994.00	1440.00
Part 26	66	16.58	10	10	17.46	304.96	99.00
Part 27	1	16.00	16	16	.	.	0.00
Part 28	80	8.45	9	10	7.72	59.62	37.00
Part 29	231	2210.13	2180	2020	647.05	418678.00	4320.00
Part 30	228	515.36	480	392	208.22	43355.00	1628.00
Part 31	230	345.95	304	2	180.64	32629.00	1232.00

As can be seen in Table 7-44 the parts do not present any specific shared characteristics. Order events (observations) vary from 1 to 231. Average daily demand varies from 2 to 2210, and median demand varies from 2 to 2180. In general the standard deviation is a significant fraction of the average demand, as can be seen in Table 7-45.

Table 7-45: Standard Deviation as Fraction of the Mean.

Part	Observations	Mean	Std Deviation	Std Deviation / Mean
Part 01	160	25.47	13.74	0.54
Part 02	160	1.99	1.24	0.62
Part 03	55	33.44	48.72	1.46
Part 04	226	62.40	30.64	0.49
Part 05	69	20.54	34.95	1.70
Part 06	71	3.13	2.14	0.69
Part 07	223	19.03	10.89	0.57
Part 08	224	19.43	11.03	0.57
Part 09	51	29.49	27.64	0.94
Part 10	23	4.09	3.37	0.82
Part 11	37	21.49	26.66	1.24

Part	**Observations**	**Mean**	**Std Deviation**	**Std Deviation / Mean**
Part 12	93	24.58	32.30	1.31
Part 13	226	8.54	4.59	0.54
Part 14	230	965.04	301.90	0.31
Part 15	226	42.94	23.22	0.54
Part 16	221	5.93	3.61	0.61
Part 17	225	5.16	2.76	0.53
Part 18	210	3.73	2.12	0.57
Part 19	219	5.16	2.92	0.57
Part 20	222	5.62	2.75	0.49
Part 21	170	2.01	1.08	0.54
Part 22	89	10.17	8.91	0.88
Part 23	203	3.14	2.49	0.79
Part 24	107	9.21	9.97	1.08
Part 25	227	350.37	181.64	0.52
Part 26	66	16.58	17.46	1.05
Part 27	1	16.00	.	
Part 28	80	8.45	7.72	0.91
Part 29	231	2210.13	647.05	0.29
Part 30	228	515.36	208.22	0.40
Part 31	230	345.95	180.64	0.52

Part 29, with a ratio of 0.29 is the lowest, while part 05 has a ratio of 1.7. This basic information is indicative that it is unlikely that any of the parts in the selection will have a normal distribution. Before looking at the various distributions, it is necessary to look at the parts from a client demand side. The parts have therefore been classified in movement categories, namely:

- Fast – Ordered for more than 200 times in the time period
- Medium – Ordered for less than 200 times, but at least 80 times in the time period
- Slow – Ordered less than 80 times, but at least 10 times in the time period
- Erratic – Ordered less than 10 times in the time period

The data furthermore shows that not all parts that are ordered with the same frequency were ordered in the same quantities. To this end a second movement category was assigned, namely:

- Fast, High – Average order above 100
- Fast, Medium – Average order below 100, but at least 29
- Fast, Low – Average order below 20
- Medium, Medium – Average order above 10
- Medium, Low – Average order below 10
- Slow, Medium – Average order above 10
- Slow, Low – Average order below 10

The single erratic part in the selection had an order quantity of 16. Table 7-46 shows the parts, sorted by movement category.

Table 7-46: Parts Sorted by Movement Category 1 and 2.

Part	**Move-ment Category**	**Movement Category 2**	**Observations**	**Mean**	**Std Deviation**	**Std Deviation/ Mean**
Part 27	Erratic	Medium	1	16.00		
Part 29	Fast	High	231	2210.13	647.05	0.29
Part 14	Fast	High	230	965.04	301.90	0.31
Part 30	Fast	High	228	515.36	208.22	0.40
Part 25	Fast	High	227	350.37	181.64	0.52
Part 31	Fast	High	230	345.95	180.64	0.52
Part 08	Fast	Low	224	19.43	11.03	0.57
Part 07	Fast	Low	223	19.03	10.89	0.57
Part 13	Fast	Low	226	8.54	4.59	0.54
Part 16	Fast	Low	221	5.93	3.61	0.61
Part 20	Fast	Low	222	5.62	2.75	0.49
Part 19	Fast	Low	219	5.16	2.92	0.57
Part 17	Fast	Low	225	5.16	2.76	0.53
Part 18	Fast	Low	210	3.73	2.12	0.57

Part	Move-ment Category	Movement Category 2	Observations	Mean	Std Deviation	Std Deviation/ Mean
Part 23	Fast	Low	203	3.14	2.49	0.79
Part 04	Fast	Medium	226	62.40	30.64	0.49
Part 15	Fast	Medium	226	42.94	23.22	0.54
Part 24	Medium	Low	107	9.21	9.97	1.08
Part 28	Medium	Low	80	8.45	7.72	0.91
Part 21	Medium	Low	170	2.01	1.08	0.54
Part 02	Medium	Low	160	1.99	1.24	0.62
Part 01	Medium	Medium	160	25.47	13.74	0.54
Part 12	Medium	Medium	93	24.58	32.30	1.31
Part 22	Medium	Medium	89	10.17	8.91	0.88
Part 10	Slow	Low	23	4.09	3.37	0.82
Part 06	Slow	Low	71	3.13	2.14	0.69
Part 03	Slow	Medium	55	33.44	48.72	1.46
Part 09	Slow	Medium	51	29.49	27.64	0.94
Part 11	Slow	Medium	37	21.49	26.66	1.24
Part 05	Slow	Medium	69	20.54	34.95	1.70
Part 26	Slow	Medium	66	16.58	17.46	1.05

Given the sequence showed in Table 7-46, the demand pattern of each part will now be analysed to identify the best-fit distribution. Given the ratio of the standard deviation to the mean, it was decided not to even attempt to test for a normal distribution, as it is highly unlikely to be present. The analysis therefore focused on the gamma distribution and the log normal distribution. The parts are discussed in the sequence shown in Table 7-46 to make it possible to compare the various demand patterns. The demand patterns proposed by Gattorna (2010) are very theoretical. Figure 7-105 provides a view of fast moving automotive parts. Figure 7-106 shows the patterns for medium moving automotive parts and Figure 7-107 show the pattern for slow moving automotive parts.

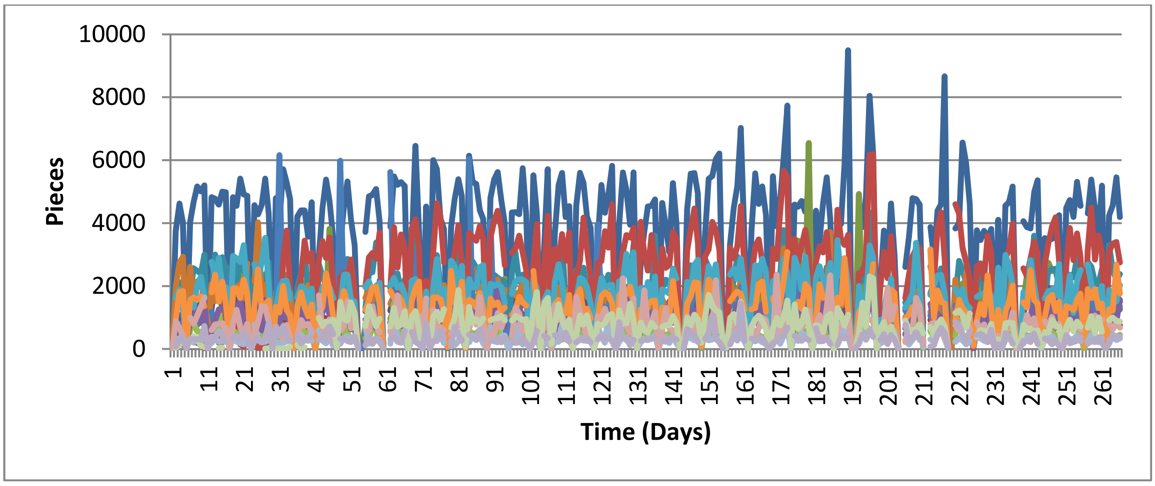


Figure 7-105: Demand Profiles for Fast Moving Automotive Parts.

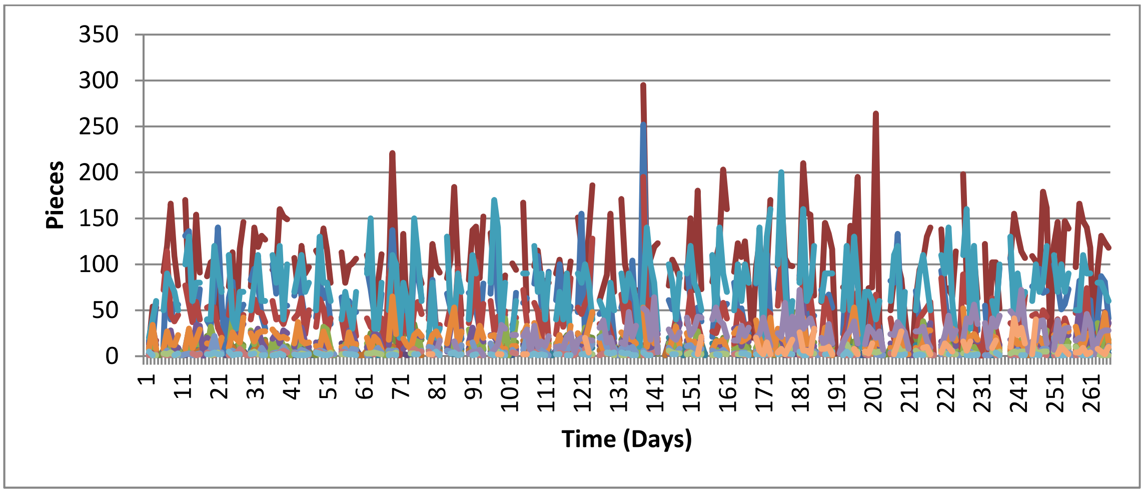


Figure 7-106: Demand Profiles for Medium Moving Automotive Parts.

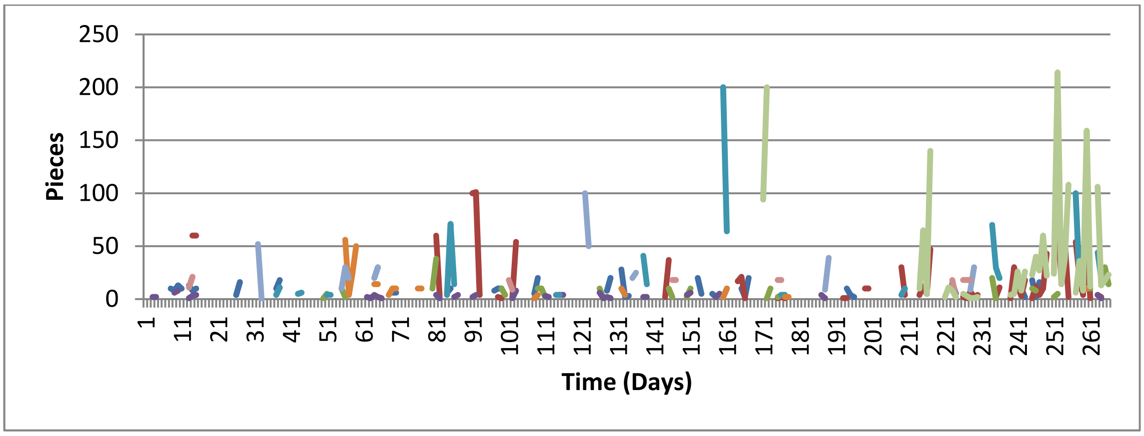


Figure 7-107: Demand Profiles for Slow Moving Automotive Parts.

As can be seen in the above graphs, it is difficult to confirm a specific demand pattern purely from observation. Each of the selected parts is analysed, within its demand group.

Part 27 is ignored as it is impossible to fit a distribution to a single observation. The rest of the parts are discussed in terms of their movement classification.

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the log normal distribution is more effective in estimating demand. The squared differences are significantly lower for the log normal distribution. Table 7-47 provides a summary of the parts and the appropriate distributions.

Table 7-47: Overview of Parts and Appropriate Distribution.

Part	Observations	Mean	Std Deviation	Movement Category	Movement Category 2	Gamma Squared Difference	Log Normal Squared Difference	Preferred Distribution
Part 27	1	16	.	Erratic	Medium	0.00	0.00	Gamma
Part 29	231	2210	647	Fast	High	2768468	30630211	Gamma
Part 14	230	965	301	Fast	High	398319	4437725	Gamma
Part 30	228	515	208	Fast	High	43854	92885	Gamma
Part 25	227	350	181	Fast	High	5390	135506	Gamma
Part 31	230	345	180	Fast	High	49348.25	65639	Gamma
Part 08	224	19	11	Fast	Low	10	595	Gamma
Part 07	223	19	10	Fast	Low	11	441	Gamma
Part 13	226	8	4	Fast	Low	2	54	Gamma
Part 16	221	5	3	Fast	Low	1	21	Gamma
Part 20	222	5	2	Fast	Low	4	38	Gamma
Part 19	219	5	2	Fast	Low	5	38	Gamma
Part 17	225	5	2	Fast	Low	4	34	Gamma
Part 18	210	3	2	Fast	Low	1	9	Gamma
Part 23	203	3	2	Fast	Low	6	1	Log Normal
Part 04	226	62	30	Fast	Medium	245	3405	Gamma
Part 15	226	42	23	Fast	Medium	57	1372	Gamma
Part 24	107	9	9	Medium	Low	25	241	Gamma

Part	Observations	Mean	Std Deviation	Movement Category	Movement Category 2	Gamma Squared Difference	Log Normal Squared Difference	Preferred Distribution
Part 28	80	8	7	Medium	Low	88	252	Gamma
Part 21	170	2	1	Medium	Low	1	1	Gamma
Part 02	160	1	1	Medium	Low	1	1	Log Normal
Part 01	160	25	13	Medium	Medium	32	1139	Gamma
Part 12	93	24	32	Medium	Medium	401	31974	Gamma
Part 22	89	10	8	Medium	Medium	599	223	Log Normal
Part 10	23	4	3	Slow	Low	5	64	Gamma
Part 06	71	3	2	Slow	Low	8	1	Log Normal
Part 03	55	33	48	Slow	Medium	3221	27623	Gamma
Part 09	51	29	27	Slow	Medium	798	3516	Gamma
Part 11	37	21	26	Slow	Medium	898	7436	Gamma
Part 05	69	20	34	Slow	Medium	8137	2470	Log Normal
Part 26	66	16	17	Slow	Medium	952	155	Log Normal

Most of the fast moving parts exhibit a gamma distribution, with the exception of Part 23. However, the Fast, High parts category does not show a very good fit to either distribution. Despite the fact that large volumes are ordered very regularly, the demand is not smooth as proposed by Gattorna (2010). This result means that even though these are service parts and the demand should be predictable, the market is not behaving rationally. It would be interesting to determine the root cause of this behaviour as part of future research. The parts in the category Fast, Low seem to be the most predictable. This result indicates parts that are ordered regularly, but without exceptional variance in the orders. Parts in the Medium, Medium category also has high variance. Again, the Medium, Low group seems to be more predictable. Parts in the Slow, Medium category show a large level of unpredictability as might be expected. Again, the parts in the Slow, Low category seem to be more predictable. In the medium and slow moving parts, the demand can be described by both the gamma and log normal distribution, with no specific predictor as to what distribution is most likely to provide the best fit.

The full detailed statistical analysis of the demand patterns are given in Appendix IX.

7.4 Simulation Analysis – Practical Environment

The results, does however then also confirm that the parts with a normal demand distribution will have too high levels of inventory. An assessment at a part level is required to select the optimum safety stock policy. Due to the extent and detailed nature of the stocked items (over 100000 parts move every month and the parts master contains over 600000 parts), it will not form part of this study. The launch period for new vehicle models discussed in Section 7.2.4 will also not form part of the practical analysis, as data is not readily available.

7.4.1 Practical Analysis – Scenario Result

The same SDSM was used to analyse the dataset that was analysed statistically. The following changes were made:

1. The simulation duration was changed to 283 days to cover the available dataset.
2. The simulation was run only once per part.
3. The lead time variance was set to zero.
4. The actual average and variance of the dataset was read into the model and used for the MIP_{Theory}, MIP_{Actual} and STS calculations.
5. The actual demand for each day was read into the simulation.
6. It is not possible to identify current and past model parts with the available data and all local parts were simulated as if they were for current models.

The simulations were run and the availability (AFR) and average inventory data compiled for both the import sourced parts and the local parts. The results of the MIP_{Theory} method is used as the base to compare improved results.

7.4.1.1 **Import Source Results – Set 1**

Table 7-48 provides a summary of the results of the three inventory management methods for imported parts from selection 1.

Table 7-48: Comparative Results for Imported Parts – Selection 1.

	MIP$_{Theory}$		MIP$_{Actual}$		Improvement		STS		Improvement	
Part	AFR	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory Change	AFR	Avg Inventory	AFR Change	Avg Inventory Change
Part 04	100	1028	100	4772	0	3744	100	932	0	-96
Part 05	100	1180	100	2546	0	1365	100	1408	0	228
Part 06	100	179	100	189	0	9	100	155	0	-25
Part 07	100	378	100	765	0	387	100	327	0	-51
Part 08	100	378	100	782	0	404	100	326	0	-51
Part 15	100	700	100	2961	0	2261	100	766	0	66
Part 12	100	1438	100	2621	0	1184	100	1650	0	213
Part 22	100	552	100	714	0	162	100	515	0	-37
Part 24	100	421	100	581	0	160	100	459	0	39
Part 25	100	4145	100	130417	0	126272	100	5217	0	1072
Part 26	100	963	100	1498	0	535	100	930	0	-33
Part 28	100	463	100	577	0	114	100	433	0	-30

The results clearly show that all three methods are effective, relative to AFR, for this group of parts. In all cases an AFR of 100 is achieved. The MIP$_{Actual}$ method requires more inventory in all cases. In most cases the inventory levels are 50% to 100% higher. The STS method requires more inventory in 5 out of 12 cases and less in the other 7 cases. Where more inventory is required, it is still significantly less than what is required for the MIP$_{Actual}$ method. This result suggests that for this group of parts the MIP$_{Theory}$ and STS methods are more effective than the MIP$_{Actual}$ method. The STS method is also a better solution than the MIP$_{Theory}$ method in 7 cases.

7.4.1.2 **Local Source Results – Set 1**

Table 7-49 provides a summary of the results of the three inventory management methods for imported parts from selection 1.

Table 7-49: Comparative Results for Local Parts – Selection 1.

	MIP_{Theory}		MIP_{Actual}		Improvement		STS		Improve-ment	
Part	AFR	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory
Part 01	78.92	60	82.1	700	3.2	640	79.13	64	0.21	4
Part 02	54.77	10	55.2	12	0.4	2	52.01	9	-2.76	-1
Part 03	22.53	279	23.0	3523	0.5	3244	22.27	266	-0.26	-13
Part 09	17.29	241	17.3	1757	0.0	1516	16.33	116	-0.96	-125
Part 10	9.58	36	9.8	56	0.3	21	9.83	153	0.26	118
Part 11	11.97	190	13.8	1203	1.9	1013	12.19	173	0.23	-17
Part 13	81.24	31	82.6	188	1.4	157	80.72	30	-0.52	0
Part 14	93.70	2733	96.8	2057466	3.1	2054733	94.29	4028	0.59	1295
Part 16	78.84	39	79.9	231	1.0	192	76.06	39	-2.77	0
Part 17	82.99	13	83.8	36	0.8	22	81.83	13	-1.16	0
Part 18	80.23	23	83.1	95	2.8	73	78.76	27	-1.47	5
Part 19	79.35	20	83.0	64	3.6	45	78.92	20	-0.42	0
Part 20	80.30	17	82.5	62	2.2	45	80.47	17	0.18	0

	MIP_{Theory}		MIP_{Actual}		Improvement		STS		Improve-ment	
Part	AFR	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory
Part 21	63.17	10	63.4	14	0.2	4	61.22	6	-1.95	-4
Part 23	75.69	17	78.8	46	3.1	29	75.96	19	0.27	2
Part 29	93.29	3053	94.1	3563903	0.8	3560850	93.61	4308	0.31	1254
Part 31	91.93	673	93.4	122691	1.5	122018	91.21	800	-0.72	127

Either of the three inventory management methods does not effectively manage these locally sourced parts. The MIP_{Actual} method manages to improve the AFR in all cases, but the average inventory is higher in all cases. In some cases the average inventory is more than 10 times as high as that required by the MIP_{Theory} method. The STS method shows mixed results. Six of 17 cases show an improvement in AFR, with 5 increasing inventory and one keeping it the same. Four cases reduce inventory for the same AFR and four cases reduce inventory and AFR. The parts in this dataset do not have consistent demand and it is likely that a completely alternative inventory management approach may be required, using a more sophisticated statistical model to describe demand.

7.4.2 Practical Analysis II – Scenario and Results

For the second practical analysis, the sample of parts was selected in a different manner. Fifteen local sourced and fifteen imported source parts were selected based on meeting the requirement of a MAD value in the system of 440. The same simulation setup was used, with the exception that 346 data points (order days) were available.

7.4.2.1 **Import Source Results – Set 2**

Table 7-50 provides the basic data on the 15 imported parts selected for the second practical analysis set. All the parts adhere to the selection criteria described above.

Table 7-50: Descriptive Statistics of the Imported Parts Adhering to the Selection Criteria Set 2.

Part	Frequency (346)	Orders/ Opportunity	Average Demand	Stdev	Avg Demand/ Stdev
Part 1	236	0.68	27.71	22.74	0.82
Part 2	209	0.60	37.95	38.64	1.02
Part 3	287	0.83	17.47	11.04	0.63
Part 4	297	0.86	19.41	23.50	1.21
Part 5	280	0.81	20.85	16.00	0.77
Part 6	291	0.84	17.69	11.76	0.66
Part 7	310	0.90	19.49	10.54	0.54
Part 8	306	0.88	18.86	10.27	0.54
Part 9	287	0.83	19.20	16.13	0.84
Part 10	287	0.83	17.47	10.23	0.59
Part 11	250	0.72	24.41	17.62	0.72
Part 12	269	0.78	25.45	18.34	0.72
Part 13	304	0.88	20.97	10.10	0.48
Part 14	275	0.79	19.53	15.84	0.81
Part 15	226	0.65	32.64	28.47	0.87

Table 7-51 provides a summary of the results of the three inventory management methods for imported parts from selection 2.

Table 7-51: Comparative Results for Imported Parts – Selection 2.

	MIP_{Theory}		MIP_{Actual}		Improvement		STS		Improve-ment	
Part	AFR	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory
Part 1	100.00	695	100.00	2008	0.00	1312	100.00	609	0.00	-86

	MIP_{Theory}		MIP_{Actual}		Improvement		STS		Improve-ment	
Part	AFR	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory
Part 2	100.00	1404	100.00	4366	0.00	2962	100.00	1332	0.00	-72
Part 3	99.54	195	100.00	559	0.46	364	95.72	169	-3.82	-26
Part 4	96.54	367	100.00	1282	3.46	915	94.73	446	-1.81	79
Part 5	99.51	304	100.00	907	0.49	603	95.53	248	-3.98	-56
Part 6	98.33	214	100.00	575	1.67	361	92.24	187	-6.09	-27
Part 7	99.10	234	100.00	641	0.90	407	100.00	332	0.90	98
Part 8	100.00	232	100.00	629	0.00	397	100.00	312	0.00	80
Part 9	97.38	246	100.00	694	2.62	448	94.59	198	-2.79	-48
Part 10	98.63	223	100.00	541	1.37	318	96.21	178	-2.43	-45
Part 11	100.00	657	100.00	1532	0.00	875	100.00	509	0.00	-147
Part 12	100.00	516	100.00	1448	0.00	933	100.00	483	0.00	-32
Part 13	98.52	262	100.00	661	1.48	399	98.28	339	-0.24	77
Part 14	95.46	317	100.00	844	4.54	527	95.12	241	-0.34	-76
Part 15	100.00	1064	100.00	3001	0.00	1937	100.00	875	0.00	-188

For this dataset the MIP_{Actual} method achieves an AFR of 100 for all cases, but with significantly higher inventory levels. Inventory levels are two to three times as high as that needed for the MIP_{Theory} method. The STS method again has mixed results. Five of 15 cases require less inventory for the same AFR, 6 cases require less inventory, but also have lower AFR values, 2 cases require more inventory for lower AFR values, 1 case increases the AFR, requiring more inventory and 1 case maintains the AFR with increased average inventory. The results suggest that the MIP_{Theory} model will not provide ideal levels of AFR, but the MIP_{Actual} method requires significantly more inventory to achieve it. In a case like this, the addition of some lead time variance in the STS calculation may result in the best solution.

7.4.2.2 **Local Source Results**

Table 7-52 provides the basic data on the 15 local parts selected for the second practical analysis set. All the parts adhere to the selection criteria described above.

Table 7-52: Descriptive Statistics of the Domestic Parts Adhering to the Selection Criteria Set 2.

Part	Frequency (346)	Orders/ Opportunity	Average Demand	Stdev	Avg Demand/ Stdev
Part 1	281	0.81	28.16	22.59	0.80
Part 2	300	0.87	22.03	11.17	0.51
Part 3	198	0.57	16.05	19.42	1.21
Part 4	290	0.84	18.14	12.56	0.69
Part 5	286	0.83	22.97	12.42	0.54
Part 6	291	0.84	17.77	15.40	0.87
Part 7	276	0.80	15.22	11.45	0.75
Part 8	300	0.87	19.43	13.41	0.69
Part 9	286	0.83	20.69	11.72	0.57
Part 10	300	0.87	20.09	10.17	0.51
Part 11	306	0.88	17.13	8.73	0.51
Part 12	277	0.80	19.62	11.08	0.56
Part 13	294	0.85	19.71	11.29	0.57

Part	**Frequency (346)**	**Orders/ Opportunity**	**Average Demand**	**Stdev**	**Avg Demand/ Stdev**
Part 14	278	0.80	19.58	11.58	0.59
Part 15	256	0.74	22.40	24.33	1.09

Table 7-53 provides a summary of the results of the three inventory management methods for local parts from selection 2.

Table 7-53: Comparative Results for Local Parts – Selection 2.

	MIP_{Theory}		MIP_{Actual}		Improvement		STS		Improvement	
Part	AFR	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory	AFR	Avg Inventory	AFR Change	Avg Inventory
Part 1	78.28	109	80.09	1326	1.72	467	79.29	166	1.01	57
Part 2	84.81	55	87.39	518	2.58	463	86.73	96	1.93	41
Part 3	55.36	86	56.34	666	0.98	580	56.20	120	0.83	34
Part 4	81.26	47	84.09	471	2.83	423	83.79	92	2.53	45
Part 5	81.40	62	82.65	605	1.25	542	81.51	110	0.10	47
Part 6	77.83	62	82.44	563	4.61	501	80.22	114	2.39	51
Part 7	76.16	43	79.89	359	3.73	316	79.08	83	2.92	40
Part 8	84.45	47	87.02	534	2.57	487	86.92	96	2.47	48
Part 9	81.25	58	82.13	517	0.88	459	81.48	96	0.23	37
Part 10	85.47	47	86.52	432	1.05	385	86.37	86	0.90	39
Part 11	87.73	29	89.74	307	2.02	278	89.74	72	2.02	43
Part 12	78.15	56	80.22	463	2.06	408	79.19	91	1.04	35
Part 13	84.17	51	86.03	470	1.86	420	85.73	86	1.57	35
Part 14	78.01	56	80.22	482	2.21	426	78.92	98	0.91	42
Part 15	72.42	97	74.13	1122	1.71	1025	73.13	159	0.71	62

None of the methods achieves an AFR of 100 for any of the scenarios. This result would suggest that even given the selection criteria, demand is obviously not normally distributed and more attention needs to be given to the demand model. However, both the MIP_{Actual} and the STS methods outperform the MIP_{Theory} method on the AFR values. The MIP_{Actual} requires around 10 times as much inventory as the MIP_{Theory} method, while the STS method only requires double the inventory.

7.4.3 Practical Analysis III – Sensitivity Analysis

For the purposes of repeating the sensitivity analysis with real data, a single imported and single domestic part number was selected. Table 7-54 shows the results of simulating the inventory and AFR for a locally sourced part over a 280 day period for the different STS structures described in Equations 7-1, 7-2, 7-3, 7-4, 7-5, 7-6 and 7-7. Figure 7-50 shows the results of simulating a local part for various STS equation structures.

Table 7-54: Results of STS Equation Changes for a Locally Supplied Part.

	2 Sigma Safety Stock	No Safety Stock	1 Sigma Safety Stock	No Lead-Time Safety Stock	No Demand Safety Stock	Half Lead-Time	Half Target
AFR	89.5	84.5	87.5	89.5	84.5	84.9	84.9
Inventory	6166	4532	5395	6166	4532	4532	4532

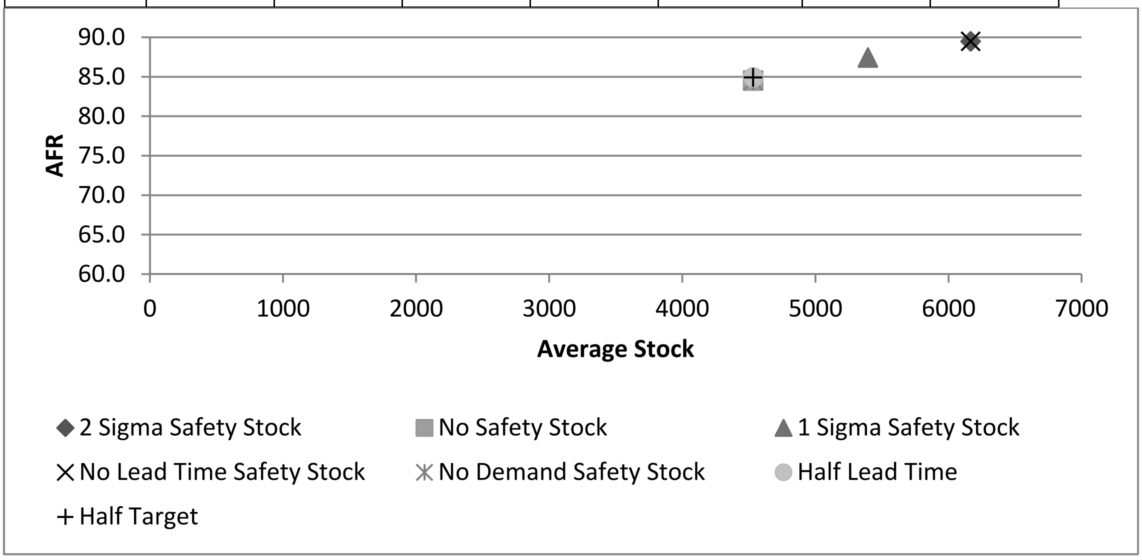


Figure 7-108: Graphical Representation of the Results of the Various Versions of the STS Equation for a Local Part.

The results indicate that the structural changes to the STS equation reduce the inventory, but it also reduces the AFR. As there is no lead time variance, the options with no lead time variance are the same as those with lead time variance. The demand variance in the real case suggests that the base equation is the best format of the equation to use for local parts where the delivery cycle is one day.

Table 7-55 shows the results of simulating the inventory and AFR for a locally sourced part over a 280 day period for the different STS structures described in Equations 7-1, 7-2,7-3, 7-4, 7-5, 7-6 and 7-7. Figure 7-109 shows the results of simulating a local part for various STS equation structures.

Table 7-55: Results of STS Equation Changes to an Import Sourced Part.

	2 Sigma Safety Stock	No Safety Stock	1 Sigma Safety Stock	No Lead-Time Safety Stock	No Demand Safety Stock	Half Lead-Time	Half Target
AFR	83.8	71.9	78.2	83.8	71.9	71.1	71.1
Inventory	21409	11807	15366	21409	11807	11176	11176

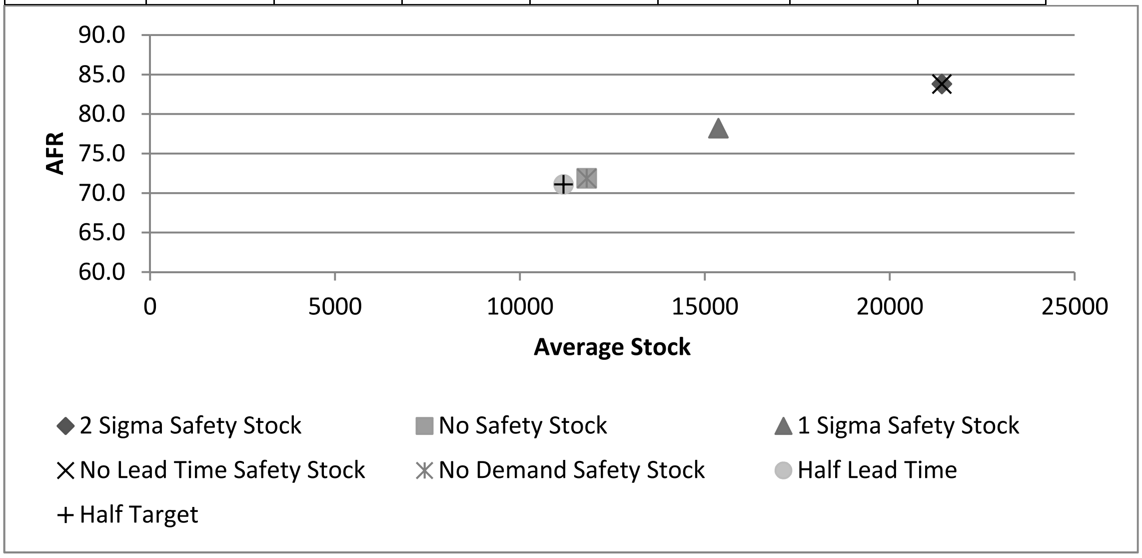


Figure 7-109: Graphical Representation of the Results of the Various Versions of the STS Equation for an Import Part.

The results indicate that the structural changes to the STS equation reduce the inventory, but it also reduces the AFR. As there is no lead time variance, the options with no lead time variance are the same as those with lead time variance. The demand variance in the real case suggests that the base equation is the best format of the equation to use for local parts where the delivery cycle is seven days, with daily order placement. Table 7-56 shows the results of simulating the inventory and AFR for a locally sourced part over a 280 day period for the different STS structures described in Equations 7-9 and 7-10.

Figure 7-110 shows the results of simulating a local part for various STS equation structures.

Table 7-56: Summarised Results of Various Adjustments to the Delivery Cycle Structure.

	Baseline	**A**	**B**	**C**	**D**	**E**	**F**
AFR	83.8	82.4	80.6	78.9	76.8	75.1	73.3
Stock	21409	18982	17391	15859	14574	13493	12470
	G	H	I	J	K	L	M
AFR	71.5	71.4	69.4	67.4	65.3	63.1	60.8
Inventory	11447	11367	10293	9266	8426	7695	7025

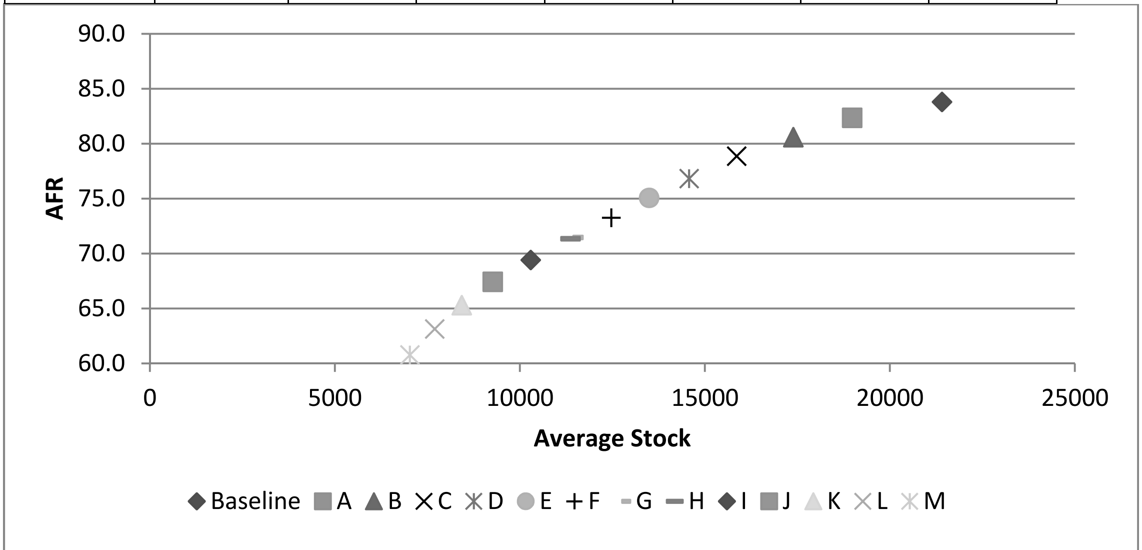


Figure 7-110: Graphical Representation of the Results of a Real Imported Part.

The results indicate that the proposed changes to the delivery cycle terms of the STS equation reduce the inventory, but it also reduces the AFR. As there is no lead time variance, the options with no lead time variance are the same as those with lead time variance. The demand variance in the real case suggests that the base equation is the best format of the equation to use for local parts where the delivery cycle is seven days, with daily order placement.

7.5 Summary

This section focused on analysing the various premises and hypothesis made in the document using a SDSM, as well as statistical analysis tools.

Firstly, the structure of the STS method is confirmed and shown to be stable, contrary to popular belief that stock-on-hand inventory management methods are inherently unstable.

It is shown that using a damping factor equal to the lead time, stabilises the output. This result holds for all 3 supply chain structures (current model domestic sourced, past mode domestic sourced and import sourced).

Secondly, the three inventory management methods, MIP_{Theory}, MIP_{Actual} and STS are compared in a set of simulated demand distribution scenarios to compare their performance relative to AFR and average inventory. MIP_{Theory} proves to be the solution requiring the least inventory, but also has the lowest AFR. MIP_{Actual} shows why it is the preferred solution with the highest AFR. However, it requires the highest amount of inventory. The STS method is positioned between the two, with improvement in AFR over the MIP_{Theory}, but with more inventory. It however requires less inventory than MIP_{Actual}. In the case of domestic current parts, the STS method provides an AFR of 100 and less inventory than MIP_{Actual}, making it ideal for a true JIT supply chain.

Thirdly, the STS method is subjected to a detailed sensitivity analysis to confirm the validity of the method and identify if there are options to improve. This is driven by the fact that the STS method has significantly higher average inventory results for the case where no variance exists in demand.

Fourthly, the three methods are compared under non-stationary demand conditions, similar to those experienced during the launch of a new vehicle model. When the system starts with no inventory, the STS method is clearly superior with the highest AFR and lowest amount of inventory throughout the analysis period for domestic sourced parts. For imported parts the MIP_{Actual} method performs better in the short term, but increase inventory significantly in the long term, while the STS method also achieves and AFR of 100, with less inventory required. When the system has start-up inventory, the STS and MIP_{Actual} methods perform similarly. The MIP_{Actual} method does have the highest AFR in the initial launch period. In the long run the STS method achieves AFR of 100 earlier with significantly less inventory than the MIP_{Actual} method.

Fifthly, the lead time of parts is subjected to statistical analysis, using a dataset for parts from import suppliers. The lead time depends on process times, shipping cycles and shipping times. (Given that local suppliers are close and adjustments to shipments can be made easily, the lead time study focused on import suppliers only.) There are four unique subsets in the data, namely:

- Key Parts from Source A;
- General Parts from Source A;

- General Parts from Source B; and
- General Parts from Source C.

Three goodness-of-fit tests are done, testing three different distributions, namely: Weibull, Gamma and Normal. While the tests provide conclusive results, a squared differences test is also applied. Based on this test, all the parts from all the sources are best described by a gamma distribution, although the normal distribution will also adequately describe the lead times. The gamma distribution does pose computational challenges, and it was decided to accept the normal distribution to describe lead times in the simulation environment.

The parts are individually analysed as to their demand distribution to determine the best-fit distribution. In a number of cases even the best fit proves to be not very good when the sum of the squared differences between the observed values and estimated values were calculated. The following was established:

- Fast, High – 5/5 Gamma Distribution
- Fast, Medium – 2/2 Gamma Distribution
- Fast, Low – 8/9 Gamma Distribution and 1/9 Log Normal Distribution
- Medium, Medium – 2/3 Gamma Distribution and 1/3 Log Normal Distribution
- Medium, Low –3 /4 Gamma Distribution and 1 /4 Log Normal Distribution
- Slow, Medium – 3/5 Gamma Distribution and 2/5 Log Normal Distribution
- Slow, Low – 1 Gamma and 1 Log Normal Distribution.

This result indicates that although it has been established that there are no normally distributed parts in the sample, there is also no predictor as to what the best-fit distribution will be.

Finally, the SDSM is applied to the practical problem of parts inventory management. A stream of real sales data (same dataset used for statistical analysis) was used as input and the simulation was allowed to place orders according to the theoretical and practical MIP method implementations.

The results indicate that for imported source parts both MIP_{Theory}, MIP_{Actual} and STS methods are adequate in terms of inventory availability. The AFR was 100% in all cases. The MIP_{Theory} method requires less inventory, although the STS method requires less inventory than the MIP_{Theory} method in some cases.

For local parts the results are different. In this case neither method achieves 100% AFR. The MIP_{Actual} method manages to add a maximum of 3.6% to the AFR with the addition of more safety inventory. Results for the STS method vary.

Next, 15 import source parts and 15 local source parts are selected, based on an average monthly demand of 440. This result translates into sales of about 20 units every day. Again, the import source parts showed 100% availability. The MIP_{Actual} method results in significantly higher inventory holding. None of the methods achieves an AFR of 100. The MIP_{Actual} and STS methods provide improved AFR values. Both methods require increased inventory, with the MIP_{Actual} method requiring significantly more inventory.

Finally, the STS sensitivity analysis is repeated on a specific part, with similar results as the theoretical sensitivity analysis.

In conclusion, the STS method is a viable solution as an inventory management method. The STS method is an improvement over the MIP_{Theory} method in terms of AFR, with less inventory required than for the MIP_{Actual} method. The demand patterns for parts do not exhibit any simple statistical distribution to make it easy to manage inventory.

8 CONCLUSIONS AND FUTURE RESEARCH

Supply chain management is complex and receives significant attention from various researchers, as evidenced by the large body of literature on the subject. Addressing the bullwhip effect is one of the most important aspects of effective supply chain and inventory management. However, it is often still out of control and overstock and understock conditions still occur frequently. This thesis aimed to address this issue. The chapter summarizes the key contributions and conclusions of the thesis and provides a number of ideas for future research.

8.1 Conclusions on Conceptual Analysis

One of the first contributions of the thesis is a supply chain characterisation framework that was developed to bridge the gap between theory and practice. The four quadrant model is based on two axes, namely: Product complexity and product life expectancy. Quadrant 1 supply chains processes products with low complexity and life expectancies measured in days to months. Quadrant 1 contains three supply chain types, focused on crops harvested for quick consumption or processing to extend the product life cycle. Quadrant 2 supply chains processes products with low complexity and life expectancies measured in years. Quadrant 2 contains one supply chain type, focusing on ores processed to simple material products such as iron ore to steel. Quadrant 3 supply chains processes products of high complexity and long life expectancies. Quadrant 3 contains two supply chain types. The automotive supply chain can be categorized into Quadrant 3. It was classified as a Class III-P supply chain where complex, long life expectancy products are designed to operate most effectively if products are serviced and maintained according to a schedule, throughout their product life. The automotive parts supply chain was selected for further study given its importance in vehicle life cycle maintenance.

The automotive parts supply chain is characterised by expectations of high levels of parts availability, as vehicles are designed to be maintained throughout their life cycles. There is, however, a large level of unpredictability in demand patterns, requiring suppliers to store sufficient inventory to service demand associated with planned maintenance and unplanned repair events. Automotive part supply continues for 15 years after production of a model ceases, requiring a wide array of items to be available. This results in space constraints within the supply chain. Just-In-Time (JIT) manufacturing results in lean supply chains, but the cost for post vehicle production can be high as the volumes required can drop significantly.

8.2 Inventory Management Methods

To implement JIT in the automotive parts supply chain a MAX/MAX inventory strategy is currently followed. This method is implemented with the Maximum Inventory Position (MIP) inventory management method. Deriving the method theoretically (MIP_{Theory}) and comparing it with the practical implementation (MIP_{Actual}) shows clear concerns regarding the dimensional consistency of the practical implementation. A stock target setting (STS) method was subsequently developed which directly tested the assumption that stock-on-hand inventory management methods are inherently unstable.

8.3 SDSM Based Analysis

A SDSM model was developed to allow the evaluation of various inventory management methods in a dynamic environment. The model is set up to allow for testing any proposed inventory management method, only requiring the calculation method to be adjusted for each alternative.

Using the SDSM, the STS method was comprehensively tested. The base structure of the model confirms the assumption that this stock-on-hand method is unstable. It was, shown however, that by applying a damping factor the method can be made stable. Setting the damping factor equal to the delivery lead time, leads to a sufficiently stable stock-on-hand method. This result indicates that there may be other stock-on-hand methods that are deemed to be unstable, that could be stabilised using different methods to damp the bullwhip effect.

Using the SDSM it was shown that the theoretical version of the method (MIP_{Theory}) may minimise inventory, but it does not maximise parts availability as measured by allocation fill rate (AFR). The actual implementation (MIP_{Actual}) improves the AFR, but increases average inventory significantly. The STS method improves AFR, while maintaining inventory levels higher than the MIP_{Theory} method does, but significantly less than the MIP_{Actual} method. Comparison between the three methods using a theoretical dataset of demand, demand variance, lead time and lead time variance scenarios showed that the STS method improves the AFR above that of MIP_{Theory} and requires significantly less inventory than the MIP_{Actual} method.

A sensitivity analysis of the STS method indicated there are some areas for improving the stock target equation, but it has to be performed with sufficient care, taking into account the operating environment. The STS method, as derived, is sufficient for use under expected demand conditions.

The SDSM was extended to include vehicle sales to generate future vehicle demand. This extension was required to compare the three methods under non-stationary demand conditions, which occur when a new vehicle model is launched. The STS method was shown to be the preferred method for domestic supplied parts when there is no start-up inventory. For imported parts, the STS method performs better in the long term, while the MIP_{Actual} method also achieves an AFR of 100. The MIP_{Actual} method, however, requires significantly more inventory. With start-up inventory the STS method is less effective in the short term, but in the long term requires less inventory to maintain an AFR of 100.

8.4 Main Conclusions

The major conclusions to draw from the evaluation of the three methods are:

- The STS method is a viable solution for inventory management in the automotive parts supply chain under JIT conditions.
- The STS method is a more effective method than the MIP_{Theory} method as it achieves higher AFR levels which is the key performance indicator.
- The STS method is a more effective method than the MIP_{Actual} method as it requires significantly less inventory for similar AFR levels.

Analysis of an extensive dataset of parts lead time and demand data showed no specific trends. Various statistical distributions can be used to approximate various parts and groups of parts. Some parts effectively showed random behaviour, supporting the case for the complexity of inventory management in the automotive parts distribution supply chain.

Despite the fact that large volumes are ordered very regularly, the demand is not smooth as proposed by Gattorna (2010). This result means that even though these are service parts and the demand should be predictable, the market is not behaving rationally. It would be interesting to determine the root cause of this behaviour as part of future research.

A practical analysis using actual data showed that there are cases where the STS method outperforms the MIP methods, but this result is dependent on the demand behaviour. The demand patterns in the actual data are highly variable and in some cases completely random. In the high volume cases where there is reasonable variance, the STS method will ensure a significant reduction in inventory, while maintaining high AFR levels. The main conclusions of this section are:

- The demand patterns are critical to selecting the appropriate inventory management method.
- The STS method can be used to reduce inventory levels and maintain AFR levels under appropriate demand conditions.

Application of the sensitivity analysis of the STS method to an actual case showed similar result to the theoretical case.

It can be concluded that the STS method is a viable solution for the automotive parts supply chain. The STS method will address both the need for high parts availability as measured in AFR, at the same time reducing the inventory levels required by the current MIP_{Actual} method that is currently in use in the automotive parts supply chain.

8.5 Future Research

Based on this thesis, it is possible to identify a number of directions for future research. This research can either use the SDSM model to assess other inventory management methods or extend the application of the STS method to better address the complexity in demand variance. Future research areas could include:

- Applying the supply chain framework to the detail design of green fields and existing supply chains. This application can be done to confirm the following three items for the purposes of designing a supply chain: a.) Location of facilities; b.) Inventory management approach; and c.) Operations strategy.
- Expansion of the SDSM to include multi-echelon supply chain analysis. The current version of the SDSM only addresses a single tier of supplier, distribution centre and dealer network. There are cases where the automotive parts supply chain includes tier 2 or even tier 3 suppliers. The SDSM can be extended and used to determine if the inventory management methods at each tier supports the need for high service levels (AFR) while maintaining a reasonable amount of inventory in the supply chain. Various combinations of inventory management

methods can be tested. For example: If only one player in the supply chain adopts the STS method, the impact on the overall AFR and inventory levels can be established. Alternatively, the results of all players utilizing the STS method, can be determined.

- Integration of the STS method into demand forecasting methods. The current study focuses on the assumption that demand has a normal distribution. Actual data proved that this is not true for all cases. The non-stationary demand analysis also showed that the STS method is less effective in the early part of the start-up period for import supplier parts. The STS method uses the average demand to date to set its stock level target. If this stock level target is set to use a demand forecast, rather than only history, it could potentially overcome this limitation and prove to be an effective method for all scenarios. This theory could again be tested through an extension of the SDSM.
- Expansion of the SDSM to include EOQ analysis to allow for analysis of alternative types of supply chains.
- Expasion of the application of the STS method to other areas where JIT is in use, such as the manufacturing environment.
- Using performance metrics from the field of multi-objective optimisation to compare different inventory management models. E.g. the S-metric which provides a numerical value to describe the trade off curve (AFR vs Inventory).

Based on this thesis, it is clear that there is significant potential to perform future research in the area of demand simulation and integrating statistical demand models in the inventory management sphere. With the proof that stock-on-hand policies can be stabilised and that appropriate policies can be developed, the path has been opened to develop a next generation set of inventory management policies for complex demand distributions.

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10 APPENDICES

APPENDIX I – VARIABLES USED IN EQUATIONS

Variables Used in Equations	**Definition**
μ	Average demand
μ_2	Average lead time
BO	Back orders
c	Unit cost
d	Known and constant demand in units per unit of time
D	Total demand over a given period of time
Damping Factor	Factor used to reduce the variance in orders to ensure the bullwhip effect is controlled
EOQ	Economic order quantity
h	Holding cost per unit per unit time
H	Lead time
K	Setup cost
K_{JIT}	Setup costs for JIT manufacturing
$K_{JIT\alpha}$	Ideal setup costs for a sell one – buy one strategy
Lead-Time	Time it takes for units to move from one location to the next location
MAD	Monthly average demand – calculated as a 6 month moving average, converted to daily demand for calculation purposes
MIP	Maximum inventory position, effectively the total pipeline inventory
OC	Order cycle
OH	Inventory on hand
OO	Inventory on order
Q	Order quantity in units
Q_{JIT}	Order quantity for a JIT inventory strategy
$Q_{JIT\alpha}$	Ideal order quantity for a sell one – buy one strategy
RP	Reorder point
RQ	Reorder quantity
S_{OH}	Inventory on hand
S_{OO}	Inventory on order
SOQ	Inventory order quantity
SS for Demand	Safety stock for demand
SS for Lead-time	Safety stock for lead time
SS_{DV}	Safety stock for demand variance
SS_{LTV}	Safety stock for lead time variance
Target	Target stock level set for the STS method
TC	Total cost per unit time

Variables Used in Equations	**Definition**
σ	Standard deviation of demand
σ_2	Standard deviation of lead time

APPENDIX II – SDSM EQUATIONS FOR MIP_{THEORY} – DOMESTIC

Appendix II provides a full listing of the iThink® SDSM equations for the MIP_{Theory} model for domestic suppliers.

In_Stock(t) = In_Stock(t - dt) + (Arrive - Shipped) * dt

INIT In_Stock = Starting_Stock_Days*Demand

INFLOWS:

Arrive = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped = Demand

MIP(t) = MIP(t - dt) + (MIP_New - MIP_Refresh) * dt

INIT MIP = MIP_Calculation

INFLOWS:

MIP_New = if MIP_Refresh>0 then MIP_Calculation/dt else 0

OUTFLOWS:

MIP_Refresh = if time/28 = int(time/28) then MIP/dt else 0

BO_en_Route(t) = BO_en_Route(t - dt) + (BO - BO_Shipped) * dt

INIT BO_en_Route = 0

TRANSIT TIME = 1

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

BO = Demand-Shipped

OUTFLOWS:

BO_Shipped = CONVEYOR OUTFLOW

Orders_en_Route(t) = Orders_en_Route(t - dt) + (Produced - Arrive) * dt

INIT Orders_en_Route = 0

TRANSIT TIME = Order_Lead_Time

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Produced = if time = int(time) then MIP_Based_Order/dt else 0

OUTFLOWS:

Arrive = CONVEYOR OUTFLOW

Total_Allocation(t) = Total_Allocation(t - dt) + (Flow_1 - Flow_2) * dt

INIT Total_Allocation = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1 = Allocation

OUTFLOWS:

Flow_2 = CONVEYOR OUTFLOW

Allocation = Shipped/Demand

Avg_Allocation = Total_Allocation/Days_per_Month*100

Base_Demand = 100

Base_Lead_Time = 7

BO_Lead_Time = 7

Days_per_Month = 30

Demand = normal(Base_Demand,Demand_Variance)

Demand_Variance = 0

MIP_Based_Order = MIP-Orders_en_Route-In_Stock-BO_en_Route

MIP_Calculation = Base_Demand*((Order_Cycle_Days)+Base_Lead_Time+2*Order_Lead_Time_variance)+2*Demand_Variance

Order_Cycle_Days = 1

Order_Flow = Produced+BO

Order_Lead_Time = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance = 0

Starting_Stock_Days = 7

Stock_Days = In_Stock/Demand

Appendix III – SDSM Equations for MIP_{Theory} – Import

Appendix III provides a full listing of the iThink® SDSM equations for the MIP_{Theory} model for import suppliers.

BO_Accum(t) = BO_Accum(t - dt) + (BO - BO_Send_to) * dt

INIT BO_Accum = 0

INFLOWS:

BO = Demand-Shipped

OUTFLOWS:

BO_Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

In_Stock(t) = In_Stock(t - dt) + (Arrive - Shipped) * dt

INIT In_Stock = Starting_Stock_Days

INFLOWS:

Arrive = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped = Demand

MIP(t) = MIP(t - dt) + (MIP_New - MIP_Refresh) * dt

INIT MIP = MIP_Calculation

INFLOWS:

MIP_New = if MIP_Refresh>0 then (MIP_Calculation)/dt else 0

OUTFLOWS:

MIP_Refresh = if time/28 = int(time/28) then MIP/dt else 0

Order_Accum(t) = Order_Accum(t - dt) + (Produced - Send_to) * dt

INIT Order_Accum = 0

INFLOWS:

Produced = MIP_Based_Order

OUTFLOWS:

Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

BO_en_Route(t) = BO_en_Route(t - dt) + (BO_Send_to - BO_Shipped) * dt

INIT BO_en_Route = 0

TRANSIT TIME = 1

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

BO_Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

OUTFLOWS:

BO_Shipped = CONVEYOR OUTFLOW

Orders_en_Route(t) = Orders_en_Route(t - dt) + (Send_to - Arrive) * dt

INIT Orders_en_Route = 0

TRANSIT TIME = Order_Lead_Time

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

OUTFLOWS:

Arrive = CONVEYOR OUTFLOW

Total_Allocation(t) = Total_Allocation(t - dt) + (Flow_1 - Flow_2) * dt

INIT Total_Allocation = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1 = Allocation

OUTFLOWS:

Flow_2 = CONVEYOR OUTFLOW

Allocation = Shipped/Demand

Avg_Allocation = Total_Allocation/Days_per_Month*100

Base_Demand = 100

Base_Lead_Time = 63

BO_Lead_Time = 7

Days_per_Month = 30

Demand = normal(Base_Demand,Demand_Variance)

Demand_Variance = 0

MIP_Based_Order = max(0,MIP-Orders_en_Route-In_Stock-BO_en_Route-Order_Accum-BO_Accum)

MIP_Calculation = Base_Demand*(Shipment_Cycle+(Order_Cycle_Days)+Base_Lead_Time+2*Order_Lead_Time_variance)+2*Demand_Variance

Order_Cycle_Days = 1

Order_Flow = Produced+BO

Order_Lead_Time = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance = 0

Run_Counter = 50

Shipment_Cycle = 7

Starting_Stock_Days = MIP_Calculation

Stock_Days = In_Stock/Demand

Appendix IV – SDSM Equations for MIP_{ACTUAL} – Domestic

Appendix IV provides a full listing of the iThink® SDSM equations for the MIP_{Actual} model for domestic suppliers.

In_Stock(t) = In_Stock(t - dt) + (Arrive - Shipped) * dt

INIT In_Stock = Starting_Stock_Days*Demand

INFLOWS:

Arrive = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped = Demand

MIP(t) = MIP(t - dt) + (MIP_New - MIP_Refresh) * dt

INIT MIP = MIP_Calculation

INFLOWS:

MIP_New = if MIP_Refresh>0 then MIP_Calculation/dt else 0

OUTFLOWS:

MIP_Refresh = if time/28 = int(time/28) then MIP/dt else 0

BO_en_Route(t) = BO_en_Route(t - dt) + (BO - BO_Shipped) * dt

INIT BO_en_Route = 0

    TRANSIT TIME = 1

    CAPACITY = INF

    INFLOW LIMIT = INF

INFLOWS:

BO = Demand-Shipped

OUTFLOWS:

BO_Shipped = CONVEYOR OUTFLOW

Orders_en_Route(t) = Orders_en_Route(t - dt) + (Produced - Arrive) * dt

INIT Orders_en_Route = 0

    TRANSIT TIME = Order_Lead_Time

    CAPACITY = INF

    INFLOW LIMIT = INF

INFLOWS:

Produced = if time=int(time) then MIP_Based_Order/dt else 0

OUTFLOWS:

Arrive = CONVEYOR OUTFLOW

Total_Allocation(t) = Total_Allocation(t - dt) + (Flow_1 - Flow_2) * dt

INIT Total_Allocation = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1 = Allocation

OUTFLOWS:

Flow_2 = CONVEYOR OUTFLOW

Allocation = Shipped/Demand

Avg_Allocation = Total_Allocation/Days_per_Month*100

Base_Demand = 100

Base_Lead_Time = 7

BO_Lead_Time = 7

Days_per_Month = 30

Demand = normal(Base_Demand,Demand_Variance)

Demand_Variance = 0

MIP_Based_Order = MIP-Orders_en_Route-In_Stock-BO_en_Route

MIP_Calculation = Base_Demand*((Order_Cycle_Days)+Base_Lead_Time+2*Order_Lead_Time_variance+2*Demand_Variance)

Order_Cycle_Days = 1

Order_Flow = Produced+BO

Order_Lead_Time = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance = 0

Starting_Stock_Days = 7

Stock_Days = In_Stock/Demand

APPENDIX V - SDSM EQUATIONS FOR MIP_{ACTUAL} – IMPORT

Appendix V provides a full listing of the iThink® SDSM equations for the MIP_{Actual} model for import suppliers.

BO_Accum(t) = BO_Accum(t - dt) + (BO - BO_Send_to) * dt

INIT BO_Accum = 0

INFLOWS:

BO = Demand-Shipped

OUTFLOWS:

BO_Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

In_Stock(t) = In_Stock(t - dt) + (Arrive - Shipped) * dt

INIT In_Stock = Starting_Stock_Days

INFLOWS:

Arrive = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped = Demand

MIP(t) = MIP(t - dt) + (MIP_New - MIP_Refresh) * dt

INIT MIP = MIP_Calculation

INFLOWS:

MIP_New = if MIP_Refresh>0 then (MIP_Calculation)/dt else 0

OUTFLOWS:

MIP_Refresh = if time/28 = int(time/28) then MIP/dt else 0

Order_Accum(t) = Order_Accum(t - dt) + (Produced - Send_to) * dt

INIT Order_Accum = 0

INFLOWS:

Produced = MIP_Based_Order

OUTFLOWS:

Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

BO_en_Route(t) = BO_en_Route(t - dt) + (BO_Send_to - BO_Shipped) * dt

INIT BO_en_Route = 0

TRANSIT TIME = 1

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

BO_Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

OUTFLOWS:

BO_Shipped = CONVEYOR OUTFLOW

Orders_en_Route(t) = Orders_en_Route(t - dt) + (Send_to - Arrive) * dt

INIT Orders_en_Route = 0

TRANSIT TIME = Order_Lead_Time

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

OUTFLOWS:

Arrive = CONVEYOR OUTFLOW

Total_Allocation(t) = Total_Allocation(t - dt) + (Flow_1 - Flow_2) * dt

INIT Total_Allocation = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1 = Allocation

OUTFLOWS:

Flow_2 = CONVEYOR OUTFLOW

Allocation = Shipped/Demand

Avg_Allocation = Total_Allocation/Days_per_Month*100

Base_Demand = 100

Base_Lead_Time = 63

BO_Lead_Time = 7

Days_per_Month = 30

Demand = normal(Base_Demand,Demand_Variance)

Demand_Variance = 0

MIP_Based_Order = max(0,MIP-Orders_en_Route-In_Stock-BO_en_Route-Order_Accum-BO_Accum)

MIP_Calculation = Base_Demand*(Shipment_Cycle+(Order_Cycle_Days)+Base_Lead_Time+2*Order_Lead_Time_variance+2*Demand_Variance)

Order_Cycle_Days = 1

Order_Flow = Produced+BO

Order_Lead_Time = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance = 0

Run_Counter = 50

Shipment_Cycle = 7

Starting_Stock_Days = MIP_Calculation

Stock_Days = In_Stock/Demand

APPENDIX VI – SDSM EQUATIONS FOR STS – DOMESTIC

Appendix VI provides a full listing of the iThink® SDSM equations for the STS model for domestic suppliers.

In_Stock(t) = In_Stock(t - dt) + (Arrive - Shipped) * dt

INIT In_Stock = Starting_Stock_Days

INFLOWS:

Arrive = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped = Demand

BO_en_Route(t) = BO_en_Route(t - dt) + (BO - BO_Shipped) * dt

INIT BO_en_Route = 0

TRANSIT TIME = 1

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

BO = Demand-Shipped

OUTFLOWS:

BO_Shipped = CONVEYOR OUTFLOW

Orders_en_Route(t) = Orders_en_Route(t - dt) + (Produced - Arrive) * dt

INIT Orders_en_Route = Order_Lead_Time*Demand

TRANSIT TIME = Order_Lead_Time

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Produced = Stock_Order

OUTFLOWS:

Arrive = CONVEYOR OUTFLOW

Total_Allocation(t) = Total_Allocation(t - dt) + (Flow_1 - Flow_2) * dt

INIT Total_Allocation = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1 = Allocation

OUTFLOWS:

Flow_2 = CONVEYOR OUTFLOW

Allocation = Shipped/Demand

Avg_Allocation = Total_Allocation/Days_per_Month*100

Base_Demand = 100

Base_Lead_Time = 7

BO_Lead_Time = 7

Damping = Order_Cycle_Days*0+Order_Lead_Time

Days_per_Month = 30

Demand = normal(Base_Demand,Demand_Variance)

Demand_Variance = 0

Order_Cycle_Days = 1

Order_Flow = Produced+BO

Order_Lead_Time = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance = 0

Starting_Stock_Days = Stock_Target

Stock_Days = In_Stock/Demand

Stock_Order = (Demand-BO)+(Stock_Target-In_Stock)/Damping

Stock_Target = Demand*Order_Cycle_Days+2*Demand_Variance*Order_Cycle_Days+2*Order_Lead_Time_variance*(Demand+Demand_Variance)

APPENDIX VII – SDSM EQUATIONS FOR STS – IMPORT

Appendix VII provides a full listing of the iThink® SDSM equations for the STS model for import suppliers.

BO_Accum(t) = BO_Accum(t - dt) + (BO - BO_Send_to) * dt

INIT BO_Accum = 0

INFLOWS:

BO = Demand-Shipped

OUTFLOWS:

BO_Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

In_Stock(t) = In_Stock(t - dt) + (Arrive - Shipped) * dt

INIT In_Stock = Stock_Target

INFLOWS:

Arrive = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped = Demand

Order_Accum(t) = Order_Accum(t - dt) + (Produced - Send_to) * dt

INIT Order_Accum = 0

INFLOWS:

Produced = Stock_Order

OUTFLOWS:

Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

BO_en_Route(t) = BO_en_Route(t - dt) + (BO_Send_to - BO_Shipped) * dt

INIT BO_en_Route = 0

TRANSIT TIME = 1

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

BO_Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

OUTFLOWS:

BO_Shipped = CONVEYOR OUTFLOW

Orders_en_Route(t) = Orders_en_Route(t - dt) + (Send_to - Arrive) * dt

INIT Orders_en_Route = Demand*Order_Lead_Time

TRANSIT TIME = Order_Lead_Time

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Send_to = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

OUTFLOWS:

Arrive = CONVEYOR OUTFLOW

Total_Allocation(t) = Total_Allocation(t - dt) + (Flow_1 - Flow_2) * dt

INIT Total_Allocation = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1 = Allocation

OUTFLOWS:

Flow_2 = CONVEYOR OUTFLOW

Allocation = Shipped/Demand

Avg_Allocation = Total_Allocation/Days_per_Month*100

Base_Demand = 100

Base_Lead_Time = 63

BO_Lead_Time = 7

Damping = Order_Cycle_Days*0+Order_Lead_Time

Days_per_Month = 30

Demand = normal(Base_Demand,Demand_Variance)

Demand_Variance = 0

Order_Cycle_Days = 1+Shipment_Cycle

Order_Flow = Produced+BO

Order_Lead_Time = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance = 0

Run_Counter = 50

Shipment_Cycle = 7

Starting_Stock_Days = Stock_Target

Stock_Days = In_Stock/Demand

Stock_Order = (Demand-BO)+(Stock_Target-In_Stock)/Damping

Stock_Target = Demand*Order_Cycle_Days+2*Demand_Variance*Order_Cycle_Days+2*Order_Lead_Time_variance*(Demand+Demand_Variance)

APPENDIX VIII – SDSM EQUATIONS FOR STS – IMPORT MATRIX (THIS VERSION WAS USED FOR SENSITIVITY ANALYSIS)

Appendix VIII provides a full listing of the iThink® SDSM equations for the STS model that was used for testing the structure of the STS equation.

BO_Accum[Dimension_1](t) = BO_Accum[Dimension_1](t - dt) + (BO[Dimension_1] - BO_Send_to[Dimension_1]) * dt

INIT BO_Accum[Dimension_1] = 0

INFLOWS:

BO[Dimension_1] = Demand-Shipped

OUTFLOWS:

BO_Send_to[Dimension_1] = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

In_Stock[Dimension_1](t) = In_Stock[Dimension_1](t - dt) + (Arrive[Dimension_1] - Shipped[Dimension_1]) * dt

INIT In_Stock[Dimension_1] = Starting_Stock_Days

INFLOWS:

Arrive[Dimension_1] = CONVEYOR OUTFLOW

OUTFLOWS:

Shipped[Dimension_1] = Demand

Order_Accum[Dimension_1](t) = Order_Accum[Dimension_1](t - dt) + (Produced[Dimension_1] - Send_to[Dimension_1]) * dt

INIT Order_Accum[Dimension_1] = Demand*Shipment_Cycle*0

INFLOWS:

Produced[Dimension_1] = Stock_Order

OUTFLOWS:

Send_to[Dimension_1] = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

BO_en_Route[Dimension_1](t) = BO_en_Route[Dimension_1](t - dt) + (BO_Send_to[Dimension_1] - BO_Shipped[Dimension_1]) * dt

INIT BO_en_Route[Dimension_1] = 0

TRANSIT TIME = 1

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

BO_Send_to[Dimension_1] = if time/Shipment_Cycle=int(time/Shipment_Cycle) then BO_Accum/dt else 0

OUTFLOWS:

BO_Shipped[Dimension_1] = CONVEYOR OUTFLOW

Orders_en_Route[Dimension_1](t) = Orders_en_Route[Dimension_1](t - dt) + (Send_to[Dimension_1] - Arrive[Dimension_1]) * dt

INIT Orders_en_Route[Dimension_1] = Demand*Order_Lead_Time

TRANSIT TIME = Order_Lead_Time

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Send_to[Dimension_1] = if time/Shipment_Cycle=int(time/Shipment_Cycle) then Order_Accum/dt else 0

OUTFLOWS:

Arrive[Dimension_1] = CONVEYOR OUTFLOW

Total_Allocation[Dimension_1](t) = Total_Allocation[Dimension_1](t - dt) + (Flow_1[Dimension_1] - Flow_2[Dimension_1]) * dt

INIT Total_Allocation[Dimension_1] = 0

TRANSIT TIME = Days_per_Month

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Flow_1[Dimension_1] = Allocation

OUTFLOWS:

Flow_2[Dimension_1] = CONVEYOR OUTFLOW

Allocation[Dimension_1] = Shipped/Demand

Avg_Allocation[Dimension_1] = Total_Allocation/Days_per_Month*100

Base_Demand[Dimension_1] = 100

Base_Lead_Time[Dimension_1] = 63

BO_Lead_Time[Dimension_1] = 7

Damping[Dimension_1] = Order_Cycle_Days*0+Order_Lead_Time

Days_per_Month[Dimension_1] = 30

Demand[Dimension_1] = normal(Base_Demand,Demand_Variance)

Demand_Variance[Dimension_1] = 0

Order_Cycle_Days[Dimension_1] = Shipment_Cycle*0+Target_Step

Order_Flow[Dimension_1] = Produced+BO

Order_Lead_Time[Dimension_1] = max(Base_Lead_Time,normal(Base_Lead_Time,Order_Lead_Time_variance))

Order_Lead_Time_variance[Dimension_1] = 0

Run_Counter = 50

Shipment_Cycle[Dimension_1] = 7

Starting_Stock_Days[Dimension_1] = Stock_Target

Stock_Days[Dimension_1] = In_Stock/Demand

Stock_Order[Dimension_1] = (Demand-BO)+(Stock_Target-In_Stock)/Damping

Stock_Target[Dimension_1] = (Order_Cycle_Days+2*Order_Lead_Time_variance)*(Demand+0*Demand_Variance)

Target_Step = GRAPH(counter(1, 8))

(1.00, 7.00), (2.00, 7.00), (3.00, 7.00), (4.00, 7.00), (5.00, 7.00), (6.00, 7.00), (7.00, 7.00), (8.00, 7.00)

APPENDIX IX – SDSM EQUATIONS FOR SERVICE PARTS DEMAND MODEL

Appendix IX provides a full listing of the iThink® SDSM equations for the service parts demand model that was used for testing the performance of the three inventory methods under non-stationary demand.

Cars_Driving_1[Dimension_1](t) = Cars_Driving_1[Dimension_1](t - dt) + (Cars_Sold[Dimension_1] - Service_1[Dimension_1]) * dt

INIT Cars_Driving_1[Dimension_1] = 0

INFLOWS:

Cars_Sold[Dimension_1] = Daily_Sales

OUTFLOWS:

Service_1[Dimension_1] = int(Cars_Driving_1/Days_Between_Services)

Cars_Driving_2[Dimension_1](t) = Cars_Driving_2[Dimension_1](t - dt) + (Service_1[Dimension_1] - Service_2[Dimension_1]) * dt

INIT Cars_Driving_2[Dimension_1] = 0

INFLOWS:

Service_1[Dimension_1] = int(Cars_Driving_1/Days_Between_Services)

OUTFLOWS:

Service_2[Dimension_1] = int(Cars_Driving_2/Days_Between_Services)

Cars_Driving_3[Dimension_1](t) = Cars_Driving_3[Dimension_1](t - dt) + (Service_2[Dimension_1] - Service_3[Dimension_1]) * dt

INIT Cars_Driving_3[Dimension_1] = 0

INFLOWS:

Service_2[Dimension_1] = int(Cars_Driving_2/Days_Between_Services)

OUTFLOWS:

Service_3[Dimension_1] = int(Cars_Driving_3/Days_Between_Services)

Cars_Driving_4[Dimension_1](t) = Cars_Driving_4[Dimension_1](t - dt) + (Service_3[Dimension_1] - Service_4[Dimension_1]) * dt

INIT Cars_Driving_4[Dimension_1] = 0

INFLOWS:

Service_3[Dimension_1] = int(Cars_Driving_3/Days_Between_Services)

OUTFLOWS:

Service_4[Dimension_1] = int(Cars_Driving_4/Days_Between_Services)

Cars_Driving_5[Dimension_1](t) = Cars_Driving_5[Dimension_1](t - dt) + (Service_4[Dimension_1] - Service_5[Dimension_1]) * dt

INIT Cars_Driving_5[Dimension_1] = 0

INFLOWS:

Service_4[Dimension_1] = int(Cars_Driving_4/Days_Between_Services)

OUTFLOWS:

Service_5[Dimension_1] = int(Cars_Driving_5/Days_Between_Services)

MAD[Dimension_1](t) = MAD[Dimension_1](t - dt) + (Demand_In[Dimension_1] - Demand_Out[Dimension_1]) * dt

INIT MAD[Dimension_1] = 0

TRANSIT TIME = 180

CAPACITY = INF

INFLOW LIMIT = INF

INFLOWS:

Demand_In[Dimension_1] = int(Service_Demand)

OUTFLOWS:

Demand_Out[Dimension_1] = CONVEYOR OUTFLOW

Average_Sales = 20

DAD[Dimension_1] = if time <=181 then MAD/time else MAD/180

Daily_Sales[Dimension_1] = logNORMAL(Average_Sales, Demand_Variance)*0+GAMMA(Shape, Scale)

Days_Between_Services = 270

Demand_Variance = 5

Scale = 1

Service_Demand[Dimension_1] = int(Service_1+Service_2+Service_3+Service_4+Service_5)

Shape = 20

APPENDIX X – STATISTICAL ANALYSIS OF PARTS DEMAND

Appendix X provides the detail statistics for all the parts used in the practical assessments.

All of the parts are discussed in terms of their movement classification.

- Fast, High – Average order above 100

This group includes Parts 29, 14, 30, 25 and 31.

The basic statistics and Goodness-of-Fit tests data for part 29 is shown in Table 10-1.

Table 10-1: Basic Statistics and Goodness-of-Fit Test Results for Part 29.

Part 29: Basic Statistical Measures			
Observations		231	
Location		Variability	
Mean	2210.13	Std Deviation	647.05
Median	2180	Variance	418678.00
Mode	2020	Range	4320

Goodness-of-Fit Tests for: Part 29	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	407.86		Zeta	7.61	
Shape	Alpha	5.42		Sigma	0.62	
Mean		2210.13			2438.18	
StdDev		949.43			1675.03	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.20	Pr > D	<0.001	0.26	Pr > D	<0.010
Cramer-von Mises (W-Sq)	2.84	Pr > W-Sq	<0.001	5.37	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	16.37	Pr > A-Sq	<0.001	29.49	Pr > A-Sq	<0.005

Quintiles for Part 29		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	80	605.99	276665.48	473.07	154507.17

5	1260	911.70	121313.59	722.69	288697.74
10	1560	1113.70	199185.48	905.85	427908.30
25	1920	1518.50	161205.46	1321.25	358507.55
50	2180	2075.77	10864.73	2009.64	29024.23
75	2540	2755.96	46638.29	3056.69	266963.39
90	2920	3480.46	314113.17	4458.38	2366600.72
95	3300	3967.31	445303.97	5588.30	5236316.89
99	3900	4992.33	1193178.27	8536.99	21501685.53
		Sum	2768468.44	Sum	30630211.52

While all three of the goodness-of-fit tests indicate clearly that the gamma distribution has the best fit, the differences squared would indicate that any estimation done by either method will be wrong. Given that these are the fastest moving, high volume part, it indicates that the chances of achieving the guaranteed service levels may be small.

The basic statistics and Goodness-of-Fit tests data for part 14 is shown in Table 10-2.

Table 10-2: Basic Statistics and Goodness-of-Fit Test Results for Part 14.

Part 14: Basic Statistical Measures			
Observations		230	
Location		Variability	
Mean	965.04	Std Deviation	301.90
Median	936	Variance	91147.00
Mode	1069	Range	2383

Goodness-of-Fit Tests for: Part 14	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	175.13		Zeta	6.78	
Shape	Alpha	5.51		Sigma	0.60	
Mean		965.04			1053.06	
StdDev		411.11			694.94	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.19	Pr > D	<0.001	0.26	Pr > D	<0.010
Cramer-von Mises (W-Sq)	2.44	Pr > W-Sq	<0.001	4.88	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	14.69	Pr > A-Sq	<0.001	27.43	Pr > A-Sq	<0.005

Quintiles for Part 14		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	25	268.30	59194.89	217.01	36868.61

5	625	401.76	49834.31	326.92	88853.47
10	699.5	489.73	44003.87	406.73	85714.86
25	809	665.66	20547.50	585.90	49773.16
50	936	907.33	821.85	878.92	3258.01
75	1069	1201.80	17634.78	1318.49	62243.26
90	1360	1515.03	24033.06	1899.30	290847.73
95	1494	1725.34	53516.81	2362.99	755138.41
99	1809	2167.79	128732.42	3559.72	3065027.52
		Sum	398319.49	Sum	4437725.03

While all three of the goodness-of-fit tests indicate clearly that the gamma distribution has the best fit, the differences squared would indicate that any estimation done by either method will be wrong. Compared to part 29, the gamma distribution does have a significant improvement in the accuracy of its estimation. In the lower 50 quintile the gamma distribution will understate demand and in the upper understate.

The basic statistics and Goodness-of-Fit tests data for part 30 is shown in Table 10-3.

Table 10-3: Basic Statistics and Goodness-of-Fit Test Results for Part 30.

Part 30: Basic Statistical Measures			
Observations		228	
Location		Variability	
Mean	515.36	Std Deviation	208.22
Median	480	Variance	43355.00
Mode	392	Range	1628

Goodness-of-Fit Tests for: Part 30	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	86.61		Zeta	6.16	
Shape	Alpha	5.95		Sigma	0.48	
Mean		515.36			529.21	
StdDev		211.27			266.36	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.10	Pr > D	<0.001	0.12	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.55	Pr > W-Sq	<0.001	1.05	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	4.14	Pr > A-Sq	<0.001	7.41	Pr > A-Sq	<0.005

Quintiles for Part 30		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	56	152.36	9284.29	156.50	10099.45
5	300	223.48	5855.92	216.34	6998.49

10	324	269.83	2934.06	257.11	4474.41
25	392	361.73	916.09	343.08	2392.97
50	480	486.79	46.10	472.71	53.17
75	596	637.97	1761.23	651.31	3059.20
90	744	797.82	2896.81	869.10	15649.01
95	876	904.76	826.91	1032.86	24606.00
99	1268	1128.96	19332.96	1427.85	25552.66
		Sum	43854.37	Sum	92885.36

While all three of the goodness-of-fit tests indicate clearly that the gamma distribution has the best fit, the differences squared would indicate that any estimation done by either method will be wrong. Compared to part 29, the gamma distribution does have a significant improvement in the accuracy of its estimation. In the lower 50 quintile the gamma distribution will understate demand and in the upper will understate the demand. The basic statistics and Goodness-of-Fit tests data for part 25 is shown in Table 10-4.

Table 10-4: Basic Statistics and Goodness-of-Fit Test Results for Part 25.

Part 25: Basic Statistical Measures			
Observations		227	
Location		Variability	
Mean	350.37	Std Deviation	181.64
Median	320	Variance	32994.00
Mode	260	Range	1440

Goodness-of-Fit Tests for: Part 25		Gamma Distribution			Log Normal Distribution		
Parameters for Distribution		Symbol	Estimate		Symbol	Estimate	
Threshold		Theta	0		Theta	0	
Scale		Sigma	93.57		Zeta	5.72	
Shape		Alpha	3.74		Sigma	0.60	
Mean			350.37			364.23	
StdDev			181.07			238.38	
Test		Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)		0.08	Pr > D	0.002	0.12	Pr > D	<0.010
Cramer-von Mises (W-Sq)		0.28	Pr > W-Sq	<0.001	0.69	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)		1.83	Pr > A-Sq	<0.001	4.39	Pr > A-Sq	<0.005
Quintiles for Part 25		Quintiles for Gamma Distribution			Quintiles for Log Normal Distribution		
Percentage	Observed	Estimated	Differences Squared		Estimated	Differences Squared	
1	20	67.07	2215.44		75.98	3134.06	
5	130	114.15	251.23		114.14	251.57	

10	170	147.41	510.15	141.79	795.87
25	240	217.64	500.07	203.73	1315.33
50	320	319.72	0.08	304.76	232.14
75	420	449.91	894.43	455.90	1288.57
90	570	593.12	534.40	655.07	7236.07
95	710	691.26	351.17	813.75	10764.79
99	890	901.57	133.82	1222.40	110487.63
		Sum	5390.80	Sum	135506.04

While all three of the goodness-of-fit tests indicate clearly that the gamma distribution has the best fit, the differences squared would indicate that any estimation done by either method will be wrong. Compared to part 29, the gamma distribution does have a significant improvement in the accuracy of its estimation. In the lower 50 quintile the gamma distribution will understate demand and in the upper understate.

The basic statistics and Goodness-of-Fit tests data for part 31 is shown in Table 10-5.

Table 10-5: Basic Statistics and Goodness-of-Fit Test Results for Part 31.

Part 31: Basic Statistical Measures			
Observations		230	
Location		Variability	
Mean	345.95	Std Deviation	180.64
Median	304	Variance	32629.00
Mode	216	Range	1232

Goodness-of-Fit Tests for: Part 31	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	93.07		Zeta	5.71	
Shape	Alpha	3.72		Sigma	0.61	
Mean		345.95			362.82	
StdDev		179.44			245.24	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.10	Pr > D	<0.001	0.14	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.59	Pr > W-Sq	<0.001	1.14	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	3.90	Pr > A-Sq	<0.001	7.35	Pr > A-Sq	<0.005

Quintiles for Part 31		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	20	65.68	2086.39	72.15	2719.75
5	148	112.10	1288.49	109.60	1474.85

10	188	144.96	1852.63	136.96	2605.52
25	240	214.40	655.35	198.75	1701.72
50	304	315.47	131.50	300.60	11.56
75	404	444.49	1639.71	454.65	2565.19
90	570	586.52	272.96	659.78	8060.11
95	676	683.90	62.34	824.48	22047.68
99	1096	892.63	41358.87	1252.38	24453.27
		Sum	49348.25	Sum	65639.64

While all three of the goodness-of-fit tests indicate clearly that the gamma distribution has the best fit, the differences squared would indicate that any estimation done by either method will be wrong. Compared to part 29, the gamma distribution does have a significant improvement in the accuracy of its estimation. It does however have a lower accuracy of estimation than part 25. The lognormal result is also much closer to the gamma result. In this case the over- and under-statement does not seem to have a pattern. In this particular case, Figure 10-1 shows that there a specific instances of very high order quantities that distort the demand pattern.

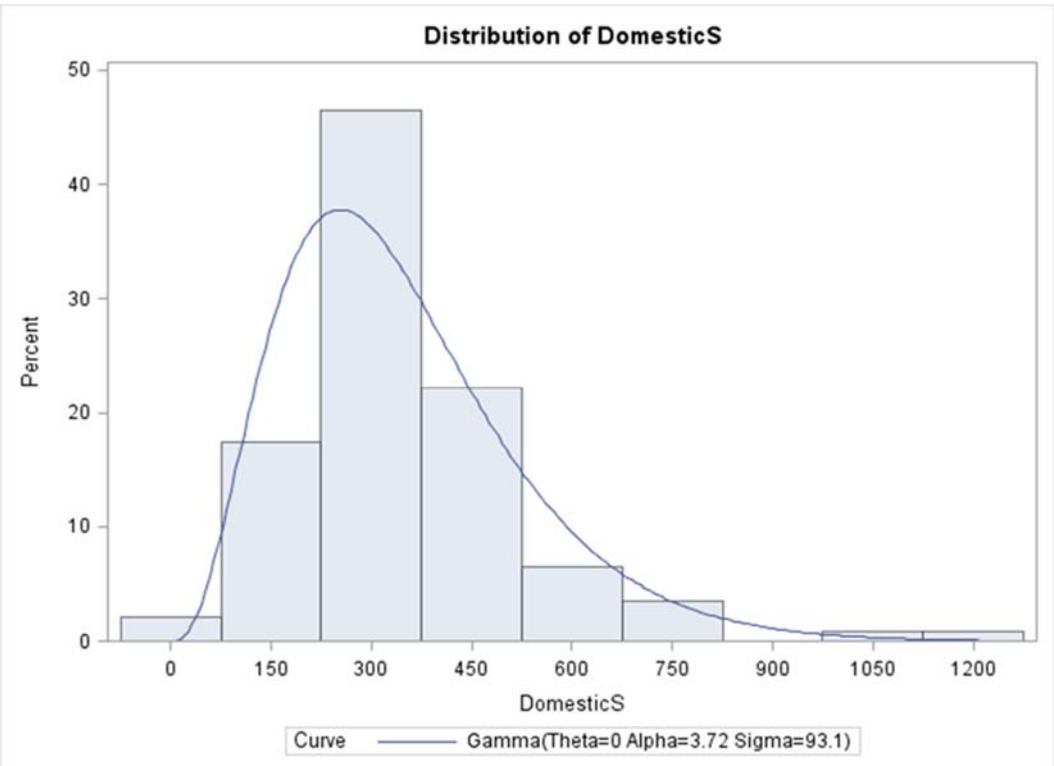

Figure 10-1: Demand Pattern for Part 31.

- Fast, Medium – Average order below 100, but at least 29

This group includes Parts 04 and 15.

The basic statistics and Goodness-of-Fit tests data for part 04 is shown in Table 10-6.

Table 10-6: Basic Statistics and Goodness-of-Fit Test Results for Part 04.

Part 4: Basic Statistical Measures			
Observations		226	
Location		Variability	
Mean	62.40	Std Deviation	30.64
Median	57	Variance	938.84
Mode	57	Range	252

Goodness-of-Fit Tests for: Part 4	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	14.94		Zeta	4.01	
Shape	Alpha	4.18		Sigma	0.54	
Mean		62.40			63.77	
StdDev		30.53			37.17	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.05	Pr > D	0.137	0.09	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.09	Pr > W-Sq	0.182	0.33	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	0.51	Pr > A-Sq	0.2	1.94	Pr > A-Sq	<0.005

Quintiles for Part 4		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	11	13.44	5.93	15.66	21.71
5	21	21.95	0.91	22.64	2.68

10	29	27.84	1.35	27.55	2.10
25	41	40.05	0.90	38.26	7.53
50	57	57.49	0.24	55.10	3.63
75	79	79.43	0.19	79.34	0.12
90	100	103.32	11.01	110.18	103.56
95	115	119.59	21.06	134.09	364.61
99	140	154.27	203.56	193.85	2899.68
		Sum	245.15	Sum	3405.61

While these parts are also sold with high frequency, the amounts are significantly lower. The goodness-of-fit tests indicate clearly that the log normal distribution has the best fit; the differences squared would indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 15 is shown in Table 10-7.

Table 10-7: Basic Statistics and Goodness-of-Fit Test Results for Part 15.

Part 15: Basic Statistical Measures						
Observations	226					
Location		Variability				
Mean	42.94	Std Deviation	23.22			
Median	40.5	Variance	539.37			
Mode	41	Range	194			
Goodness-of-Fit Tests for: Part 15	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	12.00		Zeta	3.61	
Shape	Alpha	3.58		Sigma	0.59	
Mean		42.94			44.15	
StdDev		22.70			28.49	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.06	Pr > D	0.07	0.10	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.15	Pr > W-Sq	0.025	0.48	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	0.92	Pr > A-Sq	0.021	2.69	Pr > A-Sq	<0.005
Quintiles for Part 15		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution		
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared	
1	6	7.80	3.24	9.40	11.57	
5	14	13.52	0.23	14.06	0.00	

10	18	17.60	0.16	17.42	0.34
25	28	26.29	2.93	24.92	9.50
50	40.5	39.01	2.22	37.10	11.58
75	53	55.34	5.46	55.23	4.98
90	67	73.37	40.64	79.02	144.48
95	86	85.77	0.05	97.91	141.87
99	114	112.39	2.60	146.37	1048.04
		Sum	57.53	Sum	1372.36

The goodness-of-fit tests indicate clearly that the log normal distribution has the best fit; the differences squared would indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. The gamma distribution will therefore provide a better estimation of demand.

- Fast, Low – Average order below 20

This group includes Parts 08, 07, 13, 16, 20, 19, 17, 18 and 23.

The basic statistics and Goodness-of-Fit tests data for part 08 is shown in Table 10-8.

Table 10-8: Basic Statistics and Goodness-of-Fit Test Results for Part 08.

Part 8: Basic Statistical Measures			
Observations		224	
Location		Variability	
Mean	19.43	Std Deviation	11.03
Median	18	Variance	121.70
Mode	14	Range	64

Goodness-of-Fit Tests for: Part 8		Gamma Distribution			Log Normal Distribution		
Parameters for Distribution		Symbol	Estimate		Symbol	Estimate	
Threshold		Theta	0		Theta	0	
Scale		Sigma	6.66		Zeta	2.79	
Shape		Alpha	2.92		Sigma	0.66	
Mean			19.43			20.21	
StdDev			11.37			15.02	
Test		Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)		0.06	Pr > D	0.037	0.10	Pr > D	<0.010
Cramer-von Mises (W-Sq)		0.12	Pr > W-Sq	0.066	0.48	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)		0.72	Pr > A-Sq	0.065	2.78	Pr > A-Sq	<0.005
Quintiles Part 8		Quintiles for Gamma Distribution			Quintiles for Log Normal Distribution		
Percentage	Observed	Estimated	Differences Squared		Estimated	Differences Squared	
1	2	2.72	0.52		3.47	2.15	
5	6	5.17	0.69		5.45	0.31	

10	7	7.01	0.00	6.93	0.00
25	12	11.07	0.86	10.37	2.67
50	18	17.27	0.54	16.22	3.18
75	25	25.45	0.20	25.37	0.13
90	33	34.68	2.82	37.94	24.45
95	42	41.10	0.81	48.28	39.50
99	53	55.04	4.17	75.88	523.53
		Sum	10.60	Sum	595.92

The goodness-of-fit tests indicate clearly that the log normal distribution has the best fit; the differences squared would indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. The gamma distribution will therefore provide a better estimation of demand.

The basic statistics and Goodness-of-Fit tests data for part 07 is shown in Table 10-9.

Table 10-9: Basic Statistics and Goodness-of-Fit Test Results for Part 07.

Part 7: Basic Statistical Measures			
Observations	223		
Location		Variability	
Mean	19.03	Std Deviation	10.89
Median	16	Variance	118.52
Mode	12	Range	55

Goodness-of-Fit Tests for: Part 7	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	6.52		Zeta	2.77	
Shape	Alpha	2.92		Sigma	0.65	
Mean		19.03			19.59	
StdDev		11.14			14.16	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.05	Pr > D	>0.250	0.07	Pr > D	0.011
Cramer-von Mises (W-Sq)	0.06	Pr > W-Sq	>0.250	0.26	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	0.41	Pr > A-Sq	>0.250	1.82	Pr > A-Sq	<0.005

Quintiles Part 7		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	2	2.66	0.44	3.51	2.29
5	5	5.06	0.00	5.47	0.22

10	7	6.86	0.02	6.92	0.01
25	11	10.84	0.02	10.25	0.56
50	16	16.91	0.82	15.88	0.01
75	25	24.92	0.01	24.59	0.17
90	32	33.97	3.87	36.45	19.81
95	38	40.26	5.11	46.13	66.14
99	53	53.92	0.84	71.76	352.09
		Sum	11.14	Sum	441.31

The goodness-of-fit tests indicate clearly that the log normal distribution has the best fit. However, the differences squared would indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. The gamma distribution will therefore provide a better estimation of demand.

The basic statistics and Goodness-of-Fit tests data for part 13 is shown in Table 10-10.

Table 10-10: Basic Statistics and Goodness-of-Fit Test Results for Part 13.

Part 13: Basic Statistical Measures			
Observations		226	
Location		Variability	
Mean	8.54	Std Deviation	4.59
Median	8	Variance	21.03
Mode	7	Range	27

Goodness-of-Fit Tests for: Part 13	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	2.59		Zeta	1.99	
Shape	Alpha	3.30		Sigma	0.61	
Mean		8.54			8.79	
StdDev		4.70			5.93	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.09	Pr > D	<0.001	0.13	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.22	Pr > W-Sq	0.004	0.55	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	1.32	Pr > A-Sq	0.002	3.37	Pr > A-Sq	<0.005

Quintiles Part 13		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	1.41	0.17	1.75	0.57
5	2	2.53	0.28	2.66	0.44

10	4	3.34	0.44	3.32	0.46
25	5	5.09	0.01	4.82	0.03
50	8	7.70	0.09	7.29	0.51
75	11	11.08	0.01	11.02	0.00
90	14	14.85	0.72	15.98	3.93
95	17	17.45	0.20	19.97	8.80
99	24	23.06	0.89	30.31	39.86
		Sum	2.80	Sum	54.59

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 16 is shown in Table 10-11.

Table 10-11: Basic Statistics and Goodness-of-Fit Test Results for Part 16.

Part 16: Basic Statistical Measures			
Observations		221	
Location		Variability	
Mean	5.93	Std Deviation	3.61
Median	5	Variance	13.01
Mode	4	Range	23

Goodness-of-Fit Tests for: Part 16	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	2.01		Zeta	1.60	
Shape	Alpha	2.95		Sigma	0.63	
Mean		5.93			6.03	
StdDev		3.45			4.18	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.09	Pr > D	<0.001	0.12	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.27	Pr > W-Sq	<0.001	0.36	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	1.63	Pr > A-Sq	<0.001	2.40	Pr > A-Sq	<0.005

Quintiles Part 16		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.84	0.03	1.15	0.02
5	2	1.59	0.17	1.77	0.05

10	2	2.15	0.02	2.22	0.05
25	4	3.39	0.37	3.25	0.57
50	5	5.27	0.07	4.96	0.00
75	8	7.76	0.06	7.56	0.19
90	10	10.56	0.31	11.07	1.14
95	13	12.50	0.25	13.90	0.80
99	17	16.72	0.08	21.30	18.49
		Sum	1.35	Sum	21.31

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 20 is shown in Table 10-12.

Table 10-12: Basic Statistics and Goodness-of-Fit Test Results for Part 20.

Part 20: Basic Statistical Measures			
Observations		222	
Location		Variability	
Mean	5.62	Std Deviation	2.75
Median	5	Variance	7.58
Mode	6	Range	12

Goodness-of-Fit Tests for: Part 20	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	1.52		Zeta	1.59	
Shape	Alpha	3.69		Sigma	0.57	
Mean		5.62			5.75	
StdDev		2.93			3.59	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.10	Pr > D	<0.001	0.13	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.31	Pr > W-Sq	<0.001	0.55	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	1.88	Pr > A-Sq	<0.001	3.55	Pr > A-Sq	<0.005

Quintiles Part 20		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	1.06	0.00	1.29	0.08
5	2	1.81	0.04	1.90	0.01

10	2	2.35	0.12	2.34	0.12
25	3	3.48	0.23	3.31	0.10
50	5	5.12	0.02	4.88	0.01
75	7	7.23	0.05	7.18	0.03
90	9	9.54	0.30	10.18	1.38
95	10	11.13	1.29	12.53	6.42
99	13	14.54	2.38	18.53	30.56
		Sum	4.41	Sum	38.72

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 19 is shown in Table 10-13.

Table 10-13: Basic Statistics and Goodness-of-Fit Test Results for Part 19.

Part 19: Basic Statistical Measures						
Observations	219					
Location		Variability				
Mean	5.16	Std Deviation	2.92			
Median	5	Variance	8.54			
Mode	3	Range	19			
Goodness-of-Fit Tests for: Part 19	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	1.65		Zeta	1.47	
Shape	Alpha	3.13		Sigma	0.61	
Mean		5.16			5.26	
StdDev		2.92			3.53	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.09	Pr > D	<0.001	0.11	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.27	Pr > W-Sq	<0.001	0.40	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	1.70	Pr > A-Sq	<0.001	2.64	Pr > A-Sq	<0.005
Quintiles for Part 19		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution		
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared	
1	1	0.79	0.04	1.06	0.00	
5	1	1.46	0.21	1.60	0.36	

10	2	1.95	0.00	2.00	0.00
25	3	3.02	0.00	2.89	0.01
50	5	4.63	0.14	4.36	0.40
75	7	6.73	0.07	6.59	0.17
90	9	9.08	0.01	9.54	0.29
95	11	10.71	0.08	11.91	0.83
99	12	14.23	4.99	18.05	36.65
		Sum	5.55	Sum	38.72

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 17 is shown in Table 10-14.

Table 10-14: Basic Statistics and Goodness-of-Fit Test Results for Part 17.

Part 17: Basic Statistical Measures			
Observations		225	
Location		Variability	
Mean	5.16	Std Deviation	2.76
Median	5	Variance	7.60
Mode	3	Range	13

Goodness-of-Fit Tests for: Part 17		Gamma Distribution			Log Normal Distribution		
Parameters for Distribution		Symbol	Estimate		Symbol	Estimate	
Threshold		Theta	0		Theta	0	
Scale		Sigma	1.55		Zeta	1.48	
Shape		Alpha	3.34		Sigma	0.59	
Mean			5.16			5.26	
StdDev			2.82			3.41	
Test		Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)		0.11	Pr > D	<0.001	0.11	Pr > D	<0.010
Cramer-von Mises (W-Sq)		0.35	Pr > W-Sq	<0.001	0.44	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)		2.11	Pr > A-Sq	<0.001	2.96	Pr > A-Sq	<0.005
Quintiles for Part 19		Quintiles for Gamma Distribution			Quintiles for Log Normal Distribution		
Percentage	Observed	Estimated	Differences Squared		Estimated	Differences Squared	
1	1	0.86	0.02		1.11	0.01	
5	2	1.54	0.21		1.66	0.11	

10	2	2.03	0.00	2.06	0.00
25	3	3.09	0.01	2.96	0.00
50	5	4.65	0.12	4.41	0.35
75	7	6.69	0.10	6.58	0.18
90	9	8.95	0.00	9.43	0.19
95	10	10.51	0.26	11.70	2.88
99	12	13.87	3.49	17.53	30.54
		Sum	4.21	Sum	34.27

The gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 18 is shown in Table 10-15.

Table 10-15: Basic Statistics and Goodness-of-Fit Test Results for Part 18.

Part 18: Basic Statistical Measures			
Observations		210	
Location		Variability	
Mean	3.73	Std Deviation	2.12
Median	3	Variance	4.50
Mode	3	Range	15

Goodness-of-Fit Tests for: Part 18	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	1.16		Zeta	1.15	
Shape	Alpha	3.22		Sigma	0.60	
Mean		3.73			3.79	
StdDev		2.08			2.48	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.13	Pr > D	<0.001	0.16	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.50	Pr > W-Sq	<0.001	0.71	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	3.16	Pr > A-Sq	<0.001	4.72	Pr > A-Sq	<0.005

Quintiles for Part 18		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.60	0.16	0.79	0.04
5	1	1.08	0.01	1.19	0.03

10	1	1.44	0.19	1.47	0.22
25	2	2.20	0.04	2.12	0.01
50	3	3.35	0.12	3.17	0.03
75	5	4.85	0.02	4.74	0.07
90	7	6.51	0.24	6.81	0.04
95	7	7.67	0.44	8.46	2.13
99	10	10.16	0.02	12.71	7.33
		Sum	1.25	Sum	9.91

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 23 is shown in Table 10-16.

Table 10-16: Basic Statistics and Goodness-of-Fit Test Results for Part 23.

Part 23: Basic Statistical Measures			
Observations		203	
Location		Variability	
Mean	3.14	Std Deviation	2.49
Median	2	Variance	6.20
Mode	2	Range	21

Goodness-of-Fit Tests for: Part 23	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	1.31		Zeta	0.92	
Shape	Alpha	2.41		Sigma	0.65	
Mean		3.14			3.11	
StdDev		2.03			2.27	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.18	Pr > D	<0.001	0.15	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.87	Pr > W-Sq	<0.001	0.79	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	5.26	Pr > A-Sq	<0.001	5.18	Pr > A-Sq	<0.005

Quintiles for Part 23		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.33	0.45	0.55	0.20
5	1	0.69	0.09	0.86	0.02

10	1	0.98	0.00	1.09	0.01
25	2	1.65	0.12	1.62	0.14
50	2	2.72	0.52	2.52	0.27
75	4	4.18	0.03	3.91	0.01
90	6	5.86	0.02	5.81	0.04
95	7	7.04	0.00	7.36	0.13
99	12	9.63	5.60	11.47	0.28
		Sum	6.84	Sum	1.09

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the log normal distribution is more effective in estimating demand. The squared differences are significantly lower for the log normal distribution.

- Medium, Medium – Average order above 10

This group includes Parts 01, 12 and 22.
The basic statistics and Goodness-of-Fit tests data for part 01 is shown in Table 10-17.

Table 10-17: Basic Statistics and Goodness-of-Fit Test Results for Part 01.

Part 1: Basic Statistical Measures				
Observations		160		
Location		Variability		
Mean	25.47	Std Deviation	13.74	
Median	23	Variance	188.85	
Mode	17	Range	78	
Goodness-of-Fit Tests for: Part 1	Gamma Distribution		Log Normal Distribution	
Parameters for Distribution	Symbol	Estimate	Symbol	Estimate

Threshold	Theta	0		Theta	0	
Scale	Sigma	8.50		Zeta	3.06	
Shape	Alpha	2.99		Sigma	0.67	
Mean		25.47			26.69	
StdDev		14.72			20.01	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.07	Pr> D	0.04	0.11	Pr> D	<0.010
Cramer-von Mises (W-Sq)	0.10	Pr> W-Sq	0.122	0.41	Pr> W-Sq	<0.005
Anderson-Darling (A-Sq)	0.73	Pr> A-Sq	0.063	2.72	Pr> A-Sq	<0.005

Quintiles for Part 1		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	3	3.69	0.48	4.52	2.30
5	6	6.93	0.87	7.12	1.25
10	10	9.34	0.43	9.07	0.86
25	16	14.65	1.81	13.61	5.71
50	23	22.70	0.09	21.36	2.71
75	34.5	33.29	1.47	33.51	0.99
90	42.5	45.20	7.30	50.26	60.15
95	49	53.48	20.04	64.05	226.64
99	72	71.41	0.34	100.97	839.38
		Sum	32.83	Sum	1139.98

The goodness-of-fit tests indicate clearly that the log normal distribution has the best fit. However, the differences squared would indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. The gamma distribution will therefore provide a better estimation of demand.

The basic statistics and Goodness-of-Fit tests data for part 12 is shown in Table 10-18.

Table 10-18: Basic Statistics and Goodness-of-Fit Test Results for Part 12.

Part 12: Basic Statistical Measures			
Observations		93	
Location		Variability	
Mean	24.58	Std Deviation	32.30
Median	10	Variance	1043.00
Mode	1	Range	160

Goodness-of-Fit Tests for: Part 12	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	40.11		Zeta	2.20	
Shape	Alpha	0.61		Sigma	1.56	
Mean		24.58			30.35	
StdDev		31.40			97.80	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)				0.12	Pr > D	<0.010
Cramer-von Mises (W-Sq)				0.25	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)				1.88	Pr > A-Sq	<0.005

Quintiles for Part 12		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.02	0.96	0.24	0.58
5	1	0.25	0.56	0.69	0.09

10	1	0.79	0.04	1.22	0.05
25	2	3.69	2.85	3.14	1.30
50	10	13.13	9.78	9.00	1.01
75	37	33.41	12.92	25.76	126.42
90	62	63.63	2.65	66.38	19.19
95	100	87.78	149.35	116.98	288.24
99	161	146.09	222.36	338.59	31537.22
		Sum	401.47	Sum	31974.10

The goodness-of-fit tests indicate clearly that the log normal distribution has the best fit, to the extent that the gamma distribution tests failed. However, the differences squared would indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. The gamma distribution will therefore provide a better estimation of demand.

The basic statistics and Goodness-of-Fit tests data for part 22 is shown in Table 10-19.

Table 10-19: Basic Statistics and Goodness-of-Fit Test Results for Part 22.

Part 22: Basic Statistical Measures			
Observations		89	
Location		Variability	
Mean	10.17	Std Deviation	8.91
Median	8	Variance	79.30
Mode	10	Range	57

Goodness-of-Fit Tests for: Part 22	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	5.24		Zeta	2.04	
Shape	Alpha	1.94		Sigma	0.76	
Mean		10.17			10.27	
StdDev		7.30			9.08	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.18	Pr > D	<0.001	0.13	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.25	Pr > W-Sq	0.002	0.24	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	1.38	Pr > A-Sq	0.002	1.32	Pr > A-Sq	<0.005

Quintiles for Part 22		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.71	0.08	1.31	0.10
5	2	1.74	0.07	2.20	0.04

10	2	2.62	0.39	2.90	0.81
25	5	4.81	0.04	4.60	0.16
50	8	8.48	0.23	7.69	0.10
75	10	13.72	13.83	12.84	8.06
90	20	19.92	0.01	20.37	0.14
95	20	24.36	18.99	26.85	46.92
99	58	34.22	565.65	45.08	167.00
		Sum	599.29	Sum	223.33

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the log normal distribution is more effective in estimating demand. The squared differences are significantly lower for the log normal distribution.

- Medium, Low – Average order below 10

This group includes Parts 24, 28, 21 and 02.

The basic statistics and Goodness-of-Fit tests data for part 24 is shown in Table 10-20.

Table 10-20: Basic Statistics and Goodness-of-Fit Test Results for Part 24.

Part 24: Basic Statistical Measures			
Observations		107	
Location		Variability	
Mean	9.21	Std Deviation	9.97
Median	6	Variance	99.45
Mode	2	Range	62

Goodness-of-Fit Tests for: Part 24	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	7.75		Zeta	1.74	
Shape	Alpha	1.19		Sigma	0.98	
Mean		9.21			9.27	
StdDev		8.45			11.83	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.18	Pr > D	<0.001	0.19	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.49	Pr > W-Sq	<0.001	0.45	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	3.22	Pr > A-Sq	<0.001	3.01	Pr > A-Sq	<0.005

Quintiles for Part 24		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.17	0.68	0.58	0.18
5	2	0.70	1.69	1.13	0.75

10	2	1.30	0.49	1.62	0.14
25	2	3.11	1.23	2.94	0.89
50	6	6.79	0.62	5.71	0.08
75	13	12.72	0.08	11.09	3.64
90	21	20.32	0.47	20.15	0.73
95	30	25.97	16.25	28.80	1.44
99	41	38.93	4.27	56.29	233.90
		Sum	25.78	Sum	241.75

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 28 is shown in Table 10-21.

Table 10-21: Basic Statistics and Goodness-of-Fit Test Results for Part 28.

Part 28: Basic Statistical Measures			
Observations		80	
Location		Variability	
Mean	8.45	Std Deviation	7.72
Median	9	Variance	59.62
Mode	10	Range	37

Goodness-of-Fit Tests for: Part 28	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	6.21		Zeta	1.72	
Shape	Alpha	1.36		Sigma	0.97	
Mean		8.45			8.95	
StdDev		7.24			11.15	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.19	Pr > D	<0.001	0.23	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.44	Pr > W-Sq	<0.001	0.51	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	2.46	Pr > A-Sq	<0.001	2.77	Pr > A-Sq	<0.005

Quintiles for Part 28		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.25	0.57	0.59	0.17
5	1	0.84	0.03	1.14	0.02

10	1.5	1.45	0.00	1.62	0.01
25	2	3.19	1.41	2.92	0.85
50	9	6.49	6.28	5.61	11.51
75	10	11.62	2.64	10.77	0.59
90	20	18.03	3.88	19.38	0.39
95	30	22.74	52.68	27.54	6.05
99	38	33.45	20.72	53.26	232.72
		Sum	88.19	Sum	252.31

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 21 is shown in Table 10-22.

Table 10-22: Basic Statistics and Goodness-of-Fit Test Results for Part 21.

Part 21: Basic Statistical Measures						
Observations		170				
Location		Variability				
Mean	2.01	Std Deviation	1.08			
Median	2	Variance	1.16			
Mode	1	Range	4			
Goodness-of-Fit Tests for: Part 21	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	0.51		Zeta	0.57	
Shape	Alpha	3.94		Sigma	0.51	
Mean		2.01			2.01	
StdDev		1.01			1.10	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.24	Pr > D	<0.001	0.25	Pr > D	<0.010
Cramer-von Mises (W-Sq)	1.73	Pr > W-Sq	<0.001	1.86	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	10.73	Pr > A-Sq	<0.001	11.45	Pr > A-Sq	<0.005
Quintiles for Part 21		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution		
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared	
1	1	0.41	0.35	0.54	0.22	
5	1	0.68	0.10	0.76	0.06	

10	1	0.87	0.02	0.91	0.01
25	1	1.27	0.07	1.25	0.06
50	2	1.84	0.02	1.76	0.06
75	3	2.57	0.18	2.49	0.26
90	4	3.37	0.40	3.39	0.37
95	4	3.92	0.01	4.09	0.01
99	5	5.08	0.01	5.79	0.63
		Sum	1.16	Sum	1.66

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that both the gamma and log normal distribution is more effective in estimating demand. The squared differences are slightly lower for the gamma distribution.

The basic statistics and Goodness-of-Fit tests data for part 02 is shown in Table 10-23.

Table 10-23: Basic Statistics and Goodness-of-Fit Test Results for Part 02.

Part 2: Basic Statistical Measures			
Observations		160	
Location		Variability	
Mean	1.99	Std Deviation	1.24
Median	2	Variance	1.53
Mode	1	Range	6

Goodness-of-Fit Tests for: Part 2	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	0.62		Zeta	0.53	
Shape	Alpha	3.24		Sigma	0.55	
Mean		1.99			1.98	
StdDev		1.11			1.18	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.28	Pr> D	<0.001	0.29	Pr > D	<0.010
Cramer-von Mises (W-Sq)	1.94	Pr> W-Sq	<0.001	2.00	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	11.88	Pr> A-Sq	<0.001	12.25	Pr > A-Sq	<0.005

Quintiles for Part 2		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.32	0.46	0.47	0.28
5	1	0.58	0.18	0.68	0.10

10	1	0.77	0.05	0.83	0.03
25	1	1.18	0.03	1.17	0.03
50	2	1.79	0.04	1.70	0.09
75	2.5	2.59	0.01	2.46	0.00
90	4	3.48	0.27	3.45	0.31
95	4.5	4.09	0.17	4.21	0.08
99	6	5.42	0.34	6.14	0.02
		Sum	1.55	Sum	0.94

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that both the gamma and log normal distribution is more effective in estimating demand. The squared differences are slightly lower for the log normal distribution.

- Slow, Medium – Average order above 10

This group includes Parts 03, 09, 11, 05 and 26.

The basic statistics and Goodness-of-Fit tests data for part 03 is shown in Table 10-24.

Table 10-24: Basic Statistics and Goodness-of-Fit Test Results for Part 03.

Part 3: Basic Statistical Measures			
Observations		55	
Location		Variability	
Mean	33.44	Std Deviation	48.72
Median	13	Variance	2374.00
Mode	2	Range	213

Goodness-of-Fit Tests for: Part 3	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	49.12		Zeta	2.62	
Shape	Alpha	0.68		Sigma	1.43	
Mean		33.44			37.89	
StdDev		40.53			97.62	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)				0.08	Pr > D	>0.150
Cramer-von Mises (W-Sq)				0.03	Pr > W-Sq	>0.500
Anderson-Darling (A-Sq)				0.28	Pr > A-Sq	>0.500

Quintiles for Part 3		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.05	0.90	0.50	0.25
5	1	0.52	0.23	1.31	0.10

10	2	1.47	0.28	2.21	0.04
25	5	5.94	0.89	5.24	0.06
50	13	19.13	37.63	13.71	0.51
75	36	45.84	96.88	35.88	0.02
90	106	84.48	463.05	85.25	430.52
95	159	114.96	1939.54	143.11	252.61
99	214	187.88	682.07	378.13	26939.35
		Sum	3221.47	Sum	27623.46

The goodness-of-fit tests indicate clearly that the log normal distribution does not fit the data adequately. The tests did not provide any feedback on the gamma distribution. This result means that both distributions are inadequate. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. This result indicates that even though there are 55 observations, the quantities ordered are not consistent and it would be very difficult to estimate the correct safety stock required.

The basic statistics and Goodness-of-Fit tests data for part 09 is shown in Table 10-25.

Table 10-25: Basic Statistics and Goodness-of-Fit Test Results for Part 09.

Part 9: Basic Statistical Measures			
Observations		51	
Location		Variability	
Mean	29.49	Std Deviation	27.64
Median	20	Variance	763.77
Mode	10	Range	98

Goodness-of-Fit Tests for: Part 9	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	19.81		Zeta	3.01	
Shape	Alpha	1.49		Sigma	0.88	
Mean		29.49			29.92	
StdDev		24.17			32.31	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.15	Pr > D	0.007	0.14	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.25	Pr > W-Sq	0.002	0.15	Pr > W-Sq	0.024
Anderson-Darling (A-Sq)	1.59	Pr > A-Sq	<0.001	0.95	Pr > A-Sq	0.017

Quintiles for Part 9		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	2	1.11	0.80	2.63	0.40
5	5	3.42	2.51	4.79	0.05

10	9	5.69	10.95	6.59	5.81
25	10	11.86	3.45	11.24	1.53
50	20	23.21	10.32	20.33	0.11
75	35	40.40	29.17	36.78	3.17
90	70	61.57	71.14	62.72	53.02
95	100	77.02	528.29	86.32	187.17
99	100	111.92	142.06	157.15	3265.63
		Sum	798.69	Sum	3516.88

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data, but less adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. In both cases the estimates of the 95 and above quintile are not very accurate.

The basic statistics and Goodness-of-Fit tests data for part 11 is shown in Table 10-26.

Table 10-26: Basic Statistics and Goodness-of-Fit Test Results for Part 11.

Part 11: Basic Statistical Measures			
Observations		37	
Location		Variability	
Mean	21.49	Std Deviation	26.66
Median	10	Variance	710.53
Mode	2	Range	110

Goodness-of-Fit Tests for: Part 11	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	24.77		Zeta	2.39	
Shape	Alpha	0.87		Sigma	1.24	
Mean		21.49			23.60	
StdDev		23.07			45.21	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)				0.08	Pr > D	>0.150
Cramer-von Mises (W-Sq)				0.03	Pr > W-Sq	>0.500
Anderson-Darling (A-Sq)				0.21	Pr > A-Sq	>0.500

Quintiles for Part 11		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.12	0.78	0.61	0.15
5	1	0.75	0.06	1.42	0.17

10	2	1.71	0.09	2.22	0.05
25	5	5.29	0.08	4.73	0.08
50	10	14.01	16.08	10.92	0.84
75	29	29.76	0.58	25.22	14.25
90	50	51.23	1.51	53.60	12.94
95	97	67.70	858.20	84.15	165.23
99	111	106.37	21.45	196.10	7242.50
		Sum	898.83	Sum	7436.22

The goodness-of-fit tests indicate clearly that the log normal distribution does not fit the data adequately. The tests did not provide any result for the gamma distribution. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma distribution. The gamma distribution will under estimate the demand over the 95 quintile, while the log normal distribution will overestimate the demand over the 95 quintile.

The basic statistics and Goodness-of-Fit tests data for part 05 is shown in Table 10-27.

Table 10-27: Basic Statistics and Goodness-of-Fit Test Results for Part 05.

Part 5: Basic Statistical Measures			
Observations		69	
Location		Variability	
Mean	20.54	Std Deviation	34.95
Median	5	Variance	1221.00
Mode	4	Range	199

Goodness-of-Fit Tests for: Part 5	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	28.18		Zeta	2.20	
Shape	Alpha	0.73		Sigma	1.22	
Mean		20.54			19.04	
StdDev		24.06			35.49	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)				0.22	Pr > D	<0.010
Cramer-von Mises (W-Sq)				0.51	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)				2.65	Pr > A-Sq	<0.005

Quintiles for Part 5		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.04	0.91	0.52	0.23
5	1	0.41	0.35	1.20	0.04

10	4	1.08	8.52	1.88	4.51
25	4	4.04	0.00	3.94	0.00
50	5	12.24	52.37	9.00	16.02
75	22	28.27	39.37	20.55	2.09
90	64	51.06	167.37	43.21	432.09
95	71	68.89	4.43	67.41	12.86
99	200	111.32	7864.22	155.25	2002.58
		Sum	8137.54	Sum	2470.43

The goodness-of-fit tests indicate clearly that the log normal distribution fits the data adequately. The tests for the gamma distribution did not return results. The differences squared clearly indicate that the log normal distribution is more effective in estimating demand. The squared differences are significantly lower for the log normal distribution. It should be noted, that the demand has a significant spike in demand, as can be seen in Figure 10-2.

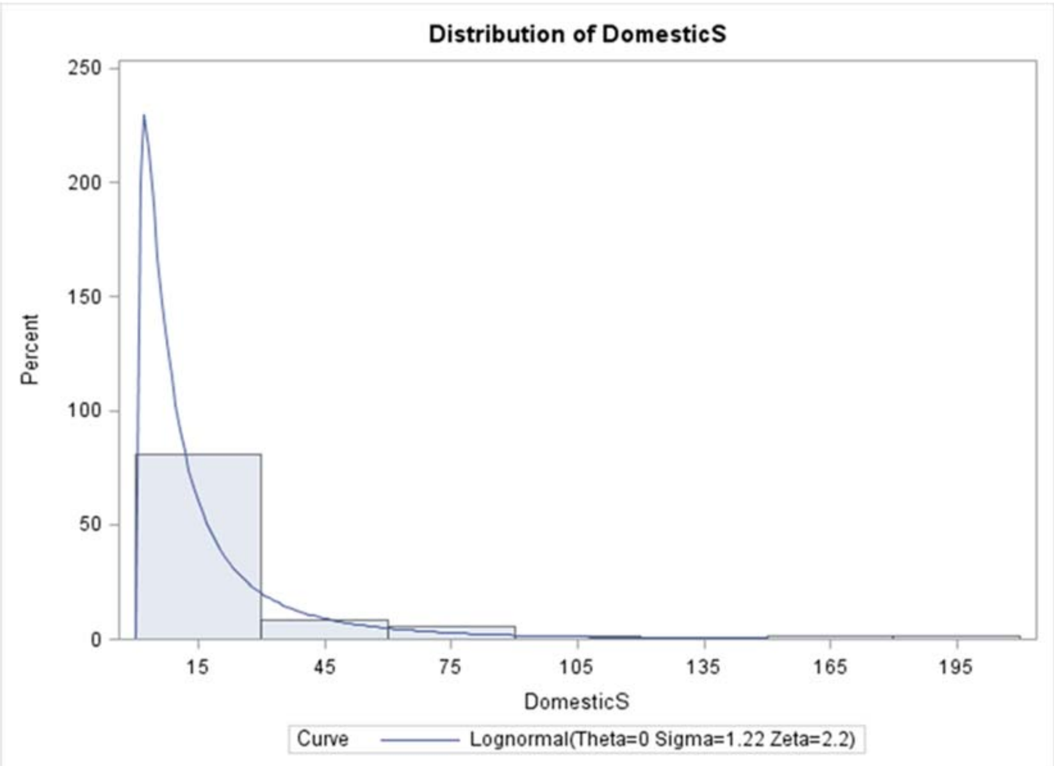

Figure 10-2: Demand Pattern for Part 05.

The basic statistics and Goodness-of-Fit tests data for part 26 is shown in Table 10-28.

Table 10-28: Basic Statistics and Goodness-of-Fit Test Results for Part 26.

Part 26: Basic Statistical Measures			
Observations		66	
Location		Variability	
Mean	16.58	Std Deviation	17.46
Median	10	Variance	304.96
Mode	10	Range	99

Goodness-of-Fit Tests for: Part 26	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	13.84		Zeta	2.34	
Shape	Alpha	1.20		Sigma	1.02	
Mean		16.58			17.40	
StdDev		15.15			23.55	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.17	Pr > D	<0.001	0.17	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.22	Pr > W-Sq	0.005	0.22	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	1.23	Pr > A-Sq	0.004	1.15	Pr > A-Sq	<0.005

Quintiles for Part 26		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.32	0.46	0.96	0.00
5	2	1.28	0.52	1.93	0.01

10	2	2.37	0.13	2.79	0.63
25	4	5.64	2.69	5.19	1.42
50	10	12.26	5.10	10.34	0.11
75	20	22.91	8.44	20.57	0.33
90	40	36.50	12.22	38.22	3.17
95	50	46.62	11.44	55.37	28.86
99	100	69.80	911.84	111.00	120.96
		Sum	952.83	Sum	155.48

The goodness-of-fit tests indicate clearly that both the gamma distribution and the log normal distribution fit the data adequately. The differences squared clearly indicate that the log normal distribution is more effective in estimating demand. The squared differences are significantly lower for the log normal distribution.

- Slow, Low – Average order below 10

This group includes Parts 10 and 06.

The basic statistics and Goodness-of-Fit tests data for part 10 is shown in Table 10-29.

Table 10-29: Basic Statistics and Goodness-of-Fit Test Results for Part 10.

Part 10: Basic Statistical Measures			
Observations		23	
Location		Variability	
Mean	4.09	Std Deviation	3.37
Median	3	Variance	11.36
Mode	1	Range	12

Goodness-of-Fit Tests for: Part 10	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	2.42		Zeta	1.08	
Shape	Alpha	1.69		Sigma	0.84	
Mean		4.09			4.21	
StdDev		3.14			4.26	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.15	Pr > D	0.239	0.16	Pr > D	0.115
Cramer-von Mises (W-Sq)	0.08	Pr > W-Sq	0.214	0.07	Pr > W-Sq	0.236
Anderson-Darling (A-Sq)	0.60	Pr > A-Sq	0.125	0.59	Pr > A-Sq	0.113

Quintile for Part 10		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.21	0.62	0.42	0.34
5	1	0.58	0.18	0.74	0.07

10	1	0.92	0.01	1.01	0.00
25	1	1.79	0.62	1.68	0.46
50	3	3.32	0.10	2.96	0.00
75	6	5.56	0.19	5.21	0.62
90	9	8.27	0.53	8.68	0.10
95	11	10.23	0.59	11.77	0.60
99	13	14.62	2.63	20.87	61.92
		Sum	5.47	Sum	64.11

The goodness-of-fit tests indicate that both the gamma distribution the log normal distribution does not fit the data adequately. The differences squared clearly indicate that the gamma distribution is more effective in estimating demand. The squared differences are significantly lower for the gamma.

The basic statistics and Goodness-of-Fit tests data for part 06 is shown in Table 10-30.

Table 10-30: Basic Statistics and Goodness-of-Fit Test Results for Part 06.

Part 6: Basic Statistical Measures			
Observations		71	
Location		Variability	
Mean	3.13	Std Deviation	2.14
Median	2	Variance	4.60
Mode	4	Range	11

Goodness-of-Fit Tests for: Part 6	Gamma Distribution			Log Normal Distribution		
Parameters for Distribution	Symbol	Estimate		Symbol	Estimate	
Threshold	Theta	0		Theta	0	
Scale	Sigma	1.28		Zeta	0.92	
Shape	Alpha	2.44		Sigma	0.68	
Mean		3.13			3.16	
StdDev		2.00			2.40	
Test	Statistic	p Value		Statistic	p Value	
Kolmogorov-Smirnov (D)	0.17	Pr > D	<0.001	0.19	Pr > D	<0.010
Cramer-von Mises (W-Sq)	0.41	Pr > W-Sq	<0.001	0.44	Pr > W-Sq	<0.005
Anderson-Darling (A-Sq)	2.55	Pr > A-Sq	<0.001	2.83	Pr > A-Sq	<0.005

Quintiles for Part 6		Quintiles for Gamma Distribution		Quintiles for Log Normal Distribution	
Percentage	Observed	Estimated	Differences Squared	Estimated	Differences Squared
1	1	0.33	0.44	0.52	0.23
5	1	0.70	0.09	0.83	0.03

10	1	0.99	0.00	1.06	0.00
25	1	1.66	0.43	1.59	0.35
50	2	2.71	0.51	2.51	0.26
75	4	4.15	0.02	3.96	0.00
90	6	5.81	0.04	5.97	0.00
95	8	6.97	1.06	7.63	0.14
99	12	9.53	6.12	12.09	0.01
		Sum	8.71	Sum	1.02