

THE OPTIMISATION OF
DAIMLERCHRYSLER'S SAP-MRP SYSTEM
THROUGH SYSTEMS ANALYSIS, DESIGN,
AND SIMULATION.

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Declaration

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and has not previously in its entirety or in part been submitted at any university for a degree.

Ek, die ondergetekende verklaar hiermee dat die werk gedoen in hierdie tesis my eie oorspronklike werk is wat nog nie voorheen gedeeltelik of volledig by enige universiteit vir 'n graad aangebied is nie.



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Synopsis

This report presents the findings of a study that started as an evaluation of the possible implementation of the Options Inventory Management Model (OIMM), developed by van Wijck and Bekker [4], at DaimlerChrysler South Africa (DCSA). The OIMM System was developed as a possible alternative to the SAP-MRP System to ensure a high Customer Service Level, with the lowest possible inventory level, under the 10 Day Option Freeze Environment.

DCSA indicated that although the OIMM System may be an ideal solution, in terms of optimising Plant Inventory levels whilst maximising Customer Service Levels, the practical problems associated with the possible implementation of this system would outweigh the associated benefits. This being the case, a directive was given to investigate the SAP-MRP System's ability to provide a high Customer Service Level under the 10 Day Option Freeze Environment and not to pursue the OIMM implementation option. The objectives of this directive were to evaluate and establish the performance capabilities of the SAP-MRP System under the 10 Day Option Freeze Environment as well as develop a system to aid in the customisation of the system.

Design of Experiments (DOE) was utilised to plan the evaluation procedure and to ensure that a consistent approach was followed. The DOE generated huge amounts of output data that represented the Usage Category Behaviour Characteristics of the SAP-MRP System. Regression Analysis was utilised to investigate this data.

A part-by-part analysis was avoided and the analysis approach followed presented results that could be applied to almost the entire range of parts, excluding bulk parts, at DCSA. The results showed that Coverage Profile alone could be used as a proactive inventory management tool to ensure maximum Customer Service Level.

The Regression Analysis revealed that various combinations of Safety Time, Minimum, and Target Coverage resulted in similar or equal Avg. Plant Inventories, Avg. Number of Orders, and Avg. Order Sizes. These findings were used to develop a Decision Support Tool that could be used by DCSA when evaluating the resultant changes caused by the proposed changes in the aforementioned Input Parameters.



Opsomming

Hierdie verslag stel die bevindinge van 'n studie voor wat begin het met die evaluering van die moontlike implementering van die "Options Inventory Management Model" (OIMM), ontwikkel vir DaimlerChrysler (DCSA) deur van Wijck en Bekker [4]. Die OIMM sisteem was ontwikkel as 'n moontlike alternatief vir die SAP-MRP sisteem om 'n hoë verbruikersdiensvlak tesame met die laagste moontlike voorraadvlak in 'n 10-dag opsie-vries omgewing te verseker.

DCSA het aangedui dat, hoewel die OIMM sisteem 'n ideale oplossing bleik te wees in terme van die optimisering van fabriek-voorraadvlakke tesame met die verbruikersdiensvlakke, die praktiese probleme wat met die moontlike implimentering daarvan geassosieer word, die geassosieerde voordele oorskry. Daar is dus opdrag gegee om die SAP-MRP sisteem se vermoë om hoë verbruikersdiensvlakke in die 10-dag opsie-vries omgewing te lewer te ondersoek en sodoende nie die implimentering van die OIMM sisteem te vervolg nie.

Die doelwitte van hierdie opdrag was die evaluering en vestiging van die prestasievermoëns van die SAP-MRP sisteem in die 10-dag opsie-vries omgewing, asook om 'n sisteem te ontwikkel wat as hulpmiddel kan dien in die geïndividualiseerde aanpassingsoptimisering daarvan.

'n Eksperimentele Ontwerp (DOE) is gebruik in die beplanning van die evalueringsprosedure en ook om te verseker dat 'n konstante benadering gevolg is. Die DOE het 'n groot hoeveelheid uitsetdata genereer wat die prestasie van die SAP-MRP sisteem se gedragseienskappe voorgestel het. Regressie-analise is uitgevoer om die data te ondersoek.

Onderdeel-by-onderdeel analise is vermy en die analise-benadering wat gevolg is het resultate gelewer wat toegepas kon word vir omtrent die hele reeks onderdele by DCSA, uitsluitende onderdele wat in grootmaat aangekoop word. Die resultate het gewys dat die "Coverage Profile" alleen gebruik kan word as 'n pro-aktiewe voorraadbestuur hulpmiddel om maksimum verbruikersdiensvlakke te verseker.

Die regressie-analise het getoon dat verskeie kombinasies van "Safety Time," "Minimum" en "Target Coverage" gelei het tot dieselfde hoeveelheid fabrieks-voorraad, bestellingsvrystellings en bestellingsgroottes. Hierdie tendense is toegepas in die ontwikkeling van 'n ondersteunende besluitnemingshulpmiddel wat deur DCSA gebruik sou kon word in die evaluering van die veranderinge wat ontstaan vanweë die voorgestelde verandering in die voorafgenoemde insetparameters.



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Thank you



Terms of Reference

Who initiated and allocated the assignment and when was the assignment received?

This project was a collaborative initiative between DaimlerChrysler South Africa (DCSA) and the Department of Industrial Engineering at the University of Stellenbosch. Pieter van Wyk, of DCSA, allocated the project to the author, which was commenced on the 6th January 2003.

Why was the student selected for this assignment?

Pieter van Wyk selected the author from a group of three applicants. All three applicants were equally well qualified in terms of academic qualifications and the required skills. The author was selected due to his clearly demonstrated interest in DCSA's internal manufacturing operations, which was indicated by his well-researched questions posed to the interviewer.

Required assignment accomplishments:

- Gain an in-depth understanding of DCSA's internal manufacturing operations in terms of processes and supporting systems.
- Assess the viability of implementing the optimised inventory control model (OIMM) at DCSA and determining the implementation methodology if implementation is viable. Viability would be determined by assessing the existing SAP-MRP System performance capabilities
- Develop a Decision Support Tool to aid in the customisation of the SAP-MRP System if the implementation of the OIMM System was not viable or required.

Hand in date:

December 2004



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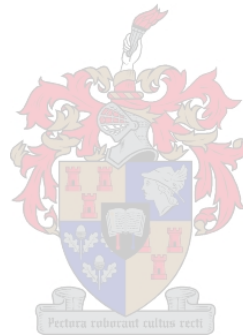
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Glossary

Absorption Ability	A term used to describe the ability of the available Plant Inventory to absorb an increase in demand.
Actual Demand	Actual demand is a measure of the actual number of vehicles that have been sequenced (scheduled) for production.
ADD	Average Daily Demand. This value is used to categorise parts into various ADD bins (Usage Categories) and is calculated by averaging the demand of the input data. In addition ADD represents ADR in the Regression Analysis phase of the project.
ADR	Average Daily Requirements. The average daily Production Requirements for a specific part. This value is used by the SAP-MRP System to calculate Statistical Range of Coverage. <i>Not the same as ADD.</i>
Available Stock	The amount of Plant Inventory available at the end of a production day.
Avg. Customer Service Level	Refer to Performance Measures.
Avg. Customer Shortages.	Refer to Performance Measures.
Avg. DCSA Service Level	Refer to Performance Measures
Avg. Harbour Inventory	Refer to Performance Measures.
Avg. Order Size	Refer to Performance Measures.
Avg. Number of Orders	Refer to Performance Measures.
Avg. Pipeline Inventory	Refer to Performance Measures.
Avg. Plant Inventory	Refer to Performance Measures.



Avg. Shortage Frequency	Refer to Performance Measures.
Avg. Total Shortages	Refer to Performance Measures.
Back-Off Days	A vehicles production schedule is planned according to its completion date. The point in the assembly process where a specific part is required is planned according to the back-off days. These are a specific number of days “backed-off” from the vehicle completion date.
Back-Flushing	The term “back-flushing” is used to describe the process whereby the parts used to assemble a specific vehicle are removed from the list of Available Stock
Behaviour Characteristics	A term that describes the manner in which a specific part or Usage Category behaves under various operating conditions e.g. extended Lead-Time or alternate Pallet Sizes.
Customer Service Level	The fraction of Production Requirements satisfied by regular sea and airfreight-first time round.
Coverage Profile	A setting within the SAP-MRP System that indicates the Minimum, Target, and Maximum Range of Coverage.
Days to Assembly	Represents the Order Lead-Time of a part. It is measured from the time of Order Release to the point where it is assembled to the motor vehicle.
DCSA	DaimlerChrysler South Africa.
Decision Support Tool	A set of tables that quantify the result of a change to Safety Time, Minimum and Target Coverage settings in terms of Avg. Plant Inventory, Avg. Order Size, and Avg. Number of Orders.
Dialog	A system that is used to convert the Gross Requirements at Option level to Gross Requirements at Part Level. Checks the build – ability of car in terms of Option Combinations.
DOE	Design of Experiments.



FI Date	Final Inspection Date. This is the point where the vehicle is fully assembled and ready for shipping/transportation to the respective dealers. The vehicle is inspected for Quality Assurance purposes.
Flip	A term coined by van Wijck and Bekker [4] to describe demand changes associated with customers changing their preferences about the Options to be built into the vehicles.
Goods Receipt Processing Time (GRPt)	The amount of time that includes the receipt processing time of the goods at the East London Harbour and the delivery of those goods to the DCSA plant.
GOP	Gross Order Requirements. Includes PAD orders as well as forecast orders i.e. 60 days (actual orders) + 6 months of orders (forecast). Indicated at Option Level.
Input Combinations	Various combinations of Safety Time, Minimum and Target Coverage.
Input Parameters	This term describes the parameters that were identified as having significant influence on the behaviour and performance of the SAP-MRP System.
Lead-Time	The number of days (calendar or working) that it takes for an order to be delivered to DCSA from a supplier in Germany.
Material Controller	Employee responsible for a particular part.
OIMM	Options Inventory Management Model. A theoretical Statistical Inventory Model Developed by van Wijck et al. [4].
Option Freeze	The point at which a customer can no longer change the Options to be assembled to his / her vehicle.
Order Receipt	Order Receipt describes an order that has been received by DCSA. The use of the term "Order Receipt" differs from "Order Release" only in the case where the VB simulation program is validated; otherwise the difference between the two terms is inconsequential.
Order Release	A term used to refer to an order that is released from the SAP-MRP System and sent to the respective supplier. Order Release is measured by Frequency and Magnitude. "Frequency" is the number of times that an order is released and "Magnitude" is the size of the order measured in multiples of Pallet Size.
PAD	Actual Orders. Real –Time Database of Production Orders already sent to the Production Plant i.e. Production Orders already sequenced. Used to update GOP as well as being an input to TBE. Include orders within frozen period. 60 days worth of orders.
Pallet Size	The number of parts per pallet. It refers to the minimum number of parts per pallet as specified in SAP Master Data.



Palletization	A term utilised to describe the way in which Pallet Size is varied when analysing the Behaviour Characteristics of a part or Usage Category as a function of Pallet Size.
Performance Measures	Refer to Appendix N for a description of each Performance Measure as well as the manner in which they are calculated.
PIR	Planned Independent Requirement. Represents a demand for which future production is planned. A PIR changes to dependent once a vehicle enters the assembly process.
Plant Inventory/Stock	These two terms both represent the total amount of parts available in the plant at any time.
PPC	Production Planning Calendar. Specifies on which calendar day's production will occur. Includes weekdays and weekend days if required.
Range of Coverage	A term used in conjunction with the Coverage Profile to indicate the number of days that a specific part's stock should last/cover given the existing Production Requirements.
Regression Analysis	A statistical technique used to develop a mathematical equation to describe the behaviour of a dependant variable in terms of selected independent input variables.
Regression Equation/s	A mathematical equation obtained Regression Analysis that describes the behaviour of a dependant variable in terms of various selected independent input variables. The accuracy of the equation is given by the R ² Value or the Adjusted R ² Value.
SAP-ERP	Systems, Applications and Products – Enterprise Resource Planning. SAP is a large-scale software package that assists in the management of a broad range of activities that exist within a business.
SAP-MRP	Systems, Applications and Products – Material Requirements Planning. A module of the SAP-ERP System. It is responsible for calculating DCSA's stock requirements and releasing orders to local and foreign suppliers.
Service Level	Refer to Customer Service Level.
Statistica	A powerful statistical software package employed in the analysis of the output data generated by the simulation tool.
TBE	Gross Order Requirements. Indicated at Part Level.
Usage Category	A term used to define a group of parts with ADD's that fall within a specified range. Measures in <i>parts per day</i> or <i>units per day</i> .
Variant	A SAP term that defines an input variable that comprises of one or many different objects for which a query must be run.
W203	Internal DCSA code for the Mercedes-Benz C-Class.



1. Introduction

This report marks the culmination of a project that began four years ago in 1999. It was originally started by Mr. Arno van der Merwe, of DaimlerChrysler South Africa, herewith known as DCSA, with the purpose of preventing possible stock-out occurrences associated with the future reduction of the Option Freeze point to 10 days before vehicle assembly. At that time it was unknown whether the SAP-MRP System would, or could, provide DCSA with an acceptable¹ Customer Service Level given the reduction of the Option Freeze point. It was for this reason that DCSA approached the Department of Industrial Engineering, University of Stellenbosch, and requested that an alternative system be developed to provide DCSA with an acceptable Customer Service Level (van Wijck et al. [4]).

A system, named Options Inventory Management Model (OIMM) was developed that was entirely different to the existing SAP-MRP System at DCSA (refer to van Wijck et al. [4]). The OIMM System made use of basic MRP stock requirement calculations coupled with a Statistical Component that increased, or decreased, the order amount such that an acceptable Avg. Customer Service Level was reached. OIMM worked in essence, but the practical implications of implementing the newly developed system seemed insurmountable as data would have to be collected for thousands of parts.

Having developed OIMM, DCSA requested that the Department of Industrial Engineering, at the University of Stellenbosch, assign the task of implementing the newly developed system to a postgraduate student as a Masters Thesis. It was at this point, in January 2003, that a study was started in order to determine a possible implementation methodology.

A simulation model of DCSA's SAP-MRP system

was developed in order to facilitate an environment in which to compare the performance of the two systems. The model simulated the demand and changes in demand per part and then created order releases based on SAP-MRP specific parameters. The simulation model showed that DCSA's SAP-MRP System could provide and maintain a high Avg. Customer Service Level (above 95%) in the 10 Day Option Freeze Environment. DCSA gave a directive to no longer investigate the OIMM implementation option after having been shown SAP-MRP's abilities in terms of Avg. Customer Service Level. The author was then instructed to investigate the performance capabilities of the SAP-MRP System and characterise its behaviour under the 10 Day Option Freeze Environment.

The chief objective of this thesis was to determine the SAP-MRP System capabilities within the 10 Day Option Freeze Environment if the OIMM System was not to be implemented at DCSA.

¹ DCSA aims for 100% Customer Service Level. Parts will be Emergency Air-Freighted, overnight if need be, to ensure that a vehicle is completed on schedule and delivered to the customer on time. Stock shortages may occur, but not at the expense of the Customer.



The aim of the Introduction is to give the reader a clear understanding of the path that has been followed by the author to the point at which this report was written. Further, two aspects are discussed in order to clarify the steps followed, namely:

- Objectives and Significance of Study.
- Methodology and Structure of Document.

1.1 Objectives and Significance of Study.

Much of what happens, at a higher level, within the SAP-MRP System at DCSA is well known and evidently understood. However, the understanding of the low-level operation has become cloudy over the course of time. A **basic** perspective of how each of the system parameters influences the SAP-MRP System exists, yet a **complete** understanding of how they influence the behaviour of the system, as a whole, as well as the affect that they have on each other is lacking.

In essence, the SAP-MRP System at DCSA operates satisfactorily within the current operating environment, while a complete understanding is lacking.

Many opinions exist as to how each parameter affects the SAP-MRP System. Many of the decisions made regarding the adjustments of system parameters are based on experience and thus a need for concrete guidelines exists.

Given the above statements, it is easy to understand why DCSA was unsure as to whether or not the SAP-MRP System would be able to provide an acceptable Avg. Customer Service Level in the 10 Day Option Freeze Environment.

Considering the above discussion, four objectives were set up, namely:

1. To develop an operational understanding of the SAP-MRP System in terms of its Input Parameters.
2. To establish a methodology with which to compare the performance of the SAP-MRP System to that of the OIMM System.
3. To establish and characterise SAP-MRP's performance capabilities under the 10 Day Option Freeze Environment.
4. To provide DCSA with a simple and easy to use decision support mechanism that could aid in customising the SAP-MRP System such that an acceptable Avg. Customer Service Level is maintained in the 10 Day Option Freeze Environment². In addition, this system should be of such a nature that it indicates the magnitude of the changes associated with a proposed alteration to the input parameter settings.

² This objective would only hold if it was proven that the implementation of OIMM was not viable or required.



It is of utmost importance to note that firstly, an operational understanding of the SAP-MRP System had to be developed and then only could a comparison be made between SAP-MRP and OIMM. These two systems had to be compared on an equal basis in order to make an educated decision as to whether the OIMM should be taken a step further and implemented.

1.2 Methodology and Structure of Document.

This report is structured to follow the methodology used to complete the objectives laid out in the previous section. Table 1 presents a tabulated representation of the report structure and it is clearly seen that the report is divided into two sections. The first, called *Preliminary Study* focuses on the activities and period spent on-site at DCSA. The second section, called *Final Study*, centres on the activities and time spent on the analysis and simulation study.

Chapter		Description
1 st Section: Preliminary Study	2	<ul style="list-style-type: none"> ➤ Select parts for which input data will be gathered. ➤ Determine Selection Criteria and availability of required data and information.
	3	<ul style="list-style-type: none"> ➤ Collect Raw Input Data. ➤ Determine which query to use and construct an easy to understand format in which to represent the data obtained via the query output. ➤ Analyse output data and determine if all the data is relevant to the study. Develop guidelines to be used in standardising future data filtering. ➤ Develop and implement an Automated Data Collection Process to replace the manual collection process. ➤ Determine the sample size based on the confidence interval half-width calculations.
	4	<ul style="list-style-type: none"> ➤ Analyse the SAP-MRP System and determine how it operates based upon specific Input Parameters.
	5	<ul style="list-style-type: none"> ➤ Steps followed to reach the final version of Simulation Program. ➤ Verification of Simulation Program. ➤ Design Issues.
2 nd Section: Final Study	6	<ul style="list-style-type: none"> ➤ Methodologies followed to facilitate simulation. ➤ Simulation Results. ➤ Worst-case Scenario Experiment. ➤ "Human Intervention" Experiment. ➤ Design of Experiments.
	7	<ul style="list-style-type: none"> ➤ Regression Analysis of DOE results. ➤ Analysis of Regression Equations.
	8	<ul style="list-style-type: none"> ➤ Application of Regression Equations and Observation of Design of Experiment Results. ➤ Decision Support Tool for Customising the SAP-MRP System.
	9	<ul style="list-style-type: none"> ➤ Conclusions. ➤ Critical Analysis of Objectives Achieved. ➤ Recommendations.

Table 1: Report Structure.

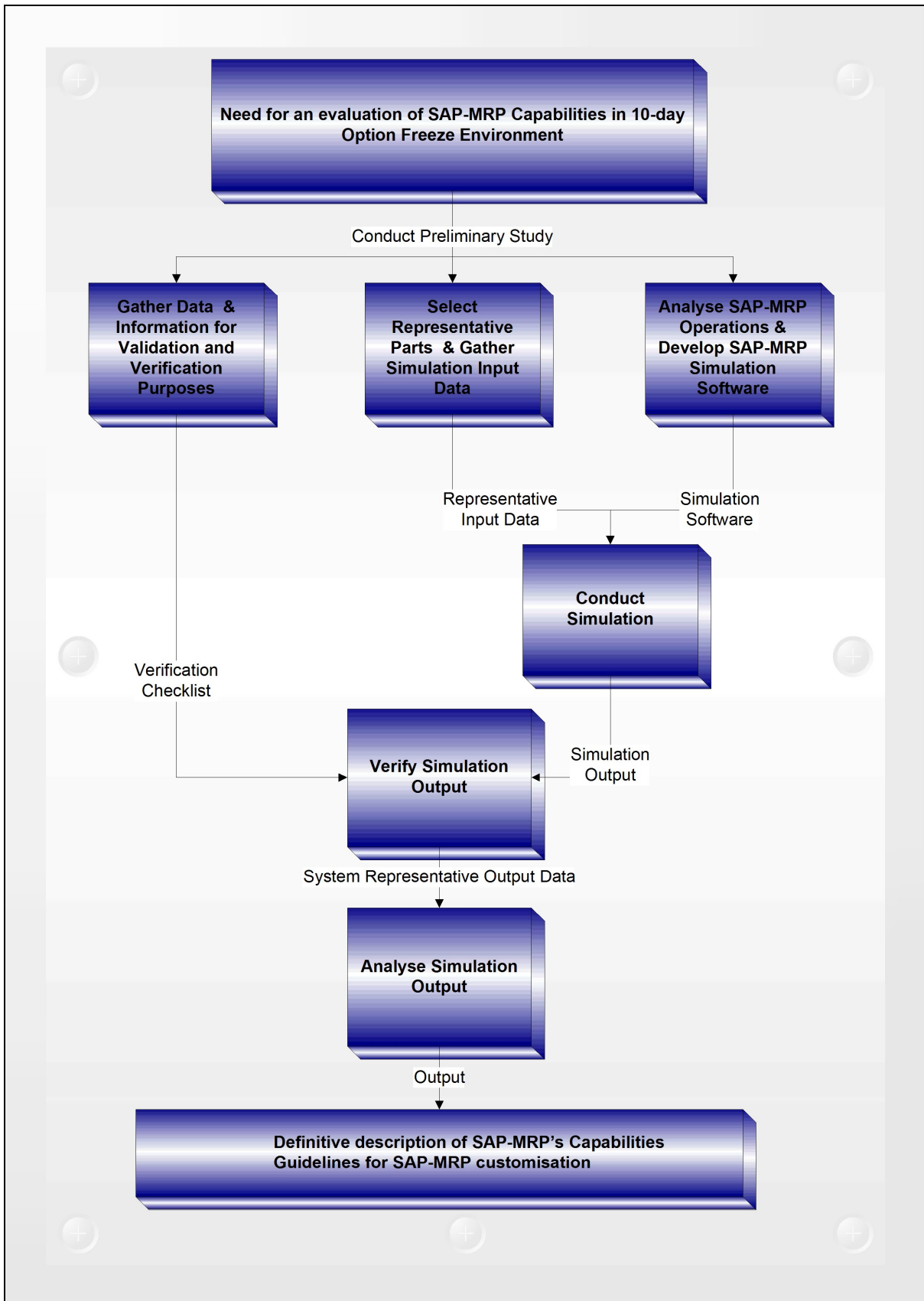


Figure 1: Graphical Representation of Thesis Methodology.

Figure 1 presents a graphical representation of the research methodology. The figure starts with the problem statement, moves through the various aspects that made up this project, and then ends with the solution.



2. Part Selection.

The previous chapter served as a brief introduction to the origin of this study as well as the basic structure of this report. In this chapter the author will discuss the steps followed in selecting a number of parts, from the thousands that are used per vehicle, which then formed the basis of the SAP-MRP evaluation. This task is not as simple as just selecting a few parts at random. It was essential that selected parts would be representative of the various aspects that affect Option related parts³.

Such a task required a progressive approach of steadily working through the available information and data in pursuit of a quality solution to the problem of deciding which parts to use. Firstly it was necessary to evaluate all the parts that represented the various aspects that influenced the problem and thereafter to work through them and filter out a few with which to work. These parts were to serve as indicators for the remaining parts with similar properties. It was then necessary to manually collect part data on a daily basis using existing queries in the SAP-MRP System. The required data was not stored at the end of each day and was in fact written over with new data every evening after each MRP run. Thus, the data had to be collected manually, but this process was replaced with an automated process much later.

Various information sources were used in order to establish which parts to use in the study. These sources varied from educated staff opinions to various internal information systems and were assimilated to produce a coherent guideline to be used in selecting a final set of parts.

2.1 Part Selection Process.

As mentioned earlier, it would have been impractical and unscientific to merely select a few parts at random and hope for the best. Furthermore, it was necessary to view the parts in context of the Option's that affected them. For the benefit of the uninformed reader it is necessary to include the following explanation of the relationship between Options, Options Codes, and Parts.

2.1.1 The Relationship between Options, Option Codes, and Parts.

A customer can select which Options e.g. Sunroof or Parktronic, they would like built into their vehicle. Each Option has an allocated code that is used in a multitude of DCSA's systems. These codes then indicate the part requirements for that specific Option. Some of these parts are unique to a specific Option, but others may also be used by additional Options. The discussed concept is illustrated in Figure 2.

³ For the purpose of this report the term *Option Related parts* refers to **non-bulk** and **non-standard** parts.

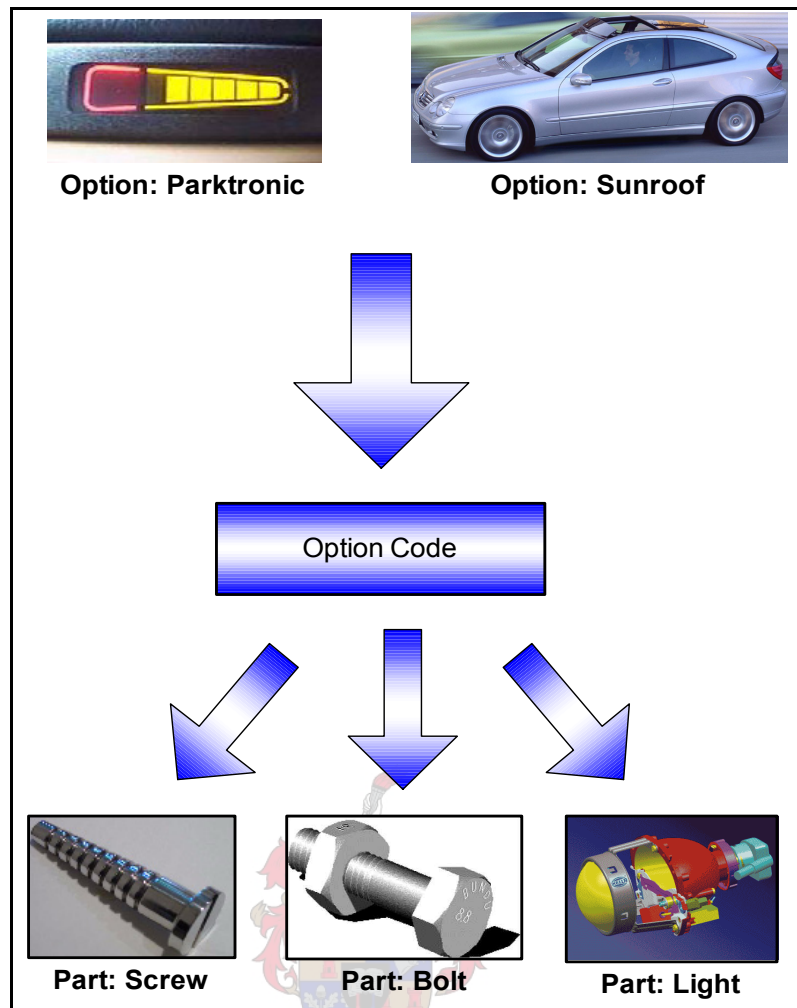


Figure 2: Options, Option Codes, and Parts.

The method used when selecting parts should now be clear. An Option was selected and then by “drilling down” using the Option Code it was possible to view all the parts associated with that Option. Ideally, a part should be selected that is unique to that Option as this allows for the tracking of changes in demand for that specific Option. Changes in Production Sequence or the addition and deletion of production days can result in undesirable data anomalies, which are then accentuated if the part is a unique indicator. This ideal situation is not always possible as the majority of parts are linked to more than just one Option. Furthermore the task of investigating the uniqueness of a part is a very time consuming and resource intensive exercise. Fortunately a Logistics team member had previously conducted such an exercise and a short list of such parts did exist.

2.2 Information Sources.

Various information sources were utilised when selecting parts for analysis. It was originally thought that these sources would quickly provide an exact list of parts that would satisfy certain criteria and although this did occur in certain circumstances, it was proven that further investigation was necessary before part selection was finalised.



Two systems, namely Dialog and SAP, were used to gather information that indicated whether the part was still in production, part number, and line station number etc. Dialog in itself is not very user friendly when compared to a Windows based system and much of the terms are indicated in abbreviated German. SAP on the other hand is a Windows based system, but the user has to have the exact part number, obtained from Dialog, in order to obtain the desired information. The availability of information played a significant role in part selection.

Four primary information sources were used when initially selecting parts for analysis, namely:

Type	Description
Educated staff opinions.	This list contained various part numbers, which were known by Logistics team members to be problem parts.
GOP analysis for W203 for 2002.	This analysis indicated the demand for specific Options as a percentage of the total cars manufactured in 2002.
Forecast Accuracy for 2002 of GOP vs. PAD.	This analysis indicated which options were critical. Critical is defined as a percentage deviation of the Actual Demand vs. Forecasted Demand. Criticality is indicated by the amber and red "robots" per month.
Unique parts per Option Code.	A Logistics team member compiled this list. A part was selected that was unique to an Option Code.

Table 2: Primary Information Sources and Descriptions.

Later it was found that all of the above information sources still did not provide a sufficient number of parts with which to conduct the analysis. At this stage, the author consulted production line personnel in order to ascertain which parts were associated with the assembly process of a part already selected for analysis. These parts were then included in the analysis only if they conformed to the Selection Criteria.

2.2.1 Information Systems and Sources.

Having completed the Part Selection Process it is now possible to stipulate which information is relevant and required for simulation as well as validation and verification exercises. Table 3 indicates this information.

Figure 3 on page 9 graphically shows the various processes and decisions used in gathering the required data.



Firstly, the various information sources previously mentioned are used to determine which Option will be used such that a part may finally be selected for analysis. The information system is utilised in selecting a part for analysis once it has been decided that the Option satisfies the selection criteria, be it high/low fluctuation or high/low runner. The selected part is then compared to the predefined Selection Criteria where after the required information is gathered for whatever purpose.

Information	Purpose	Source
Stock movement history	Validation and verification of simulation output. This information is used to determine: <ul style="list-style-type: none"> ➤ Plant stock associated with various Coverage Profiles. ➤ Stock receipt frequency. ➤ Stock receipt size. 	SAP. Obtained using SAP report <i>mb51</i> .
Planned Independent Requirement Totals.	Input to simulation program. Daily demands and associated Flips are obtained from this report. This information was originally gathered manually on a daily basis, but can now be done automatically.	SAP: Obtained using SAP query <i>se16</i> and thereafter report <i>Z04PIRSUM</i> .
Period Totals	Daily Plant Stock-level tracking. Contains demand requirements, dependent & independent, for real, actual, and Forecasted Orders. It is used to calculate average stock levels on a daily basis.	SAP: Obtained using report <i>md04</i> and <i>md05</i> .
Part numbers	All queries are executed based on part numbers.	Dialog or SAP. Preferably Dialog.
Part Vital Statistics	Indicates all the vital information pertaining to a part such as: <ul style="list-style-type: none"> ➤ Pallet size. ➤ Coverage profile. ➤ Minimum order quantity. ➤ Lead Time. 	SAP: Master data

Table 3: Where to Find Relevant Information Pertaining to this Project.

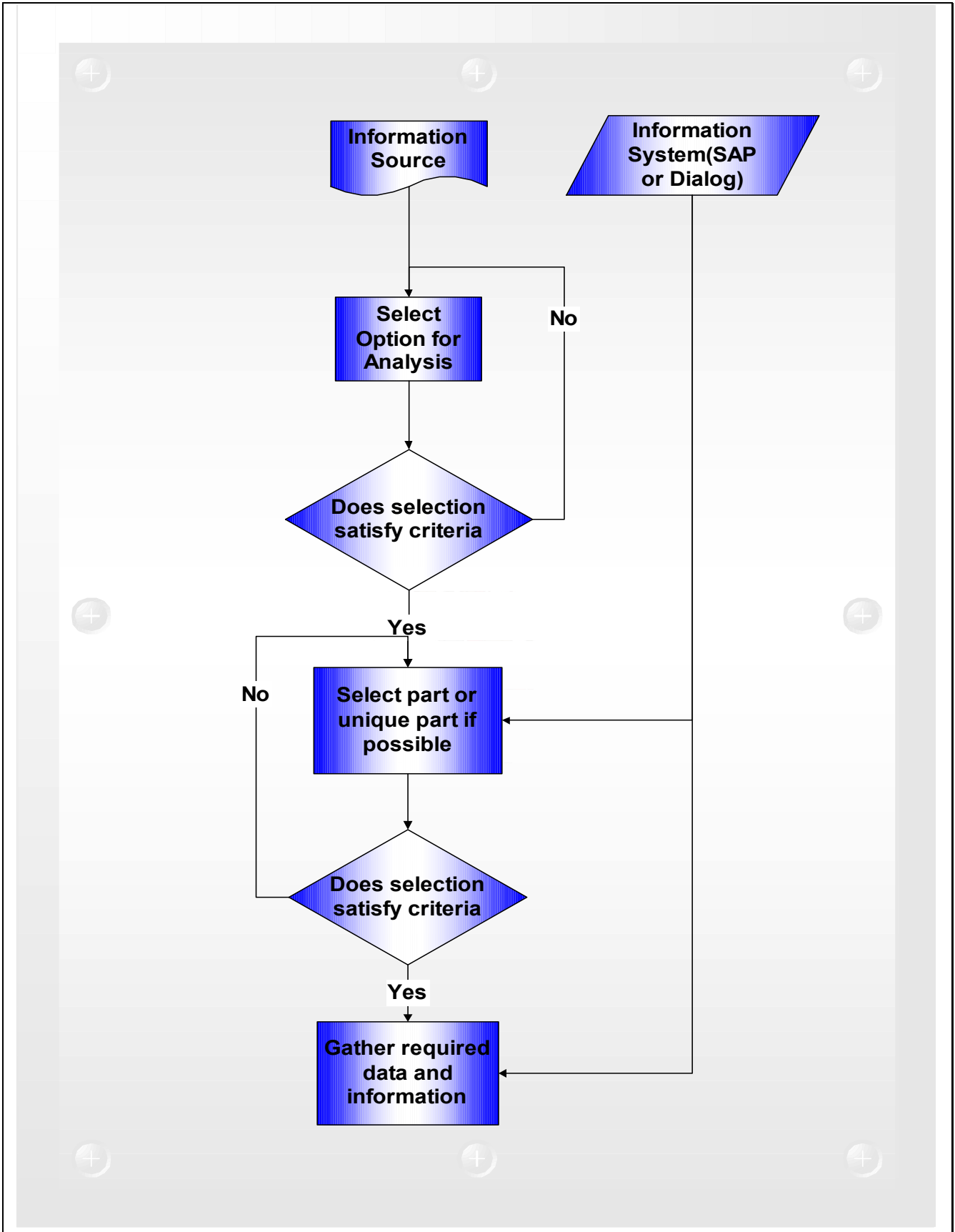


Figure 3: Information Selection and Decision Flowchart.



2.3 Information Selection Criteria.

There were two sets of Selection Criteria used in determining whether the obtained information was relevant to the study, namely Options Selection Criteria and Part Selection Criteria.

2.3.1 Options Selection Criteria.

The options selection criterion was limited to two fields, namely:

1. Demand Variability i.e. High/Low Fluctuation.
2. Demand Level i.e. High/Low Runner.

Four different Option types could be obtained by combining these two fields, namely:

1. High Runner / High Fluctuation.
2. High Runner / Low Fluctuation.
3. Low Runner/ High Fluctuation.
4. Low Runner / Low Fluctuation.

It was felt that these criteria were sufficient for testing the capabilities of the SAP-MRP System through simulation. It was reasoned that if the SAP-MRP System was capable of providing a satisfactory Avg. Customer Service Level at these four extremes then it should be able to do the same across the entire spectrum.

2.3.2 Part Selection Criteria.

The Part Selection Criteria were more extensive than that of the Option Selection Criteria, as the parts had to conform to a broad range of checks before being selected for analyses. The Criteria, variations thereof, and the checklist concerned are shown in Table 4.

Criteria	Variations	Checklist
Location of Supplier	Local or overseas	Overseas
Lead Time	60, 53, 44, or less than 44 days	53 or 44 days
Usage Classification	Standard or non-standard	Non-standard.
Order Classification	Bulk or non-bulk	Non-bulk
Financial Value	High or low value	Either
Colour Coded	Yes or no	Either

Table 4: Part Selection Criteria and Checklist.

A part had to conform to the entries under the field "Checklist" in order to qualify for analysis. Various reasons dictated as to why certain checklist field entries were decided on. A summary of these reasons are shown in Table 5 on page 11.



Checklist	Reason
Overseas Suppliers	Only overseas suppliers have long enough Lead-Times for enough Flips to occur that could then result in a stock-out occurrence. Local suppliers supply on a JIT basis i.e. they have a very short Lead-Time.
53 or 44 days	Parts with a 60 day Lead-Time do not qualify for analysis, as all of these orders are placed based on forecasted demand. Only parts that are ordered based on Customer Demands are relevant to this study. This point is explored in detail later on.
Non-standard, although standard parts were used for benchmarking.	Standard parts experience very little change in demand other than that caused by re-sequencing. This study was focused on non-standard parts that show a strong correlation to changes in Customer Demand.
Non-bulk	Bulk parts are also typically standard parts with a Lead-Time of 60 days. Furthermore bulk parts are usually ordered in very large numbers, due to Pallet Sizes, which then totally overrides their Coverage Profiles.
Either	This field does not exclude a part, but is rather used to classify a part as either a high or low value part.
Either	This field does not exclude a part, but is rather used to classify a part as either colour or non-colour coded part.

Table 5: Summary of Reasons for Deciding On Checklist Field Entries.

2.4 Forecasted Demand vs. Actual Demand.

This section aims to highlight the difference between Forecasted Demand and Actual Demand in terms of the Order Release process.

The point at which an Order Release is created is based on the Lead-Time⁴ associated with a particular part e.g. a part with a 53 day Lead-Time would result in an Order Release being created 53 days prior to its assembly line requirement. The Order Release sent to the suppliers would then reflect the demand for a specific part a certain number of days into the future. This demand can reflect Actual Customer Demands or forecasted demands depending on when DCSA receives Sales Orders from Germany. Sales Orders are received for a period between 53 and 63 days before Jig⁵, thus all the demands from Jig Day until about day 63 are demands reflecting Customer Orders. All the demands outside of this range reflect forecasted demands.

⁴ For the sake of this discussion Lead-Time includes Back-Off Days, Safety Time, Goods Receipt Processing time, and "Time at Sea."

⁵ Jig is the point at which a vehicle starts going through the assembly process.



The Sales Order receiving period only presents a problem for parts with a 60 day Lead-Time. The problem is because of a 5 day evaluation period that is required by the Material Controller to evaluate and “Firm” the proposed Order Release. This evaluation period occurs over and above the existing Lead-Time. It can now be seen that parts with a 60 day Lead-Time will always be based on forecast even if Sales Orders are received 63 days before Jig. These Sales Orders would have to be evaluated for 5 days and would thus only be ready for Order Release 58 days before Jig, 2 days too late for parts with a 60 day Lead-Time.

Figure 4 presents a graphical illustration of the above argument. It is a summarised version of the breakdown of the Order Lead-Times found in Appendix B.

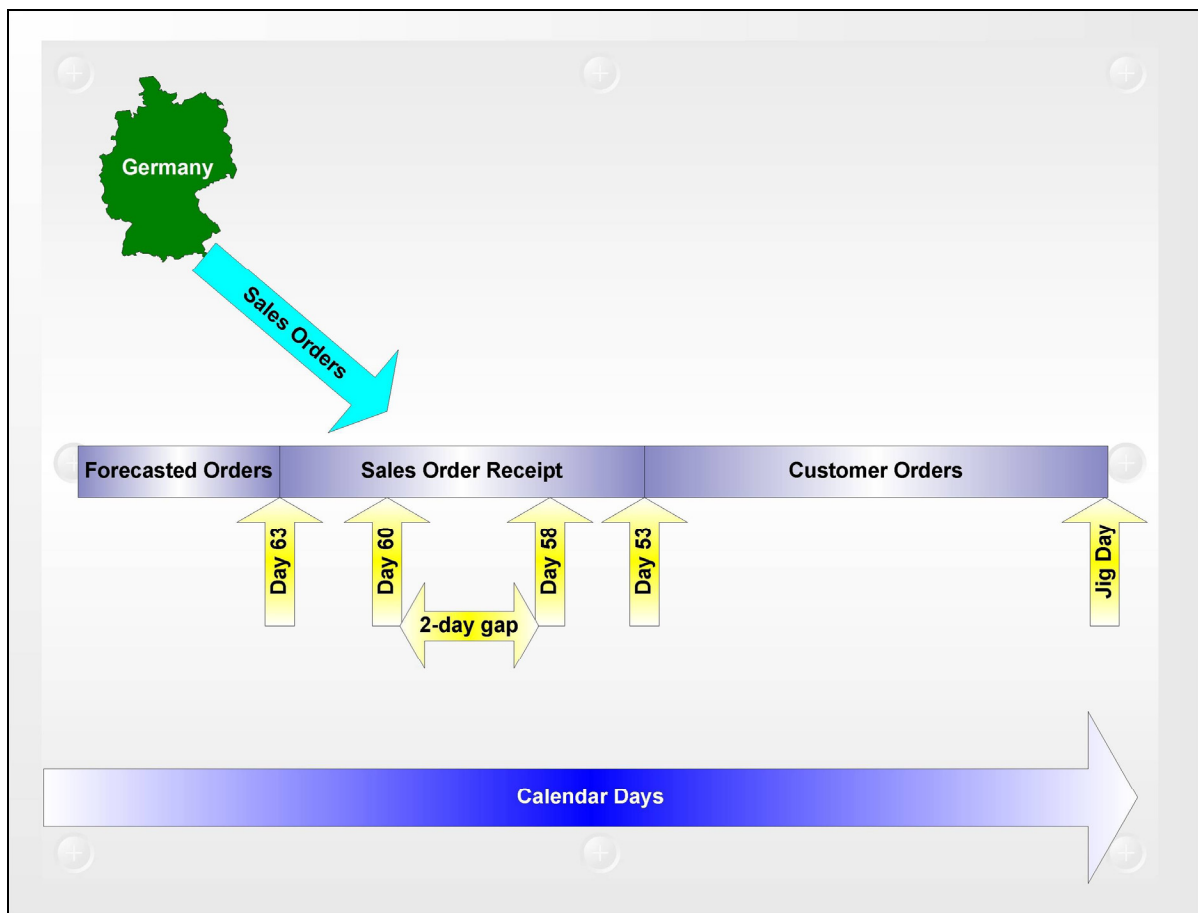


Figure 4: Forecasted Orders vs. Actual Orders.



2.5 Parts Selected for Analysis.

Table 6 is a summarised list of the parts selected for analysis based on the previous arguments. Refer to Appendix C for a detailed description of the selected parts and their vital statistics.

Recommended Part	Part Code	Runner		Fluctuation	
		Low	High	Low	High
Mercedes Star	2028800186 A		1	1	
Classic Label	2038170920 A		1	1	
Avantgarde Label	2038171120 A		1	1	
Elegance Label	2038171020 A		1	1	
Head Rest	2039709350 27D44A	1			1
Steering Wheel (Black)	2034600903 29C29A		1	1	
Steering Wheel (Blue)	2034600903 25C69A	1			1
Steering Wheel (Black Chrome Insert)	2034601503 29C29A	1			1
Steering Wheel AMG Black	2034602403 29C29A	1			1
Cover compl RH B-pillar	2036901640 21A73C		1	1	
Cover compl RH B-pillar	2036901640 7E63C		1	1	
Rim	2094000402 A		1	1	
Carpet	2096801242 29D60A	1			1
Carpet	2096801042 29D60A		1	1	
C220 Diesel Gearbox Auto	2032700400 A		1	1	
C180 Gearbox Automatic	2112703200 A		1	1	
C180 Kompressor Engine	2710106700 A		1	1	
C320 Kompressor AMG Engine	1120101144 A	1			1
C 180 Gearbox Manual	2032602102 A		1	1	
Cover, for Bracket Transmission Hydraulic	0005461781 A	1			1
	Sum	7	13	13	7

Table 6: Parts Selected for Analysis.



2.6 Summary.

The original intention was for DCSA to have already **selected the parts** by the time the study was started in January 2003. This was however, not the case and the author had to move through a steep learning curve before the selection of parts could occur. Various information sources were used in order to establish which parts to use in the study. Part selection was not as simple as just choosing a few parts at random as it was essential that the selected parts be representative of the various aspects that affect Option related parts. Existing queries were used on a daily basis to extract manually the required data once the Part Selection Process was complete.

A **Selection Methodology** was followed whereby an Option was selected and then by “drilling down,” using the Option Code, it was possible to view all the parts associated with that specific Option. Ideally the selected part should have been unique to the Option code, but this was not always possible as the majority of the parts are linked to more than just one Option.

Various information sources (of which SAP was the primary information source), in conjunction with established Selection Criteria, were utilised when selecting parts for analysis. Two Selection Criteria were established to aid in the selection of parts. The first **Selection Criterion** was based on the selection of Options; the second was focused on the selection of parts. The Part Selection Criteria were more extensive than that of the Option Selection Criteria, as the parts had to conform to a broad range of checks before being selected for analyses.

It was found that parts with a 60 day Lead-Time could not be used in the analysis because their Order Releases are based on **Forecasted Demand** and not **Actual Demand**.

While this chapter provided an overview of the problems encountered when selecting parts for analysis, the next chapter describes in detail exactly how the data was gathered per part, which SAP-queries were used, and how the output data was filtered and formatted. The chapter was designed such that anybody wanting to utilise the simulation program in future would know how to process the data into the correct format.



3. Collection of Raw Data.

In the previous chapter the methods used in selecting various parts for analyses as well as the various information sources and systems used in obtaining the required information were discussed. This chapter moves on from there and describes in detail how the data was gathered per part, which SAP-queries were used, and how the output data was filtered and formatted. This chapter has been constructed with the idea in mind that someone in the future will want to use the developed software. In this case, it is essential to know where and how to obtain the input data as well as how to prepare it for simulation. Furthermore, it is assumed that the reader is familiar with the work done by van Wijck et al. [4] given that this chapter in fact describes where and how the data was obtained for their initial work. If the reader is unfamiliar with their work on this project then it is suggested that they refer to their report (see van Wijck et al. [4]).

3.1 SAP Queries and Reports Used.

This section follows on from paragraph 2.2.1 on page 7. In this paragraph Table 3 indicated which queries and reports were used to obtain the required data and information. Table 7 lists the most significant of the set listed in Table 3.

Information	Purpose	Source
Planned Independent Requirement Totals.	Input to simulation program. Daily demands and associated Flips are obtained from this report. This information was originally gathered manually on a daily basis, but can now be done automatically.	SAP: Obtained using SAP query <i>se16</i> and thereafter report Z04PIRSUM.

Table 7: Most Significant Data from the SAP System.

This data was used as the input to the simulation program and the entire study was highly dependent on it. It should be mentioned that the Z04PIRSUM report had to be run manually every morning during the data collection phase, for each individual part. This exercise took approximately 45 to 90 minutes, depending on the quality of the output. This exercise was later automated - the process and the reasons for which it was required are described in Section 3.4 on page 34.

Another, important piece of information came from the SAP-MRP Master Data form. This form contains all the Part Vital Statistics, which are used as Input Parameters to the MRP System when calculating part requirements. In order that all relevant parameters could be used efficiently in future simulations, it was necessary to document them accordingly. A description of the parameter and the influence on the MRP System was available via the SAP Help files.

The remaining reports and queries were used for the purpose of validation and verification, as previously mentioned.



3.2 Output Data Description.

At this point, it is clear that the data from the Planned Independent Requirement Totals (Z04PIRSUM) report was fundamental to this study. In the opinion of the author, explaining every type of query output or report used is not of value to the reader. The Z04PIRSUM report required a substantial amount of data processing i.e. extracting, formatting, and filtering of the data. The investment, in terms of time and effort, far outweighs that spent on any other report or query and this then is the primary reason for describing the elements that make up and affect this report.

3.2.1 The SAP Report: Z04PIRSUM.

The output of the report was exported from SAP, saved as a text file (tab delimited), and then opened using Microsoft Excel. The data for all the parts was stored in the same Report Output - an example of this is shown in Figure 5. This grouping together necessitated the user to cut and paste the data of each part to their respective Excel files for further processing.

Final OK Date (P)	2034600903 29C29A	2034601503 29C29A	2034602403 29C29A
2003/05/13	30		
2003/05/14	71	2	1
2003/05/15	91	1	1
2003/05/16	72	3	
2003/05/19	78	2	2
2003/05/20	87	1	
2003/05/21	70		
2003/05/22	74	3	1
2003/05/23	71	2	
2003/05/26	77	3	
2003/05/27	90	2	1
2003/05/28	80		2
2003/05/29	84		
2003/05/30	91		2
2003/06/02	65	2	
2003/06/03	63		
2003/06/04	70		4
2003/06/05	65	1	
2003/06/06	55	1	2
2003/06/09	53		2
2003/06/10	69		2
2003/06/11	82	1	1
2003/06/12	101	1	
2003/06/13	88	3	1
2003/06/17	75	1	
2003/06/18	82	1	1
2003/06/19	94	2	3
2003/06/20	97		2
2003/06/23	57		2
2003/06/24	52	1	1
2003/06/25	62		
2003/06/26	56		
2003/06/27	82		1
2003/06/30	52		2
2003/07/01	1		

Figure 5: Z04PIRSUM Output.

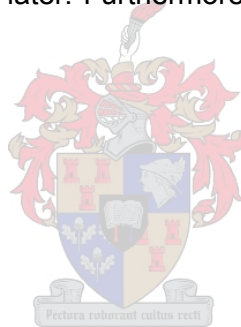
The left-hand column of Figure 5 indicates the completion date of the vehicle to which a specific part is to be assembled. The corresponding rows specify the total demand for that part on a specific "Final OK" date. An empty row indicates that no requirement exists for that specific part i.e. a zero demand. Furthermore, all the row-values represent Customer Demands and not forecasted demands – exactly what is required for the simulation input.



The date in Row One, Column One represents the Planned Independent Requirement (PIR) date. This date will always be nine production days ahead of the Report Run-Date. The reason for this is that the Independent Requirement changes to a Dependent Requirement at the point at which a Production Sales Order⁶ is created i.e. 9 days ahead of the FI-date or 3 days before Jig.

The date in Row One, Column One increments by one production day, each day. Using Figure 5 as an example, one can see that this particular report was run on the 2003/04/30, and the date in Row One, Column One was 2003/05/13. Had this report been run the following day then the date in Row One, Column One would have been 2003/05/14.

DCSA receives new Customer Orders about every 10 calendar days (called a Decade). These new Customer Orders are added to the existing PIRs from the bottom row onwards. It can now be imagined that placing the output data side-by-side creates “step” effects. If the rows are indexed against future FI dates then it is seen that the top row decrements with one row per day and that the bottom row increments with several Customer Orders every few days. Figure 6, shown below, is a graphic illustration of this behaviour. The meaning of the colours is not important for this discussion and is elaborated on later. Furthermore, the first and last entry per column has been removed for reasons given later.



⁶For the sake of this report, “Production Sales Order” refers to a Customer Order that is confirmed as an actual Sales Order. DCSA staff refer to this as a “Sales Order.”



Final OK Date (P)	2003/01/21	2003/01/22	2003/01/23	2003/01/24	2003/01/27	2003/01/28	2003/01/29	2003/01/30
2003/01/31								
2003/02/03	172							
2003/02/04	174	174						
2003/02/05	180	180	180					
2003/02/06	173	173	173	173				
2003/02/07	176	176	176	176	176			
2003/02/10	172	172	172	172	172	172		
2003/02/11	182	182	182	182	182	182	182	
2003/02/12	175	175	175	175	175	175	175	175
2003/02/13	183	183	183	182	182	182	182	182
2003/02/14	179	179	179	179	179	179	179	179
2003/02/17	178	178	178	178	178	178	178	178
2003/02/18	171	171	171	171	171	171	171	171
2003/02/19	172	172	172	173	173	173	173	173
2003/02/20	178	178	178	177	177	177	177	177
2003/02/21	175	175	175	174	174	174	174	174
2003/02/24	175	175	175	175	175	175	175	175
2003/02/25	177	177	177	177	177	177	177	177
2003/02/26	178	178	178	178	178	178	178	178
2003/02/27	169	169	169	170	170	170	170	170
2003/02/28	175	175	175	174	174	174	174	174
2003/03/03	175	175	175	175	175	175	175	175
2003/03/04	165	165	165	166	166	166	166	166
2003/03/05	169	169	169	169	169	169	169	169
2003/03/06	179	180	180	180	180	180	180	180
2003/03/07	175	175	175	175	176	176	176	176
2003/03/10	175	175	175	176	176	176	176	176
2003/03/11	172	172	172	172	172	172	172	172
2003/03/12	174	174	174	173	173	173	173	173
2003/03/13	178	178	178	178	178	178	178	178
2003/03/14	177	177	178	179	179	179	179	180
2003/03/17	178	178	178	177	177	177	178	179
2003/03/18	182	182	181	182	182	182	182	182
2003/03/19	176	176	176	176	176	176	176	177
2003/03/20				176	176	176	176	177
2003/03/24							181	181
2003/03/25							174	175
2003/03/26							172	173
2003/03/27							170	169
2003/03/28							180	181

Figure 6: PIR Step Effect (First and Last Rows Deleted).

3.2.2 Data Formatting

This section will explain the use of colour symbolism as well as the meaning of the calendar dates running down the left and across the top of Figure 6.

Dates:

The column of dates, seen under the heading *Final OK Date (P)*, represents Planned Production Days. The row of dates represents the days upon which the report was run. Therefore, using the 2nd column as an example, it is seen that the report was run on the 2003/01/21 and the result included PIRs from 2003/01/31 to 2003/03/20⁷.

⁷ The cells allocated to 2003/01/31 and 2003/03/20 are empty as these entries are deleted for reasons given in section 3.2.3 on page 20.

**Cell values:**

The value in a cell represents the demand for that part for a Planned Production Day. The value is not static and only represents the demand as it was on the day that the report was executed. It is possible to view a part's change in demand by selecting any cell and moving from left to right within the same row.

Colour:

Initially, colour was used by the author to identify quickly the various components that make up each column of data. Later on, it proved to be an excellent method of indicating where to paste new data as well as data anomalies.

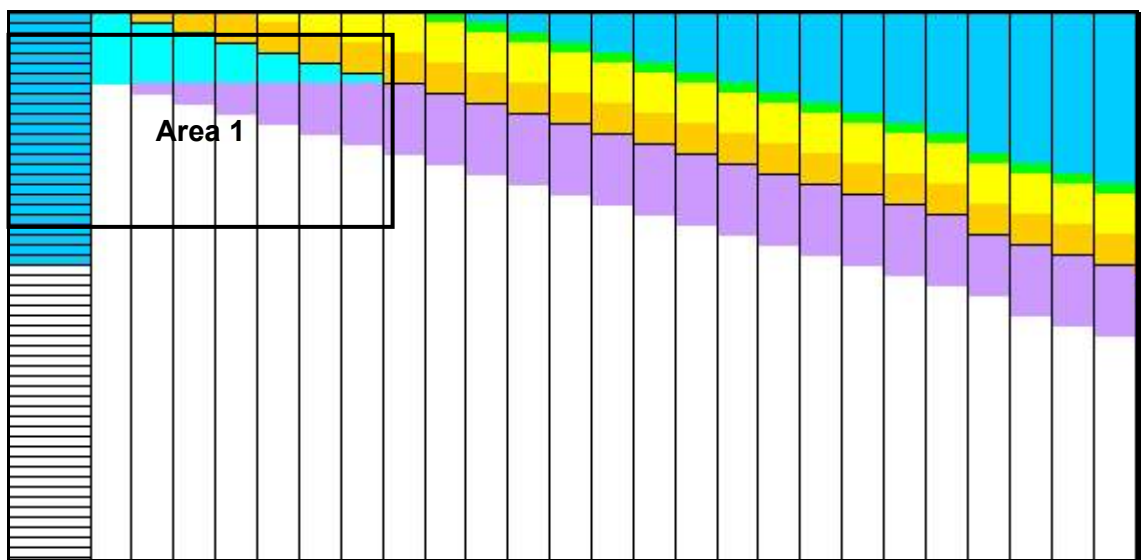


Figure 7: Zoomed-out view of Figure 6.

“Area 1” in Figure 7 indicates the position of Figure 6 within the context of the entire input data set. Figure 7 is a “zoomed-out view” of the input data set. It gives a clear indication of the various colours used as well as layout. Table 8 on page 20 lists the range of colours used as well as describing the significance of each.



Colour	Indicator	Description	Duration (working days)
	Final Inspection (FI) / Final OK	The vehicle is complete. It has undergone final inspection and all the parts used in the assembly have been "Back-Flushed" from the system.	10
	Assembly Line	The assembly starts at the body shop where the shell is assembled and then moved through the mechanical and trim lines, ending at FI.	25
	Creation of Production Sales Order	A customer order is changed to a Production Sales Order. The Production Sales Order lies in the system for 3 days before Jig day.	3
	Option Freeze (10 days before Jig) measured in calendar days i.e. left to right.	Customers are no longer permitted to alter their vehicle Options. Demand changes in this portion are attributed to changes in production sequencing or other internal changes.	10
	Option Freeze (25 days before Jig) measured in calendar days i.e. left to right.	As above	25
	Option Freeze (25 days before Jig) measured in production days i.e. top to bottom. Reference is made the bright green block.	As above	25

Table 8: Colour Legend.

There are two Option Freeze periods indicated in Table 8. They are dealt with in Section 3.3.

3.2.3 Data Anomalies.

This section assumes that the reader is familiar with the simulation method used to select an initial demand and alter it over time. Furthermore, it is assumed that the reader understands how undesirable Flip values will affect the Cumulative Flip Distribution. See van Wijck et al. [4].

According to the Oxford English Dictionary, the word anomaly in scientific terms means: "Deviation from the natural order." In the case of this study, "natural order" would refer to the expected frequency and magnitude of the daily demand changes. In general, data anomaly would then refer to a portion of data or an individual member of a data set that deviates from the expected. More specifically, the term is used to refer to the Flips associated with certain events.

There are three types of data anomalies worth discussing, namely those that are the result of:

1. Creation of Production Sales Order.
2. Alterations in the Production Sequence.
3. The Addition and Deletion of Planned Production Days.



Each of these anomalies is dealt with in such a manner that they are either included or excluded from the simulation input data. The reasons for including or excluding certain data are discussed in the following three sections.

3.2.3.1 Creation of Production Sales Order.

The process whereby Production Sales Orders are created produces an effect that generates data anomalies in the first and last row of the Z04PIRSUM report. The effect is attributed to the fact that the Actual Production rate is not synchronised with the Production Schedule. The latter statement may be confusing, but Figure 8 and the following quantitative example should help to clarify the issue.

		Actual Production Day					
		1	2	3	4	5	6
Scheduled Production Day	0	100 ⁰					
	1	100 ¹	100 ¹				
	2		100 ²	100 ²			
	3			100 ³	100 ³		
	4				100 ⁴	100 ⁴	
	5					100 ⁵	100 ⁵
	6						100 ⁶

Figure 8: Scheduled Production vs. Actual Production.

Suppose DCSA produces, on average, 200 vehicles per day. This would infer that if 200 vehicles are leaving the production line, then 200 vehicles are entering the line, assuming that the production line is in the steady-state. Furthermore, assume that the assembly process takes one day (to make the explanation easier).

Using Actual Production Day 2, from Figure 8 as an example, it is seen that 200 vehicles are entering the production line. The set of vehicles entering the line consists of two groups of scheduled vehicles. The first group consists of 100 units scheduled on “Scheduled Production Day 1” and the second group consists of 100 units scheduled on “Scheduled Production Day 2.” Superscript numbers are used to denote the days on which the production units were scheduled.

Similarly, it is seen that 200 vehicles are scheduled every day, but they are spread out over two production days. Using row 2 of “Scheduled Production Day” as an example:

200 units are scheduled on Scheduled Production Day 1 (row 1, column 1), but they are split over two days i.e. 100 units for Actual Production Day 1 and 100 units for Actual Production Day 2.

The net result is that the number of vehicles scheduled equals the number actually produced.



It should now be clear what is meant by saying that the Actual Production rate is not synchronised with the Production Schedule. A description of the First and Last-Row Anomaly will now follow.

First-Row Anomaly:

Figure 8 includes the Actual Production and Scheduled Production in one form. This differs to the Z04PIRSUM report in that the report only indicates the scheduled production days (“Scheduled Production Days” translates to “Planned Production Days” when using the report terminology). Figure 9 is the same as Figure 8 except that “Calendar Day” has replaced the “Actual Production Day” and “Scheduled Production Day” has been altered to reflect the report terminology. These changes have brought Figure 9 in line with the format of Figure 6.

The cell values in Figure 9 represent the number of vehicles scheduled / planned for production. The cell values equal to 100 represent the remainder of vehicles not yet produced from the vehicles scheduled the previous day.

		Calendar Day					
		1	2	3	4	5	6
Planned Production Day	0	100 ⁰					
	1	200 ¹	100 ¹				
	2		200 ²	100 ²			
	3			200 ³	100 ³		
	4				200 ⁴	100 ⁴	
	5					200 ⁵	100 ⁵
	6						200 ⁶

Figure 9: Scheduled Production Days Only.

The decrease in Planned Production, from 200 to 100 vehicles, will have a direct effect on the part demand associated with the assembly of those vehicles. This is seen in the Figure 10:

Final OK Date (P)	2003/01/21	2003/01/22	2003/01/23	2003/01/24	2003/01/27	2003/01/28	2003/01/29	2003/01/30	2003/01/31
2003/01/31	43								
2003/02/03	172	47							
2003/02/04	174	174	48						
2003/02/05	180	180	180	47					
2003/02/06	173	173	173	173	49				
2003/02/07	176	176	176	176	176	49			
2003/02/10	172	172	172	172	172	172	47		
2003/02/11	182	182	182	182	182	182	182	51	
			175	175	175	175	175	175	50
			183	182	182	182	182	182	182
			179	179	179	179	179	179	179
2003/02/17	178	178	178	178	178	178	178	178	178
2003/02/18	171	171	171	171	171	171	171	171	171
2003/02/19	172	172	172	173	173	173	173	173	173
2003/02/20	178	178	178	177	177	177	177	177	177
2003/02/21	175	175	175	174	174	174	174	174	174
2003/02/24	175	175	175	175	175	175	175	175	175

Figure 10: First-Row Anomaly.

The above explanation should have clearly indicated how the data anomaly in the first row of each column occurs.



Last-Row Anomaly:

This anomaly does not occur in every column, as does the first-row anomaly. This anomaly is a function of the operations within the assembly line i.e. the production rate.

At the start of the explanation, it was assumed that the assembly process takes 1 day. Suppose the production period now covers 5 days. With this assumption in place, it should be kept in mind the many processes that take place over the 5 day assembly period. Each of these processes takes a certain period to complete and has an amount of variability built into it. All of these time factors are taken into account during scheduling and are used to plan the completion date.

Final OK Date [P]	2003/01/21	2003/01/22	2003/01/23	2003/01/24	2003/01/27	2003/01/28	2003/01/29	2003/01/30
2003/03/07	175	175	175	175	176	176	176	176
2003/03/10	175	175	175	176	176	176	176	176
2003/03/11	172	172	172	172	172	172	172	172
2003/03/12	174	174	174	173	173	173	173	173
2003/03/13	178	178	178	178	178	178	178	178
2003/03/14	177	177	178	179	179	179	179	180
2003/03/17	178	178	178	177	177	177	178	179
2003/03/18	182	182	181	182	182	182	182	182
2003/03/19	176	176	176	176	176	176	176	177
2003/03/20				176	176	176	176	177
2003/03/24							181	181
2003/03/25							174	175
2003/03/26							172	173
2003/03/27							170	169
2003/03/28							180	181

Figure 11: Last-Row Anomaly.

Now imagine that a certain number of vehicles have entered the assembly line with an associated Planned Completion Date, call this date “Plan 1,” refer to Figure 11. This Plan remains unchanged until something happens on the 2003/01/24 that reduces the production rate of the assembly line. The reduced production rate results in a one day delay that affects the planned finish date of all the vehicles behind those already in the assembly line. The new Planned Completion Date is called “Plan 2.” This shift is indicated in Figure 11.

This resultant shift in planned completion dates has an effect on the part demand indicated in the Z04PIRSUM report. The shift may be such that only a handful of vehicles are delayed e.g. 10 vehicles, and the system would then reflect that only 10 vehicles would be assembled. The resultant demand for those vehicle parts will obviously be much lower than that of a normal production day. Nevertheless, these demands are shown in the report, as seen in Figure 12, and will thus form part of the simulation input data, if included. This is not desirable.

This anomaly does not occur all the time, as mentioned earlier, but it does occur often enough to warrant the deletion of the last row of every column as a precautionary measure.



Final OK Date (P)	2003/01/21	2003/01/22	2003/01/23	2003/01/24	2003/01/27	2003/01/28	2003/01/29	2003/01/30
2003/03/14	177	177	178	179	179	179	179	180
2003/03/17	178	178	178	177	177	177	178	179
2003/03/18	182	182	181	182	182	182	182	182
2003/03/19	176	176	176	176	176	176	176	177
2003/03/20	177	177	177	176	176	176	176	177
2003/03/24				1	1	1	181	181
							174	175
							172	173
2003/03/27							170	169
2003/03/28							180	181
2003/03/31							178	179

Figure 12: Effect of Delayed Vehicles on Part Demand.

3.2.3.2 Altering the Planned Production Sequence.

The Production Sequence is the order in which vehicles enter the assembly line e.g. 3 vehicles, A, B, and C, enter the assembly line in the order C, A, and B. The manner in which the vehicles are sequenced affects the demand per part reflected in the Z04PIRSUM report. Thus, the demand per part, per Planned Production Day will change if the sequencing is changed in any manner whatsoever. These changes i.e. “Flips,” will then be reflected and included in the simulation input data.

The latter is unfortunate, as large changes result in uncharacteristically large “Flips.” These large Flips can negatively bias the input data if they occur frequently enough. Upon questioning a Logistics team member, the author was advised that such large sequence changes do not happen on a regular basis. However, many of these large changes did occur in the data used for this study.

In dealing with these changes, the author devised two methods of handling these undesirable Flips. The first involved an Excel macro that filtered out the Flips based on various parameters; the other was to hard code the simulation program to ignore these changes. In the end, the second alternative proved to be the most practical (see Section 5.2.4.1 on page 66). The first alternative (see Section 7.1.3.1 on page 94), although based on sound mathematical principles, would require the author to select an initial cut-off point whereby “outliers” would be removed. The selection of this cut-off would be subjective and thus result in an element of bias.

Figure 13 and Figure 14 on page 25 display the results of changing the Production Sequence.

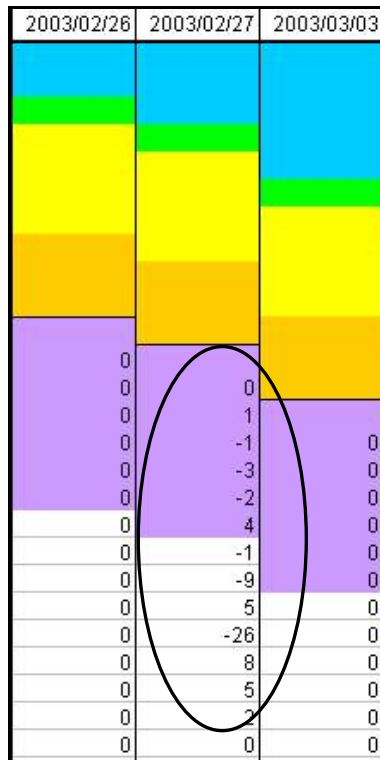


Figure 13: Flips as a Result of Sequence Change.

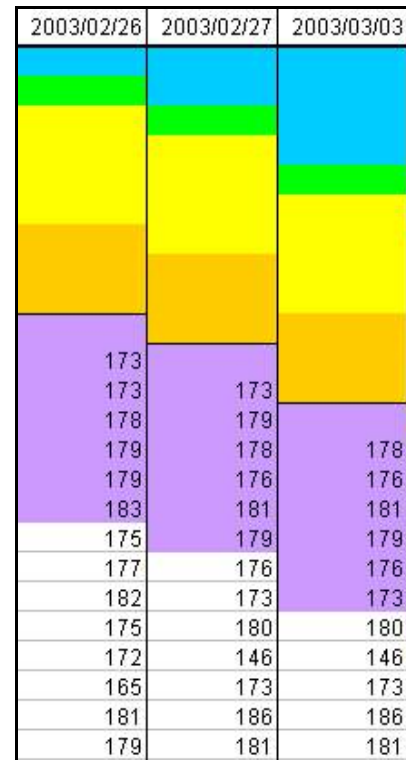


Figure 14: Demands attributed to Sequence Change.

Re-Sequencing is not out of the control of DCSA i.e. they can control where and when vehicles are rescheduled for production. The proposed sequence is manipulated until the part demand is satisfied, if it is seen that the number of available parts is not able to cover the increased demand.

Initially the author thought that re-sequencing would negatively affect the simulation process. These concerns were laid to rest when it was reasoned that no negative effect would occur if the Flips, because of re-sequencing, were similar in size and frequency to those associated with changes in Customer Demands. Large Flips were dealt with by hard coding the simulation program, which is explained in detail later on in this report.

3.2.3.3 Addition and Deletion of Planned Production Days.

The addition and deletion of Planned Production Days is another potential anomaly that can occur in the data. Usually DCSA negotiates for weekend shifts with respective labour unions at the beginning of the year. However, in 2003, it occurred later in the year. Various proposals were put on the table during the negotiating process and were then implemented in the Production Timetable. These proposals were later altered over the course of a few weeks, which resulted in the anomalies under discussion.



Figure 15 and Figure 16 indicate the effect of adding and deleting Planned Production Days. Figure 15 shows the effect on part demand. The zeros indicate that from 2003/04/01 until 2003/04/02 the production days 2003/04/29 and 2003/04/30 were no longer included in the Production Timetable (see Appendix D). Figure 16 shows the resultant Flips associated with the changes.

The possible negative influence that this anomaly could have had on the simulation program was dealt with in exactly the same manner as the re-sequencing anomaly i.e. the simulation program was hard-coded to ignore these Flips.

Final OK Date (P)	2003/03/31	2003/04/01	2003/04/02	2003/04/03	2003/04/04
2003/04/23	179	167	210	176	178
2003/04/24	178	170	170	174	174
2003/04/25	160	181	181	168	168
2003/04/29	165	0	0	164	164
2003/04/30	175	0	0	175	175
2003/05/05	171	171	171	171	171
2003/05/06	180	180	180	180	180
2003/05/07	159	159	159	159	159
2003/05/08	167	167	167	167	167
2003/05/10	177	177	177	177	177
2003/05/11	172	172	172	172	172
2003/05/12	178	178	178	178	178
2003/05/13	181	181	181	181	181

Figure 15: Demand as a Result of Addition and Deletion of Production Days.

2003/04/23	0	-12	43	-34	0
2003/04/24	0	-8	0	4	0
2003/04/25	0	21	0	-13	0
2003/04/29	0	-165	0	164	0
2003/04/30	0	-175	0	175	0
2003/05/05	0	0	0	0	0
2003/05/06	0	0	0	0	0
2003/05/07	0	0	0	0	0
2003/05/08	0	0	0	0	0
2003/05/10	0	0	0	0	0
2003/05/11	0	0	0	0	0
2003/05/12	0	0	0	0	0
2003/05/13	0	0	0	0	0

Figure 16: Flip as a Result of Addition and Deletion of Production Days.



3.3 Option Freeze: 25 Day Option Freeze vs. 10 Day Option Freeze.

The study was conducted in a simulated 10 Day Option Freeze Environment. The Option Freeze point, at the time that this study was conducted, was 25 days before Jig. Thus, all the data that was gathered was a function of this environment i.e. the point at which customers can no longer alter their Options.

The Option Freeze point, as it was then, was not always strictly adhered to as a rule for changing a customer's Options. Customers would be allowed to alter their Options depending on where their vehicles were in the line of vehicles awaiting assembly. Therefore, Flips were observed within the 25 Day Option Freeze Period along with other Flips attributed to internal operations i.e. re-sequencing etc.

Initially, it was thought that only the data outside the 25 Day Option Freeze point should be utilised as a specification, as this data would more than likely reflect the true trend in Customer Demand changes. Unfortunately, upon closer examination of the Z04PIRSUM report, very little of the data conformed to this specification. In fact, calculations showed that approximately 42.5% of the available data conformed to specification. A typical snapshot of the data is shown in Figure 17. The purple area shows the useful data section in the context of the whole.

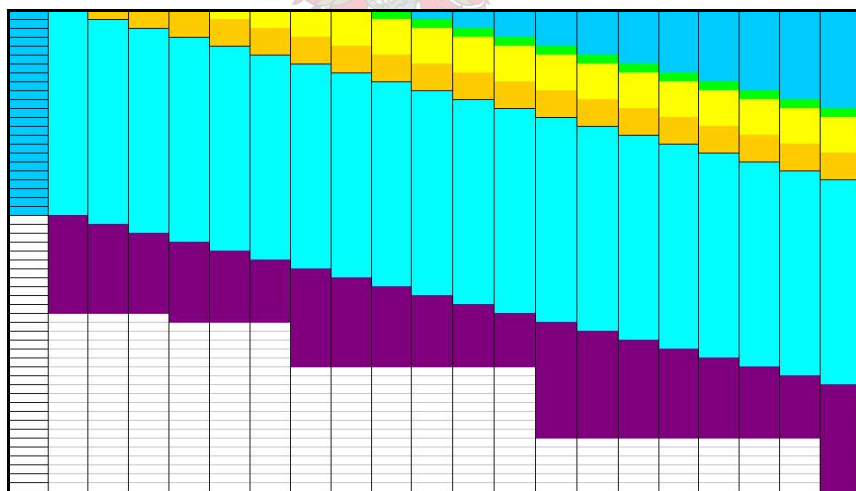


Figure 17: Portion of Data that Conforms to Specifications.

Suppose that this specification had been abided by and that only 42.5% of the available data could be used for simulation purposes. The question would then be, "How much, or for how long should data be collected such that the confidence interval half-width of the mean of the Flips is acceptably small?"

By looking at the confidence interval half-width equation, Equation 1, it is seen that the larger the sample size is the smaller the half-width. A small half-width is desirable as it gives a better estimation of the true mean of the parameter under investigation.



The following equations are utilised in calculating the required sample size in order to achieve a desired confidence interval for the true mean of the Flip.

Confidence interval half-width:

$$h = t_{n-1;1-\alpha/2} \frac{s}{\sqrt{n}} \quad \text{Equation 1}$$

Where:

$t = 1-\alpha/2$ upper critical point on the Student t-distribution

s = Standard deviation of the Flips (Refer to Equation 3)

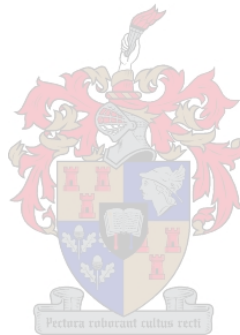
n = Sample size

Average Flip:

$$\bar{d} = \frac{\sum_{i=1}^n d_i}{n} \quad \text{Equation 2}$$

Standard deviation of the Flips:

$$s = \sqrt{\frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n-1}} \quad \text{Equation 3}$$



Confidence interval lower limit:

$$CI_L = \bar{d} - h \quad \text{Equation 4}$$

Confidence interval upper limit:

$$CI_U = \bar{d} + h \quad \text{Equation 5}$$

Equation 1 is employed in conjunction with the data outside the 25 Day Option Freeze point to calculate the period/sample size required to achieve a desired confidence interval for the true mean of the Flip. The example will highlight the reasons for using the data that fell within the 25 Day Option Freeze Period for this study.

**Example:**

The data for this example was collected over a 65 working day period for part no. 2036901640 27E63C. All Flips greater than absolute 20 were removed from the data set, because the simulation program will ignore such large values. Thus, they would effectively have no influence on the standard deviation or average of the sample. The following values apply:

$$n = 541$$

$$\alpha = 0.05$$

$$t = 1.964$$

$$s = 2.093$$

$$\text{Flip Mean} = 0.179$$

Using Equation 1, the half-width was calculated to equal 0.177.

Given the example above, the question would now be,

If the half-width is equal to 0.177 after 65 working days, then how long will it take to be equal to 0.1, 0.08, or 0.05?

The answer to this question would be based on the following variables:

- Desired half-width.
- Initial half-width.
- Original sample size.



Equation 6 on page 32 expresses the relationship between these variables and Section 3.3.1 describes the calculation in detail.

3.3.1 Required Sample Size.

Before starting the following example, the term “sample” is first defined. The definition is constructed in terms of the data used and the format upon which it is based.

“Sample” refers to the entire data set utilised in the respective calculation. The data set comprises of many data points i.e. cell values. Each column, which is collected daily, is comprised of a number of data points that fall outside of the 25 Day Option Freeze Point (indicated in purple in Figure 18). The number of points per column varies and experiences a distinctive increase about every 10 calendar days.



Each bracket in Figure 18 indicates the data points per column.

Final OK Date (P)	2003/01/22	2003/01/23	2003/01/24	2003/01/27	2003/01/28	2003/01/29	2003/01/30	2003/01/31	2003/02/03
2003/03/06	1	0	0	0	0	0	0	0	0
2003/03/07	0	0	0	0	0	0	0	0	0
2003/03/10	0	0	1	0	0	0	0	0	0
2003/03/11	0	0	0	0	0	0	0	0	0
2003/03/12	0	0	-1	0	0	0	0	0	0
2003/03/13	0	0	0	0	0	0	0	0	0
2003/03/14	0	1	1	0	0	0	0	0	0
2003/03/17	0	0	-1	0	0	0	0	0	0
2003/03/18	0	-1	1	0	0	0	0	0	0
2003/03/19	0	0	0	0	0	0	0	0	0
2003/03/20									
2003/03/24									
2003/03/25									
2003/03/26									
2003/03/27									
2003/03/28									

Figure 18: Definition of Sample Size.

The task of calculating the sample size required to obtain a small confidence interval translates to calculating the number of data points required. The number of data points per day i.e. per column, does not increase in a predictable manner, so a heuristic had to be developed to best estimate the number of days over which data had to be collected. The heuristic would assume that the number of data points is constant for all columns, thus resulting in a calculable sample size. The establishment of this heuristic leads to the question of, “What should the constant value be?”

The following approach was taken in calculating the number of data points per column according to the heuristic:

1. Count the number of data points per column.
2. Calculate the frequency of the number of data points observed per column, based upon the range of values observed.
3. Calculate the relative cumulative frequency of the observed values.
4. Calculate the expected number of data points per column.

The expected number of data points per column could then be used as an estimate of the constant number of data points per column as specified by the heuristic.

Figure 19 on page 31 is the result of following the aforementioned approach when applied to the input data.



Bin	Frequency	Relative Cumulative Frequency (RCF)	Expected Number of Data Points per Column (RCF*Bin)
3	1	1.5%	0.046
4	2	3.1%	0.120
5	7	10.8%	0.550
6	6	9.2%	0.540
7	9	13.8%	0.980
8	8	12.3%	0.960
9	9	13.8%	1.260
10	11	16.9%	1.700
11	6	9.2%	0.990
12	4	6.2%	0.720
13	1	1.5%	0.260
14	1	1.5%	0.280
Sum	65	100%	8.32

Figure 19: Expected Sample Size.

The range of observed values stretches from 3 to 14 data points per column with the expected number of points equalling 8.32 points per column. There are a few options available when deciding on the number of data points per column. Each choice has its own pros and cons, these being listed in Table 9.

Choice	Pro	Con
Minimum number of data points i.e. 3 data points per column (according to the example)	<ul style="list-style-type: none"> ➤ Most accurate point estimator due to the large sample size. Refer to Equation 1 on page 28. The large sample size would be attributed to the fact that it is assumed that only 3 data points (according to the example) are received per day when, in fact, there are actually more points being collected i.e. columns contain more than 3 data points. The data collection period would be extended so as to attain the desired sample size due to this assumption. 	<ul style="list-style-type: none"> ➤ The longest data collection period. ➤ Very large sample size. ➤ Too safe i.e. sample size too big.
Maximum number of data points i.e. 14 data points per column (according to the example)	<ul style="list-style-type: none"> ➤ Smallest sample size. ➤ The shortest data collection period. 	<ul style="list-style-type: none"> ➤ Most inaccurate point estimator due to there being less data points than required i.e. the majority of the columns actually contain less data points than assumed.
Expected number of data points. (Rounded down) i.e. 8 data points per column (according to the example)	<ul style="list-style-type: none"> ➤ Improved point estimator (compared to Min. Value). ➤ Reduced data collection period (compared to Max. value). ➤ Smaller sample size (compared to Max. value). 	<ul style="list-style-type: none"> ➤ Increased data collection period (compared to Min. Value). ➤ Worse point estimator (compared to Max. value). ➤ Larger sample size (compared to Min. value).

Table 9: Pro's and Con's per Choice.



Figure 20 depicts a timeline in calendar days. The chosen value e.g. 3, 8, or 14 data points per column, will determine for how many days data should be collected. The accuracy of the half-width remains unknown until calculated. Indicated below is the predicted effect of choosing various values representing the assumed constant number of data points collected per day i.e. the Maximum, Minimum, or Expected Value.

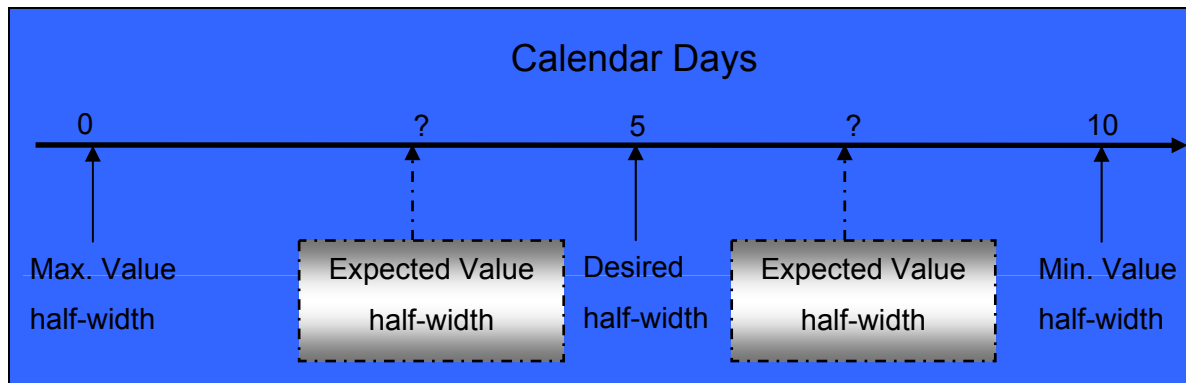


Figure 20: Timeline Depiction of Effect of Value Choice.

Accuracy is measured from 0 to 10:

- 0 - Most inaccurate.
- 5 - Desired accuracy.
- 10 - Most accurate, but superfluous data was used in the calculation.
- ? - Accuracy unknown. It could be above or below 5.

The rounded down Expected Value was chosen for the purpose of this investigation as it provided a good blend of practical applicability and scientific reasoning.

Assuming that all columns will have 8 data points and using the values from the previous example, Equation 6 yields the required sample size for a specified half-width.

Required sample size:

$$n^* = n \left(\frac{h}{h^*} \right)^2$$

Equation 6

Where:

n^* = Required sample size

n = Initial sample size

h = Initial half-width

h^* = Desired half-width



h^*	n^*	Number of Days to Collect Data = ($n^*/ 8$)
0.1	1690	212
0.08	2642	331
0.05	52583	6762

Table 10: Number of Days to Collect Data When Using Data Outside of 25 Day Option Freeze Period.

The results in Table 10 show that a considerable amount of time would have to be spent on collecting data e.g. when estimating the mean of the Flip, a desired half width of 0.1 would require data to be collected for 212 days. Based on the observations made a decision would have to be made as to what the desired half-width should be. Thereafter, an evaluation of the resultant collection period would have to be made to ascertain the practicality of such an exercise.

This example is a clear indication of how using only the data outside of the 25 Day Option Freeze Period was completely impractical in terms of collecting sufficient data for this study. A decision was made to use all the data i.e. the data inside and out of the 25 Day Option Freeze Point. The huge increase in sample size immediately reduced the time required to collect the necessary data. The following example demonstrates the effect.

Example:

$$n = 1844$$

$$\alpha = 0.05$$

$$t = 1.964$$

$$s = 2.058$$

$$\text{Flip Mean} = 0.026$$



Using Equation 1 on page 28, the half-width was calculated to equal 0.0934.

The table below gives a summarised result of the increased sample size. The calculations are based on the expected number of data points equalling 28 per column.

h^*	n^*	Number of Days to Collect Data = ($n^*/ 28$)
0.1	1629	59
0.08	2546	91
0.05	6518	233

Table 11: Effects of Increased Sample Size.



In closing:

Using all the data does imply that Flips attributed to non-Customer Demand changes i.e. data anomalies (see Section 3.2.3 on page 20), are included in the data set. This type of data i.e. non-Customer Demand change data, is separated into two different categories. The first category includes those Flips that are similar in magnitude and frequency to those attributed to Customer Demand changes. The second category includes Flips that are much larger in magnitude, but lower in frequency, than those Flips attributed to Customer Demand changes. The Flips in the latter category were not included in the analysis, in contrast to the Flips from the first category, as they were the exception and were thus filtered from the input data by the simulation program. The Flips from the first category were included because they do regularly form part of the environment, especially sequence changes, and the affects thereof had to be assessed.

Furthermore, both the OIMM and SAP-MRP simulation programs only allowed Flips to take place up and until the point of the 10 Day Option Freeze, even though the sample included changes from before and after the 25 Day Option Freeze. Figure 21 depicts graphically how the 25 Day Option Freeze data was used to simulate the 10 Day Option Freeze Environment.

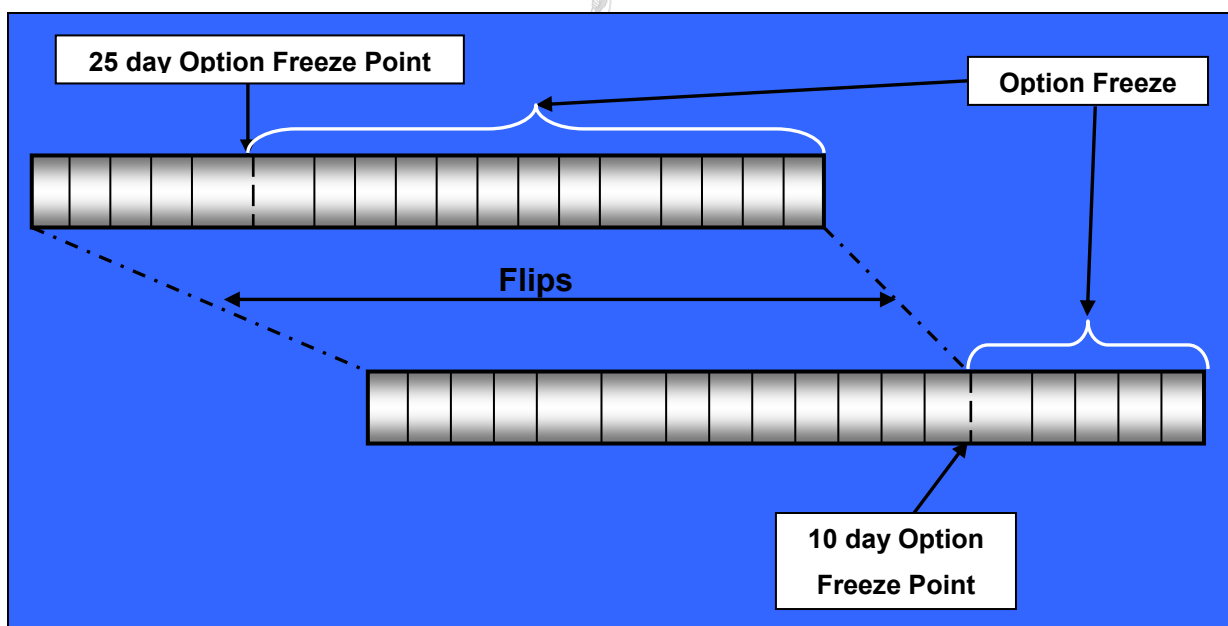


Figure 21: 25 Day Option Freeze Data used in 10 Day Option Freeze Simulation.

3.4 Automated Data Collection Process.

The process of collecting the required raw data for simulation purposes was a very time consuming exercise. DCSA had no need to store the daily Z04PIRSUM reports prior to this study and therefore there existed no automated method or system with which to collect the data. An obvious need existed for such a system, but this could only be designed and implemented once enough knowledge had been gained through the manual collection of data.



Experience showed that the system had to conform to the following specifications:

- **Format:** The demands and Flips had to be presented in a recognisable spreadsheet format. DCSA used the author's spreadsheet format as a template, but excluded the use of colour for the purpose of simplicity.
- **Spreadsheets:** Two spreadsheets are required per part. One spreadsheet would contain the daily demands; the other would indicate the associated demand changes.
- **Anomalies:** Only the anomalies that occur in the first and last row of each column would be automatically deleted. All other anomalies would be included and would only be deleted later if the user so desired.
- **Indexing:** The data would be vertically indexed against the Production Calendar and horizontally against the Calendar day upon which the report was run. The Production Calendar index would have to be refreshed every time the system was run so that the addition and deletion of calendar days could be catered for.
- **Storage:** The output i.e. the demand and Flip spreadsheets, had to be stored in an easily accessible network location.
- **Part Specification:** The user had to be able to edit the list of parts for which data was being gathered at any time.

3.4.1 Automated Data Collection Process Flow Chart.

The Automated Data Collection (ADC) process is divided into two distinct sub-processes, namely:

1. Part Extraction and Variant Maintenance.
2. Data Collection and Storage.

The first sub-process deals with the selection of the parts for which data is collected, and the maintenance of the Variant that defines these parts. The second sub-process focuses on the collection and storage of the required data.

3.4.1.1 Part Extraction and Variant Maintenance.

The Part Extraction and Variant Maintenance flow chart is shown in Figure 22.

The first step is to identify and define the part numbers for which the required data will be collected. The list of parts is then stored in the first column of an Excel-Tab delimited file. The Excel file is then the responsibility of the resident departmental SAP Business Consultant who maintains the ADC variant.

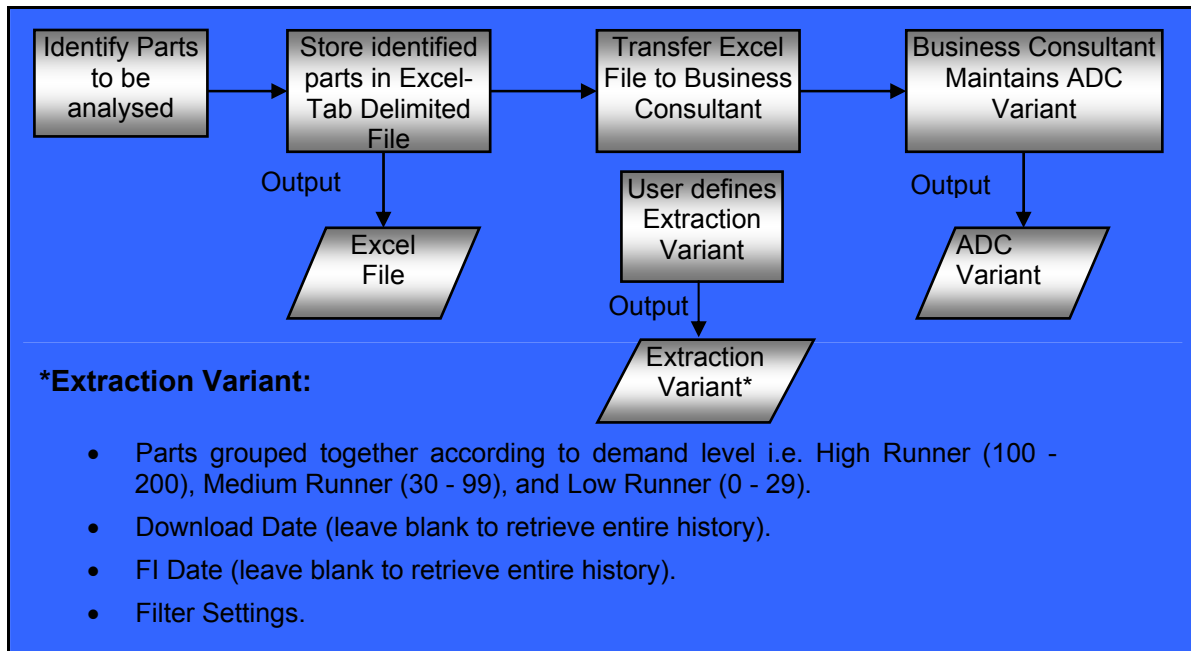


Figure 22: Part Extraction and Variant Maintenance Flow Chart.

3.4.1.2 Data Collection and Storage.

The data collection and storage flow chart is shown below.

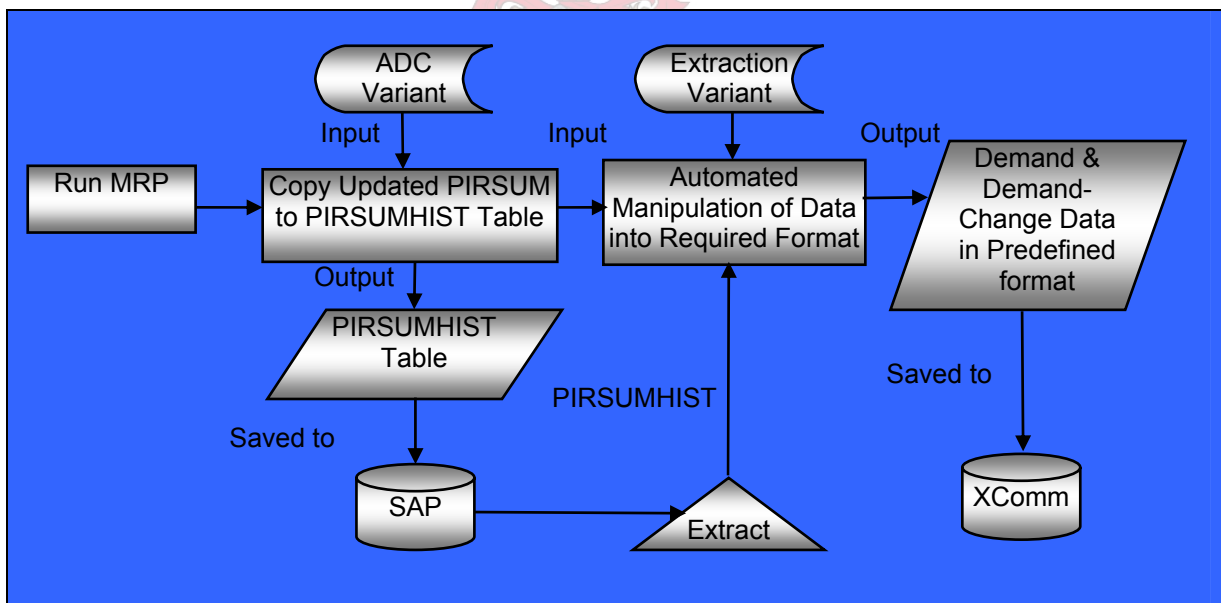


Figure 23: Data Collection and Storage Flow Chart.

A MRP run is done every night resulting in an updated copy of the Z04PIRSUM report being copied to the PIRSUMHIST table based upon the input from the ADC Variant. The PIRSUMHIST table is stored in SAP and contains historical data that covers a pre-defined period. The period length is based on the desired half-width associated with the Flip mean and is a balance between the ideal sample size and a practical sample size (discussed in Section 3.4.1.3). The PIRSUMHIST table is extracted and manipulated into the predefined format determined by the Extraction Variant and stored on the XComm network drive.



The historical demand and Flip data is now available to the user of the simulation program via the XComm drive. The user is required to filter the data according to his/her requirements and perform the Cumulative Frequency Distribution Calculations before simulation can commence. The latter process is depicted in the flow chart shown in Figure 24.

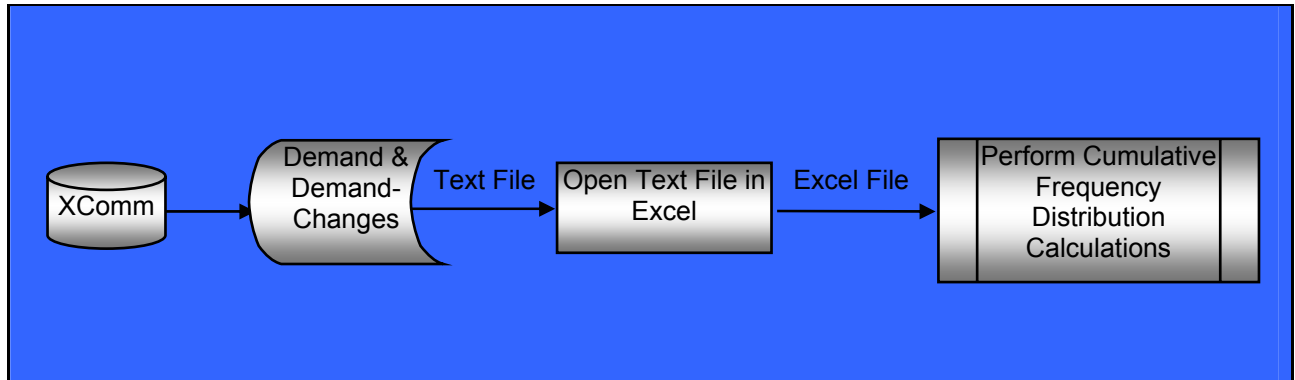


Figure 24: Simulation Input Data Extraction and Manipulation Flow Chart.

3.4.1.3 Ideal Sample Size vs. Practical Sample Size.

In an ideal world, DCSA should be able to store the required data for all Option Related parts. In this situation, the user of the simulation program would have had the data for any part at the click of a button. In reality, DCSA has limited data storage capacity and therefore careful planning has to go into part selection as well as specifying the period for which data will be collected.

Part selection is of extreme importance, because an extended length of time is required to collect enough data. In fact, this problem is the most significant drawback of the analysis. Even though a part has been selected, it will typically take about 60 working days to collect sufficient data.

In light of the statement in the previous paragraph, it is clear that a shorter data collection period would be more beneficial. However, the data sample must be statistically significant for the purpose of analysis and therein lies the problem in selecting a suitable half-width, which then has a resultant sample size.

The length of the data collection period is measured in days and is dynamic in nature. The period will always cover the most recent data i.e. from the most recent date that the report was run up and until x days into the past. The length is limited for two reasons, namely:

1. Limitations on the data storage capacity i.e. an infinite amount of data could not be stored.
2. A dynamic window would reflect the most recent trend in Customer Demand changes.



The period length is based on the required half-width of the Flip mean that is calculated using Equation 1 and Equation 6. The length is directly proportional to the variability per part i.e. a part with a High Flip Variance would require a longer period than a part with a Low Flip Variance. Furthermore, the length is also a function of the number of data points per column (see Section 3.3 on page 27).

Figure 25 demonstrates the method used to determine the half-width associated with a limited data collection period for a part with a High Flip Variance. The half-width associated with the current data sample is equal to 0.65, but the desired half-width is 0.4. Calculations show that observations for 127 working days are required to achieve this. Based on the assumption that every column comprises of 19 data points, it may be decided that 127 days is too long and that 90 days is the maximum period that the user is willing to wait. If this then were the case, then calculations would show that the half-width would be equal to 0.47 at 95% level of confidence.

The discussion in the paragraph above is intended to portray to the reader the typical operating constraints that are encountered when calculating the required data collection period. Operational constraints may dictate that the calculated collection period is too long. In such a case, the user will at least be able to quantify the repercussions of such constraints upon the half-width by employing the demonstrated equations.

Input Data	Part Number	2036901640 27E63C
	Sample Flip Mean	-0.439
	Sample Std Deviation	10.006
Confidence Interval half-width	Level of Confidence	95%
	alpha	5%
	n=	917
	degrees of freedom = n -1	916
	t-distribution	1.96
	half-width (h) =	0.65
	Confidence Interval Lower	-1.087
	Confidence Interval Upper	0.210
Required number of samples	Desired half-width (h*)	0.4
	Number of Samples (n*)	2410
Required number of days (Ideal)	Smallest Bin	19
	working days to Collect	127
	Approx no. Months (20 days)	6.4
Required number of days (Practical)	working days to collect	90
	Resultant h* =	0.47
	Level of Confidence	95%

Figure 25: Sample Size for a Part with a High Flip Variance.

Figure 26 on the following page similarly demonstrates the method used to determine the half-width for a part with a Low Flip Variance.



Input Data	Part Number	2036901640 27E63C
	Sample Flip Mean	0.000
	Sample Std Deviation	0.157
Confidence Interval half-width	Level of Confidence	95%
	alpha	5%
	n=	917
	degrees of freedom = n - 1	916
	t-distribution	1.96
	half-width (h) =	0.01
	Confidence Interval Lower	-0.010
Confidence Interval Upper	0.010	
Required number of samples	Desired half-width (h*)	0.005
	Number of Samples (n*)	3777
Required number of days (Ideal)	Smallest Bin	19
	working days to Collect	199
	Approx no. Months (20 days)	10.0
Required number of days (Practical)	working days to collect	60
	Resultant h* =	0.009
	Level of Confidence	95%

Figure 26: Sample Size for a Part with a Low Flip Variance.

3.5 Summary.

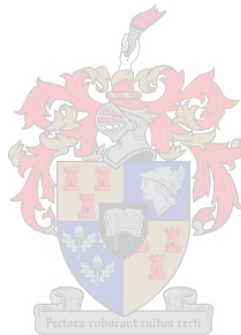
This chapter presented an in-depth discussion of all the key factors and problems that influenced the collection of the required data. These key factors and problems are highlighted below:

- A query was used to obtain the **Planned Independent Requirement** totals, required as an input to the simulation program, from the SAP System. The data from the query was placed in the **Z04PIRSUM** report, which contained the daily demands and associated Flips. This data had then to be filtered and formatted before being ready for simulation purposes. This was originally a manual process, but it was later automated.
- The output data from the report was saved as a text file and then imported into Excel where **colour** was utilised to identify the various components that make up the data. Using colour proved to be an excellent method of indicating where to paste the new data as well as highlighting any **data anomalies**.
- The occurrence of **data anomalies** was attributed to the creation of Production Sales Orders, alterations in the Production Sequence, and the addition and deletion of Planned Production Days. The creation of Production Sales Orders resulted in data anomalies occurring in the first and last row of the data column. Changes in both Production Sequence and Planned Production Days resulted in uncharacteristically large Flips that overshadowed the Flips associated with changes in Customer Demand.



- Data from the **25 Day Option Freeze Environment** had to be used to simulate the proposed **10 Day Option Freeze Environment**. This in itself created a problem because the sample size, required by the simulation program, required more data than would have been available after the author's four month stay at DCSA. This constraint forced the author to make use of that which was available. It was felt however, that this constraint did not reduce the value of the analysis because DCSA does sometimes allow changes to occur within the 25 Day Option Freeze Period.

Relevant data and a well-developed understanding of the SAP-MRP System operation were required in order to facilitate analysis. The next chapter presents the author's knowledge gained on the SAP-MRP System operation in terms of its Input Parameters.





4. How does SAP-MRP function?

This chapter describes how the SAP-MRP System operates in terms of the parameters that influence order placement. The logic that the simulation program operates on is based entirely on the observations described here.

Substantial time was spent on developing an understanding of how the various Input Parameters influenced order placement, and then a simulation program was designed based on that understanding. Unfortunately, this process was hampered by the fact that the SAP-MRP Help files were outdated (parameter terminologies had changed between versions) and unclear. This problem was aggravated because opinions were divided on what affect each parameter had on the MRP System. However, DCSA's SAP experts provided substantial assistance in developing an understanding of the MRP System and a mutually beneficial relationship was developed where both parties increased their SAP-MRP knowledge.

4.1 SAP-MRP.

An MRP System operates on the principle that an order should be placed if the Available Stock is less than a specified value i.e. a re-order point. The re-order point is dependent on the Lot-Sizing option e.g. Fixed Lot Size, Lot-for-Lot Order Quantity, Period Lot-Sizing etc. The Available Stock is calculated using the Net Requirements Calculation that is carried out every night with the MRP run.

4.1.1 Net Requirements Calculation.

Note: This entire section, as well as any sub-sections thereof, is based upon the statements and calculation methods presented in the SAP R/3 Production Planning – Material Requirements Planning Help files, pages 98 and 99.

The Net Requirements Calculation is used to check whether it is possible to cover the requirements with the available Warehouse Stock and fixed receipts already scheduled. An order proposal is created if the calculation indicates a stock shortage.

The Net Requirements Calculation is executed in three steps:

1. Determine Available Stock.
2. Calculate Scheduled Receipts.
3. Compute Shortage Quantity.

Available Stock.

The Net Requirements Calculation first calculates the available Warehouse Stock. Stocks from various storage locations are grouped together to form the Available Stock. The stocks that are included or excluded are determined by the customised settings.



Scheduled Receipts.

All material issues and receipts are taken into account. Receipts are, for example, Planned Orders or Purchase Requisitions. Issues can be classified as Customer Requirements, Planned Independent Requirements (PIRs), or Reservations.

Shortage Quantity.

The MRP System ensures that for each issue date the requirement is covered by one/several receipts or by Warehouse Stock. If requirements cannot be satisfied, then the system calculates the shortage quantity. The quantity to be produced or procured, as is the case at DCSA, is calculated during Lot-Sizing.

The Help files indicate that a difference is made between Reorder Point Planning, Forecast-Based Planning, and MRP. In each procedure, the system calculates the Available Stock differently.

A brief description follows of the Net Requirements Calculation for MRP.

4.1.1.1 Net Requirements Calculation for MRP.

In MRP, requirement quantities are maintained in the system as PIRs, Customer Requirements, Dependent Requirements, Material Reservations, as well as Forecast Requirements. The system checks every exact requirement and every Forecast Requirement to determine whether they are covered by available Warehouse Stock and/or receipts (Purchase Orders, Fixed Order Proposals, Production Orders, etc.) The Available Stock is calculated as follows:

$$\text{Available Stock} = \text{Plant Stock} + \text{Receipts} - (\text{Safety Stock} + \text{Requirements})$$

DCSA does not make use of Safety Stock on its non-bulk order parts, so Safety Stock is reduced to zero and the above equation is reduced to:

$$\text{Available Stock} = \text{Plant Stock} + \text{Receipts} - \text{Requirements}$$

4.2 SAP-MRP at DCSA – Hybrid of Two Systems?

The SAP-MRP System is a hybrid of the basic MRP System and a Statistical System. The Statistical System ensures that a certain level of stock, based on the future average demand, is always present in the plant.

The Statistical System operates over and above the MRP System. The MRP System ensures that future Production Requirements are covered by the Available Stock at that time, whereas the Statistical System ensures that the Plant Stock remains at a certain level based on various parameters.



Figure 27 presents a graphical representation of the hybrid concept. Here it is seen that SAP-MRP has to take the Production and Plant Stock Requirements into account when placing an order for a specific part.

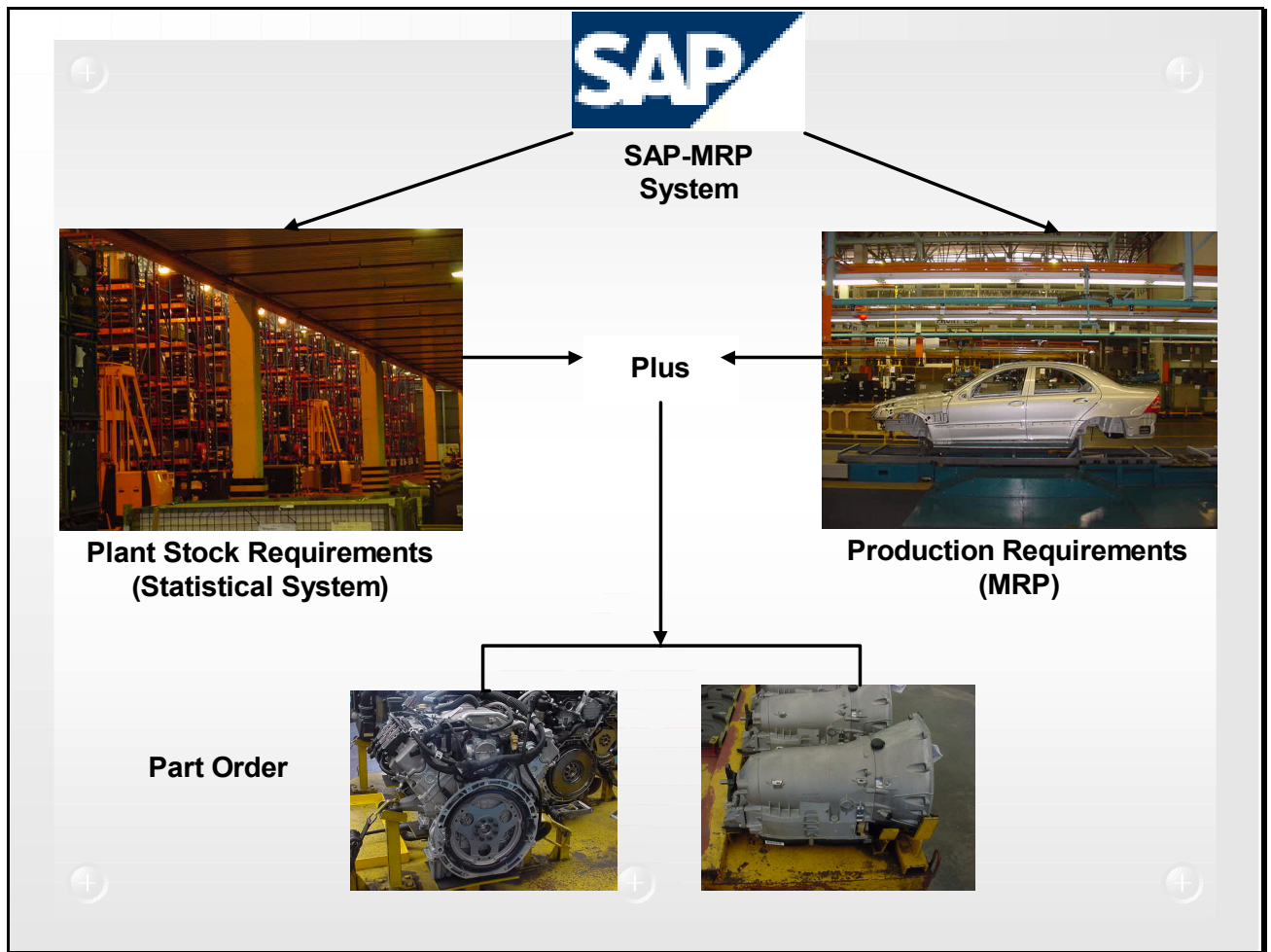


Figure 27: SAP-MRP: Hybrid of Two Systems.

The Statistical System makes use of various parameters (those indicated with an asterisk in Table 12) to determine how much of a part should be ordered. By setting these parameters to zero, which effectively switches them off, the SAP-MRP System will revert to a standard MRP System that ensures that daily Production Requirements are satisfied.

Various parameters are used to influence the SAP-MRP System in terms of the order placement. Some of the parameters operate on an individual basis, whilst others work in conjunction with each other. The level of influence that each has, varies from “none” to “strong.”



4.3 Influencing Parameters.

Seven parameters influence the frequency and magnitude of the orders placed by the MRP System as well as the Service Level of the system. Table 12 lists the parameters and presents a brief description of each.

Number	Parameter	Description
1	Coverage Profile*	The Coverage Profile is used to determine the Plant Stock level, such that it covers average Production Requirements on a specified number of days.
2	Safety Time*	The number of workdays by which the Production Requirements are brought forward on the timeline. Actual production date requirements remain unaltered. The net effect is that the required stock arrives <i>x</i> days prior to production.
3	Pallet Size	Determines the maximum number of parts available per pallet.
4	Lead-Time	Specifies the duration, in days, which it takes for a part to arrive at DCSA from the supplier.
5	Forecast Accuracy	SAP-MRP includes forecast orders as part of its order requirements calculations. Forecast accuracy is of paramount importance for these calculations.
6	Average Daily* Requirements (ADR)	ADR describes the average demand for a part on a specific day. The average is calculated over a period of <i>x</i> weeks into the future (4 weeks in the case of DCSA). The length of the period determines the number of Forecasted Orders included in the calculation.
7	Number of weeks used in ADR calculation.	The number of weeks used in the ADR calculation determines the sensitivity of the ADR to fluctuating demands. A longer period is less sensitive to fluctuation than a shorter one.

Table 12: List of Parameters and their Descriptions.

It is an objective of this study to quantify the degree of influence that each of these parameters has on the SAP-MRP System. Chapter 7 and 8 complete this objective.

An example will follow that explain and demonstrate how each parameter plays a role in the SAP-MRP System, but first some parameter definitions must be explained.

4.4 Parameter Definitions and Examples.

Small quantitative examples are used to demonstrate the influence that each parameter has on the SAP-MRP System.

Average Daily Requirements is the first to be explained as it interacts most frequently with the other parameters. The remaining parameters will follow thereafter.

Actual SAP-MRP reports are used where possible if it is felt that they contribute towards a specific example.



4.4.1 Average Daily Requirements.

The system bases its calculations on the following system settings:

- **Periods:** Month, week, or Production Planning Calendar (PPC).
- **Number of Periods** included in the calculation of the Average Daily Requirements.
- **Period Length:** Several choices are made here. DCSA uses the workday's option. The Total Requirements Quantity is divided by the number of days specified in the PPC for this period.

According to the SAP/R3 MRP Help files, the system calculates the ADR as follows:

"The system uses the defined parameters to determine the number of days by which to divide the total of the requirements. If the period is defined as a week, the period length as standard days (5 days) and the number of periods as 2, the system divides the total of the requirements by 10 days." [SAP R/3: 222]

"The following applies to requirements grouping for calculating the ADR in the periods: All requirements for the calendar period selected are totalled, including those in the past, and the system divides them by the number of days." [SAP R/3: 222]

In terms of the aforementioned system settings, DCSA uses the following:

- **Periods:** Week
- **Number of Periods:** 4
- **Period Length:** working days

This would then indicate that the sum of the Production Requirements, for a typical production week, would be divided by 20.

An extract of the part requirements, shown in Figure 28, for 2038170920 (Classic Label) is used for this example, refer to Appendix E for the entire report that was run on 2003/04/25.

The ADR is calculated for the production week 2003/05/12 to 2003/05/16.



Period	Indep. requirements
03/05/12	122
03/05/13	130
03/05/14	120
03/05/15	138
03/05/16	120
03/05/19	116
03/05/20	116
03/05/21	104
03/05/22	126
03/05/23	104
03/05/26	142
03/05/27	154
03/05/28	190
03/05/29	154
03/05/30	156
03/06/02	174
03/06/03	176
03/06/04	160
03/06/05	162
03/06/06	150

$\Sigma = 2814 \text{ units}$

Figure 28: Period Requirements for 2038170920.

Figure 28 shows the Independent Requirements for a 20 day period comprised of four working weeks, namely:

1. 2003/05/12 – 2003/05/16
2. 2003/05/19 – 2003/05/23
3. 2003/05/26 – 2003/05/30
4. 2003/06/02 – 2003/06/06

The ADR would be calculated as follows:

$$\begin{aligned}
 \text{ADR} &= \frac{\sum \text{Independent Production Req.}}{(\text{Period Length}) * (\text{No. of Periods})} && \text{Equation 7} \\
 &= \frac{2814}{20} \\
 &= 140.7
 \end{aligned}$$

Thus, the ADR is 140.7 parts per day for the period 2003/05/12 – 2003/05/16.

4.4.2 Coverage Profile.

Such is the importance of the Coverage Profile in determining how much stock is in the plant that it is attributed as the Statistical Component of the hybrid MRP System at DCSA.

The Coverage Profile makes use of three variables that all refer to the “Range of Coverage” of a specific part. This term is defined prior to Coverage Profile being closely scrutinised.



4.4.2.1 Range of Coverage.

The term “Range of Coverage” describes how long the Available Stock will last based upon the ADR as well as the assumption that there is no further stock receipts. It is calculated as follows:

$$\text{Range of Coverage}(i) = \frac{\text{Available Stock}(i)}{\text{ADR}(i)} \quad \text{Equation 8}$$

where i indicates Production Day (i)

The SAP-MRP Help files refer to “Range of Coverage,” but the system presents the user with two measures of “Coverage,” namely:

- Actual Range of Coverage.
- Statistical Range of Coverage.

Statistical Range of Coverage is as defined in Equation 8 and it is the “Range of Coverage” referred to in this discussion. Actual Range of Coverage is used to indicate how long the Available Stock will last given the future Production Requirements, and assuming no further stock receipts.

Refer to the example below for a quantitative demonstration of how the Range of Coverage is calculated.

Example:

$$\begin{aligned} \text{Available Stock on Production Day } (i) &= 562 \text{ units} \\ \text{ADR } (i) &= 130.32 \text{ units/day} \end{aligned}$$

$$\begin{aligned} \text{Range of Coverage} &= \frac{562}{130.32} \\ &= 4.312 \text{ days} \end{aligned}$$

Thus, the Range of Coverage indicates that the Available Stock will last 4.312 days based upon the ADR.

4.4.2.2 Re-Ordering Based on the Coverage Profile.

The Coverage Profile is used as regulatory control that keeps check on the Plant Stock level. An order is created if the stock level falls below a certain minimum, and a warning is given if the stock level is too high.

The Coverage Profile comprises three values, namely:

- Minimum Range of Coverage
- Target Range of Coverage
- Maximum Range of Coverage



Minimum Range of Coverage: This value indicates the minimum coverage that DCSA will accept before an Order Release is required to replenish stock levels.

Target Range of Coverage: DCSA aims to maintain the average Plant Inventory at this level.

Maximum Range of Coverage: A warning signal is given, which indicates when too much stock is or will be present in the plant. DCSA will then take action to re-schedule the Planned Receipt if it is possible to do so.

An example of a possible Coverage Profile would appear like this: (0, 1, 2). This means that the Minimum Range of Coverage = 0, Target = 1, and Maximum = 2. (DCSA actually combines another parameter, namely Safety Time, with the Coverage Profile. An example of this combination is shown further on).

The example on the following page will demonstrate how the logic is utilised when SAP-MRP assesses the stock level situation.

Example:

Given:

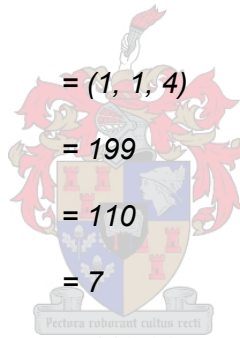
Coverage Profile = (1, 1, 4)

Available Stock (i) = 199

Independent Req. ($i+1$) = 110

Min. Lot Size = 7

ADR(i) = ADR ($i+1$) = 112.905



Where i indicates a particular Production Day

Now:

Assuming no further stock receipts:

$$\begin{aligned} \text{Range of Coverage}(i+1) &= \frac{199 - 110}{112.905} \\ &= 0.788 \text{ days} \end{aligned}$$

Here it is seen that the Range of Coverage is less than the Minimum of 1 day, thus an order has to be placed so that the resultant Range of Coverage is greater than, or equal to the Target Coverage.

Using the Min. Lot Size and iterating until the Range of Coverage ($i+1$) is greater than, or equal to 1 day, produces a planned order receipt of 28 units. The resultant Range of Coverage is equal to 1.036 days.



The following Structured English statement serves to summarise the above example:

If Range of Coverage < Min. Range of Coverage Then

Planned Receipt = 0

Do Until Range of Coverage >= Target Range of Coverage

Planned Receipt = Planned Receipt + Min. Lot Size

Range of Coverage = (Available Stock + Planned Receipt)/ADR

Loop

End If

Output Range of Coverage

4.4.3 Safety Time.

Safety Time is used to pull the **Planned Independent Requirements** forward on the timeline without changing the Actual Requirements Date. The result is that the MRP System “thinks” that the demand is required on production day “x” and calculates the Available Stock based on this demand. In fact, the demand will actually only occur 2 days later (assuming that Safety Time equals 2 days). In general, it is said that the Safety Time results in the stock, assigned to a specific days demand, being in the plant 2 days before it is required by the assembly line.

Safety Time is incorporated into the MRP calculations by adding it to the Coverage Profile i.e. if the Coverage Profile for a part is (1, 1, 4) then it will become (3, 3, 6) once the 2 day Safety Time is included. This fact is not mentioned in the Help files at all. If the user is not aware of this then they will not understand why the MRP System maintains a higher stock level than required.

If the previous example were to be repeated with Safety Time included, then the resultant planned order receipt equals 252 units.

The reader may have noticed the emphasis placed on Planned Independent Requirements in terms of the effect that Safety Time has. This is done purposefully, as Safety Time has no effect on Dependent Requirements, which is a problem on its own that is discussed briefly in 4.4.3.1.



4.4.3.1 The Effect of Safety Time on Dependent and Independent Demand.

The previous version of SAP installed at DCSA allowed Safety Time to pull both the Dependent and Independent demand forward on the timeline. The new version only allows Safety Time to have an affect on Independent Demand. This results in an overlap between Dependent and Independent Demand at the point where Production Sales Orders are created.

This overlap is clearly visible as shown in Figure 29 and Figure 30.

Period/segment	Plnd ind.req	Requirement
03/04/11	0	60
03/04/14	0	124
03/04/15	0	105
03/04/16	0	130
03/04/17	30	105
03/04/22	101	115
03/04/23	98	90
03/04/24	104	0
03/04/25	110	0
03/04/29	113	0
03/04/30	99	0
03/05/05	110	0
03/05/06	110	0
03/05/07	117	0
03/05/08	102	0

Period/segment	Plnd ind.reqmts	Requirements
03/04/17	0	105
03/04/20	0	115
03/04/23	30	90
03/04/24	101	0
03/04/25	98	0
03/04/29	104	0
03/04/30		
03/05/05	113	0
03/05/06	99	0
03/05/07	110	0
03/05/08	110	0
03/05/09	117	0
03/05/10	102	0
03/05/12	111	0
03/05/13	111	0

Figure 29: Safety Time - ON

Figure 30: Safety Time - OFF

Here it is seen that an overlap occurs for the period 2003/04/17 – 2003/04/23. By using 2003/04/23, in Figure 30, as a reference point it is seen that the Independent Demand for 30 units is pulled forward by two workdays to the 2003/04/17, in Figure 29.

The major problem associated with this “overlapping” is that the demand appears to be doubled up, which then creates a problem for the local JIT suppliers who struggle to meet this large demand. Opinions vary on the advantages and disadvantages of using Safety Time, with some preferring to remove Safety Time completely. Proponents for the removal of Safety Time argue that the same effect is achieved by increasing the Coverage Profile values such that they equal the sum of the Coverage Profile and Safety Time.

Refer to Table 13 on page 51 for an example of the proposed method to remove Safety Time.



Example:

Parameter	Safety Time	No Safety Time
Coverage Profile	(1, 1, 2)	(3, 3, 5)
Safety Time	2	0
Resultant Coverage Profile	(3, 3, 5)	(3, 3, 5)

Table 13: Safety Time Removal Proposal

The aforementioned Structured English statement would change to look like the following if Safety Time is taken into account:

If Range of Coverage < (Min. Range of Coverage + Safety Time) Then

Planned Receipt = 0

Do Until Range of Coverage >= (Target Range of Coverage + Safety Time)

Planned Receipt = Planned Receipt + Min. Lot Size

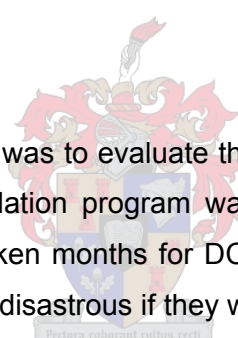
Range of Coverage = (Available Stock + Planned Receipt)/ADR

Loop

End If

Output Range of Coverage

One of the tasks of this study was to evaluate the possible solution just discussed. An obvious advantage to using the simulation program was that an answer could be provided quickly. Without this, it would have taken months for DCSA to observe the affects of removing Safety Time and the results could be disastrous if they were wrong.



4.4.4 Forecast Accuracy.

The MRP System contains 9 months of orders, with the first 60 days (production days, not calendar days) consisting of Real Orders and the remainder made up of Forecasted Orders. Figure 31 is a basic representation of the MRP output found in Appendix E.

When taking into consideration part Lead-Times i.e. 44 and 53 calendar days, and the 4 week period used to calculate the ADR, it is seen that any Orders Release is influenced by the accuracy of the Order Forecast. The 4 week period (indicated in red in Figure 32), associated with a particular Order Release, covers approximately the last two weeks of the Real Orders and the first two weeks of the Forecasted Orders.



		Period	Independent Requirements	Dependent Requirements
9 months	60 days	Real Orders		
	6 months	Forecasted Orders		

Figure 31: Basic Representation of MRP Output.

		Period	Independent Requirements	Dependent Requirements
60 days	Order Release →	Real Orders		
		Forecasted Orders		

Figure 32: Order Release combines Real and Forecasted Orders.

The balance of Forecasted vs. Real Orders and the accuracy of the Forecast are very important in the ADR calculation. The ADR can be dramatically influenced if the Forecast is too low or too high. Too high a Forecast will result in excess stock and too low a Forecast will result in stock shortages (see Section 4.4.2 for a discussion on ADR). Not too much concern needs to be given to the role that Real Orders play in the ADR. These orders are as close to the true Customer Demand as can be, which then has a positive influence on the ADR i.e. the ADR is closer to the true mean of the demand. The Forecast is based on trends in Customer Orders as well as various other factors, which at the end of the day does change to Actual Customer Demand i.e. the ADR could be far from the true mean of the demand up and until the Forecast Orders become Real.



Figure 33 is used as an example to demonstrate the difference between Real and Forecast Orders. The Lead-Time for this particular part is 44 days; therefore, the Order Release date for this part is on 2003/06/08, based on the fact that this report was run on the 2003/04/25 i.e. $2003/04/25 + 44 \text{ days} = 2003/06/08$. This order was actually released on a Sunday, so for the purpose of this example the assumption is made that it was released on 2003/06/09.

Period	Indep. requirements
Stock	
03/04/23	0
03/04/24	0
03/04/25	0
03/04/29	0
03/04/30	0
03/05/05	0
03/05/06	0
03/05/07	24
03/05/08	110
03/05/09	116
03/05/10	108
03/05/12	122
03/05/13	130
03/05/14	120
03/05/15	138
03/05/16	120
03/05/19	116
03/05/20	116
03/05/21	104
03/05/22	126
03/05/23	104
03/05/26	142
03/05/27	154
03/05/28	190
03/05/29	154
03/05/30	156
03/06/02	174
03/06/03	176
03/06/04	160
03/06/05	162
03/06/06	150
03/06/09	124
03/06/10	164
03/06/11	174
03/06/12	152
03/06/13	148
03/06/17	146
03/06/18	102
03/0	90
03/0	78
03/0	106
03/0	66
03/0	76
03/0	94
03/06/26	95
03/06/27	94
03/06/30	94
03/07/01	94
03/07/02	94
03/07/03	94
03/07/04	94
03/07/14	94
03/07/15	94
03/07/16	95
03/07/17	94

Order Release

Last Real Order

Figure 33: Extract of MRP Output for a Part with a 44 day Lead-Time.

Furthermore, it is seen that the last Real Order fell on 2003/06/26, which indicates the Orders thereafter are all Forecasted Orders.

The 4 weeks used in the ADR are indicated by the rectangular blocks, with the second block containing only 4 workdays, therefore the sum of the demands would be divided by 19 days and not the typical 20.

Only six Forecasted Orders were included in the ADR, but the number of Forecasted Orders would have increased to eleven had Lead-Time for this part been 53 calendar days. Now it is seen why parts with a 60 day Lead-Time can only make use of Forecasted Orders when calculating the ADR.



4.5 Summary.

This chapter describes how the SAP-MRP System operates in terms of the parameters that influence order placement. The process of gaining an understanding of the system was hampered because of divided opinions and outdated SAP Help files. However, DCSA's SAP experts provided substantial assistance in developing an understanding of the system.

The discussion in this chapter is divided into two sections. The first section presents the SAP-MRP System at DCSA as a hybrid system. The second goes into detail about the manner in which the Input Parameters influence the system. These two sections are summarised below.

1. The SAP-MRP System at DCSA can be described as a **hybrid of two systems**, with each system catering for **Production** and **Plant Inventory requirements respectively**. The system catering for the Plant Inventory requirements was called the Statistical System and was described as operating over and above the traditional MRP System that caters for Production Requirements.
2. Quantitative examples were used to clarify the manner in which the Input Parameters influence the system as well as a discussion presenting the problems that JIT suppliers have because of Safety Time. Furthermore, a discussion was presented of the possible negative side-effects that **incorrect Forecasted Orders** can have on the system by resulting in inaccurate Order Releases.

The foundations of the simulation program are based on the parameter relationships and system influences described in this chapter. The knowledge gained here was used to design a simulation program that would be used to assess the performance capabilities of the SAP-MRP System.

The next chapter presents the methodology followed when designing the simulation program. The reader is systematically taken through the methodology and shown how the current program was arrived at.



5. SAP-MRP Simulation Program Design.

This chapter deals with the design and development of the Visual Basic program used to simulate the SAP-MRP System at DCSA as well as the validation thereof. A brief description is given as to how the current version came into being and why the program developed by van Wijck et al. [4] is no longer used. The various design issues encountered is examined and the associated assumptions made are highlighted and discussed. Furthermore, an introduction of the software program is provided in Appendix O. This is not presented in the form of a User's Guide, but rather a discussion of how the various Input Parameters affect the simulation process.

The purpose of the SAP-MRP simulation program was to evaluate quickly the influence of various Input Parameters on specific Performance Measures, without having to interfere with the actual SAP-MRP System. These Performance Measures measured factors such as Avg. Plant Inventory, Avg. Order Size, Avg. Customer Service Level, and more. The design and development of this simulation program created a learning environment that resulted in the development of an intimate knowledge pertaining to the internal operations of the SAP-MRP System. This knowledge would prove to be invaluable when analysing the resultant affects of specific Input Parameters on the various Performance Measures.

5.1 Steps Followed to Reach the Current Version.

The current version of the simulation program is the result of three very distinct consecutive design phases. The first phase consisted of a Visual Basic Application (VBA) prototype that was designed and operated in an Excel Spreadsheet. The last two phases were all coded in Visual Basic and interfaced with Excel, which served as a mechanism with which to store and display input and output data respectively.

Each phase served as a means of refining the program and a method to improve upon the assumptions made. This proved to be an excellent formula as the current version is as close as can be to the SAP-MRP environment without taking human variability and error into account. The latter was not included as the simulation program was written to assess the capabilities of the SAP-MRP System and not the employees of DCSA.

A brief discussion is presented for each of the three phases such that the reader may gain insight as to the foundation of the simulation program.

5.1.1 Excel Spreadsheet Prototype.

The purpose of the prototype was to gain an understanding of how each of the influencing Input Parameters affected the MRP on an individual basis. As the function of each parameter became clear it was implemented in the VBA code so that its influence may be observed. Eventually all the parameters were included in this manner, which then required the program to be validated and verified.



5.1.1.1 Verification and Validation of SAP-MRP Simulation Logic.

Verification

Management, system operators, and SAP/R3 Help files were regularly consulted throughout the design phase of the SAP-MRP simulation program. Walkthroughs of the simulation program and SAP-MRP System logic were conducted with the system operators in order to verify that the model was built and designed correctly. The completion of this task confirmed that the model was designed correctly, which then required the model to be validated.

Validation

The PIRs and Dependent Requirements from the SAP-MRP output, as seen in Appendix E, were used as the input to the VBA program as well as the Part Vital Statistics obtained from the Master Data i.e. Pallet Size, Lead-Time etc. The program was then executed, which then created Order Receipts as well as computed the Available Stock and Statistical Range of Coverage. The simulation program was then validated by comparing the Order Receipts and Statistical Range of Coverage of the same SAP-MRP output to those generated by the VBA program. Figure 34 graphically depicts the validation process.

The Available Stock was not used as a method of comparison as it was felt that the Range of Coverage was a more comprehensive indicator of fit. By referring to Equation 8, on page 47, the reader may confirm that if it is known that the ADR of both systems is the same (the PIRs remain fixed for both systems) as well as the Ranges of Coverage, then the Available Quantities of the two systems must also be equal.

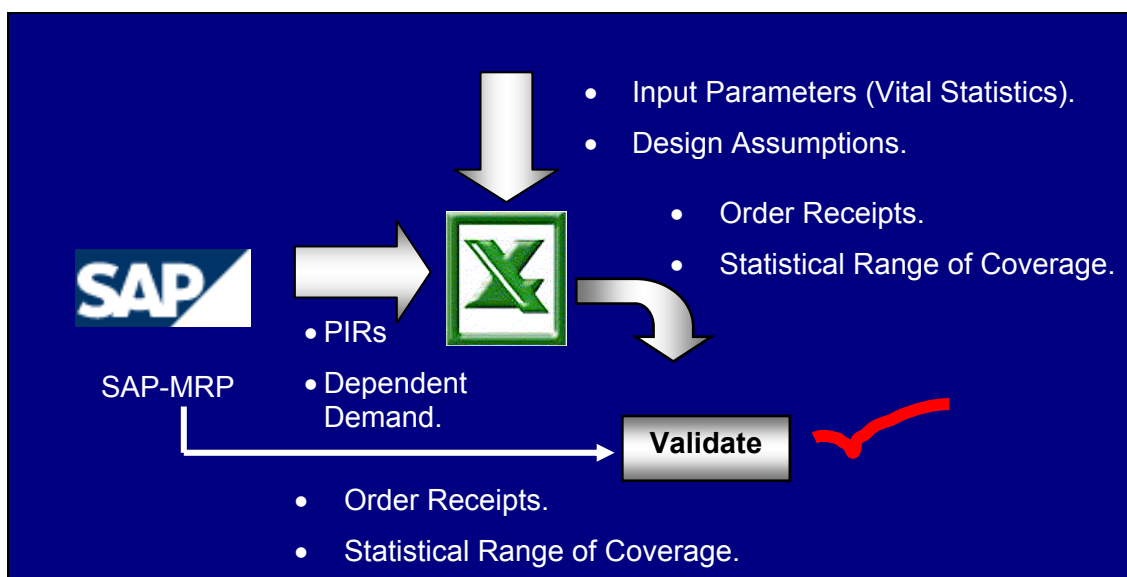


Figure 34: Validating the Excel Prototype.



5.1.1.2 Validation of Simulation Program.

Before stepping into the results, it has to be said that the SAP-MRP output had to be filtered before it was used for verification purposes. Filtering was required due to the period at which this report was run i.e. just after the plant re-opening.

DCSA shuts down over December for the Festive Season, which prevents stock from arriving in plant during this period. SAP considers this shutdown period when planning the delivery of stock to the plant and schedules the delivery dates such that a large amount of stock arrives for an extended period at the beginning of the year. The plant receives “inflated deliveries” that are much larger compared to deliveries scheduled later in the year.

The VBA program was given the opening Available Stock value and then allowed to compute and plan receipts based on future PIRs. The receipts scheduled for delivery at the start of the year were obviously much smaller than those actually planned for by SAP, as the VBA program was not influenced by plant shutdown.

Based on the facts presented here it is understandable that the data found at the beginning of the year was not used for validation purposes and was therefore removed.

The Order Receipts and Statistical Ranges of Coverage were compared to each other according to the paired t-test.

The paired t-test was used to provide a statistically sound foundation whereupon a conclusion could be drawn of whether the VBA program was designed in such a manner that it represented the SAP-MRP System accordingly.

Data from 2003/02/27 until 2003/12/06 for Part Number 2112703200 (C180 Automatic Gearbox) was used in the example presented below. Safety Time, Minimum, and Target Coverage were set according to the actual settings in the SAP-MRP System for this particular analysis. These settings were equal to (2, 2, 2) respectively, which then resulted in an average of 4 days of Coverage (ST+MC, and ST+TC both equal four) at the end of each production day. Refer to Section 4.4.2.2 and 4.4.3 on pages 47 and 49 respectively. Therefore it should be understood that the parameters employed in the comparison i.e. Receipts and Statistical Range of Coverage, were all based upon the above settings.



Paired t-test.

The paired t-test was used to evaluate statistically the simulation model. Van Wijck et al. [4] used the same method to validate the OIMM.

The following results were obtained using Equation 1 through Equation 5.

Paired t-test: Diff in Receipts		
	Mean of Diff =	0.053
	Std. Dev of Diff =	10.218
	$t_{n-1;1-\alpha/2}$ =	1.98
	half-width h =	0.154
Confidence Interval:	CL_L =	-0.101
	CL_U =	0.208

Table 14: Paired t-test for Difference in Receipts.

Where:

$n = 131$ observations

$\alpha = 5\%$

$t = 1-\alpha/2$ upper critical point on the Student t-distribution

The confidence interval of the difference *Diff* is given by **[-0.101, 0.208]**. The direction of the subtraction was *VBA – SAP*, and the confidence interval limits include zero, which means that on average *VBA = SAP*. It can therefore be concluded that Receipts created by the VBA program are equal to those created by the SAP-MRP System. This conclusion is valid at the 95% level of confidence.

The t-test was also used on the Difference between the Statistical Ranges of Coverage, and the following results were achieved.

Paired t-test: Diff Statistical Range Of Coverage.		
	Mean of Diff =	-0.25
	Std. Dev of Diff =	0.842
	$t_{n-1;1-\alpha/2}$ =	1.98
	half-width h =	0.013
Confidence Interval:	CL_L =	-0.260
	CL_U =	-0.235

Table 15: Paired t-test for Difference in Statistical Range of Coverage.



The confidence interval of the difference *Diff* is given by [-0.260, -0.235]. The direction of subtraction was *VBA – SAP*, and the confidence interval limits are both negative, which means that on average *SAP > VBA*. It can therefore be concluded that SAP-MRP has a higher Range of Coverage on average than does the VBA program. This conclusion is valid at the 95% level of confidence. The 0.25 difference in Statistical Range of Coverage is not deemed significant enough to discount the VBA program. With the average Range of Coverage equal to 4 days, it is seen that the 0.25 difference in Statistical Range of Coverage translates into a 6% (4/0.25) difference between the two systems.

The difference between the two systems is explained by taking into account the role that human error or intervention has on the parameter values obtained from SAP. Human error can be typified by orders being “Lost in Plant” (LIP) or “Damaged in Plant” (DIP). An order shifted on the timeline relative to its original requirement date, to cater for a change in Production Planning, is an example of intervention. The VBA system does not include such events in its logic as these events are primarily caused by human error rather than system error.

Based upon all the evidence presented here it is seen that the logic used in the VBA program, which is based upon the SAP-MRP Input Parameters, results in a valid representation of the actual SAP-MRP System used at DCSA. This being proven the task was now to implement the lessons learnt from the VBA model into a far more powerful and dynamic Visual Basic (VB) program.

5.1.2 Independent Version.

The next step of the simulation program development came after validating the logic upon which the VB version of the simulation program would be developed. This version had to operate independently of the OIMM System and be designed in such a manner that the two systems could be judged equally as well as independently of each other.

It was decided that the SAP-MRP simulation program would use the same input data that the OIMM used i.e. both systems would randomly draw demands and Flips from the same population data. This set-up would then allow a fair judgement to be made as to the capabilities of the SAP-MRP System as well as the performance of OIMM vs. SAP-MRP. Figure 35 illustrates the method used on a systems level.

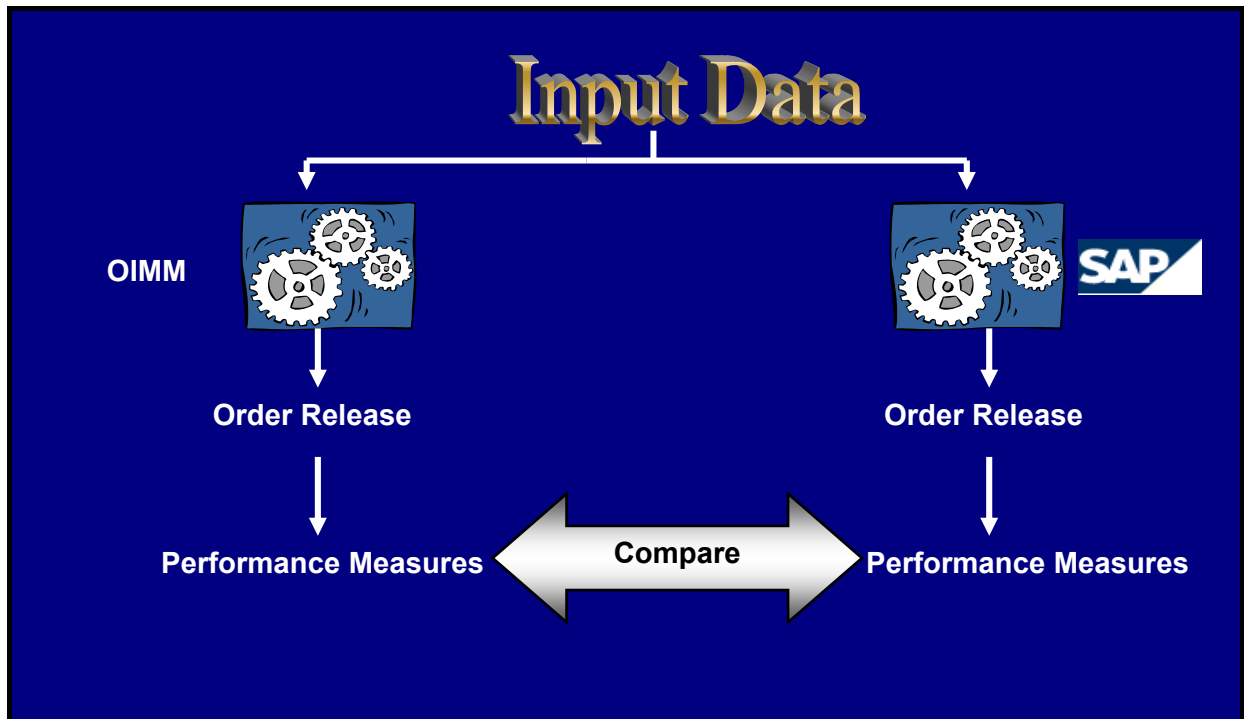


Figure 35: OIMM vs. SAP-MRP Simulation – Independent System.

The Independent System was designed in such a manner that it represented the SAP-MRP System at DCSA in its entirety. It was now possible to recreate, or observe the following:

- The frequency and magnitude in which DCSA receives its Sales Orders every Decade.
- The influence that the Sales Forecast has on the creation of Order Releases.
- The affects that the various Input Parameters have on the stock in the Harbour and Order Pipeline.

The two systems could then be compared based on the Performance Measures laid out in Appendix N.

The completion of the Independent version provided an environment in which large-scale experimentation could be carried out in order to determine which system was more superior. **It was at this stage that the directive was given to no longer pursue the OIMM implementation option and to focus on the SAP-MRP evaluation.**

The inordinate number of parameter combination settings required to fully evaluate the SAP-MRP System capabilities effectively, dictated that a certain level of automation had to be achieved. The following discussion focuses on the logic employed in the design of the Design of Experiments mode of the simulation program.



5.1.3 Automating the SAP-MRP Simulation Model for Design of Experiments.

When devising a means of automation, a Design of Experiments (DOE) methodology was used on the SAP-MRP System when evaluating the affects of Input Parameters and combinations thereof.

To simplify the approach of selecting Input Parameters to be used in the DOE, it was decided that only those parameters that could easily be changed by DCSA, without having to enter negotiations with suppliers or Head office in Germany, would be used. Only two parameters qualified, namely:

- Coverage Profile, and
- Safety Time.

The values that these parameters would assume were restricted in such a manner that they reflected the real-world operating environment at DCSA. These restrictions, and the resultant ranges within which the parameters were allowed to vary, are listed in Table 16 below.

Input Parameter	Range	Reason
Minimum Coverage	0 – 5 days	DCSA typically does not keep more than one week's supply of Plant Stock. Further, the majority of parts analysed did not have Coverage Profiles that extended further than 5 days.
Target Coverage	0 – 5 days	
Maximum Coverage	NA	Maximum Coverage was not used in the simulation, as it does not play a role in determining the frequency and magnitude of Order Releases nor plant-stock levels.
Safety Time	0 – 2 days	Safety Time was limited to a maximum of 2 days as DCSA may in fact reduce it to zero, as opposed to increasing it.

Table 16: Input Parameters selected for Automated DOE.

Appendix F presents all 63 combinations of Safety Time and Coverage Profile. Note the validity of combinations is maintained by ensuring that Target Coverage is always greater than or equal to Minimum Coverage.

This section concludes the discussion aimed at explaining the design origin of the current version of the SAP-MRP simulation program. This version was used to assess the SAP-MRP System capabilities at DCSA.

The following section will introduce and discuss the various design issues encountered and assumptions made, when designing and programming the SAP-MRP simulation program.



5.2 Design Issues.

Various design issues were encountered during the programming phase of the current version. During the process of re-creating the Sales Order environment, in which the SAP-MRP System operates at DCSA, the following serious issues were encountered:

- Converting Lead-Time from calendar days to workdays.
- Recreating Sales Order Receipts – frequency and magnitude.
- Inclusion of Forecasted Orders into the ADR.
- Maintaining realistic Customer Demand changes.
- Number of days used in the ADR calculation.

The discussion of each issue will include the assumptions used in order to overcome the associated problem.

5.2.1 Order Lead-Time Breakdown – Converting Calendar Days to Workdays.

The Lead-Time associated with a part is given in calendar days. This makes sense in terms of the time required to deliver a part from the supplier to DCSA, i.e. the delivery ship does not stop sailing over the weekend. Furthermore, the problem that defined this project lies in the fact that customers may decide to change their minds about Options to be built into their vehicles during Lead-Time. These changes, however, do not occur over the weekend and only enter the SAP System during a working week. Changes that may occur over the weekend as a result of dealerships being open will only enter the SAP System the following Monday. Based on this, the decision was made to design the simulation program such that its operation was based on working days.

Herein lies a conflict between calendar days and workdays i.e. how many workdays are there in x calendar days?

The number of workdays in x calendar days depends on the point of reference. If Monday were the point of reference then 3 calendar days would equal 3-workdays, but if Friday were the point of reference then the answer would be 1-workday i.e. Monday.

Various options were explored and it was found that the best option for the point of reference was in using the weekday on which the ship arrived. In addition, the fact that a simplified breakdown already existed, in calendar and workdays, of the various components that made up the delivery time made this logical choice easy. This simplified breakdown was updated and modified to include the operations occurring within DCSA, which contributed to the overall Lead-Time. The following factors were included:



- Back-off Time.
- Safety Time.
- Goods Receipt Processing Time (GRPt).

The modified Lead-Time breakdown is found in Appendix B for parts with a 44, 52, and 60 day Lead-Time.

Table 17 provides a summary of Appendix B for parts with 44, and 52 day Lead-Times. The various components of importance that make up Lead-Time are indicated, as well as the reference points used to measure the duration.

44 days (32 working days)			52 days (37 working days)		
Component	Duration (working days)	Reference Points	Component	Duration (working days)	Reference Points
Shipping Time (Time at sea)	14	ETD to ETA (incl. both) (Bremerhaven to East London Harbour)	Shipping Time (Time at sea)	15	ETD to ETA (incl. both)
GRPt	1	End of shipment cycle till start of Safety Time (excl. both)	GRPt	1	End of shipment cycle till start of Safety Time (excl. both)
Safety Time	2	End of GRPt till Start of Assembly (excl. both)	Safety Time	2	End of GRPt till Start of Assembly (excl. both)
Back-off time	Dependent on part		Back-off time	Dependent on part	
Order Release	32	Day of Order Release to start of Assembly (excl. both)	Order Release	37	Day of Order Release to start of Assembly (excl. both)
	22	Day of Order Release to start of Option Freeze (incl. both)		26	Day of Order Release to start of Option Freeze (incl. both)
Start of 10 Day Option Freeze	14	Start of Option Freeze to start of Assembly (incl. both)	Start of 10 Day Option Freeze	14	Start of Option Freeze to start of Assembly (incl. both)
Ship ETA	8	ETA to start of Assembly (incl. both)	Ship ETA	8	ETA to start of Assembly (incl. both)

Table 17: Summary of Lead-Time Breakdown (working days).



It is very important to take note of the reference points to which the durations are measured as well as whether they include or exclude certain points. This table assumes that Safety Time equals two days, as was the case at DCSA at the time of conducting this project. Furthermore, all part requirement dates are planned in accordance to the FI Date i.e. the date that a vehicle is complete. Back-off Time is the time used to offset the part requirements from the FI Date and is dependent on the location of the consumption point on the Assembly line.

5.2.2 Recreating Sales Order Receipts – Frequency and Magnitude.

DCSA receives Customer Sales Orders about every 10 calendar days, otherwise known in DCSA as a Decade. The number of Customer Sales Orders received each Decade varies, but is usually enough to carry DCSA to the next Decade.

Figure 36 uses colour to indicate the receipt of Sales Orders every Decade. The yellow column indicates the receipt of six days of new Sales Orders. The number of Sales Orders decreases gradually as they enter the Assembly line (where they then become Dependent Requirements and are therefore no longer included in the Independent Requirements reflected by the Z04PIRSUM report) and then is increased again by the receipt of seven days of new Sales Orders. The process repeats itself every six to seven days.

2003/03/20	2003/03/24	2003/03/25	2003/03/26	2003/03/27	2003/03/28	2003/03/31	2003/04/01	2003/04/02	2003/04/03	2003/04/04	2003/04/07	2003/04/08	2003/04/09	2003/04/10	2003/04/11	2003/04/14
181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	182
161	161	161	161	161	161	161	161	161	166	166	166	166	166	166	166	165
167	167	167	167	167	167	167	167	167	162	162	162	162	162	162	162	162
168	168	168	168	168	167	167	167	167	167	167	167	167	167	167	167	167
170	167	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182
6				166	168	166	166	166	166	166	166	166	166	166	167	167
					171	171	172	172	172	172	172	172	172	172	172	173
					158	158	158	158	158	157	157	157	157	156	156	155
					167	166	165	165	165	165	165	165	165	166	166	166
					173	176	176	175	175	175	176	176	176	174	174	174
					171	171	171	171	171	171	171	171	171	172	172	172
					171	171	171	171	171	171	172	172	172	172	171	171
					7											
											175	175	176	176	176	176
											170	170	169	169	170	170
											155	155	155	156	160	161
											168	168	168	167	169	169
											171	171	171	173	174	173
											154	154	154	153	141	141
											6			161	164	163
														41	160	160
														0	147	147
														0	148	148
															145	145
															148	148
															152	152
															7	

Figure 36: Receiving Sales Orders every Decade.

The assumption was made that DCSA receives new Sales Orders every seven days [Frequency] and that the number of Sales Orders received would be enough to carry DCSA to the next receipt i.e. six days of new Sales Orders [Magnitude]. Furthermore, the assumption was made that the Sales Orders are always received one day before the following Order Release i.e. Order Releases are never based upon a Forecasted Demand.



5.2.3 Recreating Forecasted Orders.

Sales Order Forecasts are included in the 4 week period used to calculate the ADR. The magnitude of these forecasts is dependent on a vast array of factors that cannot be included in the simulation model due to their complexity. However, it remains necessary to include these types of orders in the ADR calculations computed by the simulation program. The issue was solved by using the average demand as a baseline forecast. The simulation program then runs in a loop until it has chosen a demand at random that is within a 10 percent tolerance range of the average demand. This value is then used as the Sales Forecast for a 15 day period after which a new value is chosen at random and again kept constant for 15 days.

Figure 37 is a spreadsheet representation of the actual array created by the simulation program to represent the environment in which the SAP-MRP System operates in at DCSA. Each column represents a calendar day and each row represents the demand status for that specific part for a future production day. Refer to Figure 6 to make a comparison between the outputs obtained from the SAP-MRP System and the array presented to the reader in Figure 37. Note that the Sales Order Receipts always occur before the following Order Release.

110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
110	110	110	110	110	115	99	99	99	106	106	106	113	113	113	113	113	113	113	113
110	110	110	110	110	115	115	122	122	122	122	122	122	122	122	122	122	122	122	122
110	110	110	110	110	115	115	115	115	115	115	115	115	115	115	115	115	115	115	115
110	110	110	110	110	65	65	65	58	70	70	70	70	68	68	68	68	68	68	82
110	110	110	110	110	120	118	118	116	116	116	116	116	116	123	123	123	123	123	123
110	110	110	110	110	110	110	110	110	110	110	105	105	105	105	105	105	105	105	105
110	110	110	110	110	110	110	110	110	110	110	115	115	115	115	115	115	115	115	115
110	110	110	110	110	110	110	110	110	110	110	60	60	60	60	60	60	60	67	67
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
110	110	110	110	110	110	110	110	110	110	110	115	115	115	122	122	122	122	122	122
110	110	110	110	110	110	110	110	110	110	110	135	135	135	135	135	135	135	135	135
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	105	105
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	130	130
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	125	125
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	105	105
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	125	125
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110
110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110

Figure 37: Simulated Forecast.

The reader may refer to Figure 37 and suppose that the Forecasted Order value does not change from the indicated 110 in the first 15 day period to the 110 indicated the second 15 day period. This is not the case and it is only by coincidence that the same value was chosen for both of the 15 day forecast periods. Table 18 on page 66 presents a chart used to describe the significance of each colour used in Figure 37.



Colour	Indicator	Description
	Forecasted Orders	The Forecasted Orders remain constant for a 15 day period.
	Sales Orders	The vertical component represents the Sales Order Receipt, and the horizontal component indicates the period until the following receipt. The vertical height equals the horizontal length. Sales Orders are received every 6 days and contain 6 days worth of new Sales Orders.
	Order Release	The demand in this cell is used as the Initial demand in the Net Requirements Calculation, which then eventually results in a possible Order Release. Note that the column, for each Order Release, is 20 rows high – the same number of days used in the ADR.

Table 18: Colour table for Figure 37.

5.2.4 Customer Demand Changes.

There were two issues involved with simulating Customer Demand Changes. The first issue was that of ensuring that the Flipped demands remained within realistic bounds and the second being how strictly to adhere to the Option Freeze policy.

5.2.4.1 Maintaining Realistic Changes.

Due to the nature of the Flip input data, it is possible for a demand to be “Flipped” to a value less than zero, or a value that is invalid in terms of the production capacity of DCSA.

Negative Demand.

The simulation program is designed to set the demand to zero if a negative demand occurs because of a Flip.

Maintaining a Realistic Demand.

This section describes how the simulation program dynamically filters the input data in order to avoid the problems associated with large Flip values attributed to large scale sequence changes as well as the addition and deletion of production days.

The Flipped demand is kept within realistic bounds by setting an upper limit for the resultant Flipped demand. The upper limit is equal to the maximum demand observed in the input data for the specific part under analysis.

The program stores the demand value before flipping it. Thereafter, the program flips the demand and checks whether the resultant demand is less than or equal to the maximum observed value. If the Flipped demand is greater than the maximum value, then the program retrieves the demand stored prior to the Flip and flips it until the result is acceptable in terms of the upper limit. The Flipped demand is not defaulted to the maximum value when the Flipped value is greater than the maximum observed value. This is because it may be possible that the



pre-Flipped value was much less than the maximum value i.e. the post-Flipped value was flipped with a very large number. This concept is demonstrated in the Table 19.

	Maximum Observed Value	Pre-Flipped Value	Flip Value	Post-Flipped Value (Pre-Flipped Value + Flip Value)
Step 1	142	90	135	225
Step 2	142	90	5	95

Table 19: Dynamic Filtering Process Demonstrated.

Step 1 shows the post-Flipped value that is much higher than the maximum observed value. The magnitude of the Flip value can possibly be attributed to the addition of a production day, which would account for the high positive value. Step 2 follows on from Step 1 and shows how the same pre-Flipped value (that was stored) is Flipped once more, but just with a more realistic and smaller value. The new post-Flipped value is now acceptable as it is less than the maximum observed value.

5.2.4.2 Adhering to the Option Freeze Rule.

As stated earlier, DCSA allows customers to make Option changes within the 25 day Option freeze period depending on where their vehicles are in the system. Obviously DCSA is less likely to allow changes the closer the vehicle is to assembly. Based on this observation, it can then be said that the Option Freeze rule is not adhered to very strictly within the current Option Freeze Environment.

One could imagine that DCSA would probably adhere to the Option Freeze policy a lot stricter if the Option Freeze point was moved to 10 days before Jig. It was therefore that a similar assumption was made in accordance to this probable adherence to policy. It was assumed that Option changes would not be accepted at all within the 10 Day Option Freeze. This assumption was presented to and confirmed by DCSA.

5.2.5 Number of Days used in the ADR.

The 4 week period used in the ADR calculation uses the Production Calendar in determining how many days are actually contained within the 4 week period. A typical week would contain 5 working days, but this could be less if the week contains a public holiday or similar event.

In terms of the simulation program, the assumption was made that a week would always contain 5 working days. Therefore, the total demand within the 4 week period will always be divided by 20 days when calculating the ADR.



5.3 Summary.

This chapter was focused on the design and development of the Visual Basic program utilised in the simulation of the SAP-MRP System at DCSA. The current version of the simulation program is the result of three very distinct consecutive design phases.

1. The first phase produced a prototype developed in an Excel spreadsheet. The prototype was developed to test the knowledge gained about the SAP-MRP System operation. Furthermore, the knowledge gained and the logic, upon which the functional model would be based, was validated. This was done by comparing the performance of the prototype to that of the SAP-MRP System by means of a paired t-test.
2. The Independent version was designed so that it used the same input data as the OIMM System, which then still allowed the two systems to be compared against each other. However, the inordinate number of parameter combination settings required to evaluate the SAP-MRP System capabilities effectively, dictated that a certain level of automation had to be achieved. This automation requirement then led to the third and final phase.
3. The Automated version was designed for conducting an analysis by means of DOE. Boundaries were set for the various values that Safety Time, Minimum, and Target Coverage could assume. These values were then automatically varied within these ranges by the program. The result was that the response of the SAP-MRP System was taken from 63 different combinations of these Input Parameters.

Various design issues were encountered during the programming phase of the current version. The most significant of these issues were encountered when re-creating the Sales Order environment and involved issues such as:

- Converting Lead-Time from calendar days to workdays.
- Recreating Sales Order Receipts – frequency and magnitude.
- Inclusion of Forecasted Orders into the ADR.
- Maintaining realistic Customer Demand changes.

The conversion of Lead-Time to working days was based on the assumption of a 5 day workweek, which effectively meant that the shipping delivery cycle had to be converted to workdays too. The frequency and magnitude at which Sales Orders were received was assumed to follow a 10 day cycle, with each receipt large enough to carry DCSA to the next order receipt. Forecasted orders were calculated based on the average demand of the data samples and realistic Customer Demand changes were forced to stay below a maximum value.



At the time at which this study was undertaken DCSA allowed customers to make Option changes within the 25 day Option freeze period, depending on where their vehicles are in the system. It was however assumed that they would adhere strictly to this rule, and not allow any changes to occur during the Freeze period at all.

This chapter marks the culmination of the end of the Initial Study. The following chapter introduces the Final Study where the SAP-MRP System is evaluated by analysing the output data generated by the SAP-MRP simulation program. The results of three investigations are presented in the following chapter. These experiments were aimed at the following:

- Establishing the SAP-MRP System's Avg. Customer Service Level in the Worst-Case Scenario.
- Establishing the result of long-term human intervention on the SAP-MRP System.
- Introducing the Design of Experiments methodology followed and generating data for further analysis.



Part 2: Final Study





6. Simulation, Results, and Findings.

The advantage of utilising simulation as an analysis tool is that it can generate large amounts of data in a short period. The disadvantage, however, is that a proportionally large amount of time may be required to analyse the data such that it may yield useful information. A primary objective of this chapter is to present to the reader the methodologies employed in simplifying the analysis of the generated data. A further purpose of this chapter is to evaluate SAP-MRP System's Avg. Customer Service Level under the Worst-Case Scenario. This Worst-Case Scenario is characterised by setting Safety Time, Minimum and Target Coverage to zero, which effectively reduces the system to a basic MRP System by "switching" the Statistical Component off. This being the case the plant will carry the minimum possible inventory, which will then accentuate any weaknesses in the SAP-MRP System logic and thus result in a minimal Avg. Customer Service Level. The completion of this investigation would then indicate whether implementing a "minimum inventory" policy would adversely influence the Avg. Customer Service Level provided by the SAP-MRP System.

According to DCSA, Avg. Customer Service Level is attributed as the most important output Performance Measure of the SAP-MRP System. The output of any system is, however, a function of the quality of the input data. This input data could be provided by machine or by man, with the latter being more prone to human error. With this in mind an experiment is conducted to evaluate the long-term effect of human intervention on the performance of the SAP-MRP System.

In closing, the reader is given a brief introduction to DOE as well as the application thereof to the project.

This chapter is divided into three sections, as follows:

1. Focus is placed on the various methods used to facilitate simulation.
2. The second section presents the simulation results taken from the Worst-Case Scenario, "Human Intervention," and the DOE Experiments only.
3. The final section presents the reader with a summary of the findings obtained from the aforementioned simulation exercises.



6.1 Preparation Steps Followed to Facilitate Simulation Analysis.

This section presents a discussion on the four methodologies used to facilitate simulation. The aim is to help the reader understand the approach taken, in terms of part-exclusion and adjustment of certain part Lead-Times, in simplifying the analysis of large amounts of output data, and finally the preparation of the input data. The methodologies are as follows:

- Grouping input and output data, according to Average Demand, to avoid repetition and simplify analysis.
- Preparing and using the input data for simulation.
- Exclusion of certain parts from forming part of the simulation input data.
- Adjustment of part Lead-Times to suit simulation purposes.

6.1.1 Using the Average Daily Demand to Simplify Analysis.

Before commencement of the simulation and analysis components of this study, it was necessary to find a method to simplify the task of scrutinising the resultant output data. This exercise would have been tedious and repetitive if the output data had been analysed on a part-by-part basis. Grouping the parts according to the “Demand Level” Part Selection Criterion simplified the analysis and it was felt that this approach provided a well-balanced view of the problem.

The first step in grouping the parts according to demand level is to calculate the Average Daily Demand (ADD) for each part. Thereafter, bin sizes are defined and used to categorise parts. There are only two rules for specifying the bin size, namely:

- There should at least be two or more parts per ADD Category, and
- The range of a category should not include ADDs that are more than twice as large as the lowest ADD in that category. However, an exception is made when applying this rule to very low runners i.e. between zero and one units required per day.

There had to be more than one part per ADD Category in order to minimise the possibility of bias. Ideally, an infinite number of parts per ADD Category is preferable, but due to the manual nature in which data was collected, this was not practical.

Table 20 on page 73 shows the result of this technique when applied to the part data collected for this study. A bin size of 15 was used to categorise parts with an Average Daily Demand greater than 10 units per day. Some categories, due to the lack of sufficient data, either do not exist or contain borderline cases. However, this did not have a negative impact on the study.

Although not conforming to the first requirement the 2-4 ADD Category is included in Table 20. The reader will later learn that this category would not be used for analysis.



ADD Category	Part Number	Average Daily Demand (Units per Day)
0-1	0005461781 A	0.289
	1120101144 A	0.554
	2034601503 29C29A	0.614
	2096801242 29D60A	0.770
	2034600903 25C69A	0.809
	2034602403 29C29A	2.725
2-4	2032602102 A	3.904
15-30	2036901640 21A73C	14.122
	2039709350 27D44A	26.325
	2032700400 A	27.267
60-75	2710106700 A	66.392
	2094000402 A	75.540
76-90	2096801042 29D60A	82.197
	2034600903 29C29A	89.631
91-105	2038171120 A	94.976
	2112703200 A	108.890
106-120	2038171020 A	116.425
	2038170920 A	117.970
165-180	2036901640 27E63C	167.790
	2028800186 A	193.935

Table 20: Average Daily Demand Categories.

The reader will notice that smaller bin sizes were used to categorise parts with an Average Daily Demand less than, or equal to, 10 units per day. Discretion was necessary in this situation, as the behaviour of these parts, in terms of sensitivity to demand variability and resultant stock-out occurrences, differs greatly from the behaviour of the higher running parts. The reason for these parts receiving “special attention” is explained below.

6.1.1.1 Categorisation of Ultra Low ADD Parts.

Parts in the lowest ADD Category i.e. 0-1, are uniquely sensitive to demand fluctuations. For example, an increase in demand of just three units can result in a deviation from the original demand by as much as a 300 percent, assuming the Initial Demand was for a single unit and the Actual Demand was for 4 units. Similarly, an increase in demand of three units on a part that has an ADD of 160 units per day, would register a deviation in demand of only 1.8%.



Parts in the higher ADD Categories are more able to absorb an increase in demand than stock assigned to lower ADD Categories. This “**Absorption Ability**” is attributed to the Statistical Component of the SAP-MRP System that ensures a specific amount of stock is always in plant, over and above the Production Requirements. It can now be imagined that if a part in an ADD Category has an associated ADR of 0.2 units per day, then the resultant Plant Stock will probably be between zero and one units. Similarly, a part in a higher ADD Category with an ADR of 45 units per day would have a resultant Plant Stock level of +/- 45 units. The result is that the parts with low ADRs cannot absorb an increase in demand thus leading to a stock-out occurrence. The behaviour of these parts is completely different to the parts in higher ADD Categories, in terms of their sensitivity to fluctuating demand.

It should be clear to the reader why parts in the 0-1 ADD Category could not be grouped with parts in the 2-4 ADD Category – the maximum ADD of the latter category is 1250% more than the lowest ADD in the 0-1 ADD Category.

6.1.2 Preparing and Using the Input Data for Simulation.

Initially, there were three concepts identified with respect to the ideal method by which the input data should be used for simulation. They are as follows:

1. Group together the **input data** into a single data set per ADD Category, utilising the data set as an input to the simulation program. The data set would then become generically representative of all the parts used to form the data set.
2. The input data should remain “As-Is” i.e. an individual data set per part. The simulation output would then be analysed on a part-by-part basis.
3. Similarly, the input data should remain “As-Is” i.e. an individual data set per part. However, in this case the **output data** is grouped together according to specified criteria. The grouped output data would then be investigated and analysed to determine whether any general behaviour patterns existed within the resulting groups.

Figure 38 on page 75 presents a graphical depiction of the above discussion.

The validity of all three options was tested and it was found that only the last two options were viable. The first option was not viable because the characteristics of each part i.e. demand and Flip distribution, became “blurred” and lacked definition. This resulted in the simulation program selecting initial demand values from one part and then “Flipping” the demand with a Flip value from another part. This was not a valid model and was thus discarded. The second option was found to be applicable in a situation where the user was interested in quickly observing the effect of changing a single parameter. The third option was employed in the DOE analysis.

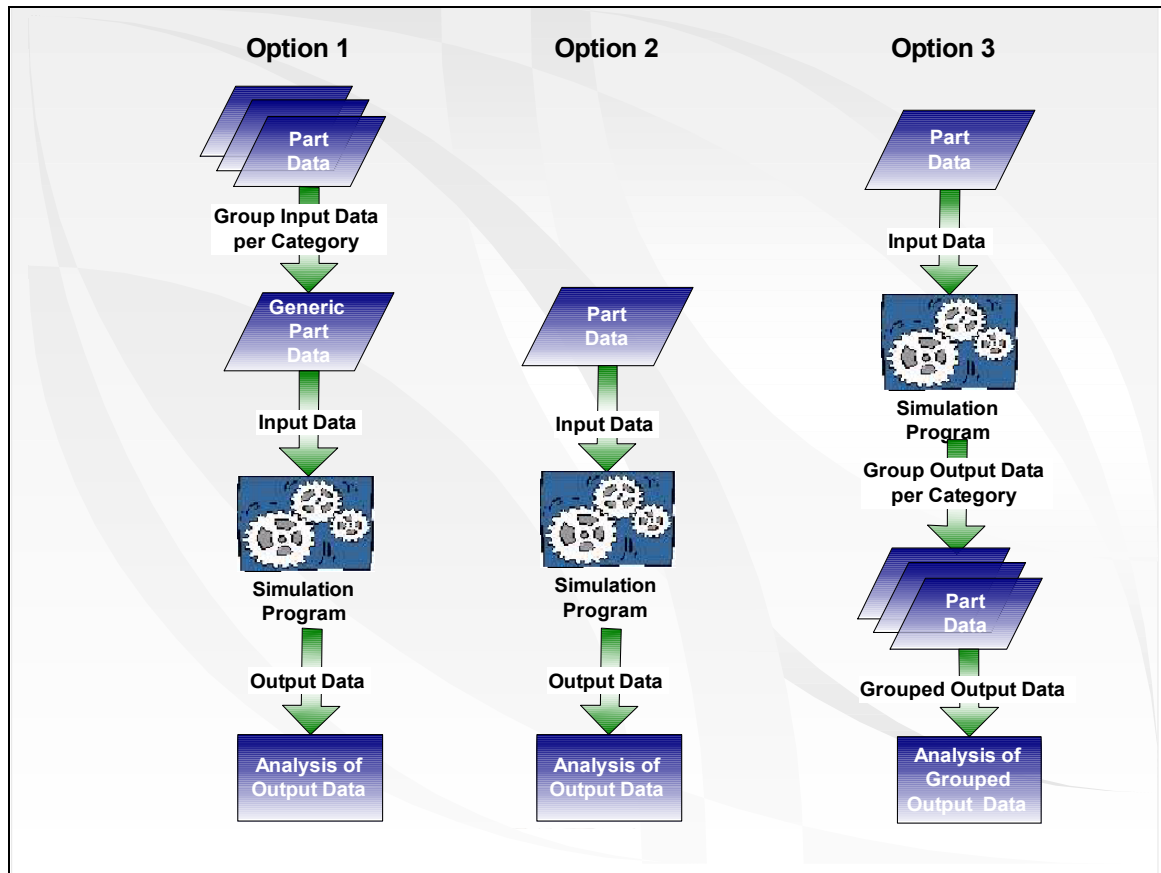


Figure 38: Using the Input Data for Simulation.

6.1.3 Excluding Parts from Input Data.

Three parts were excluded from being used as input data for the simulation program, namely:

- 2032602102 (C 180 Manual Gearbox)
- 2036901640 27E63C (Right Hand B-Pillar Cover)
- 2028800186 (Mercedes Benz Star)

The reason for the exclusion of each part is similar, even though they are placed in different categories.

Part 2032602102 was excluded, as it was the only part in the 2-4 ADD Category, which then increased the possibility of the output data being biased in a certain manner. This could have then resulted in an incorrect conclusion being drawn from the analysis of the output data, as it would only reflect the behaviour of one part. Ideally, a category should contain many different parts each with its own unique behaviour in terms of demand and demand variability. This type of situation would provide a broader view of the behaviour of that specific category, which is not the case when a category contains a single part.



Part 202880186 (Mercedes Benz Star) was excluded for the following reason:

It is a standard part with a very stable demand level, which is shown by the fact that 85.83% of the demand occurs at 198 units, as seen in Table 21 on page 76, and 97.03% of the Flips occur at zero, as seen in Table 22 on page 76. The behaviour of this part, in terms of demand variability, is vastly different to that of Option related parts. Therefore, it could not be used since it is completely dissimilar from an Option related part.

Part 2036901640 27E63C had to be excluded after Part 202880186 was removed, for the same reasons that Part 2032602102 was excluded i.e. Part 2036901640 27E63C was the only part left in the 165-180 ADD Category.

Cumulative Demand Distribution			
Bin	Freq	%	Cumulative
0.00	16	1.23%	1.23%
20.50	5	0.38%	1.61%
41.00	0	0.00%	1.61%
61.50	0	0.00%	1.61%
82.00	0	0.00%	1.61%
102.50	42	3.22%	4.82%
123.00	0	0.00%	4.82%
143.50	2	0.15%	4.98%
164.00	0	0.00%	4.98%
184.50	4	0.31%	5.28%
198.00	1121	85.83%	91.12%
205.00	116	9%	100%

1306

Table 21: Cumulative Demand Distribution of Part “202880186 A.”

Cumulative Flip Distribution			
Bin	Freq	%	Cumulative
-198	3	0.25%	0.25%
-158.4	0	0.00%	0.25%
-118.8	0	0.00%	0.25%
-79.2	1	0.08%	0.33%
-39.6	1	0.08%	0.41%
0	1175	97.03%	97.44%
39.6	27	2.23%	99.67%
0	0	0.00%	99.67%
0.1	0	0.00%	99.67%
79.2	1	0.08%	99.75%
118.8	1	0.08%	99.83%
158.4	0	0.00%	99.83%
198	2	0.17%	100.00%

1211

Table 22: Cumulative Flip Distribution of Part “202880186 A.”



6.1.4 Adjustment of Part Lead-Times.

It was necessary to adjust Lead-Time values of various parts, as is explained below. Table 23, seen below, lists the three possible Lead-Times (measured in calendar days) for imported parts.

- The majority of Option related parts have a Lead-Time of 44 days. Certain Option Related parts do not have 44 day Lead-Times due to constraints on the side of the supplier. In such cases, these parts have a Lead-Time of 53 or 60 days.
- Body Panel parts have a Lead-Time of 53 days, as they require extra time to undergo a special rust protection process before they are shipped to DCSA.
- Bulk parts are ordered based on forecast values and therefore do not need to have their Lead-Times reduced, which would result in the order being released on Customer Demand. Furthermore, these parts have very high Pallet Sizes, numbering in the thousands, so a demand change of a few hundred would have very little influence on the size of the Order Release.

Lead Time	Typical Parts
44 days	Option Related Parts
53 days	Body Panels
60 days	Bulk Parts

Table 23: Typical Lead-Times for Specific Parts.

A few of the parts that were selected for analysis had Lead-Times that exceeded the maximum of 53 days (these are the parts described earlier that are subject to supply side constraints). The Lead-Time in these cases was altered to suit the simulation program and was thus changed to 44 days (since this is what Lead-Time should have been).

Altering Lead-Times did not have a negative effect on the simulation process or on the analysis. It is argued that within the multitude of parts in use at DCSA, there is a very high possibility that an Option related part exists, with a 44 day Lead-Time and has exactly the same demand Behaviour Characteristics as the part whose Lead-Time needs to be changed. Therefore, changing Lead-Time indirectly provides a representation of a part that is valid for simulation. Furthermore, the objective of the study was in determining the SAP-MRP capabilities and not the behaviour of a specific part under the 10 Day Option Freeze Environment.



6.2 Simulation Results of the Worst-Case Scenario, “Human Intervention,” and DOE Experiments.

This section discusses the simulation results of three different experiments. These are:

1. Establish the SAP-MRP System’s Avg. Customer Service Level under the Worst-Case Scenario.
2. Effect of “Human Intervention” on the effectiveness of the SAP-MRP System.
3. Design of Experiments (DOE).

The reasons why these experiments were conducted are discussed in the subsequent paragraphs.

6.2.1 Avg. Customer Service Level under Worst-Case Scenario Experiment.

Avg. Customer Service Level was indicated by DCSA as the most decisive factor in determining which system is superior. The customer is of such importance to DaimlerChrysler that they will go to any length to ensure that a vehicle is completed on time. Issues such as inflated Plant Stock levels are considered secondary to Customer Service Level.

In general, production environments strive to maintain inventory levels as low as possible, due to associated costs such as holding, material handling and stock pilferage. Further, large inventory levels tend to hide problems and inefficiencies of the production environment. However, DCSA’s situation is unique and they need to maintain a balance between:

- The large inventory levels required due to extended Lead-Times.
- The advantages associated with low inventory levels.

When considering which of these two points should form the primary goal in terms of decision-making, it is felt that DCSA should maximise the advantages associated with the second option. This being the case DCSA would have to have prior knowledge as to whether minimising Plant Inventory levels would have an adverse result on Avg. Customer Service Level or not.

The results from an experiment aimed at determining if a “minimum inventory” policy would have an adverse result on Avg. Customer Service Level are presented in the following section.

6.2.1.1 Summary of Worst-Case Scenario Results.

Each simulation run consisted of 50 replications of 1000 production days, with Safety Time, Minimum and Target Coverage set to zero. The following points will explain the reasoning behind this analysis approach.



- Setting the Safety Time, Minimum, and Target Coverage parameters to zero effectively reduces the SAP-MRP System to a basic MRP System i.e. the Statistical Component is switched off.
- With the Statistical Component switched off, the Avg. Plant Inventory would be reduced to a bare minimum and thus minimise its ability to absorb an increase in demand.
- The reduced “Absorption Ability” would then provide an earlier indication that the SAP-MRP System could not cope with the magnitude of demand variability under analysis.

Table 24 below provides a summary of the results found in Table 44 in Appendix G.

Usage Category	Part Number	Avg. Customer Service Level	Half-width at 95% Level of Confidence
0-1	0005461781 A	0.989	0.001
	1120101144 A	0.941	0.003
	2034600903 25C69A	0.984	0.001
	2034601503 29C29A	0.986	0.001
	2034602403 29C29A	0.982	0.001
	2096801242 29D60A	0.975	0.001
15-30	2036901640 21A73C	0.989	0.001
	2039709350 27D44A	0.957	0.002
	2032700400 A	0.985	0.001
60-75	2710106700 A	0.961	0.002
	2094000402 A	0.978	0.001
76-90	2096801042 29D60A	0.974	0.001
	2034600903 29C29A	0.977	0.001
91-105	2038171120 A	0.990	0.001
	2112703200 A	0.955	0.001
106-120	2038170920 A	0.994	0.000
	2038171020 A	0.996	0.000

Table 24: Summary of SAP-MRP System Results (ST, MC, and TC = 0).

Thus, it is seen that the Avg. Customer Service Level of the SAP-MRP System, for all parts analysed, did not drop below 95%. The half-widths indicate that the Avg. Customer Service Levels are very close to their true means. **This proves that the SAP-MRP System can provide a high Avg. Customer Service Level of over 95% under the 10 Day Option Freeze Environment across the entire range of Usage Categories.** This is said at the 95% level of confidence.

This result shows that a “minimum inventory” policy would not have an adverse result on the Avg. Customer Service Levels for the majority of the parts evaluated. The lowest Avg. Customer Service Levels can be improved by means of the Coverage Profile.



6.2.2 Influence of “Human Intervention” on SAP-MRP Effectiveness.

This experiment was conducted in conjunction with the “DCSA Service Level” concept discussed in Appendix N.

In this experiment, the simulation program was instructed to place a “Coverage Maintenance Order” whenever a Coverage Profile Violation occurred. The size of the Coverage Maintenance Order would be of such a magnitude that the resultant Available Stock would be greater than or equal to the required Target Coverage level.

The idea behind this experiment was to determine what the consequences would be if DCSA were to adopt a Coverage Maintenance policy. The policy would work over and above the existing SAP-MRP System i.e. additional program instructions would have to be inserted into the system, or Material Controllers would have to control the coverage manually. Adoption of such a policy would constitute “Human Intervention.”

The policy was based on the following hypothesis:

Strict adherence to the Coverage Profile will minimise the possibility of stock-out occurrences and line stoppages, whilst maximising Avg. Customer Service Level.

Selecting one part per Usage Category and simulating 50 replications of 1000 days each tested the hypothesis. The Input Parameters were set in accordance to their SAP MasterData values i.e. as they were set in SAP at the time of this study.

The following parts were used in the experiment:

Usage Category	Part Number	Safety Time	Minimum Coverage	Target Coverage	Coverage Tolerance	Minimum Pallet Size
0-1	2034601503 29C29A	2	7	9	0	25
15-30	2032700400 A	2	1	1	0	7
60-75	2710106700 A	2	1	1	0	3
76-90	2096801042 29D60A	2	1	1	0	20
91-105	2112703200 A	2	1	1	0	7
106-120	2038170920 A	2	5	7	0	900

Table 25: Parts used in “Human Intervention” Experiment plus Parameter Settings.



6.2.2.1 Summary of Results taken from “Human Intervention” Experiments.

This section presents four graphical figures, which are summaries of the findings found in Appendix H.

Figure 39 does not clearly indicate whether the Coverage Maintenance policy improved the Avg. Customer Service Level of the “As-Is” SAP-MRP System. This is attributed to the scale of the graphs. An analysis of both Figure 40 and Figure 41, which indicate Shortages⁸, shows that the policy will not maximise the Avg. Customer Service Level, as stated in the hypothesis.

The reader will note that the Avg. Customer Service Level of the “As-Is” SAP-MRP System is already at 100 percent.

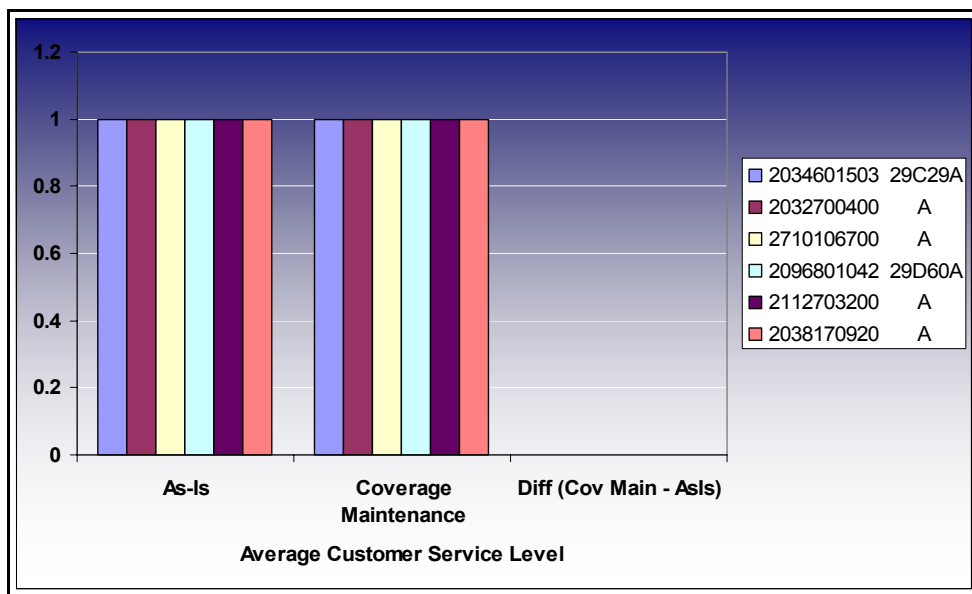


Figure 39: Avg. Customer Service Level.

Figure 40 indicates the Avg. Total Shortages. This is the measurement of the average total amount of stock that had to be ordered to cover stock-out shortages or Coverage Profile Violations. The magnitude of the shortages is a function of the demand variability specific to a part i.e. the more variable the demand of a part is, the higher the probability of stock-out or Coverage Profile violation.

Strict adherence to the policy would result in large volumes of emergency freighted stock being flown in, at considerable cost; this cost is dependent on volume and mass of the component.

⁸ Avg. Customer Service Level is inversely proportional to Shortages.

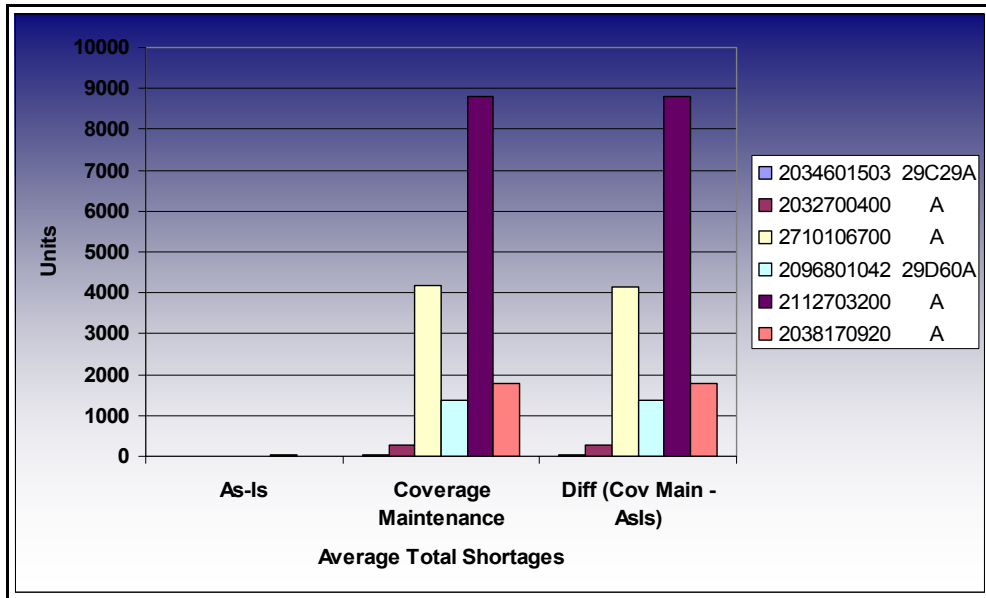


Figure 40: Avg. Total Shortages.

Figure 41 indicates that part 2112703200 would require emergency freighting more than 30 times in a period of 1000 days, which totalled to an average of almost 9000 parts (refer to Figure 40). This particular part is a C180 Automatic Gearbox, which is large, heavy, and thus very expensive to freight.

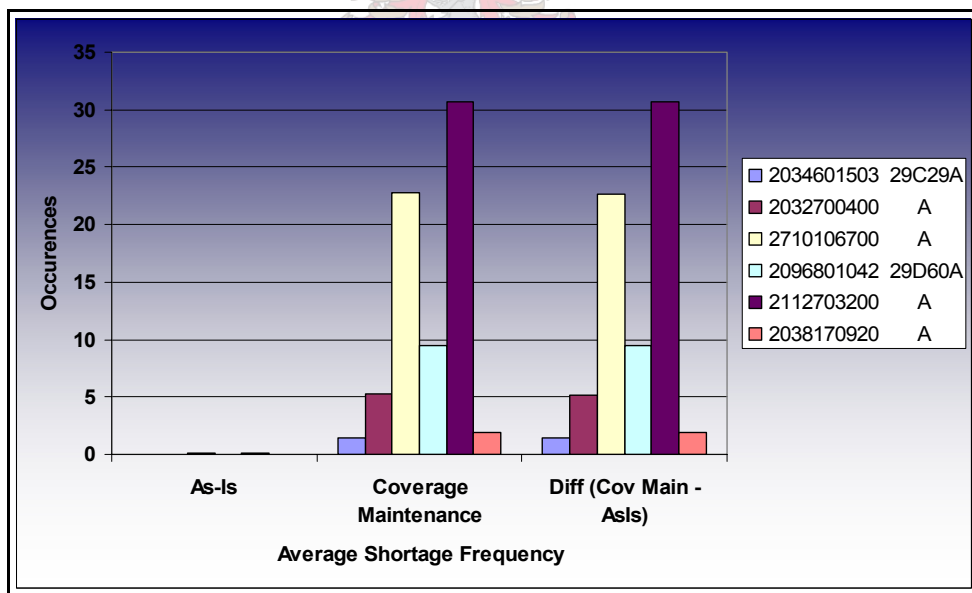


Figure 41: Avg. Shortage Frequency.

Figure 42 shows that the policy did have a small advantage in terms of the Avg. Customer Shortages. This measurement is an indicator of the amount of stock that was not available to the assembly line thus causing a line stoppage i.e. the customer did not receive the vehicle on time.

It is seen that the Coverage Maintenance policy did not experience any line stoppages for the period simulated. However, this fact is not significant when compared to the “As-Is” results, as in practical terms these results also effectively represent zero.

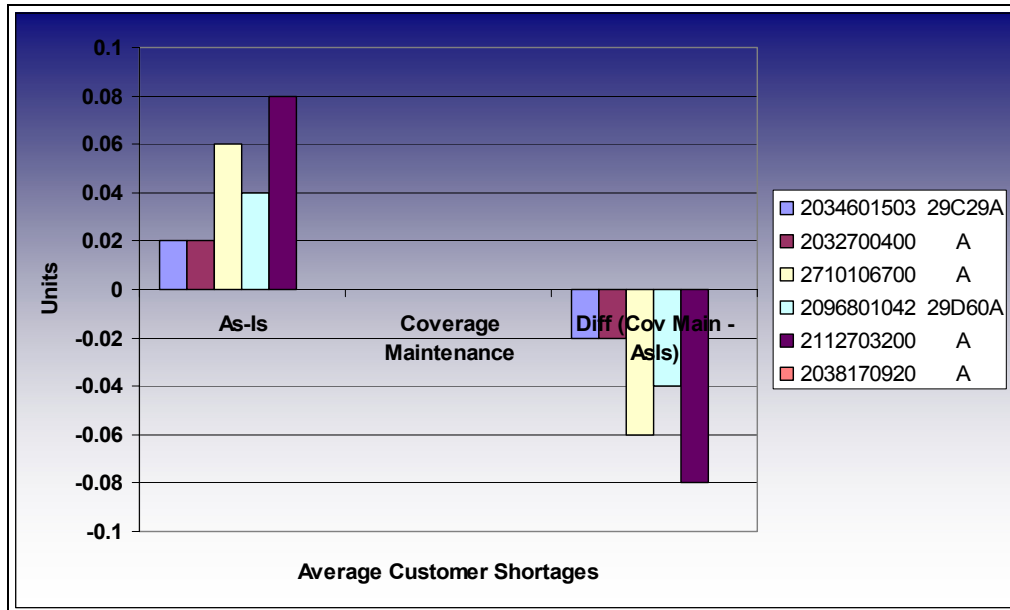


Figure 42: Avg. Customer Shortages.

In closing, the Coverage Maintenance policy did not have a significant influence on improving Avg. Customer Service Level. It is clear that the adoption of such a policy, which effectively represents human intervention, would have the distinct disadvantage of increasing expenditure on emergency freighting, and therefore reduce the effectiveness of the “As-Is” SAP-MRP System. It is therefore quite evident that long-term human intervention will eventually have a negative influence on the SAP-MRP System. In this case, “human intervention” would imply the efforts of the system operators to improve where it is not required i.e. implementing a Coverage Maintenance policy, rather than fixing the mistakes made by fellow employees.

6.2.3 Brief Introduction to the Design of Experiments Methodology.

According to the website *The Quality Portal* [2], DOE is defined as the following:

“DOE is a systematic approach to the investigation of a system or process. A series of structured tests are designed in which planned changes are made to the input variables of a process or system. The effects of these changes on a pre-defined output are then assessed.”

To put this definition into context the underlined words or phrases refer to the following entities within this study:

System: SAP-MRP System.

Planned Changes: Varying the Coverage Profile and Safety Time values within their predefined ranges. Various other Input Parameters were also adjusted, depending on the requirement.

Input Variables: Coverage Profile and Safety Time were adjusted in all instances. Certain experiments required changes to be made to Pallet Size and Lead-Time.



Predefined Output: This would refer to the following 10 Performance Measures (see Appendix N) that were used to assess the affects of the experiments:

1. Avg. Plant Inventory.
2. Avg. Pipeline Inventory.
3. Avg. Harbour Inventory.
4. Avg. Number of Orders.
5. Avg. Order Size
6. Avg. Customer Service Level.
7. Avg. DCSA Service Level.
8. Avg. Total Shortages.
9. Avg. Customer Shortages.
10. Avg. Shortage Frequency.

DOE is an important analysis tool as it allows the analyst to gain insight into the influence that each input parameter has on the output variable, as well as Input Parameters acting in combination with one another.

In general, four tasks must be completed when using DOE as an analysis tool. *The Quality Portal* identifies these tasks as being the following:

1. Identify the input variables (Input Parameters) and the output Performance Measures.
2. Define a level, per combination of input variables, to ascertain the effectiveness of that variable.
3. Develop an “experimental plan” that indicates where to set each input parameter for each run of the test.
4. Measure the response, per output parameter, for each run.

These steps were followed, which then led to the development of the “experiment plan” for Safety Time and Coverage Profile values, as seen in Appendix F. Each combination represents a level (as defined above) with a corresponding observation of a specific output parameter. No set plan was required for the Pallet Size and Lead-Time parameters, as their values were adjusted according to the requirements of the specific experiment. The reasons for this will later become clear.

Each simulation run generates an output value that corresponds to a specific level; each level being made-up of a combination of Input Parameters. If a level consisted of only 2-Input Parameters, then it would be possible to plot each output value in a 3-dimensional space, relative to the values of the Input Parameters. If a large number of different values were generated, each with its own level, then it would be possible to plot a 3-dimensional surface, much like that in Figure 43. The equation of the fitted surface/plane actually represents the equation obtained via Regression Analysis, which is later used for further analysis.

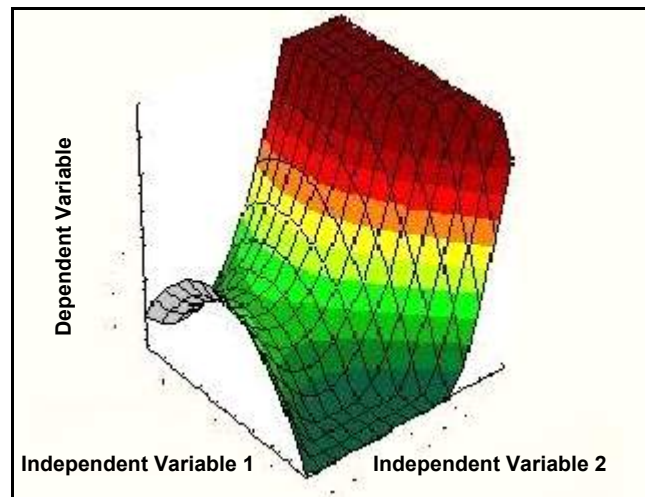


Figure 43: Input and Output Values on a 3-D Plot.

The accuracy of the equation obtained from the Regression Analysis is determined by various factors, the most important being the number of data points within the sample space. In general, the more densely populated the sample space the greater the accuracy of the equation.

The ability to populate the sample space with large numbers of data points is dependent on the output data, whose values are dependent on the input parameter settings. Imagine a system that is a function of just one input parameter, which can be set to a value of x or y . Each simulation run will produce two different outputs, one for each input parameter setting, thus populating the sample space with two different data points. Fitting a line or plane through these two points is very simple. The reader would agree that the accuracy of the system analysis, based on the fitted line/plane, is dependent on the complexity of the system being modelled. If the system were very complex, then the analyst would require more control over the various Input Parameters that influence the system, in order to improve the accuracy of the analysis. Note that “control” does not infer that the user can actually alter each input parameter. It also means that the user has the ability to document what the Input Parameters are per simulation run.

6.2.3.1 Application of the DOE Methodology:

Knowing that the results of the DOE were destined for analysis by regression meant that particular care had to be taken to ensure that the aforementioned sample space was populated with all the required data points. These data points had to reflect the influence that the following Input Parameters had on the output parameter under analysis:

- Safety Time
- Minimum Coverage
- Target Coverage
- Lead-Time
- Pallet Size
- Average Demand*
- Average Flip*
- Standard Deviation of Flip*



The parameters marked with (*) indicate that the analyst, when performing simulation runs, cannot change their values. These values are subject to Customer Demands and cannot be controlled by DCSA. Although Lead-Time and Pallet Size cannot easily be changed in practice, their values are altered to measure their influence on various Performance Measures.

The influence that a particular parameter has on the output parameter can only be measured if there are at least two or more data points in the sample space that are attributed to that input parameter. This means that if the influence that Lead-Time has on Avg. Plant Inventory has to be measured, then at least two simulation runs must be done for the same part, but with different Lead-Time values for each run.

Therefore, simulation runs were conducted with the Input Parameter settings set according to those reflected by the SAP System i.e. “As-Is.” In addition to these runs, experiments were conducted on the same parts, but with different Pallet Size and Lead-Time values in order to populate the sample space as much as possible.

6.2.3.2 Summary of DOE Results.

Table 26 on page 87 presents a summary of the experiments conducted during the DOE exercise, an example of the output is shown in Appendix I. Each experiment consisted of 50 replications of 1000 days per combination of Input Parameters.

The table indicates which parts were used as well as the settings in each experiment. A distinction is made between the “As-Is” values and the additional values used to populate the sample space. Further, it should be understood that one DOE simulation run constitutes running the simulation program 63 consecutive times with Lead-Time, Pallet Size, Average Flip and Demand, and Standard Deviation set constant. Only the Safety Time and Coverage Profile values are changed on each occasion.

The output data for each part was placed into one of four Usage Categories, namely:

- Ultra Low Runner (0-1 units per day).
- Low Runner (15-30 units per day).
- Medium Runner (60-100 units per day).
- High Runner (101 – 120 units per day).

The output data within each Usage Category was then used to represent the typical Behaviour Characteristics of all parts within that Usage Category. It would have been ideal to simulate the Behaviour Characteristics of all the parts at DCSA, but due to the impractical nature of such an undertaking, the best had to be made with that which was available. Creating additional data based on the Behaviour Characteristics of “imaginary” parts, by simply changing Lead-Time or



Pallet Size of an existing part, did this. The reader will recognise that this process is the same as that discussed in the previous section i.e. populating the sample space with additional data.

The grouped data in each Usage Category was then analysed using Regression Analysis. The results of the analysis, presented in the next chapter, provided a means of observing the Behaviour Characteristics of a typical part that would fall within a specific Usage Category.

Usage Category (Average Demand)	Part Number	Parameter: As-Is					Additional Setting	
		Lead-Time*	Pallet Size	Average Demand	Average Flip	Standard Deviation of Flip	Lead-Time*	Pallet Size
Ultra Low Runners (0-1)	0005461781 A	32	40	0.289	0.0037	0.203	NA	NA
	1120101144 A	37	3	0.5545	0.0026	0.1556	NA	NA
	203400903 25C69A	32	40	0.8092	0.0262	0.3809	37	NA
	2034601503 29C29A	32	25	0.6147	0.0011	0.1670	NA	NA
	2034602403 29C29A	32	25	0.5449	0.0016	0.3809	NA	NA
	2096801242 29D60A	32	20	0.7709	0.0057	0.2383	37	NA
Low Runners (15-30)	2036901640 21A73C	32	60	14.123	0.0261	2.1037	37/ 32	10
	2039709350 27D44A	32	1	26.325	0.0309	2.3097	37	20
	2032700400 A	37	7	27.267	0.0350	2.6199	NA	NA
Medium Runners (60-100)	2710106700 A	37	3	66.392	0.1699	5.9927	NA	NA
	2094000402 A	32	30	75.540	0.1036	7.3801	37	NA
	2096801042 29D60A	32	20	82.19	0.1241	8.0605	NA	170
	2034600903 29C29A	32	40	89.630	-0.0139	8.0118	37	100
	2038171120 A	32	900	94.975	0.2857	12.047	NA	35
High Runners (100-120)	2112703200 A	37	7	108.89	0.2061	9.7149	32	200
	2038170920 A	32	900	117.97	0.2037	12.122	NA	30, 100
	2038171020 A	32	900	116.424	0.3545	12.1129	37/ 32	35

* Indicated in working days.

Table 26: Summary of DOE Results.



6.3 Summary.

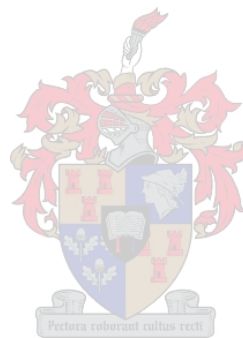
This chapter was presented in three sections. The first section presented four different methodologies that were utilised to simplify the analysis of large amounts of data. The second section presented the results of the various simulation experiments. Findings from the aforementioned experiments were summarised and presented in the final section. The key points of this chapter are presented below.

- The analysis of large amounts of data was simplified by grouping them together according to ADD Categories. These categories had to conform to two rules. The first specified that each category had to contain at least two parts. The second rule stated that the range of a category was not allowed to include ADDs that were more than twice as large as the lowest ADDs in that category (0-1 ADD Category being an exception). The application of these rules resulted in three parts being excluded from the analysis.
- Two different analysis approaches were discussed, each having their own impact on the manner in which the output data was analysed. The first approach would be utilised to analyse the Behaviour Characteristics of an individual part. The second approach focuses on the behaviour of a wide range of parts within a specific Usage Category. Both methods require that the input data be part specific i.e. the input data must not be grouped together. The second approach however, requires that the output data be grouped together to facilitate Regression Analysis.
- The majority of Option related parts have a Lead-Time of 44 days or 53 days. Some of the parts selected for analysis however, had Lead-Times of 60 days. Normally these parts would have been excluded from analysis (as these Order Releases are based on forecasted demand), but because of the limited number of parts available for analysis these parts had to be utilised. The problem was overcome by basing the analysis on the part as if it had a 44 day Lead-Time.
- A Worst-Case Scenario experiment was conducted in order to determine whether a “minimal inventory” policy would adversely influence the Avg. Customer Service Level provided by the SAP-MRP System. Setting Safety Time, Minimum and Target Coverage to zero facilitated this investigation. This experiment showed that the adoption of such an inventory policy would not have an adverse influence on the majority of parts included in the analysis.
- In addition to the Worst-Case Scenario experiment, an experiment was conducted to assess the influence of human intervention on the performance of the SAP-MRP System. This experiment showed long-term human intervention had a negative influence on the performance of the system.



- 63 different combinations of Safety Time, Minimum, and Target Coverage with values at different levels being evaluated, the results of which were placed into four specific Usage Categories. These categories ranged from Ultra Low Runners to High Runners and would later be used as inputs to the Regression Analysis.

Assessing the performance capabilities by means of DOE proved to be the most comprehensive and scientific manner to study the SAP-MRP System. This approach ensured consistency throughout the Usage Categories in terms of the Input Combinations as well as the results presented by the Regression Analysis. The next chapter presents an in-depth discussion of the Regression Analysis as well as the results thereof.





7. Regression Analysis.

Regression Analysis simplified the task of scrutinising the enormous quantity of output data generated by the simulation program. This method provided a better perspective on the particular Behaviour Characteristics of the various Usage Categories. Analysis on a part-by-part basis would have proved time-consuming thereby minimising the possibility of developing a concise and coherent method of presenting the resulting observations.

A second, but equally valid reason for using Regression Analysis was that the resultant equations could be utilised to prove, or disprove, various assumptions present at DCSA, as to the exact effect each input parameter has on the SAP-MRP System. Two sections divide this chapter. The first discusses various aspects of performing Regression Analysis, specifically those that could have a negative influence on the resultant analyses. The second demonstrates the manner in which the DOE Input Parameters were grouped together for the Regression Analysis phase. The grouping of these Input Parameters was such that they represented the manner in which the SAP-MRP System operates as well as indicating whether individual Input Parameters had a significant influence on the various Performance Measures.

Chapter 8 that follows is an extension of this chapter and has been separated for ease of reading. It quantifies the behaviour of the various Performance Measures in relation to the change of the input parameter settings and it demonstrates a technique to customise the DCSA SAP-MRP System.

7.1 Influential Factors within Regression Analysis.

Review of statistical literature highlighted various factors that play an influential role in determining/indicating the quality of the results obtained from Regression Analysis. The factors highlighted were:

- Omitted Variable Bias.
- Superfluous Variables.
- Multicollinearity.
- Sample Size.
- Goodness of Fit.
- The Relationship between Dependent and Independent Variables.
- Setting Regression Equation Intercepts to Zero.
- Normally Distributed Residuals.
- Linear Relationship between Observed and Predicted Values.

The analyst must be aware of the effects that each of these factors has on the output of the Regression Analysis. This awareness will then aid in the improvement of the analysis by highlighting those independent equation variables that should be added, removed, or modified due to possible interaction or situational irrelevance.

A discussion will follow that examines the specifics and relevance of each factor on this study.



7.1.1 Omitted Variable Bias.

Omission of independent variables from the Regression Analysis causes Omitted Variable Bias, which can then adversely affect the dependent variable. The omitted independent variable then becomes part of the noise term resulting in a possible violation of the assumption that is necessary for the minimum sum of squares error (SSE) criterion to be used as an unbiased estimator. "If the noise term of each observation is drawn from a distribution that has a mean of zero, then the sum of squared errors criterion generates estimates that are unbiased and consistent," (Sykes [3]). The omitted variable will shift the mean of the noise term (assuming that the variable is relevant to the study), thus violating this assumption. The omission of a descriptive variable could have a possible biasing effect on the constant term as well as the remaining independent variables (if they are correlated with the omitted variables). The estimated coefficients of the remaining variables will reflect the effect of the variable with which they are associated, as well as part of the effect attributed to the omitted variable.

The omitted variables problem increases the complexity of the analysis as it not only requires the analyst to gather data on more variables in order to avoid it, but because it is not always possible to observe all the variables that affect a problem.

Fortunately, the Omitted Variable Bias problem did not play a role in the analysis component of the study. This is attributed to the fact that the analyst designed the simulated system under analysis and thus had complete knowledge of all the independent variables that affected the dependent variables. Furthermore, the input data to the regression analyses was obtained from the DOE, which by nature is defined as an experiment whereby strict control is exercised over the settings of the Input Parameters.

Closely related to the omitted variables problem, is a further problem termed "error in variables." The erroneous measurement of some explanatory variables in most regression studies impacts on the accuracy of the resultant equation. However, when measuring the independent variables in conjunction with a well-designed experiment a definite exception to this generalisation exists. Walpole and Meyers [5] echo this sentiment in stating, "...independent variables are measured without error and are often controlled by the experimenter. Quite often, they occur because of an elaborately designed experiment. In fact, one [the analyst] can increase the effectiveness of the resultant predicting equation with the use of a suitable experimental plan."

Achieving a thorough understanding of the system under analysis eliminated the Omitted Variable Bias problem, which was further strengthened by the fact that thorough documentation of all input parameter levels existed.



7.1.2 Superfluous Variables.

The nature of Regression Analysis is such that the addition of any variable, relevant or not, improves the equation's ability to explain the variance within the data. "The addition of any single variable to a regression system will increase the regression sum of squares and thus reduce the error sum of squares." Walpole et al. [5].

The effect of including excessive variables can have a negative effect on the resultant equation. It is possible that an unimportant variable improves the resultant equation, which then could lead the analyst to conclude that the variable does play a significant role in the problem at hand, even though it does not. Further, it is also possible that an unimportant variable reduces the effectiveness of an equation by increasing the variance of the estimated response.

This problem of Superfluous Variables is resolved by using a two-step strategy. The first step requires the use of a statistical software package, like Statistica, which determines whether a variable improves the predictive equation itself. The second step involves analysing the behaviour of the dependant variable as a function of an independent variable. The behaviour of the dependant variable is a function of the sign and magnitude of the coefficient estimated by the Regression Analysis and would thus have a direct influence on the dependant variable behaviour. This step requires intimate knowledge of the problem at hand such that the analyst has intuitive understanding of the significance of each independent variable. The list below indicates the type of behaviour that the analyst expected from the various dependant variables i.e. Performance Measures, under analyses

- Avg. Plant Inventory is directly proportional to Safety Time, Minimum, and Target Coverage.
- Shortages are inversely proportional to Minimum Coverage.
- Avg. Pipeline Inventory is positively correlated with Days to Assembly (Lead-Time), whilst Service Levels were negatively correlated with Days to Assembly.
- The Inventory and Order Performance Measures were positively correlated with Average Daily Demand.
- Avg. Order Size was directly proportional to Pallet Size.

In addition, logic dictated that an increase in Target Coverage, whilst holding Minimum Coverage constant, would result in a reduction in the Number of Orders and increase Order Size. Similarly, an increase in Minimum Coverage, whilst holding Target Coverage constant, would result in an increase in the Number of Orders and reduce Order Size. This behaviour is explained by means of the example on the following page.

**Example:**

Note: For the purpose of this example, it is assumed that Safety Time is zero days.

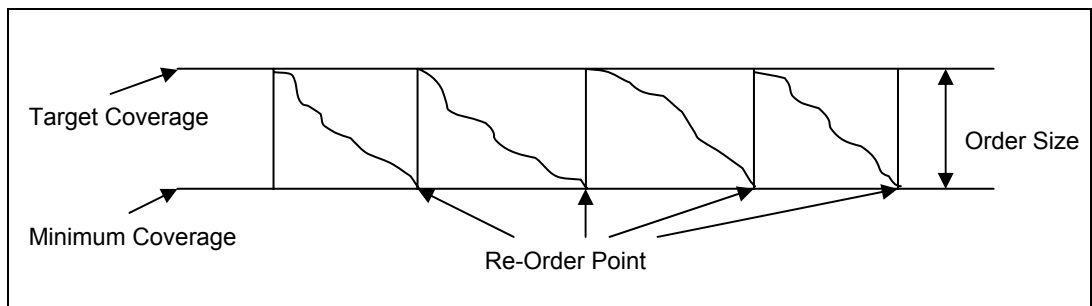


Figure 44: Interaction of Minimum Coverage and Target Coverage.

Figure 44 illustrates how and when an Order Release is created. An Order Release is created if the Available Stock divided by ADR is less than the Minimum Range of Coverage. The magnitude of the Order Release is such that the resultant Available Stock divided by the ADR is greater than or equal to the Target Coverage. The reader can now see that the magnitude of the Order Release is directly proportional to the difference between Target and Minimum Coverage. Furthermore, the frequency of Order Release creation is inversely proportional to the difference between Target and Minimum Coverage.

As with the problem of Omitted Variable Bias, the analytical power of the Statistica package helped to provide the solution. This, combined with the intimate knowledge of the system and problem at hand, enabled the analyst to examine the variable coefficients provided by Statistica and determine whether they made sense, in terms of their contribution to the predictive power of the equation.

7.1.3 Multicollinearity.

Multicollinearity is caused when two independent variables are closely correlated, thus creating a situation in which their effects are difficult to separate. It does not cause biased coefficient estimates, but increases the standard error of the estimates and thus reduces the degree of confidence that one can place in them.

The problem usually refers to changes in two variables that are so highly correlated that it is difficult to separate the changes. The relationship of a domestic household's purchasing power to income and level of taxation is an ideal example of this. In such a case, a strong correlation exists between the two, in that the higher the income, the higher the level of taxation. Excluding one of the variables in this situation can solve the problem if noting that the coefficient estimate for the remaining variables, which includes the effect of the omitted variable, will be biased.



7.1.3.1 Correlation between Input Variables.

Table 27 shows the correlation between the various Input Parameters employed in the Regression Analysis. Grouping all the data provided by the output of the DOE together into a single category and then analysing the data utilising MS-Excel provided the results shown below.

Correlation Coefficient (r)								
	Safety Time	Min Coverage	Target Coverage	Pallet Size	Days to Assembly	Avg. Daily Demand	Flip Mean	Flip Sigma
Safety Time	1							
Min Coverage	0.00	1						
Target Coverage	0.00	0.50	1					
Pallet Size	0.00	0.00	0.00	1				
Days to Assembly	0.00	0.00	0.00	-0.27	1			
Avg. Daily Demand	0.00	0.00	0.00	0.38	-0.15	1		
Flip Mean	0.00	0.00	0.00	0.46	-0.12	0.77	1	
Flip Sigma	0.00	0.00	0.00	0.45	-0.20	0.98	0.83	1

Table 27: Correlation Matrix ($\alpha = 0.05$).

It is evident that a strong correlation exists between Flip Mean, Flip Sigma, and Avg. Daily Demand as well as between Flip Sigma and Flip Mean.

The correlation between Flip Sigma and Avg. Daily Demand was expected, whilst the relationship between Flip Mean and Avg. Daily Demand was not. The aforementioned relationship is attributed to the magnitude of the demand changes associated with the various Usage Categories in the input data i.e. High Runners have higher Flip values than Low Runners due to the associated sequence changes and the addition and deletion of production days (see Section 3.2.3 on page 20). The magnitude of these demand changes increases in a linear manner across the Usage Categories, which accounts for the high correlation between Flip Sigma and Avg. Daily Demand.

The correlation between Flip Mean and Flip Sigma is understandable in a manner similar to that discussed in the previous paragraph. However, this correlation is a little unexpected, as the standard deviation of the sample was not expected to have a linear relationship with the sample mean.

A possible explanation for these relationships could lie in the fact that the input data includes Flips associated with the data anomalies as well as Flips attributed to Customer Demand changes. The results shown in Table 28 strengthen this hypothesis by showing the correlation between variables after the input data was filtered, to remove the Flips associated with the data anomalies.



Correlation Coefficient (r)								
	Safety Time	Min Coverage	Target Coverage	Pallet Size	Days to Assembly	Avg. Daily Demand	Flip Mean	Flip Sigma
Safety Time	1							
Min Coverage	0.00	1						
Target Coverage	0.00	0.50	1					
Pallet Size	0.00	0.00	0.00	1				
Days to Assembly	0.00	0.00	0.00	-0.27	1			
Avg. Daily Demand	0.00	0.00	0.00	0.38	0.15	1		
Flip Mean	0.00	0.00	0.00	-0.06	-0.07	-0.24	1	
Flip Sigma	0.00	0.00	0.00	0.39	-0.19	0.95	-0.31	1

Table 28: Correlation Matrix-Filtered ($\alpha = 0.05$).

Employing the following algorithm facilitated the data filtering process:

$$\text{Data point value} > \text{Sample Mean} + (2.698 * \text{Sample Sigma})$$

$$\text{Data point value} < \text{Sample Mean} - (2.698 * \text{Sample Sigma})$$

A data point was deleted if it was found to lie outside one of these two ranges. The 2.698 multiplying factor is in accordance with common statistical rules that are applied to identify outliers. A differentiation is made between outliers and extreme values. Extreme values are defined as those values that do not belong in a data set i.e. data anomalies. Outliers belong in a data set, but the probability of observing such a value is extremely small. All the data values greater than absolute 20 were removed from the data before applying the filtering algorithm. This was done to obtain a sample mean and sigma that were more representative of the true sample mean and sigma.

Filtering of the data presented a far better representation of the real interaction between the Input Parameters. Furthermore, this exercise produces a result that is similar to that created by the simulation program since the program itself ignores the large flip values (see Section 5.2.4.1 on page 66). It is now clear that the correlation between Flip Sigma and Flip Mean has been brought in line with expectations. Furthermore, whilst maintaining the expected relationship between Flip Sigma and Avg. Daily Demand the correlation between Flip Mean and Avg. Daily demand was reduced.

The filtering process provided a means of identifying the interacting Input Parameters as well as quantifying the interaction between them. Table 28 shows that the only noteworthy interaction occurs between Average Daily Demand and Flip Sigma.

Having identified the aforementioned interaction, the issue arose of how to deal with this interaction i.e. should an input parameter be excluded from the analysis, and if so which one?

The next Section deals with these questions and presents the action taken by the author in dealing with these issues.



Note: The filtered data was not utilised for Simulation or Regression Analysis purposes. It [the filtered data] merely provided an indication of the “real-world” interaction. Filtering of the data would have been a function of the author’s subjectivity, which would then have had a biasing affect on the output results of the Regression Analysis.

7.1.3.2 Dealing with the Highly Correlated Input Parameters.

Common practice dictates when two variables are highly correlated at least one be excluded from the Regression Analysis. In this instance, the analyst should be aware of the resultant Omitted Variable Bias.

The risk associated with this approach is that the quality of the resultant equations, indicated by the R^2 Value, might be reduced in terms of both predictive ability and capability of quantifying the influence each parameter has on the dependent variable.

With this in mind, the author initially conducted an analysis across all Usage Categories, which included all Input Parameters in the Regression Analysis. The R^2 Value for each Performance Measure equation was documented for future benchmarking.

The data was re-analysed on completion of this exercise with Flip Sigma excluded from the analysis since it was evident that Avg. Daily Demand carried more weight as a describing variable (refer to Section 4.4.2.1 on page 47).

Results showed that in most instances, the R^2 Value did not differ much from the benchmark. The only Performance Measures that showed a reduced R^2 Value were “Service Level” and “Shortages.” These reductions, however, did not present a problem in terms of the ability to analyse the behaviour of these Performance Measures. The problem was resolved by substituting the observations made on the Regression Equations with observations made on the output of the DOE. Therefore, the exclusion of Flip Sigma from the analysis was of little consequence.

7.1.4 Sample Size.

The t-statistic utilised in accepting or rejecting the Null Hypothesis is one of the tools used by the Regression Analysis in determining the statistical validity of the estimated coefficient. In most software packages, the Null Hypothesis states that the true coefficient of the variable is zero. Occasionally a large t-statistic will arise when the null hypothesis is correct. Often, in such a case, it erroneously leads to the conclusion that the null hypothesis is false.

The null hypothesis is usually rejected if it is found that the t-statistic associated with a variable estimate lies so far out in one tail of the t-distribution that such a value, or even larger in absolute value, would arise less than (typically) 5 percent of the time if the null hypothesis is true.



In order to determine the probability of drawing a specific t-statistic, one needs to know how “spread out,” (Sykes [3]), the t-distribution is. The “degrees of freedom” parameter, defined as the number of observations in the sample less the number of parameters to be estimated, is used for this purpose. Therefore, fewer degrees of freedom provide a greater probability of drawing a large t-statistic, or, the smaller the sample size, the greater the probability of drawing an estimate that is statistically significant when it is actually insignificant (Type I error, which is usual fixed by selecting a specific α). In addition, a smaller sample size reduces the probability of a significant variable being indicated as actually being significant (Type II error).

The analyst created a large amount of data by means of DOE, which reduced the chance of a Type II error in this study. This approach provided the analyst with great confidence in the accuracy of the resultant predictive equations, including the observations made upon those equations.

7.1.5 Goodness of Fit: The R^2 Value vs. the Adjusted R^2 Value.

Goodness of Fit, indicated by the R^2 or the Adjusted R^2 Value, is a measure of the variability in the data sample that is explained by the predictive equation. A high value for either indicator is desirable for predictive or forecasting purposes and a low value probably indicates the omission of important factors from the regression model.

The Adjusted R^2 Value was preferred by the analyst as it provided a means of evaluating a Regression Equation in terms of the number of Input Parameters included in the equation. “Adjusted R-squared values are used when comparing regressions using different numbers of explanatory variables. Adjusted R-squared invokes a degree of freedom correction that penalizes models somewhat for using more regressors” (Cameron [1]).

A high Adjusted R^2 Value does not necessarily mean that the predictive equation is the only equation that can be used to describe the data sample variability. Given infinite time availability, many equations would suit the data, but the question of the most suitable equation becomes academic when they have an equal Adjusted R^2 Value. Thus, the analyst may choose one equation over another should it be found that the sign and magnitude of the estimated coefficient value is more in line with the expected coefficient value.

For the purpose of this study, it was decided that an Adjusted R^2 Value of **0.9 or above could be used for prediction purposes**, due to the low percentage of unaccounted variability. It was still possible to use a value **lower than 0.9 to indicate the influence of the Input Parameters**, but this would **not be used for prediction purposes**.



7.1.6 Relationships between Independent and Dependent Variables.

The Matrix Plot function in Statistica was used as a quick visual indication of the type of relationship that existed between independent variables as well as between dependent and independent variables. The output (an example is shown in Figure 45) has all the input variables appearing diagonally on the plot, starting with the dependent variable at the top left and thereafter the independent variables moving down to the bottom right.

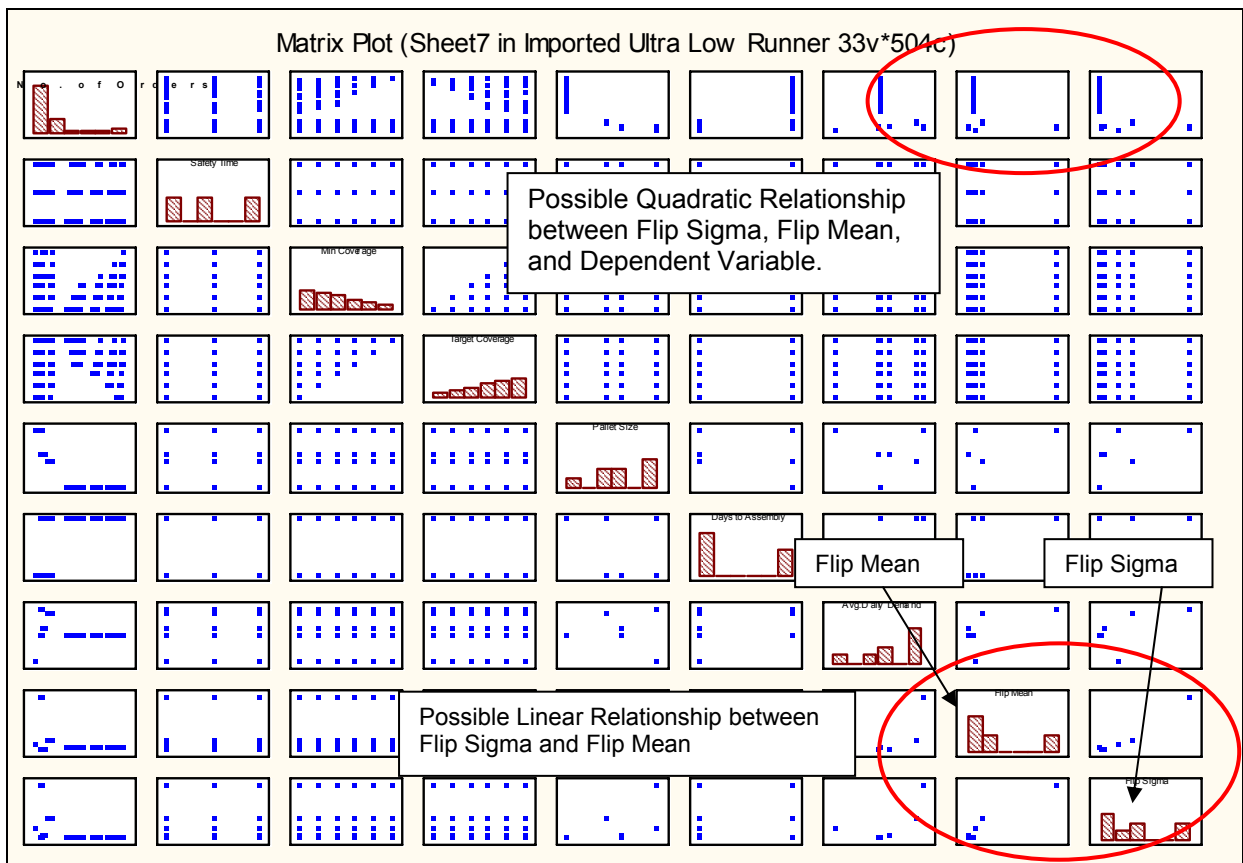


Figure 45: Example of Statistica Matrix Plot.

When examining such a plot the analyst should be looking for various relationships such as linear, random, quadratic, hyperbolic etc.

Whereas a linear relationship between independent variables would indicate Multicollinearity between them, a random relationship between independent variables would indicate variables that are not collinear, which is the ideal situation for reasons previously discussed. In a manner best described by mathematical expressions such as quadratic or hyperbolic relationships, additional relationships could exist between other variables. Figure 45 indicates examples of possible linear and quadratic relationships. The remaining graphs indicate random relationships between variables.

Having identified the possible mathematical interactions, the analyst would try to replicate these relationships by inserting data that is the result of the identified relationship. For instance, should the analyst identify a quadratic relationship between dependent variable “X” and independent



variable “Y,” he or she would insert data that was the result of squaring “Y” i.e. “Y².” A linear or random relationship would not require any change to the data by means of a mathematical transformation.

To provide for this approach, the author created the following relationships between variables:

Variable	Safety Time	Minimum Coverage	Target Coverage	Pallet Size	Days to Assembly	Avg. Daily Demand	Flip Mean
Safety Time				•		•	
Minimum Coverage	♦			•		•	
Target Coverage	♦			•		•	
Key:	♦ = The sum of i.e. +			• = The product of i.e. *			

Table 29: Synthesised Inter-Variable Relationships.

The product of Flip Mean and Days to Assembly provided an indication of the magnitude of the change in demand during a part's Lead-Time. Additionally, the relationship between Pallet Size, Safety Time, Minimum Coverage, and Target Coverage gave an indication of the proportional change in Pallet Size associated with a change in either one of these parameters.

In addition to the aforementioned, two further relationships were created to express the interaction between the product of Average Daily Demand and the sum of Safety Time and Coverage Profile. These are expressed in the following manner:

- *Avg. Daily Demand * (Safety Time + Minimum Coverage)*
- *Avg. Daily Demand * (Safety Time + Target Coverage)*

These relationships were based upon the actual interaction between Safety Time, Minimum, and Target Coverage as well as the method in which SAP uses the Average Demand to determine Plant Stock levels.

A more elaborate explanation of the above relationships is found in Section 7.2.3.1 on page 114.

As shown in Figure 45, certain independent variables displayed a quadratic relationship with the dependent variable. Common practice would include data that was representative of such a relationship. However, it was found that the advantage caused by the inclusion of these relationships, reflected by the minor improvement in the Adjusted R² Value, was outweighed by the disadvantage of confusing and often contradictory resultant coefficients. These relationships may actually be valid and warrant investigation, but such an endeavour would require far more data than that which was available for this study. Therefore, the aforementioned observed quadratic relationships were not created and the relationship between those independent and dependent variables was assumed to be of a linear nature.



An issue possibly related to the activities just discussed, is the problem of Superfluous Variables. In the case of this study, the Statistica software automatically resolved the Superfluous Variables problem using the range of the confidence interval to verify whether a variable coefficient was significant or not. A variable is deemed significant if the range does not include zero.

Example:

Imagine the hypothetical equation relating the growth of a tree (y) to three variables: rainfall (a), sunlight (b), and soil pH levels (c). The equation is expressed below

$$y = a + b + c$$

Statistica presented the following results, based on observational data.

Variable	Coefficient	Confidence Intervals		Significant
		Lower	Upper	
a	0.9	0.85	0.95	Yes
b	0.6	0.4	0.8	Yes
c	0.2	-0.1	0.5	No

Table 30: Hypothetical Regression Analysis Results.

The results show that rainfall and sunlight have a statistically significant influence on tree growth, but soil pH is not significant as the range of the confidence interval includes zero. Therefore, soil pH is not included in the Regression Equation.

In fact, the results presented by Statistica show only the statistically significant results. Therefore, it becomes unnecessary for the analyst to remove the statistically insignificant data and re-conduct the analysis.

Having resolved the Superfluous Variables problem, the author was able to use the same inter-variable relationships, as shown in Table 29, in the analysis of all Usage Categories. The result was for all Usage Categories, 15 independent variables were utilised in each Regression Analysis; these being made up of 7 standard Input Parameters and 8 synthesised Input Parameters (see Table 29 on page 99).



7.1.7 Setting the Equation Intercept to Zero.

The decision of whether the intercept should be forced through zero was subject to two criteria:

1. Is the coefficient of the intercept viable? Does it make sense?
2. Is the quality of the equation improved by including the intercept, or is it enhanced when set to zero?

Application of the first criteria resulted in rejection of most of the equations, where the intercept was not forced through zero. Listed below are examples of typical non-valid intercept coefficients:

- Negative Inventory Levels.
- Order frequencies numbering in the 10 000's when they should be in the 100's.
- Enormous negative Customer Shortages.

In such cases, the intercepts were forced through zero as they indicated that the SAP-MRP System had an invalid baseline performance even when all the Input Parameters were set to zero. Setting all the Input Parameters to zero effectively meant a specific Usage Category did not exist i.e. no parts fell within that category. This being the case there would be no Inventory, Orders, Shortages etc., and all Performance Measures would have to be zero

The only instances where the intercept coefficients satisfied the first criteria, and benefited the analysis, occurred when evaluating the SAP-MRP Avg. Customer Service Level. In this instance, the coefficients indicated a realistic baseline performance that fell between zero and one (0 and 100 percent).

The second criteria yielded similar results. It showed in the majority of the cases that the quality of the equation was improved by forcing it through zero. The quality of the equations was indicated by the distribution of the residuals and the linearity between the Observed vs. Predicted Dependent Variable when plotted against each other. This strengthened the hypotheses that Performance Measures should be zero when the Input Parameters are zero.

7.1.8 Normally Distributed Residuals.

An essential assumption of Regression Analysis is that residuals are distributed around zero (as seen in Figure 46). A *residual* indicates the difference between the observed and predicted independent variable and is utilised in calculating the error of the fitted Regression Equation. A residual plot not normally distributed around zero would indicate a biased noise component of the data. In terms of the chosen independent variables, this shows in turn that the Regression Equation does not adequately describe the behaviour of the dependent variable. In conclusion, the chosen model is unsuitable for provision of an adequate fit to the sample data.

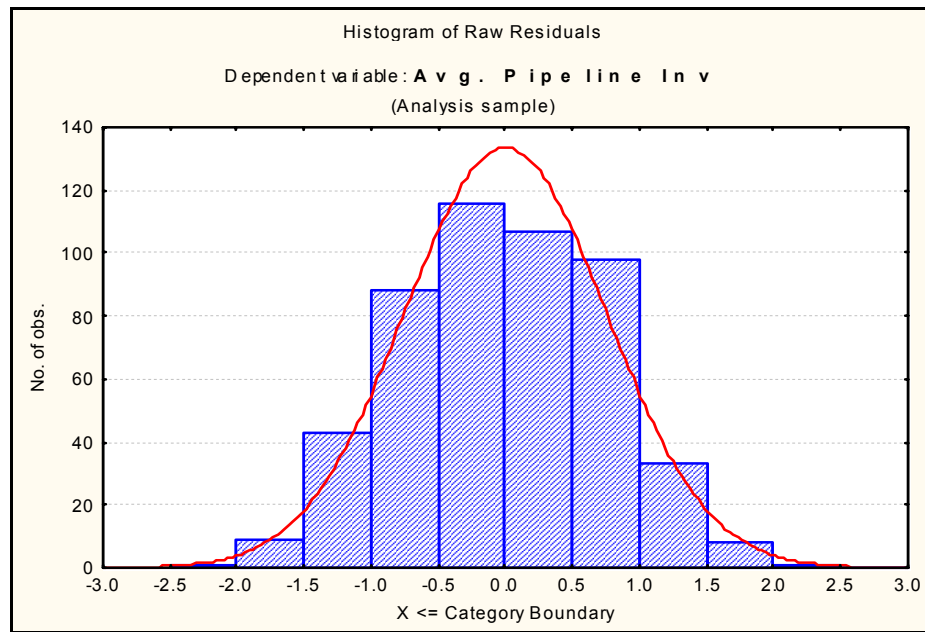


Figure 46: Normally Distributed Residual.

7.1.9 Linear Relationship between Observed and Predicted Values.

A linear relationship between the Observed and Predicted Values of a dependent variable indicates that the Regression Equation is a good model of observed data behaviour.

Figure 47 presents such a linear relationship between the Observed and Predicted Values. The 45 degree angle of the line indicates an almost 1:1 relationship between the Observed and Predicted Values. The 45 degree line indicates to what degree the Predicted Values are equal to the corresponding Observed Values, which is the ideal situation.

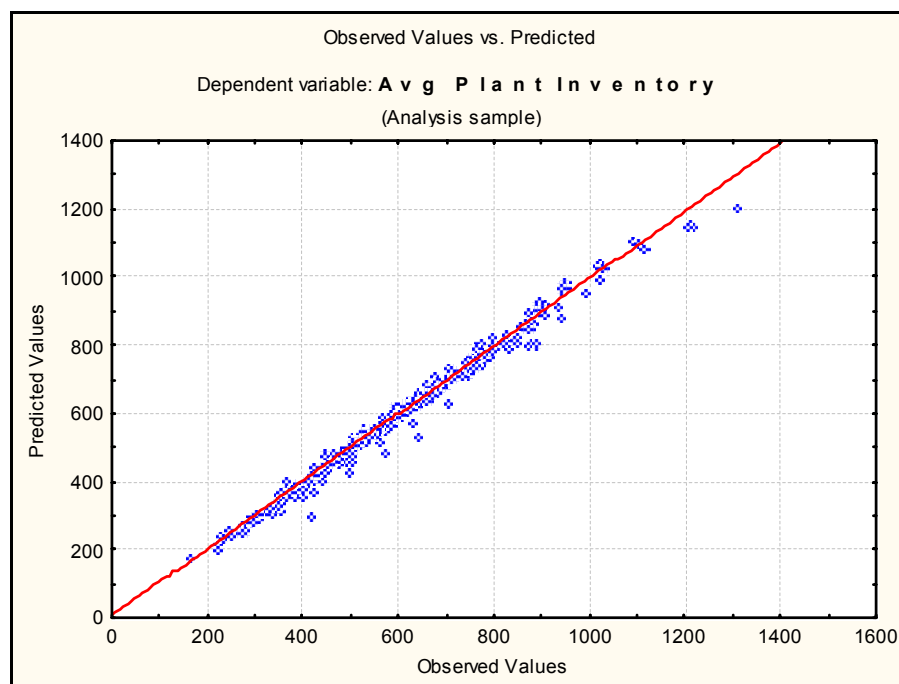


Figure 47: Linear Relationship between Predicted and Observed Values.



In the following section, the reader will note that the extent of the linear relationship is described as being “Rough,” “Fair,” or “Good,” with the latter being the ideal.

A “Rough” relationship, although not ideal, can still provide valuable information to the analyst. The reader will understand the meaning of this statement after it is clarified in section 7.2.2.2, starting on page 110.

7.2 Regression Analysis Results.

This section presents the summarised results of the Regression Analysis for all four Usage Categories. Refer to Appendix J for the detailed Statistical Results.

The reader is guided through the section in the following manner:

1. Generalised Summary of Results.
2. Significance of Input Parameters and Matrix Plot of Observations.
3. Customisation Guidelines for Safety Time and Coverage Profile Settings.

The “Generalised Summary of Results” presents a very broad indication of the quality of the Regression Equations in terms of the:

- Adjusted R^2 Value.
- Number of variables used in the equation.
- Distribution of Residuals.
- Relationship between Observed and Predicted Values.

The significance of the Input Parameters is discussed in terms of their influence on the various Performance Measures. These are summarised and presented in a matrix format.

The observations taken from the Regression Equations provided the basis for the customisation guidelines. These guidelines specify which combinations of Safety Time, Minimum and Target Coverage, produce similar result in terms of Avg. Plant Inventory, Avg. Order Size, and Avg. Number of Orders. Other than proving that the SAP-MRP System can provide the required Avg. customer Service Level, these guidelines are probably the most significant outcome of this entire study.



7.2.1 Generalised Summary of Results.

The reader may refer to Appendix J for each of the tables referred to in this summary. The Summary Tables per Usage Category are found on the following pages.

Usage Category	Table	Page
Ultra Low Runners	Table 47	L
Low Runners	Table 56	LXIII
Medium Runners	Table 66	XCI
High Runners	Table 76	CXIX

Table 31: Reference Locations of Regression Summary Tables.

Reference to the above tables shows that that the Service Level Performance Measures are described by two equations. The first describes the behaviour of Avg. Customer Service Level, in terms of an equation that has been forced through zero. The second includes the intercept of the equation. The equation intercepts of the second equation are employed later as an indication of the baseline performance of the SAP-MRP System.

Generally, each Performance Measure for all four Usage Categories has an associated Adjusted R^2 Value of 0.94 and above with the majority having values 0.99. Equations with associated values of 0.9 and above were suitable for analysis. These equations provided valuable information regarding the influence that the input variables have on the behaviour of the respective Performance Measures. The quality of the Regression Equations, indicated by the distribution of the residuals and the linear relationship between Observed and Predicted dependant variable values, was high enough for analysis purposes. The Regression Equation quality was indicated by terms such as "Rough," "Fair," and "Good." A reduction in quality and Adjusted R^2 Value from Ultra Low to High Runners is seen in the Service Level and Shortages Performance Measures. This occurrence does not reflect negatively on the value provided by the Regression Analysis, but in fact shows that the SAP-MRP System provides a high baseline Avg. Customer Service Level for these Usage Categories. This baseline performance is directly proportional to the ADD of a part and is achieved without increasing the settings of Safety Time, Minimum or Target Coverage above zero. More of this phenomenon is explained further on in this section.



7.2.2 Observations and Findings.

This section deals with the observations and findings made upon the summarised results presented in the previous section. It does not deal with the actual Regression Equations themselves or the variable coefficients, as those topics are discussed in the next section.

It is clear when reviewing the Summary Tables in Appendix J, that there are two noticeable trends, namely:

1. A downward trend (from Ultra Low to High Runners) in the magnitude of the Adjusted R^2 Values.
2. An upward trend (from Ultra Low to High Runners) in the occurrence of “Rough” linear relationships between the Observed and Predicted dependent variable values.

These two observations/trends are in fact linked to each other, as the linearity of the Observed and Predicted Values is directly proportional to the Adjusted R^2 Value. One would tend to think that both observations provide the same information rather than anything of individual value. However, each observation has provided unique and vital information that is essential to the analysis of the SAP-MRP System.

The value of each is presented below.

7.2.2.1 Downward Trend in Adjusted R^2 Values.

A noticeable downward trend across the Usage Categories is observed when examining the Adjusted R^2 Values of the Avg. Customer Service Level, (reference is made to the Service Level equations that are not forced through zero) and Avg. Customer Shortages Performance Measures. This trend is shown below in Figure 48. It shows that the Regression Equations explain less of the variability in the “Higher Runners” than they do in the Ultra Low Runners. “Higher Runners” includes the Low Runners, Medium Runners and High Runners and not Ultra Low Runners.

It is important to note in which Performance Measures that this trend is present i.e. Avg. Customer Service Level and Avg. Customer and Total Shortages. These two measures are intrinsically linked to each other, because an increase in Shortages would definitely result in a reduced Avg. Customer Service Level. Thus, one would expect their Adjusted R^2 Values to decrease together because by being able to explain the behaviour of Avg. Customer Shortages you are also explaining the behaviour of the associated Avg. Customer Service Level. In fact, if this were not the case, then there is a serious error in the simulation model.

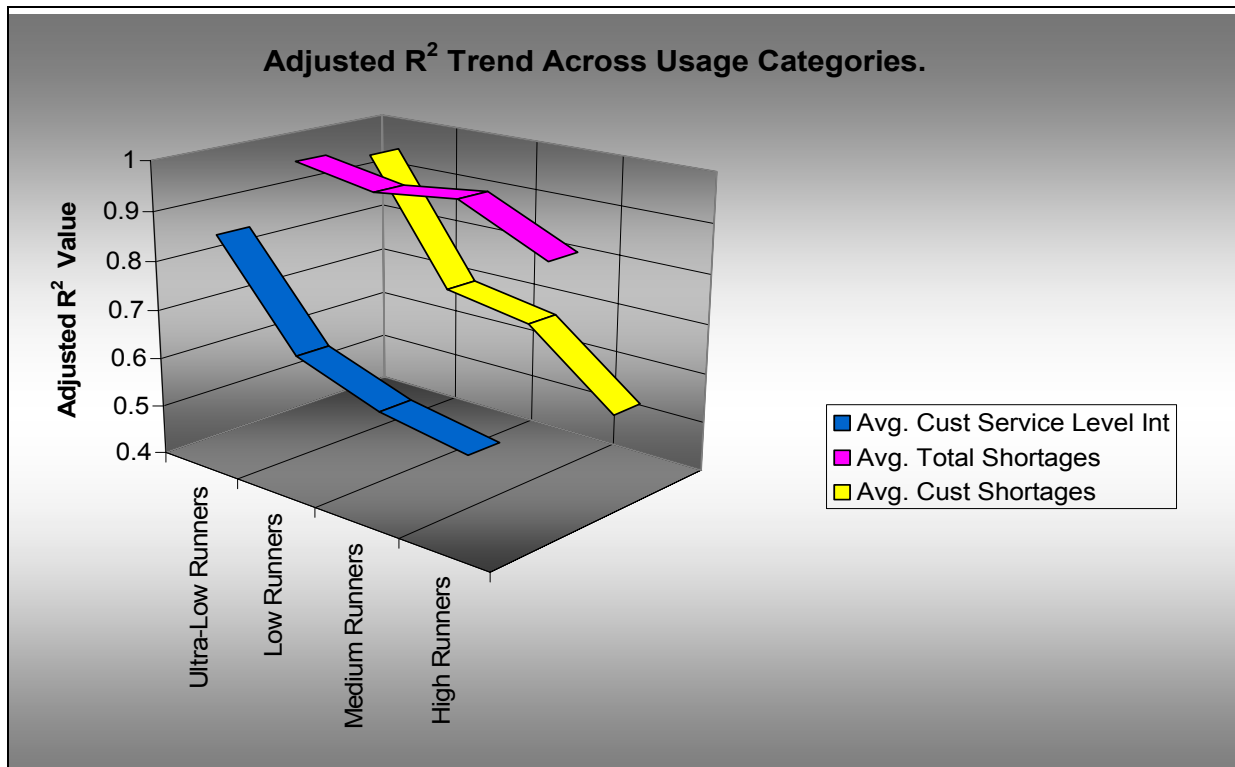


Figure 48: Adjusted R² Downward Trend across Usage Categories.

As mentioned earlier, a reduction in the Adjusted R² Values does not have negative connotations for the simulation model, fitted Regression Equations, or the SAP-MRP System. One would think that because of this trend, it is impossible to analyse the behaviour of the SAP-MRP System in terms of “Higher Runner” Service Level (the most important measure to DCSA). However, this is not true, as important information remains provided by the Avg. Customer Service Level intercepts that are utilised as baseline Service Level performance indicators

Examination of Table 47 through Table 76 revealed that the intercepts of the Avg. Customer Service Level Regression Equations not forced through zero essentially remained close to one. The Intercept values varied from 0.93 to 1.02, with the majority being above 0.97, whilst the Adjusted R² Values gradually decreased (across the Ultra Low to High Runner Usage Categories) from 0.86 to 0.57. The intercepts show that the baseline performance remained close to 100% across the Usage Categories, whilst the ability to describe the variability in Avg. Customer Service Level decreased. This then shows that the Regression Equations can account for a high Avg. Customer Service Level in the Ultra Low Runners, whilst providing little information about the comparably high Avg. Customer Service Level in the remaining Usage Categories.



It is important to bear in mind that the Regression Equation essentially comprises of two different groups of input variables. The first group are those that can be controlled by DCSA i.e. Safety Time, Coverage Profile (refer to Glossary), Lead-Time, and Pallet Size (the latter two, to a limited extent). The second group, which includes Avg. Daily Demand and Flip Mean, cannot be influenced. The values of the second group were held constant per part for all experiments across the Usage Categories, whilst the values were varied in the first group. Consequently, a direct link exists between the behaviour of the various Performance Measures and the settings of the Input Parameters. Therefore, in the context of this discussion as well as that of the other Performance Measures, the Adjusted R^2 Value actually describes the degree of influence that the Input Parameters have on Avg. Customer Service Level. The settings of the Input Parameters therefore contribute directly to the high Avg. Customer Service Level in the Ultra Low Runners as indicated by the Adjusted R^2 Value of 0.86. This deduction is further refined by the hypothesis that Avg. Customer Service Level is a direct result of the Safety Time, Coverage Profile, Pallet Size, and Lead-Time settings, whereas low Adjusted R^2 Values in the remaining Usage Categories indicate that Avg. Customer Service Level cannot be influenced or controlled by the aforementioned Input Parameters. More precisely, factors other than those included in the Regression Analysis attribute to high observed Avg. Customer Service Levels in the “Higher Running” Usage Categories. These factors are explained later.

Figure 49, seen below, further strengthens the previous discussion by indicating a downward trend across the Usage Categories in the Adjusted R^2 Value versus the lowest observed Avg. Customer Service Levels. The lowest observed values are taken from Table 24 on page 79. The figure shows that the observed Avg. Customer Service Levels increased, whilst the Adjusted R^2 Values decreased across the Usage Categories.

The combination of the trend in Adjusted R^2 Values and the observed Avg. Customer Service Levels, shown in Figure 49, further serves to illustrate that DCSA has the ability to better control the Ultra Low Runner Service Levels than it does the “Higher Runner” Service Levels. This is because the latter Usage Category has a 98% Service Level even at its worst i.e. no adjustments need to be made to the SAP-MRP System in order to improve the Avg. Customer Service Level. In contrast the Ultra Low Runner Usage Category has the lowest Avg. Customer Service Level of all the Usage Categories, which can however be improved by increasing Safety Time, Minimum or Target Coverage.

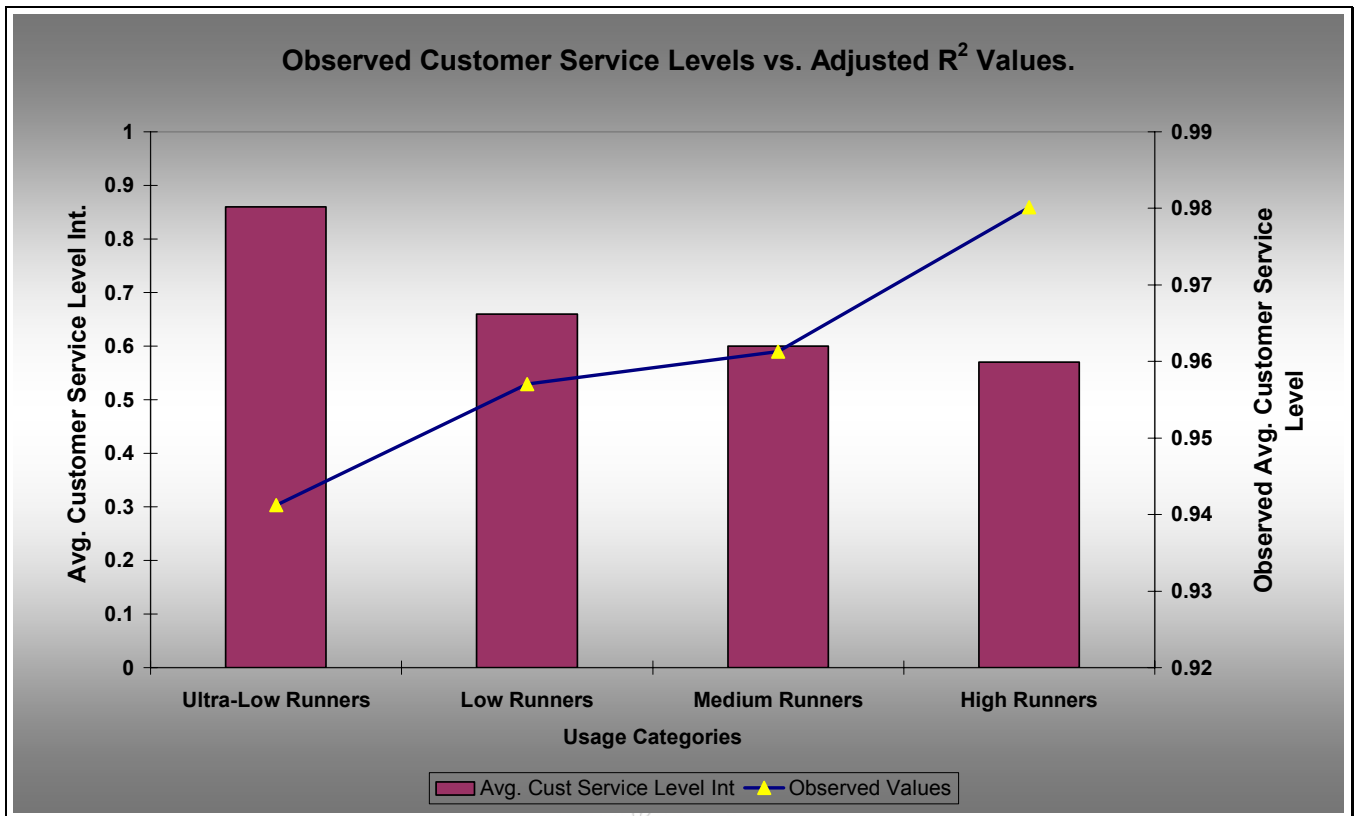


Figure 49: Observed Avg. Customer Service Levels vs. Adjusted R² Values.

The question now arises “How can DCSA improve the Avg. Customer Service Level in the Ultra Low Runners, and what will cause this improvement?” Ultra Low Runners receives focus in terms of improving Avg. Customer Service Level because it is the Usage Category with lowest Avg. Customer Service Level. Logic dictates that simply increasing the Plant Inventory levels by increasing Safety Time, Minimum and/or Target Coverage solves this problem. However, it is the author’s intent to observe the interaction between these Input Parameters when following this methodology and the influence that these interactions have on the various Performance Measures. The lessons learnt here will then be used as a benchmark when analysing the remaining Usage Categories. This will then show which Input Parameters are more influential on specific Performance Measures across the various Usage Categories.

7.2.2.1.1 Improving Avg. Customer Service Level in Ultra Low Runners.

The “Absorption Ability” (see Glossary) of the inflated stock levels, caused by the Statistical Component of the SAP-MRP System, attribute directly to the ability to have improved control over the Ultra Low Runner Service Levels. Therefore, it should be understood that DCSA could minimise the Ultra Low Runner Shortages and maximise the associated Service Levels by adjusting the Safety Time and Coverage Profile values to such a degree that the resultant stock levels can absorb any increase in demand.



The issue of improving the “Higher Runner” Service Levels is not a great concern (illustrated by the Observed Values that are almost equal to 100%), as a marginal increase in demand has a higher probability of causing a stock-out occurrence in the Ultra Low Runners, than in the “Higher Runners.”

The following example will demonstrate how the use of Safety Time and Coverage Profile can avert a stock-out occurrence in the Ultra Low Runner Usage Categories. Simultaneously, the affect of Safety Time and Coverage Profile on High Runners is demonstrated to illustrate the term “Absorption Ability.”

Example:

Imagine two parts - Part A and Part B. A is an Ultra Low Runner and B is a Medium Runner. There exists also, a demand for both parts on Production Day X, but no plant is in stock (to simplify the example). For the purpose of this example, Order Lead-Time is zero days.

	Safety Time And Coverage Profile	Part A	Part B
Scenario 1	ST = 0 MC = 0 TC = 0	ADR = 0.5 units per day Production Requirement = 2 units Pallet Size = 3 Order Release = 1 Pallet Remaining Stock = 1 unit	ADR = 82 units per day Production Requirement = 78 units Pallet Size = 7 Order Release = 12 Pallets Remaining Stock = 6 units
Scenario 2	ST = 2 MC = 1 TC = 1	ADR = 0.5 units per day Production Requirement = 2 units Pallet Size = 3 Order Release = 2 Pallets Remaining Stock = 4 units	ADR = 82 units per day Production Requirement = 78 units Pallet Size = 7 Order Release = 48 Pallets Remaining Stock = 258 units
Key			
ST = Safety Time		MC = Minimum Coverage	TC = Target Coverage

Figure 50: Stock “Absorption Ability.”

Here it is seen that a marginal increase in demand for Part A has a greater possibility of creating a stock-out occurrence, whereas a similar increase for Part B will not produce the same result.

Scenario 1 demonstrates that Part A’s Remaining Stock can absorb a maximum increase in demand of 50%, whereas the Remaining Stock in Scenario 2 can tolerate a 200% increase in demand before a stock-out occurrence. This improvement is a direct result of “activating” the Statistical Component of the SAP-MRP System i.e. setting Safety Time, Minimum Coverage, and Target Coverage to values greater than zero.



This example is also a good illustration of the reason why baseline Avg. Customer Service Level is so high for the “Higher Runner” Usage Categories. The probability of the demand for an Ultra Low Runner increasing by such a margin that a stock-out occurs is greater than that of a similar occurrence in the “Higher Running” Usage Categories. Using Scenario 1 from the previous example to illustrate this point, the probability that the demand for Part B increases by more than 6 units is less than the probability that demand for Part A increases by more than 1 unit.

7.2.2.2 “Rough” Linear Relationship between Observed and Predicted Values.

Note: The process of categorising the relationships between Observed and Predicted Values was a function of the author’s subjectivity. To simplify the categorisation process the author used the linear relationships of Avg. Plant Inventory and Avg. Customer Service Level as benchmarks of “Good” and “Rough” relationships respectively. Any relationship that fell between these benchmarks was classified as “Fair.”

The relationship between the Observed and Predicted Values was described as having a “Rough,” “Fair,” or “Good” relationship. Although a “Good” or even “Fair” relationship is ideal in terms of behaviour analysis of Performance Measures, a “Rough” relationship should not be discounted as having no analysis value. This section will describe the information that is extracted from a “Rough” linear relationship between Observed and Predicted Values

“Rough” relationships were found in two different Performance Measure Categories, namely Avg. Customer Service Level and Avg. Customer Shortages. Figure 51 on page 111 and Figure 52 on page 111 demonstrate these examples.

Three factors attribute to the shape of the plotted data shown in Figure 51. Firstly, the Observed Avg. Customer Service Levels did not rise above one. This indeed makes sense, since the system cannot achieve a Service Level greater than 100%. Secondly, the Regression Equation predicted values greater than one and thirdly, most of the Observed Values occurred between 0.999 and 1 (which accounts for the bunched-up appearance). The dispersion of the data points indicates that when utilising the Avg. Customer Service Level equation for prediction purposes, any calculated value greater than one actually equates to a value equal to one. Furthermore, examination of the scale and range of the Observed and Predicted Values reveals that the Avg. Customer Service Level for this category is practically 100%.

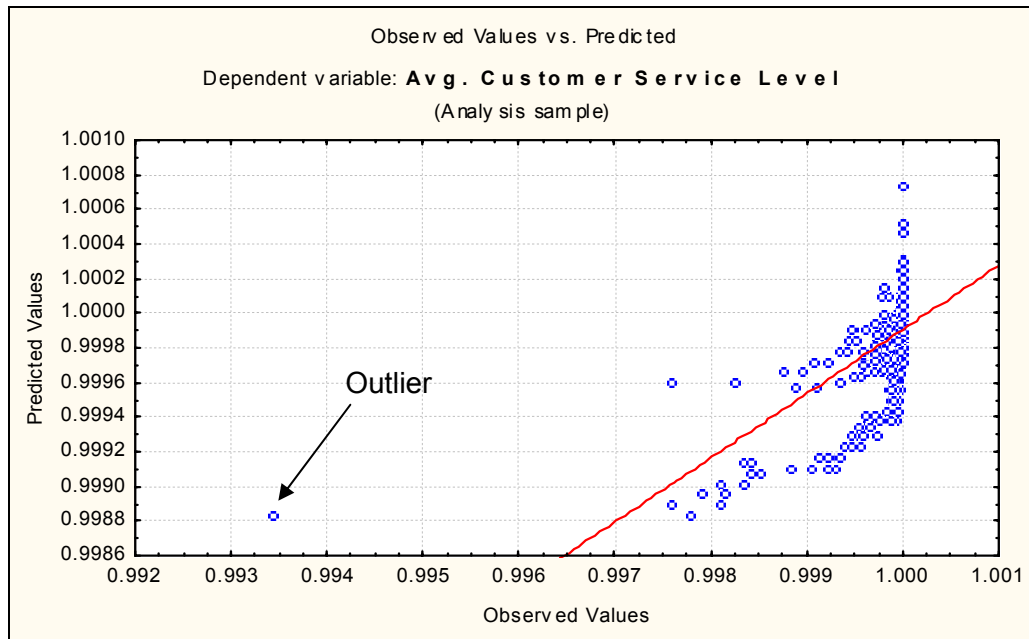


Figure 51: Example 1 of a “Rough” Linear Relationship.

Similarly, Figure 52 shows that the majority of the predicted Avg. Customer Shortages within this Usage Category that lie within the range of -2 and 2, equate to an observed value equal to zero. In addition, it is observed that this Usage Category has very few Avg. Customer Shortages over a period of 1000 days. Example 2 shows that the maximum observed shortages for that period is equal to 25 units. By examination it is seen that this data point is an outlier, so by discounting this value it is seen that the maximum value for this period is equal to 9 units in 1000 days.

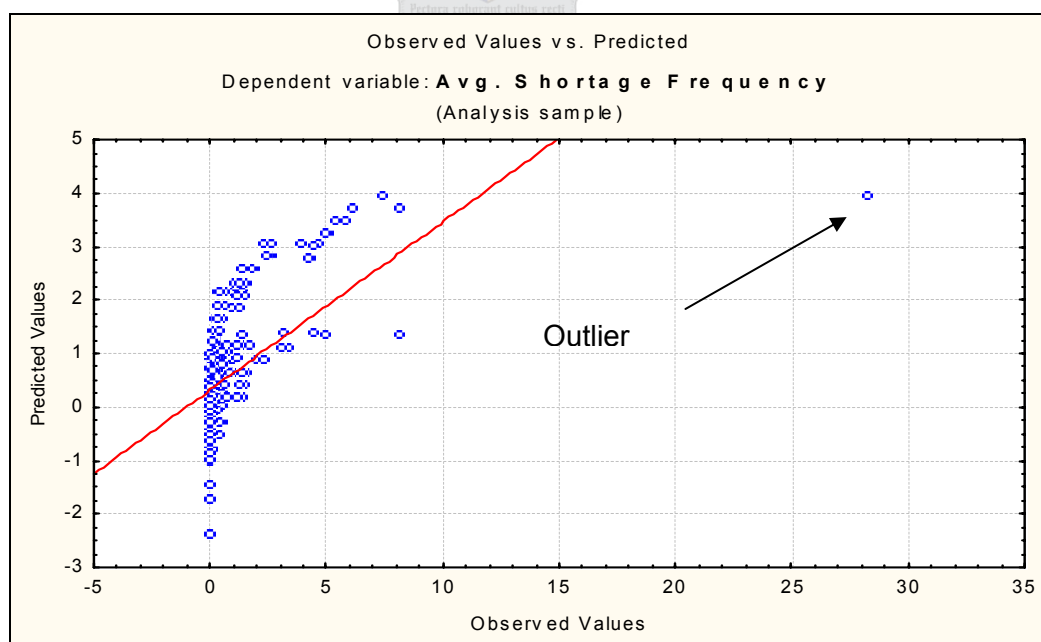


Figure 52: Example 2 of “Rough” Linear Relationship.



Note: The previous figures clearly demonstrate outlier data points (as indicated on the figures). Common practice dictates removal of these data points followed by re-analysis. In pursuing this method, it was found that removing these points did not significantly improve the analysis. Removal of one point merely placed focus on the “bunched-up” data (after re-plotting the Observed vs. Predicted Values obtained from the new Regression Equation) consequently highlighting hundreds of outlier data points. Removal of all of these points would clearly render the analysis useless. It was therefore decided to not remove any outliers.

7.2.3 Significance of Variable Coefficients and “Matrices of Observations.”

Refer to Appendix J for the detailed Regression Analysis results that include the equations and graphical plots per Usage Category.

This section presents a discussion centred on the tabulated observations contained within the “Matrix of Observations” contained in Appendix K.

The structure of each “Matrix of Observations” indicates the magnitude of a specific coefficient in terms of sign, Relative Contribution towards the Regression Equation, and order of importance for the individual independent variable.

The Relative Contribution of each variable coefficient was judged according to the Beta value assigned to the specific coefficient. The Betas indicate the rate of change of the dependent variable with respect to each of the identically scaled independent variables. Therefore, a Beta close to zero signifies a small rate of change in the dependent variable relative to that particular independent variable; a high positive Beta means a high positive rate of change.

Each cell in a matrix indicates three items of information regarding the independent variable coefficient. The following example describes the relationship between the input parameter (ST+TC) and Avg. Pipeline Inventory shown in Table 86 found in Appendix K.

<p>-:4: (12.6)</p>

The sign within the cell, and the print colour, indicate the sign of the coefficient. Secondly, the relative importance of the variable, in terms of the other variables, is shown after the sign of the variable. The value in brackets indicates the percentage contribution of the variable coefficient towards the calculated dependent variable. Hence, the reader would read this cell in the following manner:

(ST+TC) has a negative sign and contributes 12.6% towards the change in Avg. Pipeline Inventory, as well as being the fourth most influential variable in the Regression Equation. An increase in (ST+TC) results in a decrease in Avg. Pipeline Inventory.



The reader should not attempt to judge the behaviour of a respective Performance Measure by critically analysing the Relative Contribution of a single input variable such as (ST+TC). Such a technique will not yield useful results as this places the analytical focus on a very small aspect of a large system. A more valuable approach would be to “take a step back” and look at “the bigger picture.”

The reader will remember the creation of inter-variable relationships discussed earlier (see to Section 7.1.6on page 98). These relationships complicate the analysis process due to the complex interactions that they represent. The analyst cannot judge the Relative Contribution of a single input variable without taking into account the interactions that it may have with the remaining input variables. For example, the analyst may wish to quantify the role that Pallet Size plays in the Avg. Number of Orders in Ultra Low Runners. Reference to Table 86 in Appendix K will show that the input variable Pallet Size has a negative sign and only contributes 17.9% towards the change in Avg. Number of Orders. Were the process of examination to stop here, the analyst would erroneously believe that this was the total contribution of the input parameter. By “taking a step back,” it is seen that Pallet Size also interacts with Safety Time, Minimum, and Target Coverage, signifying that the analyst must also take into account the values of the aforementioned Input Parameters.

The author followed the “taking a step back” approach and viewed the Regression Equations as a “Black-Box.” “Black-Box” is an analogy used by engineers to describe a system where knowledge of the internal operations is unknown or not required. Changing certain Input Parameters and then analysing the resultant output evaluated the behaviour of a respective Performance Measure. Figure 53 illustrates this approach.

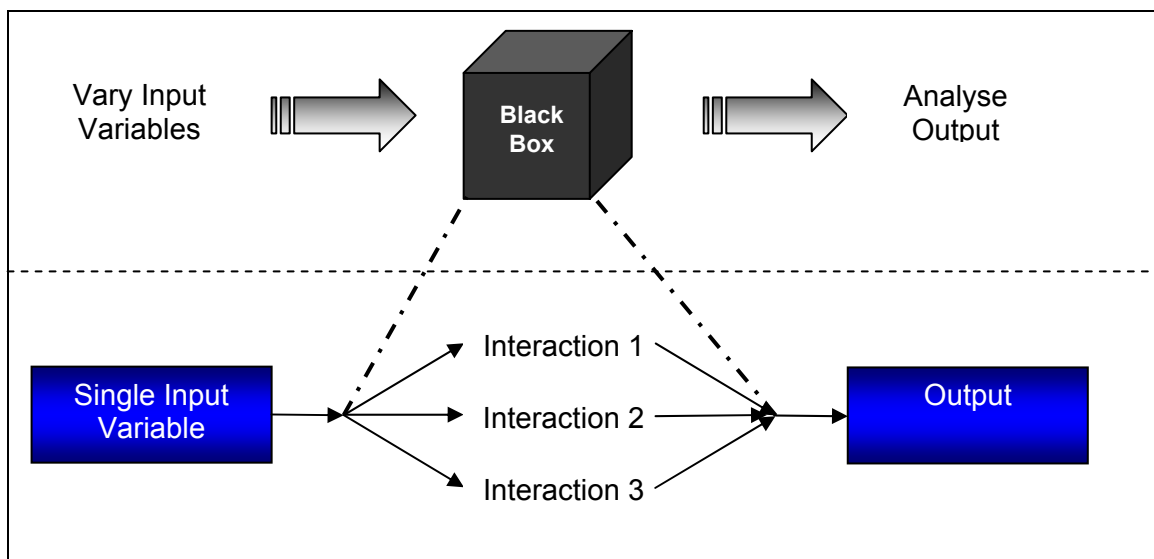


Figure 53: Black Box Approach.



Safety Time, Coverage Profile, Pallet Size and Days to Assembly were the only factors varied (across specific ranges) when analysing the behaviour of the Performance Measures, relative to their Input Parameters. A primary reason for selecting these variables for analysis was that these are the only independent input variables included in the analysis that can be controlled by DCSA. The individual influence of Flip Mean and Avg. Daily Demand on the behaviour of the Performance Measures, in terms of their relative influence, could not be assessed in a similar manner (by varying their values). This could not be done because the Regression Equations demonstrated extreme sensitivity to their values. This necessitated conducting the analysis by holding the values of these parameters constant.

Figure 53 on page 113 illustrates how the effect of varying a single input variable spreads out to interacting variables.

The following section presents a summary, per Usage Category, of the results shown in the “Matrices of Observations.” This summary will indicate the Total Relative Contribution of each input parameter in terms of their unique interaction.

7.2.3.1 Summary of “Matrices of Observations.”

Figure 54 on page 115 illustrates how the Total Relative Contribution was calculated. The column on the left (taken from the “Matrix of Observations”) represents the various equation variables contained within the Regression Equations. The column on the right represents the manner in which they were categorised in order to calculate their Total Relative Contribution.

By summing the percentage contribution of all the input variables contained within a category, the Total Relative Contribution was calculated. For example, the Total Relative Contribution of the Part Demand Characteristics Summary Category towards Avg. Plant Inventory in Ultra Low Runners is equal to 5.8% (refer to Table 32 on page 118). This Total Relative Contribution is calculated by adding up the Relative Contributions of the two equation variables contained within that Summary Category, namely: Avg. Daily Demand and Flip Mean. By referring to the Ultra Low Runner “Matrix of Observations” (Table 86 in Appendix K), it is seen that their Relative Contributions are equal to 0.0 and 5.8% respectively. The Total Relative Contribution of the remainder of the Summary Categories was calculated in a similar manner. The reader will note that there is at times a small error of 0.1% when adding up the contributions in the manner shown earlier. This error is attributed to rounding off and is not viewed as being a serious problem or detracting from the conclusions made.

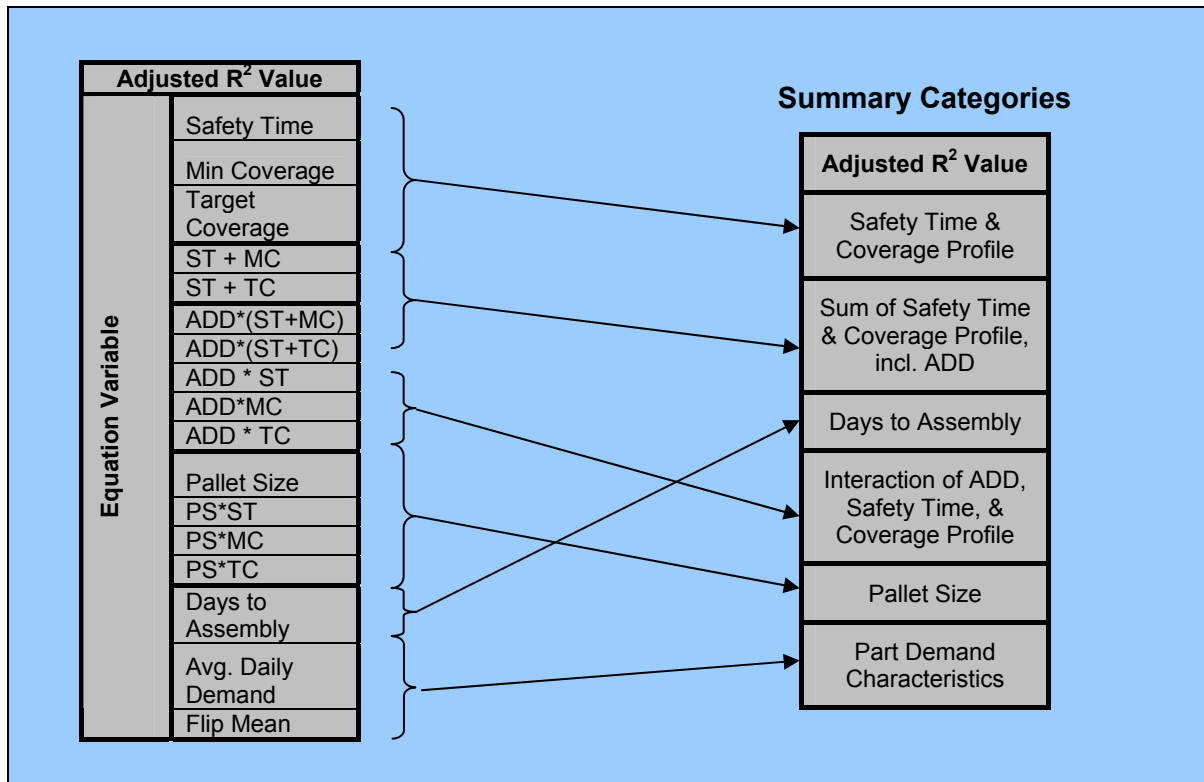


Figure 54: Creation of Summary Categories from “Matrix of Observations.”

A brief explanation will follow as to why the equation variables were categorised in the manner indicated in Figure 54.

- **Safety Time and Coverage Profile:** This Summary Category contains the following equation variables: Safety Time, Minimum Coverage, and Target Coverage, which represent the sole Relative Contribution of these particular Input Parameters. This Summary Category indicates if any of these Input Parameters played an individually significant role in the behaviour of a specific Performance Measure i.e. without interacting with any other input parameter. This Summary Category was created with the specific intent of identifying whether Safety Time, Minimum or Target Coverage had a significant influence (on their own) on the behaviour of the SAP-MRP System or not.
- **Sum of Safety Time & Coverage Profile, including ADD:** This Summary Category contains the following equation variables:
 - $(ST+MC)$ = Safety Time + Minimum Range of Coverage.
 - $(ST+TC)$ = Safety Time + Target Range of Coverage.
 - $ADD*(ST+MC)$ = Avg. Daily Demand*(ST+MC).
 - $ADD*(ST+TC)$ = Avg. Daily Demand*(ST+TC).



These equation variables indicate the Relative Contribution of the known interaction (see Section 4.4.2.2 on page 47) between Safety Time, Coverage Profile, and the Avg. Daily Requirements (represented in the regression by Average Daily Demand). The creation of this Summary Category provides a tool for the analyst to confirm whether Safety Time and Coverage Profile contributed more to the behaviour of the SAP-MRP System on an individual basis, or whether their known interaction carried more weight as a describing variable. The confirmation would come from comparing this Summary Category's contribution to that of the first Summary Category, which indicated the sole contribution of Safety Time, Minimum and Target Coverage.

- **Days to Assembly (Lead-Time):** This Summary Category describes the Relative Contribution that delivery Lead-Time has towards each of the Performance Measures.
- **Interaction of ADD, Safety Time, & Coverage Profile:** This Summary Category contains the following equation variables:
 - $ADD*ST = \text{Avg. Daily Demand} * \text{Safety Time.}$
 - $ADD*MC = \text{Avg. Daily Demand} * \text{Minimum Range of Coverage.}$
 - $ADD*TC = \text{Avg. Daily Demand} * \text{Target Coverage.}$

These equation variables were created for reasons similar to those of the first Summary Category i.e. to determine whether ST, MC, or TC on their own (as opposed to the known interaction when SAP-MRP calculates a proposed Order Release, see Section 4.4.2.2 on page 47) had a significant influence of the Performance of the SAP-MRP System or not. The only difference between these equation variables and those of the first Summary Category is the inclusion of ADD. ADD was included based on the known interaction between ADR and ST, MC, and TC (see Section 4.4.2.2 on page 47).

- **Pallet Size:** This Summary Category contains the following equation variables:
 - Pallet Size.
 - $PS*ST = \text{Pallet Size} * \text{Safety Time.}$
 - $PS*MC = \text{Pallet Size} * \text{Minimum Range of Coverage.}$
 - $PS*TC = \text{Pallet Size} * \text{Target Range of Coverage.}$

These equation variables describe the Relative Contribution of Pallet Size and the possible interaction between Pallet Size, Safety Time, and Coverage Profile. In its entirety, this Summary Category describes the Relative Contribution of Pallet Size towards the behaviour of the various Performance Measures.



-
- **Part Demand Characteristics:** This Summary Category contains the following equation variables:
- Avg. Daily Demand.
 - Flip Mean.

These equation variables quantify the behaviour of a part in terms of the average daily Production Requirements as well as the typical fluctuations in demand that a particular part experiences from the point of Order Release. This behaviour is the driving force behind the SAP-MRP System, determining what quantities are ordered (see Section 4.4.1 on page 45). The reader will note that a low Relative Contribution by this Summary Category is usually complemented by a high Relative Contribution from the 2nd Summary Category, which also includes the influence of Avg. Daily Demand. This relationship is expected and indicates that the influence of ADD is more statistically significant when it is combined with Safety Time, Minimum and Target Coverage than when it is on its own. The combined relationship of ADD and the aforementioned Input Parameters indicates that the Part Demand Characteristics of a part still have a significant influence on a specific Performance Measure.

The next four sub-sections will present the summaries of the “Matrices of Observations.”





7.2.3.1.1 Ultra Low Runners.

Note: The significant Summary Category contributions are highlighted in red. The non-highlighted contributions are insignificant relative to the highlighted contributions.

			Performance Measure									
			Inventory			Orders		Service Level		Shortages		
			Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages	
							Int. = 0	Int. = 0.98				
			Adjusted R² Value	0.99	0.99	0.99	0.94	0.99	0.99	0.86	0.97	0.95
Summary Category	1	Safety Time & Coverage Profile	0.0%	0.0%	8.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	2	Sum of Safety Time & Coverage Profile, incl. ADD	13.8%	25.9%	7.2%	24.7%	18.2%	25.6%	33.3%	22.2%	20.3%	
	3	Days to Assembly	7.7%	25.2%	11.9%	27.0%	1.8%	36.5%	4.3%	8.8%	31.4%	
	4	Interaction of ADD, Safety Time, & Coverage Profile	2.0%	0.0%	2.6%	0.0%	0.0%	0.0%	0.0%	9.5%	0.0%	
	5	Pallet Size	70.7%	19.1%	12.8%	33.6%	76.6%	17.2%	54.4%	11.8%	37.0%	
	6	Part Demand Characteristics	5.8%	29.8%	57.3%	14.8%	3.3%	20.7%	7.9%	47.8%	11.4%	

Table 32: Summary of Ultra Low Runner “Matrix of Observations.”

Inventory:

- Avg. Plant Inventory.

Pallet Size, almost completely dominates the behaviour of Avg. Plant Inventory (in comparison to the other Usage Categories) indicating that the Avg. Plant Inventory levels associated with this Usage Category are more a function of Pallet Size than any other input parameter. It is evident that Safety Time and Coverage Profile have a marginal influence on Avg. Plant Inventory, which is attributed to the control that they exercise over Plant Inventory levels. In addition, Part Demand Characteristics play a weak role in the behaviour of this Performance Measure. This observation confirms the fact that Pallet Size determines the resultant Plant Inventory levels for this Usage Category.



➤ *Avg. Pipeline Inventory.*

Safety Time and Coverage Profile have greater influence over Avg. Pipeline Inventory than in the case of Avg. Plant and Harbour Inventory. This observation is attributed to the amount of stock present in the Order Pipeline as opposed to that of the Plant and Harbour. The total amount of stock present in the Order Pipeline is usually greater than that in the Plant and Harbour. Any changes to the settings of Safety Time and Coverage Profile will show greater influence in those areas where more stock is present as opposed to those where less stock is present. Days to Assembly has a logically high influence over the behaviour of Avg. Pipeline Inventory, as the inventory levels of Order Pipeline are directly proportional to that of Order Lead-Time. Pallet Size and Part Demand Characteristics too have a strong role in determining the behaviour of this Performance Measure. This is attributed to large Pallet Sizes (relative to the ADD) and the role that ADD plays in determining Plant Inventory levels.

➤ *Avg. Harbour Inventory.*

Part Demand Characteristics dominates the behaviour of this Performance Measure. Reference to Table 86 in Appendix K shows that Avg. Daily Demand is the predominant contributor to this observation, which reflects the role that ADD plays in determining the frequency and magnitude of Order Releases. Pallet Size is the second largest contributor, which is attributed to large Pallet Sizes (relative to the ADD). Understandably, Days to Assembly contributes significantly because part of Order Lead-Time is composed of the time that stock stays in the East London harbour.

Orders:

➤ *Avg. Number of Orders.*

A broad range of Summary Categories influences Avg. Number of Orders with the strongest influence coming from Pallet Size. The behaviour of this Performance Measure is largely influenced by the contribution of Pallet Size, since a large Pallet Size (relative to the ADD) would result in less orders being placed, than would a smaller Pallet Size. The interaction between Safety Time, Coverage Profile, and Avg. Daily Demand (Summary Category 2) plays a stronger role (relative to Avg. Plant and Harbour Inventory) in determining “when” and “how much” is ordered. The role played by Safety Time and Coverage Profile in triggering Order Releases is now confirmed. It is also interesting to note that Days to Assembly is also an influential Summary Category (referring to Table 86 in Appendix K, it is seen that this input parameter has the highest single contribution towards this Performance Measure). This can be attributed to the demand changes that occur during Order Lead-Time, which result in the Available Stock being lower than



expected upon arrival of the required stock. This reduced Plant Stock in turn produces additional Order Releases.

➤ *Avg. Order Size.*

Pallet Size understandably (for this Performance Measure) almost completely dominates Avg. Order Size. The magnitude of a released order is a multiple of the Pallet Size and a single pallet will nearly always cover the requirements of this Usage Category. Therefore, the magnitude of an Order Release will usually be a function of the Pallet Size rather than the settings of Safety Time, Minimum or Target Coverage, which in this case play a minor role in determining the magnitude of an Order Release.

Service Level:

➤ *Avg. Customer Service Level.*

In terms of the Relative Contributions of each Summary Category, describing this Performance Measure proved rather complicated. The reader will note when comparing the two equations contained within Service Level i.e. Intercept = 0 and Intercept = 0.98, that no Summary Category demonstrates the same Relative Contribution. To simplify the explanation of this behaviour, the author will present both the observations made upon the output of the Ultra Low Runner DOE and the application of the relevant Regression Equations. These observations, presented in Section 8.1 on page 132, give a clear indication of the role that the various Input Parameters play in determining Avg. Customer Service Level.



Shortages:

➤ *Avg. Total Shortages.*

This Performance Measure is highly dependent on Part Demand Characteristics. Reference to Table 86 in Appendix K shows that ADD is responsible for this large contribution. A possible explanation for this could lie in the fact that the ADD term is carrying some of the influence attributed to Flip Sigma, which was removed due to Multicollinearity (refer to Section 7.1.3.1 on page 94). Flip Sigma definitely describes the variability in demand and thus stock-out occurrences would be directly proportional to Flip Sigma. Therefore an increase in ADD would result in an increase in Avg. Total Shortages. The Categories containing the input variables, Safety Time, Minimum and Target Coverage, as well as Pallet Size play an understandably important role in determining the behaviour of this Performance Measure. This observation is attributed to the manner in which this Performance Measure is calculated (see Avg. Total Shortages in Appendix N).



➤ *Avg. Customer Shortages.*

Examining the “Matrix of Observations,” shows that an increase in the sum of Safety Time and Coverage Profile effectively results in a reduction in *Avg. Customer Shortages*. This confirms that improvement in *Avg. Customer Service Levels* for Ultra Low Runners is possible by increasing the “Absorption Ability” of the Plant Stock. Days to Assembly also plays a significant role, as an increase in Lead-Time could result in additional changes in demand, which would then have a greater probability of stock-out occurrence. Pallet Size can reduce Customer Shortages, because Plant Inventory is directly proportional to Pallet Size, and an increased level of Plant Stock improves the “Absorption Ability.” Part Demand Characteristics plays an important role for the same reasons described in *Avg. Total Shortages* above.

7.2.3.1.2 Low Runners.

		Performance Measure									
		Inventory			Orders		Service Level		Shortages		
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages	
							Int. = 0	Int.=0.97			
		Adjusted R² Value	0.99	0.99	0.99	0.96	0.99	0.99	0.66	0.94	0.7
Summary Category	1	Safety Time & Coverage Profile	0.8%	0.0%	0.0%	24.7%	0.0%	0.0%	0.0%	0.0%	0.0%
	2	Sum of Safety Time & Coverage Profile, incl. ADD	28.4%	22.7%	3.1%	0.0%	1.4%	36.9%	54.7%	14.4%	17.0%
	3	Days to Assembly	3.4%	16.9%	3.0%	19.6%	0.0%	29.0%	0.0%	12.5%	29.7%
	4	Interaction of ADD, Safety Time, & Coverage Profile	0.0%	0.0%	4.4%	19.9%	73.3%	0.0%	0.0%	0.0%	0.0%
	5	Pallet Size	2.5%	5.4%	1.9%	20.8%	15.6%	9.9%	25.6%	3.7%	0.0%
	6	Part Demand Characteristics	64.9%	55.0%	87.7%	14.9%	9.6%	24.2%	19.6%	69.4%	53.3%

Table 33: Summary of Low Runner “Matrix of Observations.”



Inventory:

➤ *Avg. Plant Inventory.*

Avg. Plant Inventory is strongly influenced by Part Demand Characteristics. This indicates that it is the primary driving force behind the Plant Inventory levels as opposed to Pallet Size, which was the case in Ultra Low Runners. A definite shift in dependency has occurred between Ultra Low Runners and Low Runners, highlighted by the increased Relative Contribution of Summary Category 2. This observation indicates that Safety Time and Coverage Profile have far greater control over the magnitude of Order Releases, as opposed to Ultra Low Runners that was dominated by Pallet Size. Close examination of Table 87 in Appendix K shows that Flip Mean is the chief contributing variable in terms of determining the behaviour of this Performance Measure. This shows that the changes in demand over Order Lead-Time play a greater role in determining Avg. Plant Inventory. The latter observation is confirmed by examining the rate at which these changes occur (measured here by Flip Mean) and comparing them to the other Usage Categories, whilst keeping in mind the ADD. This point is illustrated in the following example.

Example:

Part #	ADD (Units per Day)	Flip Mean (Change in Demand per Day)	Lead-Time (calendar days)
1120101144 A (Ultra Low Runner)	0.55	0.00269	53
2032700400 A (Low Runner)	27.27	0.03500	53

Table 34: Flip Mean of Ultra Low Runner vs. Low Runner.

As seen here the Flip Mean of the Low Runner is 1200% greater than the Ultra Low Runner. This indicates that the rate of change is a lot higher for the Low Runner Usage Category, which translates to a greater increase in demand over the same Order Lead-Time as the Ultra Low Runner. The increase in demand over Lead-Time results in a decrease in Available Stock, which in turn results in additional Order Releases. Therefore, these additional Order Releases result in an increase in Avg. Plant Inventory.

➤ *Avg. Pipeline and Harbour Inventory.*

Both Avg. Pipeline and Harbour Inventory proved to be more substantially influenced by Part Demand Characteristics than any other Summary Category. Reference to Table 87 in Appendix K, shows that ADD is responsible for this contribution in both instances. This shows that DCSA can do very little to influence the behaviour of Avg. Harbour Inventory. Avg. Pipeline Inventory can be marginally influenced by the settings of Safety Time and Coverage Profile, although ADD will still be the primary driver in this Performance Measure. Once again, Days to Assembly is shown to play a role, albeit relatively low, in determining the behaviour of Avg. Pipeline Inventory.

**Orders:**

➤ *Avg. Number of Orders.*

Avg. Number of Orders shows influence from a broad range of Summary Categories, coming predominantly from Summary Category 1. Table 87 in Appendix K shows that Minimum and Target Coverage are the soul source of the 24.7% contribution towards the behaviour of this Performance Measure. This observation indicates that Safety Time is not a significant variable in this analysis. Further, in addition to ADD*ST also not being a significant contributor, analysis of Table 87 shows that ADD*MC and ADD*TC both have the same sign as do Minimum and Target Coverage in Summary Category 1. The latter observation goes one-step further in showing that Safety Time is not a significant contributor. It is interesting to note that Days to Assembly is an influential Summary Category as well. In referring to Table 87 in Appendix K, it is seen that this input parameter has the highest single contribution towards this Performance Measure. This contribution can be attributed to the demand changes that occur during Order Lead-Time, which result in the Available Stock being lower than expected upon the arrival of the Order Releases. In turn, this reduced Plant Stock results in the creation of additional Order Releases. Pallet Size also contributes a fair amount to the behaviour of this Performance Measure, since a large Pallet Size (relative to the ADD) would result in placing fewer orders, than would a small Pallet Size. Part Demand Characteristics contributes almost 15% towards the behaviour of this Performance Measure. Table 87 indicates that this contribution stems from ADD, indicating that an increase in ADD results in an increase in the frequency of Order Releases. This is a logical occurrence since an increase in ADD would result in more stock being consumed than parts with a lower ADD, thus resulting in more Orders being placed to satisfy the higher demand.

➤ *Avg. Order Size.*

Avg. Order Size proves less dominated by Pallet Size, as was the case in Ultra Low Runners. This is due to a decrease in the Pallet Size/ADD ratio for this Usage Category, which results in an improved ability to order the required amount rather than over-ordering. It becomes evident that Minimum and Target Coverage play a greater role in determining the magnitude of an Order Release. The contribution from Summary Category 4 confirms this. Table 87 shows that ADD*MC and ADD*TC are the sole contributors to the 73.3% Relative Contribution of this Summary Category. An increase in ADD*TC results in an increase in Avg. Order Size, whilst an increase in ADD*MC results in a decrease in Avg. Order Size. The reason for this behaviour is explained by referring to Figure 44 on page 93. By holding Minimum Coverage constant and increasing Target Coverage, one would effectively increase the “distance” between these two parameters.



This increase would mean that SAP-MRP would have to release an order of greater magnitude such that Available Stock/ADR \geq (Safety Time + Target Coverage). A similar observation is made by holding Target Coverage constant and increasing Minimum Coverage, except in this instance the “distance” would decrease and thus result in an order of smaller magnitude.

Service Level:

- As was the case in Ultra Low Runners the behaviour of the Performance Measure as a function of the various Input Parameters is explained in Section 8.1 on page 132.

Shortages:

- *Avg. Total Shortages.*

This Performance Measure demonstrates a profound dependence on Part Demand Characteristics. Table 87 shows that ADD and Flip Mean contribute an almost equal amount towards the behaviour of this Performance Measure. This makes sense, in that this is the only Summary Category to contain any equation variable that describes the manner in which demand changes occur i.e. Flip Mean. In addition, it is possible that ADD contains some of the influence attributed to Flip Sigma, which was removed due to Multicollinearity. Days to Assembly plays a greater role in describing the behaviour of this Performance Measure. This observation is in line with the argument presented in *Avg. Plant Inventory*, which attributed Order Lead-Time with increasing the Plant Inventory levels. In addition, Summary Category 2 also plays a role in determining the behaviour of this Performance Measure and is in-line with the method in which this Performance Measure is calculated (see *Avg. Total Shortages* in Appendix N).

- *Customer Shortages.*

This Performance Measure has an Adjusted R^2 Value that is too low for the purpose of analysis. The behaviour of this Performance Measure is described in Section 8.1 on page 132.



7.2.3.1.3 Medium Runners.

		Performance Measure									
		Inventory			Orders		Service Level		Shortages		
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages	
							Int. = 0	Int. = 1.02			
		Adjusted R² Value	0.99	0.99	0.99	0.96	0.99	0.99	0.60	0.96	0.67
Summary Category	1	Safety Time & Coverage Profile	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	2	Sum of Safety Time & Coverage Profile, incl. ADD	42.4%	32.5%	31.0%	47.7%	56.2%	51.7%	43.8%	71.9%	33.2%
	3	Days to Assembly	0.0%	36.0%	4.8%	11.2%	0.0%	13.2%	7.3%	6.3%	0.0%
	4	Interaction of ADD, Safety Time, & Coverage Profile	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Pallet Size	44.8%	2.0%	4.3%	23.4%	39.6%	3.0%	9.3%	16.7%	21.0%
	6	Part Demand Characteristics	12.8%	29.5%	59.9%	17.7%	4.2%	32.0%	39.5%	5.0%	45.8%

Table 35: Summary of Medium Runner “Matrix of Observations.”

Inventory:

- *Avg. Plant Inventory.*

Avg. Plant Inventory is predominantly influenced by Summary Category 2, indicating that this is the primary driving force behind Avg. Plant Inventory. It is in line with expectations regarding the manner in which Safety Time, Minimum and Target Coverage, are employed in maintaining Plant Inventory levels (Refer to Section 4.2 on page 42). Furthermore, this observation shows that the sum of Safety Time and Coverage Profile can be effectively used to control Avg. Plant Inventory. The reader may be surprised that Pallet Size has been assigned a high Relative Contribution, since the ADD of this Usage Category is too high to be affected by Pallet Size, as was the case with Ultra Low Runners. The reason for the high Relative Contribution is attributed to the fact that, for this Usage Category, the DOE contained experiments using parts with very large Pallet Sizes (see Table 26 on page 87) i.e. bulk parts.



➤ *Avg. Pipeline and Harbour Inventory.*

Both these Performance Measures are largely influenced by Part Demand Characteristics with Avg. Pipeline Inventory in turn, being strongly influenced by Days to Assembly. The increased ADD relative to the previous Usage Categories, which results in comparatively large volumes of parts moving through the Order Pipeline, contributes to this. Thus, any change in the length of Order Lead-Time would result in a significant, directly proportional change in the volume of parts in the Order Pipeline. It is seen that Summary Category 2 has a substantial Relative Contribution towards the behaviour of Avg. Pipeline Inventory. An increase in the sum of Safety Time and any one of the Coverage Profile components will result in an increase in Avg. Plant Inventory. This will in turn increase the frequency or magnitude of Order Releases, thus causing an increase in Avg. Pipeline Inventory. Part Demand Characteristics and Summary Category 2 primarily influence Avg. Harbour Inventory. DCSA can therefore control the inventory stored in the harbour, in a manner similar to controlling the inventory in the plant, to a limited extent.

Orders:

➤ *Avg. Number of Orders.*

This Performance Measure is influenced by a broad range of Summary Categories, with the strongest influence coming from Summary Category 2. It is seen that the interaction between Safety Time, Coverage Profile, and Avg. Daily Requirements (Summary Category 2) plays a strong role in determining “when” and “how much” is ordered. This confirms the role that the sum of Safety Time and Coverage Profile play in triggering Order Releases. It is also interesting to note that Days to Assembly is also an influential Summary Category (referring to Table 88 in Appendix K), in terms of determining the behaviour of this Performance Measure. This can be attributed to the demand changes that occur during Order Lead-Time, which result in the Available Stock being lower than expected upon the arrival of the required stock. This reduced Plant Stock then results in additional Order Releases being created. In addition, Pallet Size contributes a fair amount to the behaviour of this Performance Measure, since a large Pallet Size (relative to the Avg. Daily Demand) would result in less orders being paced, than would a small Pallet Size.

- *Avg. Order Size* is highly influenced by Pallet Size, as was the case in Ultra Low Runners. This is attributed to the large Pallet Sizes employed in the analysis of this Usage Category (see Table 26 on page 87). The sum of Safety Time and Coverage Profile is seen to play a greater role in determining the magnitude of an Order Release indicating that DCSA can exercise control over the behaviour of this Performance Measure i.e. control the average size of an Order Release.



Service Level:

- As was the case in Ultra Low Runners the behaviour of the Performance Measure as a function of the various Input Parameters is explained in Section 8.1 on page 132.

Shortages:

- Avg. Total Shortages receives a relatively low contribution from Part Demand Characteristics as compared to the two previous Usage Categories. This further highlights the fact that the higher running parts have an improved “Absorption Ability,” and thus have relatively no associated stock-out occurrences. The high Relative Contribution assigned to Summary Categories 2 and 4 echoes the manner in which this Performance Measure is calculated (see Avg. Total Shortages in Appendix N) as so does Pallet Size.
- Avg. Customer Shortages has an Adjusted R² Value that is too low for the purpose of analysis. The behaviour of this Performance Measure is described in Section 8.1 on page 132.

7.2.3.1.4 High Runners.

		Performance Measure									
		Inventory			Orders		Service Level		Shortages		
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages	
							Int. = 0	Int.=0.93			
		Adjusted R² Value	0.99	0.99	0.99	0.97	0.99	0.99	0.57	0.88	0.53
Summary Category	1	Safety Time & Coverage Profile	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	2	Sum of Safety Time & Coverage Profile, incl. ADD	85.1%	69.5%	49.1%	0.0%	52.6%	62.2%	92.2%	54.9%	26.0%
	3	Days to Assembly	0.0%	25.8%	0.0%	10.1%	3.1%	2.0%	0.0%	1.4%	42.8%
	4	Interaction of ADD, Safety Time, & Coverage Profile	1.9%	0.0%	0.0%	37.7%	0.0%	0.0%	0.0%	39.3%	0.0%
	5	Pallet Size	11.0%	0.5%	1.9%	32.7%	43.9%	0.5%	3.3%	1.0%	19.9%
	6	Part Demand Characteristics	2.0%	4.3%	49.1%	19.5%	0.4%	35.4%	4.5%	3.3%	11.2%

Table 36: Summary of High Runner “Matrix of Observations.”



Inventory:

➤ *Avg. Plant Inventory.*

Avg. Plant Inventory is predominantly influenced by Summary Category 2, which indicates that this is the primary driving force behind Avg. Plant Inventory. This is in line with expectations as this Summary Category contains the equation variable “Avg. Daily Demand,” which is a primary factor in calculating the magnitude of an Order Release such that the resultant Available Stock covers production and plant requirements (see Section 4.2 on page 42). Pallet Size has been assigned a lower Relative Contribution when compared to the value calculated in Medium Runners; even though large Pallet Sizes were used in the DOE experiments (see Table 26 on page 87). The reason for the reduction is attributed to the increased ADD, which results in a lower Pallet/ADD ratio (a Pallet/ADD ratio less than or equal to 0.5 is ideal.). The Relative Contribution of Pallet Size towards the behaviour of Avg. Plant Inventory, in any Usage Category, is said to be directly proportional to the aforementioned ratio. It is seen that Summary Category 2 has a very high Relative Contribution, indicating the sum of Safety Time and Coverage Profile can be effectively used to control Avg. Plant Inventory. Interestingly enough, it is seen that Days to Assembly has no significant Relative Contribution, which shows that changes in demand over Lead-Time have minimal influence on Avg. Plant Inventory. This further substantiates the finding that “Higher Runners” have a “default” high Service Level due to their “Absorption Ability.” This Usage Category can absorb increases in demand to such an extent that no stock-outs occur even though a net decrease in the Available Stock is caused by the increase in demand.

➤ *Avg. Pipeline Inventory.*

Avg. Pipeline Inventory is strongly influenced by both Days to Assembly as well as the sum of Safety Time and Coverage Profile. The dependency on Days to Assembly is attributed to the increased ADD relative to the previous Usage Categories, which results in comparatively large volumes of parts moving through the Order Pipeline. Thus, any change in the length of Order Lead-Time would result in a significant, directly proportional change in the volume of parts in the Order Pipeline. Summary Category 2 provides the highest Relative Contribution towards the behaviour of Pipeline Inventory. Any increase in the sum of Safety Time and any one of the Coverage Profile components will result in an increase in Avg. Plant Inventory as well as an increase in the frequency or magnitude of Order Releases. This will in turn increase the Avg. Pipeline Inventory.



➤ *Avg. Harbour Inventory.*

Part Demand Characteristics and Summary Category 2 primarily influence Avg. Harbour Inventory. Examination of Table 89 in Appendix K shows that ADD provides the highest Relative Contribution towards the behaviour of this Performance Measure. Therefore, DCSA cannot exercise large-scale control of the inventory stored in the harbour, relative to the manner in which Avg. Plant Inventory is controlled, because ADD cannot be influenced by any means.

Orders:

➤ *Avg. Number of Orders.*

Avg. Number of Orders is influenced by a broad range of Summary Categories, with the strongest influence coming from Summary Category 4. This is attributed to manner in which Order Releases are created and the influence that the “distance” between Minimum and Target Coverage has on the frequency of Order Releases. Refer to the discussion of Avg. Number of Orders in Low Runners in Section 7.2.3.1.2 on page 121. Once again, Safety Time was found not to be a significant input variable. Pallet Size provides the second largest Relative Contribution towards the behaviour of this Performance Measure with the frequency of Order Releases placed being inversely proportional to Pallet Size. Part Demand Characteristics has a significant contribution with the entire contribution coming from ADD. This observation shows that an increase in ADD results in an increased frequency of Order Releases. An increase in ADD results in a higher rate of stock consumption, which then results in an increased rate of Order Releases in order to satisfy the higher demand.

➤ *Avg. Order Size.*

Pallet Size plays a significant role in determining Avg. Order Size. In addition to this being attributed to large Pallet Sizes, it is also a logical conclusion since the magnitude of an Order Release will always be a multiple of the Pallet Size. Part Demand Characteristics has a small significant Relative Contribution, whilst the sum of Safety Time and Coverage Profile has a high Relative Contribution of 52.6%. This indicates that DCSA can control the Avg. Order Size by means of the sum of the Safety Time and Coverage Profile settings.

Service Level:

- As was the case in Ultra Low Runners the behaviour of the Performance Measure as a function of the various Input Parameters is explained in Section 8.1 on page 132.

**Shortages:**

- Avg. Total Shortages has an Adjusted R^2 Value that is too low for the purpose of analysis. The behaviour of this Performance Measure is described in Section 8.1 on page 132.
- Avg. Customer Shortages has an Adjusted R^2 Value that is too low for the purpose of analysis. The behaviour of this Performance Measure is described in Section 8.1 on page 132.

7.3 Summary.

Regression Analysis provided a means of analysing the large quantities of data generated by the DOE, which was conducted in the previous chapter. This data was grouped according to ADD into one of four Usage Categories, which ranged from Ultra Low Runner to High Runner. Each Usage Category was utilised as a **generic indicator** of all the parts at DCSA that would fall into these Usage Categories. In addition, these Usage Categories were felt to **represent the typical Part Demand Characteristics** associated with the aforementioned DCSA parts. Thus, analysing these Usage Categories, opposed to a part-by-part analysis, **provided a concise and coherent method of presenting the resulting observations** made on the associated SAP-MRP System performance. Furthermore, the Regression Equations provided a means of **proving or disproving the various assumptions** present at DCSA, as to the exact influence each input parameter has on the SAP-MRP System.

The key points of this chapter are highlighted below.

- Review of statistical literature highlighted various factors that play an influential role in the quality of the results obtained from Regression Analysis. Of these factors, **Multicollinearity** had the most impact on this study. Flip Sigma and ADD were highly correlated, which resulted in **Flip Sigma being removed** from the analysis. Flip Mean and ADD displayed a similar, albeit reduced, level of correlation. Flip Mean or ADD could however, not be excluded from the analysis without causing Omitted Variable Bias or reducing the Adjusted R^2 Value.
- The input data obtained from the DOE was placed in 10 different worksheets, with each of them representing one of the 10 Performance Measures. Regression Analysis was performed on each of the Usage Categories by importing the respective workbooks into Statistica.
- The **quality** of the Regression Analysis was judged according to the **Adjusted R^2 Value**, **the linear relationship between Observed and Predicted Values**, and the **Normal Distribution of the Residuals**.



-
- Two Performance Measure Categories, namely: Inventory and Orders, consistently displayed high quality results across all four Usage Categories. The result of this being that the **Regression Equations** for these Usage Categories could be used for **accurate analysis, prediction, and critical examination purposes**. The Usage Categories displayed a **downward trend** (across the Usage Categories from Ultra Low to High Runners) in quality of the Service Level and Shortages Performance Measures, but this in itself **produced valuable information** regarding the **importance of the Coverage Profile settings in lower running parts**.
 - Results from the Regression Analysis consistently showed that **on an individual basis Safety Time, Minimum, and Target Coverage are not significant contributors** towards the behaviour of any of the SAP-MRP Performance Measures. In contrast, the analysis showed that **the sum of the aforementioned Input Parameters were significant contributors**, thus showing that **Safety Time specifically is not a significant contributor** towards the behaviour of any of the Performance Measures **particularly Avg. Customer Service Level**. Further, the analysis showed that Pallet Size was the dominant factor with respect to the behaviour of the Inventory Performance Measures of the Ultra Low Usage Category. However, this influence was reduced in the case of the Low, Medium and High Runner Usage Categories, which were primarily influenced by their associated ADDs. These two observations showed that efforts to reduce Avg. Plant Inventory, by reducing Pallet Size, would only be effective in the Ultra Low Runner Usage Category. The associated inventories of the higher running Usage Categories are only really influenced by the sum of Safety Time, Minimum, and Target Coverage as well as the ADD. Therefore, focus should be placed on the settings of Safety Time, Minimum, and Target Coverage when attempting to reduce Avg. Plant Inventory for the aforementioned Usage Categories.



8. Usage Category Behaviour & Customisation Guidelines.

The final section of the previous chapter presented generalised observations and findings taken from the “Matrices of Observations” given per Usage Category. Grouping together and categorising these findings described the Total Relative Contributions of the Input Parameters in terms of their interactions with other input variables. However, no explanation was given of the manner in which a specific input parameter influences a particular Performance Measure e.g. How does Pallet Size influence Avg. Customer Service Level in the Medium Runners? The first section of this chapter quantifies the influence that each input parameter has on the various Performance Measures. The second section demonstrates the development of the Decision Support Tool that indicates changes in Avg. Plant Inventory, Avg. Number of Orders, and Avg. Order Size for a specific part resulting from adjusted Safety Time, Minimum and Target Coverage Profile settings.

8.1 Analysis of Regression Equations and DOE Observations.

Refer to Appendix L for the detailed result discussed within the following sub-sections.

This section discusses and presents the findings arrived at as a result of the analysis of the Regression Equations as well as the observations made on the results of the DOE. The discussion differs from that presented at the end of the previous chapter due to explanations that demonstrate how specific Input Parameters affect the various Performance Measures.

The reader will notice that the results contained within Appendix L are a combination of those obtained from the Regression Analysis as well as observations made on the output of the DOE. The reason behind this is due to the Adjusted R^2 Values that were too low in certain instances to permit investigation, so the results from the DOE were utilised for analysis purposes instead.

The Performance Measures were plotted as a function of the sum of Safety Time and Coverage profile i.e. (ST+MC) and (ST+TC), where the output of the DOE was analysed. The reason for this approach lies in the fact that results presented by the Regression Analysis consistently showed that these variables were more statistically significant describing variables as opposed to ST, MC, and TC on their own. Examination of the “Matrices of Observations” found in Appendix K will prove this statement, as well as the summarised results presented in the previous chapter.

The analysis was conducted by using a randomly selected part utilised in the DOE (see Table 26 on page 87). Only Regression Equations with suitably high Adjusted R^2 Values (0.9 and above), were employed for the purpose of analysis.



The influence of the following Input Parameters was assessed:

- Pallet Size (termed “The Effect of Palletization”).
- Lead-Time (termed “The Effect of Days to Assembly”).
- Safety Time, Minimum, and Target Coverage (termed “The Effect of Safety Time and Coverage Profiles Combinations”).

It was not possible to assess the influence of Flip Mean and Days to Assembly, as these Input Parameters were unique part identifiers. Any deviation from the values used in the DOE (for these particular input parameters) created invalid results, as the deviations indicated that the analyst was investigating a part that was not included in the DOE.

Assessment of the influence of the Input Parameters bullet listed above was possible as the DOE varied these Input Parameters per part. Observations made on the DOE backed up the analysis of the Regression Equations in those instances where the author felt the Regression Equation responses might be overly sensitive to the values of the Input Parameters.

Typical questions this section aims to answer are as follows:

- What influence does Pallet Size have on [select Performance Measure]?
- How does the length of Order Lead-Time influence [select Performance Measure]?
- How do the settings of Safety Time and Coverage Profile influence [select Performance Measure]?

Presentation of answers to these questions follows in the four sub-sections.

Note: It is important to read the instructions in Appendix L before continuing.



8.1.1 Ultra Low Runners.

Note: The Safety Time, Minimum and Target Coverage Profile settings for the graphs indicating the influence of Lead-Time and Pallet Size were (2, 4, 5) respectively.

Where indicated otherwise, the following two parts were used for the analysis:

Part #	Pallet Size	Lead-Time (calendar days)	Lead-Time (working days)
0005461781 A	40	44	32
1120101144 A	3	53	37

Palletization: Referring from Figure 214 to Figure 219.

An increase in Pallet Size (from 3 to 40) results in:

- Avg. Plant Inventory increased by 270% and 420% for parts “0005461781” and “1120101144” respectively, with an associated 733.3% increase in Pallet Size.
- A reduction in Avg. Pipeline Inventory of 10.6% and 17.8% for parts “1120101144” and “0005461781” respectively.
- Avg. Harbour Inventory increased by 3.65% and 7.1 % for parts “0005461781” and “1120101144” respectively.
- A large reduction in the Avg. Number of Orders and an increase in Avg. Order Size of 928.6%.
- A definite improvement in Avg. Customer Service Level, right across the range of Safety Time and Coverage Profile Combinations.

Days to Assembly: Referring from to Figure 220 to Figure 225.

An increase in Order Lead-Time (ranging from 32 to 37 working days) results in:

- An increase in Avg. Plant Inventory of 1.71% for “0005461781” and an increase of 8% for “1120101144.”
- Avg. Pipeline Inventory increases by 17.6% for “0005461781” and 6% for “1120101144.”
- Avg. Harbour Inventory increased by 3.1% and 5.8% for parts “0005461781” and “1120101144” respectively.
- No change in the Avg. Number of Orders, except for those parts with smaller Pallet Sizes e.g. 3 units as opposed to 40 units per pallet, which showed an increase of 18.8%.
- No change to Avg. Order Size for both parts.
- A reduced Avg. Customer Service Level and an increase in Avg. Customer Shortages, for those parts with smaller Pallet Sizes.



Safety Time and Coverage Profile Combinations: Referring from Figure 226 to Figure 231.

An increase in Input Combination from 1 to 63 results in:

- A reduction in Avg. Plant Inventory of 46% for parts with large Pallet Sizes and an increase of 30% in Avg. Plant Inventory for parts with small Pallet Sizes.
- Avg. Harbour Inventory increased by 34.5% and 6.6% for parts “0005461781” and “1120101144” respectively.
- An increase in Avg. Pipeline Inventory of 1.8% for “1120101144” and an increase of 15.5% for “0005461781.”
- Unchanged Avg. Order Size for large Pallet Sizes. Parts with small Pallet Sizes are influenced by variation in Safety Time and Coverage Profile.
- Definite control over the Avg. Number of Orders placed for parts with small Pallet Sizes. A reduction in the Avg. Number of Orders placed for parts with large Pallet Sizes and an increase for parts with small Pallet Sizes.
- A considerable increase in Avg. Customer Service Level for parts with small Pallets Sizes. Parts with large Pallet Sizes have a “default” high Avg. Customer Service Level.
- A reduction in Avg. Customer Shortages regardless of Pallet Size.

8.1.1.1 Critical Commentary.

Upon closer inspection of the graphs contained in Figure 226 and Figure 231 it is seen that there is a slight upward or downward trend, depending on which graph is being examined. This trend is generally attributed to the incremental increase in Safety Time (see Table 90 in Appendix L).

If considering the gradient of the trend to be an indicator of the magnitude of the influence that Safety Time has on the various Performance Measures, then it is clear that it does not play a significant role in influencing the behaviour of a Performance Measure, as compared to that of Minimum and Target Coverage.

Figure 229 on page CLXXX, which does not group Input Combinations together (refer to the discussion presented at the start of Appendix L), it is seen that the General Gradient (representing the gradual increase in Safety Time) is not as steep as the Partial Gradient, which indicates the result of Target Coverage increasing from 1 to 5 days.

On examination of the Input Combinations, it is evident that Minimum Coverage is the primary driving force behind the incremental increase in the Input Combinations. The reason for this is simply that Target Coverage cannot be lower than Minimum Coverage. Therefore, if Minimum Coverage increases and the maximum value that Target Coverage may assume remains



constant (as was in this study), then the range of values that Target Coverage may assume becomes less. Based on this explanation and the trends in Figure 230 and Figure 232, it should therefore be clear that the simultaneous increase in Avg. Customer Service Level and reduction in Avg. Customer Shortages is attributed to Minimum Coverage being as far away as possible from zero.

Therefore, to minimise Avg. Customer Shortages and maximise Avg. Customer Service Level, DCSA must set the value of Minimum Coverage to be as high as possible. This action will not result in a dramatic increase in Avg. Plant Inventory as shown in Figure 226, which would be their primary concern. This advice also holds true for parts with large Pallet Sizes and in fact causes a reduction in Avg. Plant Inventory. The value of the Target Coverage setting will depend on various factors, such as the frequency and magnitude of Order Receipts that DCSA wish to handle. Safety Time can be set to zero as it has been shown that it does not have a significant influence and does not justify the problem associated with its use (see Section 4.4.3.1 on page 50).

8.1.2 Low Runners.

Note: The Safety Time, Minimum and Target Coverage Profile settings for the graphs indicating the influence of varying Lead-Time and Pallet Sizes were (2, 2, 2) respectively.

The following two parts were utilised in this analysis unless where indicated otherwise.

Part #	Pallet Size	Lead-Time (calendar days)	Lead-Time (working days)
2039709350 27D44A	1	44	32
2032700400 A	7	53	37

Palletization: Referring to Figure 233 through Figure 236.

An increase in the value of Pallet Size (from 1 to 60 units) results in:

- An increase of 18% in Avg. Plant Inventory relative to the 59 000% increase in Pallet Size value.
- A decrease in Avg. Pipeline Inventory of 1.8% and practically no change in Avg. Harbour Inventory.
- An increase in Avg. Order Size of 181%, with a large decrease of 48% in the Avg. Number of Orders.
- An increase in Avg. Customer Service Level as is seen in Figure 235 where (ST+MC) and (ST+TC) both equal zero. The larger Pallet Size of 60 units has an associated Avg. Customer Service Level of 98.9%, whereas the Pallet Size of 10 units has an Avg. Customer Service Level of 96.8%. Note that the advantage of larger Pallet Sizes is



reduced as soon as the Statistical Component of the MRP System is “activated” i.e. where $(ST+MC)$ equals 0, and $(ST+TC) = 1$.

- A considerable reduction in Customer Shortages is seen in Figure 236 where $(ST+MC)$ and $(ST+TC)$ both equal zero. The larger Pallet Size of 60 units has an associated Avg. Customer Shortages of 18 units, whereas the Pallet Size of 10 units has an Avg. Customer Shortages of 70 units. Note that the advantage of larger Pallet Sizes is reduced as soon as the Statistical Component of the MRP System is “activated” i.e. where $(ST+MC)$ equals 0, and $(ST+TC) = 1$.

Days to Assembly: Referring to Figure 237 through Figure 241.

An increase in Order Lead-Time (ranging from 32 to 37 working days) results in:

- No change in Avg. Harbour or Avg. Plant Inventory.
- An increase of 7% in Avg. Pipeline Inventory.
- An increase of about 12% in the Avg. Number of Orders.
- No change to the Avg. Order Size.
- A decrease in Avg. Customer Service Level (very small).
- Neither Avg. Customer Service Level nor Avg. Customer Shortages prove to be sensitive to the length of Order Lead-Time.

Safety Time and Coverage Profile Combinations: Referring from Figure 242 to Figure 246.

An increase in Input Combination from 1 to 63 results in or shows that:

- No change in Avg. Harbour Inventory.
- Slight deviations in Avg. Pipeline Inventory, indicating a very gradual increase of 13.2% in the average inventory present in the Order Pipeline.
- A gradual increase of 244% in Avg. Plant Inventory across the range of Input Combinations. The pattern exhibited shows that Avg. Plant Inventory can definitely be controlled by the setting values of Safety Time, Minimum and Target Coverage.
- Certain Input Combinations result in similar values of Avg. Order Size and Avg. Number of Orders as seen in Figure 243. These Performance Measures can definitely be controlled by Safety Time and Coverage Profile settings.
- Avg. Customer Service Level is improved from 96% to almost 100%. Avg. Customer Service Level increases from 96% to 98.2% as soon as the Statistical Component is “activated.” This is seen where $(ST+MC) = 0$ and $(ST+TC) = 1$.



- A reduction in Avg. Customer Shortages is observed when the Statistical Component is “activated.”

8.1.2.1 Critical Commentary.

When examining Figure 242 through Figure 246, Safety Time can once again be seen to have a minimal influence upon the behaviour of the respective Performance Measures. The reasons for this are similar to those discussed in the Critical Commentary of the Ultra Low Runners.

An interesting pattern is seen in the graphs shown in Figure 242 and Figure 243. These patterns show that a variety of Input Combinations result in similar or equal levels of Avg. Plant Inventory, Avg. Order Size, and Avg. Number of Orders. (The term “similar” is discussed at the end of this sub-section). The observations made on these two figures suggests that identifying the Safety Time, Minimum and Target Coverage settings that result in these similar or equal values could lend itself towards the customisation of the SAP-MRP System at DCSA.

Close examination of Figure 244 and Figure 245 shows that specific combinations of (ST+MC) and (ST+TC) result in reduced Avg. Customer Service Levels or increased Avg. Customer Shortages respectively. This occurs where both (ST+MC) and (ST+TC) are equal. In addition, this observation is reversed when (ST+MC) is low, whilst (ST+TC) is high e.g. (ST+MC) is 2, and (ST+TC) is 7. Investigation of this relationship shows that this pattern always occurs when the difference between Minimum and Target Coverage is at its highest (refer to the proof below). It is evident, therefore, that setting Minimum and Target Coverage as equal produces a negative result. They should rather be set so that the difference between the two is greater than, or equal to, one. A proof of this argument continues in the discussion below.

Proof:

$$ST + MC = X$$

$$ST + TC = Y$$

$$\text{with } X \leq Y$$

By inspection of Table 90 in Appendix L it is seen that Target Coverage is always equal to 5 days when (ST+TC) is at its highest.

$$\text{Therefore, } ST + 5 = Y$$

Solving two simultaneous equations in terms of Minimum Range of Coverage:

$$ST = X - MC : (1)$$

$$ST = Y - 5 : (2)$$

results in

$$MC = X - Y + 5$$



Substitution of any of the (ST+MC) and (ST+TC) values (where (ST+TC) is at its highest, while (ST+MC) is at its lowest) shows that Target Coverage is as far away as possible from the Minimum Coverage.

8.1.2.1.1 Definition of the term “similar.”

At this stage the reader will probably question the term “similar” within the context of Avg. Plant Inventory, Avg. Order Size, and Avg. Number of Orders. Stepping into an in-depth discussion regarding the definition of this term will disrupt the flow of this section. Therefore, for the time being the reader must understand that “similar” Avg. Plant Inventory values vary between 1 and 10% of each other. Similar values of Avg. Order Size and Avg. Number of Orders vary within a narrower margin. A comprehensive discussion regarding the definition of this term is found in Section 8.2.1 on page 143.

8.1.3 Medium Runners.

Note: The Safety Time, Minimum and Target Coverage Profile settings for the graphs indicating the influence of varying Lead-Time and Pallet Sizes were (2, 2, 2) respectively.

Where indicated otherwise, the following two parts were used for the analysis:

Part #	Pallet Size	Lead-Time (calendar days)	Lead-Time (working days)
2710106700 A	3	53	37
2094000402 A	30	44	32

Palletization: Referring to Figure 247 through Figure 251.

An increase in Pallet Size value (from 3 to 900 units) results in:

- A marginal increase of 4% in Avg. Pipeline Inventory.
- No change to Avg. Harbour Inventory.
- A 170% increase in Avg. Plant Inventory, but only after Pallet Size had increased by 29 900%.
- A large reduction of 94.1% in Avg. Number of Orders with an associated increase of over 1800% in Avg. Order Size.
- A marginal increase in Avg. Customer Service Level, which is practically 100% even for parts with small Pallet Sizes.
- A large reduction in Customer Shortages. The advantage of larger Pallet Sizes is reduced as soon as the Statistical Component of the MRP System is activated as is seen in Figure 251.



Days to Assembly: Referring to Figure 253 through Figure 257.

- An increase in Order Lead-Time (ranging from 32 to 37 working days) results in:
- An increase of 9% in Avg. Pipeline Inventory.
- No change in Avg. Harbour Inventory or Avg. Plant Inventory.
- A 6% increase in Avg. Number of Orders with no change in Avg. Order Size.
- No noticeable change in Avg. Customer Service Level or Avg. Customer Shortages.

Safety Time and Coverage Profile Combinations: Referring from Figure 258 to Figure 262.

An increase in Input Combinations from 1 to 63 results in or shows that:

- An increase of 11% in Avg. Harbour Inventory.
- A reduction of 3.4% in Avg. Pipeline Inventory for “2710106700,” whilst “209400402” shows a marginal increase of 2.9% in Avg. Pipeline Inventory. The difference in behaviour is not large in practical terms, but a possible explanation is found in Critical Commentary at the end of this section.
- An increase of 292% in Avg. Plant Inventory. The pattern exhibited by the behaviour of this Performance Measure shows that Avg. Plant Inventory can definitely be controlled by the settings of Safety Time, Minimum and Target Coverage.
- A relationship exists in Figure 259 similar to that discussed in Low Runners. This suggests that the frequency and magnitude of Order Releases can be controlled by the settings of Safety Time and Coverage Profile.
- Avg. Customer Service Level is improved as seen in Figure 261, although minimally when taking into consideration the scale of the improvement. Avg. Customer Service Level is 0.977 (97.7%) before activation of the Statistical Component.
- A large reduction in the occurrence of Customer Shortages. The reduction is accentuated when the Statistical Component is “activated.”

8.1.3.1 Critical Commentary

The observations made here are similar to those made in the Low Runner Category, therefore the commentary would be much the same in terms of Customisation opportunities and the influence that setting (ST+MC) and (ST+TC) equal to each other has. The only noticeable difference between the two Usage Categories is that Avg. Customer Service Level and Avg. Customer Shortages stabilise far quicker. This observation is attributed to the increase in ADD and occurs about where (ST+MC) and (ST+TC) both equal two. The increase in ADD increases this Usage Category’s “Absorption Ability” and thus reduces stock-out occurrences.



The difference in behaviour observed in Avg. Pipeline Inventory, when increasing the Input Combinations from 1 to 63, is possibly attributed to the Pallet Sizes used in this experiment. Plant Inventory levels are at their lowest when the Input Combinations are at their lowest, thus the associated “Absorption Ability” is drastically reduced. In such a situation large Pallet Sizes help minimise the stock-out occurrences and consequently reduce the rate of Emergency Orders, which is the case in this experiment. Therefore, a decrease in Emergency Orders will reduce the Avg. Pipeline Inventory. This advantage, in terms of large Pallet Sizes, is reduced as the Input Combinations increase because the Statistical Component improves the “Absorption Ability” and not Pallet Size. Therefore, the reduction in Avg. Pipeline Inventory for “2710106700” is attributed to the reduction in stock-out occurrences and the increase for “209400402” is attributed to the increase in Input Combinations.

8.1.4 High Runners.

Note: The Safety Time, Minimum and Target Coverage Profile settings for the graphs indicating the influence of varying Lead-Time and Pallet Sizes were (2, 2, 2) respectively.

Where indicated otherwise, the following two parts were used for the analysis:

Part #	Pallet Size	Lead-Time (calendar days)	Lead-Time (working days)
2038170920 A	30	44	32
2038171020 A	35	53	37

Palletization: Referring to Figure 264 through Figure 268.

An increase in Pallet Size value (from 7 to 900 units) results in:

- An increase in Avg. Plant Inventory. Avg. Plant Inventory levels increase by more than 100% with an associated 12 757 % increase in Pallet Size. This indicates that Avg. Plant Inventory in the High Runner Category is not sensitive (in terms of the increase in Plant Inventory relative to the increase in Pallet Size) to an increase in Pallet Size. This would also mean that attempts to reduce Avg. Plant Inventory for non-bulk parts by reducing Pallet size are quite futile.
- No change in Avg. Harbour Inventory as well as Avg. Pipeline Inventory.
- A reduction of 81.7% in the Avg. Number of Orders with an associated increase of 764.3% in Avg. Order Size.
- A very small increase Avg. Customer Service Level relative to the increase in Pallet Size. Reference to Figure 267 shows that a Pallet Size of 35 units has an Avg. Customer Service Level of 98.7% and Pallet Size of 900, for the same part, has an Avg. Customer Service Level of 99.6%.



- A substantial reduction in the occurrence of Avg. Shortage Frequencies. The effect is reduced as soon as the Statistical Component is “activated.”

Days to Assembly: Referring to Figure 269 through Figure 274.

An increase in Order Lead-Time (ranging from 32 to 37 working days) results in:

- A 15% increase in Avg. Pipeline Inventory.
- No change in Avg. Plant inventory as well as Avg. Harbour Inventory.
- An 8.3% increase in Avg. Order Size.
- A 5.2% increase in Avg. Number of Orders.
- No change to Avg. Customer Service Level as well as Avg. Customer Shortages.

Safety Time and Coverage Profile Combinations: Referring from Figure 275 to Figure 279.

An increase in Input Combination from 1 to 63 results in or shows that:

- A very slight deviation in Avg. Pipeline and Avg. Harbour Inventory. This indicates little can be done in the way of influencing them. Avg. Pipeline Inventory and Avg. Harbour Inventory show a 5% and 3.6% increase across the Input Combination range respectively.
- An increase of 931.7% in Avg. Plant Inventory. Deviations in Avg. Plant Inventory indicate the magnitude of inventory in the plant is controllable, by means of Safety Time, Minimum and Target Coverage settings.
- A relationship, similar to that discussed in Low Runners, is exhibited in Figure 276. This suggests that control of the frequency and magnitude of Order Releases is possible by use of the settings of Safety Time, Minimum and Target Coverage.
- Avg. Customer Service Level is improved, but minimally, when consideration is taken of the scale of this improvement. Avg. Customer Service Level is already 0.98 (98% for “2038171020”) before activation of the Statistical Component.
- A large reduction in the occurrence of Avg. Customer Shortages. The reduction is accentuated when the Statistical Component is “activated.”



8.1.4.1 Critical Commentary.

The observations made here are similar to those made in the Low and Medium Runner Category, therefore the commentary would be much the same in terms of customisation opportunities and the influence of setting (ST+MC) and (ST+TC) equal to each other. The only noticeable difference between the two Usage Categories is that Avg. Customer Service Level and Avg. Customer Shortages stabilise far more quickly. This is attributed to higher running Usage Categories being able to absorb greater fluctuations in demand than lower running Usage Categories. The observation is made where (ST+MC) and (ST+TC) both equal three.

8.2 Customising.

Refer to Appendix M for the tables and figures discussed here.

The previous section highlighted the possibility of analysing the behaviour of Avg. Plant Inventory, Avg. Number of Orders, and Avg. Order Size and thus determining which combinations of Safety Time, Minimum, and Target Coverage produced similar results. This section first qualifies the term “similar” within the context of Avg. Plant Inventory, Avg. Number of Orders, and Avg. Order Size. The second part of this section presents the analyses method utilised to develop the Decision Support Tool that quantifies the resultant change in Avg. Plant Inventory, Avg. Order Size, and Avg. Number of Orders as a function of altered Safety Time and Coverage Profile settings.

8.2.1 Qualifying the term “similar.”

Identifying the combinations of Safety Time, Minimum and Target Coverage that result in similar or equal levels of Avg. Plant Inventory, Avg. Number of Orders, and Avg. Order Size was a direct result of the method employed by SAP-MRP in determining Stock Requirements. Reference is made to the manner in which Safety Time, Minimum and Target Coverage are summed i.e. (ST+MC) and (ST+TC), when creating an Order Release. Refer to the end of Section 4.4.3.1 on page 50.

The influence that (ST+MC) and (ST+TC) have on the SAP-MRP System is that any combination of Safety Time, Minimum or Target Coverage settings, which result in equal values of (ST+MC) and (ST+TC), will result in equal Avg. Plant Inventory levels. Table 37 below shows three examples of different Safety Time, Minimum and Target Coverage settings that result in equal values of (ST+MC) and (ST+TC).

ST, MC, TC	ST+MC	ST+TC
0, 5, 5	5	5
1, 4, 4	5	5
2, 3, 3	5	5

Table 37: Input Combinations that Result in Equal Avg. Plant Inventory Levels.



The only difference between the influences that these various Input Combinations have on the SAP-MRP System is the manner in which orders arrive at DCSA. This difference is attributed to the Safety Time setting which causes orders to arrive in plant x days before they are required.

Table 91 through Table 94 show the Avg. Plant Inventory levels for Ultra Low through High Runner Usage Categories as a function of the various Input Combinations. Table 95 shows how the Input Combinations have been sorted and grouped together where the settings of Safety Time, Minimum and Target Coverage result in equal values of (ST+MC) and (ST+TC). The reader will now observe examples of Avg. Plant Inventory levels that are equal or similar. Table 38 below is an extract of Table 95 and shows the Avg. Plant Inventory levels for two different parts that are associated with three alternative Input Combinations. Input Combinations 17, 34, and 50 have (ST, MC, and TC) values of (0, 3, 4), (1, 2, 3), and (2, 1, 2) respectively, which all result in (ST+MC) and (ST+TC) both equalling (3) and (4) respectively.

Combination	2038170920	A	2038171020	A
17	290.3		352.0	
34	290.6		352.2	
50	290.7		357.0	

Table 38: Extract of Table 95.

Examination of Table 95 shows similar Avg. Plant Inventory levels within grouped Input Combinations that differ more from each other than those shown in Table 38. Input Combinations 21, 40, and 58 are examples of this. The difference in inventory levels may question the validity upon which the reasoning for grouping Input Combinations is based. It was for this reason that the analyst chose to utilise the paired t-test to prove statistically that the Input Combinations belong in the groups that they are placed in.

8.2.1.1 Statistical Analysis of Input Combination Grouping.

Part “2112703200 A” with a Pallet Size of 7 units and Lead-Time of 37 working days was utilised in this analysis.

The statistical analysis of the Input Combination grouping was approached from two directions. The first approach compared the DOE results for each Input Combination. This approach indicated the Avg. Plant Inventory levels associated with parts that had never had their Safety Time, Minimum and Target Coverage settings altered. The second approach varied the Input Combinations during a single simulation run, which represented the “real world” situation where DCSA alters the settings of Safety Time, Minimum and Target Coverage “on the fly.”



The paired t-test was conducted on Approach 1 by comparing the average plant inventories associated with each of the 50 replications that make up the Avg. Plant Inventory per simulation run. Approach 2 was analysed by altering the settings of Safety Time, Minimum and Target Coverage during a simulation run and then capturing the Day End Stock levels. This process was repeated 50 times such that the Avg. Plant Inventory resulting from each change could be calculated. Input Combinations 21, 40, and 58 were compared for each approach and the results are shown in Table 39 below. *Mean Diff* indicates the average difference between the Input Combinations shown in the first column.

Input Combination (From) – (To)	Approach 1				Approach 2			
	Mean Diff	h	Confidence Interval		Mean Diff	h	Confidence Interval	
			CL _U	CL _L			CL _U	CL _L
(58) - (21)	14.9	13.7	28.6	1.2	0.6	18.6	19.2	-18.0
(58) - (40)	15.8	13.8	29.6	2.0	-9.1	18.1	9.0	-27.3
(21) - (40)	-0.9	14.3	15.2	-13.4	-9.8	21.5	11.7	-31.2
Key								
h = Half width			CL _U = Confidence Interval Upper Limit			CL _L = Confidence Interval Lower Limit		

Table 39: Statistical Results of Input Combination Analysis. $\alpha = 0.05$, $n = 50$.

Approach 1:

The results in Table 39 show that, for Approach 1, the Avg. Plant Inventory for Input Combination 58 is greater than both the Avg. Plant Inventories associated with Input Combinations 21 and 40. Furthermore, the Avg. Plant Inventory for Input Combination 21 is equal to the Avg. Plant Inventory associated with Input Combination 40 because the confidence interval includes zero. This conclusion is valid at the 95% level of confidence.

Approach 2:

All three confidence intervals include zero, which shows that none of the Avg. Plant Inventories within a specific Input Combination group are greater than any of the other Avg. Plant Inventories within that same group. This conclusion is valid at the 95% level of confidence.

Conclusion:

The findings from Approach 1 show that parts with unchanged Safety Time, Minimum and Target Coverage settings can have significantly different Avg. Plant Inventories even though their (ST+MC) and (ST+TC) values are equal. Safety Time is the only factor that can be attributed with the observed difference because it results in more orders arriving within a simulation period. Even though the number of received orders may differ slightly, it seems to be significant enough to result in marginally increased Avg. Plant Inventory levels.



The most significant finding comes from Approach 2, which shows that no significant change in Avg. Plant Inventory occurs when changing the settings of Safety Time, Minimum and Target Coverage “on the fly” such that (ST+MC) and (ST+TC) remain constant. The **magnitudes** of the DOE Avg. Plant Inventories were comparably equal to that of the Avg. Plant Inventories taken from Approach 2. Therefore, the DOE values are utilised in the development of the Decision Support Tool to represent the Avg. Plant Inventories resulting from changes made “on the fly.” **The reader should note that the methods upon which these values are derived are not substituted, but merely their Avg. Plant Inventory values.** This paragraph validates the manner in which the Input Combinations were grouped.

The previous paragraph strengthens the foundation upon which the Decision Support Tool is built by proving that various Input Combinations, which result in equal (ST+MC) and (ST+TC) values, have **similarly equal Avg. Plant Inventories**. This proof is only valid where changes to the Safety Time, Minimum and Target Coverage settings occur “on the fly.”

The following section presents the method utilised in the development of the Decision Support Tool. It concludes this chapter by showing how the Tool can be used to customise the SAP-MRP System at DCSA.

8.2.2 Development of the Decision Support Tool.

The results obtained from the DOE were used as an input to this analysis. This was done to avoid any problems associated with the small margin of error resulting from the Regression Equations.

A simplified method was needed to represent the groups of various Input Combinations that result in similar or equal Avg. Plant Inventories. The result of this exercise is seen in Table 96. The third column displays the (ST+MC) and (ST+TC) values with the various Input Combinations, which result in these values, being found in the last three columns on the right. These columns are titled “Combo 1,” “Combo 2,” and “Combo 3.” Each of the 33 unique values found in the “(ST+MC), (ST+TC)” column are assigned a “Coded Number.” These “Coded Numbers” are utilised in conjunction with Table 99, Table 100 and Table 101 to indicate the magnitudes of the resultant changes in Avg. Plant Inventory, Avg. Order Size, and Avg. Number of Orders. The magnitudes of the resultant changes were calculated by using the means of the Avg. Plant Inventories within a specific group of Input Parameters. This method does not detract from the results as the Avg. Plant Inventories within a specific group are comparably equal.

A different method than that used to identify the Input Combinations that result in equal or similar Avg. Plant Inventories was needed in the case of Avg. Number of Orders and Avg. Order Size. The graphs of the results obtained from the DOE were utilised for this purpose. Simply “drawing” a horizontal line across the graph and checking which points lay on that line provided a method of identifying the various combinations of Safety Time, Minimum, and Target Coverage. Drawing a



line vertically down from those intersections then indicated which Input Combinations resulted in similarly equal Avg. Number of Orders or Avg. Order Sizes. Figure 55 on page 147 clearly indicates how this exercise was conducted. The reader should see that six different levels of Avg. Number of Orders and Avg. Order Size exist indicating that six different groups of Input Combinations result in equal or similar levels of the aforementioned Performance Measures.

The pattern exhibited in Figure 55 indicates the typical pattern that Avg. Order Size and Avg. Number of Orders follow with respect to the various Input Combinations. This pattern is seen in all of the Usage Categories except for Ultra Low Runners because of the influence that large Pallet Sizes has on this Usage Category.

The pattern that Avg. Number of Orders follows is independent of Usage Category, therefore it is possible to create a single table that presents the various Input Combinations that result in similar Avg. Number of Orders. These results are seen in Table 97, found in Appendix N.

Table 98 represents the Avg. Order Sizes associated with each of the six identified categories. These values are known to be dependent on Pallet Size. Therefore, this table is purely intended to give the user an indication of the magnitude of the Avg. Order Size associated with a specific Usage Category.

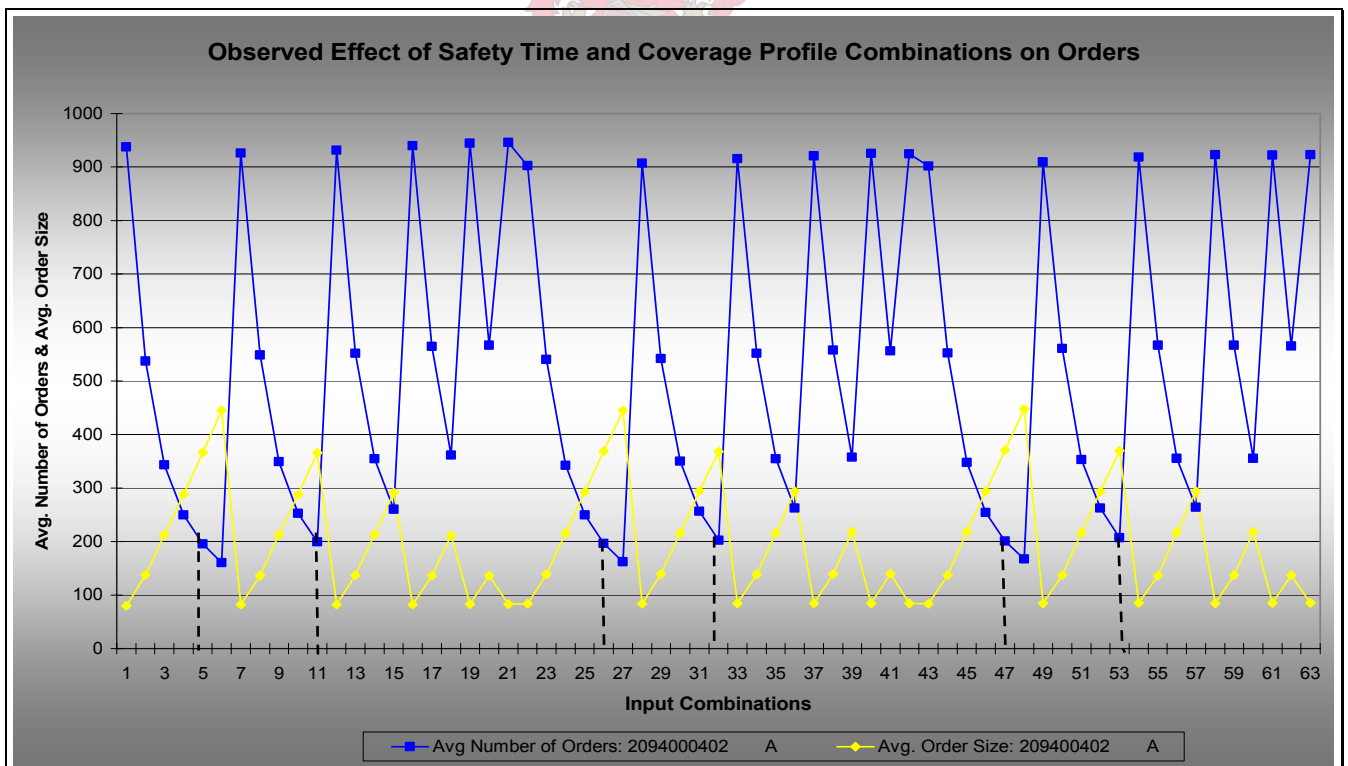


Figure 55: Combinations with Equal Avg. Number of Orders. Medium Runners.

The following discussion will present how these observations are utilised to customise the SAP-MRP environment, in terms of Safety Time and Coverage Profile.



8.2.3 Application of Customisation Tables.

The application of the observations made in the analysis just presented, is explained by means of possible scenarios at DCSA that would require the settings of Safety Time, Minimum, and Target Range of Coverage to be changed.

Example 1:

Part “2710106700 A” is a Medium Runner part with an associated ADD of 66.4 units per day and a Pallet Size of 3 units. Table 40 lists the settings applicable to the “As-Is” and “To-Be” situations.

	“As-Is” Situation	“To-Be” Situation
ST	2	2
MC	3	1
TC	3	2

Table 40: Example 1: Part Vital Statistics for the “As-Is” and “To-Be” Situations.

In order to remain as close as possible to the “real-world” situation, it is assumed that Pallet Size and Order Lead-Time remain constant.

Typical questions that would be centred on such a proposed change would be:

- By how much will the Avg. Plant Inventory change i.e. what is the magnitude of the change?
- How will this change influence the frequency and magnitude of the received orders?
- Will Avg. Customer Service Level be negatively or positively influenced?

By using Table 96 (see Appendix N) and the fact that (ST+MC) and (ST+TC) both equal 5 i.e. “5,5” and referring to the second column of the table, it is seen that this combination has been assigned a “Code Number” of 25 (seen in the first column under the heading “Coded No.”). Similarly, the “To-Be” settings are assigned a “Code Number” of 16. Therefore, DCSA is proposing to go from a Code Number 25 to a Code Number 16.

Using these codes in combination with Table 100, shows that going from a Code Number 25 to a Code Number 16 will result in a 12% decrease in Avg. Plant Inventory.

In terms of the change to the frequency and magnitude of the Order Receipts:

Using Table 97 (in Appendix N) it is seen that the “As-Is” combination (ST = 2, MC = 3. and TC = 3 i.e. “2, 3, 3”) has been placed into Category 6, whereas the “To-Be” i.e. “2, 1, 2,” is placed in Category 5. Using these Category classifications in combination with Table 98, shows that Avg. Number of Orders (measured over 1000 days) will reduce from 948.10 to 635.31 orders, and the Avg. Order Size will increase from 71.38 to 106.24 parts per order.



In closing, Avg. Customer Service Level is, for all intensive purposes 100% regardless of settings of Safety Time and Coverage Profile as has previously well documented. Therefore, the proposed change will not reduce Avg. Customer Service Level.

Close inspection of Table 99 through Table 101 (both in Appendix M) will reveal that these tables are not symmetrical. This is attributed to the manner in which the changes were calculated and is explained by the means of the following simplified example:

An increase in Avg. Plant Inventory of 5 units to 10 units, equates to a 100% increase in Avg. Plant Inventory. In reverse, the change from 10 units to 5 units results in 50% decrease.

Therefore, it is necessary for the user to be mindful of this when using the tables and not think that going from a Code Number “X” to “Code Number “Y” will have the same percentage change as going from a Code Number “Y” to a Code Number “X.”

Of course, the user can utilize the tables in any order he chooses in order to answer a specific question e.g. DCSA may wish to reduce the Avg. Order Size of a specific part due to a specific Material Handling constraint. The following example will demonstrate how the user could utilise the tables as a Decision Support Tool.

Example 2:

	“As-Is” Situation	“To-Be” Situation
ST	2	?
MC	1	?
TC	3	?

Table 41: Example 2: Part Vital Statistics for the “As-Is” and “To-Be” Situations.

For the purpose of this example it is assumed that DCSA has decided to do away with Safety Time and that Pallet Size and Order Lead-Time do not change. In addition, the High Runner part, “2038170920 A,” with an associated ADD of 117.97 units per day, and Pallet Size of 30 units is under investigation.

Referring to Table 97 it is seen that the “As-Is” situation has been placed in Category 4. Table 98 shows that this Category has the third highest Avg. Order Size. DCSA could decide that the magnitude of the Avg. Order Size associated with Category 6 is far more in line with the requirements placed on them by the Material Handling Constraints.



Referring back to Table 97, DCSA can now select a setting combination from the range of possible Input Combinations in Category 6. Any of these settings will reduce the Avg. Order Size, so the selection will now be subject to further requirements. From the evidence presented in the previous section, DCSA knows that a significant improvement in Avg. Customer Service Level occurs as soon as the Statistical Component is “activated.” Therefore, the minimum prerequisite would be that Minimum or Target Coverage be greater than or equal to one. The various Input Combination settings in Category 6 that conform to the specified restriction are:

0, 1, 1
0, 2, 2
0, 3, 3
0, 4, 4
0, 5, 5

Assuming that DCSA selects the second setting combination i.e. (0, 2, 2) then the “As-Is” and “To-Be” situation would be as follows:

	“As-Is” Situation	“To-Be” Situation
ST	2	0
MC	1	2
TC	3	2

Table 42: Solution Settings for Example 2.

Following the method shown in the previous example would show that changing from the “As-Is” to the “To-Be” (Code Number 20 to a Code Number 7) situation would result in a 38% decrease in Avg. Plant Inventory.

Therefore, the outcome of the proposed change is summarised as follows: “Changing the settings of Safety Time, Minimum, and Target Coverage from the “As-Is” to the “To-Be” situation will result in Avg. Order Size decreasing from 330.9 to 128.98 units per order. Furthermore, Avg. Number of Orders will increase from 349.24 to 924.03 orders per 1000 days, and Avg. Plant Inventory will decrease by 38%.

These two examples should now have demonstrated the decision support power that lies within these findings.

The Decision Support Tool has been developed to quantify changes in specific Performance Measures. Unfortunately the tables that form part of this tool are part specific and inferences about other parts, which fall within the same Usage Category of an already analysed part, cannot be made without a reduction in accuracy. Regression Analyses showed that “Higher Runners” Avg. Plant Inventory is predominantly influenced by ADD. The result of this is that the reduction in



accuracy is directly proportional to the difference between the ADD's of the analysed and non-analysed part.

8.3 Summary.

This chapter discussed and quantified the degree of influence that various Input Parameters have on the behaviour of the Inventory, Orders, Service Level, and Shortages Performance Measures. The settings of the selected Input Parameters were varied across specific ranges such that the analyst may observe their influence on the aforementioned Performance Measures. Only Regression Equations with Adjusted R^2 Values above 0.9 were utilised for this part of the analysis.

Analyses of the observed results taken from the DOE showed that **Avg. Customer Service Level** and Avg. Customer Shortages were **maximised** and minimised respectively where **Minimum Coverage was set as high as possible**. Setting this input parameter as high as possible **did not increase Avg. Plant Inventory** by much for the Ultra Low Runners and in fact **reduced Avg. Plant Inventory for parts with large Pallet Sizes**. This observation does not follow for the remaining Usage Categories as Avg. Plant Inventory is strongly influenced by Minimum Coverage. Observations for the "Higher Running" Usage Categories showed that Avg. Customer Service Level and Avg. Customer Shortages were **maximised and minimised** respectively in those instances **where Minimum and Target Coverage differed by at least 1 day**.

Observing the behaviour of Avg. Plant Inventory, Avg. Number of Orders, and Avg. Order Size showed that various combinations of the sum of Safety Time, Minimum, and Target Coverage resulted in similar values of the aforementioned Performance Measures. These observations led the way for the development of a **Decision Support Tool**. This tool will be used in future **to aid DCSA in customising the Input Parameters of the SAP-MRP System for a specific part**.



9. Conclusions and Recommendations.

This four-section chapter discusses the main findings of the thesis by consolidating the results from the previous chapters. It examines the degree to which the four objectives set for this thesis were realised. This is done by critical examination of; **firstly** the understanding developed regarding the operation of the SAP-MRP System; **secondly** DCSA's directive to not compare the SAP-MRP System to the OIMM System developed by van Wijck et al. [4]; **thirdly** the implementation methodology to be followed should the OIMM System prove viable or failing this, establishing and characterising SAP-MRP's performance capabilities under the 10 Day Option Freeze Environment; and **fourthly** the Decision Support Tool developed to aid DCSA in customising the SAP-MRP environment.

9.1 Critical Examination of the Understanding Developed of the SAP-MRP System.

The first objective was to develop an understanding of the operation of the SAP-MRP System at DCSA, as the knowledge gained would form the foundation for the entire thesis. Information found in literature such as the SAP-MRP Help files and User guides as well as local expertise at DCSA provided a basic understanding of the system operation. However, extensive experimentation and personal observations contributed to the in-depth, system specific knowledge.

The in-depth knowledge was achieved by firstly developing a simulation prototype in an Excel spreadsheet. This prototype was benchmarked and validated against Actual and Proposed Order Releases created by SAP-MRP. The experience and knowledge gained here was then transferred to a more dynamic environment and developed into a functional simulation model.

The author had to make several assumptions when designing and creating the functional model. These assumptions were required to overcome certain difficulties that were encountered when recreating the Sales Order environment (see Section 5.2 on page 62). More specifically, these assumptions were focused on creating a method to generate Sales Forecasts such that they were as functional as the actual Sales Forecasts utilised by the SAP-MRP System. The method of recreating the forecasted Sales Orders was based on the average demand calculated from the input data. In reality, the **magnitude** (not the manner in which they are assumed to be received by the simulation program) of the forecasted Sales Orders, received from Sales in Germany, are calculated in a far more complex manner than that of the assumed method. This assumption does not have a negative influence on the results generated by the project, it [the project] however does not indicate the negative consequences associated with an error in the manner in which the forecasted Sales Orders are calculated.



The performance of the SAP-MRP System is very sensitive to the accuracy of the forecasted Sales Orders received from Germany and any shortfall in this accuracy will result in severe repercussions for DCSA. For the purpose of this study, the “Sales Department” were afforded the benefit of the doubt in terms of accuracy of the forecasts. This meant that the simulation program created forecasted Sales Orders that promoted the creation of accurate Order Releases, which minimised the probability of stock-outs occurring due to bad forecasting.

In addition to the assumptions made regarding the creation of forecasted Sales Orders, the author had to assume that there was no human error involved in the operation of the SAP-MRP System. Although human error does have an adverse influence on the performance of the system, it is understandable that such anomalies require a proactive, rather than reactive management approach. To include all possible problems attributed to human error would open the study to an exponential growth in complexity of no benefit/value to the project. Therefore, design of the simulation program necessitated the exclusion of both human error and analysis thereof.

Excluding the assumptions made regarding the creation of forecasted Sales Orders and the problems associated with human error, it is the author’s opinion that the operation of the SAP-MRP System has been successfully recreated. This opinion is based on the following:

- The paired t-test (see section 5.1.1 on page 55) proved that the logic upon which the simulation program was based, did indeed replicate the actual SAP-MRP System’s logic.
- The response of the simulated SAP-MRP System was indicative of that documented in the Help files. Reference is made to the fact that:
 - The frequency with which Order Releases are created is inversely proportional to the difference between Minimum and Target Coverage (Refer to Figure 227, Figure 243, Figure 259, and Figure 276).
 - An increase in the Minimum Range of Coverage results in an increase in Plant Inventory levels.

9.2 Critical Examination of DCSA’s Directive to not Compare the OIMM System to the SAP-MRP System.

The second objective involved developing a comparison methodology with which to compare the performance of the SAP-MRP System to that of the OIMM performance. This objective was completed with the development of various Performance Measures and the completion of the independent simulation program. An actual comparison of the two systems was not undertaken, due to a directive from DCSA not to pursue the OIMM implementation option. The directive was received after they were shown that the SAP-MRP System could maintain a high Avg. Customer Service Level in the 10 Day Option Freeze Environment.



Ideally, a comparison should have been made between the OIMM System and the SAP-MRP System. This comparison would have shown which of the two systems actually provides the optimum balance between Plant Inventory levels and Customer Service Levels. Ensuring high Customer Service Levels by maintaining high Plant Inventory levels is not the ideal approach, even if the plant does not own the inventory (as is the case at DCSA). Maintaining inflated inventory levels results in penalty costs that are ultimately deferred to the client, regardless of who owns the inventory. Therefore, the current policy of maintaining large inventory levels in order to maximise Customer Service Level, under which DCSA currently operates, is not a competitive policy at all. Unnecessary costs reduce a company's profit margin, which at the end of the day, is all that shareholders are interested in.

The analysis of the behaviour of the SAP-MRP System showed that if DCSA were to adopt a "minimal inventory" policy that the resultant Avg. Customer Service Level provided by the SAP-MRP System would not be adversely influenced. In fact, the lowest observed Avg. Customer Service Level was 94.1%. This observation was made on a C-category part, in terms of ABC classification, which means that the low Avg. Customer Service Level can be remedied by increasing the associated stock levels without a large increase in inventory holding or material holding costs.

9.3 Critical Examination of the Characterisation of the SAP-MRP's Performance Capabilities.

Given that the OIMM System did not have to be implemented, the third objective required that the performance capabilities of the SAP-MRP System be characterised under the 10 Day Option Freeze Environment.

The author found that a distinct difference in performance existed between parts with very low Average Daily Requirements and those with high Average Daily Requirements. Ultra Low Runners were found to be the most prone to stock-out occurrences as well as their associated Avg. Plant Inventory levels being almost completely dominated by their Pallet Sizes. In contrast, the remaining Usage Categories were far less prone to stock-out occurrences, with the highest runners being the least prone.

The characterised performance capabilities are discussed by first presenting findings that highlighted the two dominating factors that influence the Performance Measures of Ultra Low Runners. Thereafter, a discussion will follow that summarises the general findings and observations.



9.3.1 Ultra Low Runners: Stock-Out Occurrences.

The accentuated susceptibility of Ultra Low Runners to stock-out occurrences is attributed to the magnitude in demand change as a percentage of the average daily demand. Even if the Planned Production Day requirements experience a marginal increase in demand of two or three units, this increase may represent 300% to 500% in terms of the ADD⁹. Increasing the “Absorption Ability” of associated plant inventories, which is directly proportional to the setting of Minimum Range of Coverage, effectively deals with this susceptibility. Increasing the Minimum Range of Coverage will not create a massive increase in Avg. Plant Inventory, as would be the case with higher running parts, but result in keeping only a “handful” of extra parts in the plant (see Figure 226 in Appendix L).

An interesting note on the influence that an Ultra Low Runner, which is experiencing a gradual increase in ADD, has on the performance of the SAP-MRP System is that such an occurrence serves only to improve the Avg. Customer Service Level and reduce stock-out occurrences. This will occur without any human intervention i.e. no changes to the settings of Safety Time and Coverage Profile is required. This self-actuating improvement is linked to the role that the ADR and Coverage Profile play in determining Plant Inventory levels i.e. a gradually increasing demand will increase the ADR, which will in turn result in higher Plant Inventory levels that then improve the stock’s “Absorption Ability.” However, this automatic improvement is heavily dependent on the forecasted Sales Order provided by Sales in Germany, due to the forecasted component that is included in the calculation of the ADR (see section 4.4.4 on page 51).

The frequency of stock-out occurrences were found to decrease as the ADD of the Usage Categories increased. The reasons for this will become clear in the following three sections.

9.3.2 Ultra Low Runners: Palletization.

It was found that Pallet Size had an overwhelming influence on the Ultra Low Runner Avg. Plant Inventory. In fact, Pallet Size was found to completely override the settings of Safety Time and Coverage Profile. Therefore, the only value provided by the Coverage Profile is the “trigger effect” of the Minimum Coverage setting. This “trigger effect” would signal the creation of an Order Release, which would then create an order that would override the Target Coverage because of the Available Stock associated with the arrival of the order. Large Pallet Sizes should not be viewed in a negative light as they effectively improve the “Absorption Ability” of the Plant Inventory. This behaviour is accentuated in Ultra Low Runners where the larger Pallet Sizes reduced stock-out occurrences and increased Avg. Customer Service Level (see Figure 218 and Figure 219 in Appendix L).

⁹ Using part “1120101144 A” that had an ADD of +/- 0.5 units per day at the time of this study.



In closing, it should be noted that the percentage increase in Avg. Plant Inventory is very low in comparison to the percentage increase in Pallet Size. This shows that any efforts to manage the inventory levels in the plant, by means of reducing Pallet Size are futile.

9.3.3 General Findings.

This section is subdivided into three subsections. Each subsection presents a topic regarding the behaviour of the SAP-MRP System in terms of specific input parameter/ parameters. These subsections are presented as follows:

1. Usage Category Dependency and Control of Plant Inventory Levels.
2. Lead-Time.
3. Safety Time and Coverage Profile Combinations.

9.3.3.1 Usage Category Dependency and Control of Plant Inventory Levels.

The dependency of the Usage Categories upon the Safety Time and Coverage Profile settings to ensure suitably high Avg. Customer Service Levels decreases in an almost linear fashion. Ultra Low Runners are far more dependent on the settings than are the Low, Medium, or High Runners. Figure 56 is a graphical representation of this dependency, with zero representing “Low” and one representing “High.”

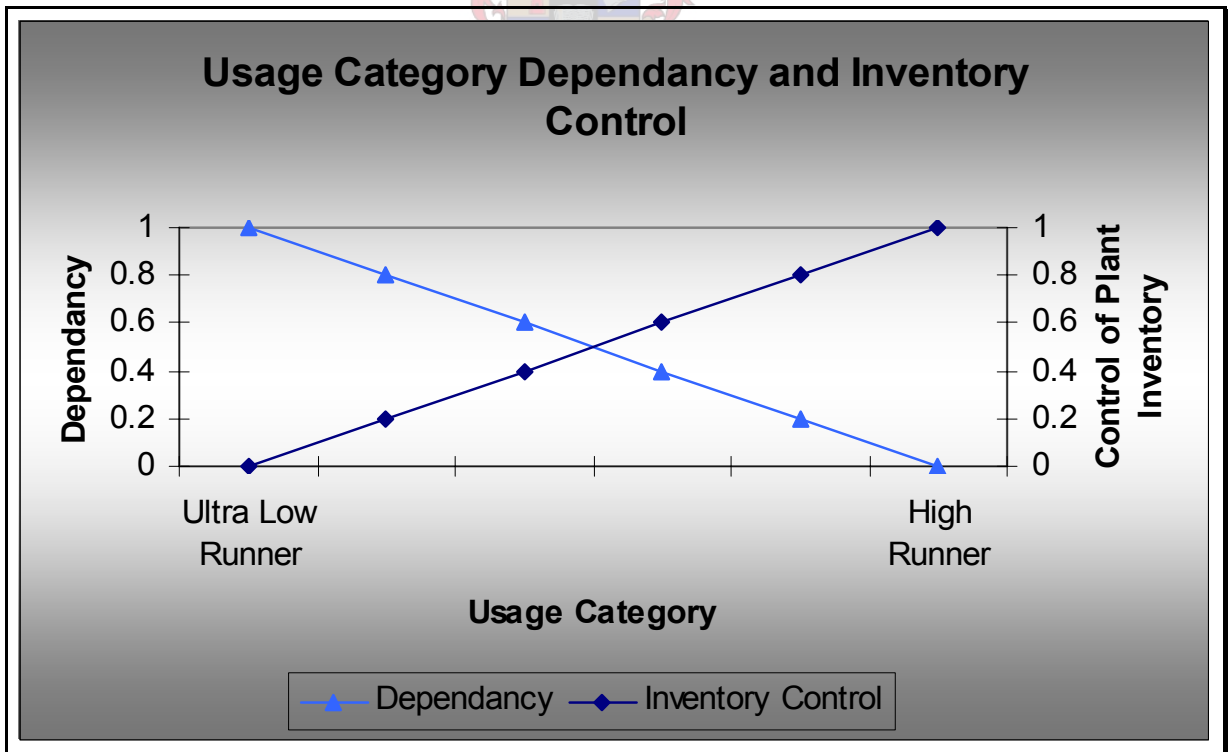


Figure 56: Trend in Usage Category Dependency and Inventory Control.



The graph shows the two extremes of the Usage Categories included in this study, with Ultra Low Runners being the lowest and High Runners being the highest. Ultra Low Runners represent parts with an ADD of between zero and one units per day, whereas High Runners represent parts with an ADD of between 100 and 120 units per day. Gaps within the ADD are found between Ultra Low and Low Runners (2-14 units per day), Low and Medium Runners (31-59 units per day), and for parts with an ADD greater than 120 units per day. Given the observations made on the included Usage Categories, it is the opinion of the author that the same conclusion would have been drawn, regarding the linear relationships shown in Figure 56, had all Usage Categories been studied. In other words, there is no reason to believe that the excluded Usage Categories would have displayed behaviour that contradicted the observed “linear” relationship.

In addition, Figure 56 illustrates the relationship between Usage Categories and the ability to control Plant Inventory levels. The low control over Ultra Low Runners is attributed to the overriding effect of large pallets. This influence becomes diminished as the ADD increases, which explains the improved levels of control exercised over the higher running Usage Categories. **The improved control levels mean that DCSA can manipulate the Plant Inventory levels according to their requirements. This control is exercised by means of the Coverage Profile.**

Similar to the findings made on the Ultra Low Runners, it was found that large Pallet Sizes had an overriding influence on the Target Range of Coverage. However, examination of figures in Appendix L (refer to Figure 214, Figure 233, Figure 247, Figure 264) shows that **the negative side-effect of large Pallet Sizes only becomes evident when size of a pallet ranges in the hundreds**. As with Ultra Low Runners, any attempts to control inventory levels by reducing Pallet Sizes, is viewed as futile. In addition, large Pallet Sizes (+100) are usually associated with bulk parts (screws, nuts, etc.) and the storage area required, relative to the volume of parts, is insignificant when compared to the space needed to store items such as engines and gearboxes.

When examining Ultra Low Runners it was found that large Pallet Size values reduced Avg. Customer Shortages and increased Avg. Customer Service Level. When examining the remainder of the Usage Categories, however, it was seen that this advantage existed only when Safety Time and Coverage Profile were set to zero. Setting any one of these Input Parameters to a value greater than zero resulted in the aforementioned advantages being marginalised.



9.3.3.2 Lead-Time.

It was found that the negative side-effects of an extended Order Lead-Time were accentuated in Ultra Low Runners. Side-effects such as increased Avg. Plant Inventory and reduced Avg. Customer Service Level had a higher rate of occurrence in the Ultra Low Runners than any other Usage Category. When examining the higher running Usage Categories it is seen that parts with longer Lead-Times actually have lower Avg. Plant Inventories than those with shorter Lead-Times. This reduction is attributed to the increased size of the “window of opportunity” in which Customer Demand changes can occur. The increased demand is satisfied by the Available Stock, but does not result in stock-out occurrences, due to the associated “Absorption Ability” associated with the higher running Usage Categories.

Results showed that these negative consequences were marginalized as soon as Minimum or Target Coverage was greater than zero. These observations are in line with those made on the Avg. Customer Service Levels and Avg. Customer Shortages that were reduced by the activation of Minimum or Target Coverage.

9.3.3.3 Safety Time and Coverage Profile Combinations.

Characterising the behaviour of the SAP-MRP System, in terms of Safety Time and Coverage Profile Combinations, provided valuable insight into the influence that each of these parameters has on the system as well as the consequences of their interactions.

This analysis approach yielded results that not only confirmed the behaviour descriptions found in the Help files (frequency of order placement in terms of the difference between Minimum and Target Coverage), but also quantified the importance of each parameter.

- The Regression Analysis proved that, excluding the other Input Parameters; **the behaviour of the SAP-MRP System is almost entirely a function of the sum of Safety Time and Minimum, or Target Coverage.** Given the problems (refer to section 4.4.3 on 49) associated with the use of Safety Time, it is confidently said that dropping its use will cause no adverse side-effects. Should DCSA wish to maintain the Plant Inventory levels associated with a specific combination, which includes Safety Time, they will need merely to increase Minimum and Target Coverage such that they equal the sum of the original values e.g. $MC^{New} = ST^{Old} + MC^{Old}$.



- **Results showed that Minimum Coverage is the primary driving force behind the performance of the SAP-MRP System.** It is credited as being the primary tool with which to maximise Avg. Customer Service Level and minimise Avg. Customer Shortages. Further, the “Absorption Ability,” associated with a specific Usage Category, is directly proportional to the magnitude of the Minimum Coverage setting. However, “Absorption Ability” is only maximised when Target Coverage is greater than Minimum Coverage i.e. setting the Input Parameters equal to each other does not allow “Absorption Ability” to come into play.

Other than indicating the relative importance of each input parameter, the analysis showed that various combinations of the input settings resulted in similar Avg. Plant Inventories and Avg. Number of Orders. Recognising the patterns in the aforementioned Performance Measures, paved the way for the development of a Decision Support Tool that could be used in customising the SAP-MRP System at DCSA.

9.4 Critical Analysis of Decision Support Tool.

This objective was focused on developing a Decision Support Tool that could aid in customising the SAP-MRP System such that an acceptable Avg. Customer Service Level is maintained in the 10 Day Option Freeze Environment. With the exception of proving that the SAP-MRP System can provide/maintain a suitably high Avg. Customer Service Level, the completion of this objective yielded a product that is viewed by the author as being the most valuable outcome of this study.

The Decision Support Tool is capable of indicating how a proposed change in the settings of Safety Time or Coverage Profile will influence Avg. Plant inventory, Avg. Order Size, and Avg. Number of Orders for a specific part. The foundation of the Decision Support Tool is based on the knowledge that various combinations of Safety Time, Minimum and Target Coverage result in similar or equal Avg. Plant Inventories. Additional analyses also showed that various combinations of these Input Parameters result in similar or equal Avg. Number of Orders, and Avg. Order Size. These findings were exhibited in all Usage Categories, except for Ultra Low Runners due to the overriding influence of large Pallet Sizes.

The accuracy of the Decision Support Tool, in terms of predicting the change in Avg. Plant Inventory for a specific part, is unquestionable. However, the accuracy of a generalised prediction, which is based upon a Usage Category, is subject to variation due to the degree of influence that ADD has on the behaviour of this Performance Measure. In addition, large Pallet Size are influential factors that should not be disregarded when making generalised predictions. A rule of thumb that could be used is that the Pallet Size/ADD ratio should not be greater than 0.5 (1.0 may still be tolerated in very high runners i.e. +120 units per day). Large Pallet Sizes are typically associated with bulk parts and ultimately present the same problems encountered with Ultra Low Runners.



The accuracy of the Decision Support Tool, in terms of predicting the change in Avg. Order Size and Avg. Number of Orders, for a specific part or Usage Category is dependant on Pallet Size. Avg. Order Size is the most influenced, because the size of an order is usually a multiple of the Pallet Size. The Decision Support Tool is only capable of indicating whether a proposed change will result in an increase/decrease in Avg. Order Size. However, the accuracy of Avg. Number of Orders is not adversely affected by Pallet Size as long as the Pallet Size/ADD ratio remains less than or close to 0.5.

There are distinct boundaries between the Categories (refer to Table 97 in Appendix M) defined for Input Combinations that result in similar Avg. Number of Orders. This Performance Measure is dependent on Pallet Size, but the Category boundaries are independent thereof. This means that the Input Combinations that define a Category will remain in that Category regardless of the size of a pallet (bulk parts not included).

In addition to those parts included in this study, the author would have preferred to have had data on a wider array of parts. Such data would have been utilised to increase the “working envelope” of the Decision Support Tool and provide information, regarding the influence of a proposed change, on parts with ADDs not included in this study. It would have then been possible to refine the definition of a Usage Category such that it included a smaller spread of parts e.g. change the High Runner 100 – 120 parts/day to 100 – 110 parts/day. Such a move would have improved the capabilities of the Decision Support Tool and allowed for more accurate generalised predictions to be made upon Usage Categories. Considering the fact that DCSA does not produce much more than 200 vehicles per day and that each vehicle is unique, it is safe to say that the “working envelope” only needs to be extended up to parts with an ADD of 200 units per day.

Based upon the discussion in the previous paragraph it should be clear that DCSA would have to gather data for a very wide range of parts if they were to implement the simulation program into their SAP-MRP System. This prerequisite is accentuated by the fact that the data collection period stretches over a few months.

9.5 Recommendations.

Based upon the investigation conducted in this study, the data received/used, and the results obtained, it is the author’s opinion that DCSA can reduce the Option Freeze to 10 days before Jig. This recommendation can be implemented without the risk of adversely influencing the Avg. Customer Service Level or increasing the probability of stock-out occurrence. Extensive simulations, analysis, and observations have repeatedly proved and shown that a reduction in Avg. Customer Service Level can be avoided by using the Coverage Profile as a proactive inventory management tool.



Various approaches can be taken to implement the proposed 10 Day Option Freeze Environment, two of which are as follows: This **first** approach is to gradually decrease the Option Freeze point and maintain a vigilant eye on the Performance Measures i.e. Avg. Customer Service Level, Avg. Plant Inventory etc. Any adverse side-effects should be dealt with by following the guidelines laid down in this report regarding the use of Coverage Profile. The **second** approach is similar to the first, except that the reduction in Option Freeze point is only applied to a limited number of Option related parts. This approach will limit any possible negative side-effects to a small portion of DCSA’s inventory. In addition, it is recommended that this approach be implemented on specific Options that are primarily supplied by local suppliers. Figure 57 depicts this concept graphically.

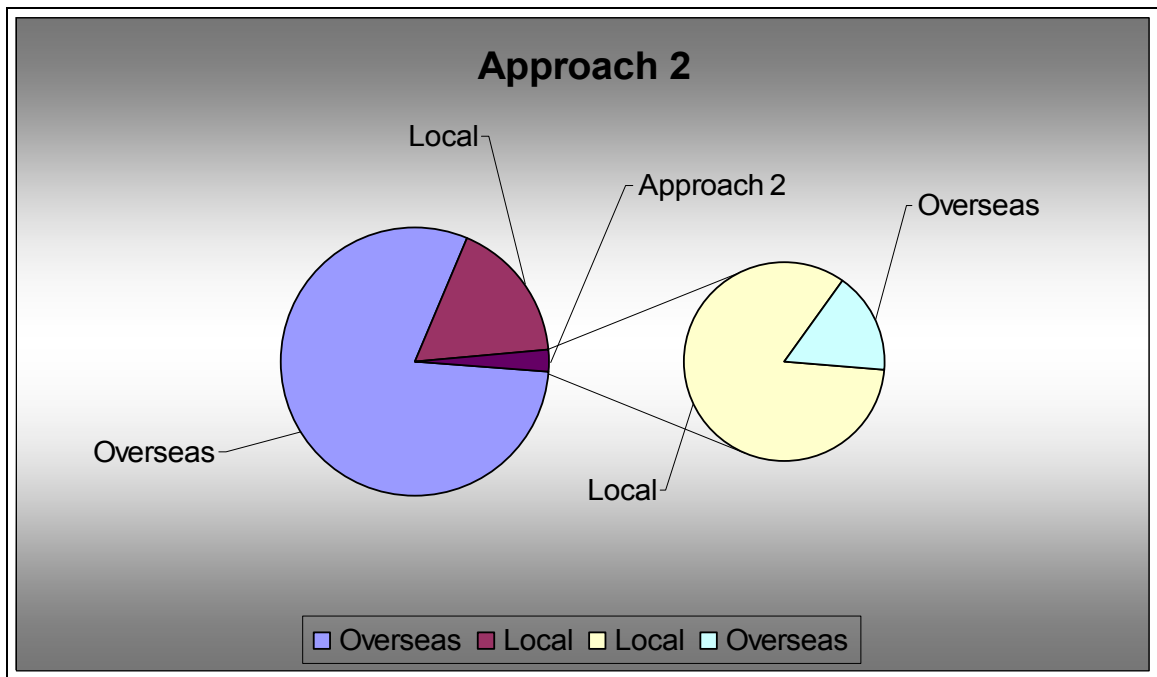


Figure 57: Approach 2.

This approach will reduce the number of parts that are adversely influenced by the changes in demand, which occur during an extended Lead-Time, and thus limit the stock-out occurrences to the remaining small portion of foreign supplied parts.

Car interiors are an excellent candidate for this approach. Local suppliers already supply the majority of these parts. DCSA could consult with these vendors and advise them of the changes, whilst bulking up on the foreign supplied parts. The overseas supplied parts would have to be managed by means of specially developed Coverage Profiles that would operate independently of the existing Profiles. DCSA will have to observe the behaviour of these parts once these changes have been implemented and the affects have moved through the system. These parts are used as a “test bed” with which to establish Coverage Profile setting guidelines to be used when the Option Freeze point is reduced for all Options.



The author admits that the second approach is more difficult in terms of planning, Option selection, and the logistics involved, when comparing it to the first approach. In practical terms, DCSA may choose to follow the first approach when it is considered that they have already reduced the Option Freeze point to 25 days successfully. However, the author would like to highlight that a point may be reached where an adverse side-effect becomes accentuated due to the reduction of the Option Freeze Point. This side-effect will not be limited to a few parts, as would be the case if the second approach had been followed, but will affect all parts. According to this study the side-effects are more pronounced in the Ultra Low Runners, but the author feels that these effects will also be felt in the Low Runners. It is obvious that the costs involved with a reactive solution to such a wide reaching stock-out occurrence will be exorbitant.

It has been stated that the Coverage Profile can be used as a proactive inventory management tool, yet it has not been made clear what this approach entails. DCSA currently uses the Coverage Profile to firstly, cover Production Requirements, and secondly to ensure Plant Inventory levels are maintained at specific levels that cover the weekly delay in the arrival of the supply ship. This approach has worked in the past, but it runs the risk of falling short if / when the Option Freeze point is reduced. DCSA should make a slight change in the manner in which Coverage Profiles are set and assigned to the relevant parts. In future, each Usage Category should be assigned a customised set of Coverage Profiles. These Coverage Profiles should be set such that they take into account the ADD, Pallet Size, and susceptibility to changes in Customer Demand. When setting the Coverage Profiles it should be remembered, that Pallet Size is only really a factor when dealing with Ultra Low Runners. In general, Ultra Low Runners will have a higher Minimum Range of Coverage than the remainder of the Usage Categories, as well as a more pronounced difference between Target and Minimum Coverage. It is unnecessary to have the Minimum Range of Coverage for the higher running Usage Categories set as high, except in a case where one of the categories includes a part/Option susceptible to large changes in Customer Demand. Such a part would advocate an increased Minimum coverage, but such a solution is not ideal since accurate Sales Forecasts would go further in solving this problem.

When making changes to the settings of the Coverage Profile, DCSA should keep in mind that it would take some time before these changes take effect and extended Lead-Times would aggravate this problem. However, it was originally thought that it would take far longer due to the large amounts of inventory stored in the plant. The latter assumption was incorrect as proven when an investigation to determine the time required for a change to take effect was undertaken.

Figure 58 shows that an increase in Plant Inventory occurs as soon as the first order (*point 198*), resulting from the change in Coverage Profile, arrives at DCSA. This order is inflated (*Receipt Spike*), which then results in a sudden jump in Plant Inventory. Thereafter, the Order Size reduces to normal values. It is now seen that this effect is more accentuated in the higher running Usage Categories.

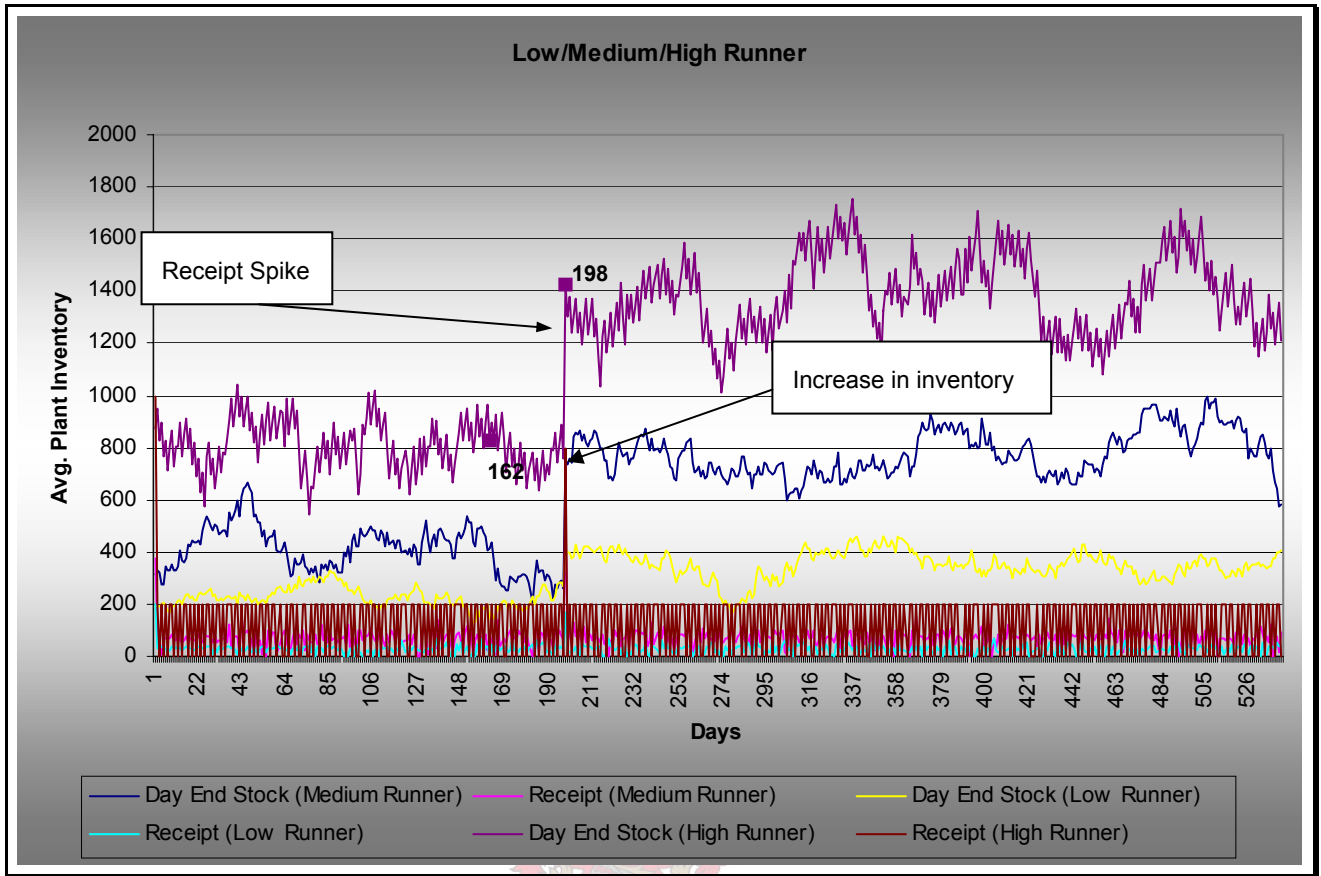


Figure 58: Increase from (2, 3, 3) to (2, 8, 8) on Day 162.

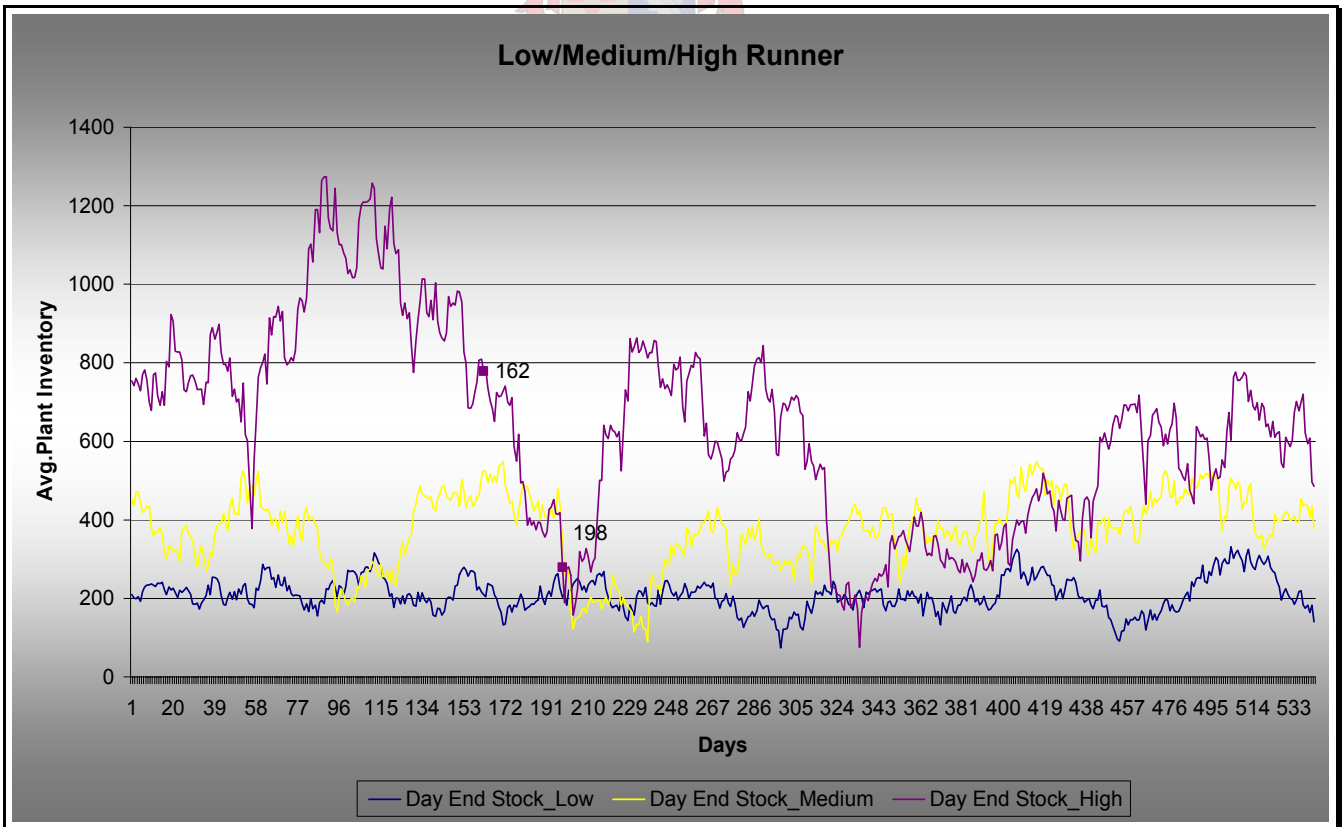


Figure 59: Decrease from (2, 3, 3) to (2, 1, 1) on Day 162.



A reduction in the Plant Inventory takes effect almost as quickly as an increase does. This is shown in Figure 59. The MRP System simply does not schedule the delivery of any parts for a few days, which allows the Available Stock to be consumed by production until the Minimum Coverage is reached. Once this point has been reached, the MRP System resumes the delivery of parts to maintain the specified Coverage Profile requirements. Furthermore, the “post-change” inventory level fluctuations (after point 198 in Figure 59) should be noted. A person observing Plant Inventory levels before and after the implemented changes may incorrectly conclude that they have not taken effect. This incorrect conclusion would be based upon the observation that, on occasions, the “post-change” inventory levels are equal to that of the “pre-change levels.” This conclusion would be incorrect, as these levels are subject to ADR, Available Stock, and Coverage Profile settings. Therefore, the seemingly unchanged inventory levels are attributed to an increased ADR coupled with a low Range of Coverage associated with the Available Stock. The increased ADR would have resulted in the Range of Coverage being lower than the Minimum Range of Coverage, which in turn would result in a large increase in Plant Inventory to satisfy the Target Range of Coverage. In the end, the Avg. Plant Inventory will be lower because of the altered Coverage Profile.

In closing, the author will highlight a few observations made whilst on site at DCSA.

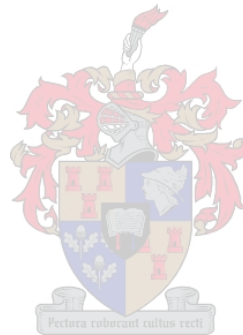
- The incorrect Lead-Times were allocated to various parts. More specifically, parts that should have 44 or 53 day Lead-Times were assigned 60 day Lead-Times. This error results in the order requirements being based on Forecasted Orders rather than actual Customer Demands. The problem associated with these incorrect orders could result in over inflated stock levels, or worse still - stock-out occurrences. The latter results in unnecessary emergency air freighting.
- Material Controllers are not aware of the role that they can play in improving the efficiency of the SAP-MRP System, by investigating their parts and making changes where applicable. By taking a proactive approach, they can simplify their jobs and improve the quality of the output. In addition, most of the controllers are not aware of the role that Coverage Profile and Safety Time play in influencing the SAP-MRP System.
- LIPs and DIPs (parts that are Lost-In-Plant (LIP) and Damaged-In-Plant (DIP)) are approached in a reactive manner. In future, human error will be more responsible for stock-out occurrences than any other influencing parameter and more accentuated in the lower running Usage Categories. Material Handling employees will have to become more vigilant when storing and moving inventory.

On a personal note, the author feels that the experience gained from this project and at DCSA is invaluable. Many valuable lessons in terms of academia and professionalism and will form a fundamental part of successfully completing future projects.



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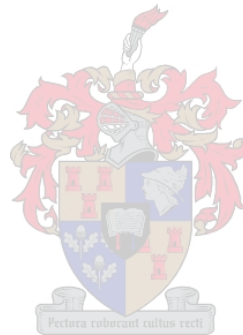
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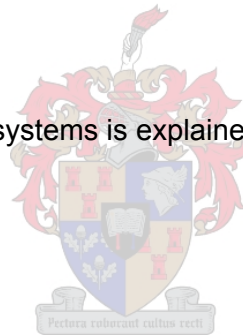
Appendix A IT Roadmap Explained



This Appendix starts with DCSA's "IT Roadmap." The roadmap shows the manner in which information travels from point of origin to the point of destinations. DCSA's primary information source, in terms of information systems, is DaimlerChrysler Germany. Germany provides sales forecasts and actual orders to DCSA, which is then utilised for planning and production purposes. Various information systems are involved in the processing of this information, such as:

- Dialog
- GOP
- TBE
- PAD
- SAP
- PLUS
- JPP
- VPPS
- ASF

The significance and purpose of these systems is explained in the paragraphs that follow.



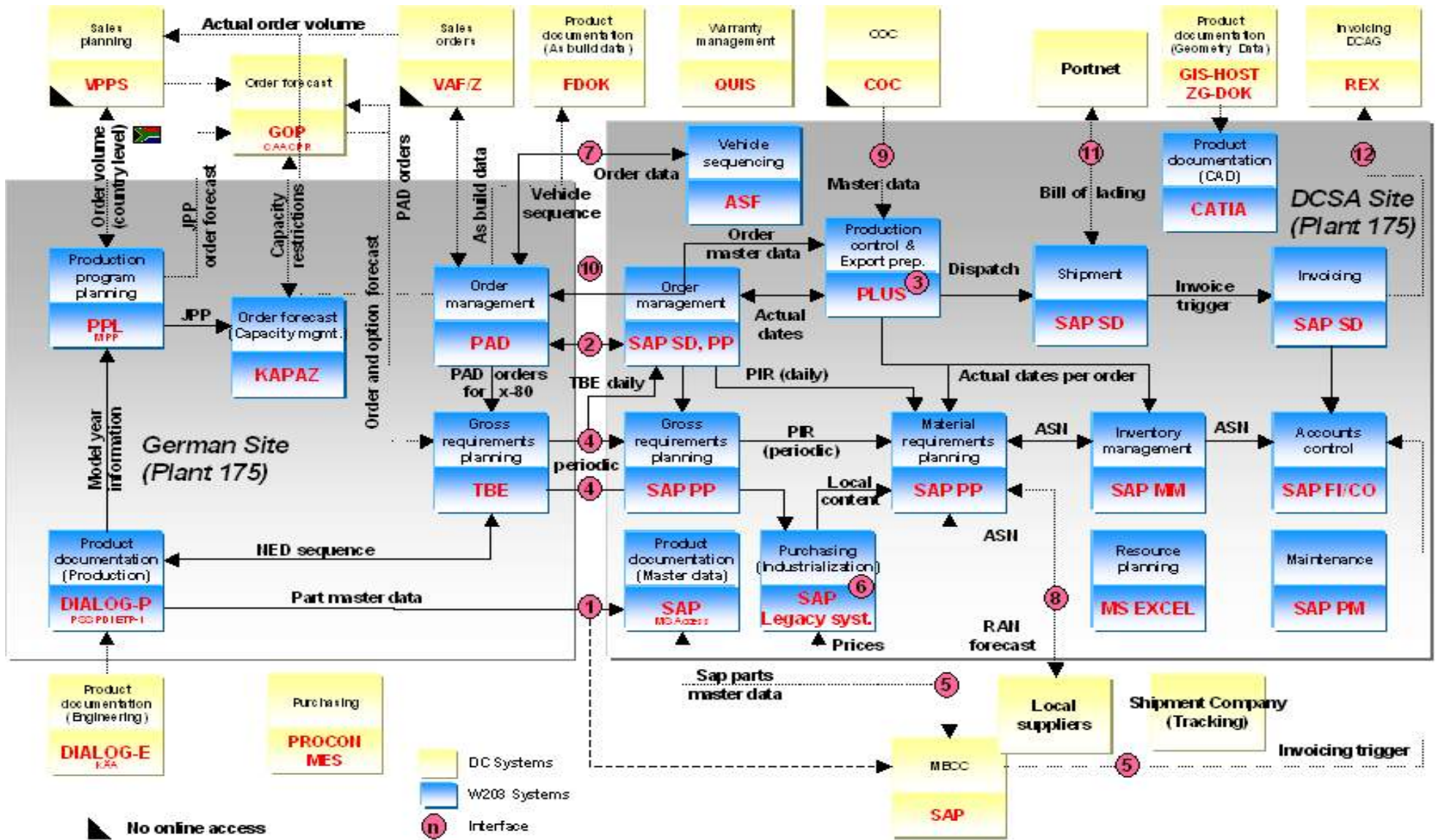


Figure 60: DCSA's IT Roadmap.

Key	
PAD	Actual Orders. Real – time database of Production Orders already sent to the Production Plant i.e. Production Orders already sequenced. Used to update GOP as well as being an input to TBE. Include orders within frozen period. 60 days worth of orders.
GOP	Gross Order Requirements. Includes PAD orders as well as forecast orders i.e. 60 days (actual orders) + 6 months of orders (forecast). Indicated at Option Level.
PIR	Planned Independent Requirement. Output of the Net Requirements plan. PIR is at part level.
TBE	Gross Order Requirements. Indicated at Part Level.
PLUS	Production Control. Produces a build plan per car i.e. Job Card.
DIALOG	System that is used to convert the Gross Requirements at Option level to Gross Requirements at Part Level. Checks the build – ability of car in terms of Option Combinations.
JPP	Yearly Production Program. Contains actualised orders (orders that have actually been produced in the past months) as well as the adjusted Forecasted Orders (Forecasted Orders are adjusted such that the yearly production volume is still achieved as well as including changes in the market).
VPPS	Market Requirements Production Program. This production program reflects the latest trends in the market. It is used to adjust the JPP such that the Forecasted Orders take into account the latest changes in the market place.
ASF	System used to assign and keep track of vehicle production sequences. The system assigns Sales Orders with a production number, dates (due and planned date) and ASF codes (internal production code).

Note: Most of the terms highlighted in the Key table are abbreviations of the German system names. The employees at DCSA refer to these systems by these abbreviated names and not the full German names. It is for this reason that the author has referred to the abbreviated names and not the German names.

GOP.

Inputs:

- VPPS (Reflects Market Requirements. Received on a monthly basis, in the middle of the month)
- Capacity Restrictions
- JPP (Yearly Production Program. Received on a Monthly basis, at the end of the month)
- PAD

Output:

- Gross Requirements Plan, at Option Level. (60 days of Actual Orders, plus 6 months of Forecasted Orders).

Explanation:

The **GOP** is run three times a month. It is at this point the **JPP** is updated with the latest trends in the market, taken from the **VPPS**. The aforementioned process produces a production plan for the remaining months of the year that has been adjusted to take into account market trends as well as Actual Production volumes that have occurred in the past. The Actual Production volumes would be taken from **PAD** via a “snapshot” that would reflect the latest production achievements of **actual orders**.

Example: If the production volume of March was overachieved by 10 units, then the following month's planned production volume is decreased by 10 units in order to maintain the planned production volume. Similarly, if the Market demanded 25 more units than previously forecasted, then the planned production volume would be increased by 25 units.

The output of the **GOP** consists of two components: the 1st being actual orders for the next 60 days (3 months, at 20 working days per month) and the 2nd being forecasted sales for the next six months. This output is sent to **TBE** where the Gross Order Requirements are converted from Option Code Level to a Part Code Level.

TBE.Inputs:

- GOP
- PAD
- DIALOG

Output:

- Gross Requirements Plan, at part level, that covers 9 months. (60 days of Actual Orders, plus 7 months of Forecasted Orders)

Explanation:

TBE receives Gross Requirements Plan, at Option Code Level, from **GOP**. The 1st component of the **GOP**, actual orders for the next 60 days, is overwritten with the latest actual orders within **PAD**. This is because the **GOP** is run three times a month and that the input, which **GOP** originally received from **PAD**, is outdated by a few days. The orders resident in the **PAD** system reflect any changes made to confirmed orders, on a real time basis it is therefore necessary for the **PAD** system to communicate with the **TBE (Daily)** system on a daily basis. This is done so that **TBE** can calculate the Gross Order Requirements based on the latest data.

The latest **TBE** is compared with the previous **TBE** data to determine which part numbers have changed. These changes could be due to engineering changes, part obsolescence, or a change in Forecast Requirements. Only those Options, whose requirement demands have changed, are then passed onto the next process (**SAP PP-Gross Requirements Planning**).

Process in general:

The updated **GOP** is compared with the rules in **DIALOG** that apply to Option combinations. (**DIALOG** is responsible for checking the build-ability of a motor vehicle with respect to the Option combinations chosen by the customer.) Manual corrections are done, to the Option combinations, where it is found that a customer has chosen Options that cannot be combined. The **DIALOG** rules are then used to convert the Option code combinations into gross **part** requirements per vehicle, once the build-ability of a car has been confirmed.

The aforementioned general process is split into two separate processes, namely: **TBE Periodic** and **TBE Daily**.

TBE Periodic: *TBE Periodic = 60 days of Actual Orders + 7 months of Forecasted Orders*

This process is run three times a month and is used to determine the gross requirements per part for **bulk** and **non-bulk** parts. The bulk and non-bulk parts also include critical parts. Critical parts are those parts that are subject to high fluctuations in their level of demand.

TBE Periodic does not contain any data pertaining to the production number of the units to be built, because it is linked to the GOP that does not have any production number detail, but it does contain data pertaining to the parts and the dates at which they are required. **TBE Periodic** contains data about forecasted and actual requirements. There is no need to link the requirements of a **non-critical part** to an actual production number **as long as** there is a requirement date i.e. the part is used to fulfil the requirement as long as the part is in stock on the requirement date.

The **critical part** requirements from **TBE periodic** will also have no production number assigned to them, but this “problem” is resolved by overwriting the results from **TBE periodic** with the results from **TBE Daily**, which does contain the production number. However, the overwriting only occurs in the SAP Production Planning – Material Requirements Planning system.

TBE Daily: *TBE Daily = 2 months of Actual Orders*

This process is run every night. It is used to determine the gross requirements per part for **critical** parts.

TBE Daily contains data pertaining to the production number and parts required for the unit to be produced, but has no data pertaining to the requirement date. The results of the TBE Daily are sent to the SAP Order Management system, in which the production number and requirement dates are stored. The production number from TBE daily is linked to the production number in SAP, which in it-self is linked to the requirement date.

The gross requirements per part are sent to the **SAP Production Planning** module, after the **TBE Periodic** or **TBE Daily** process has been completed, where they are used as an input to the Material Requirements Planning calculations that ultimately determines the Net Requirements per part.

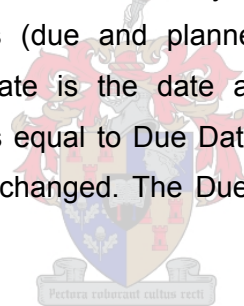
PAD.

Inputs:

- Sales Orders
- ASF
- PLUS
- SAP SD, PP

Output:

- Actual Sales Orders, for the next 60 days, that have been sequenced and assigned production numbers, dates (due and planned dates), as well as ASF codes (internal production codes). Due Date is the date at which the vehicle is first Sequenced for production. Planned Date is equal to Due Date when vehicle is first Sequenced, but it may change if the Sequence is changed. The Due Date remains fixed and is used to measure Performance.



Explanation:

New Sales Orders, received every Decade, are sent to **ASF** via **PAD**. These new Sales Orders are then sequenced, in ASF, and assigned a production number, dates (due and planned dates), as well as **ASF** codes (internal production codes). These Sales Orders are then sent back to **PAD** where they are added to the existing Sales Orders that have already been through the sequencing process.

PAD sends the production numbers and dates to the **SAP Production Planning Module – Order Management System**. No order details are provided to **SAP** at this stage, but they are sent to **SAP** 15 days before the vehicle enters the Bodyshop. The delay is done purposefully so as to reduce the electronic “traffic” between the **PAD** and **SAP** Systems. The reason for the delay is that many changes in the order requirements can occur from the time that an order is placed until the time that the order goes into Option Freeze. Communicating all these changes from **PAD** to **SAP** would result in high volumes of electronic traffic. Option freeze occurs 25 days before Bodyshop, therefore any order details that are sent from **PAD** to **SAP** 15 days before Bodyshop are finalized and no further changes can occur.

PAD sends the Master Data to **PLUS**. The Master Data contains no information regarding the parts that are required to build a specific car or a production number; rather it contains data pertaining to the Option Codes required by the cars to be built. **PLUS** generates a picking list by combining the Master Data and the relevant order details resident in **SAP**.

PLUS updates **PAD** with the movements of the sequenced cars, i.e. as the vehicles move through the various production points, via the **SAP Production Planning Module**.

SAP PP: Gross Requirements Planning.

Inputs:

- TBE Periodic

Output:

- Gross Requirements Plan, at part level, specifying the usage zone and requirement date at the related usage zone. (60 days of Actual Orders, plus 6 months of Forecasted Orders).

Explanation

The **SAP Production Planning – Gross Requirements Planning System** is responsible for converting the Gross Requirements, received from **TBE periodic**, into **Planned Independent Requirements - Periodic (PIR - Periodic)**. The PIR's are part requirements that are to be used, on a specific date, to fulfil an order requirement. These PIR's are not assigned to a Production Order as they are based on **TBE Periodic**. (Refer to **TBE Periodic**).

The difference between the **Gross Requirements** in the **TBE system** and the **Gross Requirements** in the **SAP Production Planning** system is that the latter system specifies **where** and **when** the parts are required, as opposed to the date **at which the car is planned to be complete** e.g. Part 2036901640 27E63C is required at Line Zone (**where**) 1 on the 27th March 03 (**when**). In the case of TBE, it would specify that a part is required on the date that the **entire car** is to be completed.

The requirement date is calculated using the back-off tables that are stored in **SAP**. These tables specify how many days before a car's completion is a specific part required. The number of days that a part is backed-off from the completion date is dependent on the Line Zone at which it is fitted to a car.

Example: The back-off table indicates that a part fitted at the Mechanical Line must be available, to that line, 3 days before the planned completion date of the car to which the part is to be fitted.

All requirements planned in the **SAP Production Planning – Gross Requirements Planning System** do not have any production numbers (due to **TBE Periodic** not having production numbers) associated with the requirements. It is due to this fact, as well as **TBE Periodic** being run every 10 days, that any change in requirements dates could result in a over / short supply of the required stock. This occurrence will only happen for parts whose demand was obtained from TBE Periodic. These parts include those with 60 day Lead-Times and bulk parts.

Reason: The **TBE Gross Requirements Planning System** is updated with the change in requirements via **GOP** (which in turn is updated via the **SAP Production Planning Module – Order Management System**). These updates will only be reflected in the following **TBE Periodic** run, this results in a delay between the time that a requirement date is changed until the time that the change is reflected in both Gross Requirements Planning systems (**TBE Periodic** and **SAP**). This delay is the direct cause for a possible over / short supply of stock. This problem is not such a major issue, as this anomaly would only occur with non-critical parts.

The Gross Requirements from the **SAP Production Planning – Gross Requirements Planning System** is sent to the **SAP Production Planning – Material Requirements Planning System**, where the Net Requirements are calculated per part, as well as to the **SAP Purchasing System**.

The SAP Purchasing System is used to indicate to the SAP Production Planning – Material Requirements Planning System whether or not a part should be purchased from a local supplier or from an overseas supplier.

SAP Production Planning – Material Requirements Planning.

Inputs:

- SAP Production Planning – Gross Requirements Planning (PIR Periodic)
- SAP Production Planning – Order Management System (PIR Daily)
- PLUS (Actual Order Dates) –Triggers Consumption (Indicates that part has been used)
- ASN

Output:

- Firmed Purchase Orders.
- Planned Purchase Orders (used for forecasting requirements to suppliers).
- Delivery Schedule (Local Suppliers).
- JIT schedule (Local JIT suppliers).

Explanation:

This system is responsible for calculating the Net Requirements per part. Further, this system is responsible for creating, storing, and releasing orders to relevant suppliers / vendors (local or overseas) at the correct moment such that the part requirements are satisfied.

The Net Requirement calculations are based upon the following formula:

$$\text{Net Requirements} = \text{Stock-on-Hand} + \text{Planned Receipts} - \text{Safety Stock} - \text{Requirements}$$

The amount resulting from this calculation is then adjusted, using certain rules, to cater for “Palletization” as well as “stock performance parameters” i.e. Minimum and Target Stock Coverage.

The “Requirements” in this calculation refer to the PIR (daily) and PIR (periodic) amounts.

The Net Requirement is transmitted to the relevant supplier / vendor by means of a RAN.

A RAN is a special order number – formerly introduced by Nissan and Toyota, in which the following data is encoded:

- Part number.
- Quantity.
- Pallet.
- Date.

The quantity indicated on the RAN will always follow the rules below in terms of Option related parts.

- The quantity ordered may never be less than the specified Minimum Order Quantity.
- The quantity of one RAN may never exceed the Maximum Container Quantity.
- The quantity required must always be in multiples of the Minimum Order Quantity.

Further the material for one RAN may not be “stuffed” (packed) into many different containers.

The precise time at which a purchase order is released is based upon various parameters, such as:

- Order Lead-Time.
- Safety-time.
- Goods Receipt Processing time (GRPt).
- Back-Off time.

The RANs are released on a daily basis and transmitted via WEBEDI to Mercedes Benz Consolidation Centre (MBCC), which then transmits the requirements to the relevant suppliers / vendors on a weekly basis. As well as transmitting RANs the **SAP Production Planning – Material Requirements Planning** system also transmits a 9 month requirements forecast. The 1st three months are made up of actual orders and the remaining 6 months are Forecasted Orders.

The **SAP Production Planning – Material Requirements Planning** system receives an Advanced Shipping Notification (ASN) when a ship leaves the harbour in Germany. The ASN is used to indicate:

- Part number.
- Actual Quantity Shipped.
- Estimated Time of Arrival (ETA).
- Ship.
- Container.
- RAN #.

The ASNs ultimate purpose is that material tracking i.e. where is the material and when is it going to arrive. In the case of an emergency i.e. the ASN indicates that the required stock is not going to arrive on time, and then the MRP controller is required to take action. He / she will then place an Emergency RAN (ERAN). The emergency stock will then be flown or shipped in depending on the level of the emergency.

PLUS: Production Control and Export Preparation.

Inputs:

- PAD – Order Master Data.
- SAP Production Planning – Order Management System (Actual Dates).
- COC¹⁰ – Master Data.

Output:

- Dispatch Information.
- Actual Dates per Order.

Explanation:

Only a brief explanation is given of this system. Although it [PLUS] does provide input data to various systems that play a role in the Net Requirements calculation of the **SAP Production Planning – Material Requirements Planning** system, it does not directly affect the part requirements or the associated requirement dates. Reason: Vehicles are sequenced in ASF and PLUS ensures that the vehicles are manufactured according to that sequence. This system is primarily focused on production control, order tracking, and quality assurance.

PLUS is responsible for maintaining the parameters representing the current production environment. These parameters entail:

- Leading / Receiving groups.
- Engineering Change (EC) part or new part decisions.
- User profiles.
- Vehicle technical attributes.

¹⁰ Certificate of Conformity. Indicates where a car was built. Required by European countries.

Special orders are created in PLUS, additional to PAD/SAP orders. The order details pertaining to these Special Orders have to be entered into the system manually. Special Orders are created for:

- Project Cars.
- Tests limited to the Body and Paint Shop PLUS sends a message, 5 days before the start of a vehicle production, to the Supply-In-Line-Sequence (SILS) suppliers notifying them of the specific parts required for each individual vehicle. PLUS receives a vehicle's order data 2 days before the start of production. The data includes:
 - Production Number.
 - Order Configuration.
 - Sales / Production codes.
 - Order Dates.
 - Sequence Number.
 - PLUS Parts (critical part numbers).

PLUS uses all of the above information to initiate the start of the production process, which occurs in the Body Shop, as well as control and keep track of the entire vehicle assembly process. Defect and re-work data is captured at quality control stations, which is then used to indicate to SAP that extra parts are required to cater for the defects.

Quality control stations stationed at various points on the production and assembly line, check for production and assembly defects as the vehicle moves along the line. All of these stations are required to sign-off that a vehicle has passed the respective tests. PLUS maintains a check of all of the quality tests that are to be performed and will not release a vehicle for dispatch unless it has passed all the tests. This process is used to ensure that all dispatched vehicles conform 100% to the DCSA quality control measures.

Appendix B Lead-Time Breakdown



44 Day Lead Time (32 Working Days)

RAN's are transmitted 5 days a week. Tuesday through Saturday

Cumulative Calendar Day (Start at Order Release)	Cumulative Calendar Day per Category	Cumulative Work Day per Category	Weekday	Description
			Friday	
			Saturday	
			Sunday	
			Monday	
	1	1	Tuesday	
	2	2	Wednesday	
	3	3	Thursday	
	4	4	Friday	
	5	4	Saturday	DCSA Receives Customer Order (9 to 20 Calendar Days prior to Order Release)
Customer Orders Received	6	5	Sunday	
	7	6	Monday	
	8	7	Tuesday	
	9	8	Wednesday	
	10	9	Thursday	
	11	9	Friday	
	1		Saturday	
	2		Sunday	
	3	1	Monday	
	4	2	Tuesday	
	1	1	Wednesday	Controller Evaluates Order Request
	2	2	Thursday	
	3	3	Friday	
	4		Saturday	
	5		Sunday	
1	1	1	Monday	MBCC Receives RAN's & transmits Delivery Schedule to German vendor / plant
2	2	2	Tuesday	
3	3	3	Wednesday	
4	4	4	Thursday	
5	5	5	Friday	
6	6		Saturday	
7	7		Sunday	
8	1	1	Monday	
9	2	2	Tuesday	Handling time at BLG. Batched Orders are packed according to RAN's
10	3	3	Wednesday	
11	4	4	Thursday	
12	5	5	Friday	
13	6		Saturday	
14	7		Sunday	
15	1	1	Monday	Container Transport to Bremerhaven
16	2	2	Tuesday	
17	1	1	Wednesday	shipment cycle MBCC-E
18	2	2	Thursday	
19	3	3	Friday	
20	1		Saturday	Ship ETD
21	2		Sunday	
22	3	1	Monday	
23	4	2	Tuesday	
24	5	3	Wednesday	
25	6	4	Thursday	
26	7	5	Friday	
27	8		Saturday	
28	9		Sunday	
29	10	6	Monday	Time at Sea
30	11	7	Tuesday	
31	12	8	Wednesday	
32	13	9	Thursday	
33	14	10	Friday	
34	15		Saturday	
35	16		Sunday	
36	17	11	Monday	
37	18	12	Tuesday	
38	19	13	Wednesday	
39	20	14	Thursday	Ship ETA.
40	1	1	Friday	
41	2		Saturday	shipment cycle DCSA
42	3		Sunday	
43	4	2	Monday	
44	5	3	Tuesday	
45	1	1	Wednesday	Goods Receipt Processing Time
46	1	2	Thursday	Goods Available to Line. ML/T1/T2
47	2	3	Friday	
48	3		Saturday	
49	4		Sunday	
50	5	4	Monday	Independent Requirement Date
51	6	5	Tuesday	
52	7	6	Wednesday	Actual FI Date
53	8	7	Thursday	Export Preparation

63 Calendar Days before JIG

Note
If a RAN is scheduled to be transmitted on a Sunday or a Monday, then SAP will transmit the RAN's on a Saturday to ensure that the suppliers / vendors can supply on time

53 Calendar Days before JIG

MRP Releases Order
22 Working Days to 10 - Day Option Freeze. 34 Working Days to Assembly

Option Freeze Starts (Current). 25 Working Days before JIG. Changes may still occur on this day!

Option Freeze Starts (Proposed). 10 Working Days before JIG. 12 Working Days before ML/T1/T2. Changes may still occur on this day!

Create Sales Order

JIG (Y). Check point 2016

Production

FI (X). Check point 6400

Figure 61: Order Lead-Time Breakdown 44 calendar days.

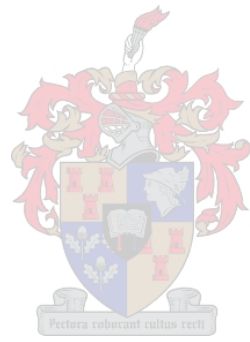
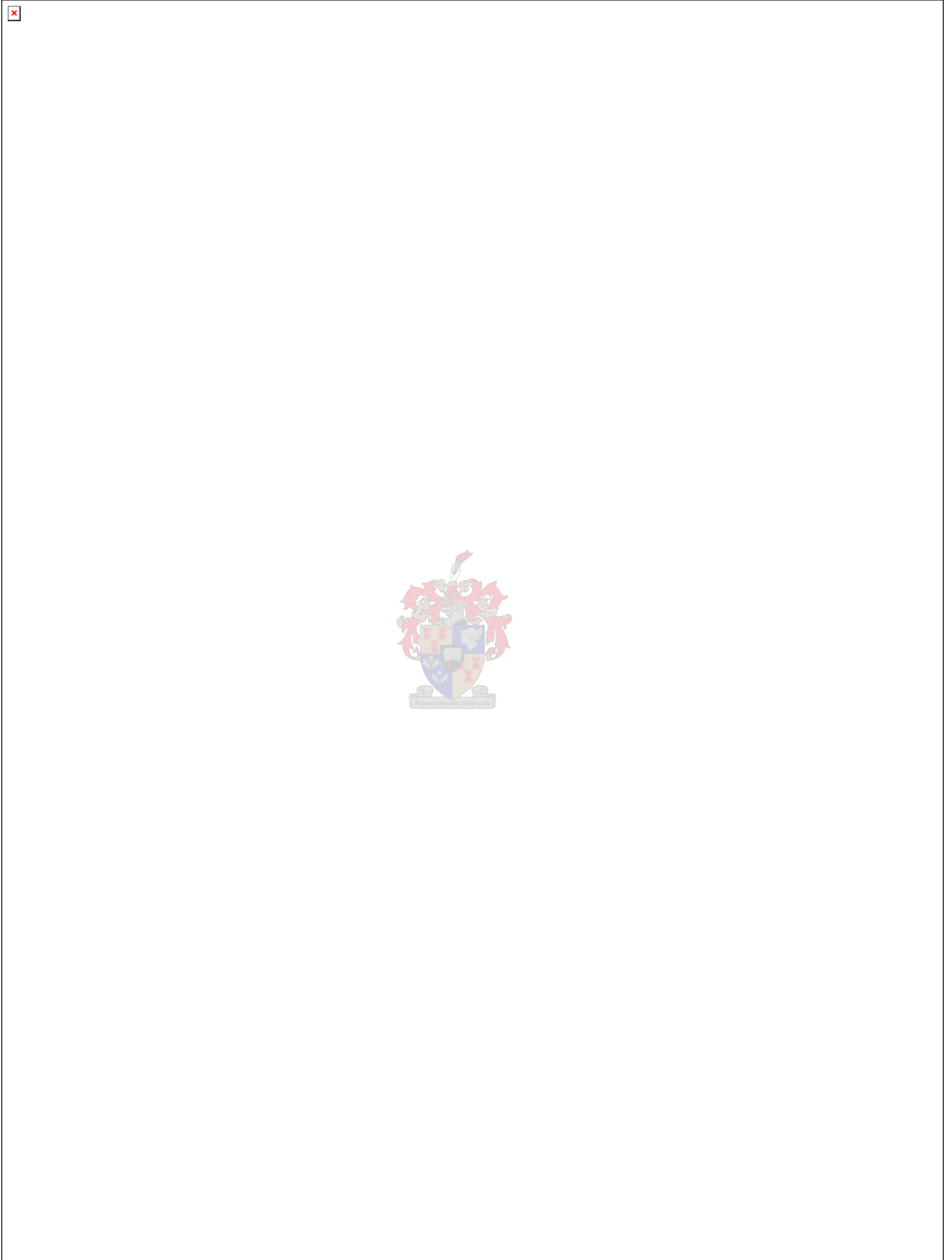


Figure 62: Order Lead-Time Breakdown 53 calendar days.

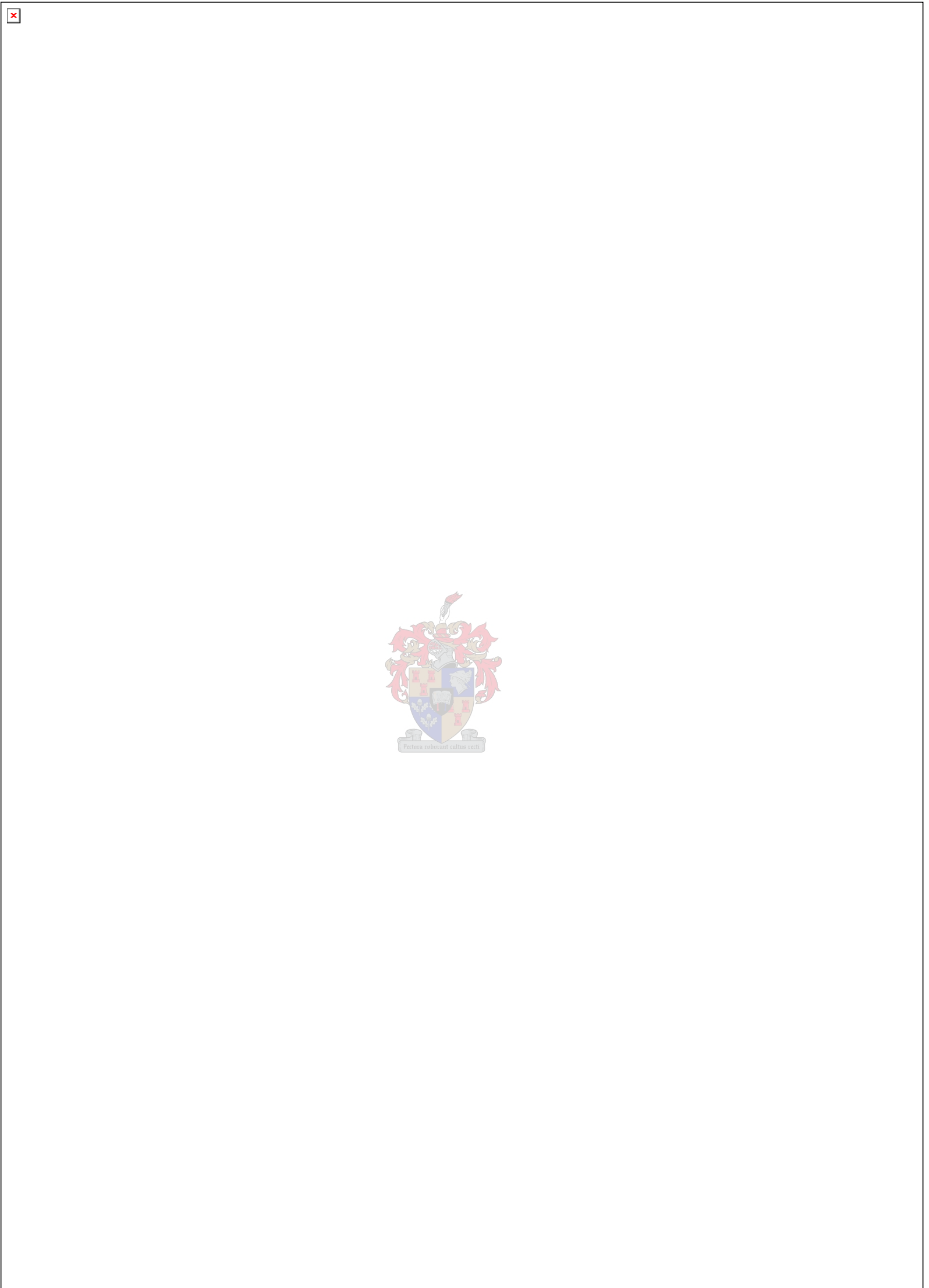


Figure 63: Order Lead-Time Breakdown 60 calendar days

Appendix C Parts Selected for Analysis



Category	Sub - Category	Part Type	Recommended Part	Part Code	Lead-Time (days)	Min Lot Size	Max Lot Size	Rounding Value	Reason
Standard	Singular	Badge	Mercedes Star	2028800186 A	60	864	NA	864	Benchmark. Imported part
	Equipment Package	Badge	Classic Label	2038170920 A	44	900	2607300	900	Use Labels as a unambiguous method of focusing on the various Equipment Packages
		Badge	Avantgarde Label	2038171120 A	44	900	2607300	900	
		Badge	Elegance Label	2038171020 A	44	900	2655900	900	
Colour Coded Parts	Local	High Runner	Head Rest	2039709350 27D44A	0	1	NA	1	Commonly Subjected to Variation, Lead-Time within DCSA Option Freeze Period. Used as forecast back-up
	Imported (CMH)	High Runner, High Value	Steering Wheel	2034600903 29C29A	62	40	NA	40	Imported parts supplied from CMH. High Runner. Commonly Subjected to Interior Variation
		Low Runner, High Value	Steering Wheel	2034600903 25C69A	62	40	NA	40	Imported parts supplied from CMH. Low Runner. Commonly Subjected to Interior Variation
	Imported	Exotic (Low Value)	Steering Wheel (Black Chrome Insert)	2034601503 29C29A	60	25	1050	25	Imported Part. Exotic. Low Value. Commonly Subjected to Interior Variation
		Exotic (High Value)	Steering Wheel AMG Black	2034602403 29C29A	60	25	675	25	Imported Part. Exotic. High Value. Commonly Subjected to Interior Variation
		Low Runner, Low Value	Cover comp RH B-pillar	2036901640 21A73C	44	60	3360	60	Commonly Subjected to Interior Colour Variation. Short Lead-Time
		High Runner, Low Value	Cover comp RH B-pillar	2036901640 27E63C	44	6	3360	84	Commonly Subjected to Interior Colour Variation. Short Lead-Time
High Runner	Medium Value	Imported	Rim	2094000402 A	60	30	NA	30	The UK requires this option by legislation. Therefore it is a high runner that has recently required a large amount of airfreight
		Imported	Carpet	2096801242 29D60A	60	20	NA	20	
		Imported	Carpet	2096801042 29D60A	60	20	NA	20	
	High Value	Imported	C220 Diesel Gearbox Auto	2032700400 A	53	7	126	7	The part focused on is representative of HR/HV (medium) parts. Ave 600 orders per month
		Imported	C180 Gearbox Automatic	2112703200 A	53	7	126	7	The part focused on is representative of HR/HV parts. Ave 2000 orders per month
		Imported	C180 Kompressor Engine	2710106700 A	53	3	36	3	The part focused on is representative of HR/HV parts. Ave 1000 orders per month
Low Runner	High Value	Imported	C320 Kompressor AMG Engine	1120101144 A	60	3	36	3	Very High Value, high variation
		Imported	C 180 Gearbox Manual	2032602102 A	53	7	126	7	The part focused on is representative of LR/HV (medium) parts. Ave 75 orders per month.
		Imported	Cover, for bracket transmission hydraulic	0005461781 A	60	40	62000	40	"Exotic" Option Part, with an associated high variation (Ave 123.63% deviation of Forecast vs. Actual, 3% Built in 2002)

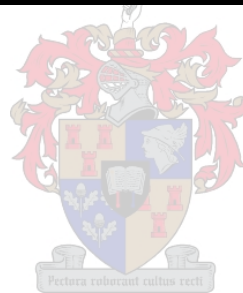
Appendix D Production Calendar



DAIMLERCHRYSLER East London - South Africa		Production Calendar 2002 Plant - East London						SOURCE: 175. PPC COMPILER: Victor Ngese *2. 2994 ISSUE: 12.09.2002 VERSION 3.3 Ident: PPC on/Eintsv5*(F) / ProdPlan/Calenders			
1 = Calendarweek	22 = Working Days	10 = Decade Border	241 = Total Actual Days	238 = Total Effective Days	◆ =	Red = Saturday Shifts	Blue = Bridging Saturday	Green = Half Days	Light Blue = Annual Shutdown	Purple = Public Holidays	Dark Purple = Non Productive Day
January	February	March	April	May	June	July	August	September	October	November	December
1 Tue 1	1 Fri 32	1 Fri 60	1 Family D 14 91	1 Workers Day 121	1 Sat 152	1 Mon 27 182	1 Thur 213	1 Sun 244	1 Tue 274	1 Fri 305	1 Sun 336
2 Wed 2	2 Sat 33	2 Sat 61	2 Tue 92	2 Thur 122	2 Sun 153	2 Tue 183	2 Fri 214	2 Mon 36 245	2 Wed 275	2 Sat 306	2 Mon 49 338
3 Thur 3	3 Sun 34	3 Sun 62	3 Wed 93	3 Fri 123	3 Mon 23 154	3 Wed 184	3 Sat 215	3 Tue 246	3 Thur 276	3 Sun 307	3 Tue 337
4 Fri 4	4 Mon 6 35	4 Mon 10 63	4 Thur 94	4 Sat 124	4 Tue 155	4 Thur 185	4 Sun 216	4 Wed 247	4 Fri 277	4 Mon 45 308	4 Wed 338
5 Sat 5	5 Tue 36	5 Tue 64	5 Fri 95	5 Sun 125	5 Wed 156	5 Fri 186	5 Mon 32 217	5 Thur 248	5 Sat 278	5 Tue 45 309	5 Thur 339
6 Sun 6	6 Wed 37	6 Wed 65	6 Sat 96	6 Mon 19 126	6 Thur 157	6 Sat 187	6 Tue 218	6 Fri 249	6 Sun 279	6 Wed 310	6 Fri 340
7 Mon 2 7	7 Thur 38	7 Thur 66	7 Sun 97	7 Tue 127	7 Fri 158	7 Sun 188	7 Wed 219	7 Sat 250	7 Mon 280	7 Thur 311	7 Sat 341
8 Tue 8	8 Fri 39	8 Fri 67	8 Mon 15 98	8 Wed 128	8 Sat 159	8 Mon 189	8 Thur 220	8 Sun 251	8 Tue 41 281	8 Fri 312	8 Sun 342
9 Wed 9	9 Sat 40	9 Sat 68	9 Tue 99	9 Thur 129	9 Sun 160	9 Tue 28 190	9 Women's Day 221	9 Mon 37 252	9 Wed 282	9 Sat 313	9 Mon 50 343
10 Thur 10	10 Sun 41	10 Sun 69	10 Wed 100	10 Fri 130	10 Mon 24 161	10 Wed 191	10 Sat 222	10 Tue 253	10 Thur 283	10 Sun 314	10 Tue 344
11 Fri 11	11 Mon 7 42	11 Mon 11 70	11 Thur 101	11 Sat 131	11 Tue 162	11 Thur 192	11 Sun 223	11 Wed 254	11 Fri 284	11 Mon 46 315	11 Wed 345
12 Sat 12	12 Tue 43	12 Tue 71	12 Fri 102	12 Sun 132	12 Wed 163	12 Fri 193	12 Mon 33 224	12 Thur 255	12 Sat 285	12 Tue 316	12 Thur 346
13 Sun 13	13 Wed 44	13 Wed 72	13 Sat 103	13 Mon 20 133	13 Thur 164	13 Sat 194	13 Tue 225	13 Fri 256	13 Sun 286	13 Wed 317	13 Fri 347
14 Mon 3 14	14 Thur 45	14 Thur 73	14 Sun 104	14 Tue 134	14 Fri 165	14 Sun 195	14 Wed 226	14 Sat 257	14 Mon 42 287	14 Thur 318	14 Sat 348
15 Tue 15	15 Fri 46	15 Fri 74	15 Mon 16 105	15 Wed 135	15 Sat 166	15 Mon 29 196	15 Thur 227	15 Sun 258	15 Tue 288	15 Fri 319	15 Sun 349
16 Wed 16	16 Sat 47	16 Sat 75	16 Tue 106	16 Thur 136	16 Sun 167	16 Tue 197	16 Fri 228	16 Mon 38 259	16 Wed 289	16 Sat 320	16 Day off 51 350
17 Thur 17	17 Sun 48	17 Sun 76	17 Wed 107	17 Fri 137	17 Mon 25 168	17 Wed 198	17 Sat 229	17 Tue 260	17 Thur 290	17 Sun 321	17 Tue 351
18 Fri 18	18 Mon 8 49	18 Mon 12 77	18 Thur 108	18 Sat 138	18 Tue 169	18 Thur 199	18 Sun 230	18 Wed 261	18 Fri 291	18 Mon 47 322	18 Wed 352
19 Sat 19	19 Tue 50	19 Tue 78	19 Fri 109	19 Sun 139	19 Wed 170	19 Fri 200	19 Mon 34 231	19 Thur 262	19 Sat 292	19 Tue 323	19 Thur 353
20 Sun 20	20 Wed 51	20 Wed 79	20 Sat 110	20 Mon 21 140	20 Thur 171	20 Sat 201	20 Tue 232	20 Fri 263	20 Sun 293	20 Wed 324	20 Fri 354
21 Mon 4 21	21 Thur 52	21 Human Rights 80	21 Sun 111	21 Tue 141	21 Fri 172	21 Sun 202	21 Wed 233	21 Sat 264	21 Mon 43 294	21 Thur 325	21 Sat 355
22 Tue 22	22 Fri 53	22 Fri 81	22 Mon 17 112	22 Wed 142	22 Sat 173	22 Mon 30 203	22 Thur 234	22 Sun 265	22 Tue 295	22 Fri 326	22 Sun 356
23 Wed 23	23 Sat 54	23 Sat 82	23 Tue 113	23 Thur 143	23 Sun 174	23 Tue 204	23 Fri 235	23 Mon 39 266	23 Wed 296	23 Sat 327	23 Mon 52 357
24 Thur 24	24 Sun 55	24 Sun 83	24 Wed 114	24 Fri 144	24 Mon 26 175	24 Wed 205	24 Sat 236	24 Heritage Day 267	24 Thur 297	24 Sun 328	24 Tue 358
25 Fri 25	25 Mon 9 56	25 Mon 13 84	25 Thur 115	25 Sat 145	25 Tue 176	25 Thur 206	25 Sun 237	25 Wed 268	25 Fri 298	25 Mon 48 329	25 Christmas 359
26 Sat 26	26 Tue 57	26 Tue 85	26 Fri 116	26 Sun 146	26 Wed 177	26 Fri 207	26 Mon 35 238	26 Thur 269	26 Sat 299	26 Tue 330	26 Day off Good 360
27 Sun 27	27 Wed 58	27 Wed 86	27 Freedom Day 117	27 Mon 22 147	27 Thur 178	27 Sat 208	27 Tue 239	27 Fri 270	27 Sun 300	27 Wed 331	27 Fri 361
28 Mon 5 28	28 Thur 59	28 Thur 87	28 Sun 118	28 Tue 148	28 Fri 179	28 Sun 209	28 Wed 240	28 Sat 271	28 Mon 44 301	28 Thur 332	28 Sat 362
29 Tue 29		29 Good Friday 88	29 Mon 18 119	29 Wed 149	29 Sat 180	29 Mon 31 210	29 Thur 241	29 Sun 272	29 Tue 302	29 Fri 333	29 Sun 363
30 Wed 30		30 Sat 89	30 Tue 120	30 Thur 150	30 Sun 181	30 Tue 211	30 Fri 242	30 Mon 40 273	30 Wed 303	30 Sat 334	30 Mon 1 364
31 Thur 31		31 Easter Sunday 90		31 Fri 151		31 Wed 212	31 Sat 243		31 Thur 304		31 Tue 365
18,5	20	18,5	20,5	22	19	17,5	22	22	23,5	21	13,5

Figure 64: Example of DCSA Production Calendar

Appendix E Requirements Report



Material.. 2038170920

A

TYPE PLATE - CLASSIC.

Plant..... 1750

Page 1

MRP type..... ZM	Material type.. ZRAW	Unit..... EA
MRP controller. 5G1	MRP group..... Z031	Lot size..... ZL
Purchasing group312	Processing ind. X	Fixed lot size.. 0
Repl. lead time 44	Warehouse stock 2,965	Min. lot size.. 900
Procurement typeF	Planned issues. 16,166	Max. lot size.. 2,607,300
SpecialProc.key	Fixed issues... 0	Safety stock... 900
Sp. procurement	Planned receipts 10,800	Reorder level.. 0
Coverage..... Z02	Firm receipts.. 3,615	Max.stock lvl.. 0

MRP date..... 2003/04/25

Period	Indep.requirements	Requirements	Receipts	Available quantity	ATP quantit
Stock				2,065	2,293
03/04/23	0	36	0	2,029	0
03/04/24	0	94	0	1,935	0
03/04/25	0	136	0	1,799	0
03/04/29	0	122	0	1,677	0
03/04/30	0	158	0	1,519	0
03/05/05	0	126	0	1,393	0
03/05/06	0	144	900	2,149	642
03/05/07	24	114	0	2,011	0
03/05/08	110	0	0	1,901	0
03/05/09	116	0	0	1,785	0
03/05/10	108	0	0	1,677	0
03/05/12	122	0	0	1,555	0
03/05/13	130	0	0	1,425	0
03/05/14	120	0	0	1,305	0
03/05/15	138	0	0	1,167	0
03/05/16	120	0	0	1,047	0
03/05/19	116	0	0	931	0
03/05/20	116	0	900	1,715	900
03/05/21	104	0	0	1,611	0
03/05/22	126	0	0	1,485	0
03/05/23	104	0	0	1,381	0
03/05/26	142	0	0	1,239	0
03/05/27	154	0	900	1,985	900
03/05/28	190	0	0	1,795	0
03/05/29	154	0	0	1,641	0
03/05/30	156	0	0	1,485	0
03/06/02	174	0	0	1,311	0
03/06/03	176	0	0	1,135	0
03/06/04	160	0	0	975	0
03/06/05	162	0	0	813	0
03/06/06	150	0	0	663	0
03/06/09	124	0	900	1,439	900
03/06/10	164	0	0	1,275	0
03/06/11	174	0	0	1,101	0
03/06/12	152	0	0	949	0
03/06/13	148	0	0	801	0
03/06/17	146	0	0	655	0
03/06/18	102	0	0	553	0
03/06/19	90	0	0	463	0
03/06/20	78	0	0	385	0
03/06/23	106	0	900	1,179	900
03/06/24	66	0	0	1,113	0
03/06/25	76	0	0	1,037	0
03/06/26	95	0	0	942	0
03/06/27	94	0	0	848	0
03/06/30	94	0	0	754	0
03/07/01	94	0	0	660	0
03/07/02	94	0	0	566	0
03/07/03	94	0	0	472	0

Material.. 2038170920

A

TYPE PLATE - CLASSIC.

Plant..... 17Page 2 Material..

MRP type..... ZM

Material type.. ZRAW

Unit..... EA

Period	Indep.requirements	Requirements	Receipts	Available quantity	ATP quantit
03/07/04	94	0	0	378	0
03/07/14	94	0	900	1,184	900
03/07/15	94	0	0	1,090	0
03/07/16	95	0	0	995	0
03/07/17	94	0	0	901	0
03/07/18	94	0	0	807	0
03/07/21	94	0	0	713	0
03/07/22	94	0	0	619	0
03/07/23	94	0	0	525	0
03/07/24	94	0	0	431	0
03/07/25	94	0	900	1,237	900
03/07/28	94	0	0	1,143	0
03/07/29	107	0	0	1,036	0
03/07/30	107	0	0	929	0
03/07/31	106	0	0	823	0
03/08/01	107	0	0	716	0
03/08/04	106	0	0	610	0
03/08/05	107	0	0	503	0
03/08/06	106	0	900	1,297	900
03/08/07	107	0	0	1,190	0
03/08/08	107	0	0	1,083	0
03/08/11	106	0	0	977	0
03/08/12	107	0	0	870	0
03/08/13	106	0	0	764	0
03/08/14	107	0	0	657	0
03/08/15	106	0	0	551	0
03/08/18	107	0	0	444	0
03/08/19	107	0	900	1,237	900
03/08/20	106	0	0	1,131	0
03/08/21	107	0	0	1,024	0
03/08/22	106	0	0	918	0
03/08/25	107	0	0	811	0
03/08/26	106	0	0	705	0
03/08/27	98	0	0	607	0
03/08/28	97	0	0	510	0
03/08/29	97	0	0	413	0
03/09/01	98	0	900	1,215	900
03/09/02	97	0	0	1,118	0
03/09/03	97	0	0	1,021	0
03/09/04	98	0	0	923	0
03/09/05	97	0	0	826	0
03/09/08	97	0	0	729	0
03/09/09	98	0	0	631	0
03/09/10	97	0	0	534	0
03/09/11	97	0	0	437	0
03/09/12	98	0	900	1,239	900
03/09/15	97	0	0	1,142	0
03/09/16	97	0	0	1,045	0
03/09/17	98	0	0	947	0
03/09/18	97	0	0	850	0
03/09/19	97	0	0	753	0
03/09/22	98	0	0	655	0
03/09/23	97	0	0	558	0
03/09/25	97	0	0	461	0
03/09/26	88	0	0	373	0
03/09/29	88	0	900	1,185	900
03/09/30	88	0	0	1,097	0
03/10/01	87	0	0	1,010	0

Material.. 2038170920

A

TYPE PLATE - CLASSIC.

Plant..... 17Page 3 Material..

MRP type..... ZM

Material type.. ZRAW

Unit..... EA

Period	Indep.requirements	Requirements	Receipts	Available quantity	ATP quantit
03/10/02	88	0	0	922	0
03/10/03	88	0	0	834	0
03/10/06	88	0	0	746	0
03/10/07	87	0	0	659	0
03/10/08	88	0	0	571	0
03/10/09	88	0	0	483	0
03/10/10	88	0	0	395	0
03/10/13	87	0	900	1,208	900
03/10/14	88	0	0	1,120	0
03/10/15	88	0	0	1,032	0
03/10/16	88	0	0	944	0
03/10/17	87	0	0	857	0
03/10/20	88	0	0	769	0
03/10/21	88	0	0	681	0
03/10/22	88	0	0	593	0
03/10/23	87	0	0	506	0
03/10/24	88	0	0	418	0
03/10/27	88	0	900	1,230	900
03/10/28	87	0	0	1,143	0
03/10/29	94	0	0	1,049	0
03/10/30	94	0	0	955	0
03/10/31	94	0	0	861	0
03/11/03	94	0	0	767	0
03/11/04	93	0	0	674	0
03/11/05	94	0	0	580	0
03/11/06	94	0	0	486	0
03/11/07	94	0	0	392	0
03/11/10	94	0	900	1,198	900
03/11/11	93	0	0	1,105	0
03/11/12	94	0	0	1,011	0
03/11/13	94	0	0	917	0
03/11/14	94	0	0	823	0
03/11/17	94	0	0	729	0
03/11/18	93	0	0	636	0
03/11/19	94	0	0	542	0
03/11/20	94	0	0	448	0
03/11/21	94	0	0	354	0
03/11/24	94	0	0	260	0
03/11/25	93	0	900	1,067	900
03/11/26	70	0	0	997	0
03/11/27	70	0	0	927	0
03/11/28	69	0	0	858	0
03/12/01	70	0	0	788	0
03/12/02	70	0	0	718	0
03/12/03	69	0	0	649	0
03/12/04	70	0	0	579	0
03/12/05	70	0	0	509	0
03/12/06	69	0	0	440	0
03/12/08	70	0	0	370	0
03/12/09	69	0	0	301	0
03/12/10	1	0	0	300	0
04/01/14	1	0	0	299	0
StLcSt 0310				0	0
StLcSt 0510				0	0
StLcSt 0530				590	0

Material.. 2038170920

A

TYPE PLATE - CLASSIC.

Plant..... 17Page 4 Material..

MRP type..... ZM

Material type.. ZRAW

Unit..... EA

Period	Indep.requirements	Requirements	Receipts	Available quantity	ATP quantit
StLcSt 0710				0	0
StLcSt 0720				0	0
StLcSt 0740				0	0
StLcSt 0810				0	0
03/02/27	0	0	15	15	0

*Appendix F Safety Time and Coverage
Profile Combinations*



Simulation Run	Safety Time	Minimum Coverage	Target Coverage
1	0	0	0
2	0	0	1
3	0	0	2
4	0	0	3
5	0	0	4
6	0	0	5
7	0	1	1
8	0	1	2
9	0	1	3
10	0	1	4
11	0	1	5
12	0	2	2
13	0	2	3
14	0	2	4
15	0	2	5
16	0	3	3
17	0	3	4
18	0	3	5
19	0	4	4
20	0	4	5
21	0	5	5
22	1	0	0
23	1	0	1
24	1	0	2
25	1	0	3
26	1	0	4
27	1	0	5
28	1	1	1
29	1	1	2
30	1	1	3
31	1	1	4
32	1	1	5
33	1	2	2
34	1	2	3
35	1	2	4
36	1	2	5
37	1	3	3
38	1	3	4
39	1	3	5
40	1	4	4
41	1	4	5
42	1	5	5
43	2	0	0
44	2	0	1
45	2	0	2
46	2	0	3
47	2	0	4
48	2	0	5
49	2	1	1
50	2	1	2
51	2	1	3
52	2	1	4
53	2	1	5
54	2	2	2
55	2	2	3
56	2	2	4
57	2	2	5
58	2	3	3
59	2	3	4
60	2	3	5
61	2	4	4
62	2	4	5
63	2	5	5

Table 43: Input Parameter Combinations

*Appendix G Half-widths of Safety Time,
Minimum, & Target Coverage
set to Zero.*



Part No.	Avg. Customer Service Level	Standard Deviation of Customer Service Level	Tinv (0.05,49)	Half-width	Upper	Lower
0005461781 A	0.989	0.004	2.010	0.001	0.990	0.988
1120101144 A	0.941	0.009	2.010	0.003	0.944	0.939
203400903 25C69A	0.984	0.003	2.010	0.001	0.985	0.983
2034601503 29C29A	0.986	0.004	2.010	0.001	0.987	0.985
2034602403 29C29A	0.982	0.005	2.010	0.001	0.983	0.980
2096801242 29D60A	0.975	0.004	2.010	0.001	0.976	0.974
2036901640 21A73C	0.989	0.002	2.010	0.001	0.990	0.989
2039709350 27D44A	0.957	0.006	2.010	0.002	0.959	0.955
2032700400 A	0.985	0.004	2.010	0.001	0.986	0.984
2710106700 A	0.961	0.005	2.010	0.002	0.963	0.960
2094000402 A	0.978	0.003	2.010	0.001	0.979	0.977
2096801042 29D60A	0.974	0.004	2.010	0.001	0.975	0.973
2034600903 29C29A	0.977	0.004	2.010	0.001	0.978	0.976
2038171120 A	0.990	0.002	2.010	0.001	0.990	0.989
2112703200 A	0.955	0.005	2.010	0.001	0.957	0.954
2038170920 A	0.994	0.002	2.010	0.000	0.995	0.994
2038171020 A	0.996	0.001	2.010	0.000	0.996	0.995

Table 44: Half-Widths of SAP-MRP. (ST, MC, and TC = 0). Alpha = 0.05, n =50

*Appendix H Summary of “Human
Intervention” Simulation*



Category	Part Number	"As-Is"	Coverage Maintenance	Diff (Cov Main. – "As-Is")
Avg. Plant Inventory	2034601503 29C29A	23.1840992	24.68481636	1.500717163
	2032700400 A	202.0014191	204.7531281	2.751708984
	2710106700 A	353.1619568	370.6696472	17.50769043
	2096801042 29D60A	515.3459473	525.3568726	10.01092529
	2112703200 A	542.6511841	587.0775757	44.4263916
	2038170920 A	1678.474243	1746.846436	68.37219238
Avg. Pipeline Inventory	2034601503 29C29A	19.07452202	18.22727013	-0.847251892
	2032700400 A	982.0907593	977.6157837	-4.474975586
	2710106700 A	2533.971436	2516.80249	-17.16894531
	2096801042 29D60A	2665.818359	2662.400635	-3.417724609
	2112703200 A	4202.222656	4169.210449	-33.01220703
	2038170920 A	3720.044434	3662.181885	-57.86254883
Avg. Harbour Inventory	2034601503 29C29A	1.135443211	1.074050784	-0.061392426
	2032700400 A	54.70539856	54.58930588	-0.116092682
	2710106700 A	140.8704529	140.2851105	-0.585342407
	2096801042 29D60A	171.4865875	171.1286011	-0.35798645
	2112703200 A	234.5706635	231.1139679	-3.456695557
	2038170920 A	237.9417725	235.4582214	-2.483551025
Avg. Number of Orders	2034601503 29C29A	24.71999931	23.71999931	-1
	2032700400 A	902.0599976	900.039978	-2.020019531
	2710106700 A	960.2000122	957.8800049	-2.320007324
	2096801042 29D60A	936.1400146	933.5	-2.640014648
	2112703200 A	959.4000244	956.9199829	-2.480041504
	2038170920 A	130.8999939	128.8600006	-2.039993286
Avg. Order Size	2034601503 29C29A	25	25	0
	2032700400 A	29.71996117	29.63741875	-0.082542419
	2710106700 A	71.93097687	71.522995	-0.407981873
	2096801042 29D60A	90.16133881	90.30131531	0.139976501
	2112703200 A	119.3647385	118.4916687	-0.873069763
	2038170920 A	906.8766479	906.9858398	0.109191895
Avg. Customer Service Level	2034601503 29C29A	0.999967217	1	3.27826E-05
	2032700400 A	0.99999225	1	7.7486E-07
	2710106700 A	0.99992728	1	7.27177E-06
	2096801042 29D60A	0.99997884	1	2.11596E-05
	2112703200 A	0.999970555	1	2.94447E-05
	2038170920 A	1	1	0
Avg. DCSA Service Level	2034601503 29C29A	0.999166667	0.936293662	-0.062873006
	2032700400 A	0.999977887	0.994195998	-0.005781889
	2710106700 A	0.999937296	0.976279199	-0.023658097
	2096801042 29D60A	0.999956846	0.989792883	-0.010163963
	2112703200 A	0.999916673	0.967878401	-0.032038271
	2038170920 A	1	0.984695494	-0.015304506
Avg. Total Shortages	2034601503 29C29A	0.5	37	36.5
	2032700400 A	1.820000052	267.9599915	266.1399914
	2710106700 A	12.96000004	4170.47998	4157.51998
	2096801042 29D60A	11.60000038	1382	1370.4
	2112703200 A	27.44000053	8815.660156	8788.220156
	2038170920 A	0	1764	1764
Avg. Customer Shortages	2034601503 29C29A	0.02	0	-0.02
	2032700400 A	0.02	0	-0.02
	2710106700 A	0.059999999	0	-0.059999999
	2096801042 29D60A	0.039999999	0	-0.039999999
	2112703200 A	0.079999998	0	-0.079999998
	2038170920 A	0	0	0
Avg. Shortage Frequency	2034601503 29C29A	0.02	1.480000019	1.46000002
	2032700400 A	0.02	5.21999979	5.199999791
	2710106700 A	0.059999999	22.71999931	22.65999931
	2096801042 29D60A	0.039999999	9.520000458	9.480000459
	2112703200 A	0.079999998	30.73999977	30.65999977
	2038170920 A	0	1.960000038	1.960000038

Table 45: Results from "Human Intervention" Experiment.

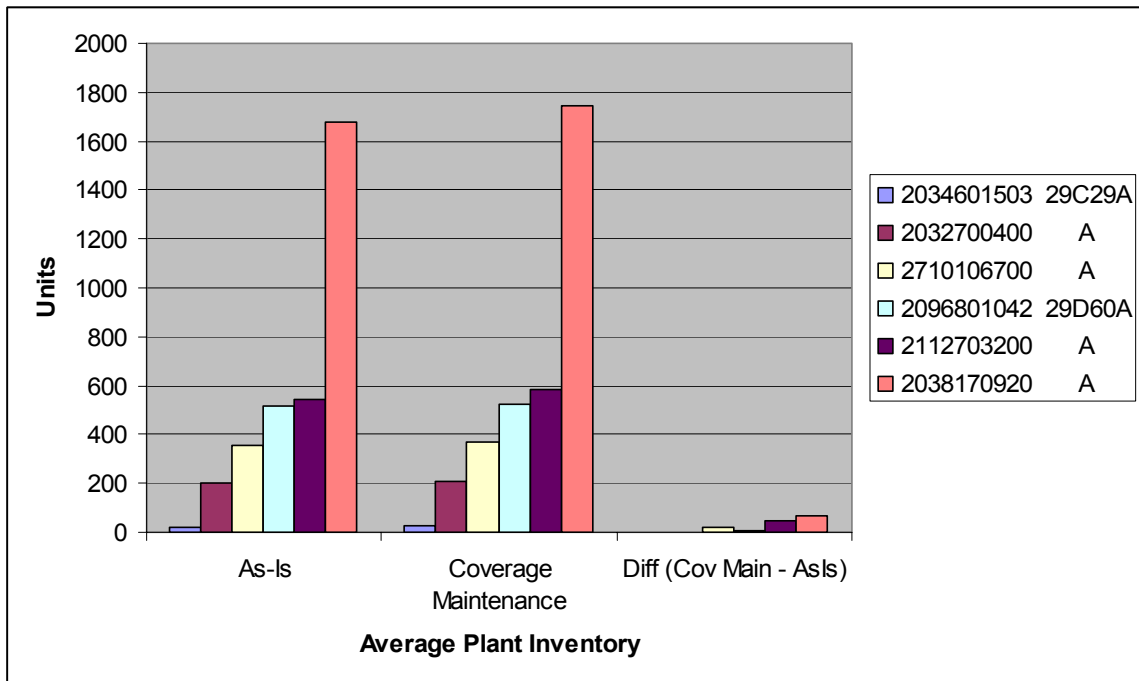


Figure 65: “Human Intervention”: Avg. Plant Inventory.

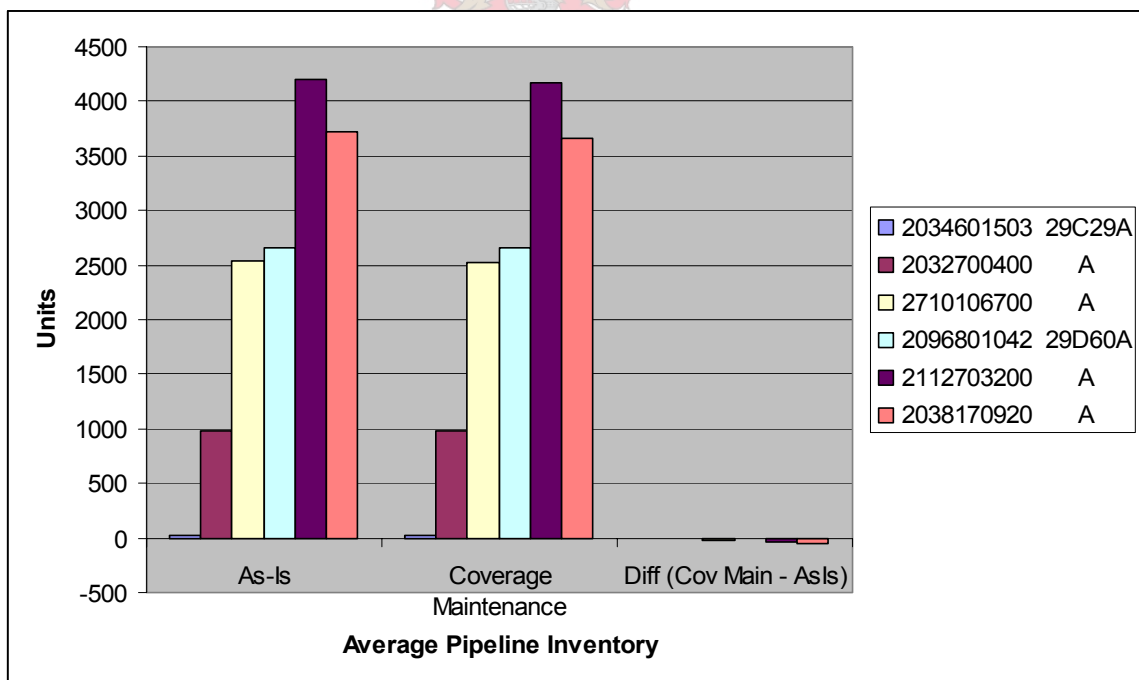


Figure 66: “Human Intervention”: Avg. Pipeline Inventory.

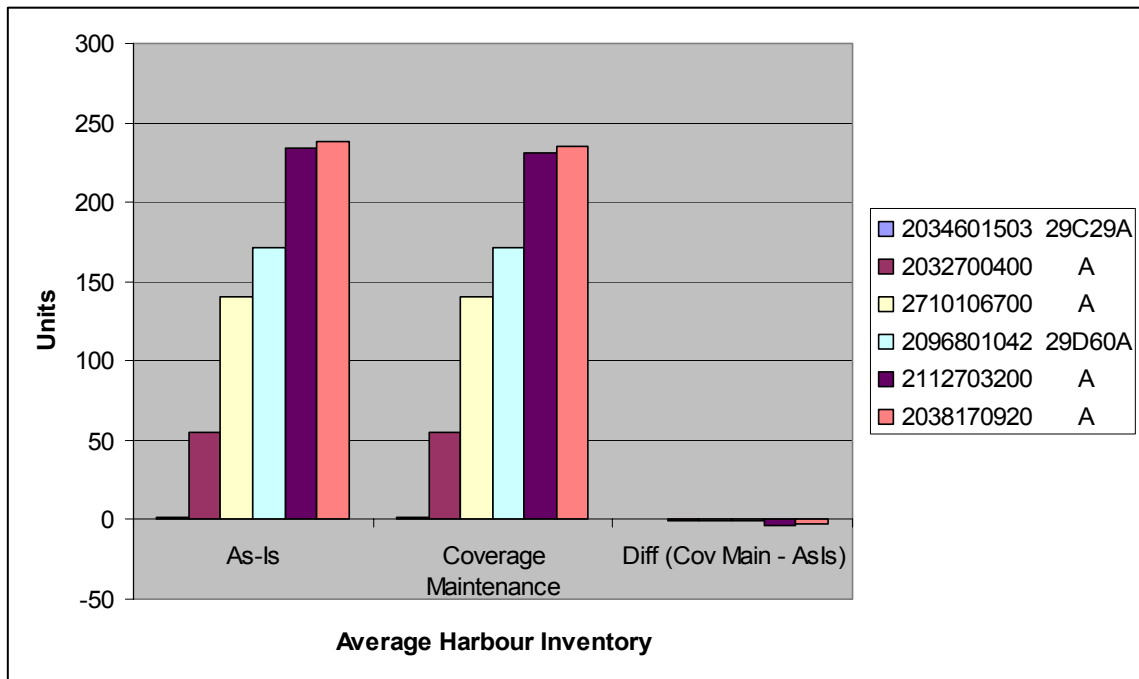


Figure 67: “Human Intervention”: Avg. Harbour Inventory.

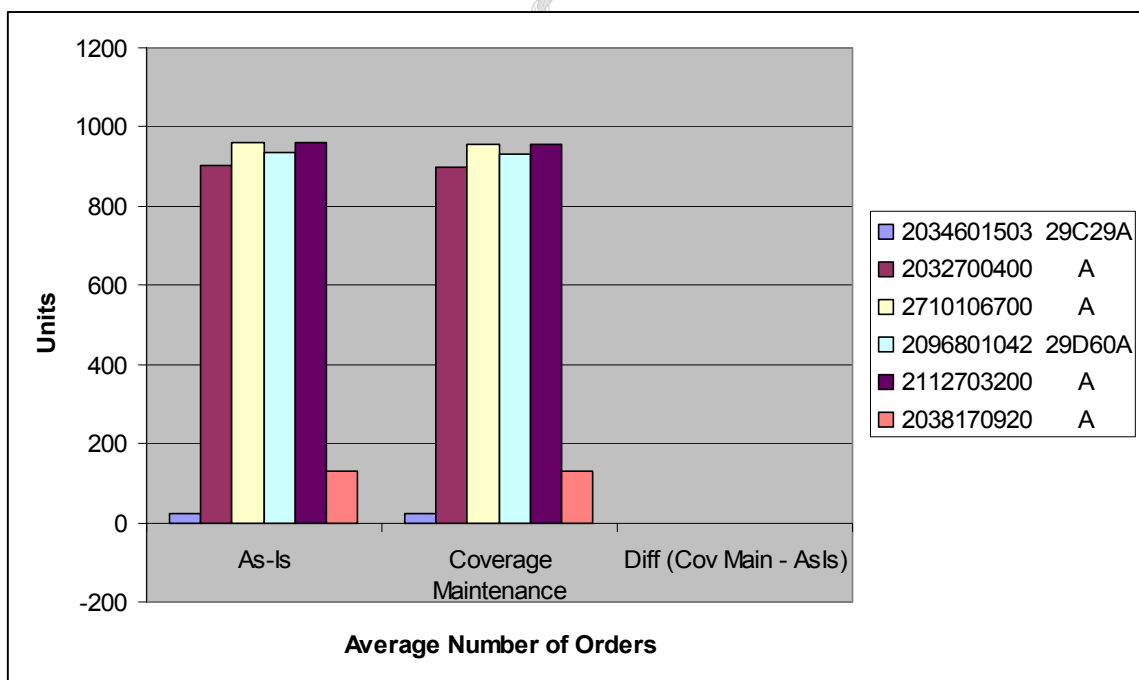


Figure 68: “Human Intervention”: Avg. Order Numbers.

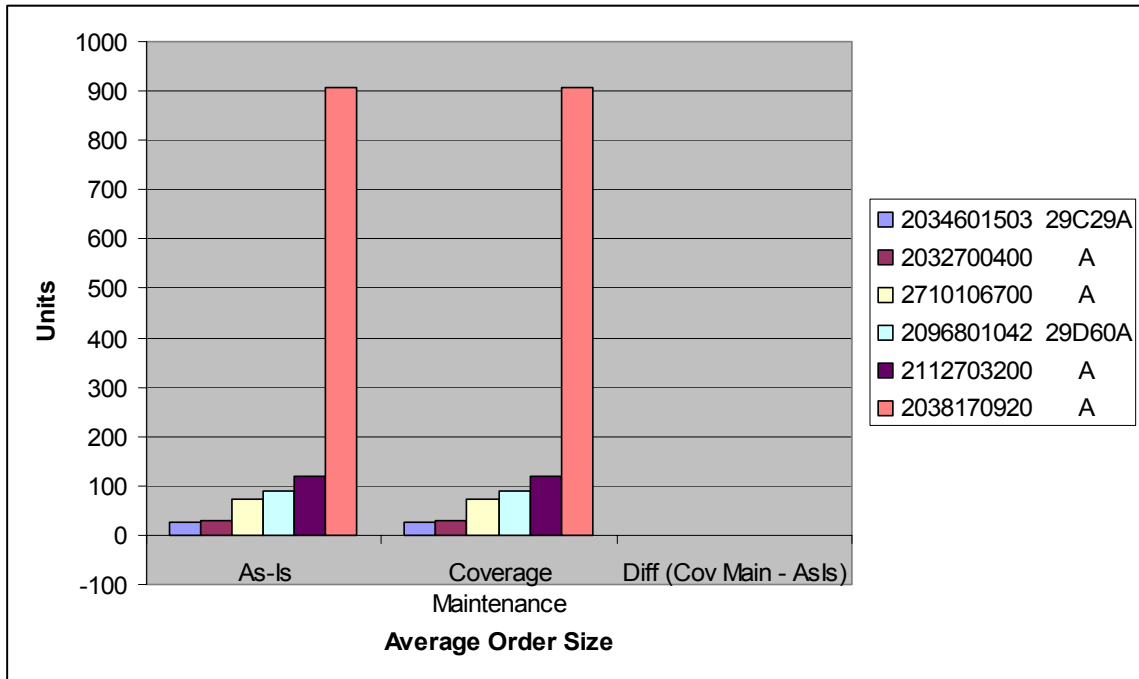


Figure 69: "Human Intervention": Avg. Order Size.

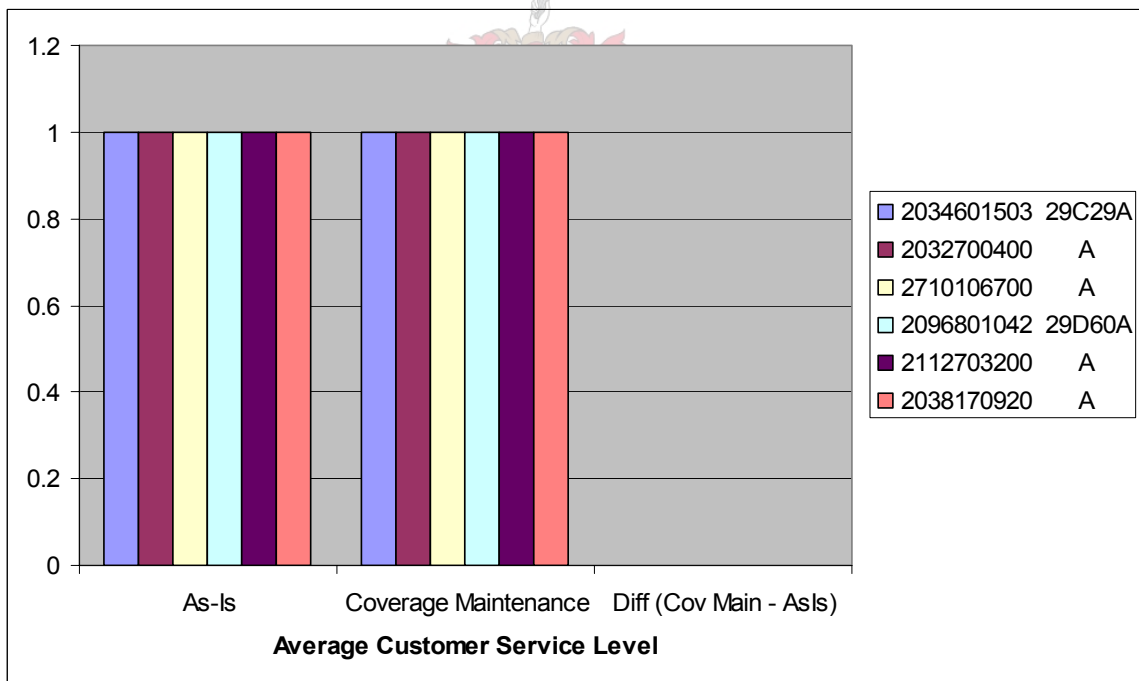


Figure 70: "Human Intervention": Avg. Customer Service Level.

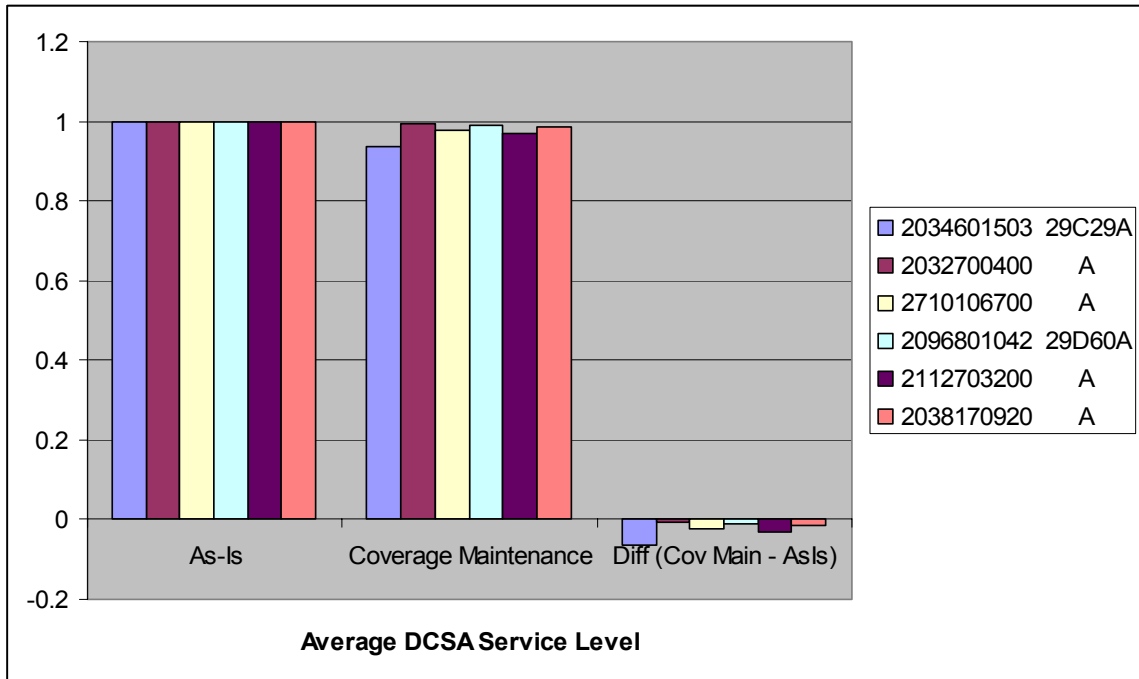


Figure 71: "Human Intervention": Avg. DCSA Service Level.

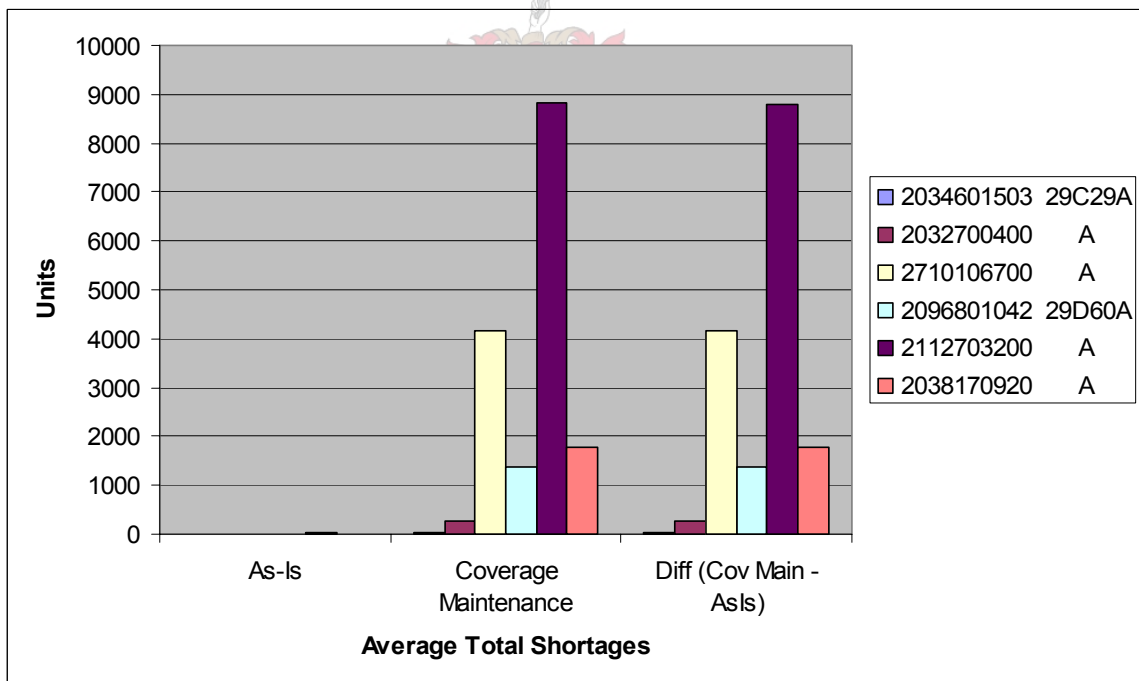


Figure 72: "Human Intervention": Avg. Total Shortages.

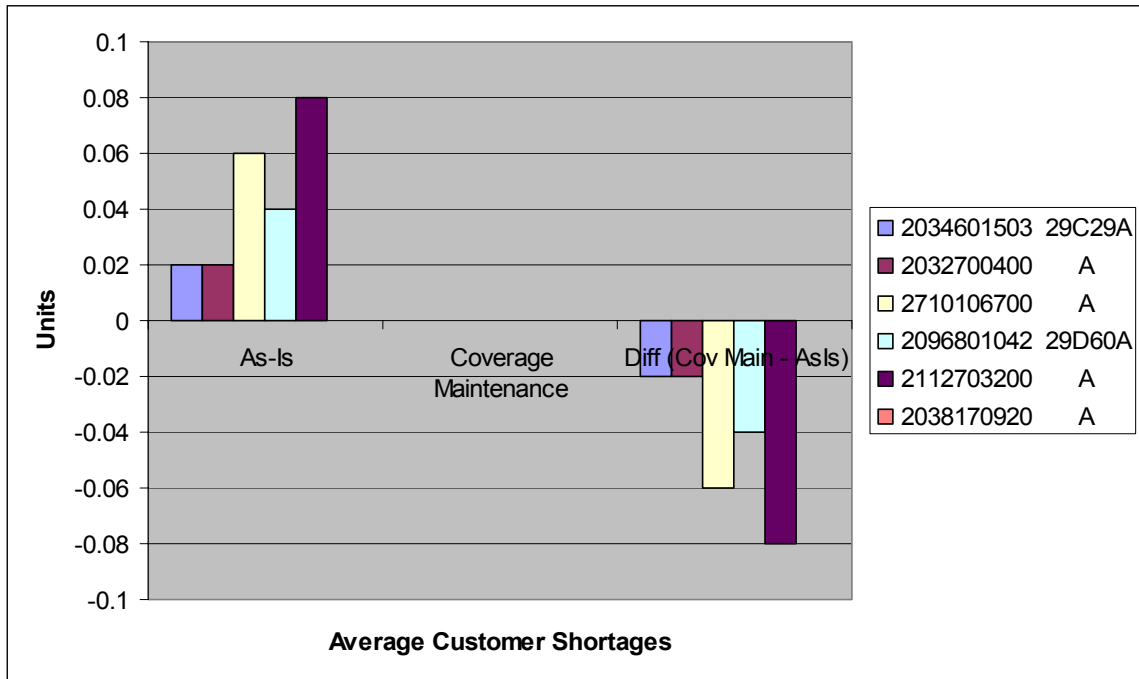


Figure 73: "Human Intervention": Avg. Customer Shortages.

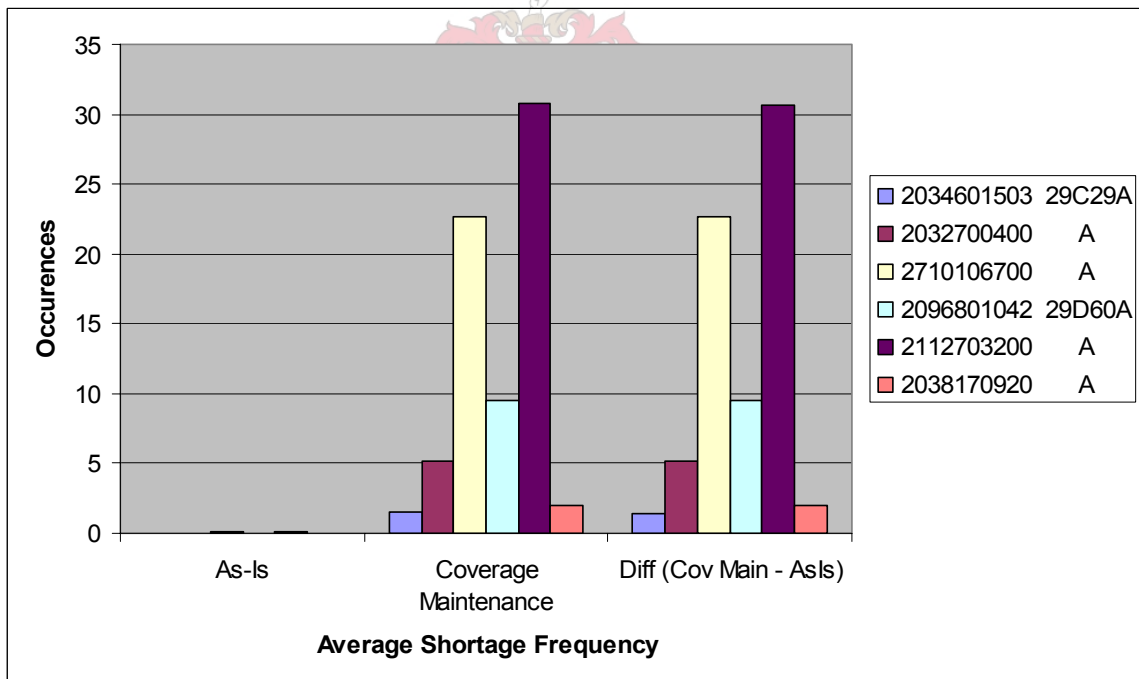
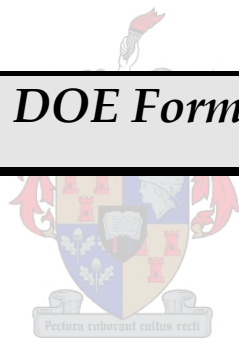


Figure 74: "Human Intervention": Avg. Shortage Frequency.

Appendix I DOE Format Snapshot



SAP Simulation Settings	
Part number 1 = 2112703200	A
Order lead time = 37 days	
Days until Assembly = 39 days	
Time to option freeze = 27 days	
Number of simulated days = 1000 days	
Number of cars/day = 204 cars	
Pallet size = 7 units	

MRP Settings	
Safety Time = 2 days	
Minimum Coverage = 5 days	
Target Coverage = 5 days	
Min Order Quantity = 7 units	
Avg. Daily Req. Window = 4 weeks	
Maintain Coverage = False	

Simulation Summary		
Category	Sub-Category	SAP-MRP Simulation
Inventory	Average Plant Inventory	982.7125854
	Average Pipeline Inventory	4218.285645
	Average Harbour Inventory	233.9888306
Orders	Average Number of Orders	959.8200073
	Average Order Size	120.2457886
Service Level	Average Customer Service Level	1
	Average DCSA Service Level	1
Shortages	Average Total Shortages	0
	Average Customer Shortages	0
	Average Shortage Frequency	0
Statistical Range of Coverage	Avg. Stat Range of Coverage	NA
	Avg. Stat Range of Coverage at Sales Order Create	8.484125137

Avg. Inventory of all 50 replications

These averages are extracted and placed in the Worksheets for Regression Analysis

Repl	SAP - Avg. Inventory	SAP - Cust. Service Level	SAP - DCSA Service Level	SAP - Total Num Orders	SAP - Avg. Order Size	SAP - Total Shortages
1	995.246521	1	1	951	120.3175583	0
2	936.4771729	1	1	959	120.3357697	0
3	948.6248779	1	1	964	121.0404587	0
4	994.3103027	1	1	961	119.3059311	0
5	974.0117188	1	1	961	120.8574371	0
6	990.4059448	1	1	956	120.5010452	0
7	950.616394	1	1	958	120.6367416	0
8	974.0148926	1	1	957	120.6969681	0
9	1020.52179	1	1	963	119.8286591	0
10	941.213623	1	1	965	121.3502579	0
11	951.1987305	1	1	964	121.8029022	0
12	1052.696045	1	1	962	119.0945969	0
13	941.3825684	1	1	959	121.1824799	0
14	1005.72583	1	1	967	120.0496368	0

Replication 1 to 50

Avg. Inventory for replication 1 to 50

Figure 75: DOE Output for Simulation Run-Combo 63. (Before Filtering and Formatting).

Combination	Average Plant Inventory	Safety Time	Min Coverage	Target Coverage	Pallet Size	Days to Assembly	Avg. Daily Demand	Part Number	
1	424.3232727	0	0	0	30	32	117.97	2038170920	A
2	513.0409546	0	0	1	30	32	117.97	2038170920	A
3	583.795166	0	0	2	30	32	117.97	2038170920	A
4	654.3981323	0	0	3	30	32	117.97	2038170920	A
5	709.5720215	0	0	4	30	32	117.97	2038170920	A
6	778.3780518	0	0	5	30	32	117.97	2038170920	A
7	534.2530518	0	1	1	30	32	117.97	2038170920	A
8	609.645874	0	1	2	30	32	117.97	2038170920	A
9	690.3780518	0	1	3	30	32	117.97	2038170920	A
10	750.9542847	0	1	4	30	32	117.97	2038170920	A
11	817.0215454	0	1	5	30	32	117.97	2038170920	A
12	651.5335693	0	2	2	30	32	117.97	2038170920	A
13	731.6397095	0	2	3	30	32	117.97	2038170920	A
14	794.1930542	0	2	4	30	32	117.97	2038170920	A
15	860.0192261	0	2	5	30	32	117.97	2038170920	A
16	767.31427	0	3	3	30	32	117.97	2038170920	A
17	863.0166626	0	3	4	30	32	117.97	2038170920	A
18	916.4064941	0	3	5	30	32	117.97	2038170920	A
19	887.8835449	0	4	4	30	32	117.97	2038170920	A
20	971.1832275	0	4	5	30	32	117.97	2038170920	A
21	1012.154297	0	5	5	30	32	117.97	2038170920	A
22	533.9943848	1	0	0	30	32	117.97	2038170920	A
23	626.6046753	1	0	1	30	32	117.97	2038170920	A
24	692.0117188	1	0	2	30	32	117.97	2038170920	A
25	748.8161011	1	0	3	30	32	117.97	2038170920	A
26	818.6199341	1	0	4	30	32	117.97	2038170920	A
27	875.9819336	1	0	5	30	32	117.97	2038170920	A
28	655.9876709	1	1	1	30	32	117.97	2038170920	A
29	737.5139771	1	1	2	30	32	117.97	2038170920	A
30	806.7363892	1	1	3	30	32	117.97	2038170920	A
31	866.1863403	1	1	4	30	32	117.97	2038170920	A
32	925.1883545	1	1	5	30	32	117.97	2038170920	A
33	773.0558472	1	2	2	30	32	117.97	2038170920	A
34	848.2347412	1	2	3	30	32	117.97	2038170920	A
35	928.920105	1	2	4	30	32	117.97	2038170920	A
36	991.2299194	1	2	5	30	32	117.97	2038170920	A
37	897.8811646	1	3	3	30	32	117.97	2038170920	A
38	981.8880615	1	3	4	30	32	117.97	2038170920	A
39	1046.897217	1	3	5	30	32	117.97	2038170920	A
40	1014.722107	1	4	4	30	32	117.97	2038170920	A

Figure 76: DOE Results-Filtered, Formatted, & Placed in Workbook. (After Filtering and Formatting)

*Appendix J Regression Analyses
Application & Results*



Application.

This section deals with the various activities involved with the application of Regression Analysis to the output data generated by the DOE. The reader is presented with both steps followed in preparation of the input data and the methodology used when operating the Statistica software.

The approach used in conducting the Regression Analysis is divided into two sections, namely:

1. Preparation of the Input Data.
2. Operation of the Statistica Software Package.

The Regression Analysis technique presented here is one of many available in terms of Multiple Linear Regression, but was found to be the most efficient for investigating this data.

Preparation of the Input Data.

As discussed earlier, a single DOE run constitutes 63 simulation runs, with each run generating a new spreadsheet. Each spreadsheet contains the ten Performance Measures used to indicate the effect of the Safety Time and Coverage Profile settings. The output data from these DOE runs had to be consolidated and formatted in such manner that each Performance Measure was represented as a function of the Input Parameters.

The development of an Excel macro to scan automatically through all 63 spreadsheets eliminated time-consuming manual searches. The macro extracted and sorted the required data, then exported the consolidated results to the respective Performance Measure spreadsheets where each output value was represented as a function of the input parameter settings used in its respective simulation run.

The process discussed in the previous paragraph had to be repeated for each part, including the “imaginary parts,” which were used as an input to the DOE.

The next step in the preparation process was to group the consolidated data according to the Usage Categories defined earlier. This required transfer of data from each Performance Measure spreadsheet to a single spreadsheet representing a specific Usage Category. Thus, each Usage Category had one Excel Workbook containing ten Performance Measure spreadsheets. Each spreadsheet held the results from each part that fell within the defined Usage Category.

These Usage Category Workbooks were then imported into Statistica where they were analysed by means of Regression Analysis. Rather than merely describing the behaviour of a single part, the results of the Regression Analysis would now describe the behaviour of a specific Usage Category.

Appendix I contains a snapshot of the data “before” and “after” the data preparation process. Figure 75 in Appendix I shows a snapshot of the DOE output data before it was processed. The “Simulation Summary” at the top of Figure 75 contains the average values of the various parameters for that particular simulation run. The values of these parameters are then extracted and placed in separate spreadsheets depending on the Performance Measure i.e. Avg. Customer Service Level goes to the Avg. Customer Service Level spreadsheet. Figure 76, (also in Appendix I) shows a snapshot of the data after it was extracted and placed in the associated spreadsheets. The spreadsheet shown in this figure indicates the Avg. Plant Inventory for 40 of the 63 DOE Input Combinations.

Figure 77, on the following page, presents a flow chart representing the entire data preparation process, just discussed.



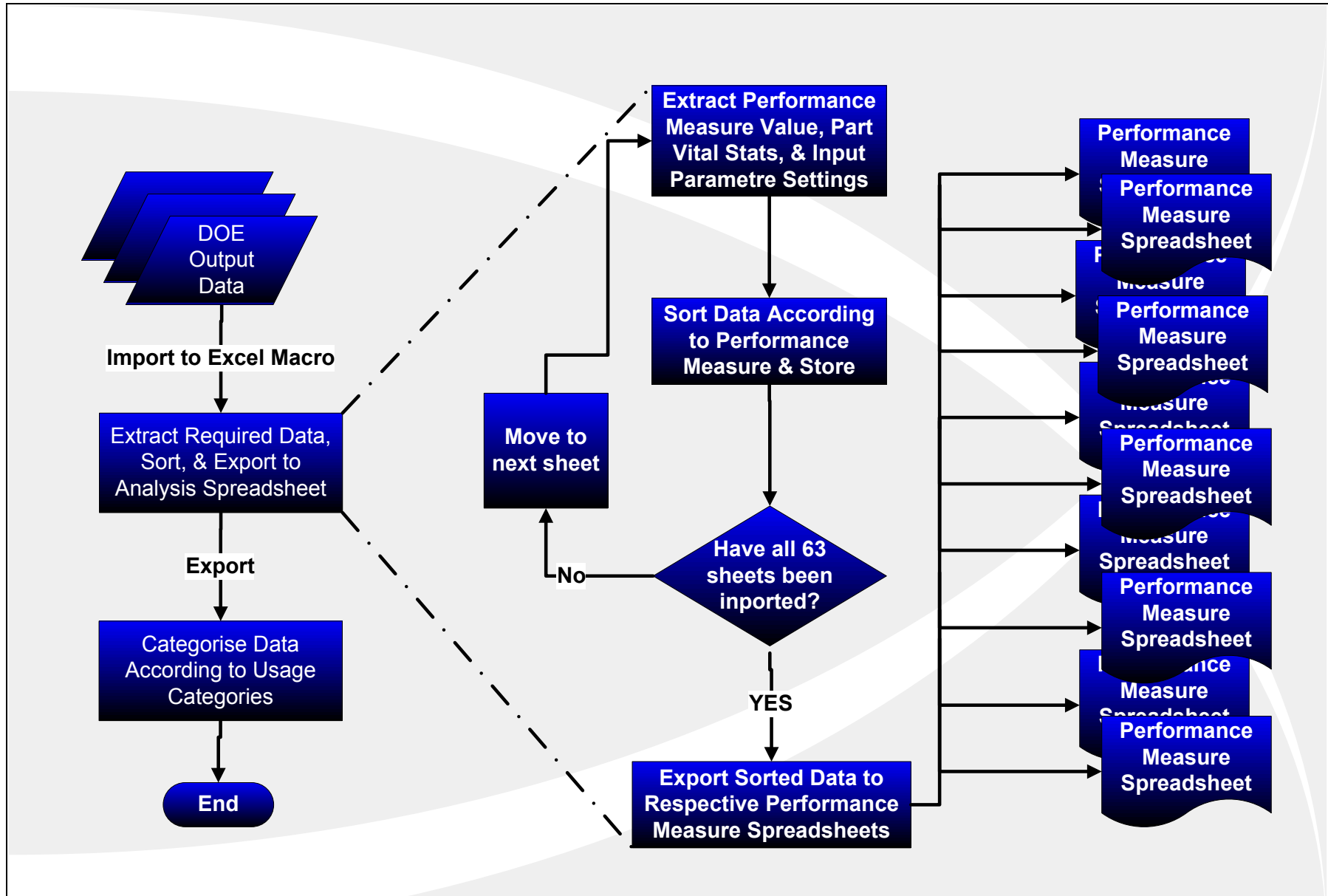


Figure 77: Flow Chart of Data Preparation for Regression Analysis.

Operation of the Statistica Software.

The operation of the Statistica software involved a 6-step process. Table 46 indicates the steps followed, the purpose of each, as well as the checkpoints used.

Step	Process	Purpose	Checkpoints
1	Import Usage Category Workbook	Acquire required data for analysis.	<ul style="list-style-type: none"> Have all 10 worksheets been imported from the Workbook?
2	Construct Matrix Plot	Determine relationship between independent variables, as well as between dependent and independent variables.	<ul style="list-style-type: none"> Do the matrix plots indicate a linear, quadratic, or random relationship between variables?
3	Develop inter-independent variable relationships	The Matrix plots may indicate that a specific relationship exists between independent variables. This relationship should be included in the input data.	<ul style="list-style-type: none"> Have all the possible relationships been covered i.e. inter-independent or dependent-independent.
4	Execute "Forward Stepwise" Regression	Obtain a quick estimation of how many independent variables are required for a suitably high R^2 Value. This is used as a guide for "Best Subsets" Regression.	<ul style="list-style-type: none"> Set equation intercept to zero. (Except for Service Level Analysis) How many independent variables were used to arrive at the final equation? What was the Adjusted R^2 Value?
5	Execute "Best Subsets" Regression	Develop an equation, with a high "Adjusted R^2 " (0.9 and above) that describes the relationship between a Performance Measure and the Input Parameters. The equation must avoid the problems associated with Multicollinearity.	<ul style="list-style-type: none"> Set equation intercept to zero. (Except for Service Level Analysis) Set the maximum number of subsets equal to the number of variables used in Forward Stepwise regression. Select the "best subsets" according to the "Adjusted R^2" values.
6	Analyse Results	Determine if the behaviour of the resultant equation is consistent with expectations, in terms of the behaviour of the dependant variable behaviour as a function of independent variables. Evaluate the normality of the residuals.	<ul style="list-style-type: none"> Are the results consistent with expectations, in terms of the dependant variable behaviour? Is the "Adjusted R^2" value equal to or above 0.9? Are the residuals normally distributed? Is the relationship between the Observed and Predicted Values linear?

Table 46: Statistica Steps Followed.

The highlighted text in Table 46 indicates the various factors to be taken into account when using the Statistica software in conducting the Regression Analysis. These factors are discussed in the next section.

Figure 78 presents a flow chart representation of the steps presented in Table 46.

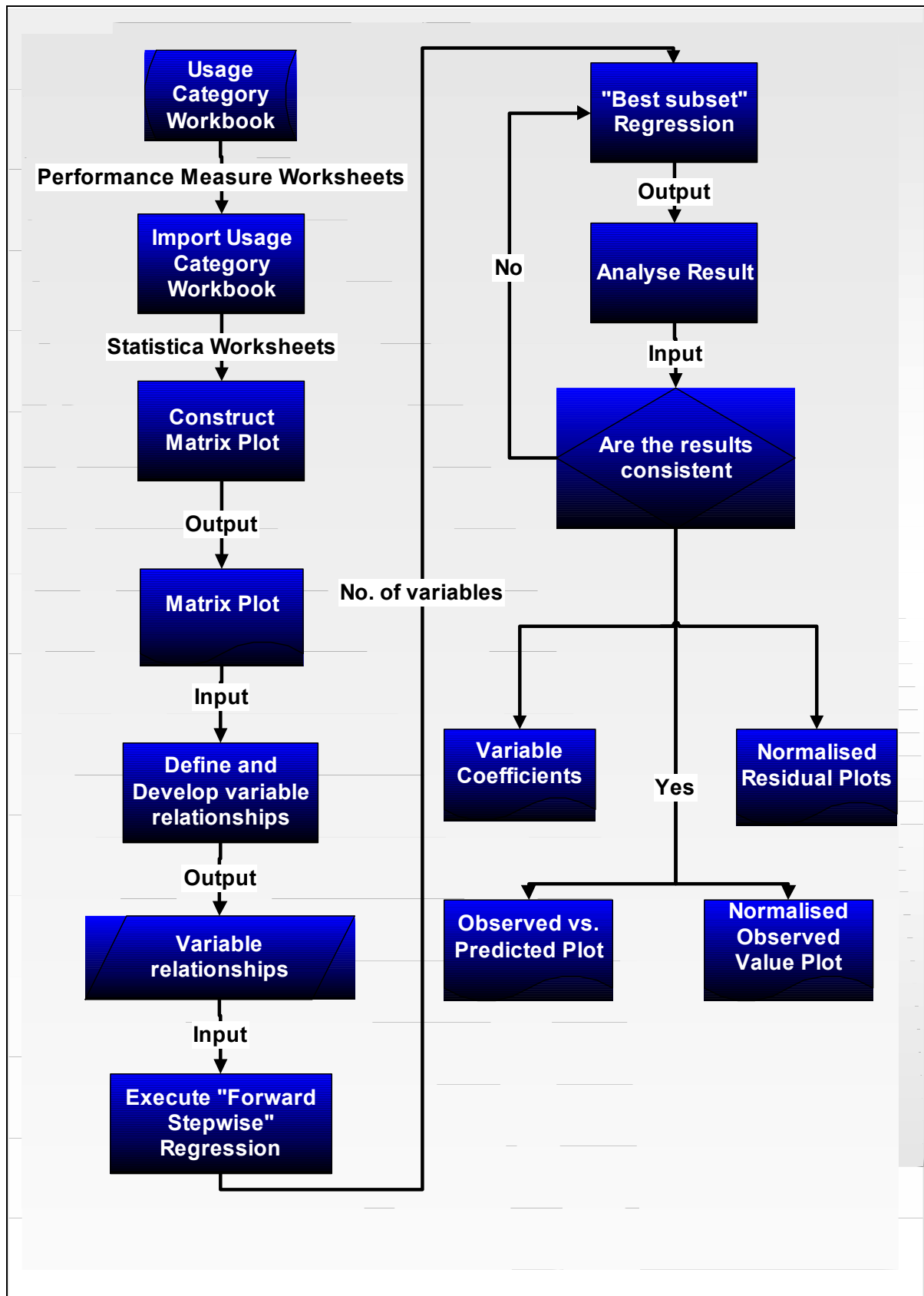


Figure 78: Flow Chart of Statistica Steps Followed.

Results

Note: The results from the Regression Equations are presented per Usage Category and in the following order:

1. Avg. Plant Inventory.
2. Avg. Pipeline Inventory.
3. Avg. Harbour Inventory.
4. Avg. Number of Orders.
5. Avg. Order Size.
6. Avg. Customer Service Level.
7. Avg. Total Shortages.
8. Avg. Customer Shortages.

The reader is presented with a tabulated summary of the regression analysis for each Usage Category at the beginning of Usage Category section. The tables indicate the number of variables included in the Regression Equation, the Adjusted R^2 Value, whether the residuals were normally distributed, and whether the Observed vs. Predicted dependant variables had a “Rough”, “Fair”, or “Good” linear relationship.

Each Performance Measure contains the following information:

- Equation Coefficients. The coefficients are found in the first column. Multiplying the input variable by its coefficient and then summing the lot obtain the output of the equation. The Beta coefficients, utilised in calculating the individual Relative Contribution, are found fourth from the right.
- Top 10 “best subsets” Adjusted R^2 Values with first entry being relevant to the analysis.
- Distribution of Residuals. Normally distributed with zero mean is ideal.
- Plot of Observed vs. Predicted Values. A 45 degree line is ideal.

The only difference in the order in which the information per Performance Measures is presented occurs in “Avg. Customer Service Level.” In this instance, the “Plot of Observed vs. Predicted Values” is followed by the results of the Regression Equations where the intercept was not forced through zero.

Ultra Low Runners.



			Quality Indicators					
			Adjusted R ² Value	Number of Variables	Intercept	Studentized Residual Distribution (Normal & Zero Mean. Yes /No?)	Observed vs. Predicted	
							Linear Relationship?	
							0	Rough
1	Fair							
2	Good							
Performance Measure	Inventory	Avg. Plant Inv.	0.99	8	0	Yes	1	
		Avg. Pipeline Inv.	0.99	10	0	Yes	1	
		Avg. Harbour Inv.	0.99	10	0	Yes	1	
	Orders	Avg. Number of Orders	0.94	10	0	Yes	1	
		Avg. Order Size	0.99	11	0	Yes	2	
	Service Level	Avg. Customer Service Level	0.99	7	0	Yes	0	
			0.86	9	0.98	NA	NA	
	Shortages	Avg. Total Shortages	0.97	8	0	Yes	1	
		Avg. Customer Shortages	0.95	9	0	Yes	1	

Table 47: Ultra Low Runner Regression Analysis Summary.

The “NA” fields indicate that the Residual Distribution and Observed vs. Predicted plots were not required. These plots were shown to be the same as the corresponding zero-intercept-equation plots.

Start of Avg. Plant Inventory

Variable	Avg. Plant Inv. Parameter	Avg. Plant Inv. Std Err	Avg. Plant Inv. t	Avg. Plant Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Plant Inv. Beta	Avg. Plant Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-0.5638	0.089226	-6.3191	0.000000	-0.7391	-0.3885	-0.077273	0.012229	-0.101299	-0.053247
ST + TC										
ADD*(ST+MC)	1.3748	0.116857	11.7647	0.000000	1.1452	1.6044	0.125768	0.010690	0.104764	0.146772
ADD*(ST+TC)										
ADD * ST	0.8031	0.184714	4.3476	0.000017	0.4401	1.1660	0.029992	0.006899	0.016438	0.043546
ADD*MC										
ADD * TC										
Pallet Size	0.6977	0.006720	103.8255	0.000000	0.6845	0.7109	0.885357	0.008527	0.868603	0.902111
PS*ST	-0.0477	0.003796	-12.5750	0.000000	-0.0552	-0.0403	-0.078203	0.006219	-0.090422	-0.065984
PS*MC	-0.0267	0.002242	-11.9073	0.000000	-0.0311	-0.0223	-0.075760	0.006363	-0.088261	-0.063259
PS*TC										
Days to Assembly	0.0765	0.005237	14.6015	0.000000	0.0662	0.0867	0.112541	0.007708	0.097397	0.127684
Avg. Daily Demand										
Flip Mean	145.7148	6.937857	21.0029	0.000000	132.0836	159.3460	0.085690	0.004080	0.077674	0.093707

Table 48: Equation Variables & Betas. Avg. Plant Inventory. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Plant In Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.998315	8		
2	0.998315	8		
3	0.998315	8		
4	0.998304	8		
5	0.998297	8		-0.049499
6	0.998293	8		-0.056931
7	0.998291	8		
8	0.998289	8		-0.060645
9	0.998281	8		
10	0.998281	8		-0.040833

Figure 79: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

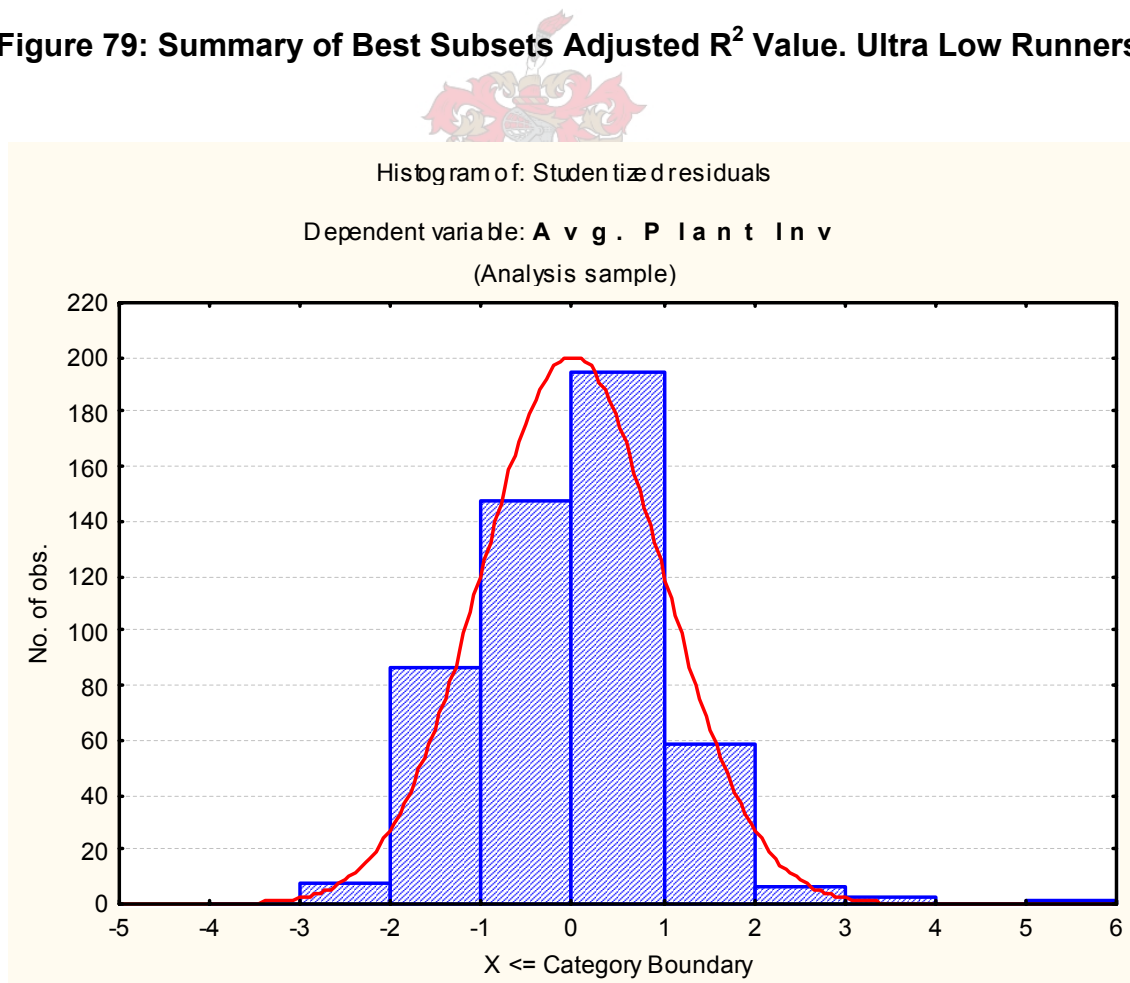


Figure 80: Studentized Residuals. Avg. Plant Inventory. Ultra Low Runners.

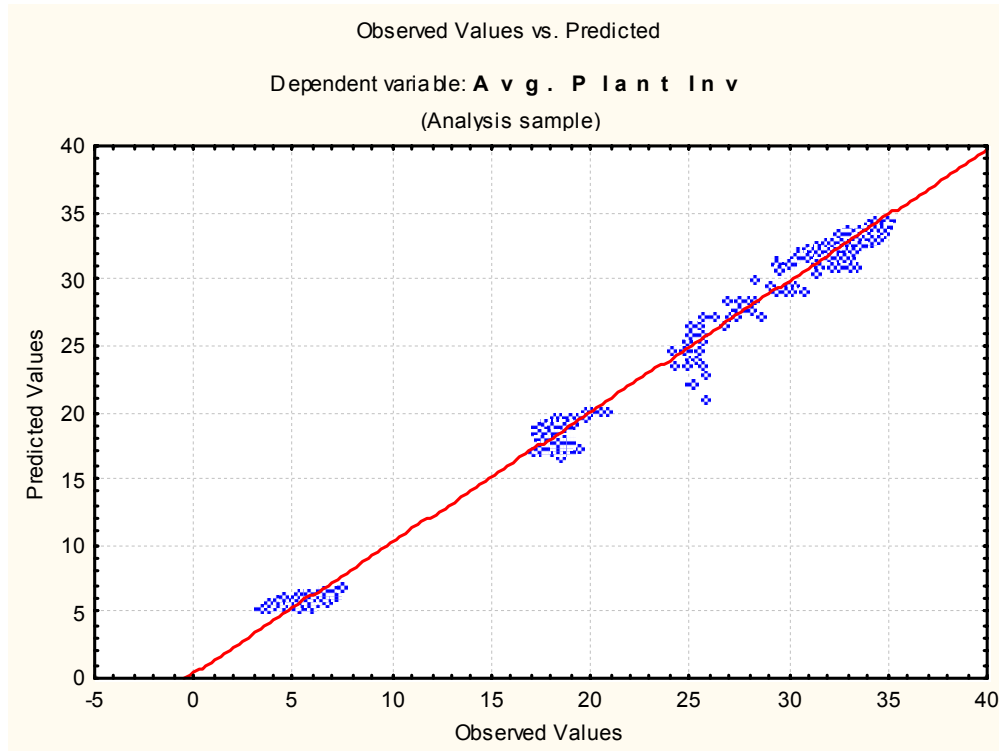


Figure 81: Observed vs. Predicted Avg. Plant Inventory. Ultra Low Runners.

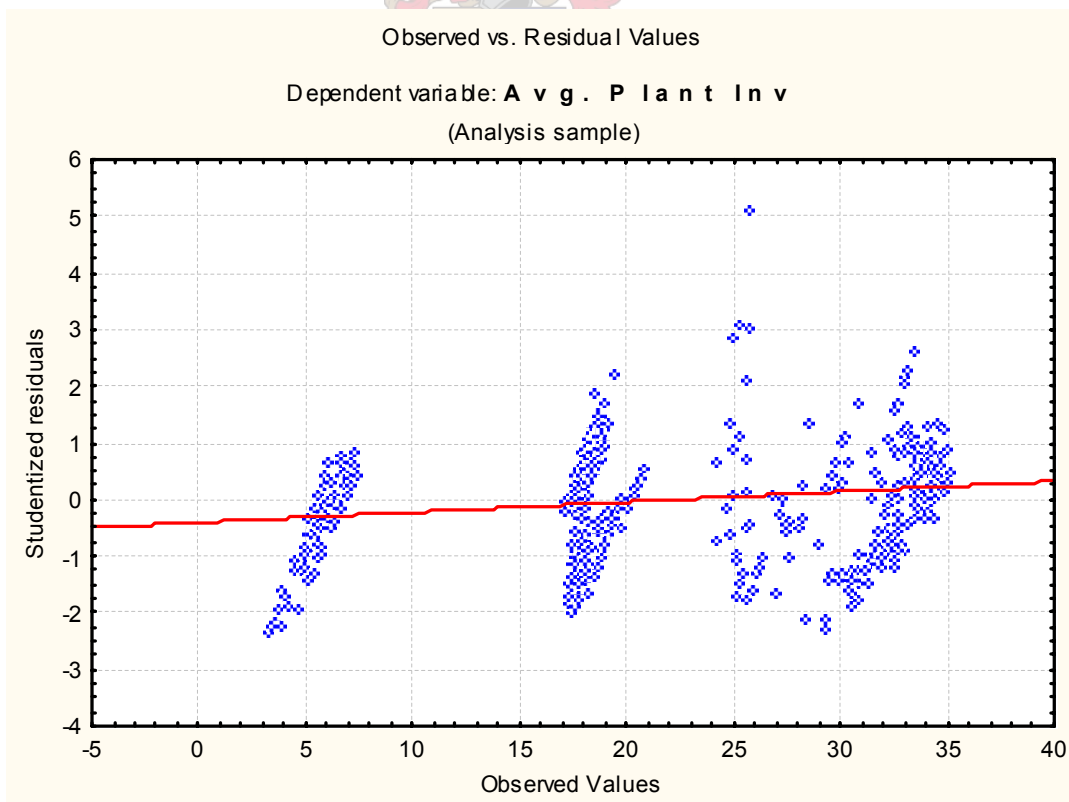
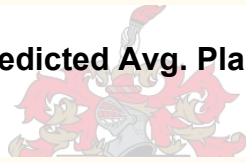


Figure 82: Observed vs. Residual Avg. Plant Inventory. Ultra Low Runners.
End of Avg. Plant Inventory

Start of Avg. Pipeline Inventory

Variable	Avg. Pipeline Inv. Parameter	Avg. Pipeline Inv. Std Err	Avg. Pipeline Inv. t	Avg. Pipeline Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Pipeline Inv. Beta	Avg. Pipeline Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	-1.17164	0.097401	-12.0290	0.000000	-1.36301	-0.98026	-0.260709	0.021673	-0.303293	-0.218126
ADD*(ST+MC)	0.82278	0.098782	8.3293	0.000000	0.62870	1.01686	0.083024	0.009968	0.063440	0.102609
ADD*(ST+TC)	1.28587	0.146539	8.7749	0.000000	0.99795	1.57379	0.190992	0.021766	0.148228	0.233757
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.18820	0.008916	-21.1088	0.000000	-0.20572	-0.17068	-0.263437	0.012480	-0.287958	-0.238917
PS*ST	0.01532	0.002865	5.3466	0.000000	0.00969	0.02095	0.027678	0.005177	0.017507	0.037850
PS*MC	0.01068	0.002271	4.7024	0.000003	0.00622	0.01514	0.033427	0.007109	0.019460	0.047394
PS*TC	0.01049	0.002425	4.3256	0.000018	0.00572	0.01525	0.068345	0.015800	0.037301	0.099389
Days to Assembly	0.32008	0.012132	26.3826	0.000000	0.29625	0.34392	0.519656	0.019697	0.480956	0.558356
Avg. Daily Demand	18.77281	0.617604	30.3962	0.000000	17.55936	19.98627	0.599035	0.019708	0.560314	0.637756
Flip Mean	24.07481	7.538877	3.1934	0.001496	9.26259	38.88702	0.015616	0.004890	0.006008	0.025224

Table 49: Equation Variables & Betas. Avg. Pipeline Inventory. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Pipeline Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.997993	10			
2	0.997965	10			
3	0.997960	10		-0.016226	
4	0.997956	9			
5	0.997954	10			
6	0.997953	10			
7	0.997953	10	0.022404		
8	0.997953	10	-0.055074		
9	0.997952	10			
10	0.997952	10			

Figure 83: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

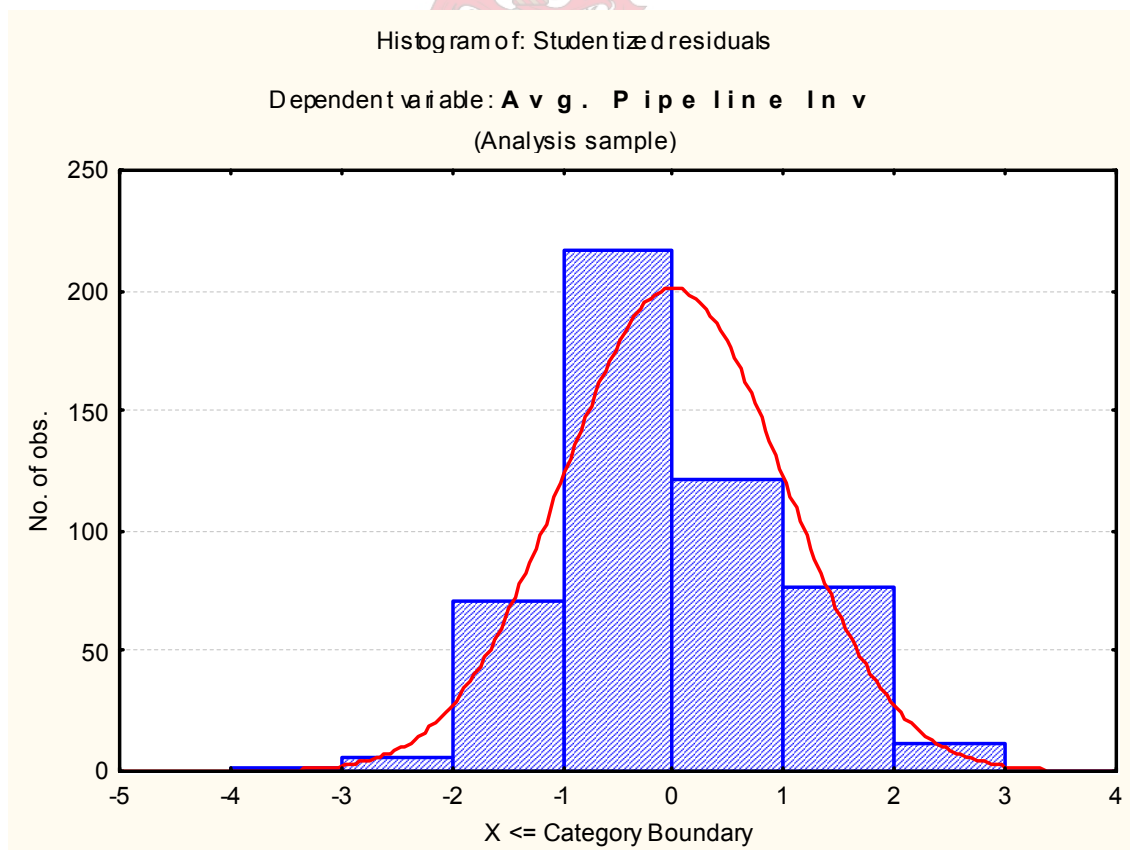


Figure 84: Studentized Residuals. Avg. Pipeline Inventory. Ultra Low Runners.

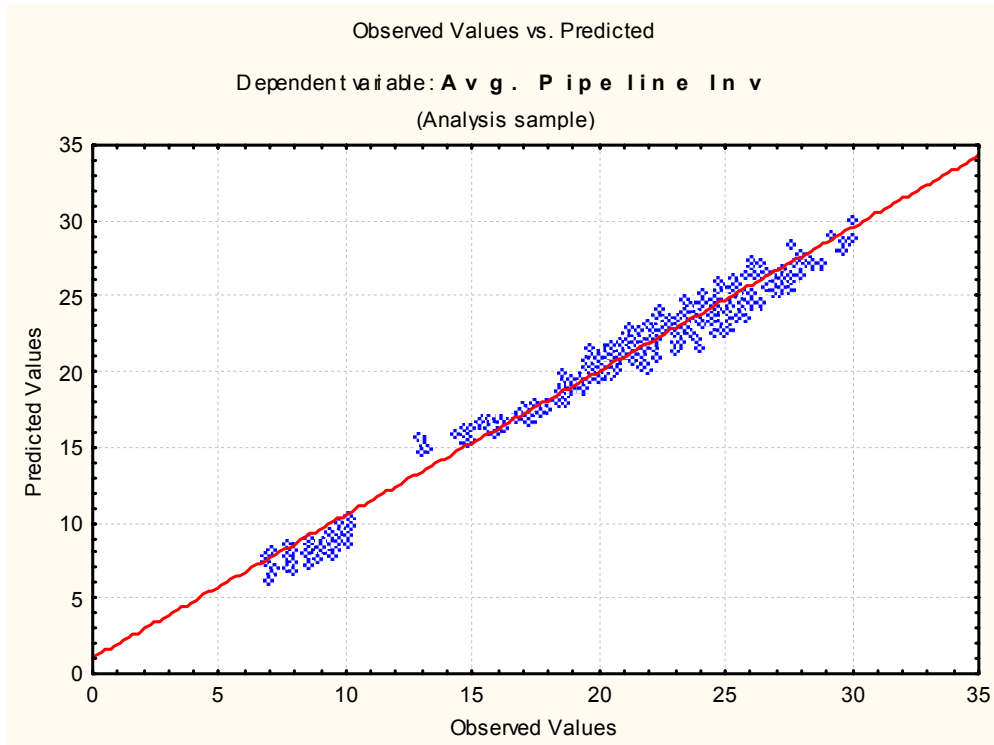
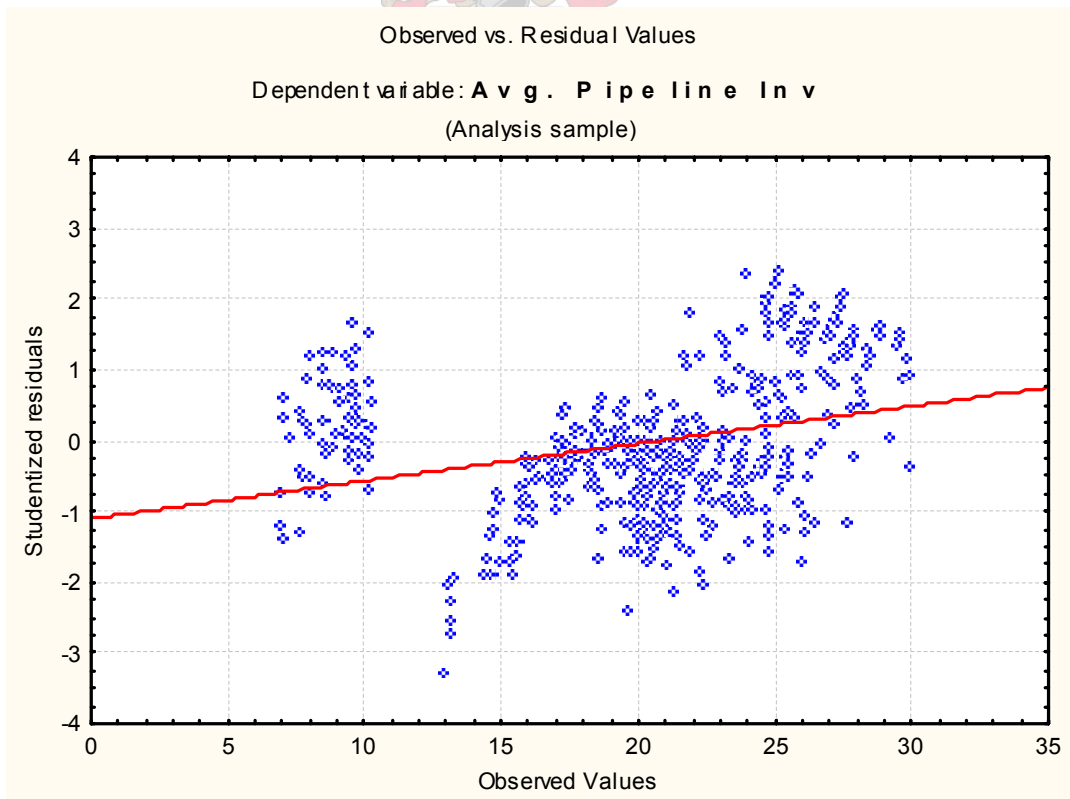
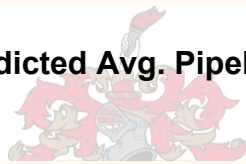


Figure 85: Observed vs. Predicted Avg. Pipeline Inventory. Ultra Low Runners.



**Figure 86: Observed vs. Residual Avg. Pipeline Inventory. Ultra Low Runners.
End of Avg. Pipeline Inventory**

Start of Avg. Harbour Inventory

Variable	Avg. Harbour Inv. Parameter	Avg. Harbour Inv. Std Err	Avg. Harbour Inv. t	Avg. Harbour Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Harbour Inv. Beta	Avg. Harbour Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time	-0.08737	0.011574	-7.5486	0.000000	-0.11011	-0.06463	-0.097602	0.012930	-0.123006	-0.072198
Min Coverage	-0.01713	0.006370	-2.6898	0.007392	-0.02965	-0.00462	-0.033152	0.012325	-0.057369	-0.008936
Target Coverage										
ST + MC										
ST + TC										
ADD*(ST+MC)	0.06383	0.008462	7.5429	0.000000	0.04720	0.08046	0.116588	0.015457	0.086219	0.146957
ADD*(ST+TC)										
ADD * ST	0.05661	0.017841	3.1729	0.001604	0.02155	0.09166	0.042210	0.013304	0.016072	0.068349
ADD*MC										
ADD * TC										
Pallet Size	-0.00466	0.000348	-13.3949	0.000000	-0.00535	-0.00398	-0.118197	0.008824	-0.135535	-0.100860
PS*ST	0.00132	0.000218	6.0752	0.000000	0.00090	0.00175	0.043286	0.007125	0.029287	0.057285
PS*MC	0.00077	0.000119	6.4769	0.000000	0.00054	0.00101	0.043825	0.006766	0.030531	0.057120
PS*TC										
Days to Assembly	0.00653	0.000514	12.6935	0.000000	0.00552	0.00754	0.191767	0.015108	0.162084	0.221450
Avg. Daily Demand	1.49719	0.025449	58.8315	0.000000	1.44719	1.54719	0.864776	0.014699	0.835895	0.893656
Flip Mean	-4.87460	0.377327	-12.9188	0.000000	-5.61596	-4.13323	-0.057234	0.004430	-0.065939	-0.048530

Table 50: Equation Variables & Betas. Avg. Harbour Inventory. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Harbour Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.998206	10		0.135898	
2	0.998206	10		0.135898	
3	0.998206	10	-0.078461		
4	0.998206	10	-0.097602	-0.033152	
5	0.998206	10	-0.078461		
6	0.998206	10	-0.097602	-0.033152	
7	0.998206	10	-0.078461		
8	0.998206	10	-0.097602	-0.033152	
9	0.998206	10		0.135898	
10	0.998184	9	-0.099432		

Figure 87: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

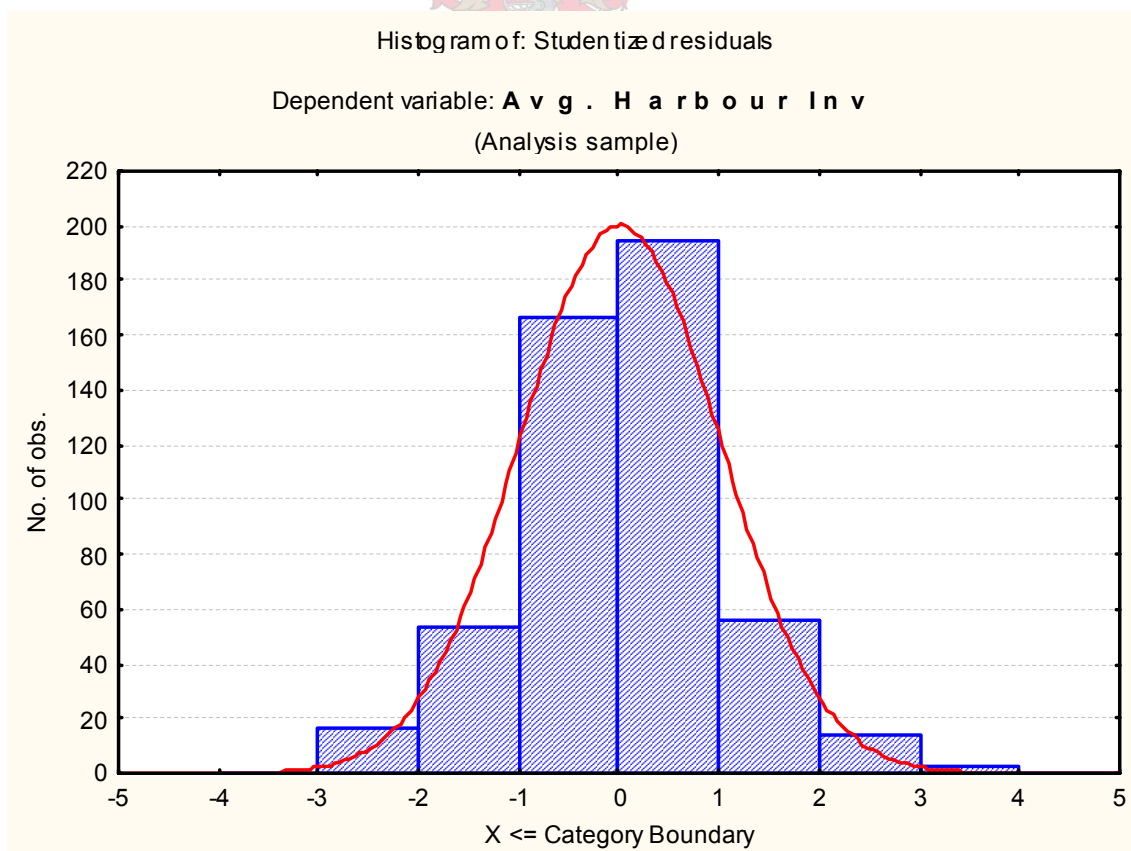


Figure 88: Studentized Residuals. Avg. Harbour Inventory. Ultra Low Runners.

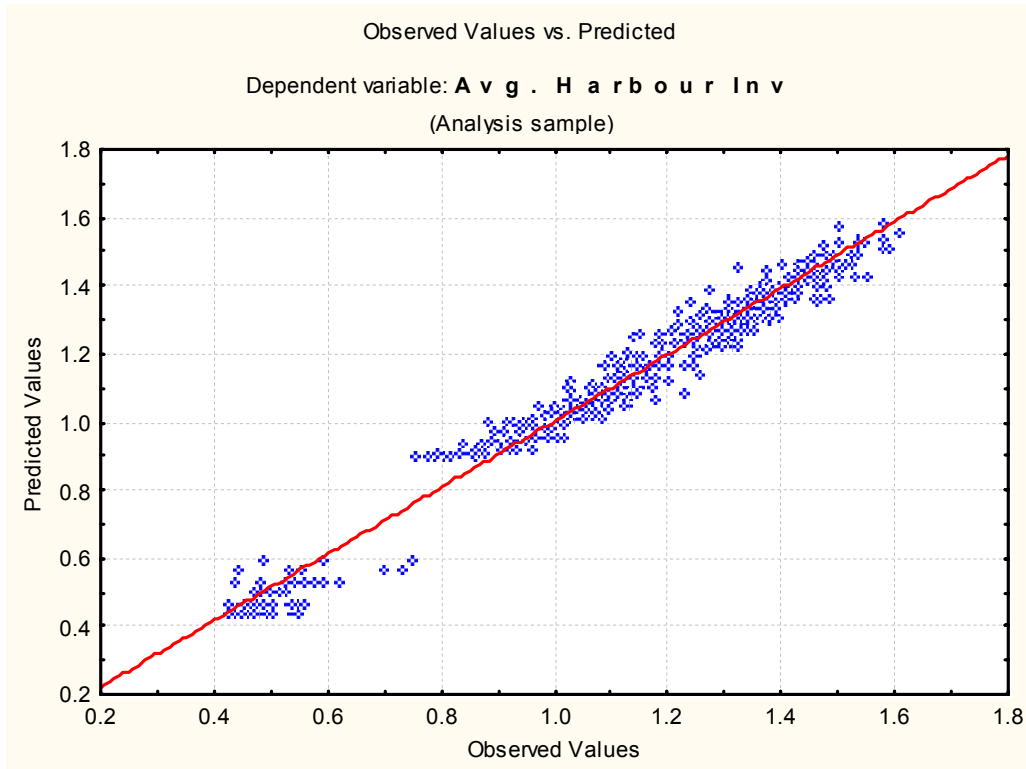


Figure 89: Observed vs. Predicted Avg. Harbour Inventory. Ultra Low Runners.

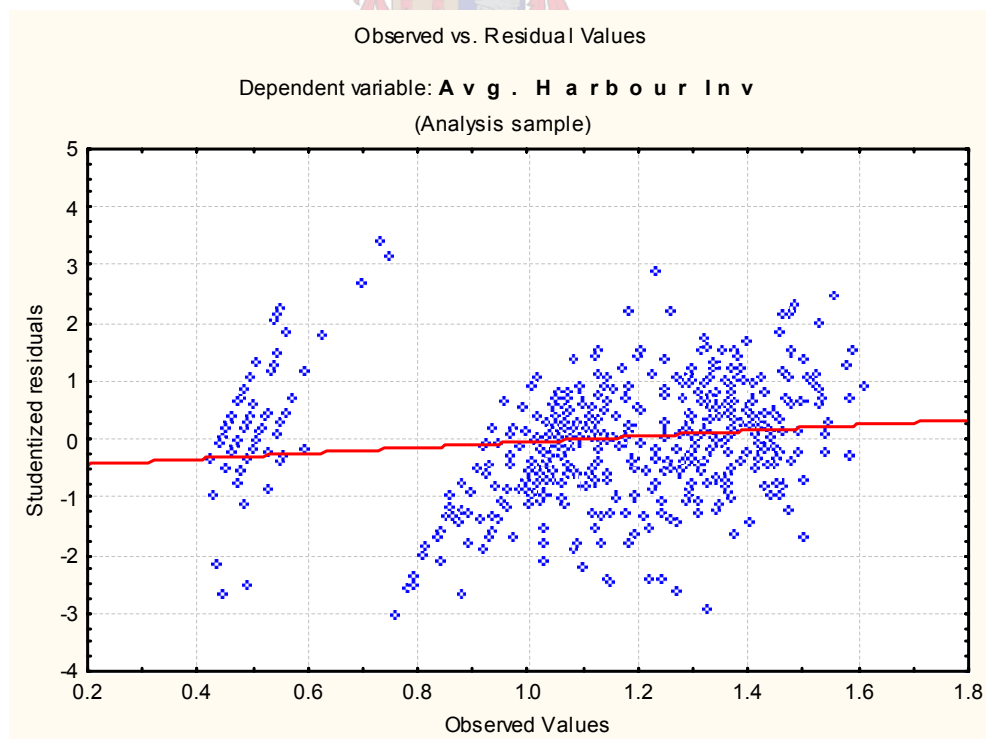


Figure 90: Observed vs. Residual Avg. Harbour Inventory. Ultra Low Runners.

End of Avg. Harbour Inventory

Start of Avg. Number of Orders

Variable	Avg. Number of Orders Parameter	Avg. Number of Orders Std Err	Avg. Number of Orders t	Avg. Number of Orders p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Number of Orders Beta	Avg. Number of Orders Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	24.123	1.6789	14.3680	0.000000	20.824	27.422	1.38262	0.096229	1.19355	1.57169
ST + TC	-11.282	1.0558	-10.6851	0.000000	-13.356	-9.207	-0.95179	0.089076	-1.12681	-0.77678
ADD*(ST+MC)	-11.191	2.0155	-5.5524	0.000000	-15.151	-7.231	-0.42814	0.077109	-0.57964	-0.27664
ADD*(ST+TC)										
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-3.778	0.1244	-30.3613	0.000000	-4.022	-3.533	-2.00482	0.066032	-2.13455	-1.87508
PS*ST	-0.484	0.0448	-10.8021	0.000000	-0.572	-0.396	-0.33159	0.030697	-0.39190	-0.27128
PS*MC	-0.488	0.0371	-13.1536	0.000000	-0.561	-0.415	-0.57878	0.044002	-0.66524	-0.49233
PS*TC	0.341	0.0364	9.3478	0.000000	0.269	0.412	0.84152	0.090024	0.66465	1.01840
Days to Assembly	4.915	0.1510	32.5442	0.000000	4.619	5.212	3.02560	0.092969	2.84294	3.20827
Avg. Daily Demand	-84.309	6.8833	-12.2485	0.000000	-97.833	-70.785	-1.02000	0.083276	-1.18362	-0.85639
Flip Mean	2570.253	105.2540	24.4195	0.000000	2363.452	2777.054	0.63211	0.025885	0.58125	0.68297

Table 51: Equation Variables & Betas. Avg. Number of Orders. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. No. of C					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.940144	10			
2	0.939483	10			
3	0.938656	10			
4	0.938301	10	0.311212	0.644671	
5	0.938301	10		0.105636	
6	0.938301	10	-0.060989		
7	0.938231	9			
8	0.938219	10		0.984244	
9	0.938154	10			
10	0.938144	10			

Figure 91: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

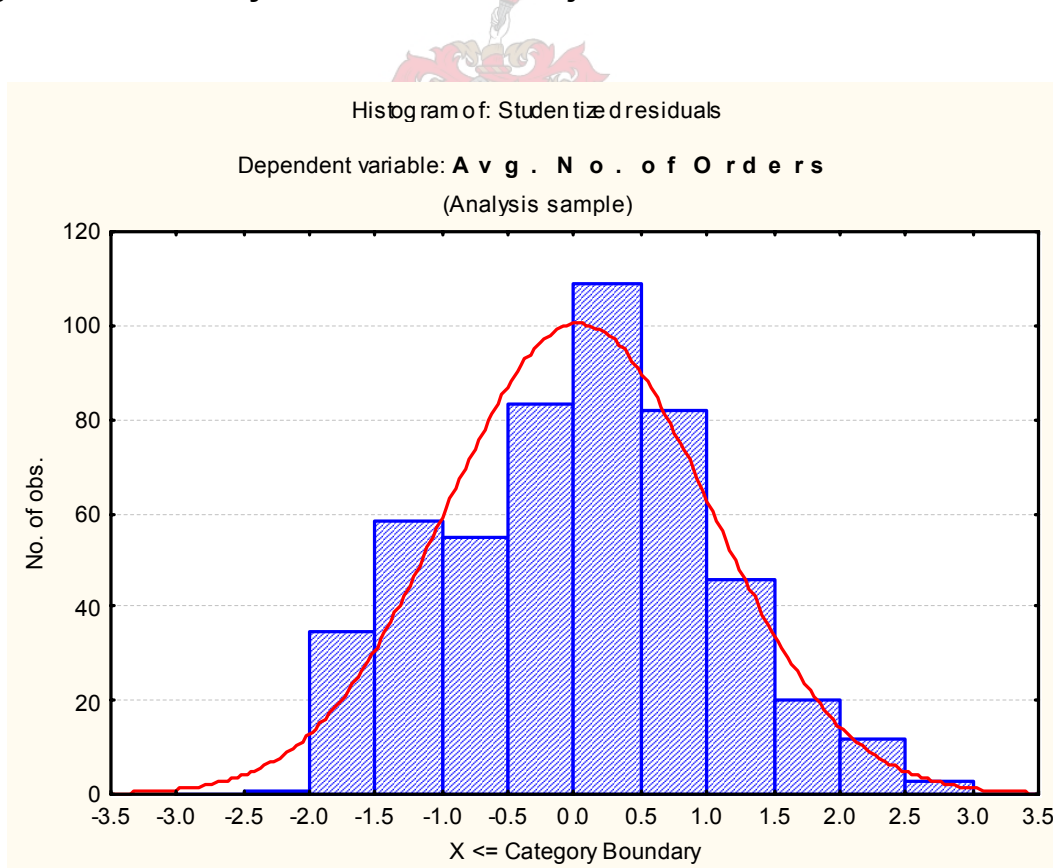


Figure 92: Studentized Residuals. Avg. Number of Orders. Ultra Low Runners.

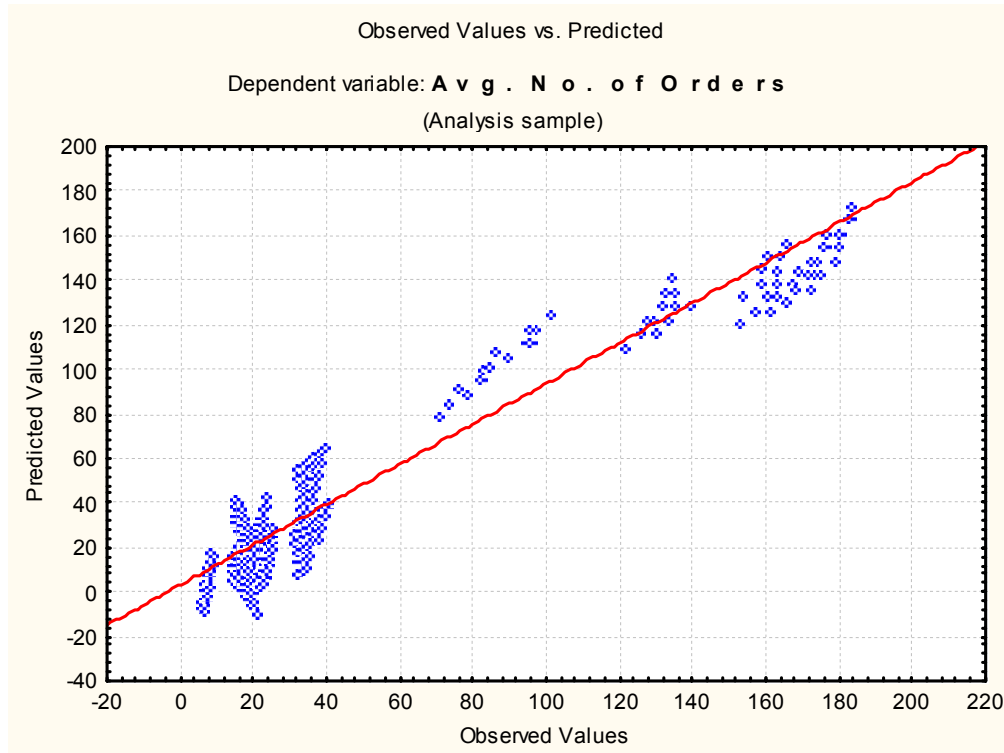


Figure 93: Observed vs. Predicted Avg. Number of Orders. Ultra Low Runners.

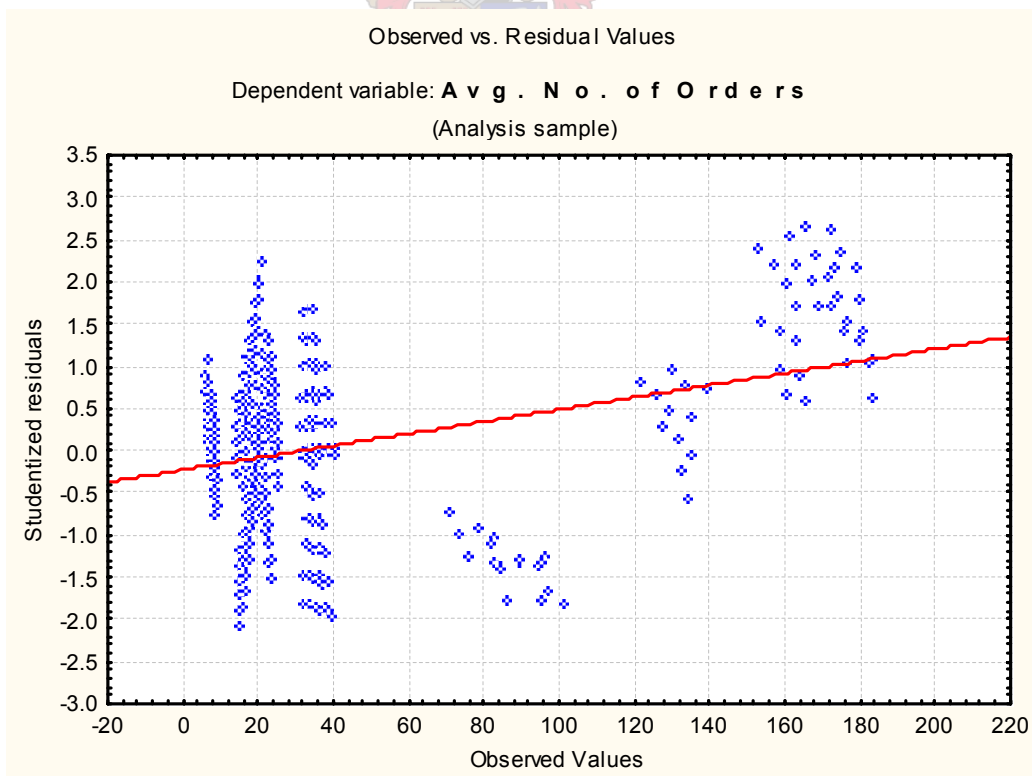
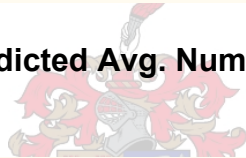


Figure 94: Observed vs. Residual Avg. Number of Orders. Ultra Low Runners.

End of Avg. Number of Orders

Start of Avg. Order Size

Variable	Avg. Order Size Parameter	Avg. Order Size Std Err	Avg. Order Size t	Avg. Order Size p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Order Size Beta	Avg. Order Size Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-0.73408	0.044681	-16.4293	0.000000	-0.82187	-0.64629	-0.079237	0.004823	-0.088713	-0.069761
ST + TC	0.79464	0.041683	19.0638	0.000000	0.71274	0.87654	0.126256	0.006623	0.113244	0.139269
ADD*(ST+MC)	0.30526	0.058949	5.1785	0.000000	0.18944	0.42109	0.021995	0.004247	0.013650	0.030340
ADD*(ST+TC)	-0.36950	0.056171	-6.5781	0.000000	-0.47987	-0.25914	-0.039188	0.005957	-0.050893	-0.027483
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.98534	0.002868	343.5966	0.000000	0.97970	0.99097	0.984816	0.002866	0.979185	0.990447
PS*ST	0.01637	0.001001	16.3611	0.000000	0.01440	0.01834	0.021123	0.001291	0.018586	0.023659
PS*MC	0.01634	0.000828	19.7334	0.000000	0.01471	0.01797	0.036519	0.001851	0.032883	0.040155
PS*TC	-0.01690	0.000816	-20.7087	0.000000	-0.01850	-0.01530	-0.078623	0.003797	-0.086082	-0.071163
Days to Assembly	0.02243	0.003902	5.7469	0.000000	0.01476	0.03009	0.025997	0.004524	0.017109	0.034885
Avg. Daily Demand	-1.26079	0.198649	-6.3468	0.000000	-1.65109	-0.87049	-0.028726	0.004526	-0.037619	-0.019834
Flip Mean	43.63846	2.424833	17.9965	0.000000	38.87417	48.40274	0.020212	0.001123	0.018005	0.022418

Table 52: Equation Variables & Betas. Avg. Order Size Inventory. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Order S Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.999894	11			
2	0.999894	11			
3	0.999894	11		-0.056429	
4	0.999894	11		-0.057728	
5	0.999891	11		-0.048381	
6	0.999890	11			
7	0.999890	11			
8	0.999889	11			
9	0.999889	11			
10	0.999889	11			

Figure 95: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

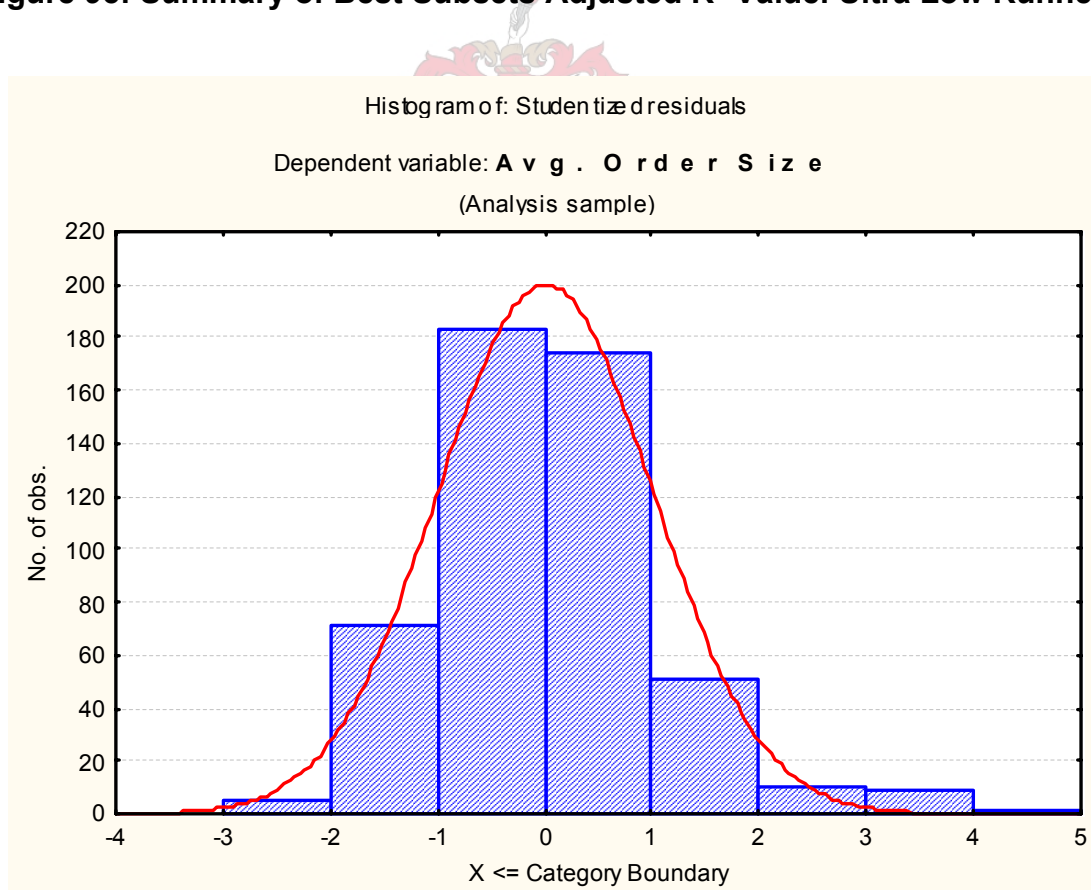


Figure 96: Studentized Residuals. Avg. Order Size. Ultra Low Runners.

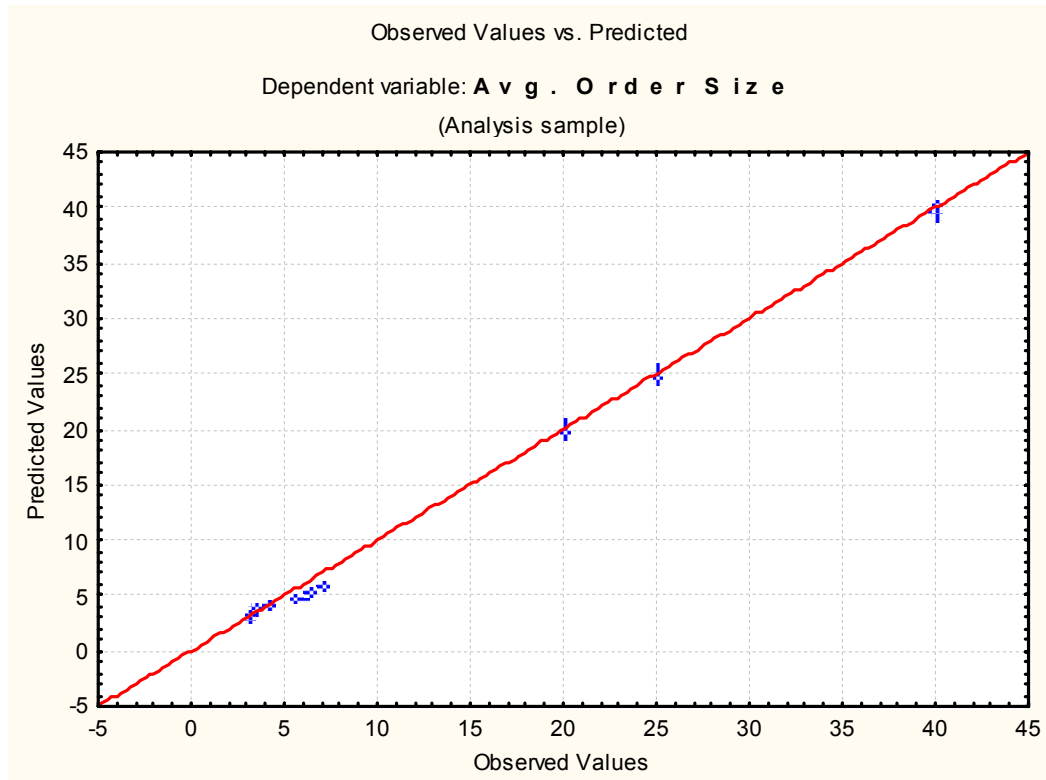
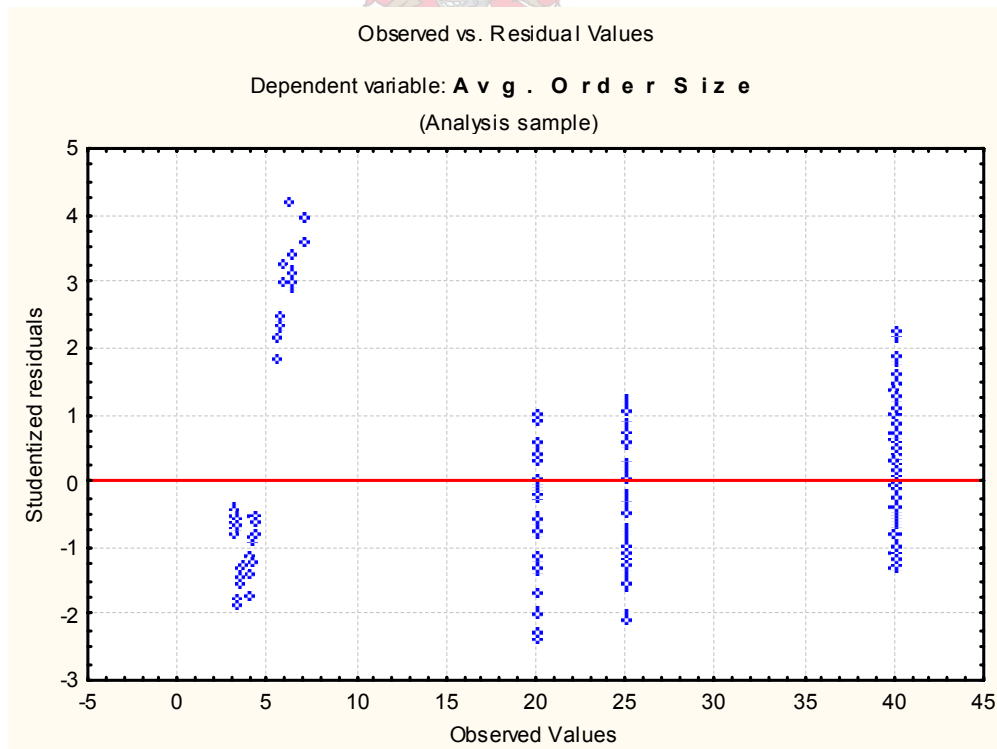


Figure 97: Observed vs. Predicted Avg. Order Size. Ultra Low Runners.



**Figure 98: Observed vs. Residual Avg. Order Size. Ultra Low Runners.
End of Avg. Order Size**

Start of Avg. Customer Service Level.

Variable	Avg. Cust Service Level Parameter	Avg. Cust Service Level Std Err	Avg. Cust Service Level t	Avg. Cust Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Cust Service Level Beta	Avg. Cust Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	0.05260	0.004130	12.7355	0.000000	0.04449	0.06072	0.248011	0.019474	0.209750	0.286273
ADD*(ST+MC)										
ADD*(ST+TC)	-0.05393	0.005654	-9.5378	0.000000	-0.06504	-0.04282	-0.169723	0.017795	-0.204686	-0.134761
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.00707	0.000378	18.6966	0.000000	0.00633	0.00781	0.209655	0.011214	0.187623	0.231686
PS*ST										
PS*MC										
PS*TC	-0.00051	0.000083	-6.0964	0.000000	-0.00067	-0.00034	-0.070241	0.011522	-0.092878	-0.047603
Days to Assembly	0.01732	0.000514	33.6611	0.000000	0.01631	0.01833	0.595737	0.017698	0.560965	0.630510
Avg. Daily Demand	0.38039	0.026190	14.5241	0.000000	0.32893	0.43184	0.257187	0.017708	0.222396	0.291978
Flip Mean	-5.80905	0.319693	-18.1707	0.000000	-6.43717	-5.18093	-0.079840	0.004394	-0.088473	-0.071207

Table 53: Equation Variables & Betas. Avg. Customer Service Level. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.998380	7			
2	0.998270	7			
3	0.998269	7			
4	0.998266	7		0.004598	
5	0.998265	7			
6	0.998262	6			
7	0.998261	7			
8	0.998260	7	0.002115		
9	0.998260	7	0.056190		
10	0.998260	7			

Figure 99: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

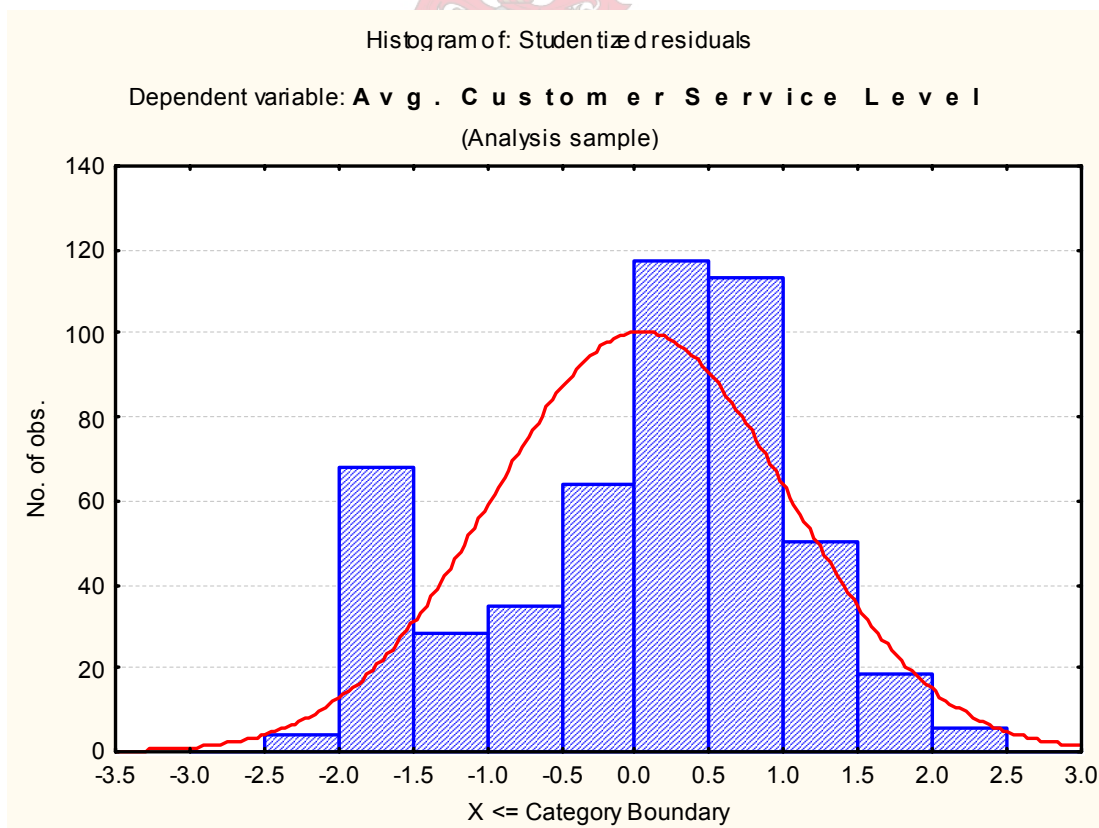


Figure 100: Studentized Residuals. Avg. Customer Service Level. Ultra Low Runners.

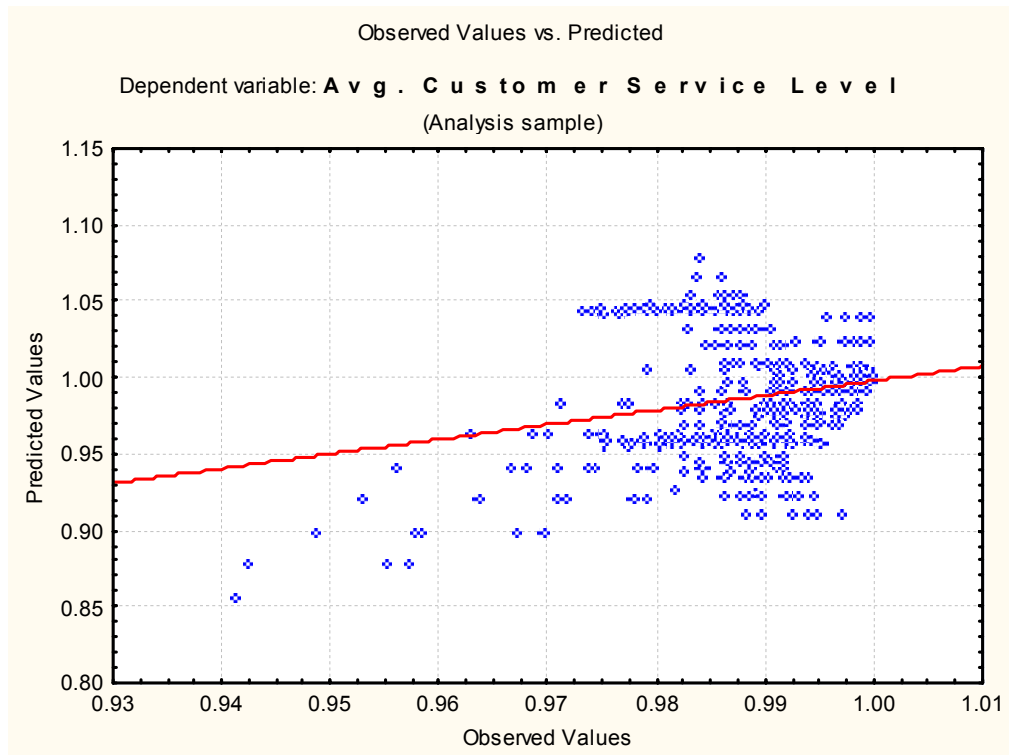


Figure 101: Observed vs. Predicted Avg. Customer Service Level. Ultra Low Runners.

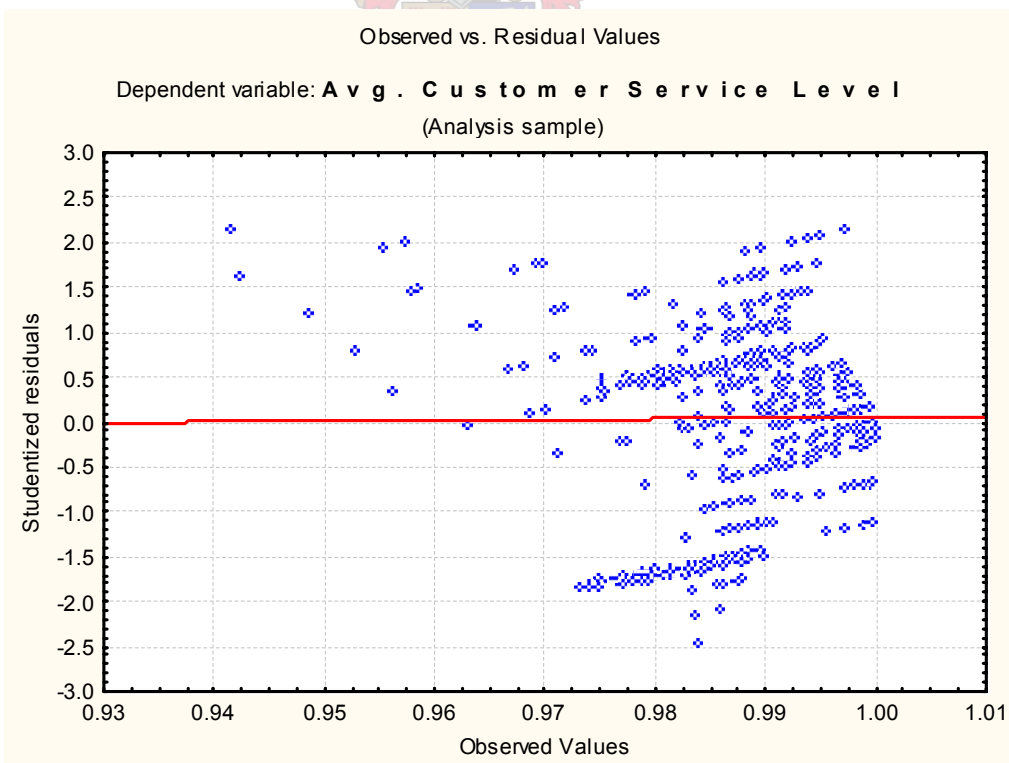
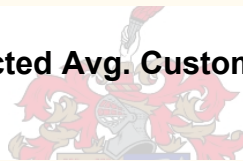


Figure 102: Observed vs. Residual Avg. Customer Service Level. Ultra Low Runners.

Variable	Avg. Cust Service Level Parameter	Avg. Cust Service Level Std Err	Avg. Cust Service Level t	Avg. Cust Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Cust Service Level Beta	Avg. Cust Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Intercept	0.980042	0.003048	321.4878	0.00	0.974052	0.986031				
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	0.005243	0.000348	15.0603	0.00	0.004559	0.005927	1.013606	0.067303	0.881370	1.145842
ST + TC	0.001682	0.000263	6.4061	0.00	0.001166	0.002198	0.325274	0.050776	0.225511	0.425038
ADD*(ST+MC)	-0.000946	0.000358	-2.6432	0.01	-0.001649	-0.000243	-0.131472	0.049739	-0.229198	-0.033745
ADD*(ST+TC)										
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.000947	0.000038	25.1747	0.00	0.000873	0.001021	1.312493	0.052135	1.210059	1.414927
PS*ST	-0.000069	0.000011	-6.3022	0.00	-0.000090	-0.000047	-0.209882	0.033303	-0.275314	-0.144449
PS*MC	-0.000082	0.000009	-9.1151	0.00	-0.000100	-0.000065	-0.450710	0.049447	-0.547862	-0.353558
PS*TC	-0.000052	0.000009	-5.7539	0.00	-0.000070	-0.000034	-0.428794	0.074522	-0.575213	-0.282375
Days to Assembly	-0.000690	0.000079	-8.7486	0.00	-0.000846	-0.000535	-0.190126	0.021732	-0.232824	-0.147427
Avg. Daily Demand										
Flip Mean	-0.307177	0.028540	-10.7630	0.00	-0.363252	-0.251102	-0.350140	0.032532	-0.414058	-0.286222

Table 54: Equation Variables & Betas. Avg. Customer Service Level Intercept. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Custom Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.860460	9			
2	0.859863	9			
3	0.859713	9			
4	0.859414	9			
5	0.858901	9			
6	0.858838	9			
7	0.858772	8			
8	0.858542	9			
9	0.858542	9		-0.318196	
10	0.858542	9		-0.038397	

Figure 103: Summary of Best Subsets Adjusted R² Value. Intercept. Ultra Low Runners.

End of Avg. Customer Service Level



Start of Avg. Total Shortages

Variable	Avg. Total Shortages Parameter	Avg. Total Shortages Std Err	Avg. Total Shortages t	Avg. Total Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Total Shortages Beta	Avg. Total Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	-12.984	1.7266	-7.51964	0.000000	-16.376	-9.591	-0.363624	0.048357	-0.458633	-0.268615
ADD*(ST+MC)	-23.470	2.2409	-10.47314	0.000000	-27.872	-19.067	-0.298068	0.028460	-0.353985	-0.242150
ADD*(ST+TC)										
ADD * ST										
ADD*MC										
ADD * TC	19.288	2.6886	7.17398	0.000000	14.005	24.570	0.282851	0.039427	0.205386	0.360317
Pallet Size	1.305	0.1719	7.58851	0.000000	0.967	1.643	0.229854	0.030290	0.170342	0.289366
PS*ST										
PS*MC	-0.306	0.0519	-5.89432	0.000000	-0.408	-0.204	-0.120529	0.020448	-0.160705	-0.080353
PS*TC										
Days to Assembly	-1.285	0.2766	-4.64361	0.000004	-1.828	-0.741	-0.262483	0.056526	-0.373542	-0.151423
Avg. Daily Demand	287.585	15.4942	18.56085	0.000000	257.143	318.028	1.154986	0.062227	1.032725	1.277247
Flip Mean	3293.052	216.1131	15.23763	0.000000	2868.442	3717.662	0.268843	0.017643	0.234178	0.303508

Table 55: Equation Variables & Betas. Avg. Total Shortages. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Total S					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.970860	8			
2	0.970722	8			
3	0.970686	8			
4	0.970649	8	-0.151337		
5	0.970617	8			
6	0.970458	8			
7	0.970458	8	-0.088879		
8	0.970458	8	-0.235104		
9	0.970453	8			
10	0.970453	8	-0.075118		

Figure 104: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

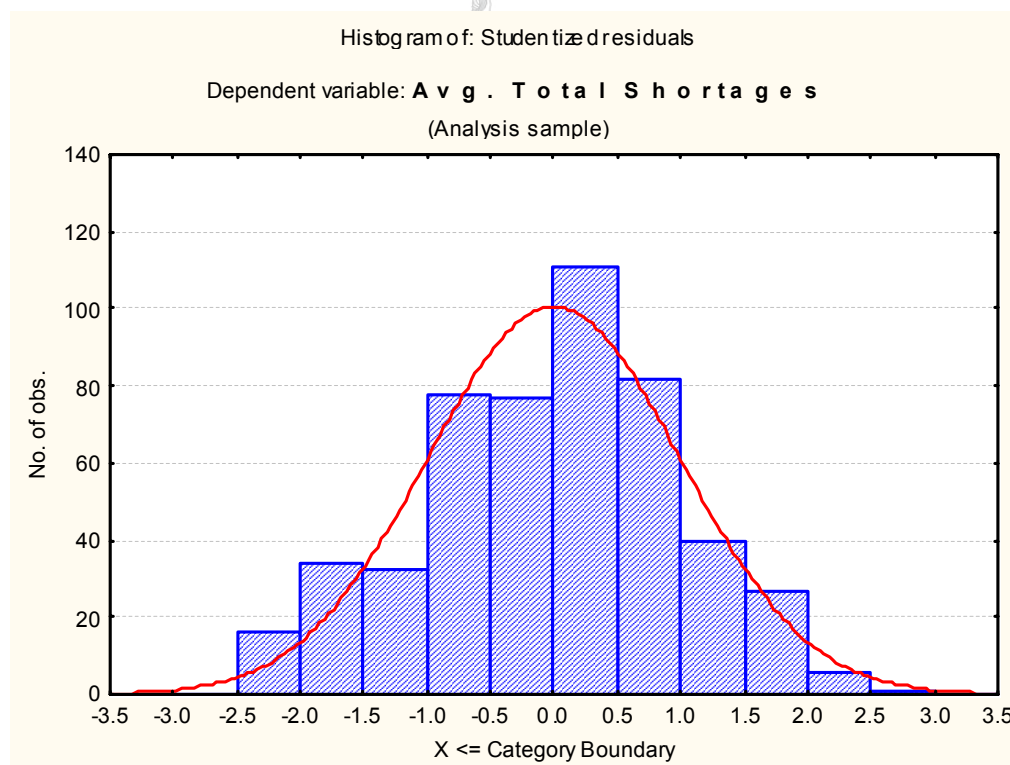


Figure 105: Studentized Residuals. Avg. Total Shortages. Ultra Low Runners.

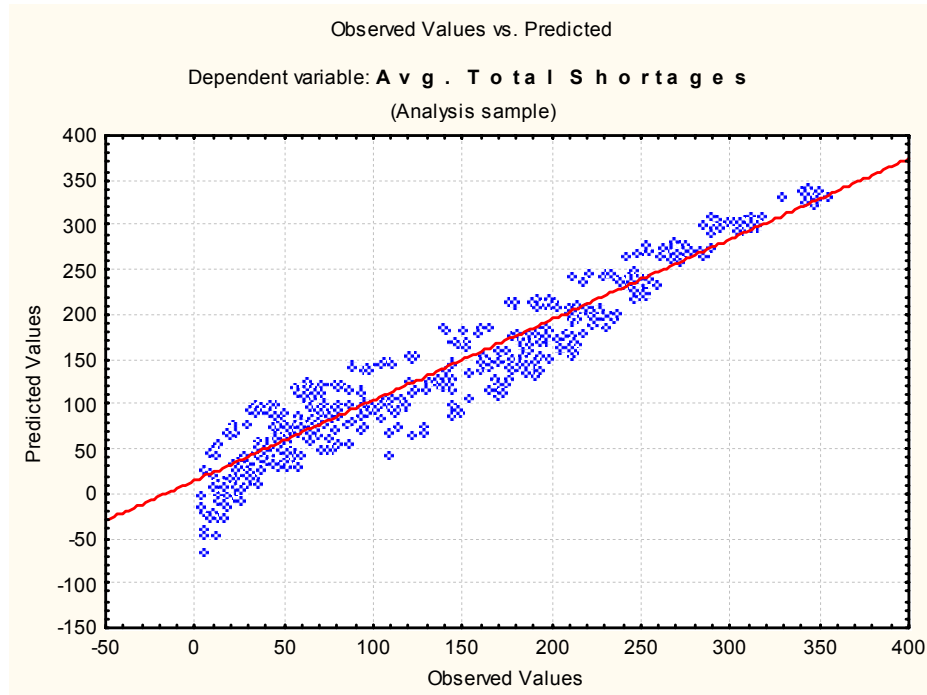


Figure 106: Observed vs. Predicted Avg. Total Shortages. Ultra Low Runners.

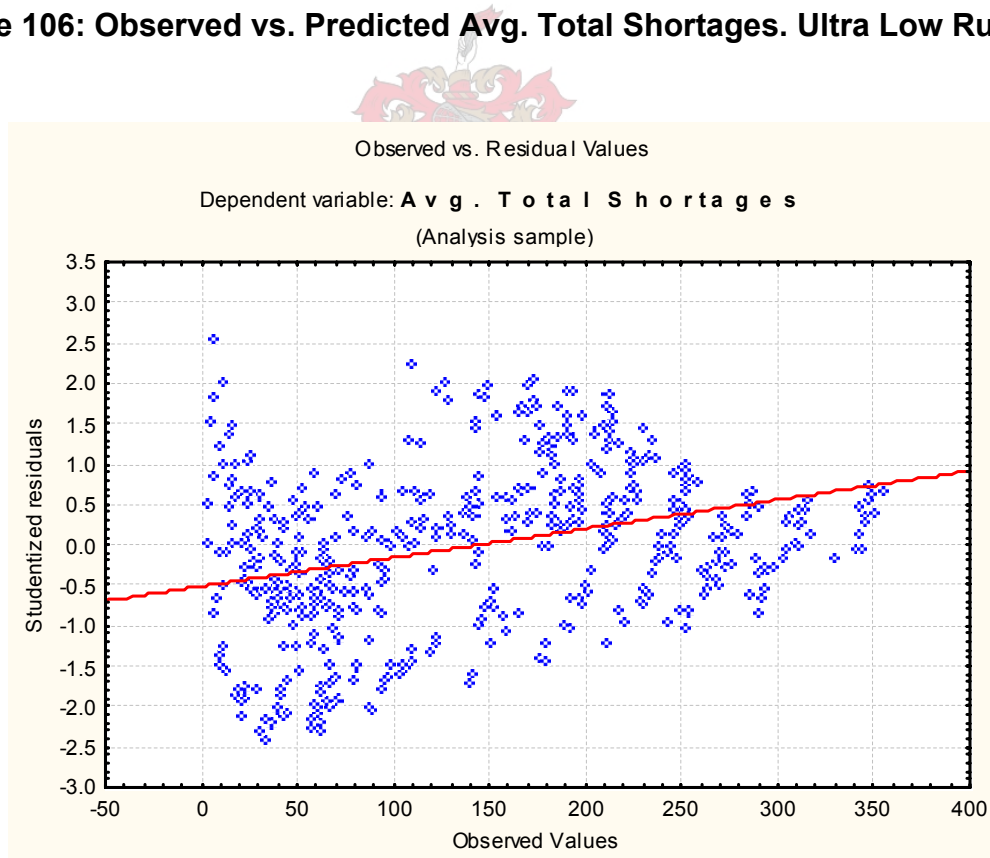


Figure 107: Observed vs. Residual Avg. Total Shortages. Ultra Low Runners.

End of Avg. Total Shortages

Start of Avg. Customer Shortages

Variable	Avg. Customer Shortages Parameter	Avg. Customer Shortages Std Err	Avg. Customer Shortages t	Avg. Customer Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Shortages Beta	Avg. Customer Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-1.92852	0.12554	-15.3617	0.000000	-2.17517	-1.6819	-0.83231	0.054181	-0.93876	-0.72586
ST + TC	-0.75446	0.12273	-6.1471	0.000000	-0.99560	-0.5133	-0.47928	0.077969	-0.63247	-0.32609
ADD*(ST+MC)										
ADD*(ST+TC)										
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.38003	0.01414	-26.8734	0.000000	-0.40781	-0.3522	-1.51867	0.056512	-1.62971	-1.40764
PS*ST	0.02826	0.00522	5.4187	0.000000	0.01801	0.0385	0.14579	0.026905	0.09293	0.19866
PS*MC	0.03352	0.00432	7.7674	0.000000	0.02504	0.0420	0.29956	0.038566	0.22379	0.37533
PS*TC	0.02305	0.00424	5.4401	0.000000	0.01473	0.0314	0.42878	0.078820	0.27392	0.58365
Days to Assembly	0.43902	0.01530	28.6858	0.000000	0.40895	0.4691	2.03483	0.070935	1.89546	2.17420
Avg. Daily Demand	5.94288	0.57806	10.2807	0.000000	4.80712	7.0786	0.54139	0.052661	0.43793	0.64486
Flip Mean	104.51488	11.96720	8.7334	0.000000	81.00212	128.0276	0.19355	0.022161	0.15000	0.23709

Figure 108: Equation Variables & Betas. Avg. Customer Shortages. Ultra Low Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.954010	9			
2	0.952871	9			
3	0.952787	9			
4	0.952715	9			
5	0.952707	9		0.115497	
6	0.952707	9		-0.182519	
7	0.952707	9			
8	0.952707	9	-0.066682		
9	0.952707	9	-0.382401	-0.546841	
10	0.952707	9	-0.210341	-0.546841	

Figure 109: Summary of Best Subsets Adjusted R² Value. Ultra Low Runners.

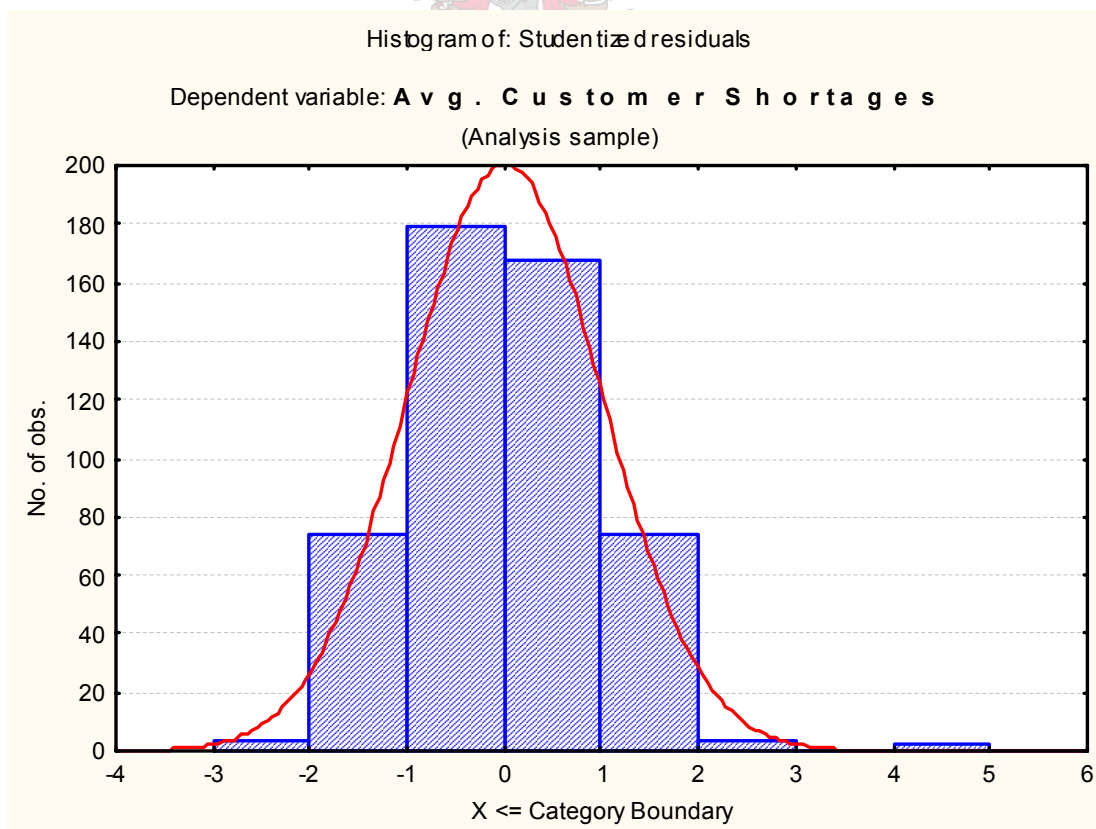


Figure 110: Studentized Residuals. Avg. Customer Shortages. Ultra Low Runners.

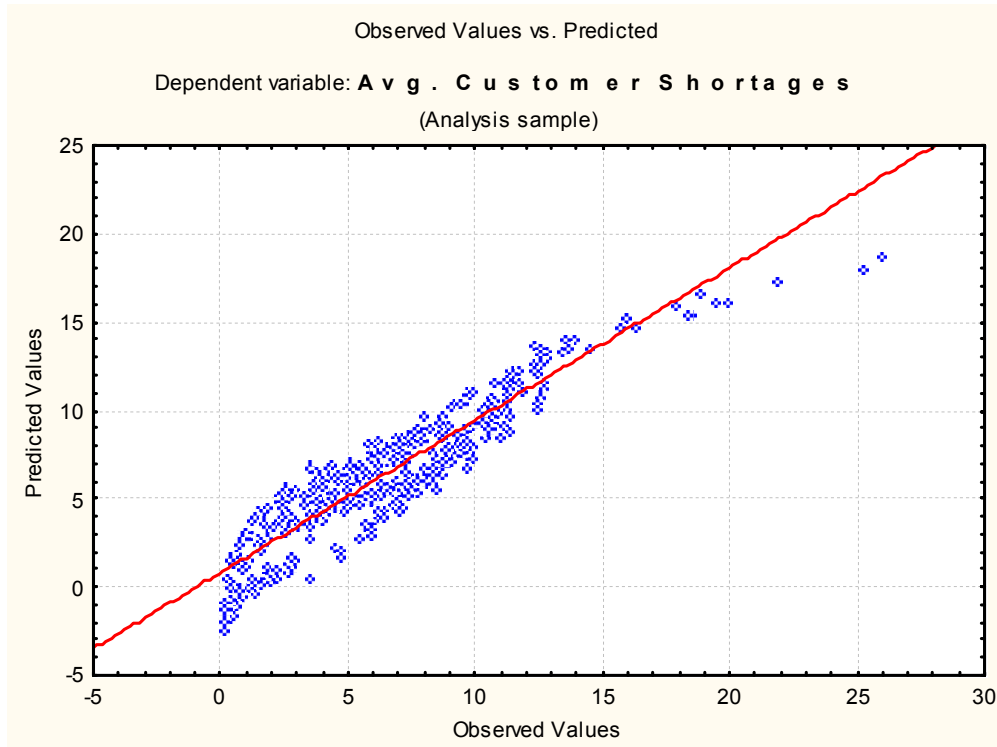


Figure 111: Observed vs. Predicted Avg. Customer Shortages. Ultra Low Runners.

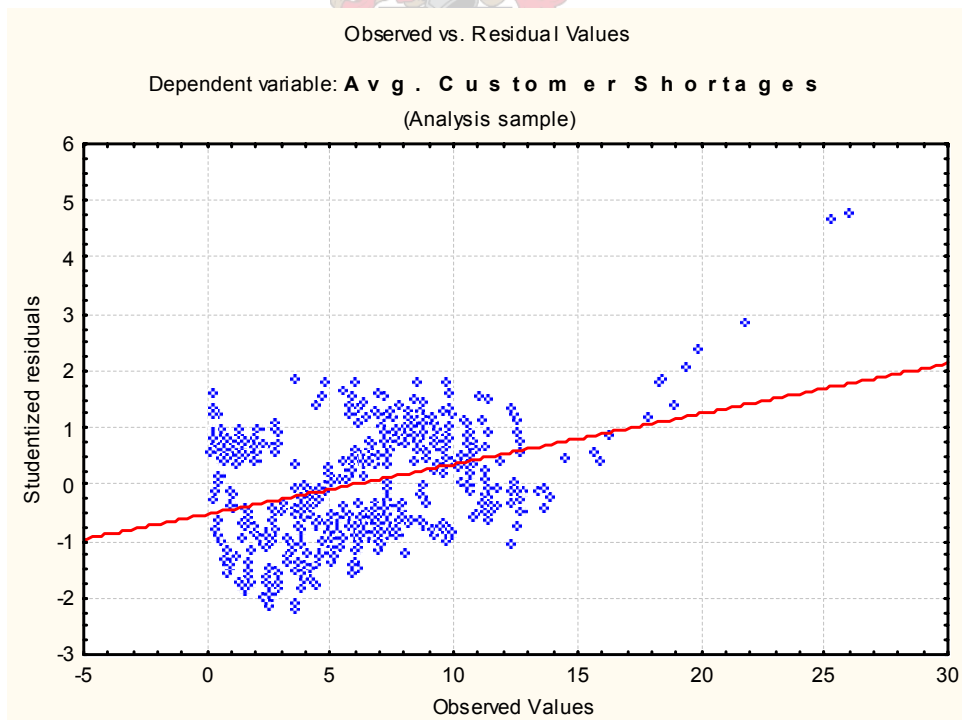


Figure 112: Observed vs. Residual Avg. Customer Shortages. Ultra Low Runners.

End of Avg. Customer Shortages

Low Runners.



			Quality Indicators					
			Adjusted R ² Value	Number of Variables	Intercept	Studentized Residual Distribution (Normal & Zero Mean. Yes /No?)	Observed vs. Predicted	
							Linear Relationship?	
							0	Rough
1	Fair							
2	Good							
Performance Measure	Inventory	Avg. Plant Inv.	0.99	7	0	Yes	2	
		Avg. Pipeline Inv.	0.99	9	0	Yes	1	
		Avg. Harbour Inv.	0.99	9	0	Yes	1	
	Orders	Avg. Number of Orders	0.96	9	0	No	1	
		Avg. Order Size	0.99	7	0	Yes	2	
	Service Level	Avg. Customer Service Level	0.99	7	0	Yes	0	
			0.66	7	0.97	NA	NA	
	Shortages	Avg. Total Shortages	0.94	9	0	Yes	1	
		Avg. Customer Shortages	0.70	5	0	Yes	0	

Table 56: Low Runner Regression Analysis Summary.

The “NA” fields indicate that the Residual Distribution and Observed vs. Predicted plots were not required. These plots were shown to be the same as the corresponding zero-intercept-equation plots.

Start of Avg. Plant Inventory

Variable	Avg. Plant Inv. Parameter	Avg. Plant Inv. Std Err	Avg. Plant Inv. t	Avg. Plant Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Plant Inv. Beta	Avg. Plant Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage	-1.477	0.2901	-5.0915	0.000001	-2.047	-0.91	-0.02762	0.005425	-0.03829	-0.01695
Target Coverage										
ST + MC										
ST + TC	-3.926	0.6868	-5.7170	0.000000	-5.277	-2.58	-0.15286	0.026737	-0.20543	-0.10028
ADD*(ST+MC)										
ADD*(ST+TC)	0.936	0.0322	29.0509	0.000000	0.873	1.00	0.77689	0.026742	0.72430	0.82947
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.362	0.0216	16.7579	0.000000	0.319	0.40	0.08048	0.004803	0.07104	0.08993
PS*ST										
PS*MC										
PS*TC										
Days to Assembly	-0.390	0.1322	-2.9524	0.003354	-0.650	-0.13	-0.11293	0.038252	-0.18815	-0.03772
Avg. Daily Demand	-4.639	0.3622	-12.8069	0.000000	-5.351	-3.93	-0.82724	0.064593	-0.95426	-0.70023
Flip Mean	5635.397	367.7109	15.3256	0.000000	4912.338	6358.46	1.29693	0.084625	1.13053	1.46334

Table 57: Equation Variables & Betas. Avg. Plant Inventory. Low Runners.

Summary of best subsets; variable(s): Average Plant Inventory Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.996006	7		-0.027623
2	0.995991	7		-0.029208
3	0.995974	7		
4	0.995959	7		
5	0.995951	7		
6	0.995924	7		
7	0.995923	6		-0.027623
8	0.995918	7		
9	0.995918	7		
10	0.995918	7		

Figure 113: Summary of Best Subsets Adjusted R² Value. Low Runners.

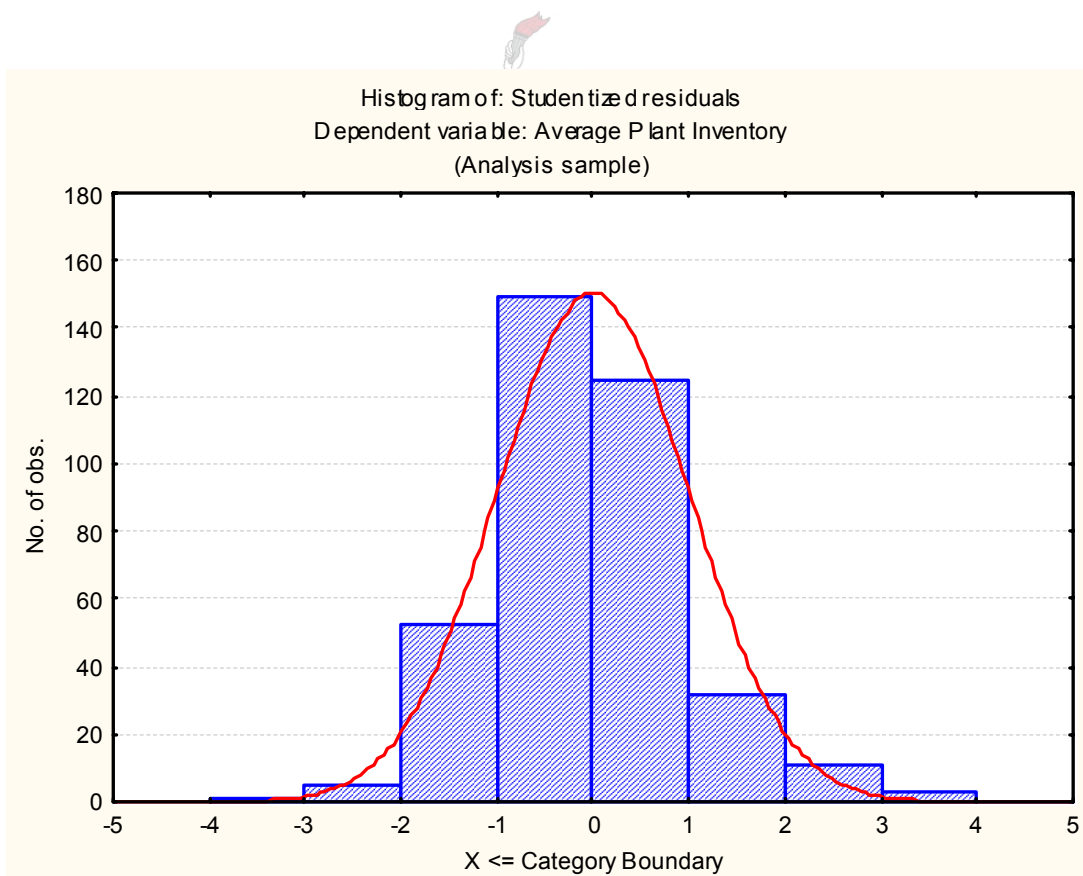


Figure 114: Studentized Residuals. Avg. Plant Inventory. Low Runners.

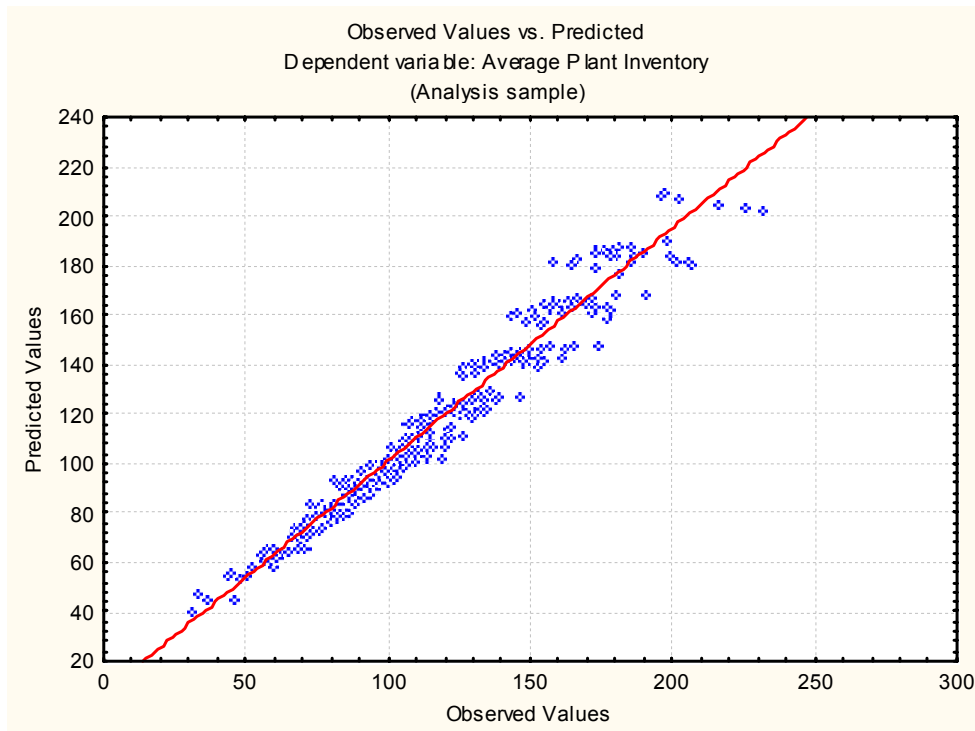


Figure 115: Observed vs. Predicted Avg. Plant Inventory. Low Runners.

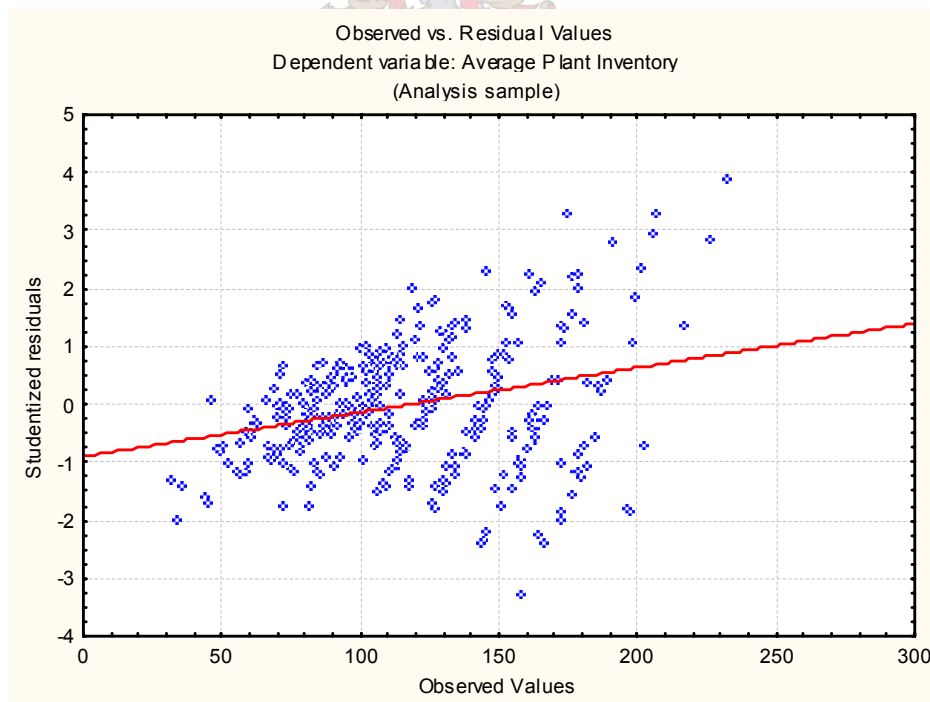


Figure 116: Observed vs. Residual Avg. Plant Inventory. Low Runners.

End of Avg. Plant Inventory

Start of Avg. Pipeline Inventory

Variable	Avg. Pipeline Inv. Parameter	Avg. Pipeline Inv. Std Err	Avg. Pipeline Inv. t	Avg. Pipeline Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Pipeline Inv. Beta	Avg. Pipeline Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	-51.9	4.001	-12.9833	0.000000	-59.8	-44.1	-0.313326	0.024133	-0.360781	-0.265870
ADD*(ST+MC)	0.5	0.069	6.7656	0.000000	0.3	0.6	0.040597	0.006000	0.028797	0.052396
ADD*(ST+TC)	1.8	0.175	10.5627	0.000000	1.5	2.2	0.237540	0.022489	0.193318	0.281762
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-2.0	0.274	-7.2864	0.000000	-2.5	-1.5	-0.068964	0.009465	-0.087576	-0.050353
PS*ST	0.4	0.100	4.2260	0.000030	0.2	0.6	0.018778	0.004443	0.010040	0.027516
PS*MC										
PS*TC	0.4	0.065	6.5936	0.000000	0.3	0.6	0.054161	0.008214	0.038009	0.070314
Days to Assembly	9.8	0.694	14.1460	0.000000	8.4	11.2	0.439836	0.031093	0.378695	0.500978
Avg. Daily Demand	36.8	1.846	19.9125	0.000000	33.1	40.4	1.015563	0.051001	0.915273	1.115852
Flip Mean	-11684.4	1843.384	-6.3386	0.000000	-15309.2	-8059.5	-0.416607	0.065726	-0.545852	-0.287363

Table 58: Equation Variables & Betas. Avg. Pipeline Inventory. Low Runners.

Summary of best subsets; variable(s): Average Pipeline Inventory					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.997610	9			
2	0.997599	9			
3	0.997576	9			
4	0.997572	9		0.026953	
5	0.997533	9	-0.060549		
6	0.997533	9	0.026421		
7	0.997533	9			
8	0.997518	9	-0.072570		
9	0.997518	9	0.009822		
10	0.997518	9			

Figure 117: Summary of Best Subsets Adjusted R² Value. Low Runners.

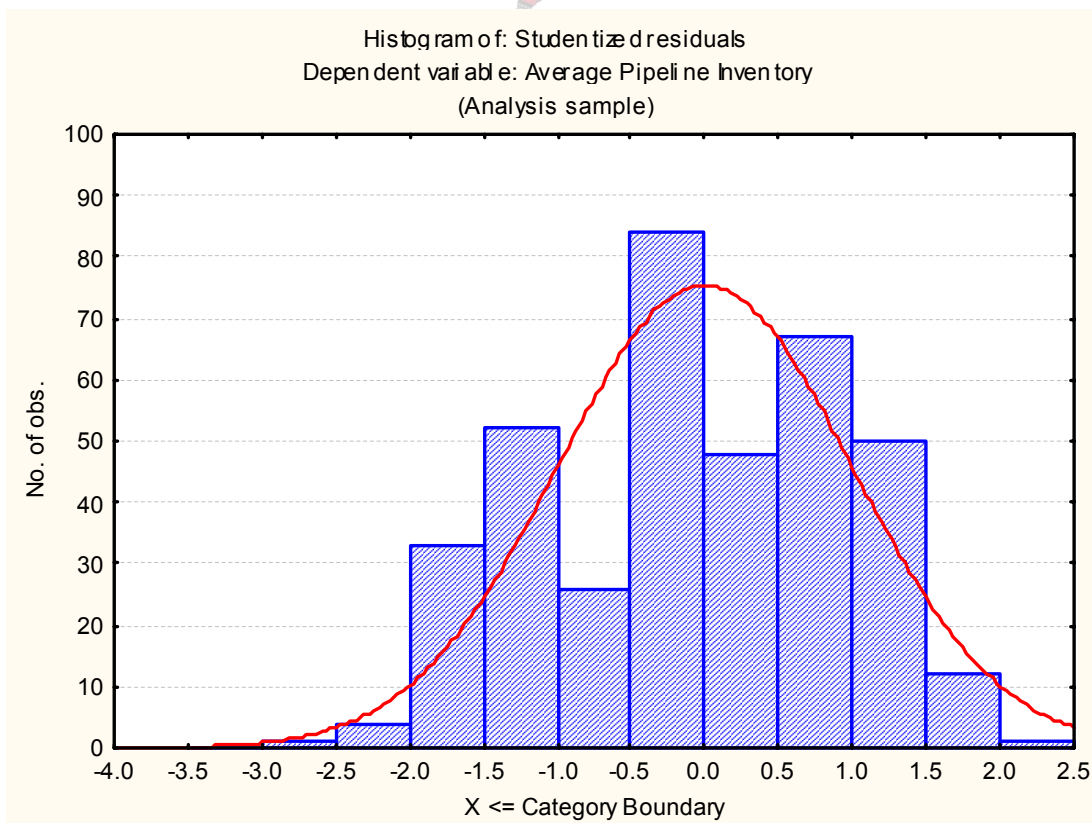


Figure 118: Studentized Residuals. Avg. Pipeline Inventory. Low Runners.

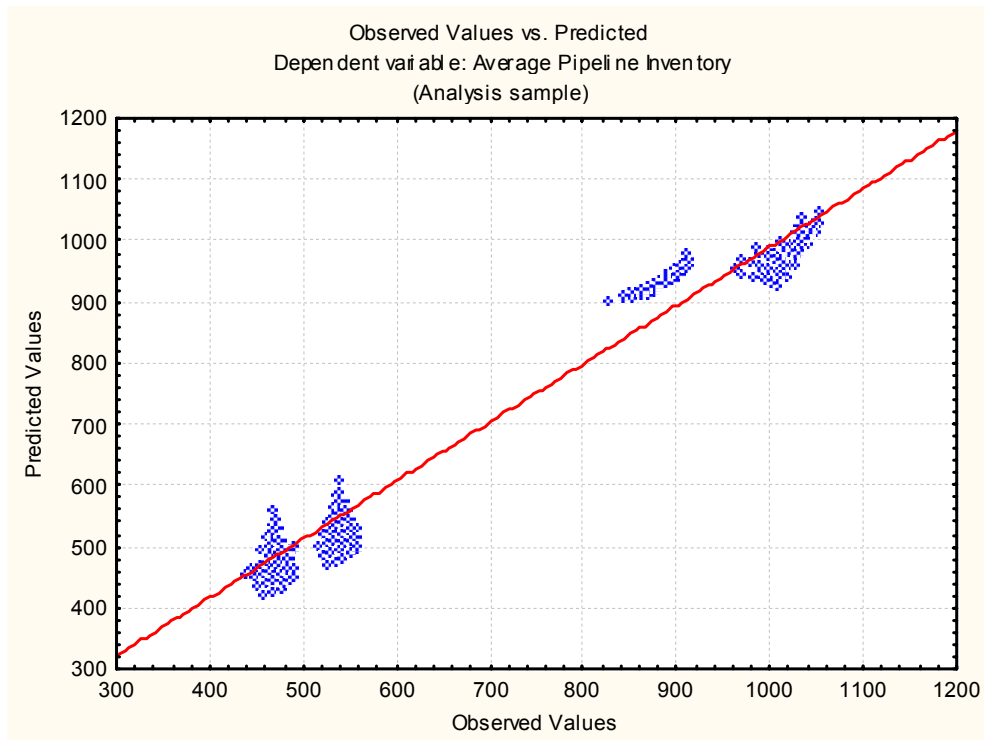


Figure 119: Observed vs. Predicted Avg. Pipeline Inventory. Low Runners.

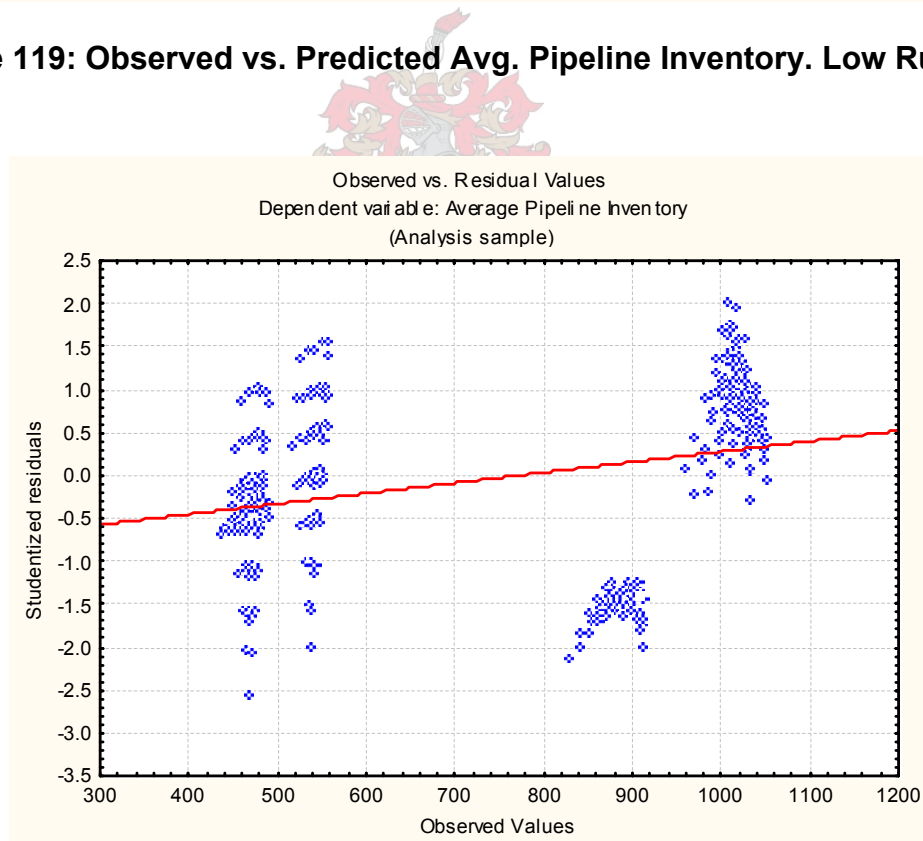


Figure 120: Observed vs. Residual Avg. Pipeline Inventory. Low Runners.
End of Avg. Pipeline Inventory

Start of Avg. Harbour Inventory

Variable	Avg. Harbour Inv. Parameter	Avg. Harbour Inv. Std Err	Avg. Harbour Inv. t	Avg. Harbour Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Harbour Inv. Beta	Avg. Harbour Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	0.471	0.02944	16.0062	0.000000	0.413	0.529	0.051325	0.003207	0.045019	0.057630
ADD*(ST+MC)										
ADD*(ST+TC)										
ADD * ST										
ADD*MC	0.024	0.00119	20.5116	0.000000	0.022	0.027	0.027274	0.001330	0.024660	0.029889
ADD * TC	-0.026	0.00166	-15.4951	0.000000	-0.029	-0.022	-0.046870	0.003025	-0.052818	-0.040922
Pallet Size	0.011	0.00320	3.5046	0.000513	0.005	0.018	0.006994	0.001996	0.003070	0.010919
PS*ST										
PS*MC	0.006	0.00095	5.8820	0.000000	0.004	0.007	0.007821	0.001330	0.005207	0.010436
PS*TC	-0.007	0.00098	-7.2285	0.000000	-0.009	-0.005	-0.016178	0.002238	-0.020580	-0.011777
Days to Assembly	0.061	0.00853	7.1475	0.000000	0.044	0.078	0.049356	0.006905	0.035777	0.062935
Avg. Daily Demand	2.395	0.02311	103.6203	0.000000	2.349	2.440	1.194748	0.011530	1.172075	1.217421
Flip Mean	-413.496	25.75737	-16.0535	0.000000	-464.146	-362.846	-0.266234	0.016584	-0.298845	-0.233623

Table 59: Equation Variables & Betas. Avg. Harbour Inventory. Low Runners.

Summary of best subsets; variable(s): Average Harb					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.999845	9			
2	0.999844	9			
3	0.999843	9			
4	0.999843	9			
5	0.999842	9	0.005329		
6	0.999842	9			
7	0.999842	9	0.014903		
8	0.999842	9	0.003149		
9	0.999842	9	0.014150		
10	0.999842	9			

Figure 121: Summary of Best Subsets Adjusted R² Value. Low Runners.

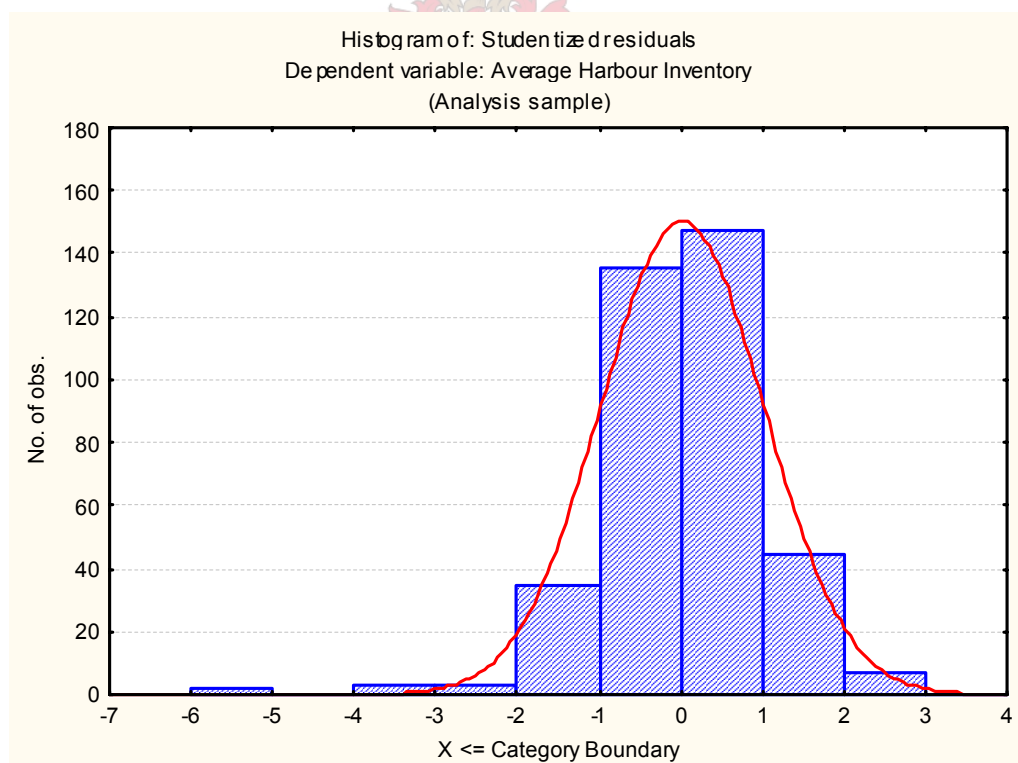


Figure 122: Studentized Residuals. Avg. Harbour Inventory. Low Runners.

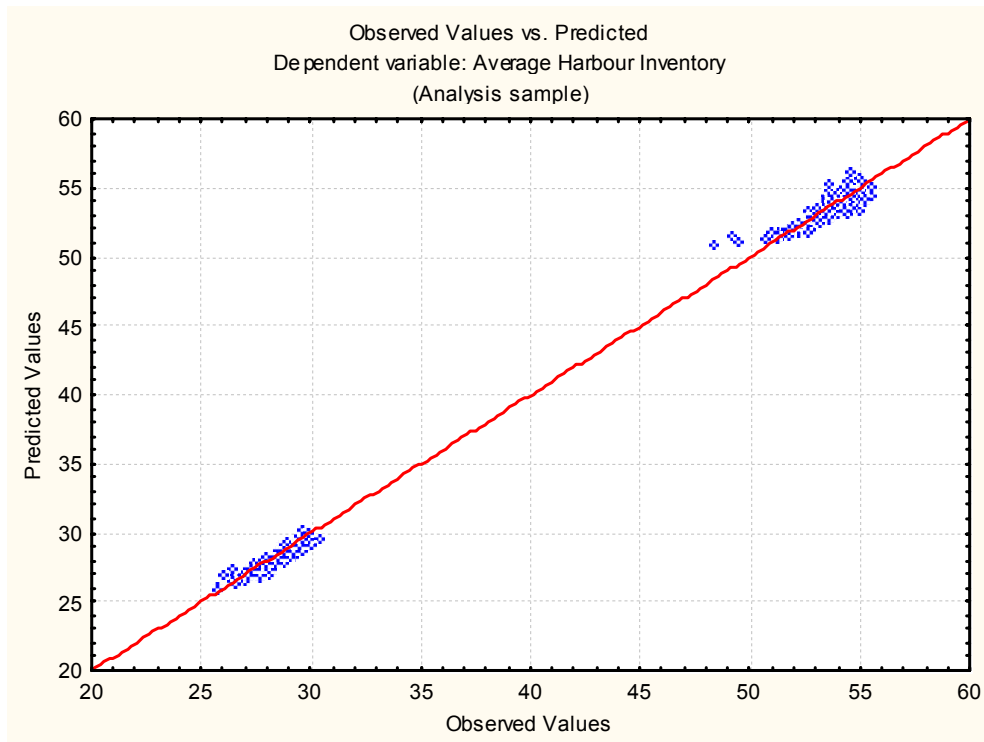
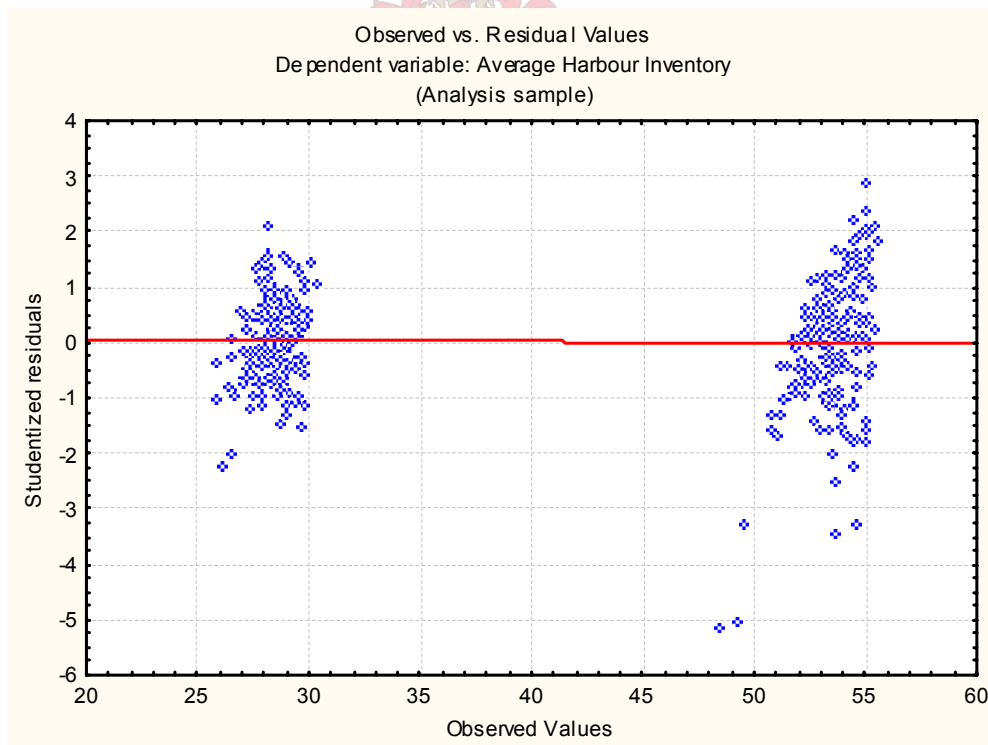


Figure 123: Observed vs. Predicted Avg. Harbour Inventory. Low Runners.



**Figure 124: Observed vs. Residual Avg. Harbour Inventory. Low Runners.
 End of Avg. Harbour Inventory**

Start of Avg. Number of Orders

Variable	Avg. Number of Orders Parameter	Avg. Number of Orders Std Err	Avg. Number of Orders t	Avg. Number of Orders p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Number of Orders Beta	Avg. Number of Orders Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage	129.54	15.86	8.17	0.00	98.36	160.71	0.57	0.07	0.43	0.70
Target Coverage	-72.98	13.97	-5.22	0.00	-100.45	-45.51	-0.52	0.10	-0.72	-0.33
ST + MC										
ST + TC										
ADD*(ST+MC)										
ADD*(ST+TC)										
ADD * ST										
ADD*MC	2.29	0.66	3.48	0.00	1.00	3.58	0.21	0.06	0.09	0.33
ADD * TC	-4.36	0.59	-7.43	0.00	-5.51	-3.20	-0.66	0.09	-0.84	-0.49
Pallet Size	-6.31	0.60	-10.46	0.00	-7.50	-5.12	-0.33	0.03	-0.39	-0.27
PS*ST										
PS*MC	-2.20	0.21	-10.48	0.00	-2.61	-1.79	-0.26	0.02	-0.30	-0.21
PS*TC	1.75	0.20	8.73	0.00	1.36	2.15	0.33	0.04	0.26	0.41
Days to Assembly	12.78	1.23	10.39	0.00	10.36	15.20	0.86	0.08	0.70	1.03
Avg. Daily Demand	15.70	1.83	8.56	0.00	12.09	19.30	0.65	0.08	0.50	0.80
Flip Mean										

Table 60: Equation Variables & Betas. Avg. Number of Orders. Low Runners.

Summary of best subsets; variable(s): Average Numl					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.967323	9		0.566531	
2	0.967155	9			
3	0.966864	9			
4	0.966701	9		0.472739	
5	0.966496	9		0.566531	
6	0.966339	8		0.795852	
7	0.966325	9		0.795852	
8	0.966325	9		0.795852	
9	0.966325	9		0.795852	
10	0.966285	9	0.412453	0.795852	

Figure 125: Summary of Best Subsets Adjusted R² Value. Low Runners.

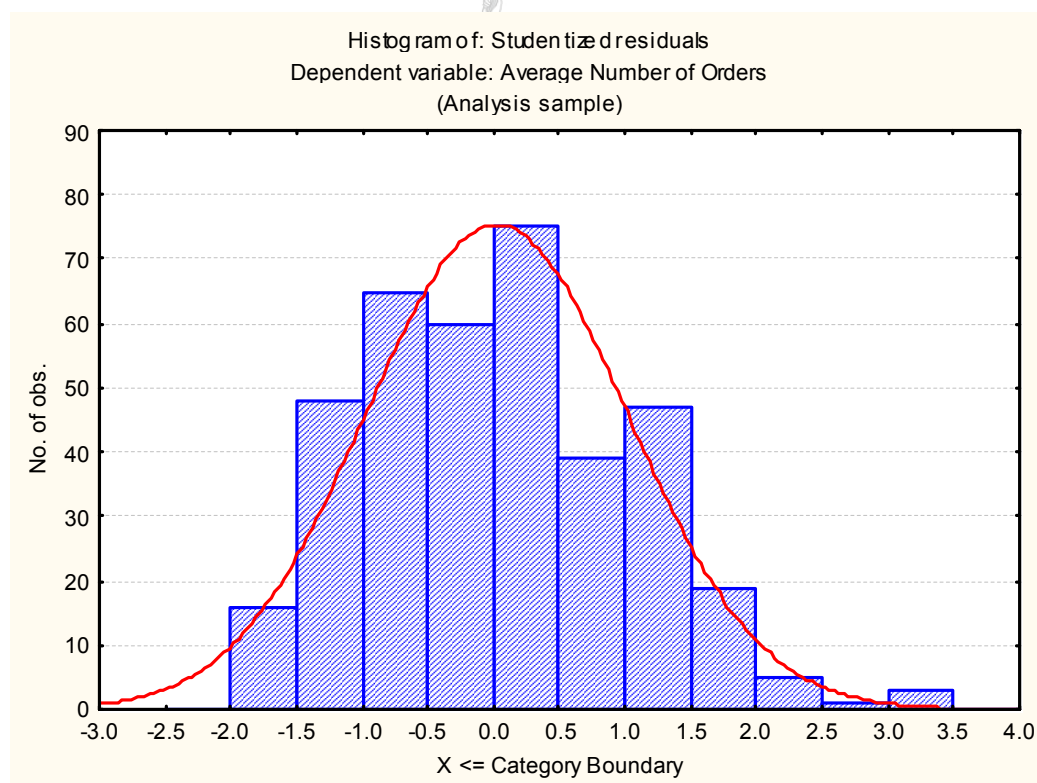


Figure 126: Studentized Residuals. Avg. Number of Orders. Low Runners.

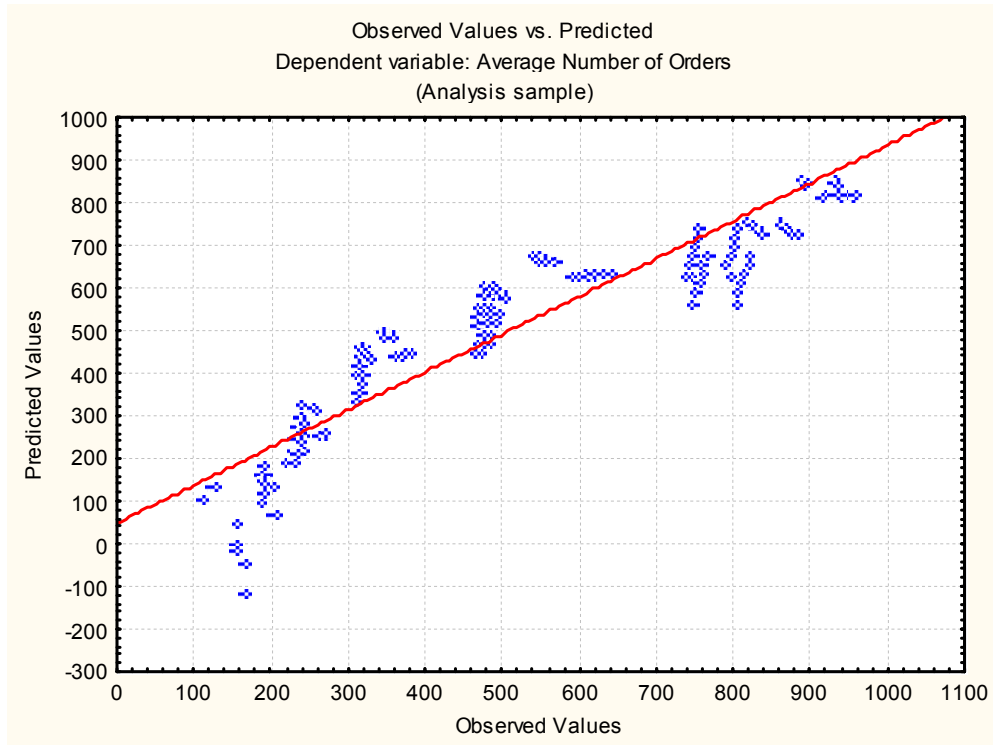
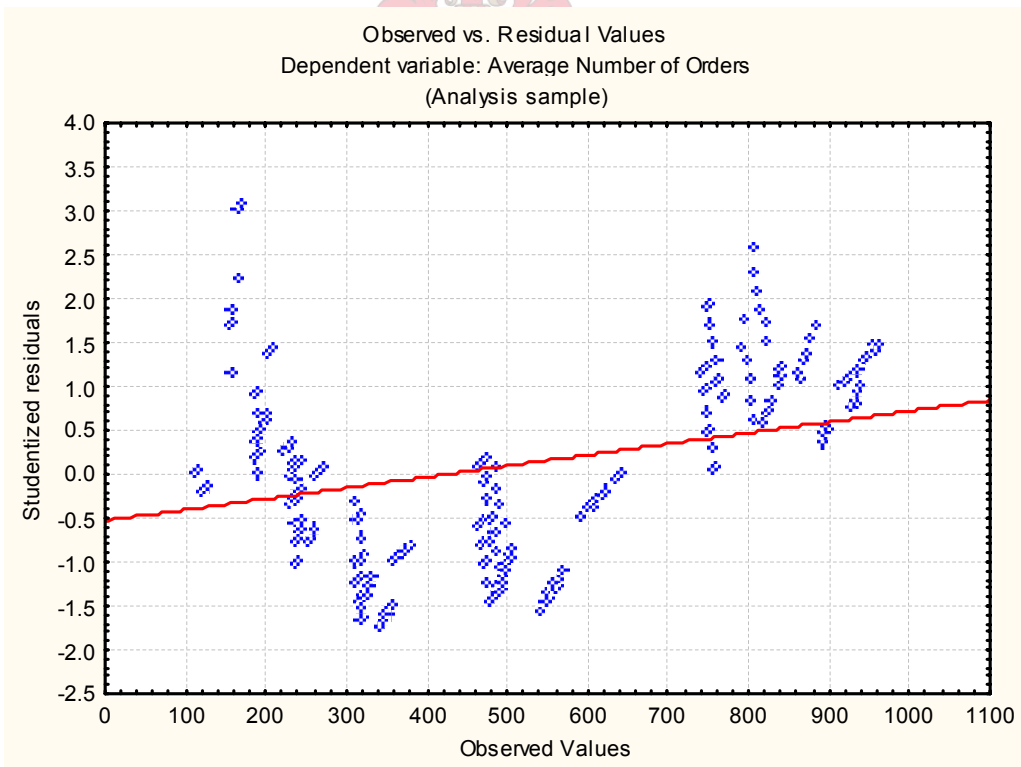


Figure 127: Observed vs. Predicted Avg. Number of Orders. Low Runners.



**Figure 128: Observed vs. Residual Avg. Number of Orders. Low Runners.
End of Avg. Number of Orders**

Start of Avg. Order Size

Variable	Avg. Order Size Parameter	Avg. Order Size Std Err	Avg. Order Size t	Avg. Order Size p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Order Size Beta	Avg. Order Size Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	0.515451	0.187625	2.7472	0.006303	0.146509	0.884394	0.035018	0.012747	0.009953	0.060083
ADD*(ST+MC)										
ADD*(ST+TC)										
ADD * ST										
ADD*MC	-0.978642	0.010949	-89.3827	0.000000	-1.000172	-0.957112	-0.681011	0.007619	-0.695993	-0.666029
ADD * TC	0.961492	0.013196	72.8599	0.000000	0.935543	0.987441	1.092597	0.014996	1.063109	1.122084
Pallet Size	0.665838	0.027780	23.9679	0.000000	0.611211	0.720465	0.258641	0.010791	0.237421	0.279860
PS*ST										
PS*MC	0.049981	0.008772	5.6980	0.000000	0.032733	0.067230	0.043413	0.007619	0.028431	0.058395
PS*TC	-0.053776	0.008903	-6.0405	0.000000	-0.071282	-0.036270	-0.076275	0.012627	-0.101106	-0.051445
Days to Assembly										
Avg. Daily Demand	0.745705	0.035398	21.0660	0.000000	0.676099	0.815312	0.232066	0.011016	0.210405	0.253728
Flip Mean										

Table 61: Equation Variables & Betas. Avg. Order Size Inventory. Low Runners.

Summary of best subsets; variable(s): Average Order					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.994900	7			
2	0.994881	7			
3	0.994881	7	0.013872		
4	0.994880	7	0.013378		
5	0.994880	7			
6	0.994859	7			
7	0.994857	7			
8	0.994857	7			
9	0.994857	7			
10	0.994857	7			

Figure 129: Summary of Best Subsets Adjusted R² Value. Low Runners

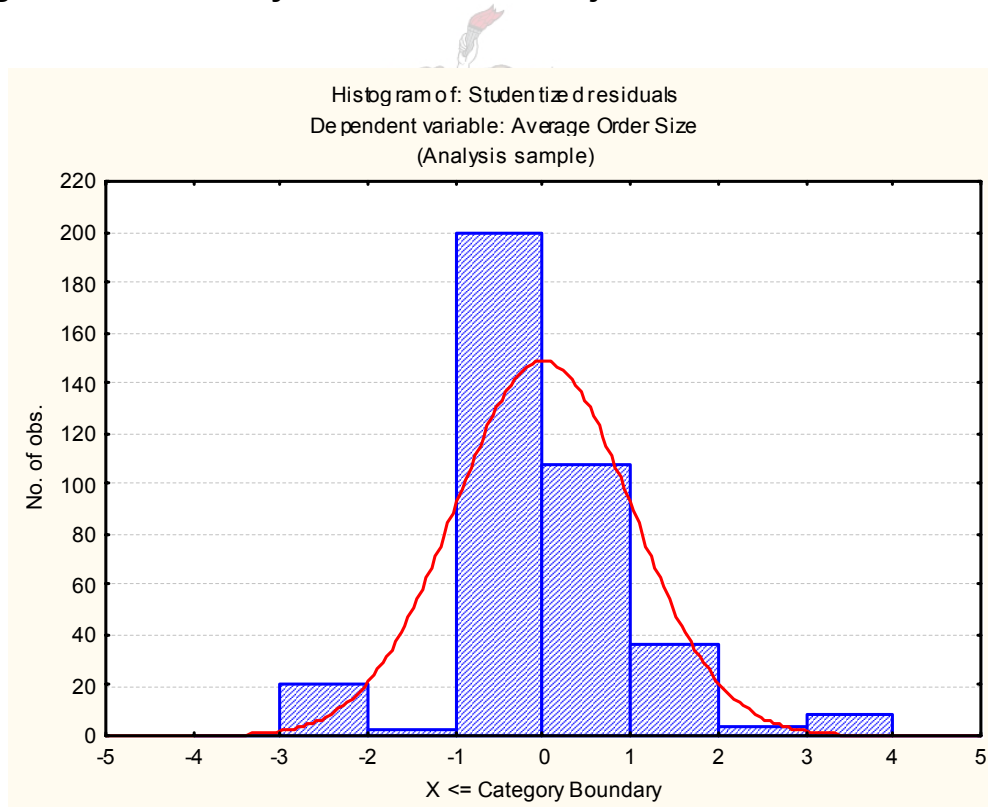


Figure 130: Studentized Residuals. Avg. Order Size. Low Runners.

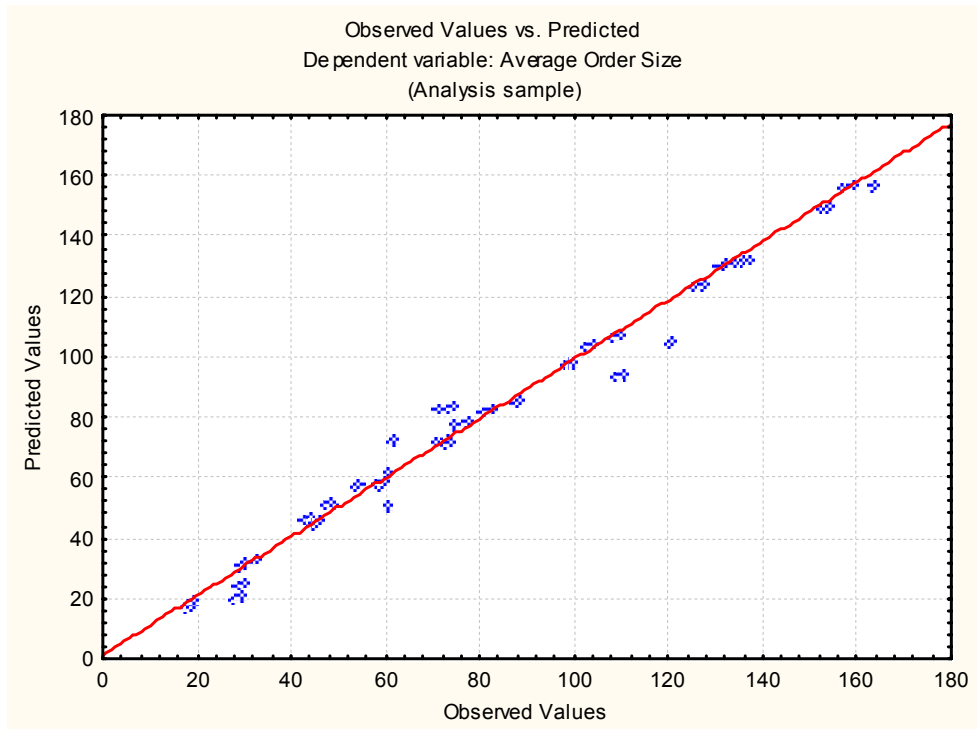


Figure 131: Observed vs. Predicted Avg. Order Size. Low Runners.

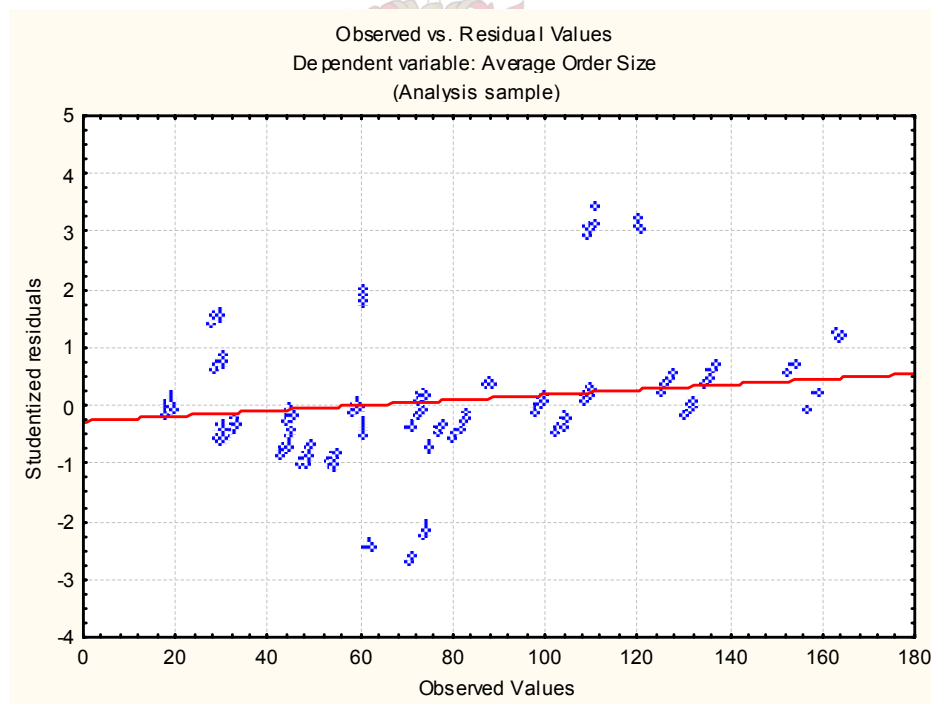


Figure 132: Observed vs. Residual Avg. Order Size. Low Runners.
End of Avg. Order Size

Start of Avg. Customer Service Level

Variable	Avg. Customer Service Level Parameter	Avg. Customer Service Level Std Err	Avg. Customer Service Level t	Avg. Customer Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Service Level Beta	Avg. Customer Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	0.07528	0.004764	15.8010	0.000000	0.06591	0.08465	0.352017	0.022278	0.308210	0.395825
ADD*(ST+MC)										
ADD*(ST+TC)	-0.00287	0.000199	-14.4091	0.000000	-0.00326	-0.00248	-0.286344	0.019872	-0.325420	-0.247267
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.00341	0.000370	9.2294	0.000000	0.00269	0.00414	0.091244	0.009886	0.071804	0.110684
PS*ST	-0.00060	0.000136	-4.4047	0.000014	-0.00087	-0.00033	-0.020655	0.004689	-0.029876	-0.011434
PS*MC										
PS*TC	-0.00062	0.000088	-6.9657	0.000000	-0.00079	-0.00044	-0.060097	0.008628	-0.077063	-0.043132
Days to Assembly	0.01442	0.000927	15.5591	0.000000	0.01260	0.01624	0.501089	0.032206	0.437761	0.564418
Avg. Daily Demand										
Flip Mean	15.16570	1.111654	13.6425	0.000000	12.97976	17.35163	0.419208	0.030728	0.358785	0.479631

Table 62: Equation Variables & Betas. Avg. Customer Service Level. Low Runners.

Summary of best subsets; variable(s): Average Custo					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.997260	7			
2	0.997164	7	0.081731		
3	0.997164	7	-0.013421		
4	0.997164	7			
5	0.997145	7			
6	0.997145	7			
7	0.997145	7			
8	0.997128	7		0.005577	
9	0.997125	7			
10	0.997125	6			

Figure 133: Summary of Best Subsets Adjusted R² Value. Low Runners.

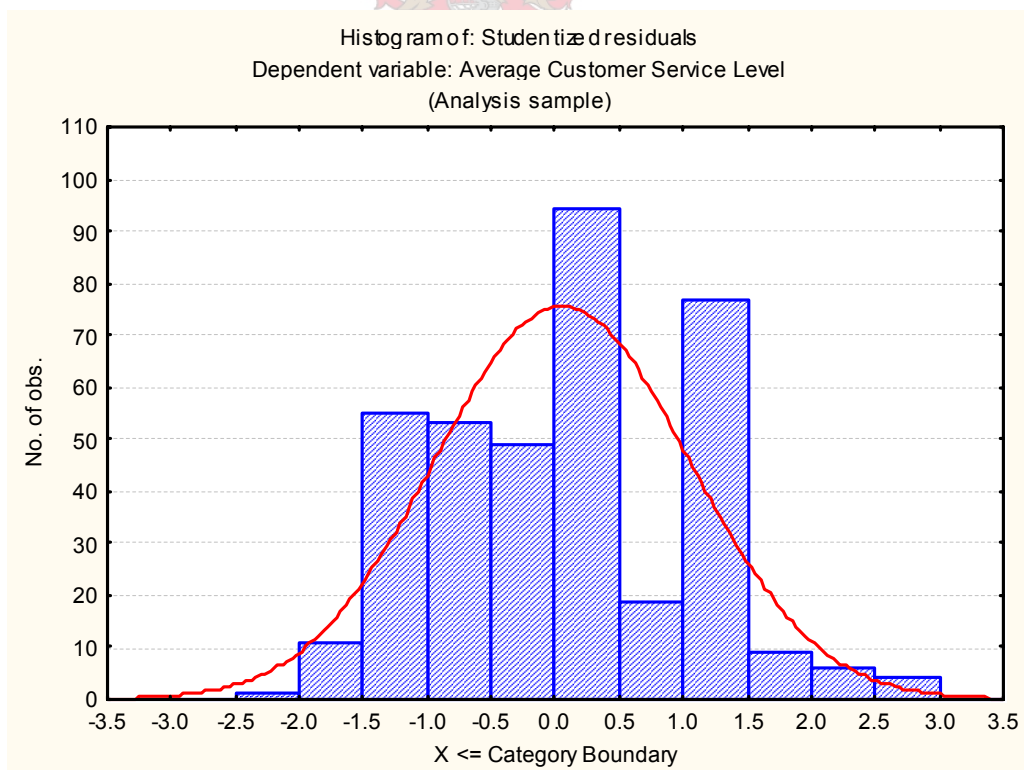


Figure 134: Studentized Residuals. Avg. Customer Service Level. Low Runners.

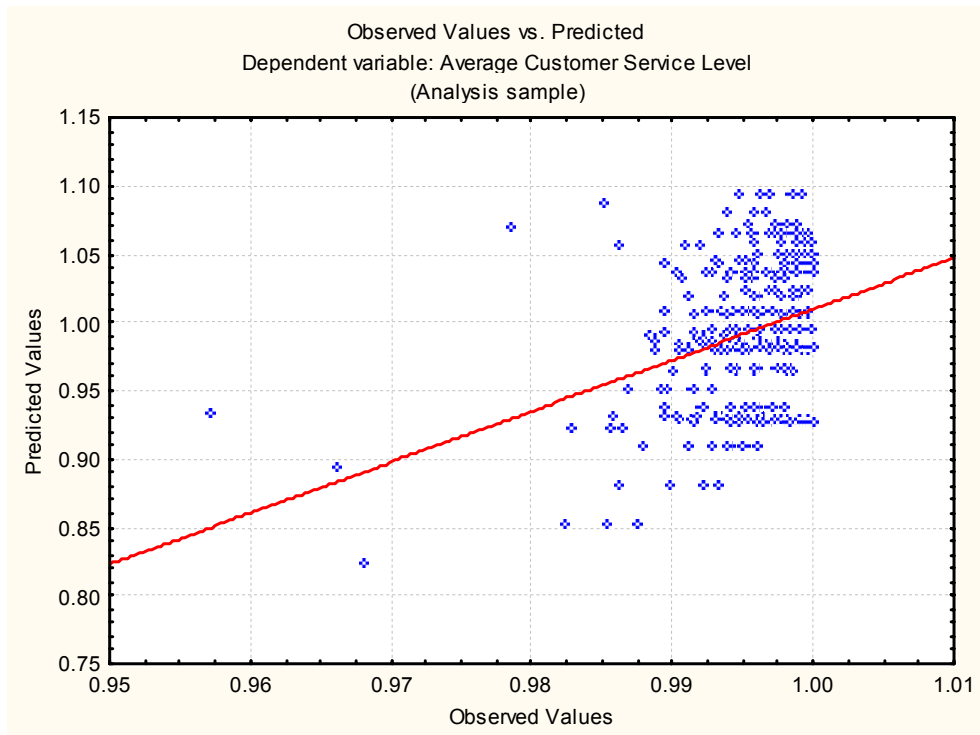


Figure 135: Observed vs. Predicted Avg. Customer Service Level. Low Runners.

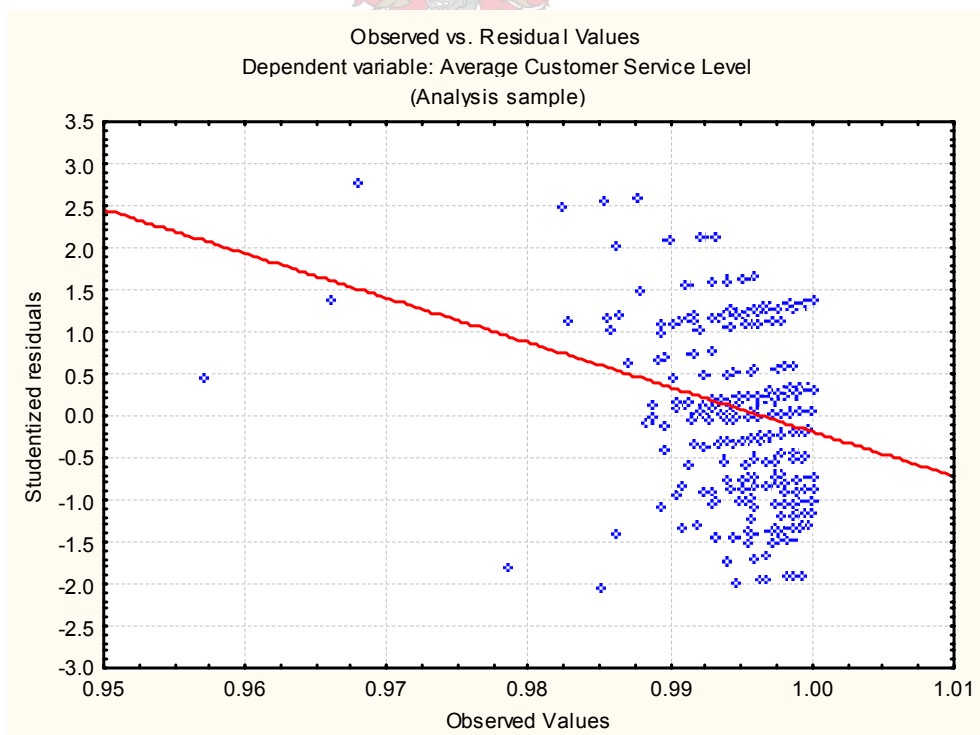


Figure 136: Observed vs. Residual Avg. Customer Service Level. Low Runners.

Variable	Avg. Customer Service Level Parameter	Avg. Customer Service Level Std Err	Avg. Customer Service Level t	Avg. Customer Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Service Level Beta	Avg. Customer Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Intercept	0.9696	0.0020	481.9882	0.0000	0.9656	0.9735				
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	0.0013	0.0001	12.4760	0.0000	0.0011	0.0015	0.4856	0.0389	0.4091	0.5622
ST + TC	0.0025	0.0003	8.0883	0.0000	0.0019	0.0032	0.9501	0.1175	0.7191	1.1810
ADD*(ST+MC)										
ADD*(ST+TC)	-0.0001	0.0000	-5.2165	0.0000	-0.0001	0.0000	-0.6510	0.1248	-0.8964	-0.4056
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.0001	0.0000	5.4986	0.0000	0.0001	0.0002	0.4947	0.0900	0.3178	0.6717
PS*ST	0.0000	0.0000	-2.8202	0.0051	0.0000	0.0000	-0.1307	0.0463	-0.2218	-0.0396
PS*MC										
PS*TC	0.0000	0.0000	-4.3663	0.0000	0.0000	0.0000	-0.3519	0.0806	-0.5104	-0.1934
Days to Assembly										
Avg. Daily Demand										
Flip Mean	0.6202	0.0666	9.3070	0.0000	0.4891	0.7512	0.7475	0.0803	0.5896	0.9055

Table 63: Equation Variables & Betas. Avg. Customer Service Level Intercept. Low Runners.

Summary of best subsets; variable(s): Average Cust Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.656709	7			
2	0.655736	7		0.587974	
3	0.654021	7		0.429348	
4	0.654021	7		0.429348	
5	0.654021	7		0.429348	
6	0.653764	7		0.433752	
7	0.653650	7			
8	0.653626	7	-0.084358		
9	0.653626	7			
10	0.653626	7		0.154017	

Figure 137: Summary of Best Subsets Adjusted R² Value. Intercept. Low Runners.

End of Avg. Customer Service Level



Start of Avg. Total Shortages

Variable	Avg. Total Shortages Parameter	Avg. Total Shortages Std Err	Avg. Total Shortages t	Avg. Total Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Total Shortages Beta	Avg. Total Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	162.8	19.104	8.5214	0.000000	125.2	200.4	0.85105	0.099872	0.65466	1.04744
ADD*(ST+MC)	-11.8	0.412	-28.5520	0.000000	-12.6	-11.0	-0.89125	0.031215	-0.95263	-0.82987
ADD*(ST+TC)	-2.4	0.926	-2.5527	0.011091	-4.2	-0.5	-0.26341	0.103190	-0.46633	-0.06050
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	9.7	0.961	10.1092	0.000000	7.8	11.6	0.29027	0.028713	0.23381	0.34673
PS*ST	-2.4	0.519	-4.6309	0.000005	-3.4	-1.4	-0.09282	0.020043	-0.13223	-0.05340
PS*MC	-2.0	0.311	-6.3692	0.000000	-2.6	-1.4	-0.13259	0.020817	-0.17352	-0.09165
PS*TC										
Days to Assembly	44.6	3.563	12.5178	0.000000	37.6	51.6	1.73266	0.138416	1.46048	2.00485
Avg. Daily Demand	186.7	9.662	19.3187	0.000000	167.7	205.7	4.46999	0.231381	4.01499	4.92498
Flip Mean	-167894.0	9754.718	-17.2116	0.000000	-187075.8	-148712.2	-5.18853	0.301456	-5.78132	-4.59574

Table 64: Equation Variables & Betas. Avg. Total Shortages. Low Runners.

Summary of best subsets; variable(s): Average Total Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.949453	9			
2	0.949043	9			
3	0.948803	9			
4	0.948699	8			
5	0.948625	9			
6	0.948622	9	0.019184		
7	0.948622	9			
8	0.948622	9	0.188384		
9	0.948575	9		0.013909	
10	0.948561	9			

Figure 138: Summary of Best Subsets Adjusted R² Value. Low Runners.

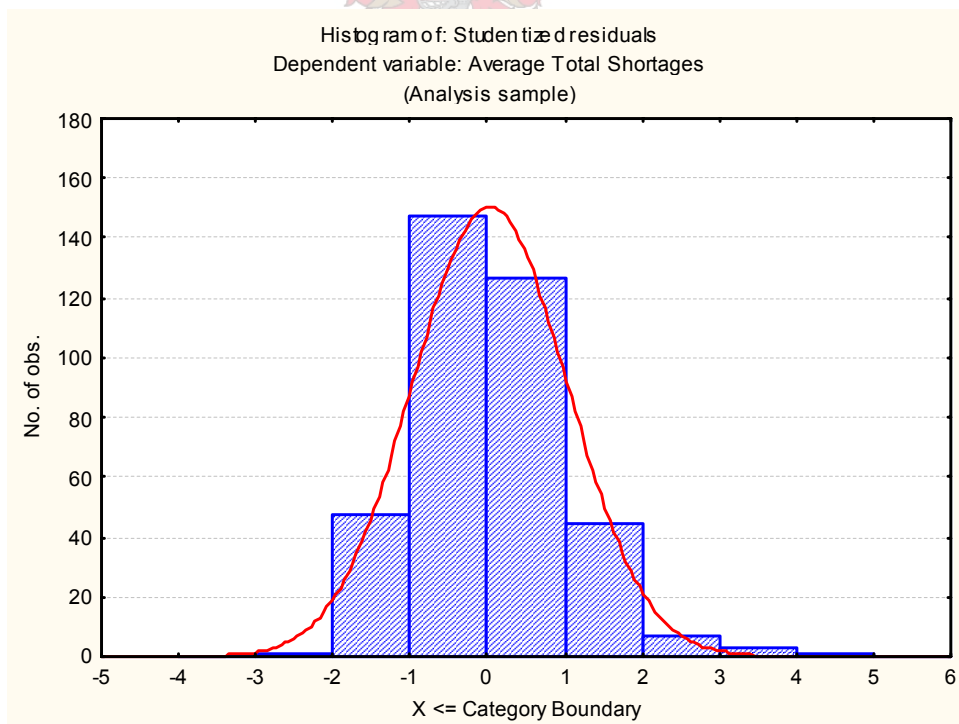


Figure 139: Studentized Residuals. Avg. Total Shortages. Low Runners.

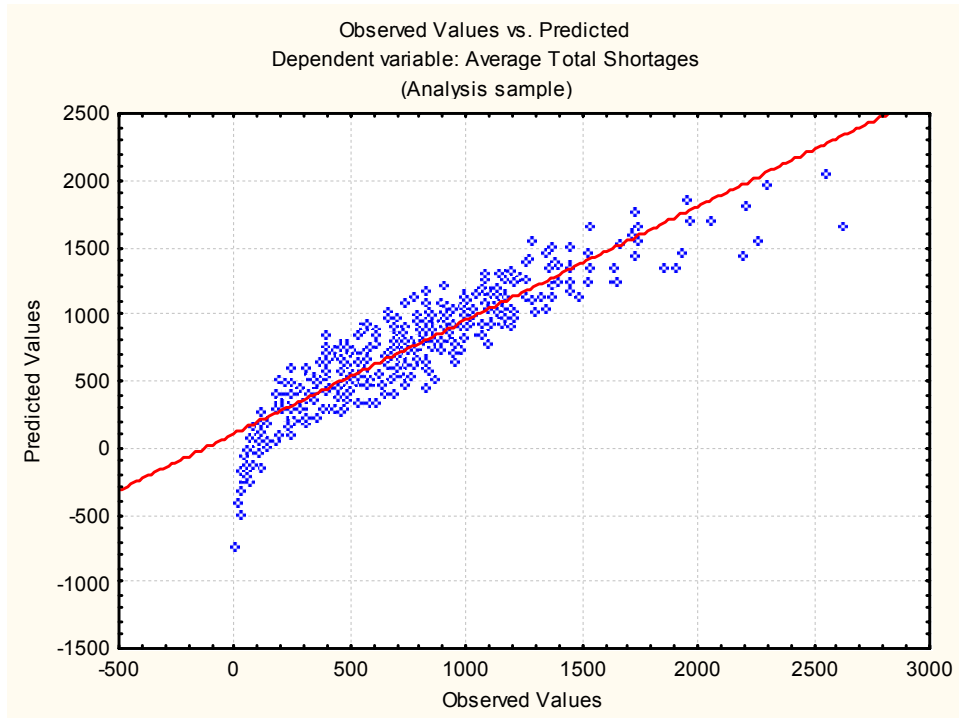
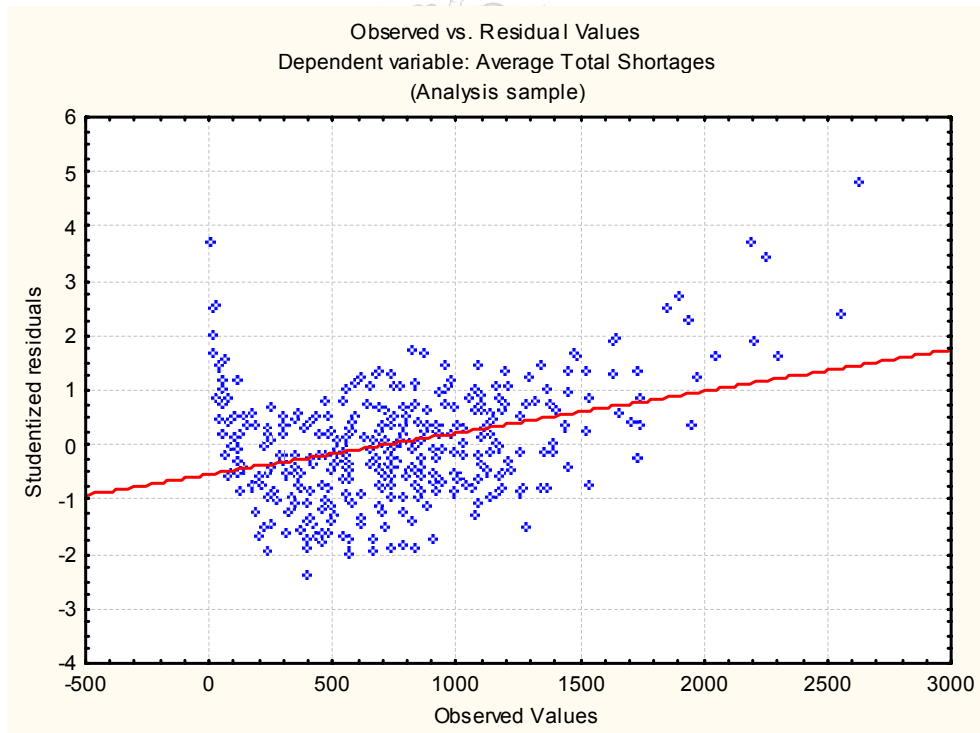


Figure 140: Observed vs. Predicted Avg. Total Shortages. Low Runners.



**Figure 141: Observed vs. Residual Avg. Total Shortages. Low Runners.
End of Avg. Total Shortages**

Start of Avg. Customer Shortages

Variable	Avg. Customer Shortages Parameter	Avg. Customer Shortages Std Err	Avg. Customer Shortages t	Avg. Customer Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Shortages Beta	Avg. Customer Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-2.16592	0.285976	-7.5738	0.000000	-2.72824	-1.60359	-0.486582	0.064246	-0.612911	-0.360253
ST + TC										
ADD*(ST+MC)										
ADD*(ST+TC)	-0.11530	0.013489	-8.5478	0.000000	-0.14183	-0.08878	-0.812988	0.095111	-1.000008	-0.625967
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size										
PS*ST										
PS*MC										
PS*TC										
Days to Assembly	0.92022	0.116202	7.9192	0.000000	0.69173	1.14872	2.261333	0.285550	1.699843	2.822823
Flip*Days to Ass	1.19944	0.321070	3.7358	0.000216	0.56811	1.83078	1.816891	0.486351	0.860557	2.773225
Avg. Daily Demand	-1150.35526	369.426093	-3.1139	0.001989	-1876.77415	-423.93637	-2.248717	0.722155	-3.668721	-0.828712
Flip Mean										

Table 65: Equation Variables & Betas. Avg. Customer Shortages. Low Runners.

Subset No.	Summary of best subsets; variable(s): Average Customer Shortages; Adjusted R square and standardized regression coefficients for each submodel				
	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.700025	5			
2	0.695347	5			
3	0.693238	5			
4	0.693050	4			
5	0.692446	5			
6	0.692388	5	0.023414		
7	0.692388	5	-0.182317	-0.356337	
8	0.692388	5		-0.040554	
9	0.692366	5			
10	0.692358	5			

Figure 142: Summary of Best Subsets Adjusted R² Value. Low Runners.

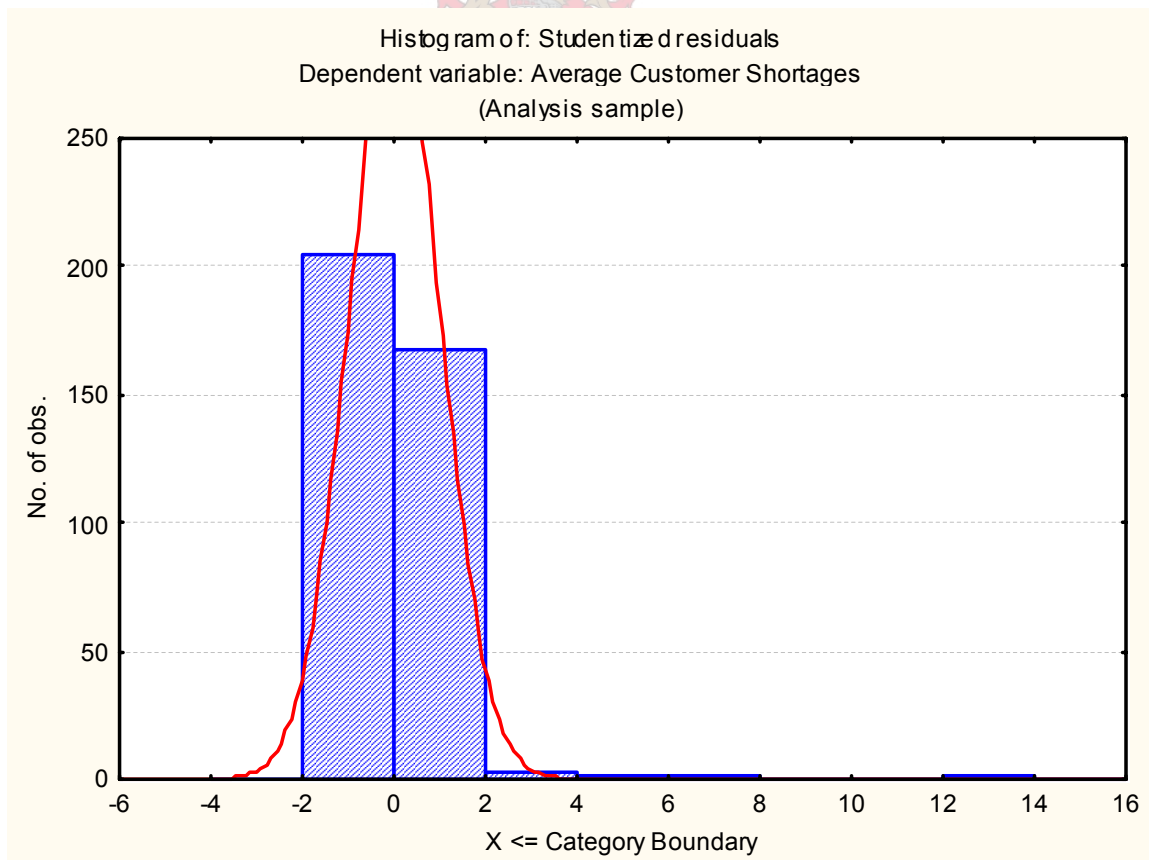


Figure 143: Studentized Residuals. Avg. Customer Shortages. Low Runners.

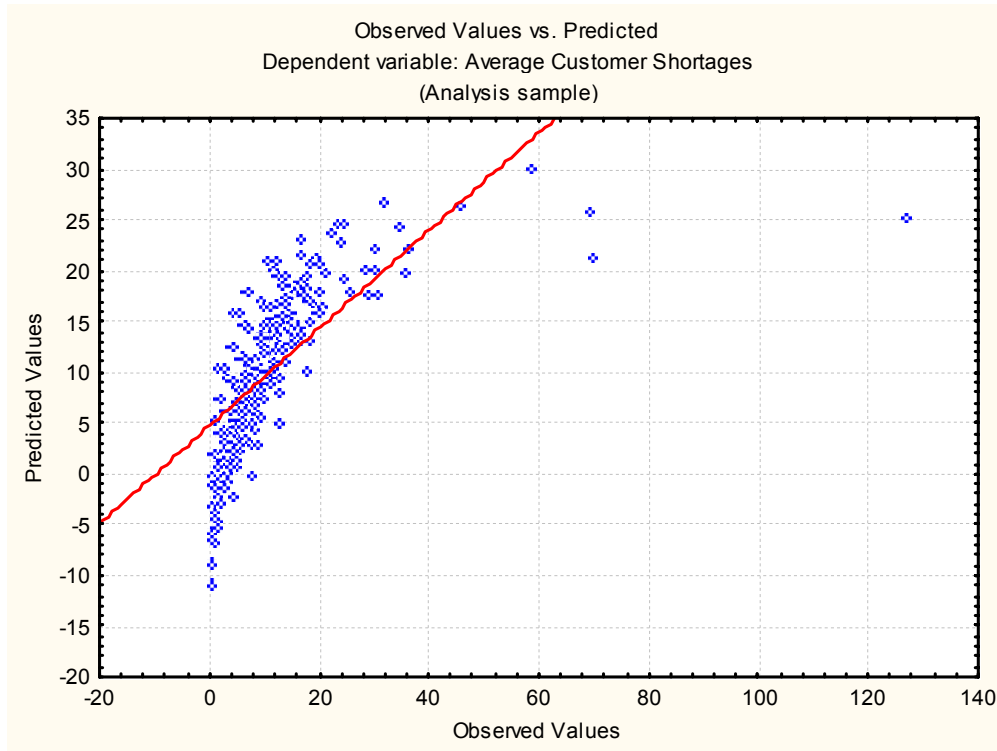
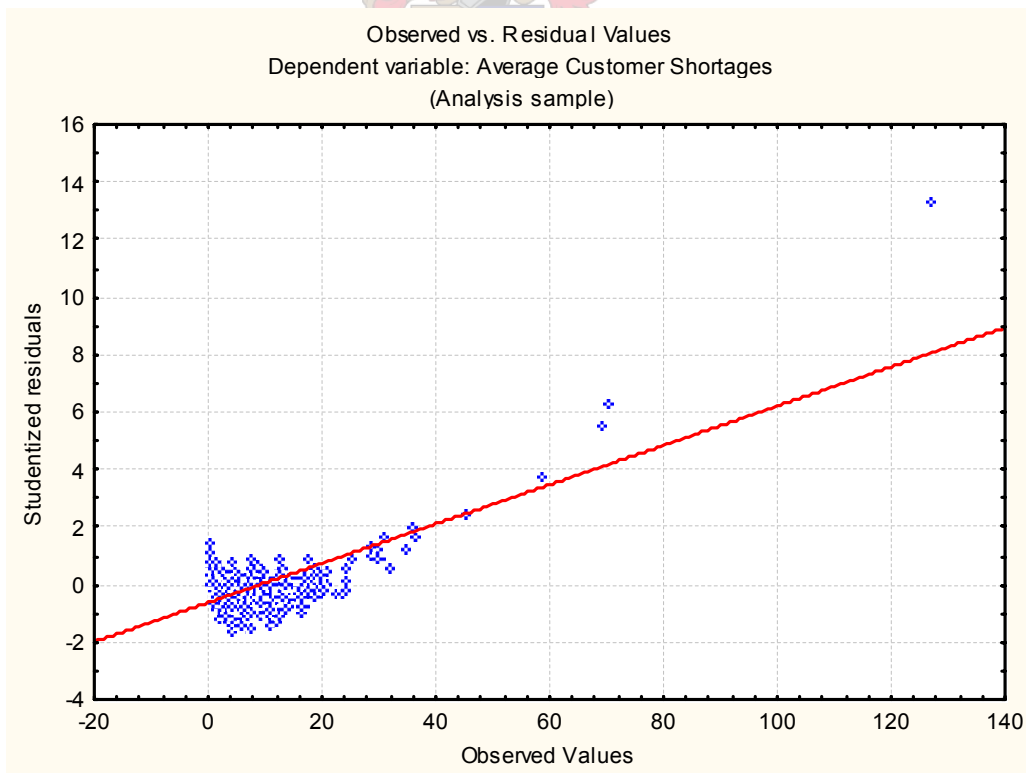
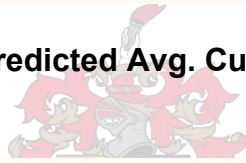
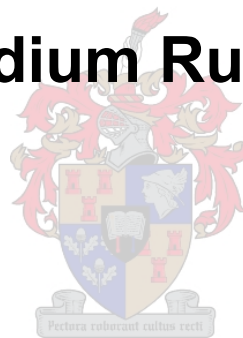


Figure 144: Observed vs. Predicted Avg. Customer Shortages. Low Runners.



**Figure 145: Observed vs. Residual Avg. Plant Inventory. Low Runners.
End of Avg. Customer Shortages**

Medium Runners.



			Quality Indicators					
			Adjusted R ² Value	Number of Variables	Intercept	Studentized Residual Distribution (Normal & Zero Mean. Yes /No?)	Observed vs. Predicted	
							Linear Relationship?	
							0	Rough
		1	Fair					
		2	Good					
Performance Measure	Inventory	Avg. Plant Inv.	0.99	8	0	Yes	2	
		Avg. Pipeline Inv.	0.99	9	0	Yes	1	
		Avg. Harbour Inv.	0.99	9	0	Yes	1	
	Orders	Avg. Number of Orders	0.96	9	0	No	1	
		Avg. Order Size	0.99	7	0	Yes	2	
	Service Level	Avg. Customer Service Level	0.99	8	0	Yes	0	
			0.60	9	1.02	NA	NA	
	Shortages	Avg. Total Shortages	0.96	9	0	Yes	1	
		Avg. Customer Shortages	0.67	7	0	Yes	0	

Table 66: Medium Runner Regression Analysis Summary.

The “NA” fields indicate that the Residual Distribution and Observed vs. Predicted plots were not required. These plots were shown to be the same as the corresponding zero-intercept-equation plots.

Start of Avg. Plant Inventory

Variable	Avg. Plant Inv. Parameter	Avg. Plant Inv. Std Err	Avg. Plant Inv. t	Avg. Plant Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Plant Inv. Beta	Avg. Plant Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-12.8462	0.97199	-13.2164	0.000000	-14.7553	-10.9370	-0.083201	0.006295	-0.095566	-0.070836
ST + TC										
ADD*(ST+MC)										
ADD*(ST+TC)	0.8426	0.01210	69.6396	0.000000	0.8188	0.8663	0.674416	0.009684	0.655394	0.693438
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.8359	0.01245	67.1215	0.000000	0.8114	0.8603	0.527322	0.007856	0.511891	0.542754
PS*ST	-0.0678	0.00489	-13.8504	0.000000	-0.0774	-0.0581	-0.055182	0.003984	-0.063008	-0.047356
PS*MC	0.0124	0.00332	3.7243	0.000216	0.0058	0.0189	0.017433	0.004681	0.008239	0.026627
PS*TC	-0.0869	0.00342	-25.4020	0.000000	-0.0936	-0.0802	-0.200144	0.007879	-0.215621	-0.184668
Days to Assembly										
Avg. Daily Demand	0.7504	0.04779	15.7007	0.000000	0.6565	0.8442	0.129031	0.008218	0.112888	0.145173
Flip Mean	297.2944	13.13565	22.6326	0.000000	271.4932	323.0957	0.100421	0.004437	0.091706	0.109136

Table 67: Equation Variables & Betas. Avg. Plant Inventory. Medium Runners.

Summary of best subsets; variable(s): Avg. Plant In Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.996718	8			
2	0.996668	8			
3	0.996655	8			
4	0.996650	8			
5	0.996646	8			
6	0.996644	8			
7	0.996643	7			
8	0.996641	8			
9	0.996641	8			
10	0.996638	8			

Figure 146: Summary of Best Subsets Adjusted R² Value. Medium Runners.

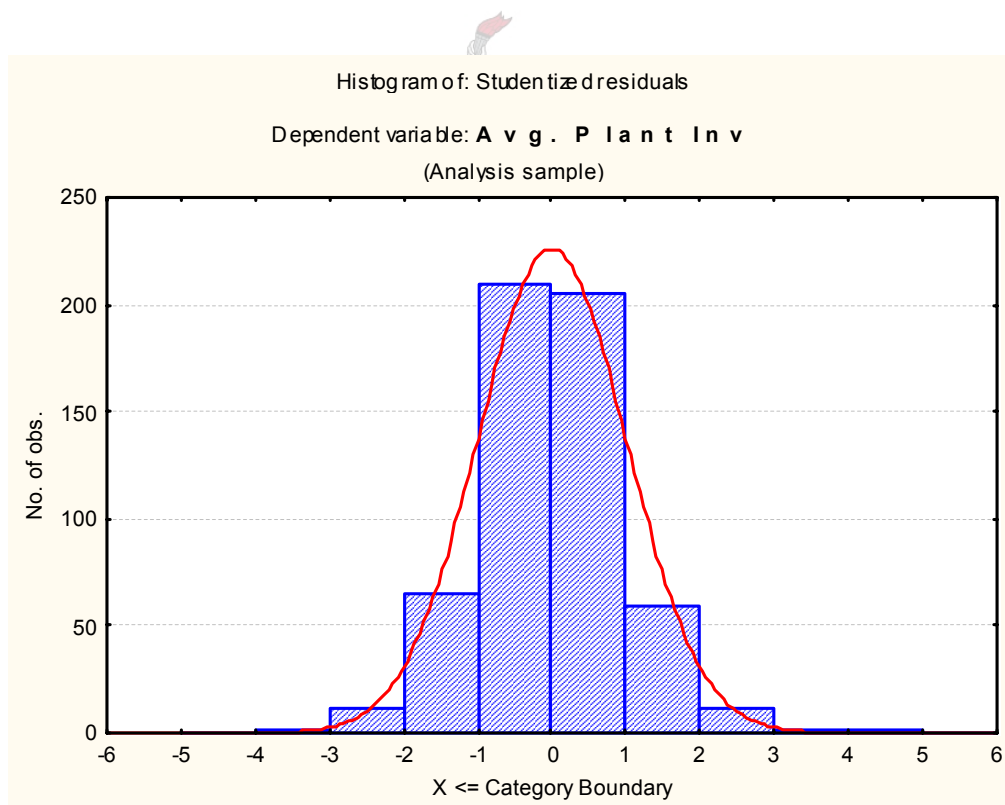


Figure 147: Studentized Residuals. Avg. Plant Inventory. Medium Runners.

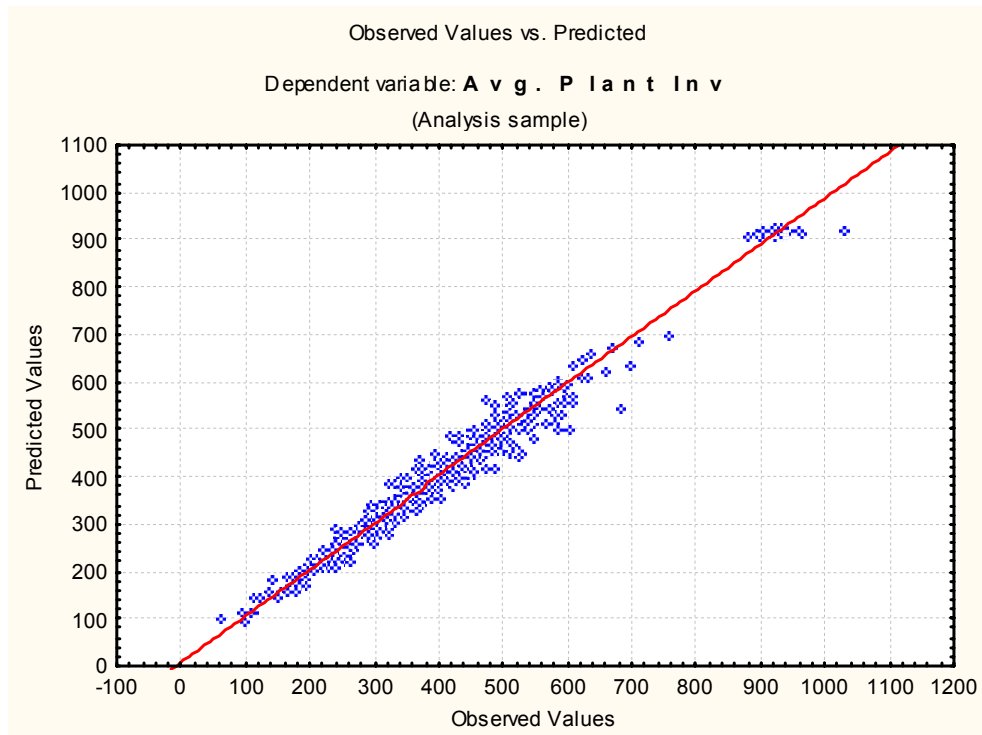


Figure 148: Observed vs. Predicted Avg. Plant Inventory. Medium Runners.

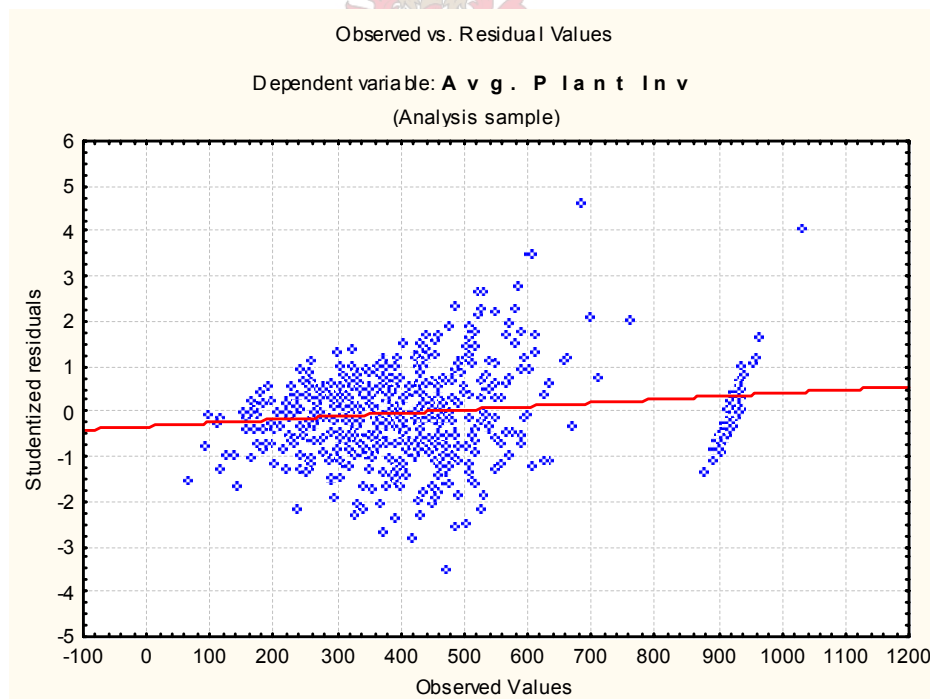


Figure 149: Observed vs. Residual Avg. Plant Inventory. Medium Runners.
End of Avg. Plant Inventory

Start of Avg. Pipeline Inventory

Variable	Avg. Pipeline Inv. Parameter	Avg. Pipeline Inv. Std Err	Avg. Pipeline Inv. t	Avg. Pipeline Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Pipeline Inv. Beta	Avg. Pipeline Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	-145.405	13.09200	-11.1064	0.000000	-171.120	-119.689	-0.237445	0.021379	-0.279438	-0.195451
ADD*(ST+MC)	0.524	0.03266	16.0318	0.000000	0.459	0.588	0.048764	0.003042	0.042790	0.054739
ADD*(ST+TC)	1.543	0.15802	9.7669	0.000000	1.233	1.854	0.211596	0.021665	0.169042	0.254150
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.158	0.02556	-6.1746	0.000000	-0.208	-0.108	-0.017057	0.002763	-0.022484	-0.011631
PS*ST	0.029	0.01388	2.1228	0.034213	0.002	0.057	0.004111	0.001937	0.000307	0.007916
PS*MC	0.041	0.00824	4.9186	0.000001	0.024	0.057	0.009790	0.001991	0.005881	0.013700
PS*TC										
Days to Assembly	46.532	1.25648	37.0335	0.000000	44.064	49.000	0.550935	0.014877	0.521714	0.580156
Avg. Daily Demand	13.035	0.53137	24.5318	0.000000	11.992	14.079	0.383954	0.015651	0.353211	0.414696
Flip Mean	1164.263	37.70703	30.8765	0.000000	1090.198	1238.328	0.067363	0.002182	0.063078	0.071648

Table 68: Equation Variables & Betas. Avg. Pipeline Inventory. Medium Runners.

Summary of best subsets; variable(s): Avg. Pipeline Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.999246	9			
2	0.999242	8			
3	0.999241	9			
4	0.999241	9			
5	0.999241	9		-0.001458	
6	0.999241	9			
7	0.999241	9			
8	0.999241	9			
9	0.999241	9			
10	0.999241	9			

Figure 150: Summary of Best Subsets Adjusted R² Value. Medium Runners.

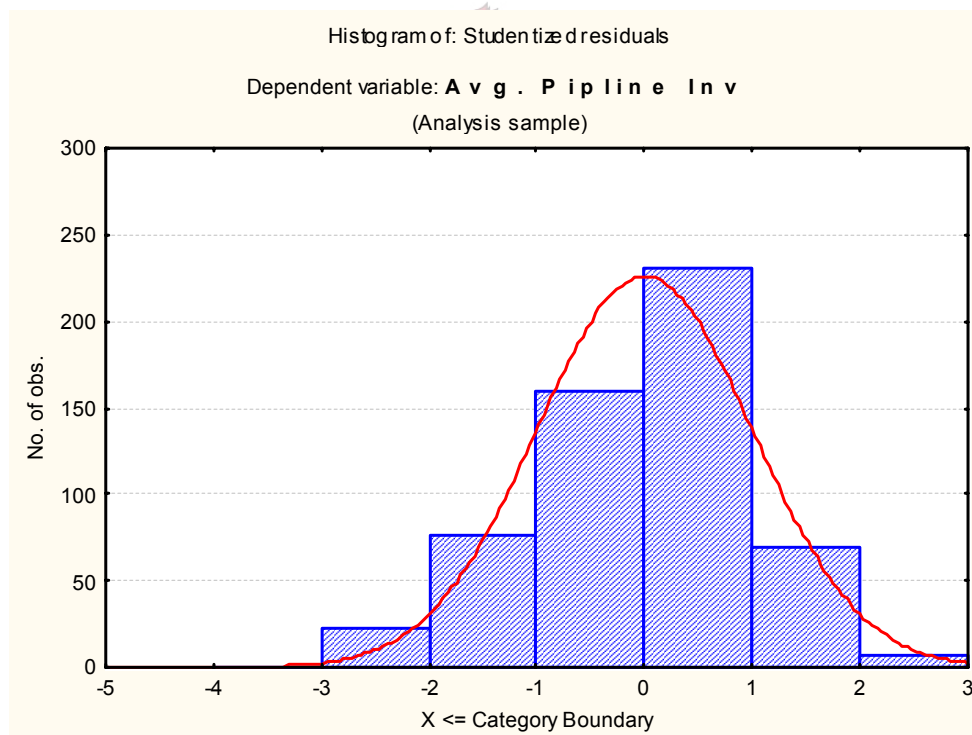


Figure 151: Studentized Residuals. Avg. Pipeline Inventory. Medium Runners.

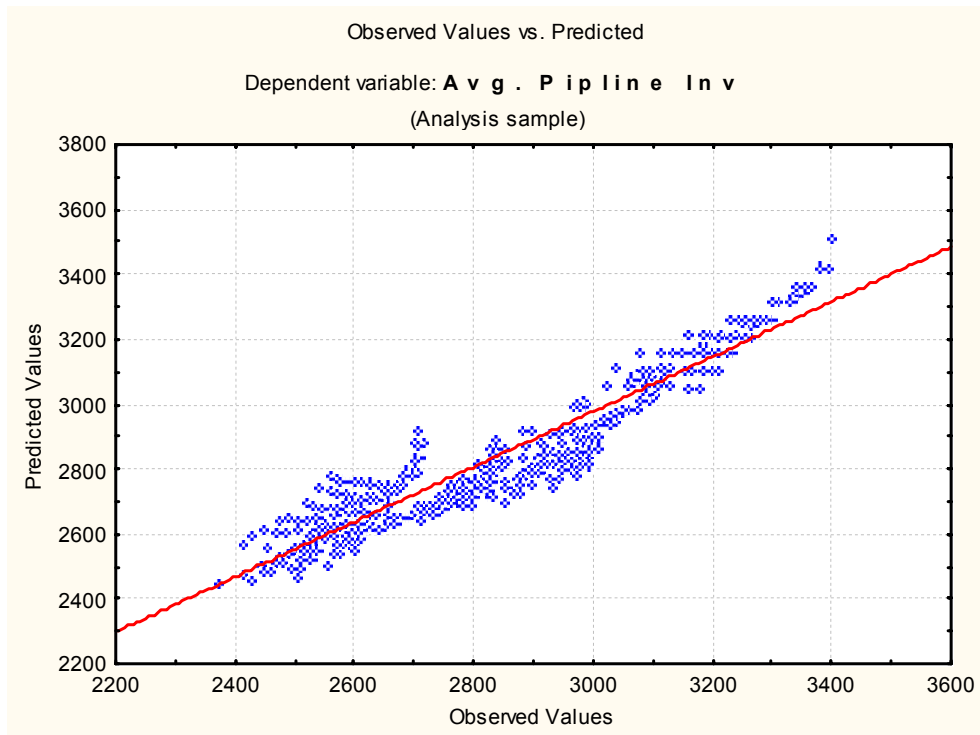
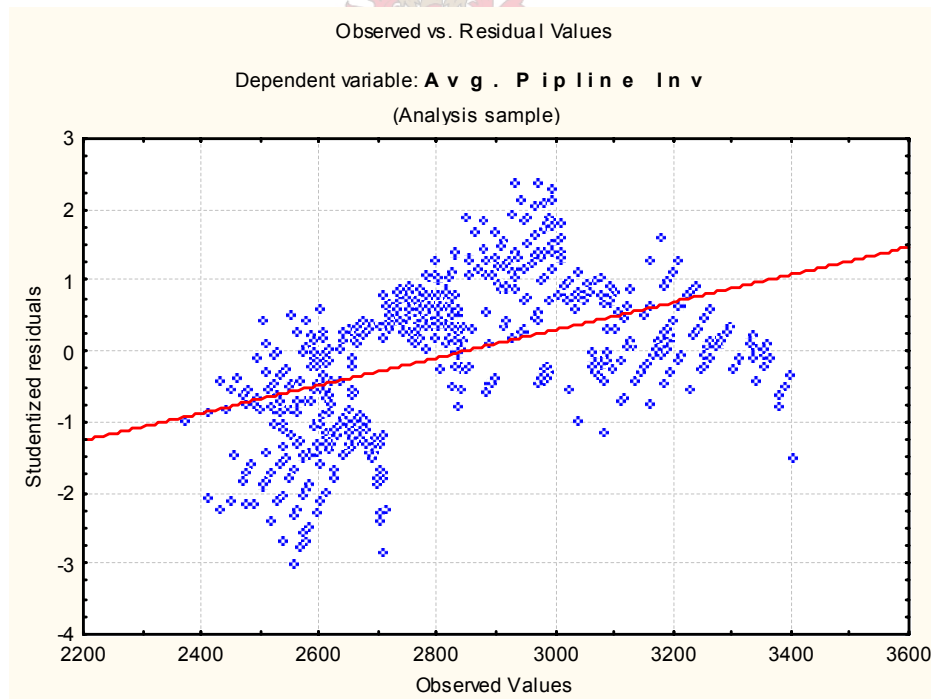


Figure 152: Observed vs. Predicted Avg. Pipeline Inventory. Medium Runners.



**Figure 153: Observed vs. Residual Avg. Pipeline Inventory. Medium Runners.
End of Avg. Pipeline Inventory**

Start of Avg. Harbour Inventory

Variable	Avg. Harbour Inv. Parameter	Avg. Harbour Inv. Std Err	Avg. Harbour Inv. t	Avg. Harbour Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Harbour Inv. Beta	Avg. Harbour Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	1.8983	0.182614	10.3950	0.000000	1.53958	2.2570	0.036491	0.003510	0.029596	0.043387
ST + TC	9.0392	0.903927	9.9999	0.000000	7.26370	10.8147	0.255774	0.025578	0.205534	0.306014
ADD*(ST+MC)										
ADD*(ST+TC)	-0.1165	0.010777	-10.8123	0.000000	-0.13769	-0.0954	-0.276818	0.025602	-0.327106	-0.226530
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.0226	0.001719	-13.1450	0.000000	-0.02598	-0.0192	-0.042320	0.003219	-0.048644	-0.035996
PS*ST	0.0055	0.000940	5.8940	0.000000	0.00369	0.0074	0.013395	0.002273	0.008931	0.017859
PS*MC	0.0055	0.000549	10.0514	0.000000	0.00444	0.0066	0.023121	0.002300	0.018603	0.027639
PS*TC										
Days to Assembly	-0.4305	0.085310	-5.0462	0.000001	-0.59806	-0.2629	-0.088320	0.017502	-0.122698	-0.053941
Avg. Daily Demand	1.9805	0.036062	54.9184	0.000000	1.90965	2.0513	1.010800	0.018405	0.974648	1.046953
Flip Mean	90.4013	2.561217	35.2962	0.000000	85.37051	95.4321	0.090633	0.002568	0.085589	0.095677

Table 69: Equation Variables & Betas. Avg. Harbour Inventory. Medium Runners.

Summary of best subsets; variable(s): Avg. Harbour Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.998956	9		
2	0.998952	9		
3	0.998945	9		
4	0.998945	9		
5	0.998943	9		0.025536
6	0.998935	9		
7	0.998933	9		
8	0.998929	9		
9	0.998924	9		
10	0.998922	9		

Figure 154: Summary of Best Subsets Adjusted R² Value. Medium Runners.

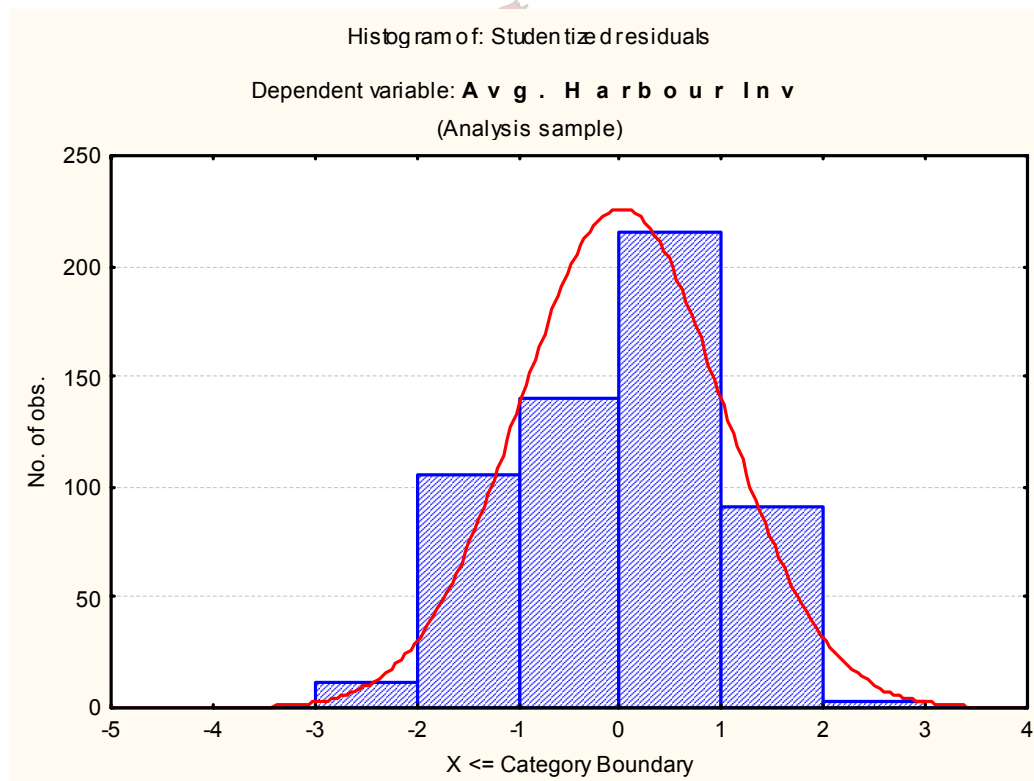


Figure 155: Studentized Residuals. Avg. Harbour Inventory. Medium Runners.

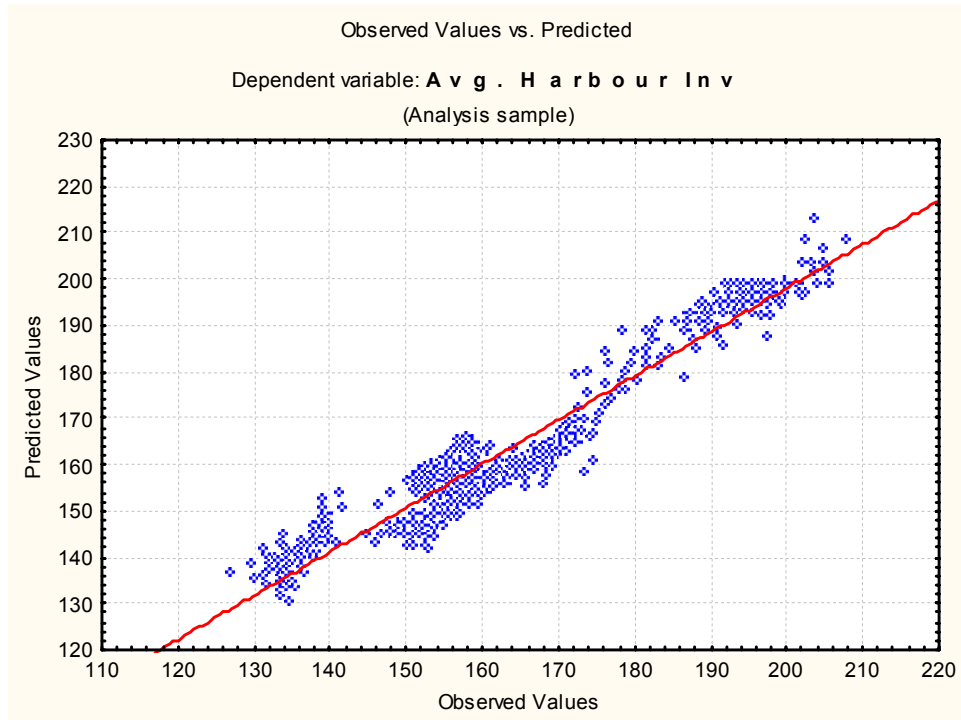
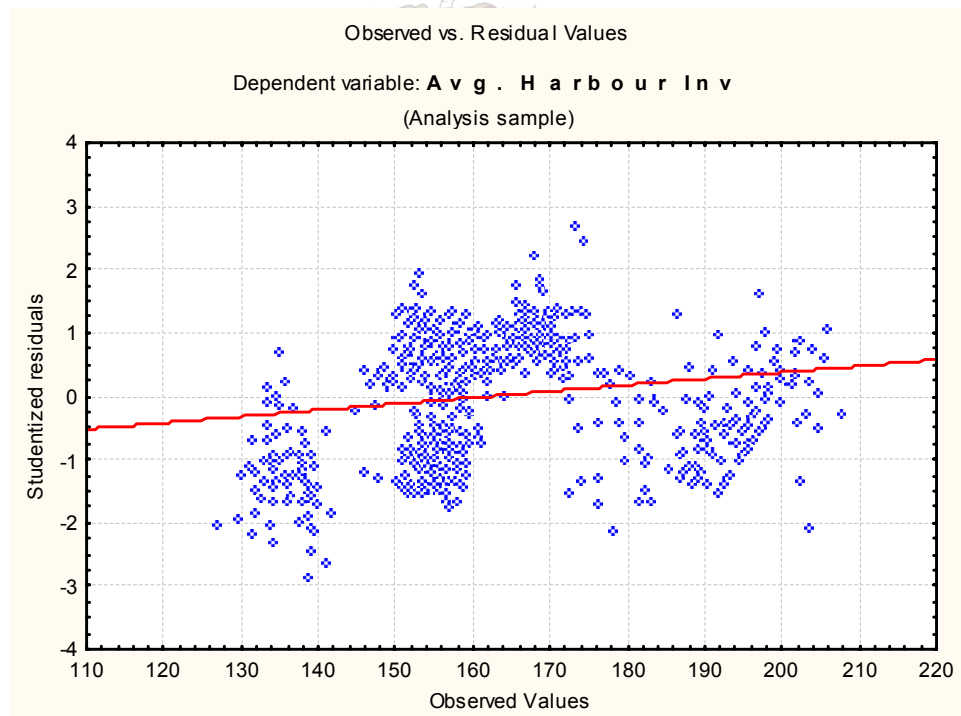


Figure 156: Observed vs. Predicted Avg. Harbour Inventory. Medium Runners.



**Figure 157: Observed vs. Residual Avg. Harbour Inventory. Medium Runners.
End of Avg. Harbour Inventory**

Start of Avg. No. of Orders

Variable	Avg. Number of Orders Parameter	Avg. Number of Orders Std Err	Avg. Number of Orders t	Avg. Number of Orders p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Number of Orders Beta	Avg. Number of Orders Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	171.0361	3.74353	45.6884	0.000000	163.683	178.3893	1.029700	0.022537	0.98543	1.073969
ST + TC	-69.2769	18.04951	-3.8382	0.000138	-104.730	-33.8236	-0.613914	0.159950	-0.92809	-0.299736
ADD*(ST+MC)										
ADD*(ST+TC)	-1.1907	0.21979	-5.4173	0.000000	-1.622	-0.7590	-0.885882	0.163529	-1.20709	-0.564675
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.8883	0.04219	-21.0544	0.000000	-0.971	-0.8054	-0.520927	0.024742	-0.56953	-0.472328
PS*ST										
PS*MC	-0.1978	0.01258	-15.7211	0.000000	-0.222	-0.1731	-0.259325	0.016495	-0.29173	-0.226924
PS*TC	0.2146	0.01315	16.3207	0.000000	0.189	0.2404	0.459455	0.028152	0.40416	0.514752
Days to Assembly	9.2289	1.71468	5.3823	0.000000	5.861	12.5970	0.592975	0.110171	0.37657	0.809377
Avg. Daily Demand	5.4594	0.73281	7.4499	0.000000	4.020	6.8988	0.872631	0.117133	0.64256	1.102706
Flip Mean	209.3053	50.92573	4.1100	0.000046	109.276	309.3348	0.065718	0.015990	0.03431	0.097126

Table 70: Equation Variables & Betas. Avg. Number of Orders. Medium Runners.

Summary of best subsets; variable(s): Avg. No of O				
Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.959589	9		
2	0.959313	9		0.729958
3	0.959052	9		
4	0.958951	8		0.726371
5	0.958921	9		0.637100
6	0.958916	9		
7	0.958896	9		0.726568
8	0.958879	9		0.726371
9	0.958878	9		0.726371
10	0.958878	9		0.726371

Figure 158: Summary of Best Subsets Adjusted R² Value. Medium Runners.

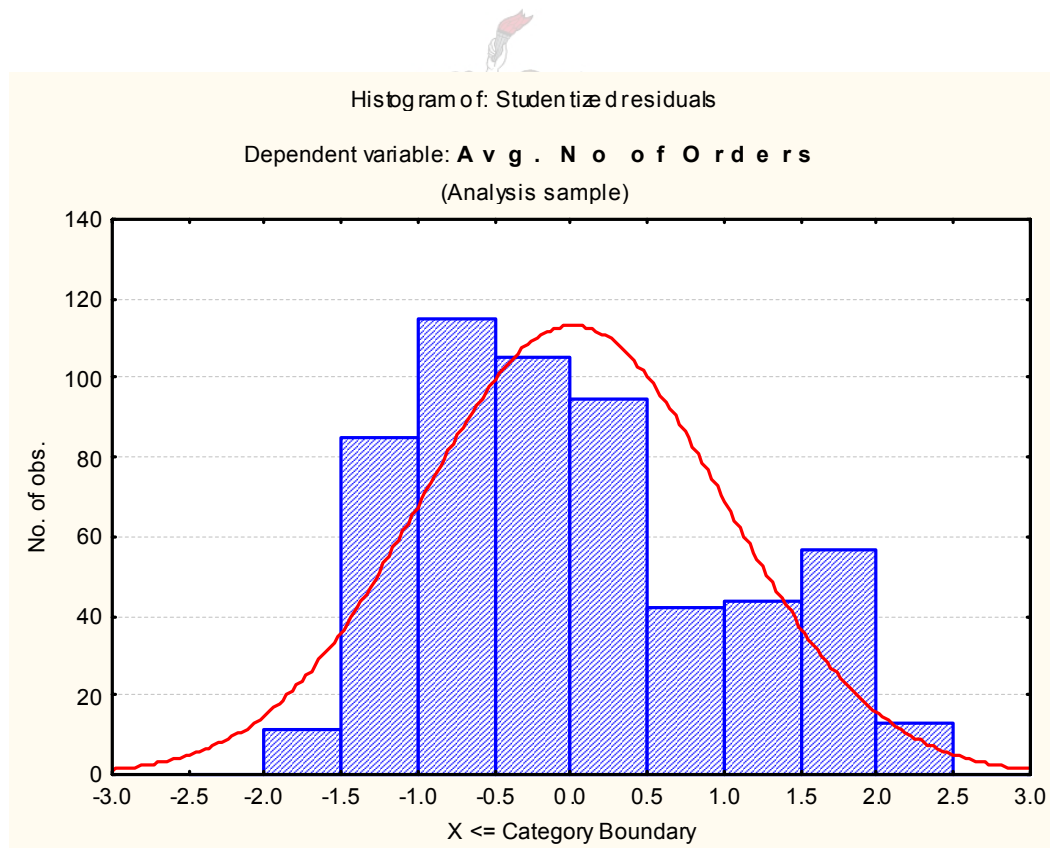


Figure 159: Studentized Residuals. Avg. Number of Orders. Medium Runners.

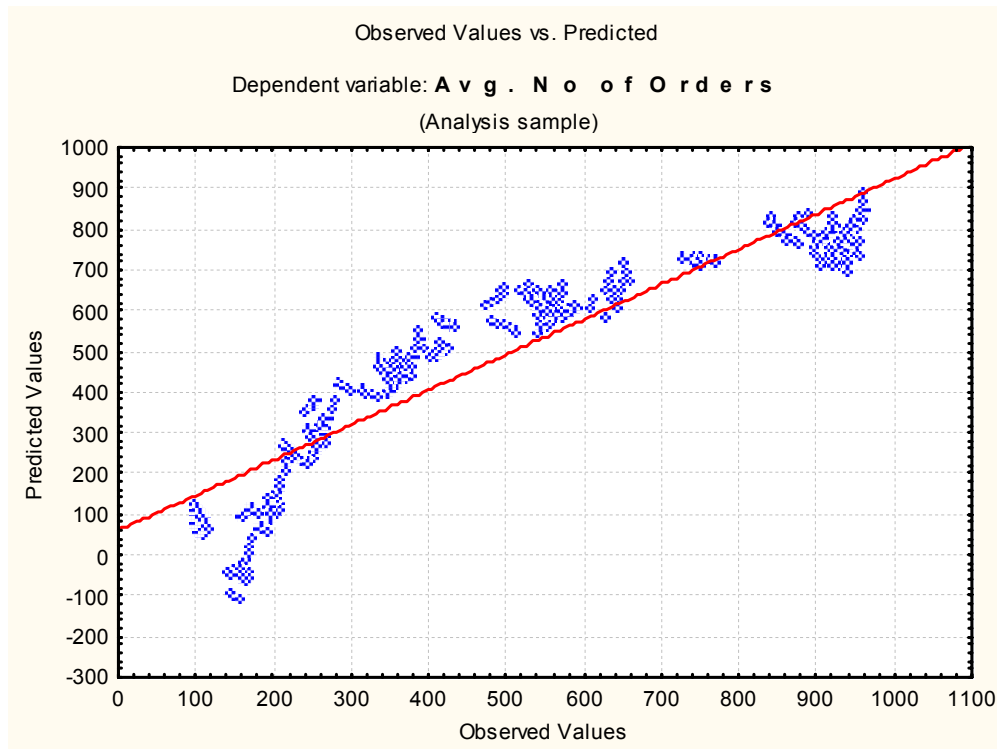
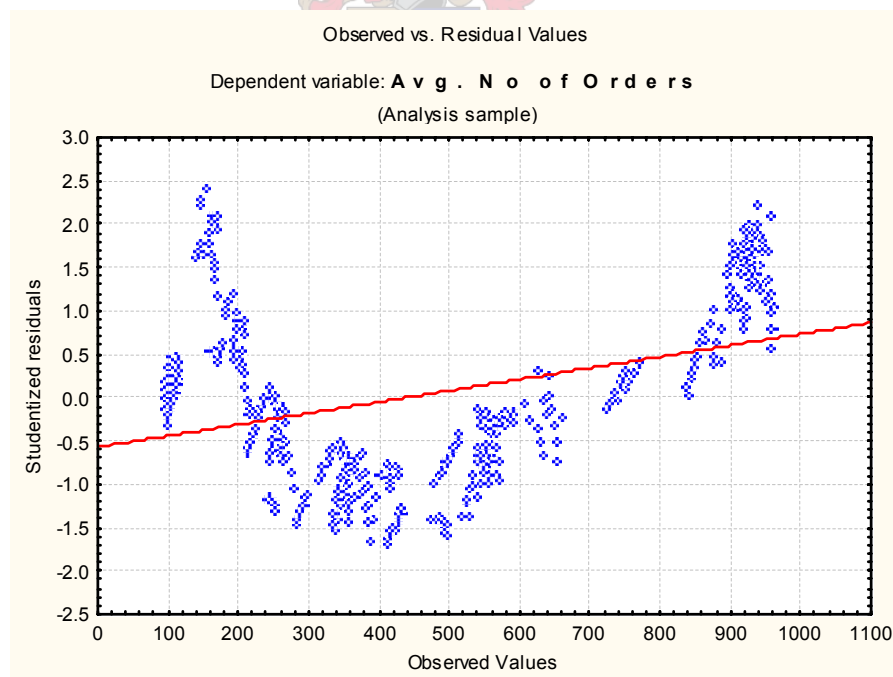


Figure 160: Observed vs. Predicted Avg. Number of Orders. Medium Runners.



**Figure 161: Observed vs. Residual Avg. Number of Orders. Medium Runners.
End of Avg. Number of Orders**

Start of Avg. Order Size

Variable	Avg. Order Size Parameter	Avg. Order Size Std Err	Avg. Order Size t	Avg. Order Size p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Order Size Beta	Avg. Order Size Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC										
ADD*(ST+MC)	-1.0140	0.007226	-140.325	0.00	-1.0282	-0.9998	-0.701623	0.005000	-0.711444	-0.691802
ADD*(ST+TC)	1.0226	0.007226	141.514	0.00	1.0084	1.0368	1.041519	0.007360	1.027062	1.055975
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.9115	0.006462	141.059	0.00	0.8988	0.9242	0.731691	0.005187	0.721502	0.741880
PS*ST										
PS*MC	0.1041	0.002038	51.090	0.00	0.1001	0.1081	0.186912	0.003659	0.179726	0.194098
PS*TC	-0.1051	0.002038	-51.584	0.00	-0.1091	-0.1011	-0.308183	0.005974	-0.319917	-0.296448
Days to Assembly										
Avg. Daily Demand	0.3095	0.027586	11.221	0.00	0.2554	0.3637	0.067731	0.006036	0.055875	0.079587
Flip Mean	143.3872	7.815076	18.348	0.00	128.0367	158.7376	0.061630	0.003359	0.055032	0.068228

Table 71: Equation Variables & Betas. Avg. Order Size Inventory. Medium Runners.

Summary of best subsets; variable(s): Avg. Order S Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.998116	7			
2	0.998110	7			
3	0.998052	7			
4	0.998035	7			
5	0.997720	7			
6	0.997698	7	0.016829		
7	0.997697	7			
8	0.997697	6			
9	0.997694	7			
10	0.997694	7		0.003127	

Figure 162: Summary of Best Subsets Adjusted R² Value. Medium Runners.

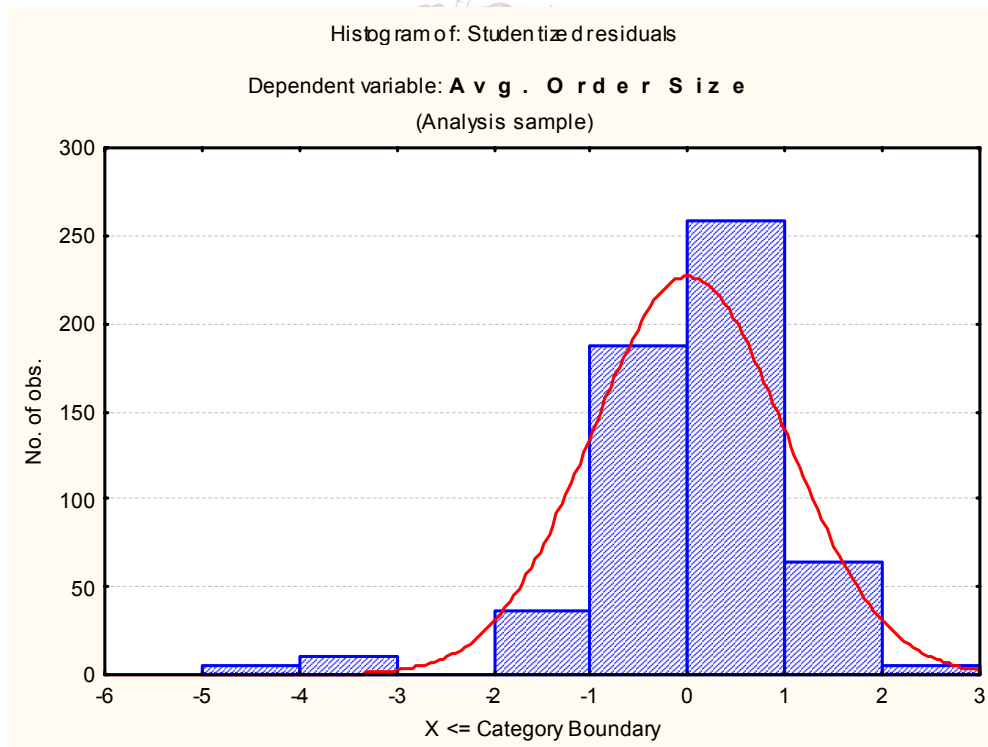


Figure 163: Studentized Residuals. Avg. Order Size. Medium Runners.

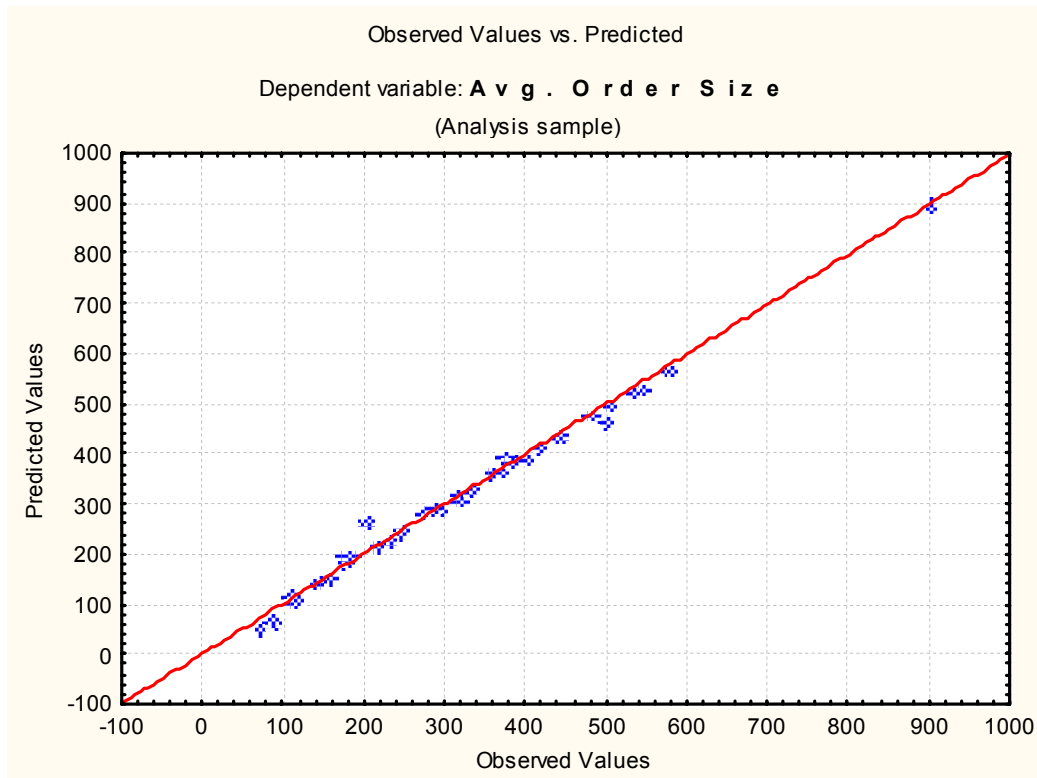
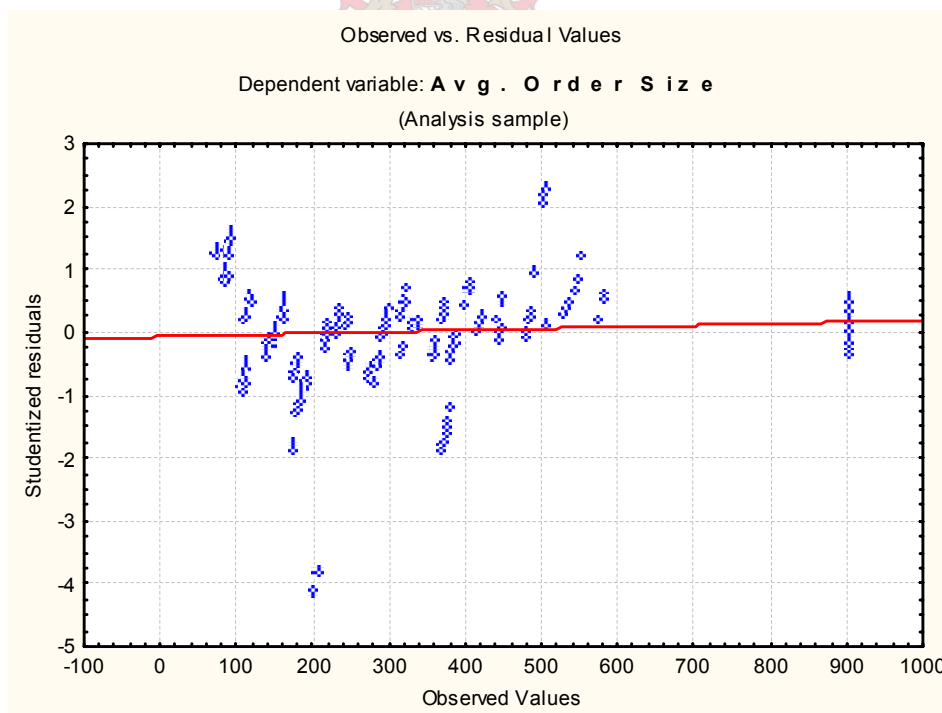


Figure 164: Observed vs. Predicted Avg. Order Size. Medium Runners.



**Figure 165: Observed vs. Residual Avg. Order Size. Medium Runners.
End of Avg. Order Size**

Start of Avg. Customer Service Level

Variable	Avg. Customer Service Level Parameter	Avg. Customer Service Level Std Err	Avg. Customer Service Level t	Avg. Customer Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Service Level Beta	Avg. Customer Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	0.123042	0.005011	24.5522	0.000000	0.113198	0.132885	0.574933	0.023417	0.528937	0.620928
ADD*(ST+MC)										
ADD*(ST+TC)	-0.001479	0.000062	-23.9019	0.000000	-0.001601	-0.001358	-0.580377	0.024282	-0.628071	-0.532683
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.000115	0.000013	-8.5601	0.000000	-0.000141	-0.000088	-0.035501	0.004147	-0.043647	-0.027355
PS*ST	0.000022	0.000005	4.3330	0.000017	0.000012	0.000032	0.008878	0.002049	0.004853	0.012902
PS*MC										
PS*TC	0.000021	0.000003	6.6521	0.000000	0.000015	0.000027	0.023645	0.003554	0.016663	0.030627
Days to Assembly	0.008722	0.000476	18.3050	0.000000	0.007786	0.009658	0.295484	0.016142	0.263777	0.327191
Avg. Daily Demand	0.008382	0.000206	40.7506	0.000000	0.007978	0.008786	0.706438	0.017336	0.672387	0.740489
Flip Mean	0.056943	0.014005	4.0659	0.000055	0.029434	0.084453	0.009427	0.002319	0.004873	0.013982

Table 72: Equation Variables & Betas. Avg. Customer Service Level. Medium Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.999152	8			
2	0.999131	8			
3	0.999131	8			
4	0.999131	8			
5	0.999130	8			
6	0.999130	8			
7	0.999130	8	0.159246		
8	0.999130	8	0.004898		
9	0.999130	8			
10	0.999129	8			

Figure 166: Summary of Best Subsets Adjusted R² Value. Medium Runners.

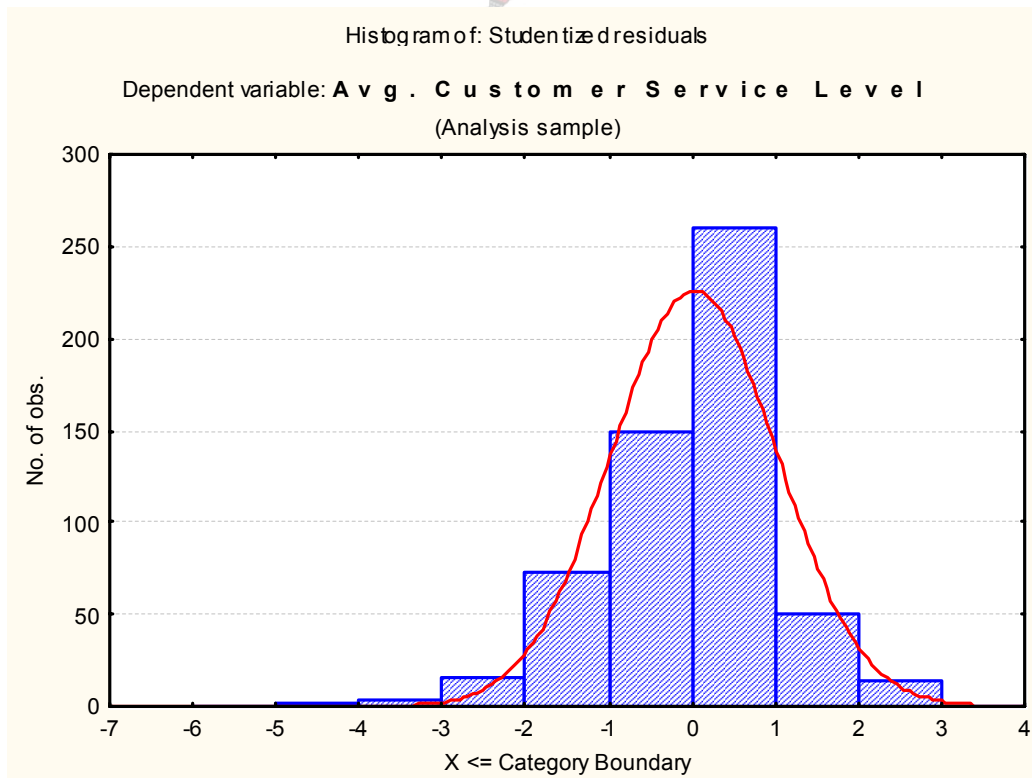


Figure 167: Studentized Residuals. Avg. Customer Service Level. Medium Runners.

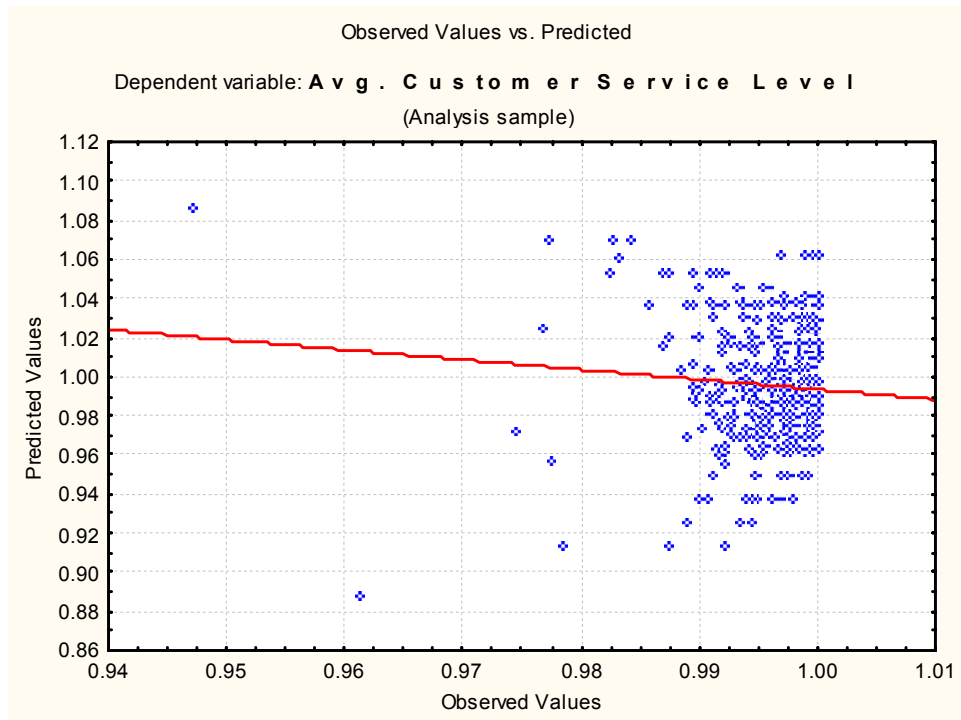


Figure 168: Observed vs. Predicted Avg. Customer Service Level. Medium Runners.

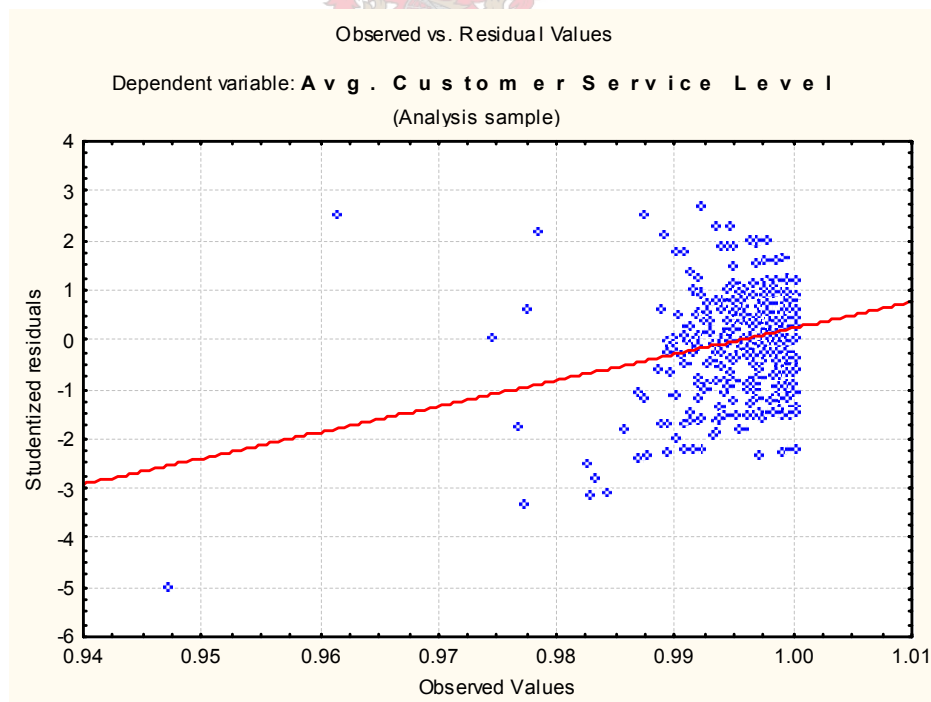


Figure 169: Observed vs. Residual Avg. Customer Service Level. Medium Runners.

Variable	Avg. Customer Service Level Parameter	Avg. Customer Service Level Std Err	Avg. Customer Service Level t	Avg. Customer Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Service Level Beta	Avg. Customer Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Intercept	1.015438	0.002992	339.4266	0.000000	1.009562	1.021315				
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	0.000646	0.000090	7.1985	0.000000	0.000469	0.000822	0.24047	0.033406	0.17486	0.306087
ADD*(ST+MC)	0.000017	0.000001	15.8311	0.000000	0.000015	0.000019	0.53661	0.033896	0.47003	0.603184
ADD*(ST+TC)										
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.000003	0.000001	4.7957	0.000002	0.000002	0.000004	0.16524	0.034456	0.09756	0.232919
PS*ST										
PS*MC										
PS*TC										
Days to Assembly	-0.000250	0.000060	-4.1430	0.000040	-0.000369	-0.000132	-0.12935	0.031222	-0.19068	-0.068025
Avg. Daily Demand	-0.000192	0.000017	-11.2674	0.000000	-0.000225	-0.000158	-0.38618	0.034274	-0.45350	-0.318860
Flip Mean	-0.014126	0.001418	-9.9616	0.000000	-0.016911	-0.011341	-0.31468	0.031589	-0.37673	-0.252631

Table 73: Equation Variables & Betas. Avg. Customer Service Level Intercept. Medium Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.604697	6			
2	0.603987	6			
3	0.602508	6			
4	0.601316	6			
5	0.601075	6			
6	0.599679	6			
7	0.597779	6			
8	0.594434	6			
9	0.594210	6			
10	0.594035	6			

Figure 170: Summary of Best Subsets Adjusted R² Value. Intercept. Medium Runners.

End of Customer Service Level



Start of Total Shortages

Variable	Avg. Total Shortages Parameter	Avg. Total Shortages Std Err	Avg. Total Shortages t	Avg. Total Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Total Shortages Beta	Avg. Total Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC	-2280.400	89.3877	-25.5113	0.00	-2455.98	-2104.823	-2.17973	0.085442	-2.34756	-2.01190
ADD*(ST+MC)	-14.940	0.4020	-37.1671	0.00	-15.73	-14.150	-0.81453	0.021915	-0.85758	-0.77148
ADD*(ST+TC)	33.977	1.0633	31.9539	0.00	31.89	36.065	2.72671	0.085332	2.55909	2.89432
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	11.206	0.3962	28.2805	0.00	10.43	11.984	0.70882	0.025064	0.65959	0.75805
PS*ST	-2.343	0.1604	-14.6075	0.00	-2.66	-2.028	-0.19133	0.013098	-0.21706	-0.16560
PS*MC	-1.381	0.1126	-12.2664	0.00	-1.60	-1.160	-0.19533	0.015924	-0.22660	-0.16405
PS*TC	-1.016	0.1113	-9.1221	0.00	-1.23	-0.797	-0.23457	0.025714	-0.28508	-0.18406
Days to Assembly	72.675	3.6386	19.9735	0.00	65.53	79.822	0.50367	0.025217	0.45413	0.55320
Avg. Daily Demand										
Flip Mean	11764.787	430.2090	27.3467	0.00	10919.76	12609.814	0.39844	0.014570	0.36982	0.42706

Table 74: Equation Variables & Betas. Avg. Total Shortages. Medium Runners.

Summary of best subsets; variable(s): Avg. Total St					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.964485	9			
2	0.964091	9			
3	0.962490	9			
4	0.962096	9			
5	0.961236	9		-0.555717	
6	0.960390	9			
7	0.960375	9	-0.304197		
8	0.960375	9			
9	0.960375	9	-0.644600		
10	0.960339	8			

Figure 171: Summary of Best Subsets Adjusted R² Value. Medium Runners.

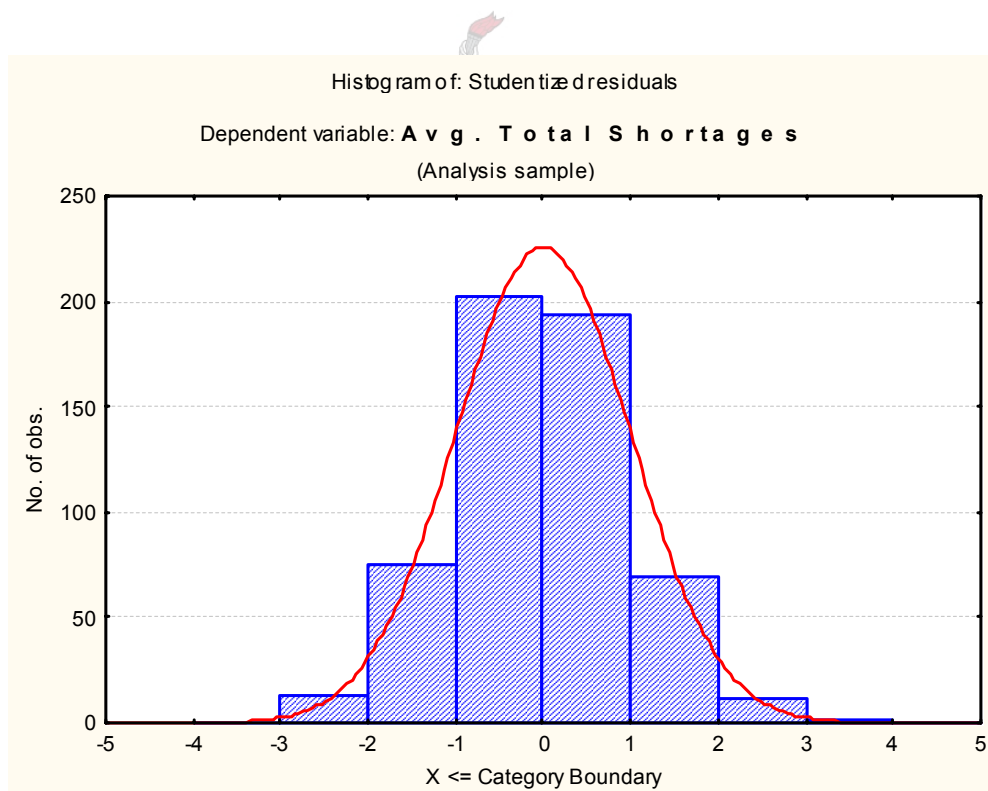


Figure 172: Studentized Residuals. Avg. Total Shortages. Medium Runners.

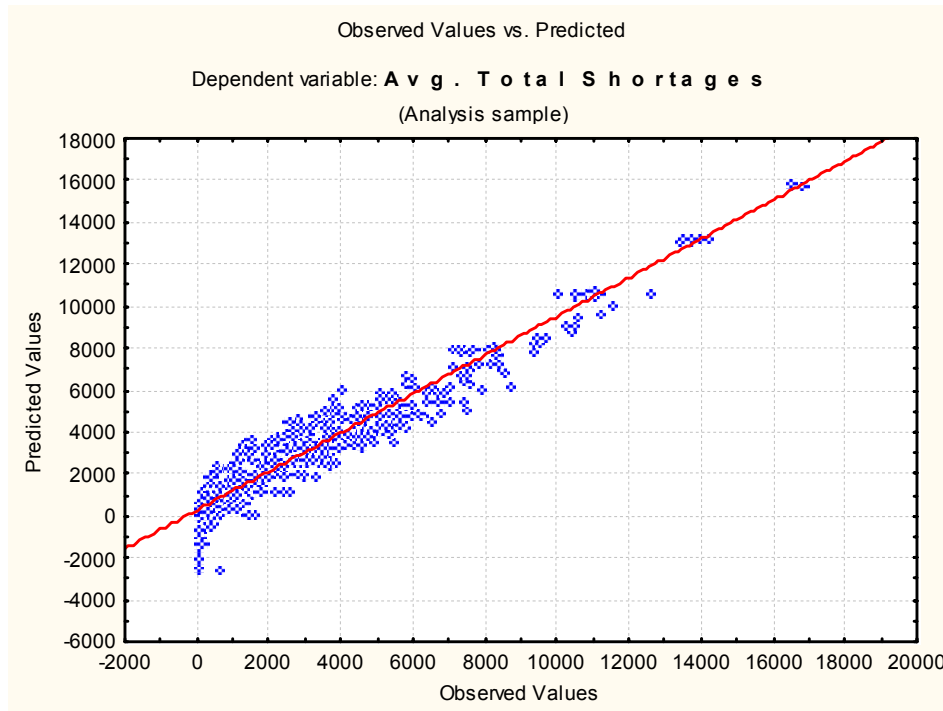
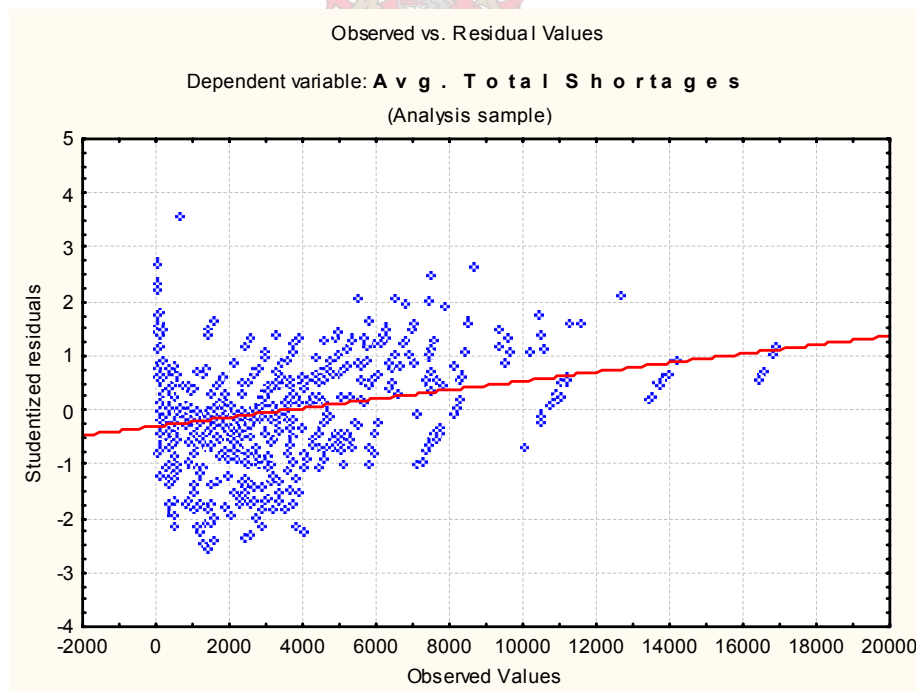


Figure 173: Observed vs. Predicted Avg. Total Shortages. Medium Runners.



**Figure 174: Observed vs. Residual Avg. Total Shortages. Medium Runners.
End of Avg. Total Shortages**

Start of Avg. Customer Shortages

Variable	Avg. Customer Shortages Parameter	Avg. Customer Shortages Std Err	Avg. Customer Shortages t	Avg. Customer Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Shortages Beta	Avg. Customer Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-2.84059	0.272421	-10.42718	0.000000	-3.37568	-2.30549	-0.579498	0.055576	-0.68866	-0.470336
ST + TC										
ADD*(ST+MC)										
ADD*(ST+TC)	-0.03786	0.003663	-10.33557	0.000000	-0.04505	-0.03066	-0.954502	0.092351	-1.13590	-0.773105
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.02686	0.003921	-6.85106	0.000000	-0.03456	-0.01916	-0.533765	0.077910	-0.68680	-0.380733
PS*ST	0.00445	0.001539	2.89512	0.003938	0.00143	0.00748	0.114278	0.039473	0.03675	0.191811
PS*MC										
PS*TC	0.00444	0.000918	4.83638	0.000002	0.00264	0.00624	0.322147	0.066609	0.19131	0.452982
Days to Assembly										
Avg. Daily Demand	0.34136	0.015047	22.68686	0.000000	0.31181	0.37091	1.848931	0.081498	1.68885	2.009009
Flip Mean	24.95087	4.134940	6.03415	0.000000	16.82898	33.07276	0.265468	0.043994	0.17905	0.351882

Table 75: Equation Variables & Betas. Avg. Customer Shortages. Medium Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.677266	7			
2	0.677121	7			
3	0.676507	7			
4	0.674840	7			
5	0.674402	7		0.355516	
6	0.674402	7	-0.205257		
7	0.674402	7	-0.439896	-0.406406	
8	0.673818	7			
9	0.673673	7			
10	0.673673	7			

Figure 175: Summary of Best Subsets Adjusted R² Value. Medium Runners.

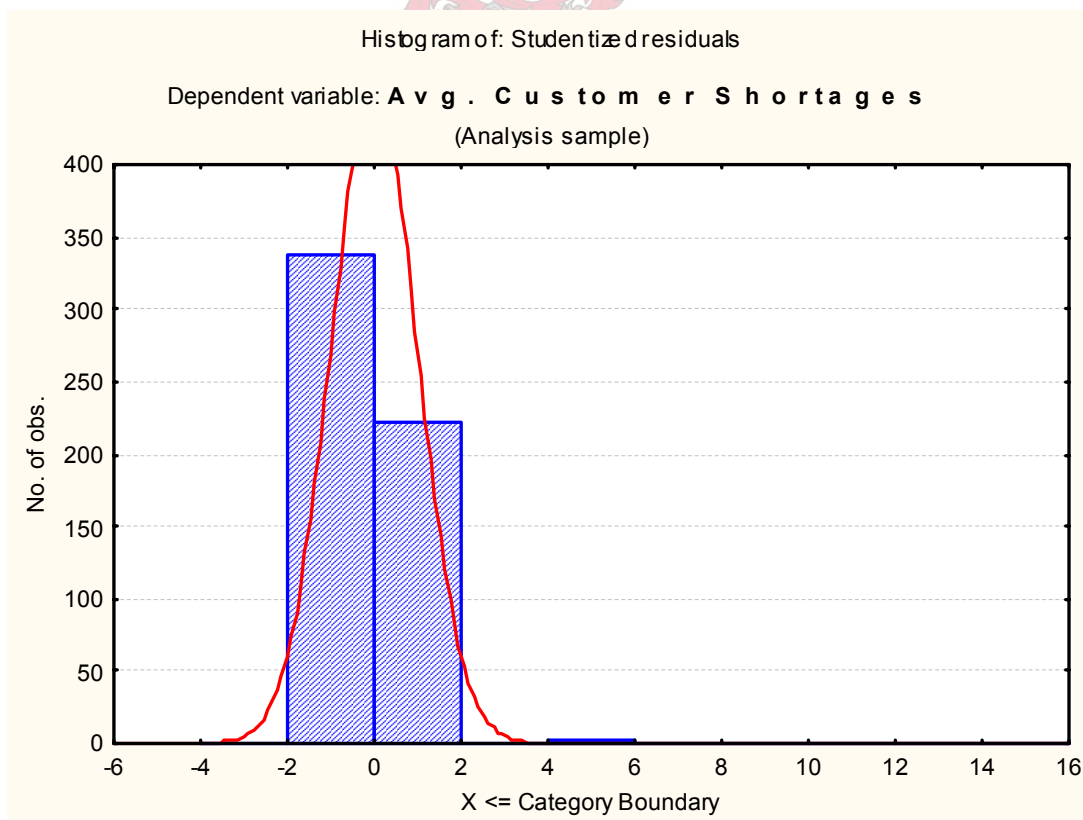


Figure 176: Studentized Residuals. Avg. Customer Shortages. Medium Runners.

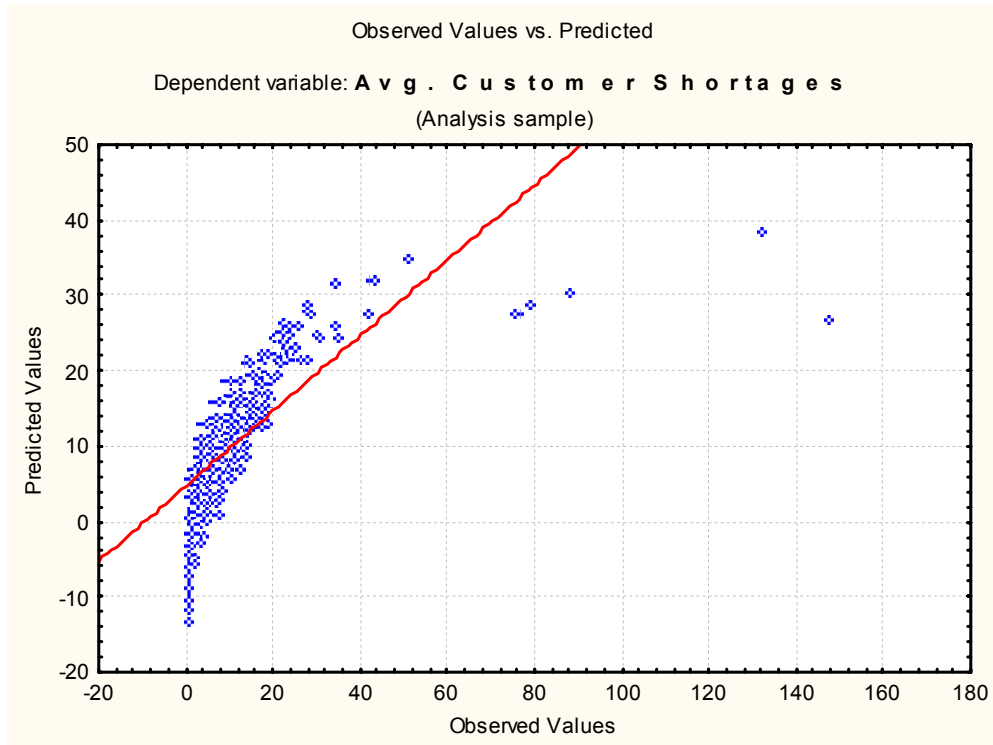
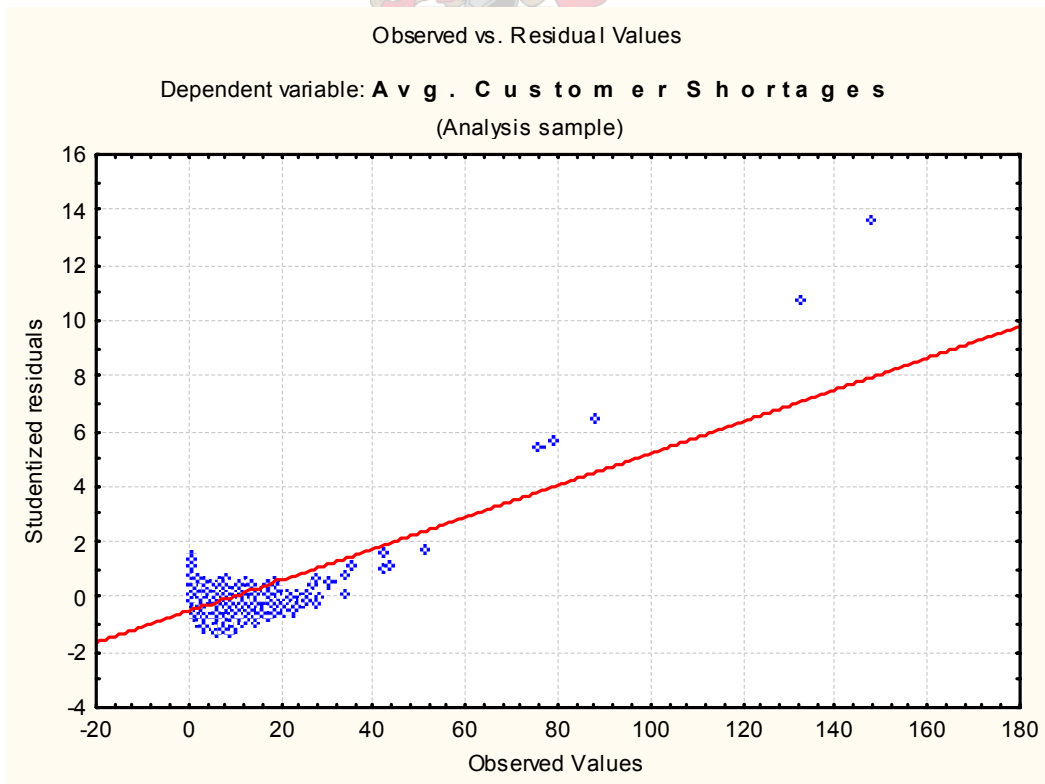
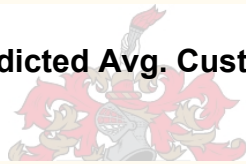


Figure 177: Observed vs. Predicted Avg. Customer Shortages. Medium Runners.



**Figure 178: Observed vs. Residual Avg. Customer Shortages. Medium Runners.
End of Avg. Customer Shortages**

High Runners.



			Quality Indicators					
			Adjusted R ² Value	Number of Variables	Intercept	Studentized Residual Distribution (Normal & Zero Mean. Yes /No?)	Observed vs. Predicted	
							Linear Relationship?	
							0	Rough
1	Fair							
2	Good							
Performance Measure	Inventory	Avg. Plant Inv.	0.99	10	0	Yes	1	
		Avg. Pipeline Inv.	0.99	10	0	Yes	1	
		Avg. Harbour Inv.	0.99	10	0	Yes	1	
	Orders	Avg. Number of Orders	0.97	7	0	Yes	1	
		Avg. Order Size	0.99	8	0	Yes	2	
	Service Level	Avg. Customer Service Level	0.99	8	0	Yes	0	
			0.57	8	0.93	NA	NA	
	Shortages	Avg. Total Shortages	0.88	10	0	Yes	1	
		Avg. Customer Shortages	0.53	7	0	Yes	0	

Table 76: High Runner Regression Analysis Summary.

The “NA” fields indicate that the Residual Distribution and Observed vs. Predicted plots were not required. These plots were shown to be the same as the corresponding zero-intercept-equation plots.

Start of Avg. Plant Inventory

Variable	Avg. Plant Inv. Parameter	Avg. Plant Inv. Std Err	Avg. Plant Inv. t	Avg. Plant Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Plant Inv. Beta	Avg. Plant Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-196.886	74.25271	-2.6516	0.008269	-342.776	-50.996	-0.88276	0.332921	-1.53688	-0.228648
ST + TC	-160.042	52.87973	-3.0265	0.002603	-263.939	-56.145	-1.05623	0.348991	-1.74192	-0.370542
ADD*(ST+MC)	1.901	0.64726	2.9369	0.003469	0.629	3.173	0.98169	0.334257	0.32495	1.638435
ADD*(ST+TC)	1.935	0.45902	4.2164	0.000030	1.034	2.837	1.47120	0.348923	0.78564	2.156754
ADD * ST	-0.068	0.01660	-4.1090	0.000047	-0.101	-0.036	-0.04424	0.010766	-0.06539	-0.023084
ADD*MC	-0.031	0.00892	-3.5050	0.000498	-0.049	-0.014	-0.02616	0.007464	-0.04083	-0.011497
ADD * TC	-0.019	0.00557	-3.4396	0.000632	-0.030	-0.008	-0.02779	0.008079	-0.04366	-0.011916
Pallet Size	0.509	0.01012	50.2736	0.000000	0.489	0.528	0.32981	0.006560	0.31692	0.342701
PS*ST										
PS*MC	0.150	0.01345	11.1244	0.000000	0.123	0.176	0.23627	0.021239	0.19454	0.277997
PS*TC										
Days to Assembly										
Avg. Daily Demand										
Flip Mean	265.512	49.21186	5.3953	0.000000	168.822	362.202	0.10194	0.018895	0.06482	0.139066

Table 77: Equation Variables & Betas. Avg. Plant Inventory. High Runners.

Summary of best subsets; variable(s): Avg. Plant In				
Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.990281	10		
2	0.990221	10		
3	0.990166	10		
4	0.990163	9		
5	0.990161	10		
6	0.990161	10		
7	0.990161	10		
8	0.990161	10		
9	0.990161	10		
10	0.990157	10		

Figure 179: Summary of Best Subsets Adjusted R² Value. High Runners.

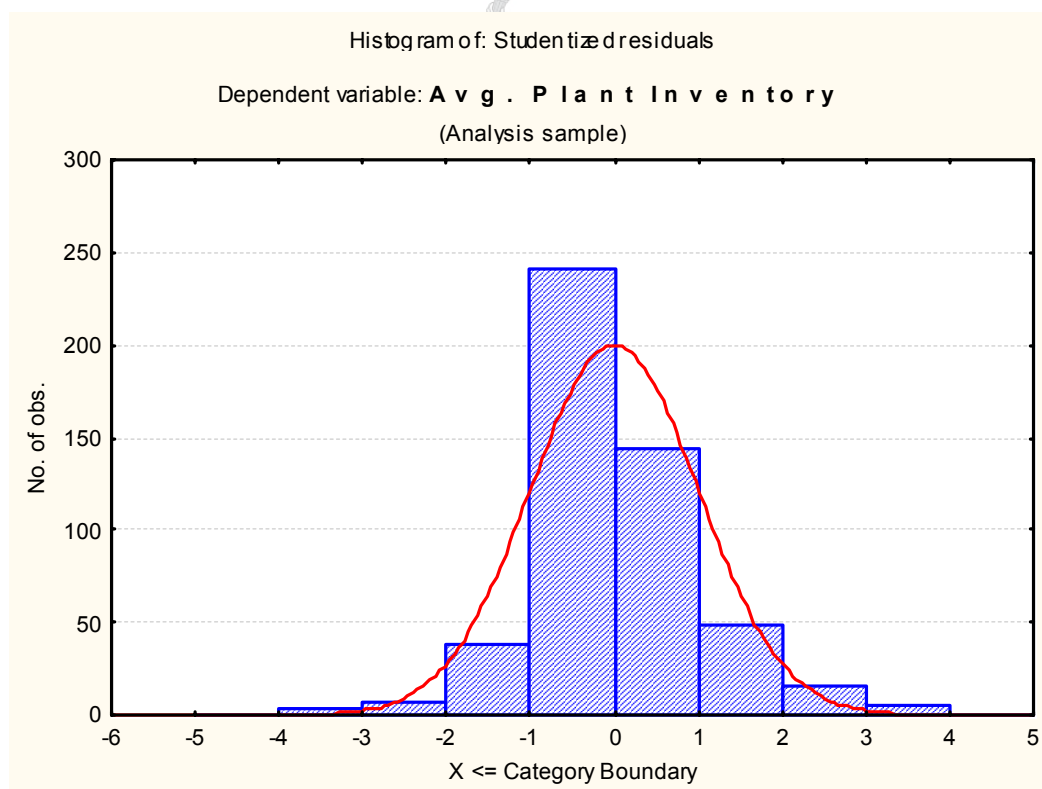


Figure 180: Studentized Residuals. Avg. Plant Inventory. High Runners.

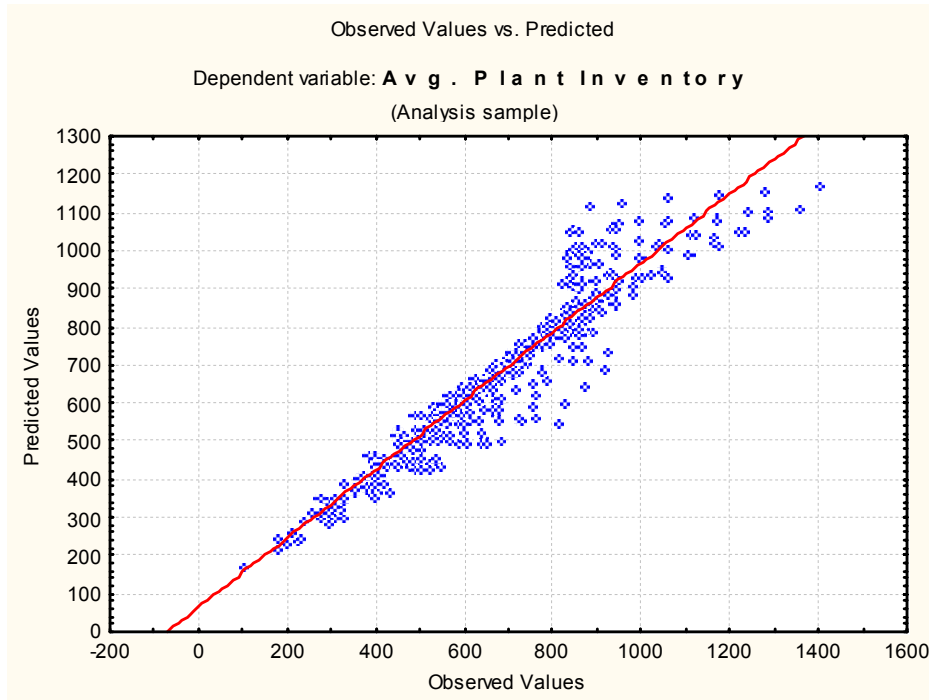
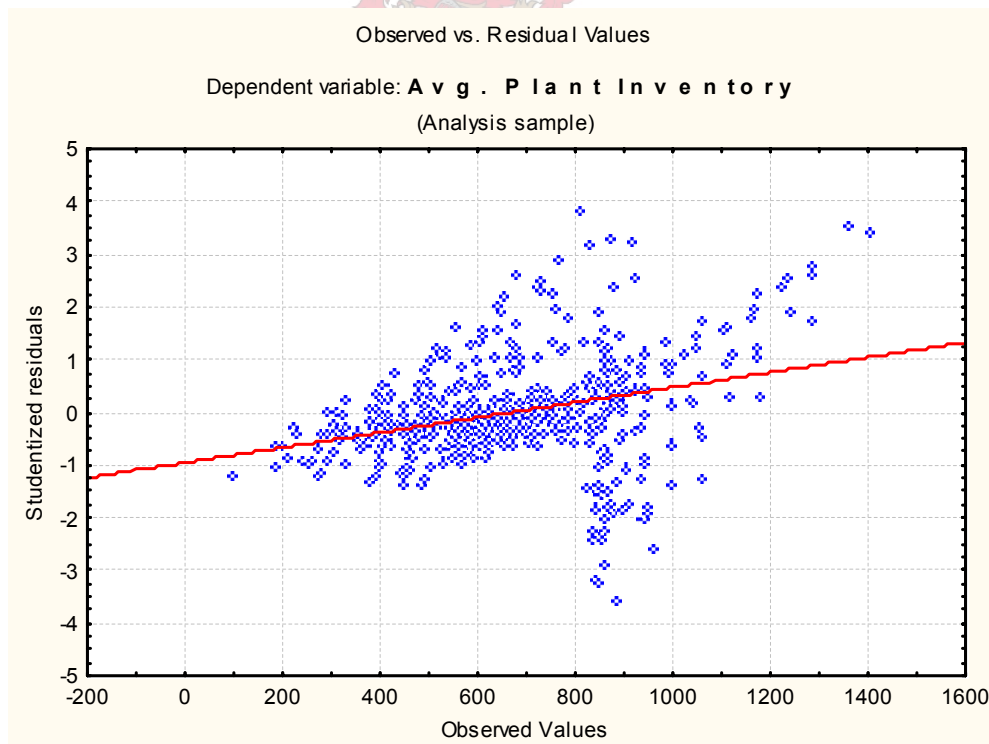


Figure 181: Observed vs. Predicted Avg. Plant Inventory. High Runners.



**Figure 182: Observed vs. Residual Avg. Plant Inventory. High Runners.
End of Avg. Plant Inventory**

Start of Avg. Pipeline Inventory

Variable	Avg. Pipeline Inv. Parameter	Avg. Pipeline Inv. Std Err	Avg. Pipeline Inv. t	Avg. Pipeline Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Pipeline Inv. Beta	Avg. Pipeline Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	601.426	49.35358	12.18606	0.000000	504.457	698.395	0.484178	0.039732	0.406113	0.562242
ST + TC	-631.667	35.57401	-17.75641	0.000000	-701.562	-561.772	-0.748526	0.042155	-0.831351	-0.665700
ADD*(ST+MC)	-4.848	0.43025	-11.26799	0.000000	-5.693	-4.003	-0.449529	0.039894	-0.527913	-0.371146
ADD*(ST+TC)	5.367	0.30909	17.36553	0.000000	4.760	5.975	0.732586	0.042186	0.649699	0.815472
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.076	0.01136	-6.70130	0.000000	-0.098	-0.054	-0.008861	0.001322	-0.011459	-0.006263
PS*ST	0.021	0.00596	3.51640	0.000478	0.009	0.033	0.003151	0.000896	0.001390	0.004912
PS*MC	0.015	0.00373	3.94141	0.000093	0.007	0.022	0.003825	0.000970	0.001918	0.005731
PS*TC										
Days to Assembly	105.658	1.08471	97.40678	0.000000	103.527	107.790	0.896266	0.009201	0.878187	0.914344
Avg. Daily Demand	4.098	0.31193	13.13857	0.000000	3.485	4.711	0.120172	0.009146	0.102201	0.138143
Flip Mean	-425.855	30.63218	-13.90220	0.000000	-486.040	-365.669	-0.029358	0.002112	-0.033507	-0.025209

Table 78: Equation Variables & Betas. Avg. Pipeline Inventory. High Runners.

Summary of best subsets; variable(s): Avg. Pipe Inv Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.999862	10		
2	0.999862	10		0.366538
3	0.999861	10		
4	0.999860	10		
5	0.999860	10		0.354685
6	0.999859	10		0.320270
7	0.999859	10		0.320270
8	0.999859	10		0.320270
9	0.999859	10		0.320270
10	0.999859	10		0.320270

Figure 183: Summary of Best Subsets Adjusted R² Value. High Runners.

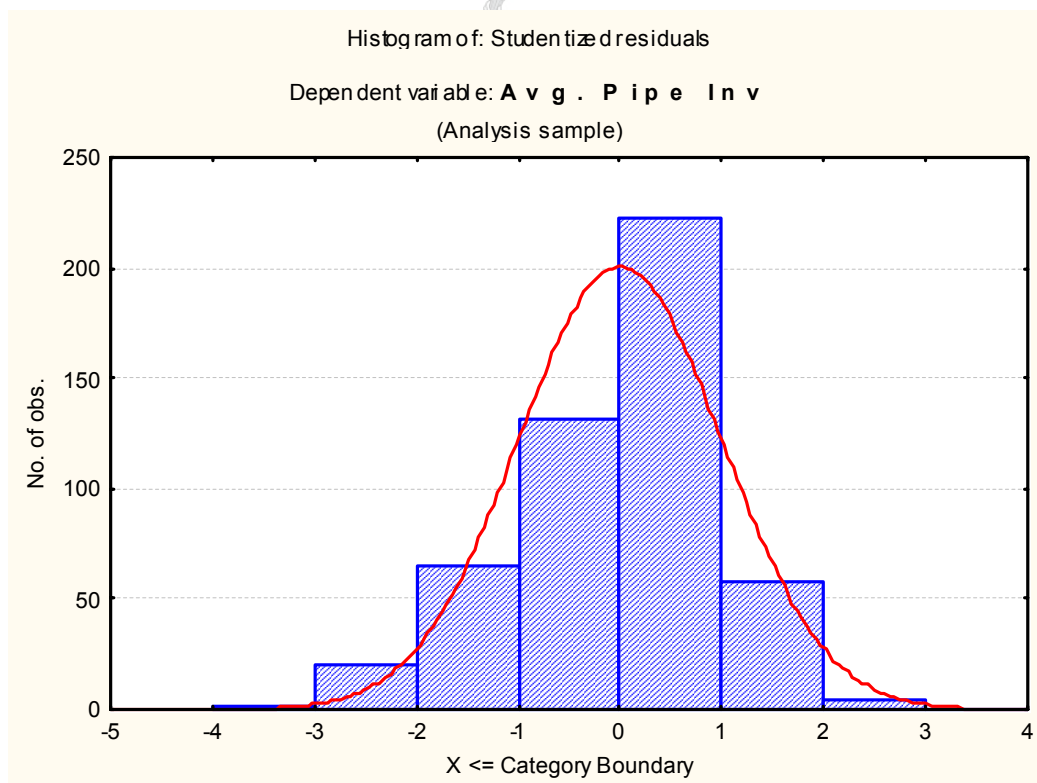


Figure 184: Studentized Residuals. Avg. Pipeline Inventory. High Runners.

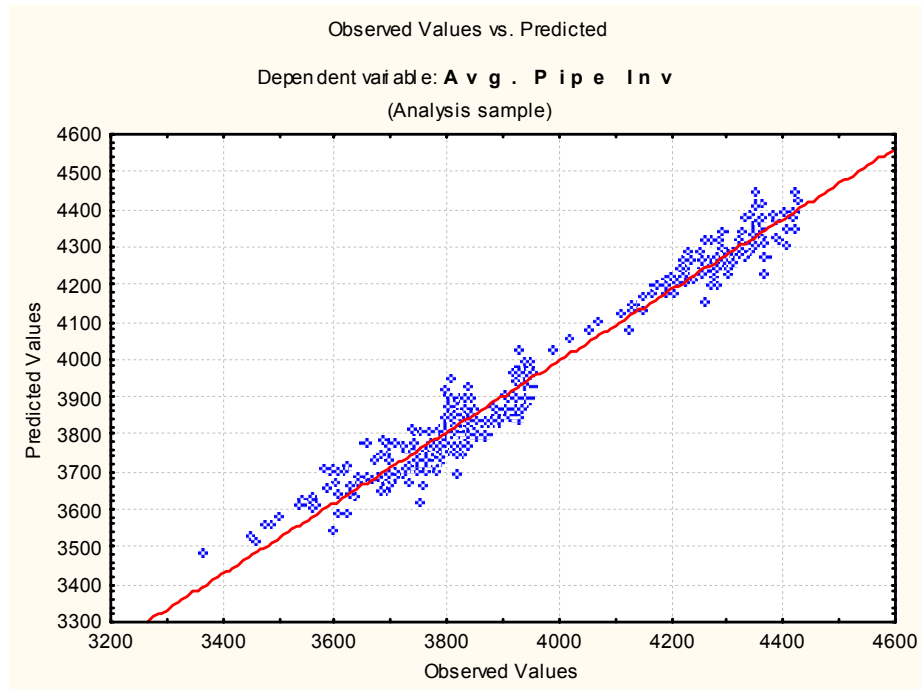
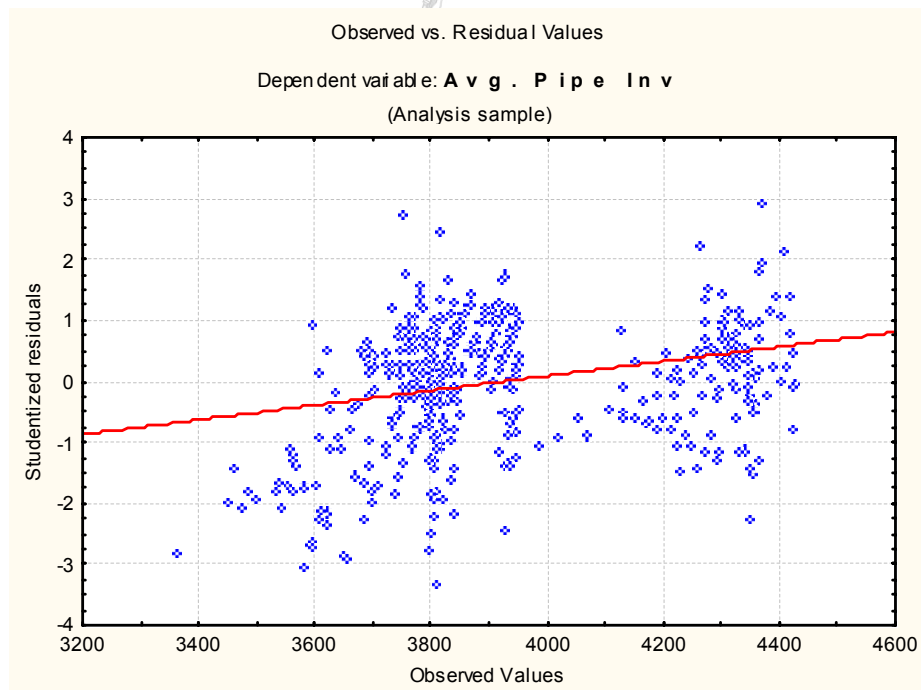


Figure 185: Observed vs. Predicted Avg. Pipeline Inventory. High Runners.



**Figure 186: Observed vs. Residual Avg. Pipeline Inventory. High Runners.
End of Avg. Pipeline Inventory**

Start of Avg. Harbour Inventory

Variable	Avg. Harbour Inv. Parameter	Avg. Harbour Inv. Std Err	Avg. Harbour Inv. t	Avg. Harbour Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Harbour Inv. Beta	Avg. Harbour Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	28.90848	3.733590	7.7428	0.000000	21.57280	36.24415	0.401388	0.051840	0.299534	0.503243
ST + TC	6.82815	2.540513	2.6877	0.007437	1.83660	11.81969	0.139553	0.051923	0.037536	0.241569
ADD*(ST+MC)	-0.22868	0.032622	-7.0102	0.000000	-0.29278	-0.16459	-0.365717	0.052169	-0.468219	-0.263216
ADD*(ST+TC)	-0.06899	0.022216	-3.1053	0.002010	-0.11264	-0.02534	-0.162401	0.052298	-0.265155	-0.059648
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.01016	0.001163	-8.7402	0.000000	-0.01245	-0.00788	-0.020407	0.002335	-0.024995	-0.015820
PS*ST	0.00297	0.000447	6.6444	0.000000	0.00209	0.00385	0.007704	0.001159	0.005426	0.009982
PS*MC	0.00126	0.000335	3.7592	0.000191	0.00060	0.00191	0.005647	0.001502	0.002695	0.008598
PS*TC	0.00091	0.000329	2.7663	0.005881	0.00026	0.00156	0.006676	0.002413	0.001934	0.011418
Days to Assembly										
Avg. Daily Demand	2.03779	0.006743	302.2134	0.000000	2.02454	2.05104	1.030551	0.003410	1.023851	1.037251
Flip Mean	-32.35573	2.195808	-14.7352	0.000000	-36.67000	-28.04145	-0.038471	0.002611	-0.043601	-0.033341

Table 79: Equation Variables & Betas. Avg. Harbour Inventory. High Runners.

Summary of best subsets; variable(s): Avg. Harbour Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.999770	10			
2	0.999768	10			
3	0.999768	10	-0.048053		
4	0.999768	10	0.127734	0.304471	
5	0.999768	10			
6	0.999768	10	0.169500	0.304471	
7	0.999768	10		0.304471	
8	0.999768	10		0.083230	
9	0.999768	10		0.010889	
10	0.999768	10	-0.006287		

Figure 187: Summary of Best Subsets Adjusted R² Value. High Runners.

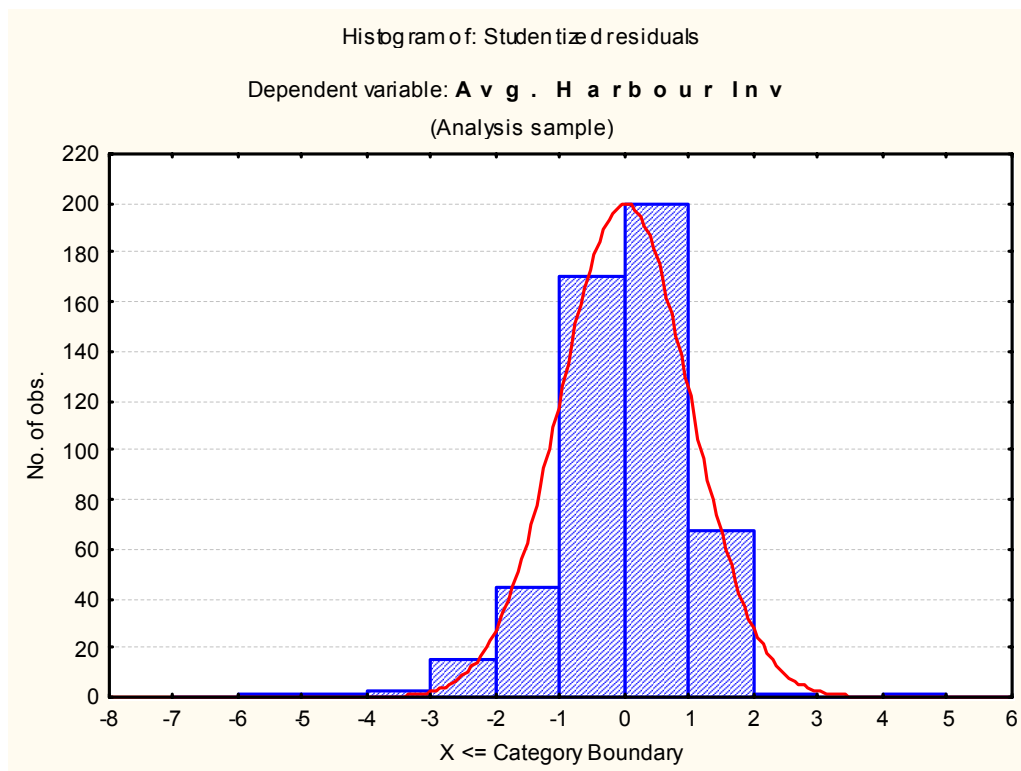


Figure 188: Studentized Residuals. Avg. Harbour Inventory. High Runners.

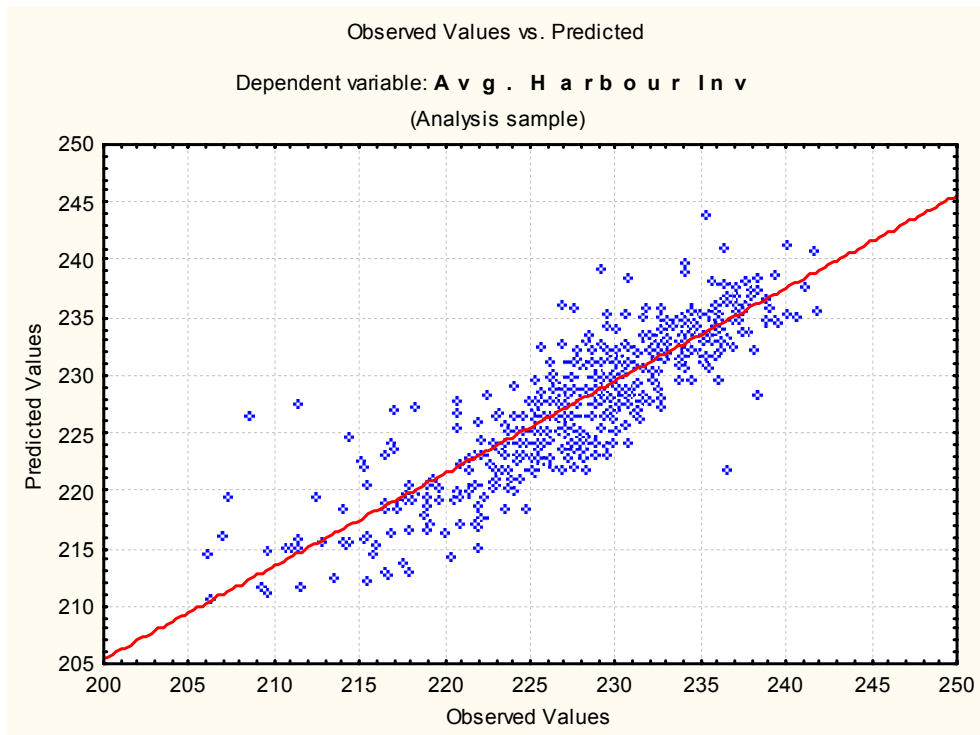
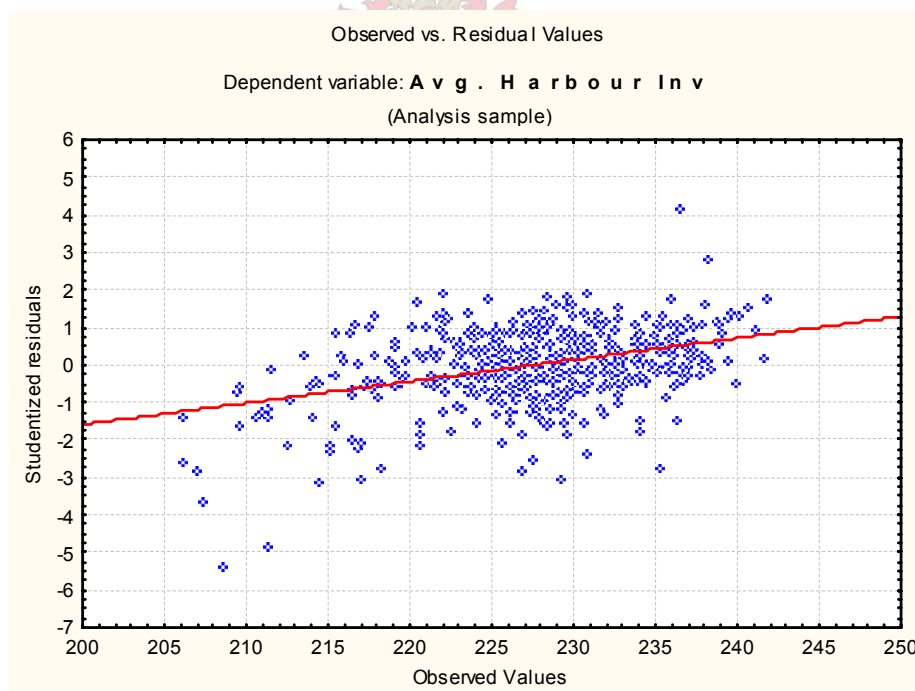


Figure 189: Observed vs. Predicted Avg. Harbour Inventory. High Runners.



**Figure 190: Observed vs. Residual Avg. Harbour Inventory. High Runners.
End of Avg. Harbour Inventory**

Start of Avg. Number of Orders

Variable	Avg. Number of Orders Parameter	Avg. Number of Orders Std Err	Avg. Number of Orders t	Avg. Number of Orders p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Number of Orders Beta	Avg. Number of Orders Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC										
ST + TC										
ADD*(ST+MC)										
ADD*(ST+TC)										
ADD * ST										
ADD*MC	1.5524	0.033775	45.9631	0.00	1.4860	1.6188	0.80819	0.017584	0.77365	0.84274
ADD * TC	-1.5205	0.033775	-45.0180	0.00	-1.5868	-1.4541	-1.29264	0.028714	-1.34906	-1.23622
Pallet Size	-0.7798	0.027340	-28.5212	0.00	-0.8335	-0.7261	-0.72092	0.025277	-0.77058	-0.67126
PS*ST										
PS*MC	-0.2042	0.008506	-24.0066	0.00	-0.2209	-0.1875	-0.42212	0.017584	-0.45667	-0.38757
PS*TC	0.2020	0.008506	23.7430	0.00	0.1852	0.2187	0.68175	0.028714	0.62534	0.73817
Days to Assembly	8.3295	1.583354	5.2607	0.00	5.2186	11.4404	0.56103	0.106646	0.35150	0.77057
Avg. Daily Demand	4.6650	0.480384	9.7111	0.00	3.7212	5.6089	1.08614	0.111845	0.86639	1.30589
Flip Mean										

Table 80: Equation Variables & Betas. Avg. Number of Orders. High Runners.

Summary of best subsets; variable(s): Avg. No of O				
Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.967372	7		
2	0.967345	7		
3	0.966989	7		0.801880
4	0.966961	7		
5	0.966935	7		
6	0.966494	7		
7	0.966410	7		0.799548
8	0.965909	7		
9	0.965886	7		
10	0.965810	7		

Figure 191: Summary of Best Subsets Adjusted R² Value. High Runners.

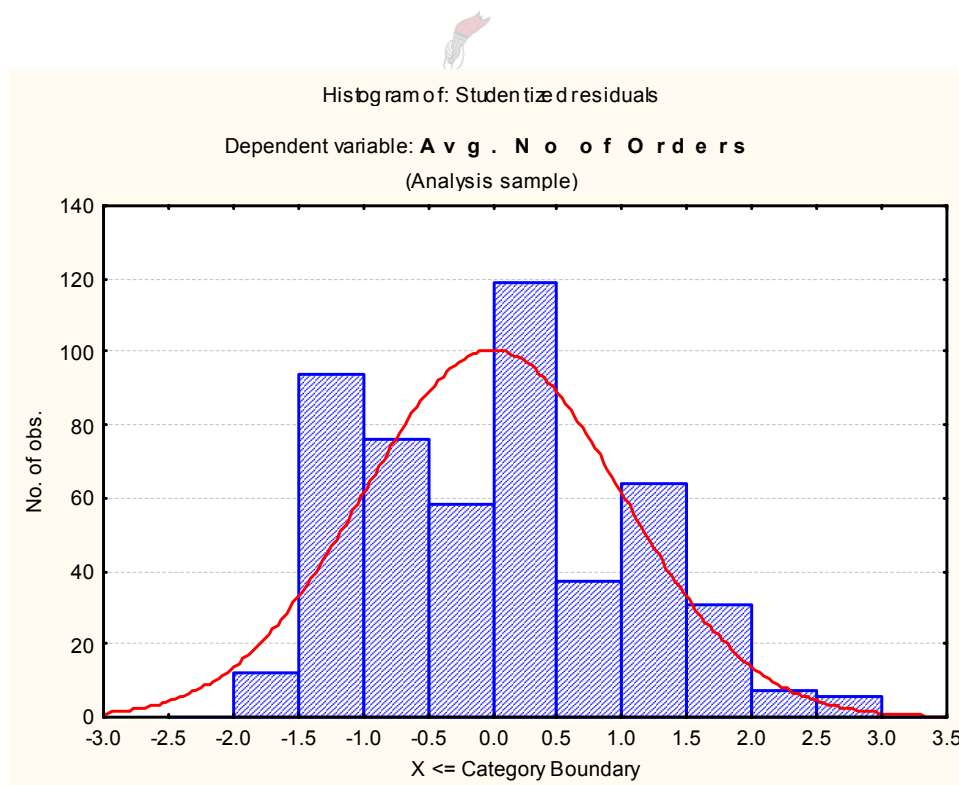


Figure 192: Studentized Residuals. Avg. Number of Orders. High Runners.

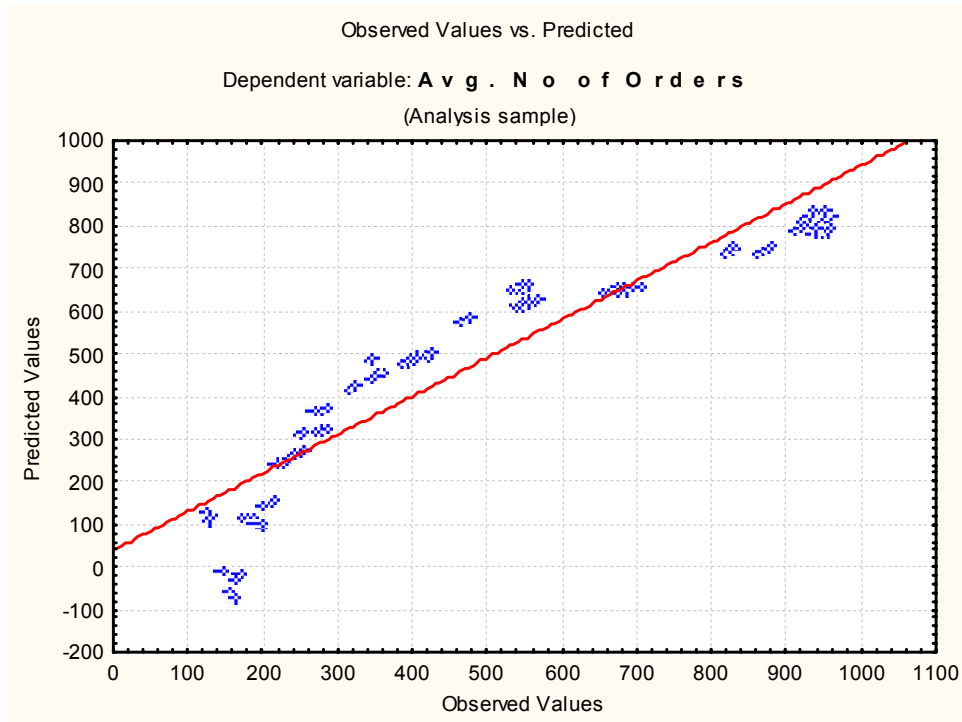
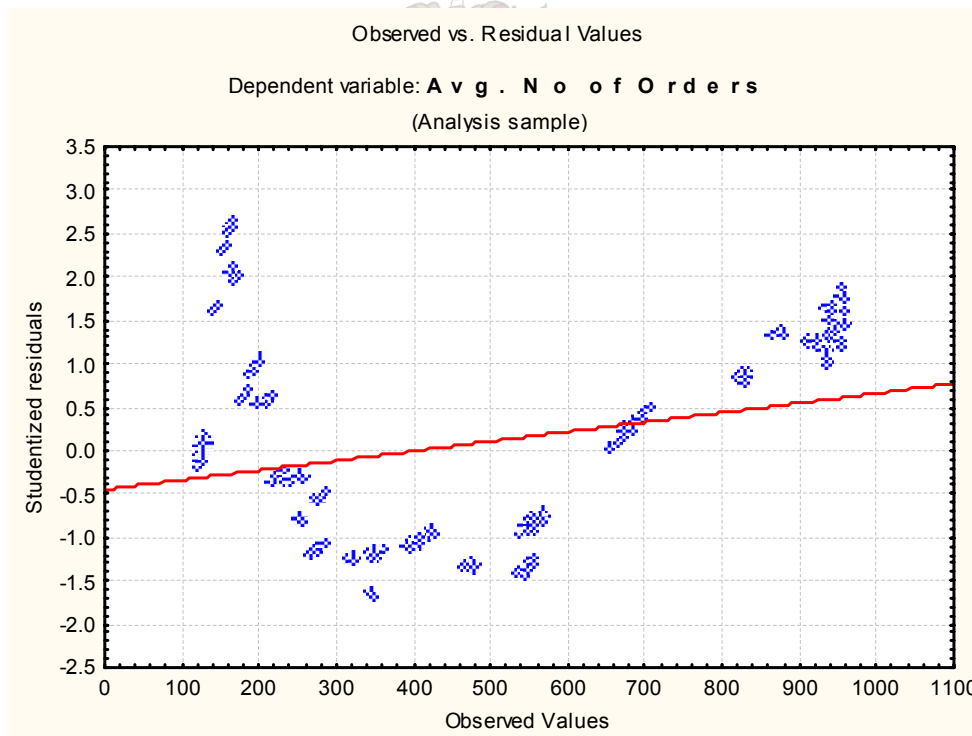


Figure 193: Observed vs. Predicted Avg. Number of Orders. High Runners.



**Figure 194: Observed vs. Residual Avg. Number of Orders. High Runners.
End of Avg. Number of Orders**

Start of Avg. Order Size

Variable	Avg. Order Size Parameter	Avg. Order Size Std Err	Avg. Order Size t	Avg. Order Size p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Order Size Beta	Avg. Order Size Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-73.3032	9.54612	-7.6788	0.000000	-92.0591	-54.5474	-0.426759	0.055576	-0.535952	-0.317566
ST + TC										
ADD*(ST+MC)	-0.3928	0.08360	-4.6982	0.000003	-0.5571	-0.2285	-0.263384	0.056060	-0.373529	-0.153240
ADD*(ST+TC)	1.0375	0.00708	146.5097	0.000000	1.0236	1.0514	1.024033	0.006990	1.010301	1.037766
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.9229	0.00558	165.3963	0.000000	0.9120	0.9339	0.777113	0.004698	0.767882	0.786345
PS*ST										
PS*MC	0.1303	0.00187	69.6847	0.000000	0.1267	0.1340	0.245388	0.003521	0.238469	0.252306
PS*TC	-0.1320	0.00185	-71.2213	0.000000	-0.1357	-0.1284	-0.405901	0.005699	-0.417099	-0.394704
Days to Assembly	1.6307	0.13034	12.5108	0.000000	1.3746	1.8867	0.100031	0.007996	0.084321	0.115740
Avg. Daily Demand										
Flip Mean	27.4183	13.04452	2.1019	0.036066	1.7889	53.0476	0.013669	0.006503	0.000892	0.026446

Table 81: Equation Variables & Betas. Avg. Order Size Inventory. High Runners.

Summary of best subsets; variable(s): Avg. Order S					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.998658	8			
2	0.998650	8			
3	0.998650	8			
4	0.998649	7			
5	0.998648	8			
6	0.998647	8			
7	0.998647	8			
8	0.998647	8			
9	0.998647	8			
10	0.998647	8			

Figure 195: Summary of Best Subsets Adjusted R² Value. High Runners.

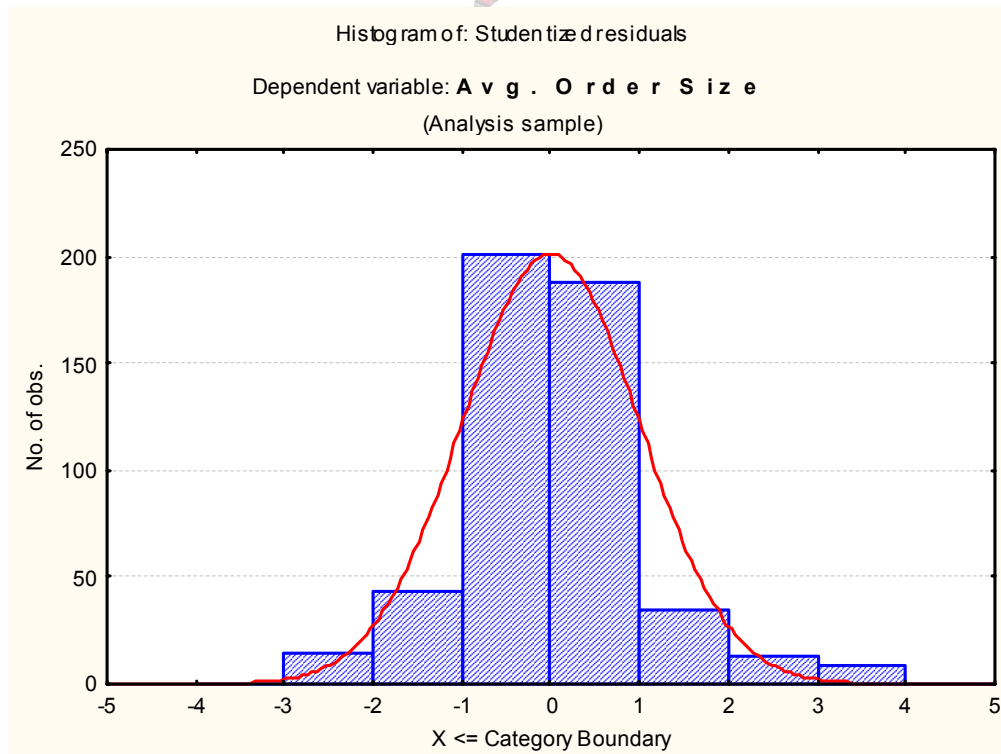


Figure 196: Studentized Residuals. Avg. Order Size. High Runners.

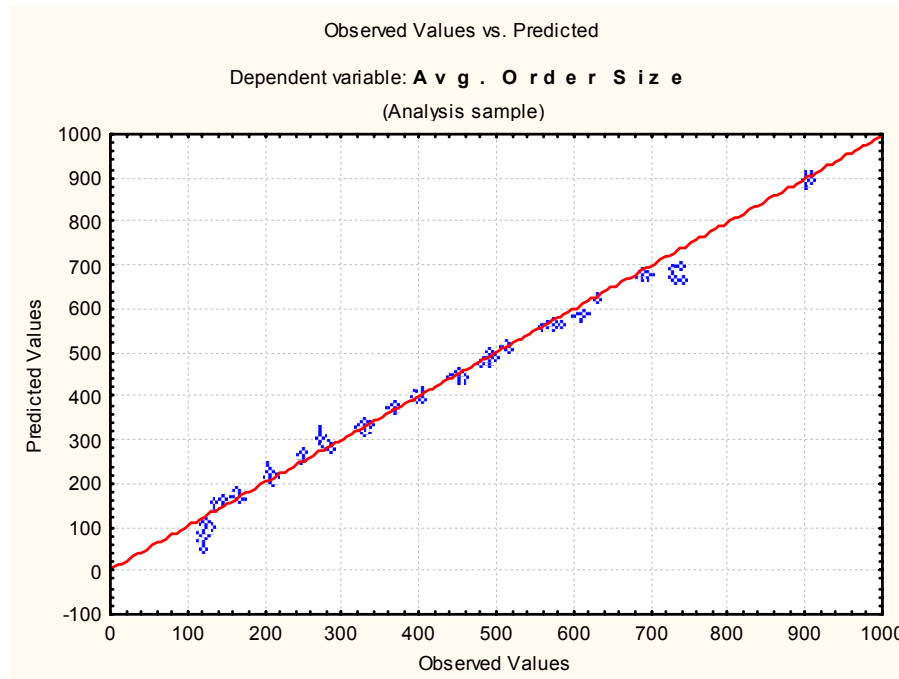
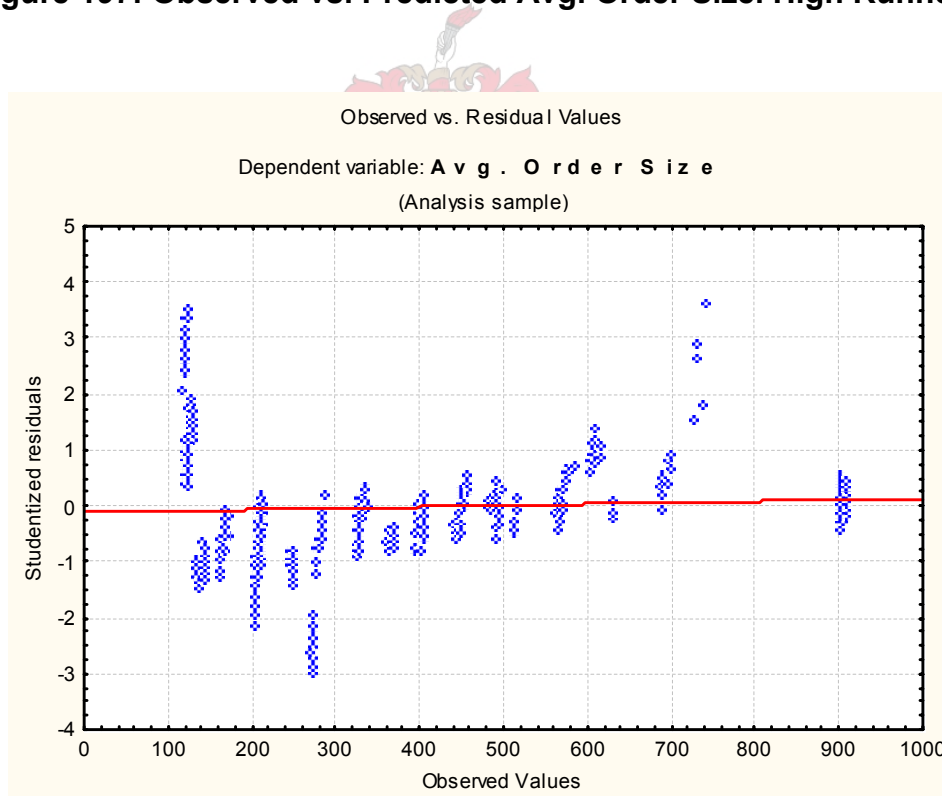


Figure 197: Observed vs. Predicted Avg. Order Size. High Runners.



**Figure 198: Observed vs. Residual Avg. Order Size. High Runners.
End of Avg. Order Size**

Start of Avg. Customer Service Level

Variable	Avg. Plant Inv. Parameter	Avg. Plant Inv. Std Err	Avg. Plant Inv. t	Avg. Plant Inv. p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Plant Inv. Beta	Avg. Plant Inv. Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	0.000943	0.000340	2.7692	0.005829	0.000274	0.001611	0.002987	0.001079	0.000868	0.005106
ST + TC	0.177595	0.004005	44.3419	0.000000	0.169726	0.185464	0.828361	0.018681	0.791657	0.865065
ADD*(ST+MC)										
ADD*(ST+TC)	-0.001546	0.000035	-44.1078	0.000000	-0.001614	-0.001477	-0.830323	0.018825	-0.867309	-0.793336
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.000012	0.000003	-3.5044	0.000499	-0.000019	-0.000005	-0.005577	0.001591	-0.008704	-0.002450
PS*ST	0.000003	0.000001	2.4816	0.013409	0.000001	0.000006	0.001908	0.000769	0.000397	0.003418
PS*MC										
PS*TC	0.000003	0.000001	3.8312	0.000144	0.000001	0.000005	0.005147	0.001343	0.002507	0.007786
Days to Assembly	0.001617	0.000228	7.0999	0.000000	0.001170	0.002065	0.053999	0.007606	0.039056	0.068943
Avg. Daily Demand	0.008188	0.000069	119.1526	0.000000	0.008053	0.008323	0.945038	0.007931	0.929455	0.960621
Flip Mean										

Table 82: Equation Variables & Betas. Avg. Customer Service Level. High Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	
1	0.999898	8			
2	0.999897	8			
3	0.999897	8			
4	0.999897	8			
5	0.999897	8		0.001839	
6	0.999897	8			
7	0.999897	8			
8	0.999897	8			
9	0.999897	8		0.002073	
10	0.999897	8		0.002073	

Figure 199: Summary of Best Subsets Adjusted R² Value. High Runners.

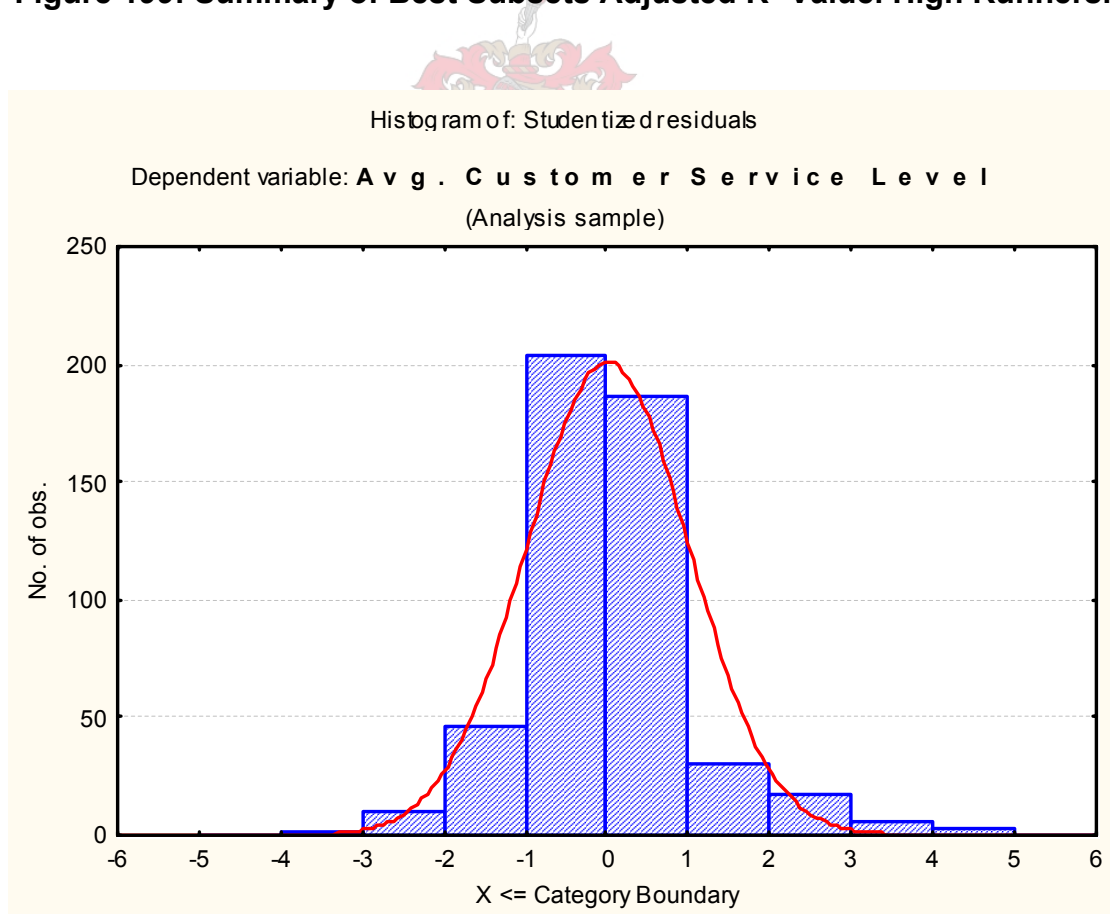


Figure 200: Studentized Residuals. Avg. Customer Service Level. High Runners.

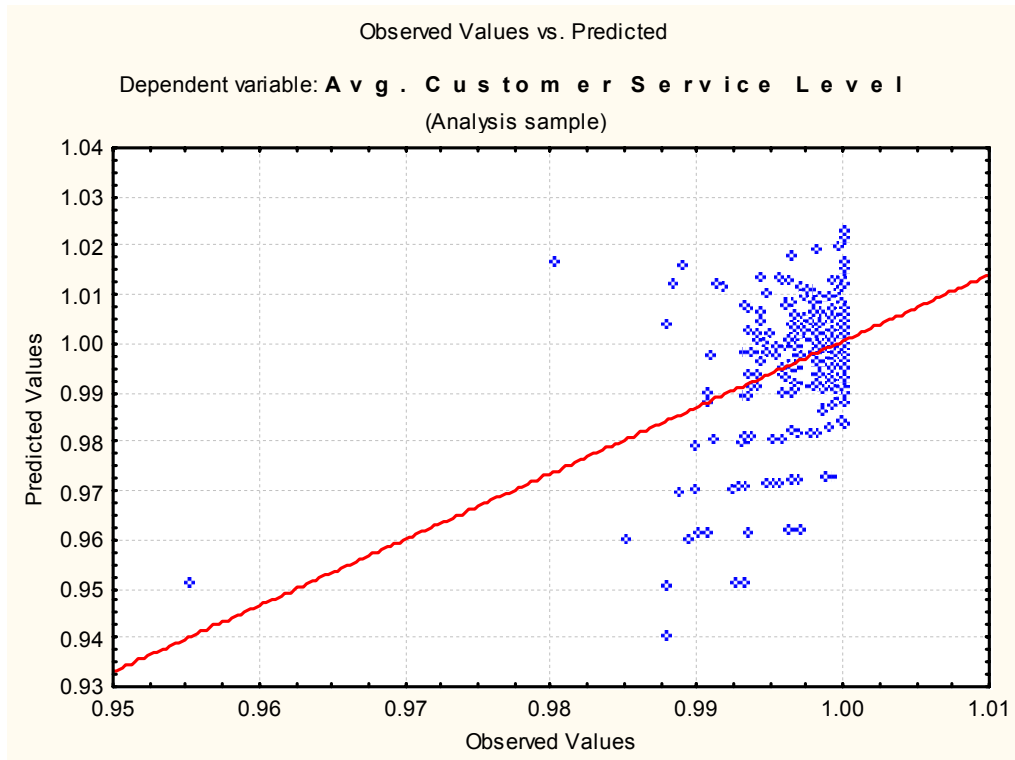


Figure 201: Observed vs. Predicted Avg. Customer Service Level. High Runners.

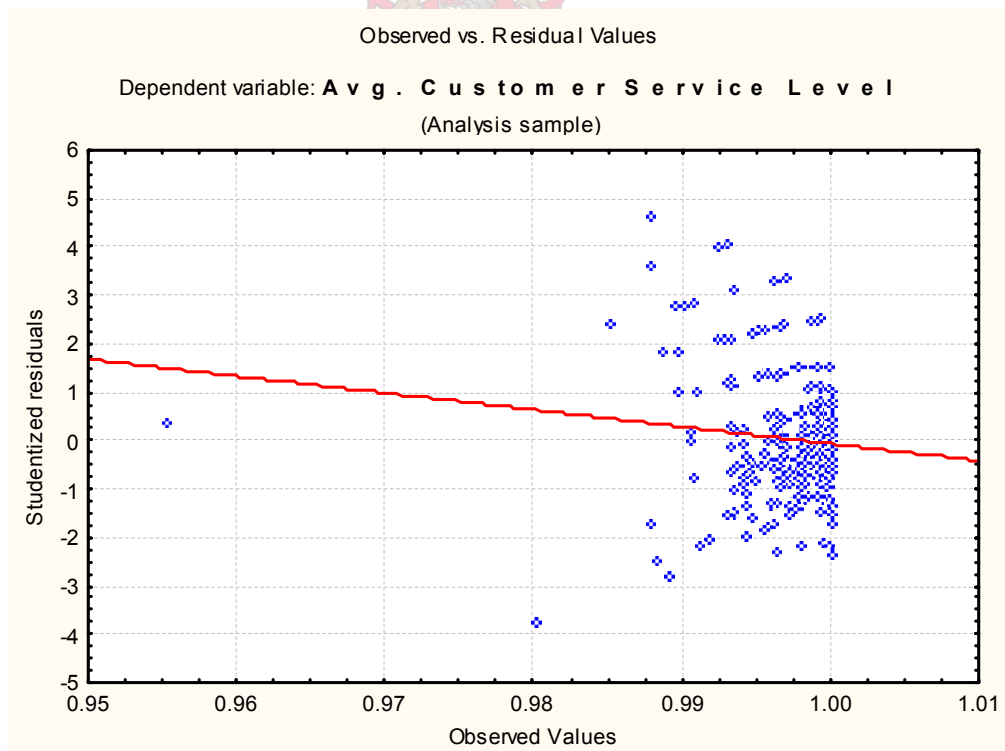
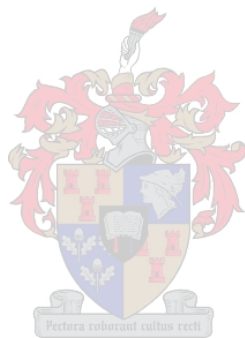


Figure 202: Observed vs. Residual Avg. Customer Service Level. High Runners.

Variable	Avg. Customer Service Level Parameter	Avg. Customer Service Level Std Err	Avg. Customer Service Level t	Avg. Customer Service Level p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Service Level Beta	Avg. Customer Service Level Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Intercept	0.930663	0.005650	164.7285	0.000000	0.919563	0.941763				
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	0.014956	0.001772	8.4412	0.000000	0.011475	0.018437	7.7823	0.921932	5.9709	9.59363
ST + TC	0.000509	0.000081	6.2877	0.000000	0.000350	0.000669	0.2651	0.042163	0.1823	0.34795
ADD*(ST+MC)	-0.000122	0.000015	-7.9291	0.000000	-0.000152	-0.000092	-7.3139	0.922412	-9.1262	-5.50155
ADD*(ST+TC)										
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	0.000003	0.000001	4.2357	0.000027	0.000001	0.000004	0.2913	0.068767	0.1562	0.42639
PS*ST										
PS*MC										
PS*TC	-0.000001	0.000000	-3.6325	0.000310	-0.000001	0.000000	-0.2572	0.070810	-0.3963	-0.11809
Days to Assembly										
Avg. Daily Demand	0.000525	0.000050	10.5955	0.000000	0.000428	0.000622	0.5882	0.055510	0.4791	0.69722
Flip Mean	0.007633	0.001357	5.6231	0.000000	0.004966	0.010300	0.1696	0.030159	0.1103	0.22884

Table 83: Equation Variables & Betas. Avg. Customer Service Level Intercept. High Runners.



Summary of best subsets; variable(s): Avg. Custom Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.574683	7			
2	0.573780	7			
3	0.571123	7			
4	0.570721	7			
5	0.567753	7		5.32198	
6	0.567753	7		-0.07532	
7	0.567753	7			
8	0.567753	7	0.041252		
9	0.567753	7		-3.21315	
10	0.567753	7	1.759914		

**Figure 203: Summary of Best Subsets Adjusted R² Value. Intercept. High Runners.
End of Avg. Customer Service Level**



Start of Avg. Total Shortages

Variable	Avg. Total Shortages Parameter	Avg. Total Shortages Std Err	Avg. Total Shortages t	Avg. Total Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Total Shortages Beta	Avg. Total Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-15446.59	969.420	-15.93384	0.000000	-17351.28	-13541.89	-12.9744	0.814269	-14.5743	-11.3746
ST + TC	14455.55	963.108	15.00928	0.000000	12563.26	16347.84	17.8726	1.190768	15.5330	20.2122
ADD*(ST+MC)										
ADD*(ST+TC)										
ADD * ST										
ADD*MC	123.33	8.451	14.59332	0.000000	106.72	139.93	8.4368	0.578127	7.3009	9.5727
ADD * TC	-122.19	8.367	-14.60486	0.000000	-138.63	-105.75	-13.6502	0.934631	-15.4865	-11.8138
Pallet Size	2.62	0.312	8.42495	0.000000	2.01	3.24	0.3188	0.037845	0.2445	0.3932
PS*ST	-0.83	0.192	-4.32972	0.000018	-1.21	-0.45	-0.1301	0.030043	-0.1891	-0.0710
PS*MC	-0.50	0.106	-4.68939	0.000004	-0.71	-0.29	-0.1355	0.028894	-0.1923	-0.0787
PS*TC										
Days to Assembly	87.93	26.799	3.28122	0.001107	35.28	140.59	0.7782	0.237183	0.3122	1.2443
Avg. Daily Demand	34.55	7.782	4.43988	0.000011	19.26	49.84	1.0570	0.238068	0.5892	1.5247
Flip Mean	-10980.78	834.294	-13.16175	0.000000	-12619.98	-9341.57	-0.7898	0.060009	-0.9077	-0.6719

Table 84: Equation Variables & Betas. Avg. Total Shortages. High Runners.

Summary of best subsets; variable(s): Avg. Total St Adjusted R square and standardized regression coefficients for each submodel				
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage
1	0.883737	10		
2	0.883624	10		
3	0.882627	10		-8.34371
4	0.881606	10		
5	0.881478	10		
6	0.881460	10		
7	0.881443	9		
8	0.881423	10		-8.97834
9	0.881333	9		-9.08147
10	0.881303	10		

Figure 204: Summary of Best Subsets Adjusted R² Value. High Runners.

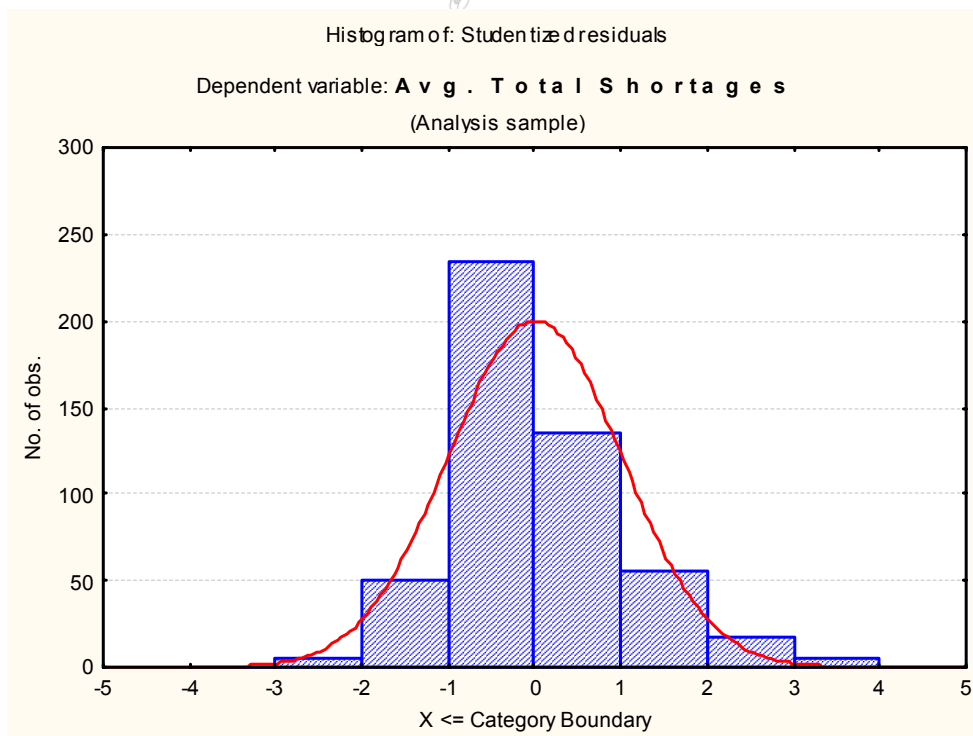


Figure 205: Studentized Residuals. Avg. Total Shortages. High Runners.

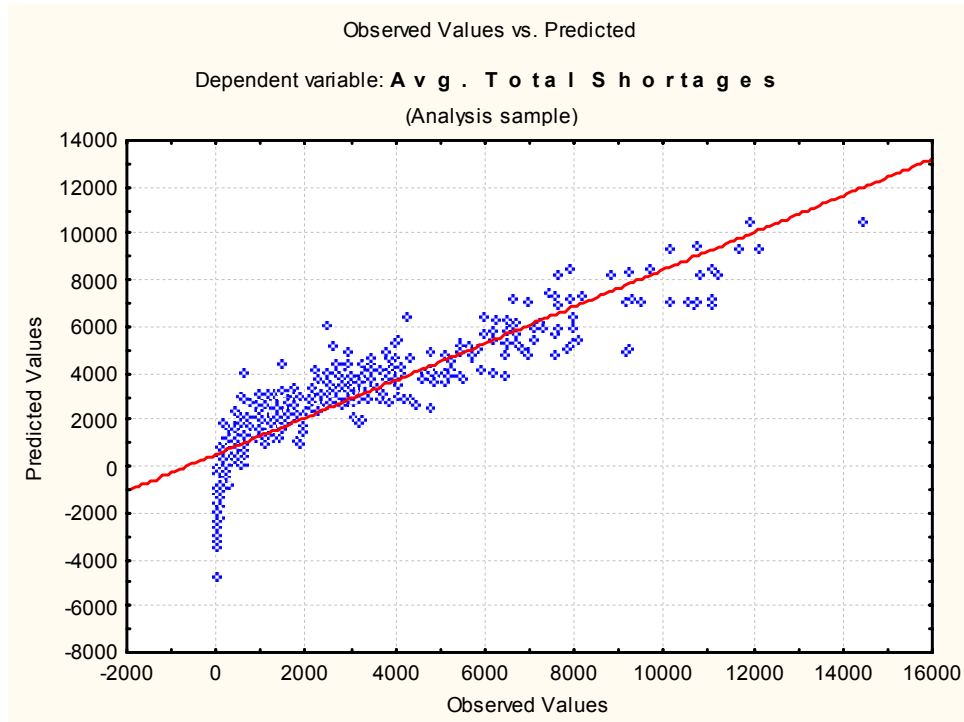
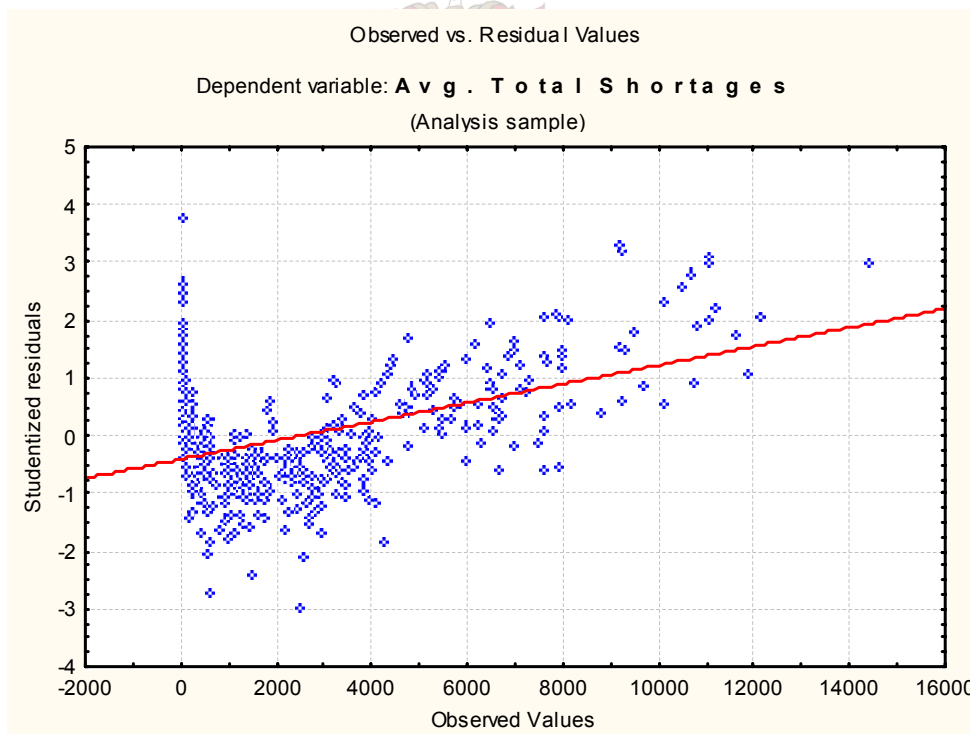


Figure 206: Observed vs. Predicted Avg. Total Shortages. High Runners.



**Figure 207: Observed vs. Residual Avg. Total Shortages. High Runners.
End of Avg. Total Shortages**

Start of Avg. Customer Shortages

Variable	Avg. Customer Shortages Parameter	Avg. Customer Shortages Std Err	Avg. Customer Shortages t	Avg. Customer Shortages p	-95.00% Cnf. Limit	+95.00% Cnf. Limit	Avg. Customer Shortages Beta	Avg. Customer Shortages Std. Err. Beta	-95.00% Cnf. Limit	+95.00% Cnf. Limit
Safety Time										
Min Coverage										
Target Coverage										
ST + MC	-2.042955	0.264664	-7.71906	0.000000	-2.56295	-1.522957	-0.55999	0.072546	-0.70253	-0.41745
ST + TC										
ADD*(ST+MC)										
ADD*(ST+TC)	-0.020774	0.002609	-7.96181	0.000000	-0.02590	-0.015648	-0.96542	0.121256	-1.20366	-0.72718
ADD * ST										
ADD*MC										
ADD * TC										
Pallet Size	-0.014499	0.002566	-5.64945	0.000000	-0.01954	-0.009457	-0.57480	0.101745	-0.77471	-0.37490
PS*ST	0.002816	0.001007	2.79723	0.005354	0.00084	0.004794	0.14414	0.051528	0.04290	0.24538
PS*MC										
PS*TC	0.003109	0.000617	5.04192	0.000001	0.00190	0.004321	0.45011	0.089273	0.27471	0.62551
Days to Assembly	0.869905	0.050224	17.32057	0.000000	0.77123	0.968583	2.51249	0.145058	2.22748	2.79749
Avg. Daily Demand										
Flip Mean	-28.060874	4.971906	-5.64389	0.000000	-37.82942	-18.292330	-0.65867	0.116704	-0.88796	-0.42937

Table 85: Equation Variables & Betas. Avg. Customer Shortages. High Runners.

Summary of best subsets; variable(s): Avg. Custom					
Adjusted R square and standardized regression coefficients for each submodel					
Subset No.	Adjusted R square	No. of Effects	Safety Time	Min Coverage	T
1	0.534443	7			
2	0.533378	7			
3	0.532776	7			
4	0.532547	7			
5	0.529059	7			
6	0.528633	7		-0.394195	
7	0.528557	7		0.333473	
8	0.528557	7	-0.192531		
9	0.528557	7	-0.419097	-0.392424	
10	0.528511	7			

Figure 208: Summary of Best Subsets Adjusted R² Value. High Runners.

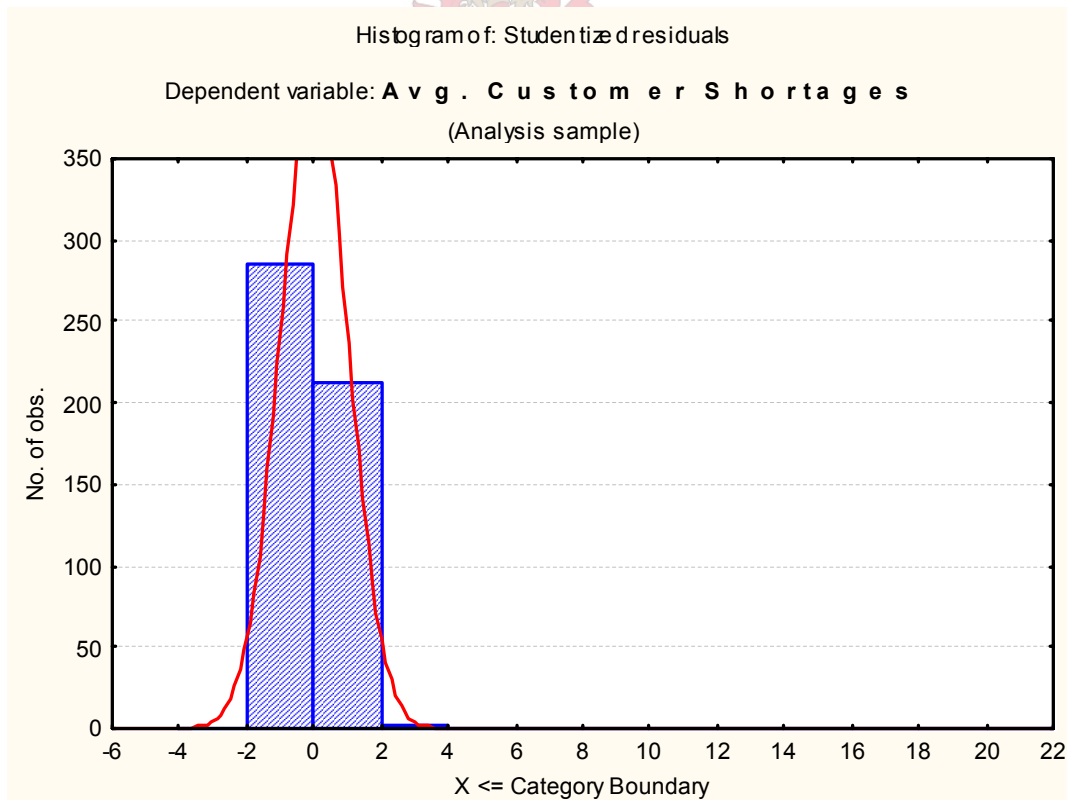


Figure 209: Studentized Residuals. Avg. Customer Shortages. High Runners.

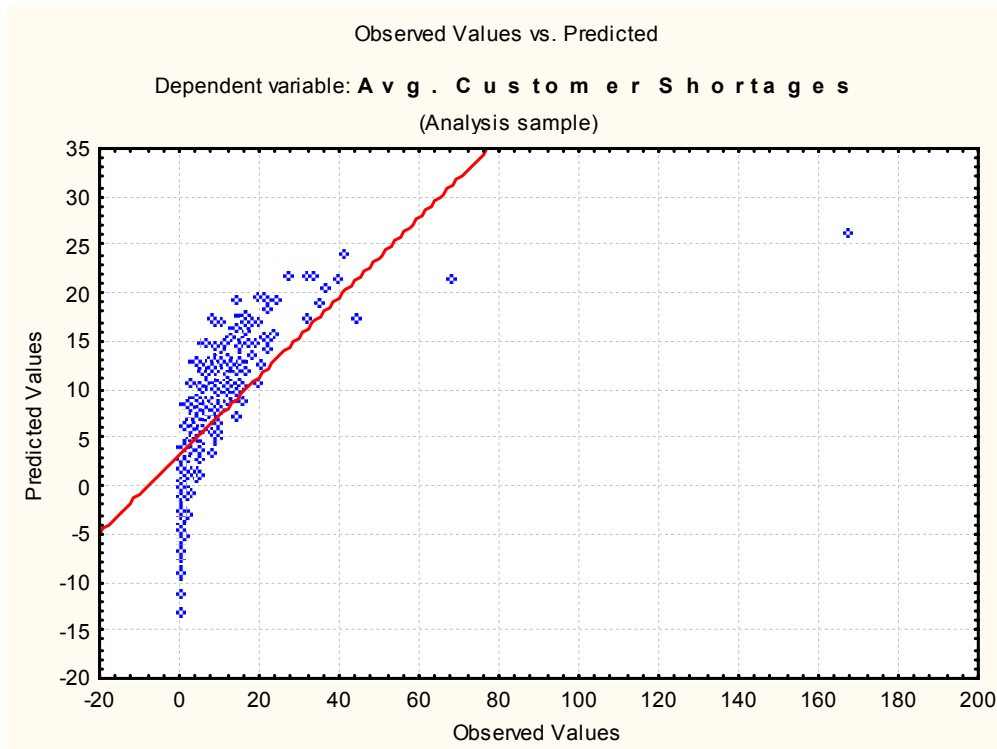


Figure 210: Observed vs. Predicted Avg. Customer Shortages. High Runners.

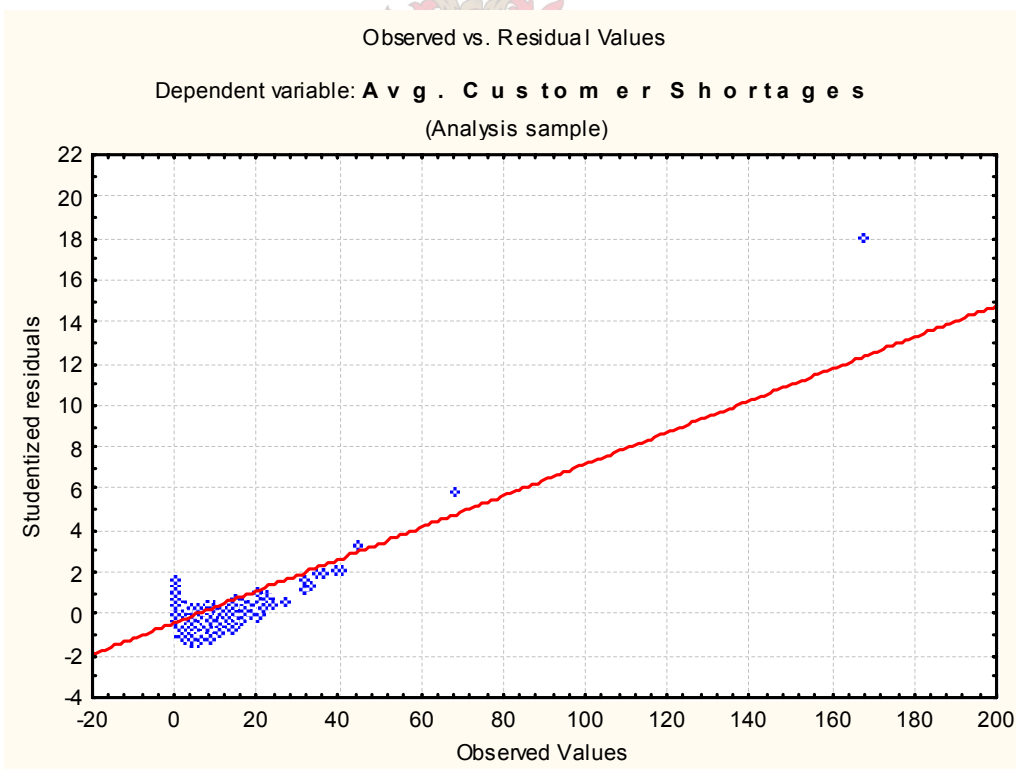


Figure 211: Observed vs. Residual Avg. Customer Shortages. High Runners.

End of Avg. Customer Shortages

*Appendix K Statistica Matrices of
Observations.*



		Performance Measure								
		Inventory			Orders		Service Level		Shortages	
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages
Int. = 0	Int. = 0.98									
Adjusted R² Value		0.99	0.99	0.99	0.94	0.99	0.99	0.86	0.97	0.95
Equation Variable	Safety Time	Null	Null	-:5: (6.1)	Null	Null	Null	Null	Null	Null
	Min Coverage	Null	Null	-:10: (2.1)	Null	Null	Null	Null	Null	Null
	Target Coverage	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ST + MC	-:6: (5.3)	Null	Null	+:3: (12.3)	-:3: (5.4)	Null	+:2: (23)	Null	-:3: (12.9)
	ST + TC	Null	-:4: (12.6)	Null	-:5: (8.5)	+:2: (8.6)	+:3: (15.2)	+:6: (7.4)	-:2: (12.2)	-:5: (7.4)
	ADD*(ST+MC)	+:2: (8.6)	+:6: (4)	+:4: (7.2)	-:9: (3.8)	+:9: (1.5)	Null	-:9: (3)	-:3: (10)	Null
	ADD*(ST+TC)	Null	+:5: (9.3)	Null	Null	-:5: (2.7)	-:5: (10.4)	Null	Null	Null
	ADD * ST	+:8: (2)	Null	+:9: (2.6)	Null	Null	Null	Null	Null	Null
	ADD*MC	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ADD * TC	Null	Null	Null	Null	Null	Null	Null	+:4: (9.5)	Null
	Pallet Size	+:1: 60.2)	-:3: (12.8)	-:3: (7.3)	-:2: (17.9)	+:1: (67.3)	+:4: (12.9)	+:1: (29.7)	+:7: (7.7)	-:2: (23.5)
	PS*ST	-:5: (5.3)	+:9: (1.3)	+:8: (2.7)	-:10: (3)	+:10: (1.4)	Null	-:7: (4.8)	Null	+:9: (2.3)
	PS*MC	-:7: (5.2)	+:8: (1.6)	+:7: (2.7)	-:8: (5.2)	+:6: (2.5)	Null	-:3: (10.2)	-:8: (4)	+:7: (4.6)
	PS*TC	Null	+:7: (3.3)	Null	+:6: (7.5)	-:4: (5.4)	-:7: (4.3)	-:4: (9.7)	Null	+:6: (6.6)
	Days to Assembly	+:3: (7.7)	+:2: (25.2)	+:2: (11.9)	+:1: (27)	+:8: (1.8)	+:1: (36.5)	-:8: (4.3)	-:6: (8.8)	+:1: (31.4)
Avg. Daily Demand	Null	+:1: (29.1)	+:1: (53.8)	-:4: (9.1)	-:7: (2)	+:2: (15.8)	Null	+:1: (38.7)	+:4: (8.4)	
Flip Mean	+:4: (5.8)	+:10: (0.8)	-:6: (3.6)	+:7: (5.6)	+:11: (1.4)	-:6: (4.9)	-:5: (7.9)	+:5: (9)	+:8: (3)	

Table 86: Ultra Low Runner Matrix of Observations, (Alpha = 0.05).

		Performance Measure								
		Inventory			Orders		Service Level		Shortages	
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages
Int. = 0	Int.=0.97									
Adjusted R² Value		0.99	0.99	0.99	0.96	0.99	0.99	0.66	0.94	0.7
Equation Variable	Safety Time	Null	Null	Null	Null	Null	Null	Null	Null	Null
	Min Coverage	-:7: (0.8)	Null	Null	+:4: (12.9)	Null	Null	Null	Null	Null
	Target Coverage	Null	Null	Null	-:5: (11.8)	Null	Null	Null	Null	Null
	ST + MC	Null	Null	Null	Null	Null	Null	+:5: (12.7)	Null	-:5: (6.4)
	ST + TC	-:4: (4.7)	-:4: (12)	+:3: (3.1)	Null	+:7: (1.4)	+:3: (20.3)	+:1: (24.9)	+:5: (6.1)	Null
	ADD*(ST+MC)	Null	+:8: (1.6)	Null	Null	Null	Null	Null	-:4: (6.4)	Null
	ADD*(ST+TC)	+:3: (23.7)	+:5: (9.1)	Null	Null	Null	-:4: (16.5)	-:3: (17.1)	-:7: (1.9)	-:4: (10.7)
	ADD * ST	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ADD*MC	Null	Null	+:6: (1.6)	+:9: (4.8)	-:2: (28.2)	Null	Null	Null	Null
	ADD * TC	Null	Null	-:5: (2.8)	-:2: (15.1)	+:1: (45.2)	Null	Null	Null	Null
	Pallet Size	+:6: (2.5)	-:6: (2.6)	+:9: (0.4)	-:7: (7.5)	+:3: (10.7)	+:5: (5.3)	+:4: (13)	+:6: (2.1)	Null
	PS*ST	Null	+:9: (0.7)	Null	Null	Null	-:7: (1.2)	-:7: (3.4)	-:9: (0.7)	Null
	PS*MC	Null	Null	+:8: (0.5)	-:8: (5.8)	+:6: (1.8)	Null	Null	-:8: (1)	Null
	PS*TC	Null	+:7: (2.1)	-:7: (1)	+:6: (7.6)	-:5: (3.2)	-:6: (3.5)	-:6: (9.2)	Null	Null
	Days to Assembly	-:5: (3.4)	+:2: (16.9)	+:4: (3)	+:1: (19.6)	Null	+:1: (29)	Null	+:3: (12.5)	+:1: (29.7)
	Avg. Daily Demand	-:2: (25.3)	+:1: (39)	+:1: (71.7)	+:3: (14.9)	+:4: (9.6)	Null	Null	+:2: (32.1)	+:3: (23.8)
Flip Mean	+:1: (39.6)	-:3: (16)	-:2: (16)	Null	Null	+:2: (24.2)	+:2: (19.6)	-:1: (37.3)	-:2: (29.5)	

Table 87: Low Runner Matrix of Observations, (Alpha = 0.05).

		Performance Measure								
		Inventory			Orders		Service Level		Shortages	
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages
Int. = 0	Int.=1.02									
Adjusted R² Value		0.99	0.99	0.99	0.96	0.99	0.99	0.6	0.96	0.67
Equation Variable	Safety Time	Null	Null	Null	Null	Null	Null	Null	Null	Null
	Min Coverage	Null	Null	Null	Null	Null	Null	Null	Null	Null
	Target Coverage	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ST + MC	-6: (4.7)	Null	+7: (2)	+1: (19.4)	Null	Null	Null	Null	-3: (12.5)
	ST + TC	Null	-3: (15.5)	+3: (13.9)	-4: (11.6)	Null	+3: (25.7)	+4: (13.6)	-2: (27.4)	Null
	ADD*(ST+MC)	Null	+6: (3.2)	Null	Null	-3: (22.6)	Null	+1: (30.3)	-3: (10.2)	Null
	ADD*(ST+TC)	+1: (37.7)	+4: (13.8)	-2: (15.1)	-2: (16.7)	+1: (33.6)	-2: (26)	Null	+1: (34.3)	-2: (20.7)
	ADD * ST	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ADD*MC	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ADD * TC	Null	Null	Null	Null	Null	Null	Null	Null	Null
	Pallet Size	+2: (29.5)	-7: (1.1)	-6: (2.3)	-6: (9.8)	+2: (23.6)	-5: (1.6)	+5: (9.3)	+4: (8.9)	-4: (11.6)
	PS*ST	-7: (3.1)	+9: (0.3)	+9: (0.7)	Null	Null	+8: (0.4)	Null	-9: (2.4)	+7: (2.5)
	PS*MC	+8: (1)	+8: (0.6)	+8: (1.3)	-8: (4.9)	+5: (6)	Null	Null	-8: (2.5)	Null
	PS*TC	-3: (11.2)	Null	Null	+7: (8.7)	-4: (9.9)	+6: (1.1)	Null	-7: (2.9)	+5: (7)
	Days to Assembly	Null	+1: (36)	-5: (4.8)	+5: (11.2)	Null	+4: (13.2)	-6: (7.3)	+5: (6.3)	Null
Avg. Daily Demand	+4: (7.2)	+2: (25.1)	+1: (55)	+3: (16.5)	+6: (2.2)	+1: (31.6)	-2: (21.8)	Null	+1: (40)	
Flip Mean	+5: (5.6)	+5: (4.4)	+4: (4.9)	+9: (1.2)	+7: (2)	+7: (0.4)	-3: (17.8)	+6: (5)	+6: (5.7)	

Table 88: Medium Runner Matrix of Observations, (Alpha = 0.05).

		Performance Measure								
		Inventory			Orders		Service Level		Shortages	
		Avg. Plant Inv.	Avg. Pipeline Inv.	Avg. Harbour Inv.	Avg. Number of Orders	Avg. Order Size	Avg. Customer Service Level		Avg. Total Shortages	Avg. Customer Shortages
Int. = 0	Int.=0.93									
Adjusted R² Value		0.99	0.99	0.99	0.97	0.99	0.99	0.57	0.88	0.53
Equation Variable	Safety Time	Null	Null	Null	Null	Null	Null	Null	Null	Null
	Min Coverage	Null	Null	Null	Null	Null	Null	Null	Null	Null
	Target Coverage	Null	Null	Null	Null	Null	Null	Null	Null	Null
	ST + MC	-4: (17.1)	+4: (13.9)	+2: (18.4)	Null	-3: (13.1)	+7: (0.1)	+1: (46.7)	-3: (23.1)	-5: (9.5)
	ST + TC	-2: (20.5)	-2: (21.5)	+5: (6.4)	Null	Null	+3: (31)	+5: (1.6)	+1: (31.8)	Null
	ADD*(ST+MC)	+3: (19)	-5: (12.9)	-3: (16.8)	Null	-5: (8.1)	Null	-2: (43.9)	Null	Null
	ADD*(ST+TC)	+1: (28.5)	+3: (21.1)	-4: (7.5)	Null	+1: (31.4)	-2: (31.1)	Null	Null	-2: (16.5)
	ADD * ST	-8: (0.9)	Null	Null	Null	Null	Null	Null	Null	Null
	ADD*MC	-10: (0.5)	Null	Null	+3: (14.5)	Null	Null	Null	+4: (15)	Null
	ADD * TC	-9: (0.5)	Null	Null	-1: (23.2)	Null	Null	Null	-2: (24.3)	Null
	Pallet Size	+5: (6.4)	-8: (0.3)	-7: (0.9)	-4: (12.9)	+2: (23.9)	-5: (0.2)	+4: (1.7)	+8: (0.6)	-4: (9.8)
	PS*ST	Null	+10: (0.1)	+8: (0.4)	Null	Null	+8: (0.1)	Null	-10: (0.2)	+7: (2.5)
	PS*MC	+6: (4.6)	+9: (0.1)	+10: (0.3)	-7: (7.6)	+6: (7.5)	Null	Null	-9: (0.2)	Null
	PS*TC	Null	Null	+9: (0.3)	+5: (12.2)	-4: (12.5)	+6: (0.2)	-6: (1.5)	Null	+6: (7.7)
	Days to Assembly	Null	+1: (25.8)	Null	+6: (10.1)	+7: (3.1)	+4: (2)	Null	+7: (1.4)	+1: (42.8)
Avg. Daily Demand	Null	+6: (3.5)	+1: (47.3)	+2: (19.5)	Null	+1: (35.4)	+3: (3.5)	+5: (1.9)	Null	
Flip Mean	+7: (2)	-7: (0.8)	-6: (1.8)	Null	+8: (0.4)	Null	+7: (1)	-6: (1.4)	-3: (11.2)	

Table 89: High Runner Matrix of Observations, (Alpha = 0.05).

*Appendix L Analysis of Regression
Equations & Observations.*



Important:

The reader is advised to read the following guidelines before examining the graphs contained within this Appendix

1. ALWAYS PAY ATTENTION AND PLEASE NOTE THE SCALE OF THE GRAPH.
2. If the reader is unsure which Performance Measure/Measures is/are described in the figure, then the figure title (found **below** the figure) will always refer to the correct Performance Measure regardless of title given **in** the figure.
3. Figure titles starting with the words “Effect of.....” always refer to the results of the application of the applicable Regression Equation.
4. Figure titles starting with the words “Observed effects of...” always refer to the observations made on the output of the DOE.
5. If a generalised Performance Measure is found within the figure title (found **below** the figure), then that figure contains more than one result e.g. *Inventory* contains the results of Plant, Harbour, and Pipeline Inventory.
6. Any value greater than one in an “Effect of..... On Service Level” is actually equal to a Service Level of 1 i.e. 100%
7. Any values less than zero in an “Effect of.....on Shortages” are equal to zero.
8. Any values less than zero in an “Effect of.....on Orders” are equal to a very small number, relative to the remaining numbers. Refer to Figure 243.

In addition, the reader must understand the manner in which the X-Axis of the graphs containing the results of the observations made on the results of the DOE, are categorised.

Figure 212 is an extract taken from Figure 215 and is used to illustrate how to read the X-Axis. The legend at the bottom of Figure 212 contains the following information:

- Part Number: The part number used in the analysis.
- ST+MC: Safety Time + Minimum Range of Coverage.
- ST+TC: Safety Time + Target Range of Coverage.

In general, the categories, which are in the legend, are printed from left to right, and should be read from bottom to top, respectively, when reading the X-Axis.

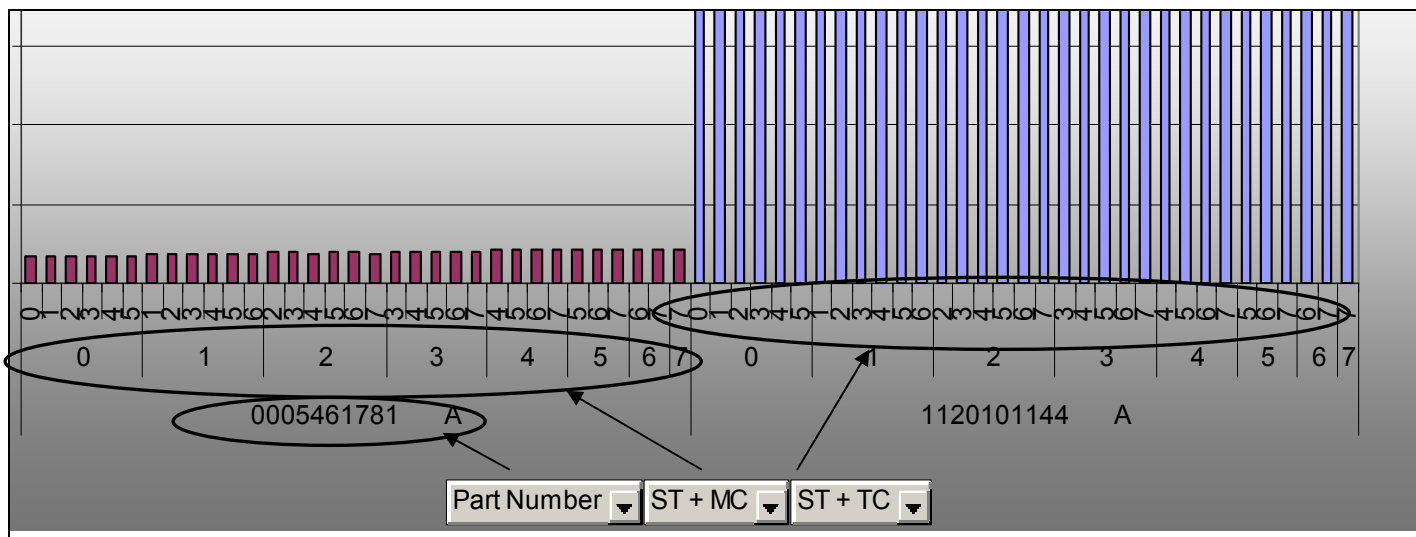


Figure 212: Understanding the X-Axis.

The combination of the fields (ST+MC) and (ST+TC) effectively represents all the combinations of the Safety Time and Coverage Profile values used in the DOE. Refer to Appendix F.

The point at which (ST+MC) and (ST+TC) both equal zero, equates to the first combination setting i.e. Safety Time, Minimum, and Target Coverage all equal zero. The point at which (ST+MC) equals 7 and (ST+TC) also equals 7, equates to the 63rd combination in which Safety Time, Minimum, and Target Coverage equalled 2, 5, 5 respectively. Therefore, it should be understood that the points in-between represent the various combinations, shown in Appendix F, moving from left to right.

Refer to Table 90, in Appendix L, for the X-Axis Key that will help in understanding which combination is represented by (ST+MC) and (ST+TC) values on the graph.

Upon examination of the X-Axis Key, the reader will note that a few of the Input Combinations, when summed, equal the same value.

Example: If (ST+MC) =2, and (ST+MC) = 2, then the possible Safety Time and Coverage Profile Combinations are:

ST	MC	TC
2	0	0
1	1	1
0	2	2

Using the values given, and Figure 213, shown below, it is seen that Avg. Plant Inventory, for all these combinations, is equal to about 219 units. Similar observations are made for other Input Combinations. In addition, this behaviour is the same for all the parts included in this study.

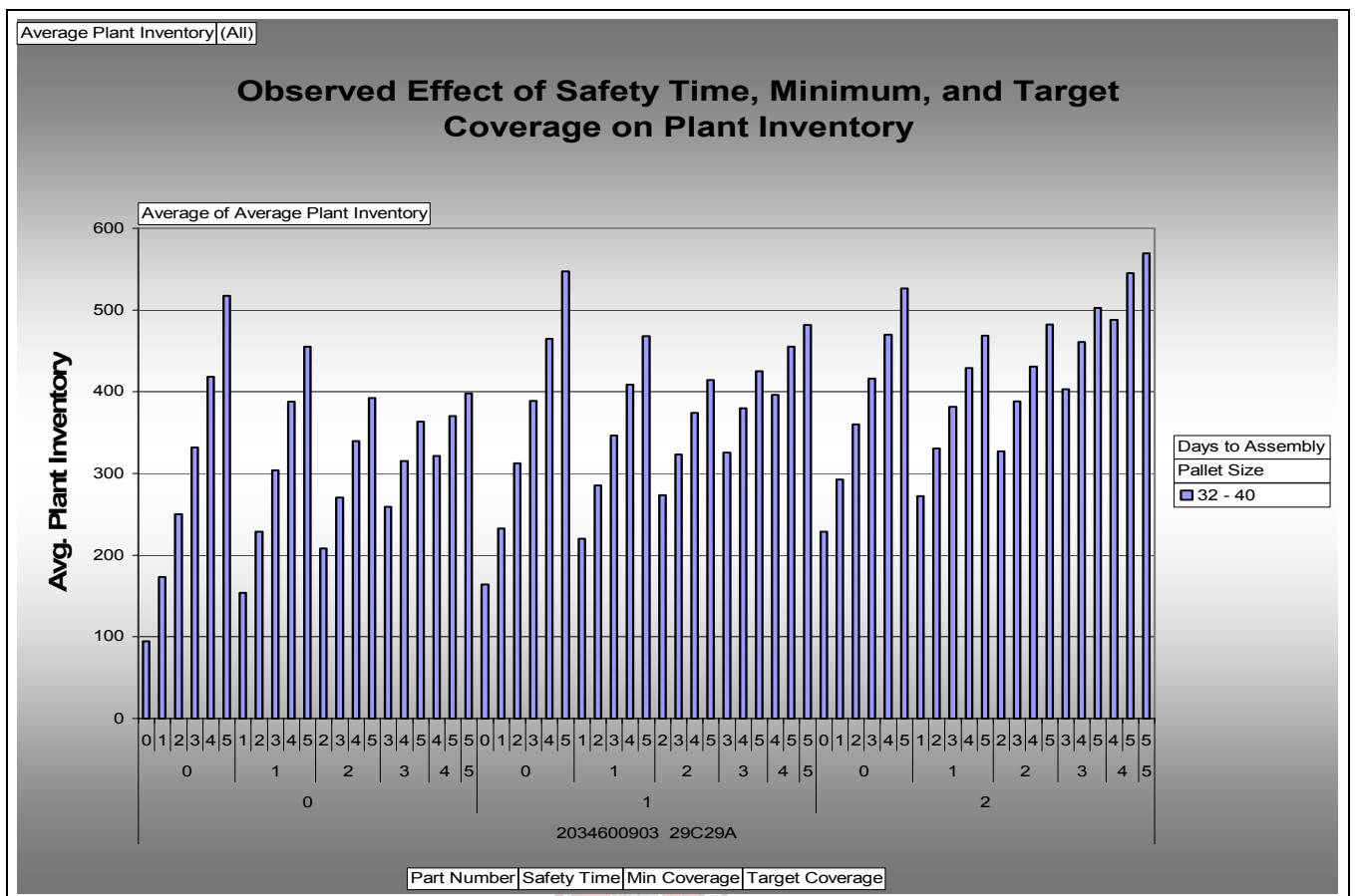


Figure 213: Equal Plant Inventories – Different Settings.

This finding, combined with the fact that emphasis has been placed on the interaction of the sum of Safety Time and Coverage Profile, lends itself towards the manner in which the Performance Measures have been analysed. By referring to Figure 212 and Figure 213, it is seen that the value associated with the point at which (ST+MC) and (ST+TC) both equals 2, actually represents the average inventory of three different Input Combinations. Grouping the Input Combinations, or the averaging of the associated inventory levels, does not present invalid results. This is because the average of values with equal magnitude results in an answer that is equal to the original numbers e.g. the average of 3+3+3 equals 3. The reader must keep in mind that all the measurements are taken over a period of 1000 days. Therefore, if a graph indicates that the number of Customer Shortages is equal to 18, then the result should be interpreted as “18 shortages in 1000 days.”

Inspection of the various parts, used in the analysis to be presented, will show that the parts used in the Regression Equations were not always used in the observations made on the results provided by the DOE. This was done for a very specific reason. The parts used in the Regression Equations did not always have equal Pallet Size or Lead-Time values, which then allowed generalisations to be made. These generalisations were then backed up by the observations made on the DOE results, which compared parts with equal Lead-Time or Pallet Size values. Referring to Figure 214 and Figure 215, it is seen that the parts used in the first figure were not used in the second figure. The parts used in the first figure had different Lead-Times i.e. 32 and 37 working days, and the resultant observations made

thereupon ignored the possible influence that Lead-Time could have on the analysis. However, the second figure presents the results based upon the analysis of parts with equal Lead-Times. These results are seen to be the same as the generalised observations.

ST+MC	ST+TC	Simulation Run	Safety Time	Minimum Coverage	Target Coverage
0	0	1	0	0	0
0	1	2	0	0	1
0	2	3	0	0	2
0	3	4	0	0	3
0	4	5	0	0	4
0	5	6	0	0	5
1	1	7	0	1	1
1	2	8	0	1	2
1	3	9	0	1	3
1	4	10	0	1	4
1	5	11	0	1	5
2	2	12	0	2	2
2	3	13	0	2	3
2	4	14	0	2	4
2	5	15	0	2	5
3	3	16	0	3	3
3	4	17	0	3	4
3	5	18	0	3	5
4	4	19	0	4	4
4	5	20	0	4	5
5	5	21	0	5	5
1	1	22	1	0	0
1	2	23	1	0	1
1	3	24	1	0	2
1	4	25	1	0	3
1	5	26	1	0	4
1	6	27	1	0	5
2	2	28	1	1	1
2	3	29	1	1	2
2	4	30	1	1	3
2	5	31	1	1	4
2	6	32	1	1	5
3	3	33	1	2	2
3	4	34	1	2	3
3	5	35	1	2	4
3	6	36	1	2	5
4	4	37	1	3	3
4	5	38	1	3	4
4	6	39	1	3	5
5	5	40	1	4	4
5	6	41	1	4	5
6	6	42	1	5	5
2	2	43	2	0	0
2	3	44	2	0	1
2	4	45	2	0	2
2	5	46	2	0	3
2	6	47	2	0	4
2	7	48	2	0	5
3	3	49	2	1	1
3	4	50	2	1	2
3	5	51	2	1	3
3	6	52	2	1	4
3	7	53	2	1	5
4	4	54	2	2	2
4	5	55	2	2	3
4	6	56	2	2	4
4	7	57	2	2	5
5	5	58	2	3	3
5	6	59	2	3	4
5	7	60	2	3	5
6	6	61	2	4	4
6	7	62	2	4	5
7	7	63	2	5	5

Table 90: X-Axis Key.

Ultra Low Runners.



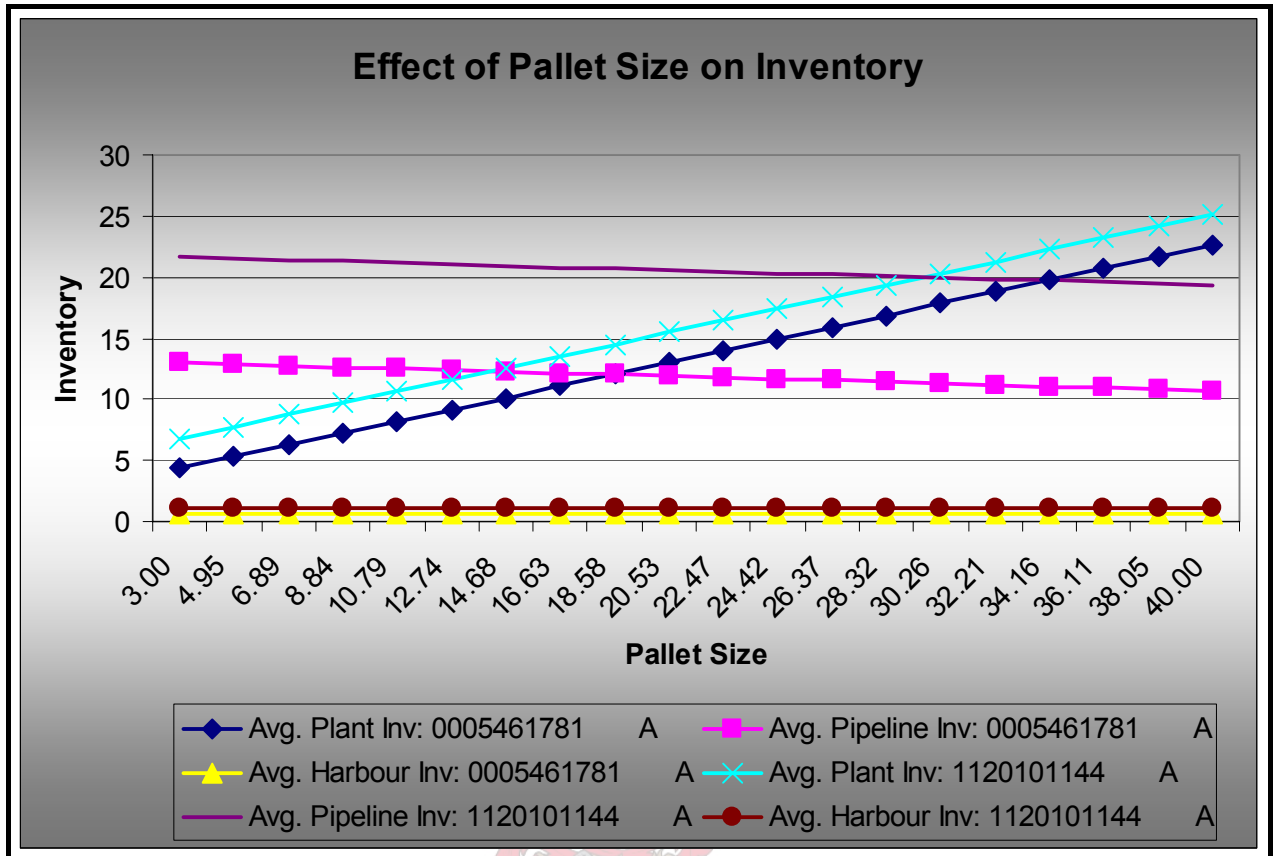


Figure 214: Effect of Palletization on Inventory. Ultra Low Runners.

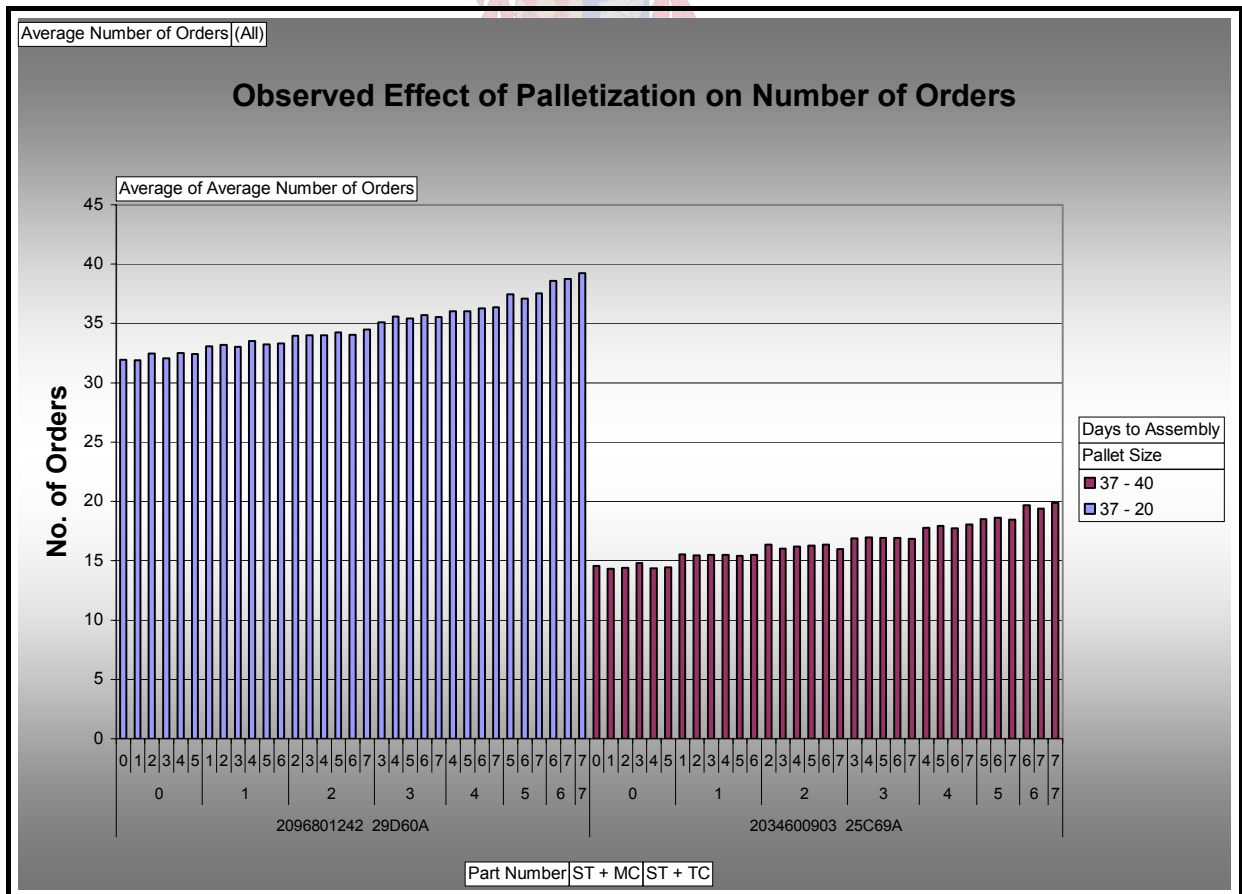


Figure 215: Observed Effect of Palletization on Number of Orders. Ultra Low Runners.

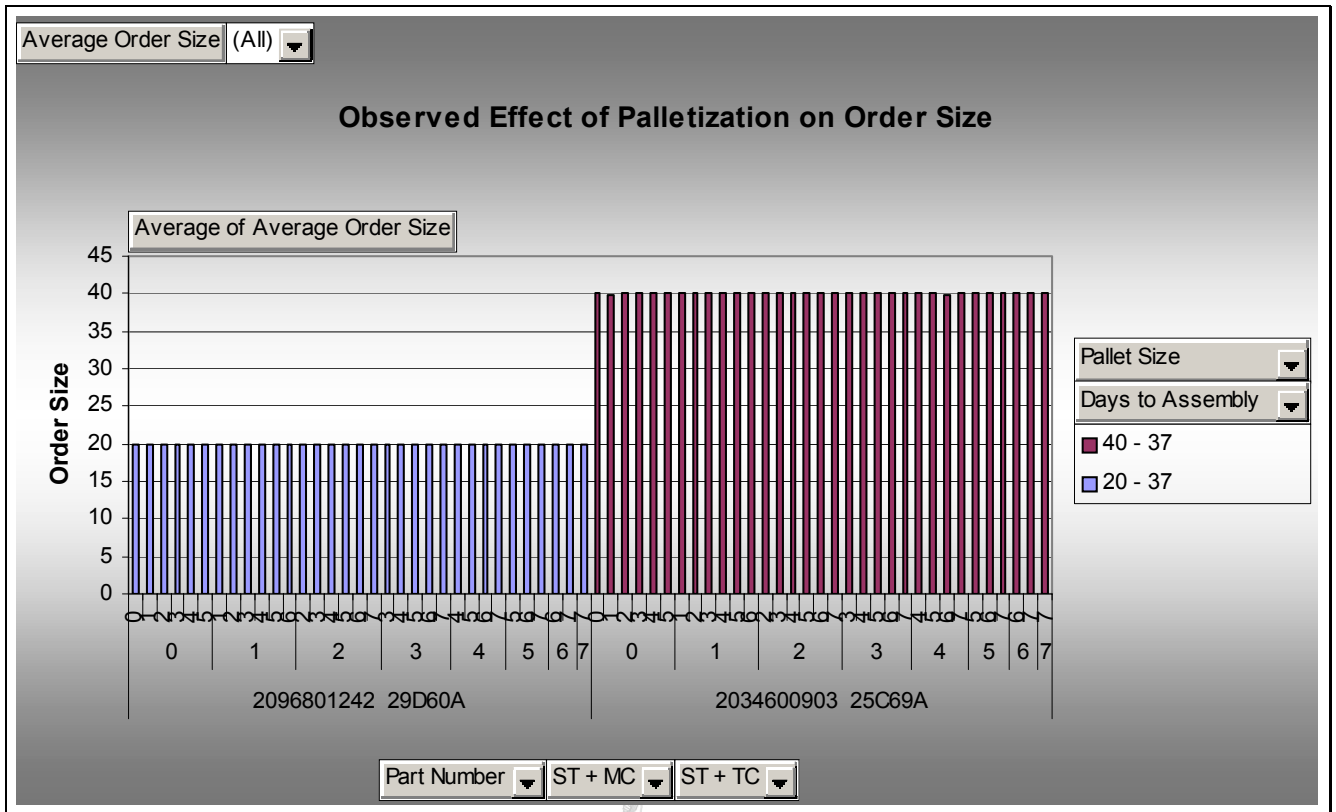


Figure 216: Observed Effect of Palletization on Orders Size. Ultra Low Runners.

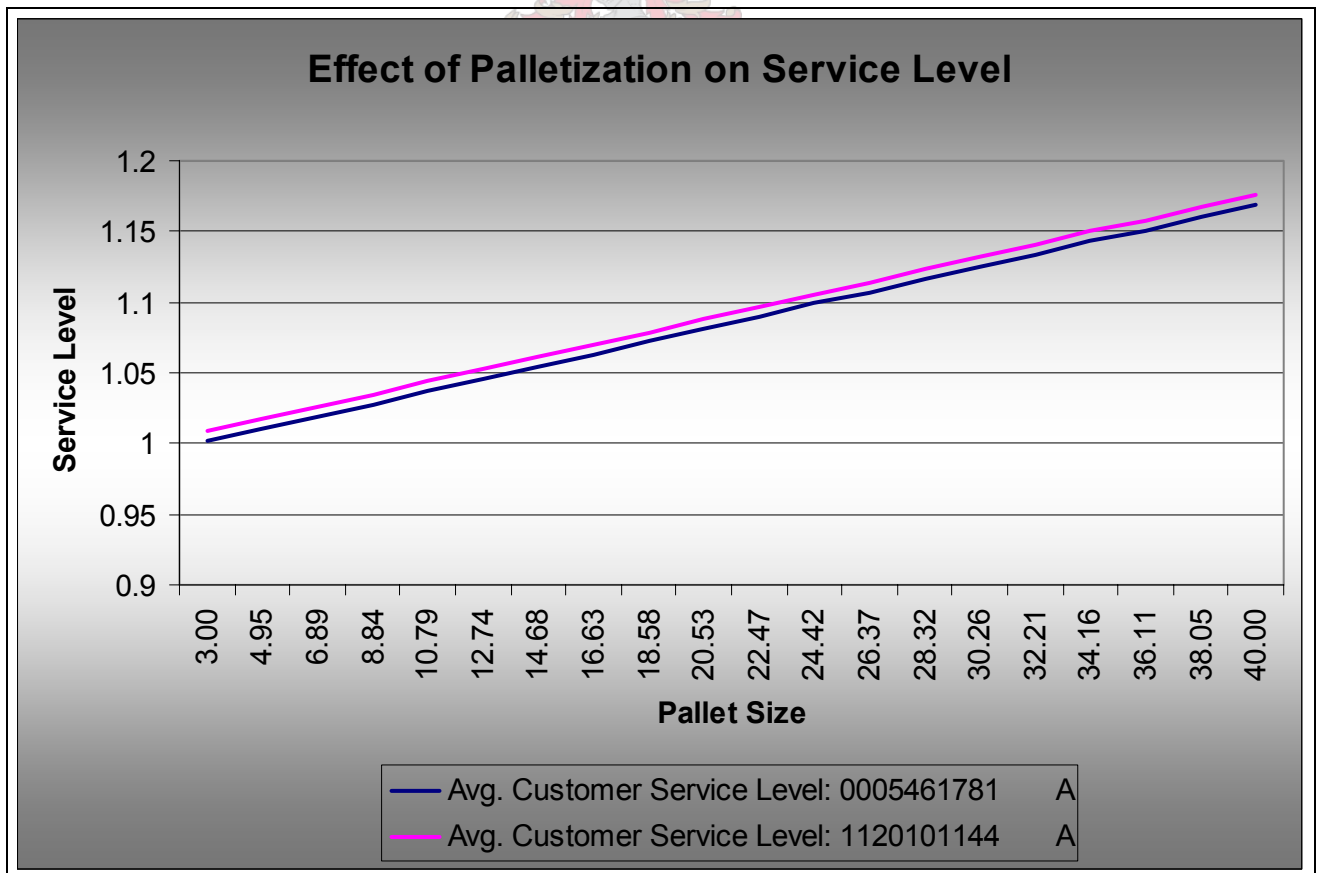


Figure 217: Effect of Palletization on Service Level. Ultra Low Runners.

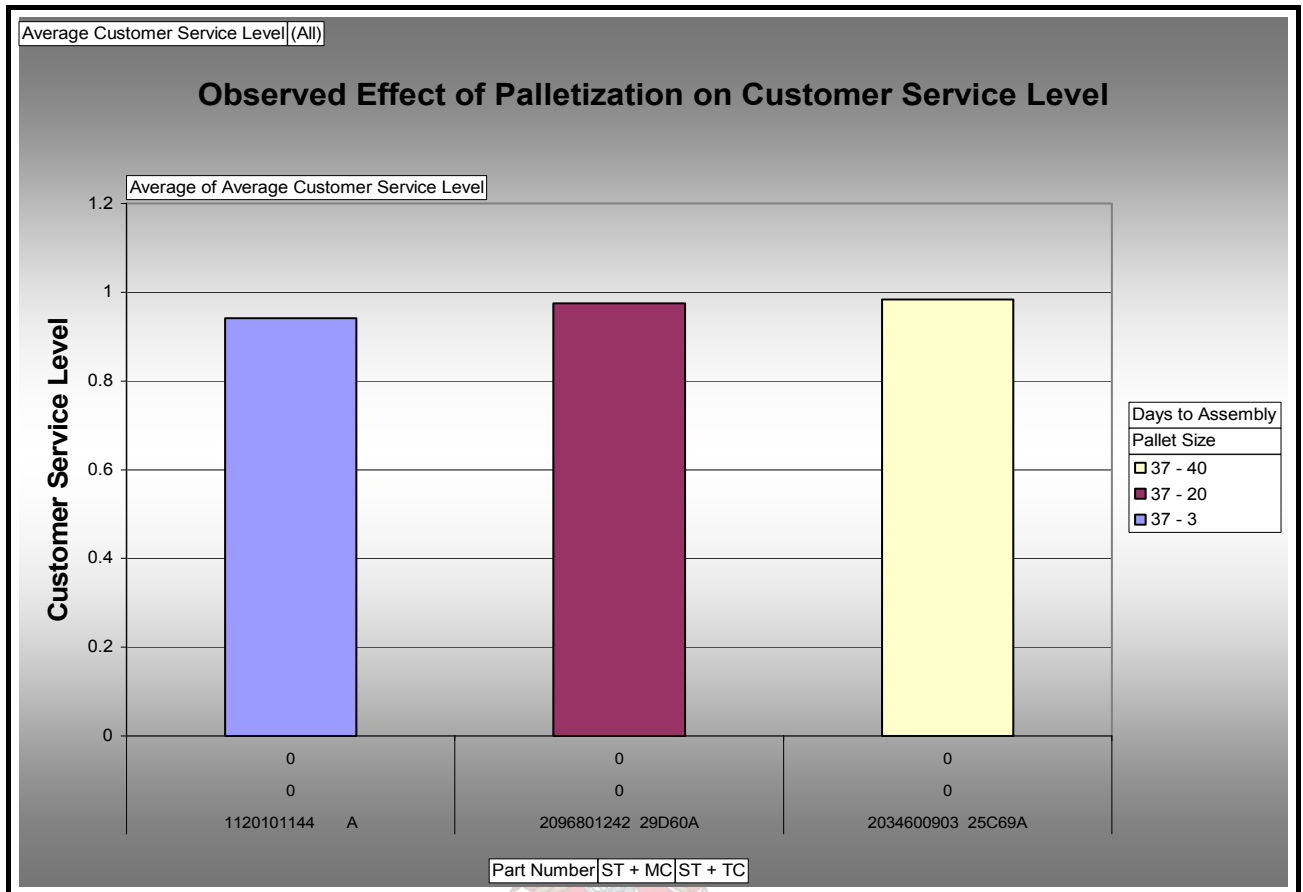


Figure 218: Observed Effect of Palletization on Customer Service Level. Ultra Low Runners.

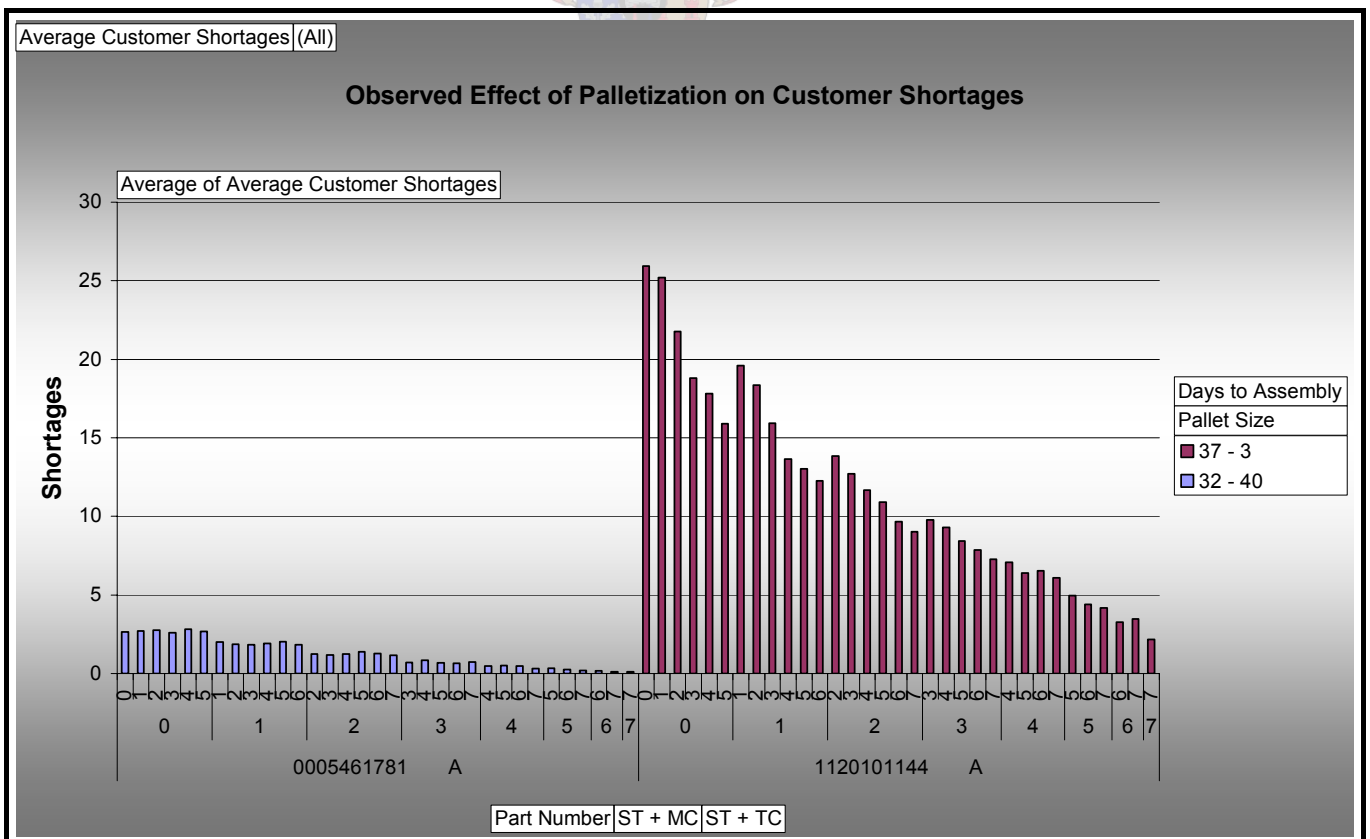


Figure 219: Observed Effect of Palletization Customer Shortages. Ultra Low Runners.

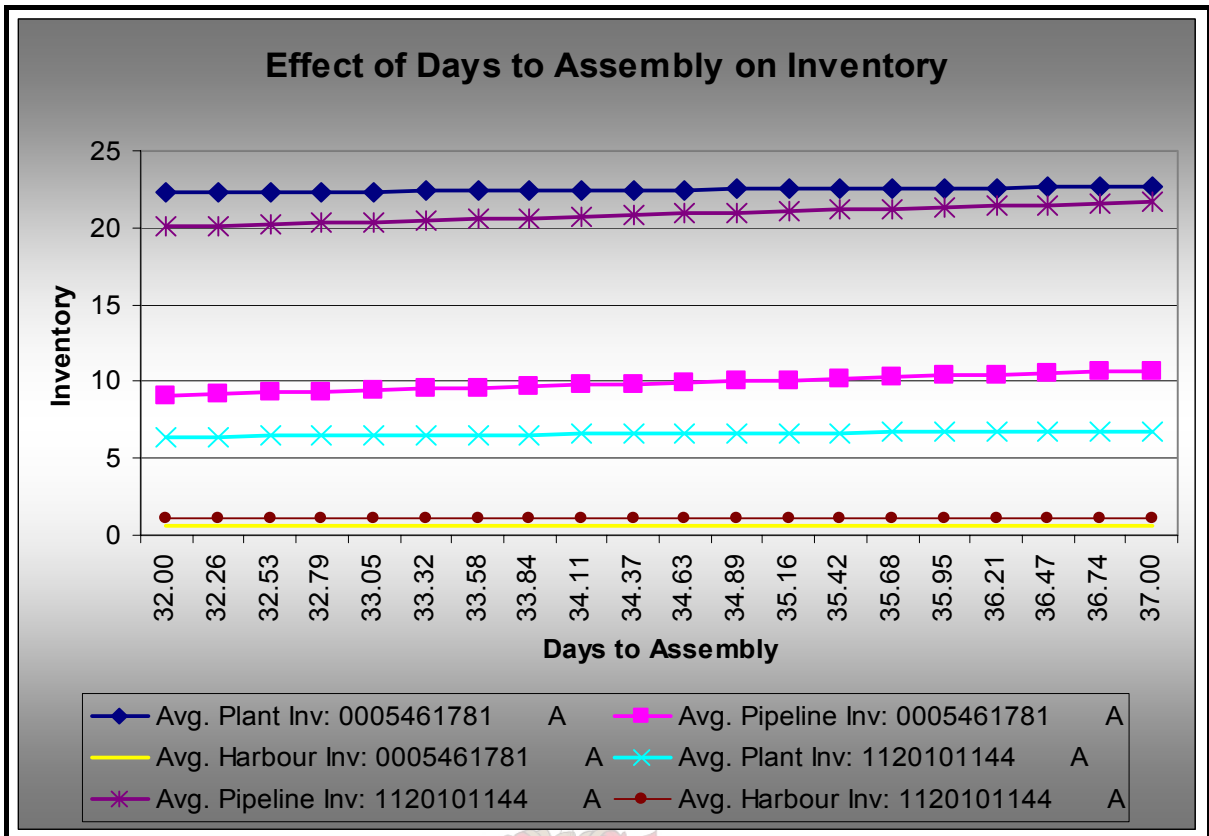


Figure 220: Effect of Days to Assembly on Inventory. Ultra Low Runners.

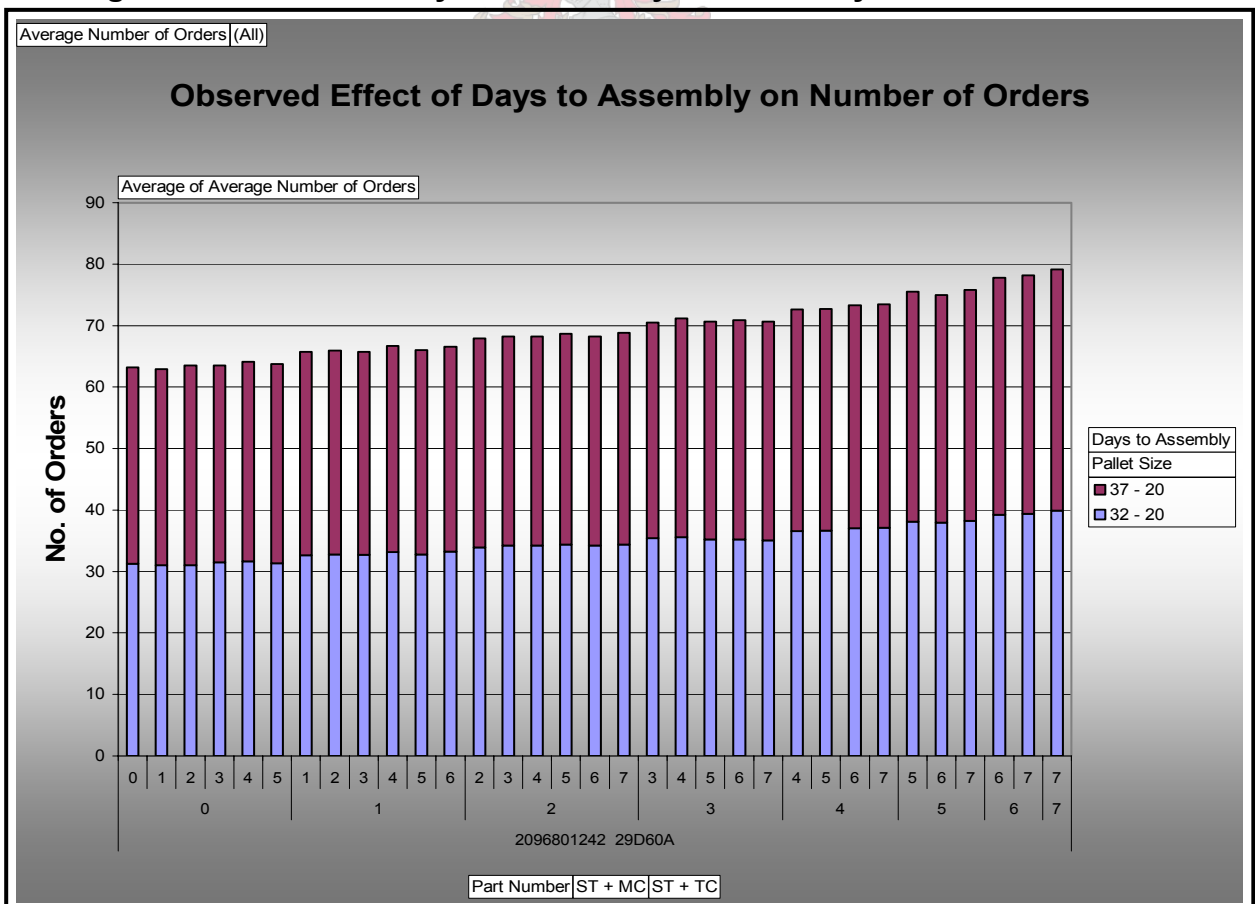


Figure 221: Observed Effect of Days to Assembly on Number of Orders. Ultra Low Runners.

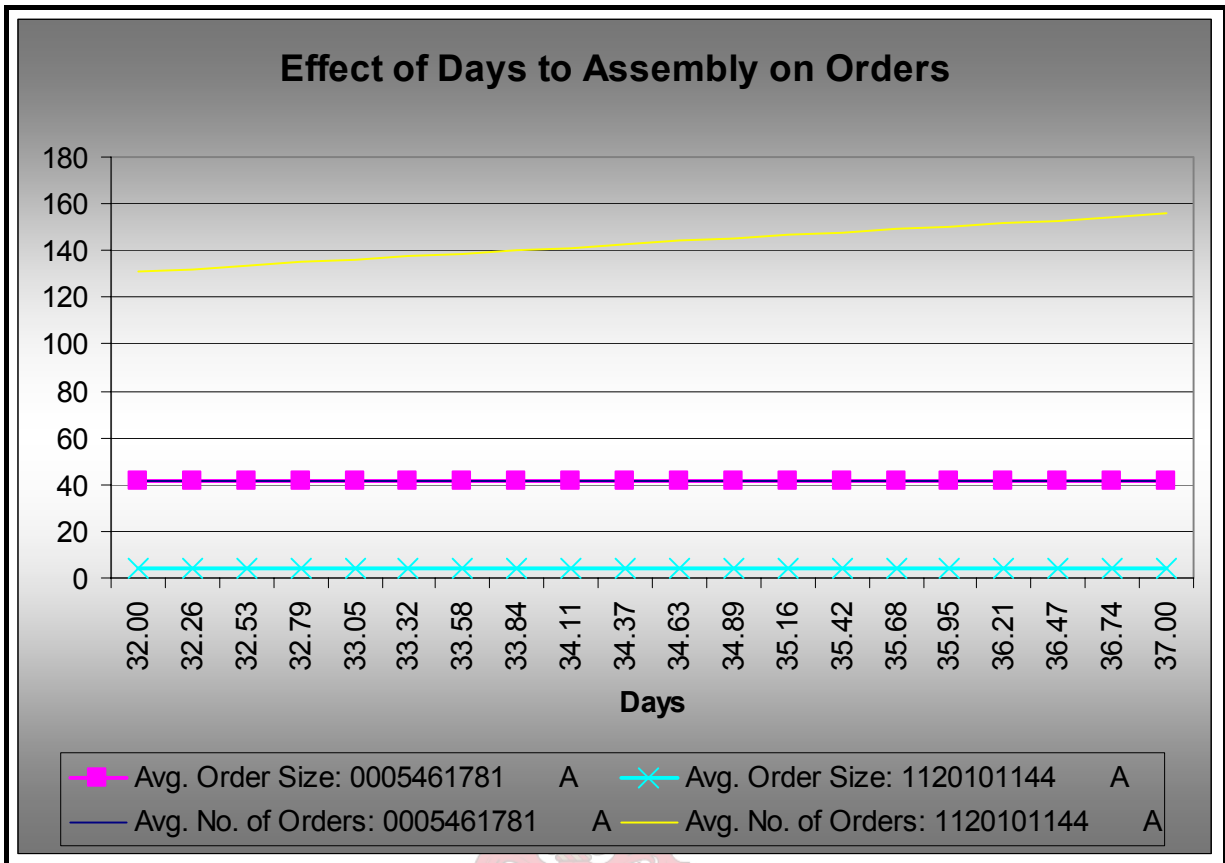


Figure 222: Effect of Days to Assembly on Orders. Ultra Low Runners.

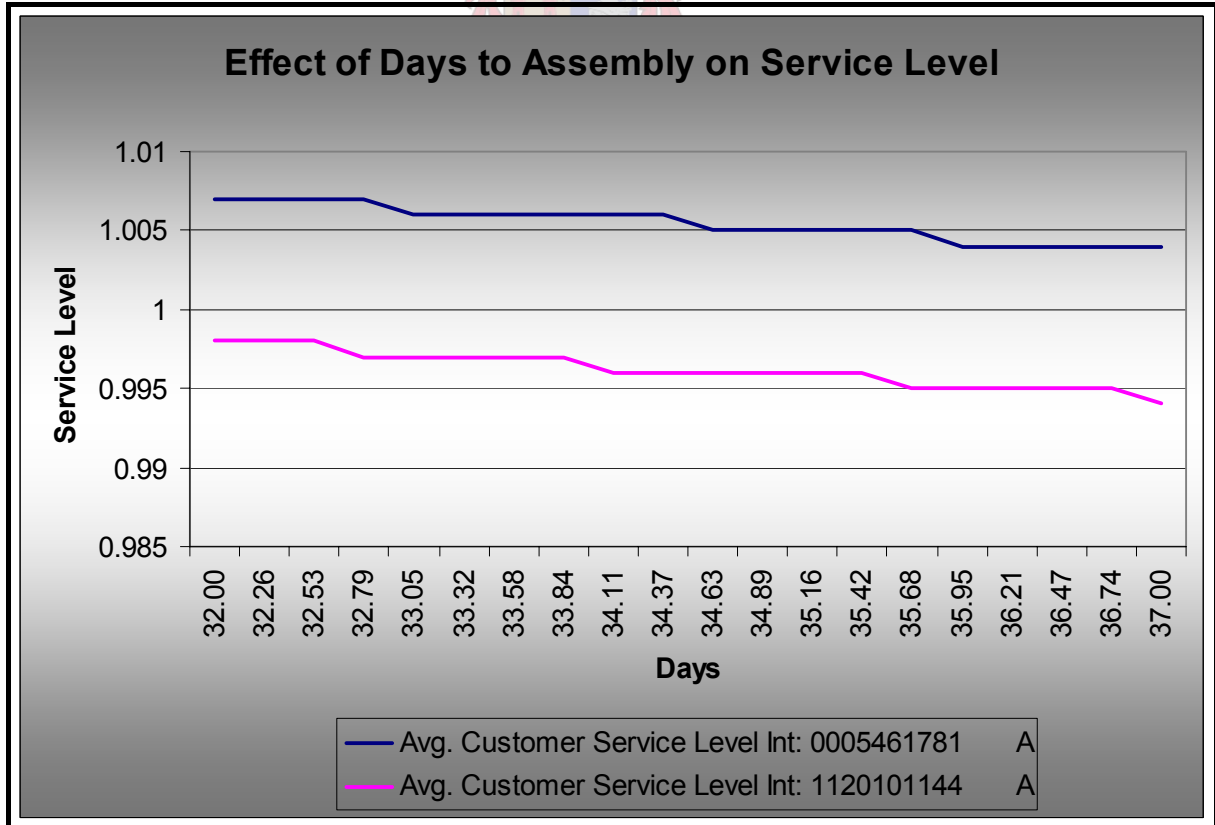


Figure 223: Effect of Days to Assembly on Service Level. Ultra Low Runners.

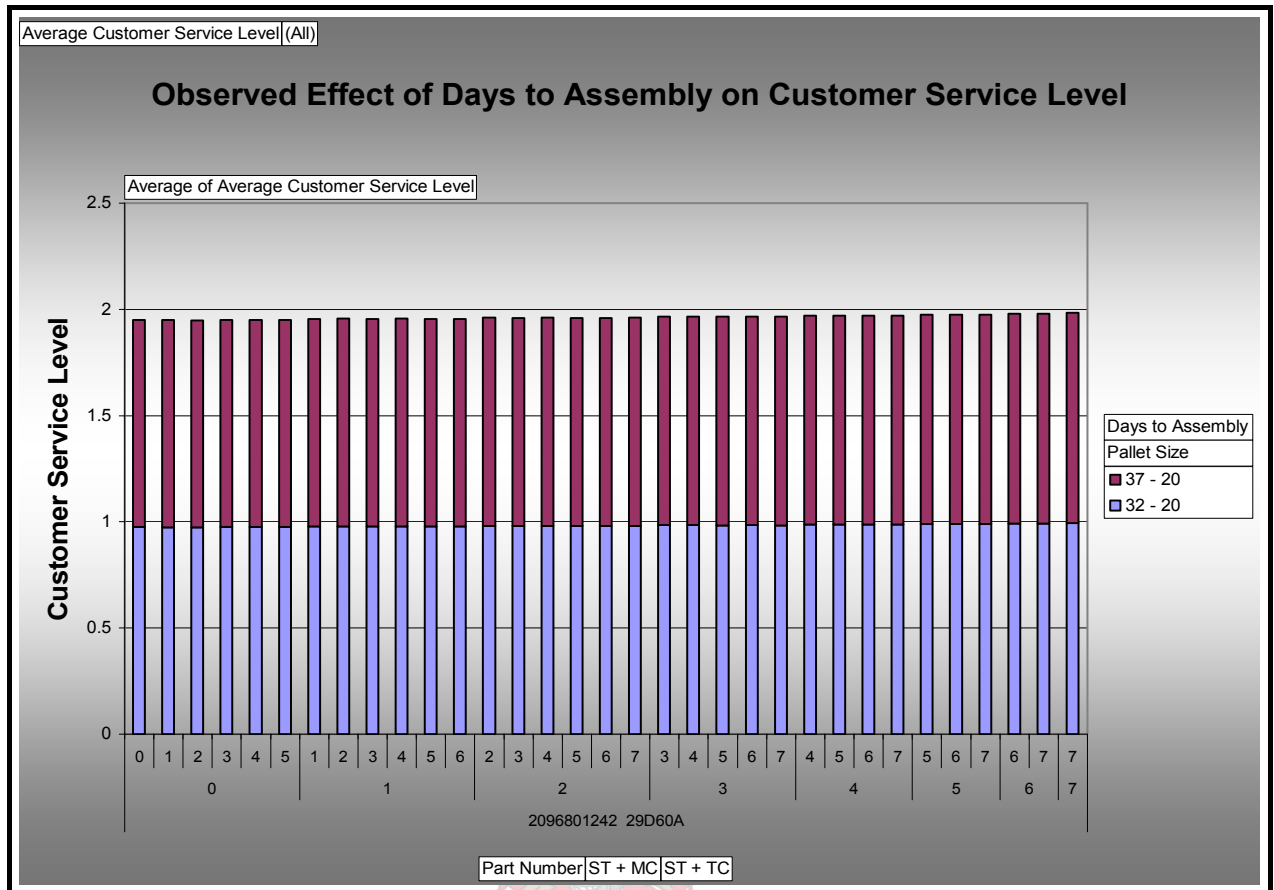


Figure 224: Observed Effect of Days to Assembly on Customer Service Level. Ultra Low Runners.

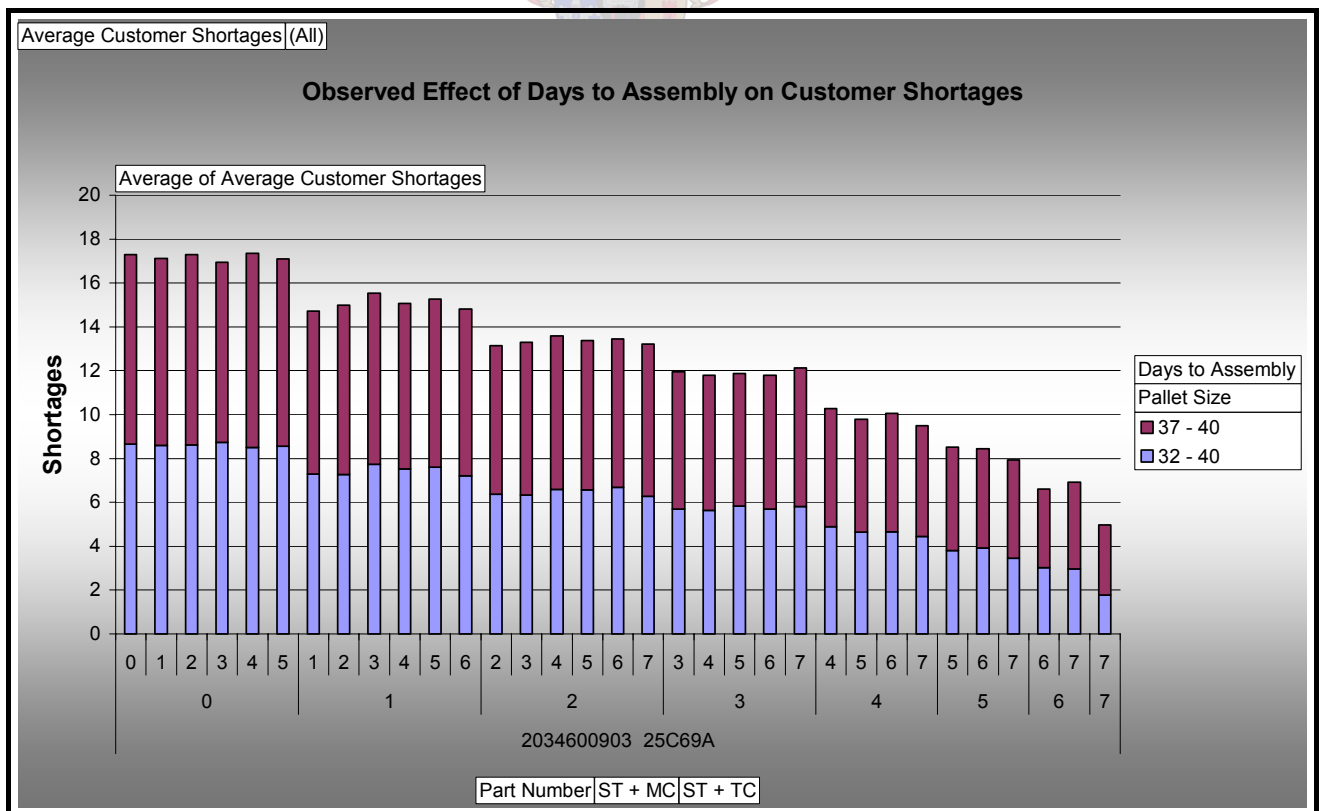


Figure 225: Observed Effect of Days to Assembly on Customer Shortages. Ultra Low Runners.

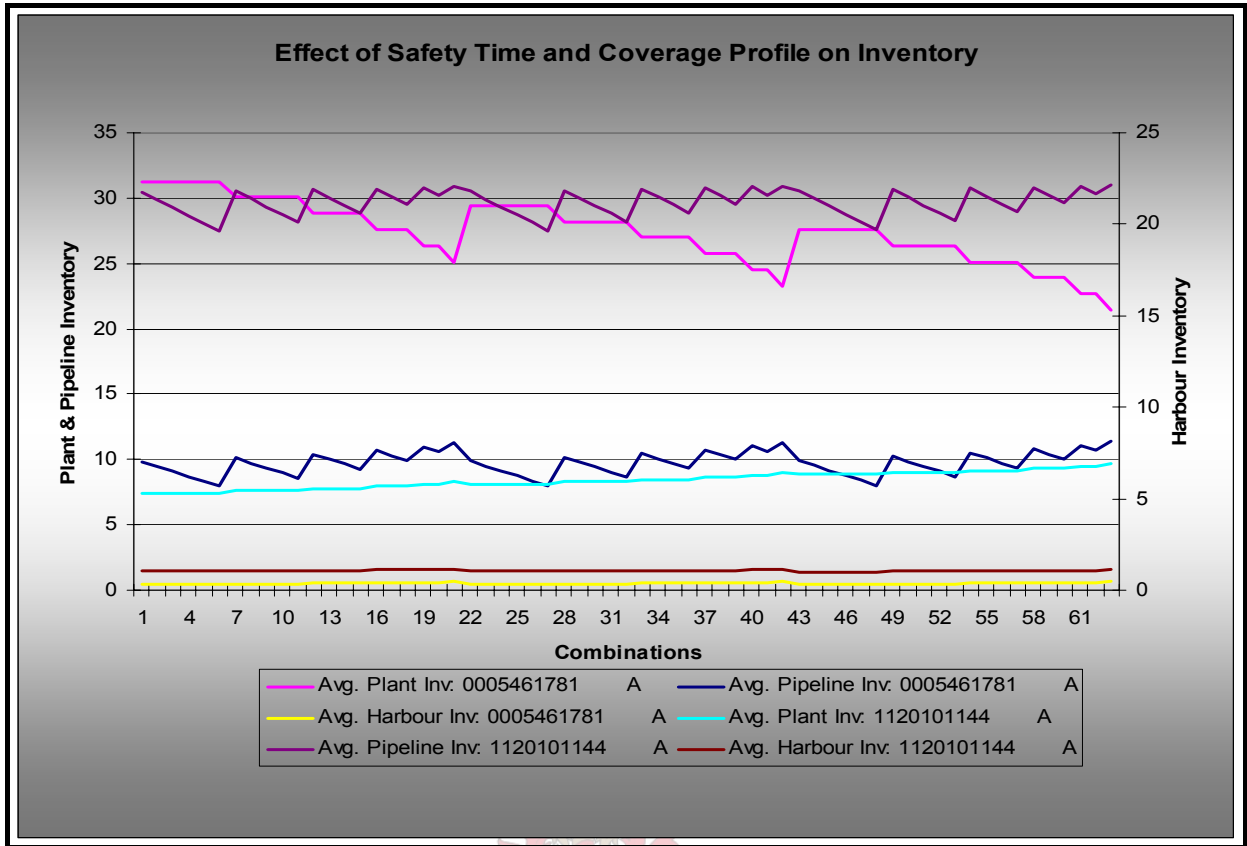


Figure 226: Effect of Safety Time & Coverage Profile Combinations on Inventory. Ultra Low Runners.

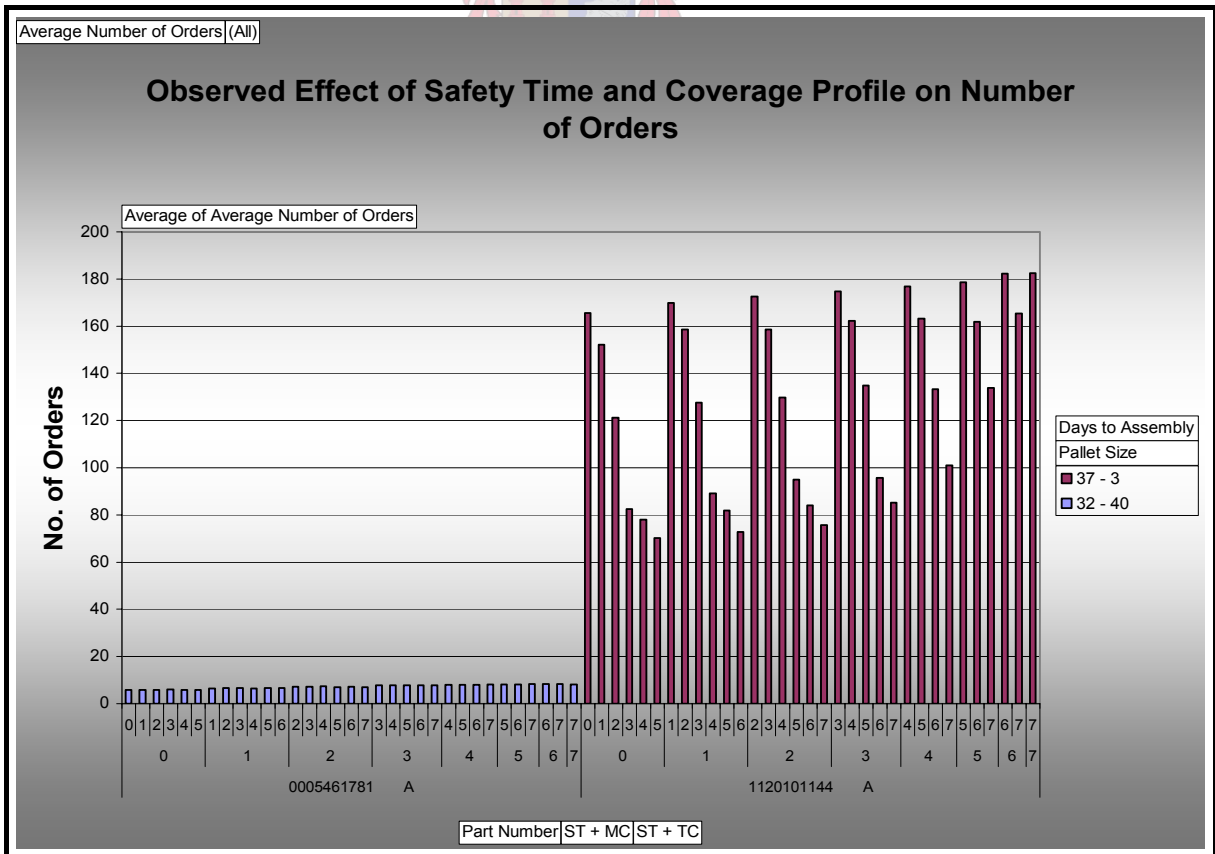


Figure 227: Observed Effect of Safety Time & Coverage Profile Combinations on Number of Orders. Ultra Low Runners.

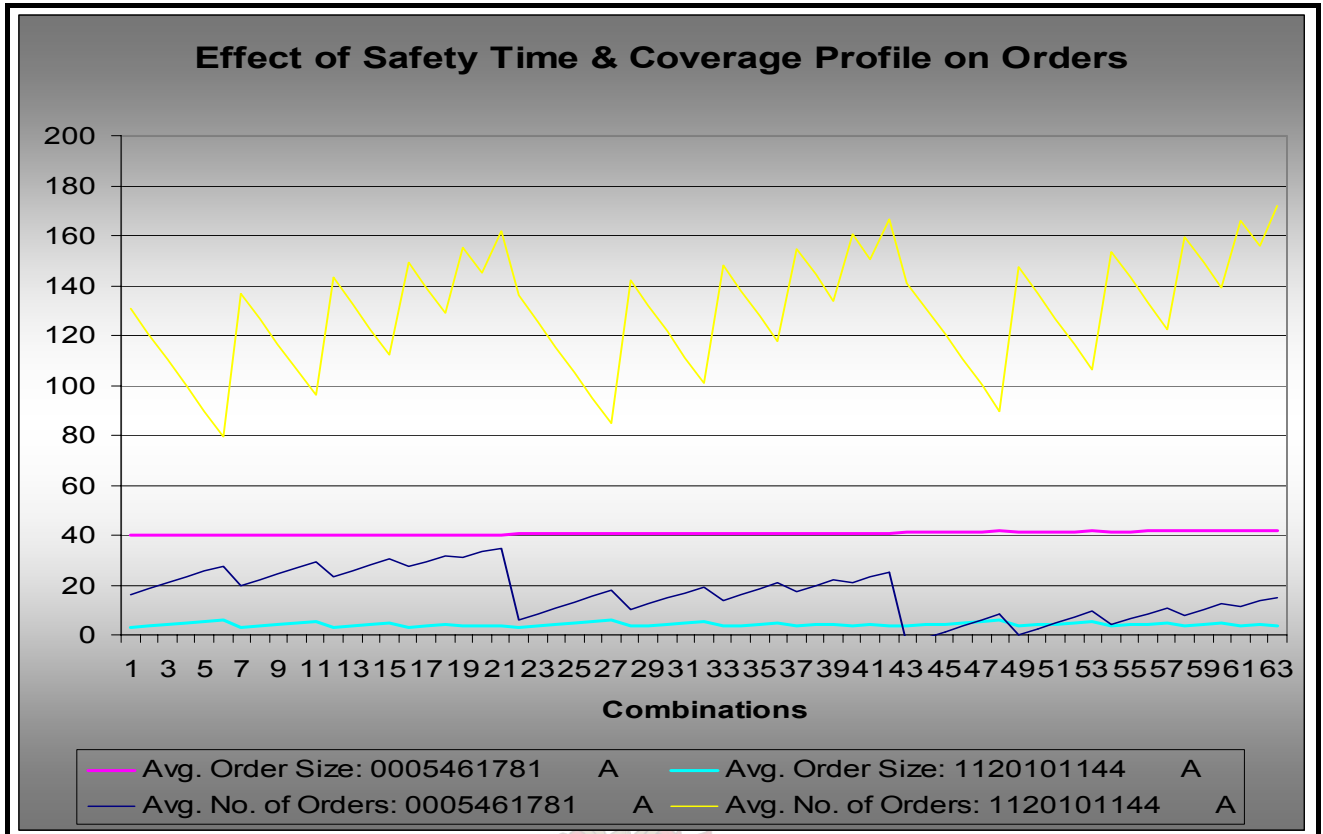


Figure 228: Effect of Safety Time & Coverage Profile Combinations on Orders. Ultra Low Runners.

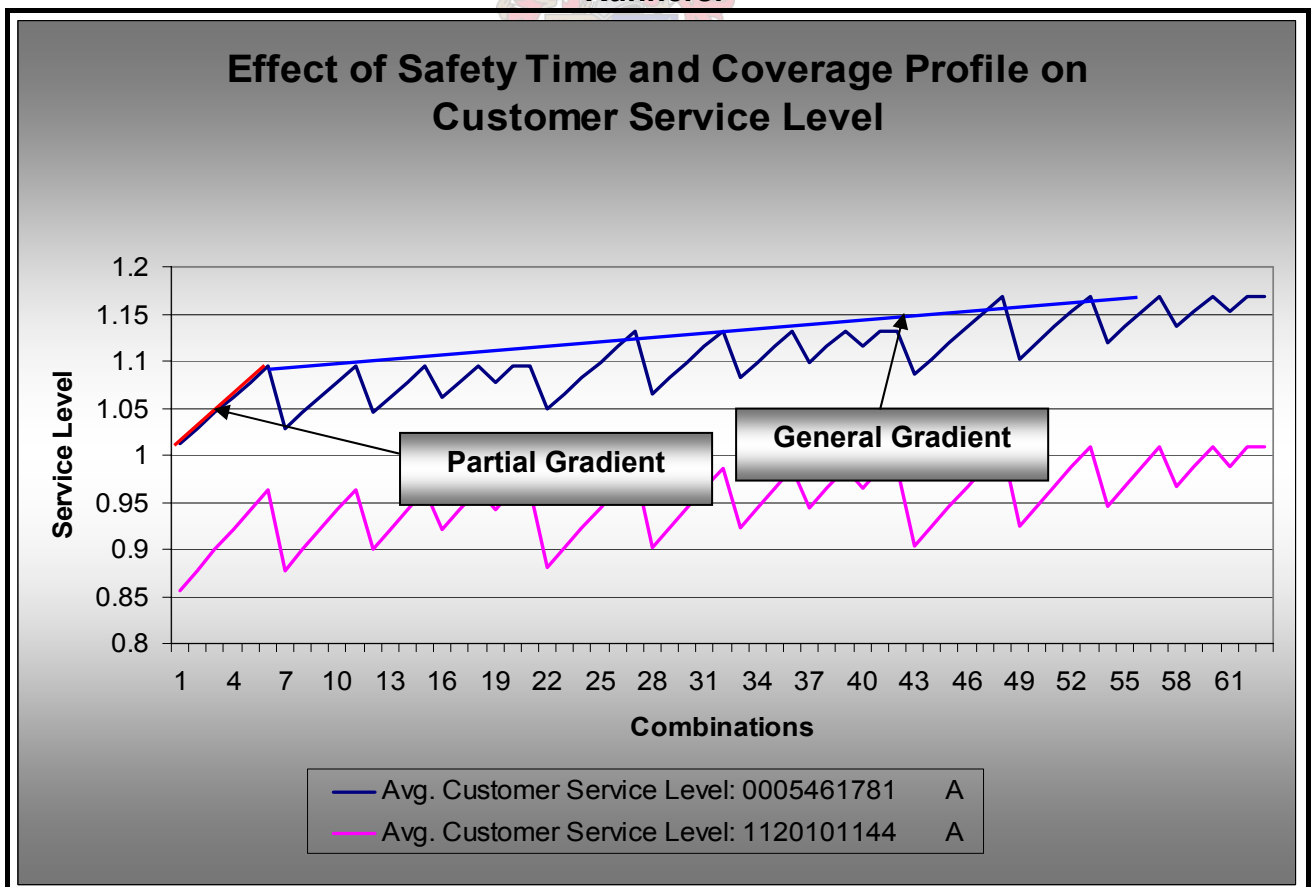


Figure 229: Effect of Safety Time & Coverage Profile Combinations on Customer Service Level. Ultra Low Runners.

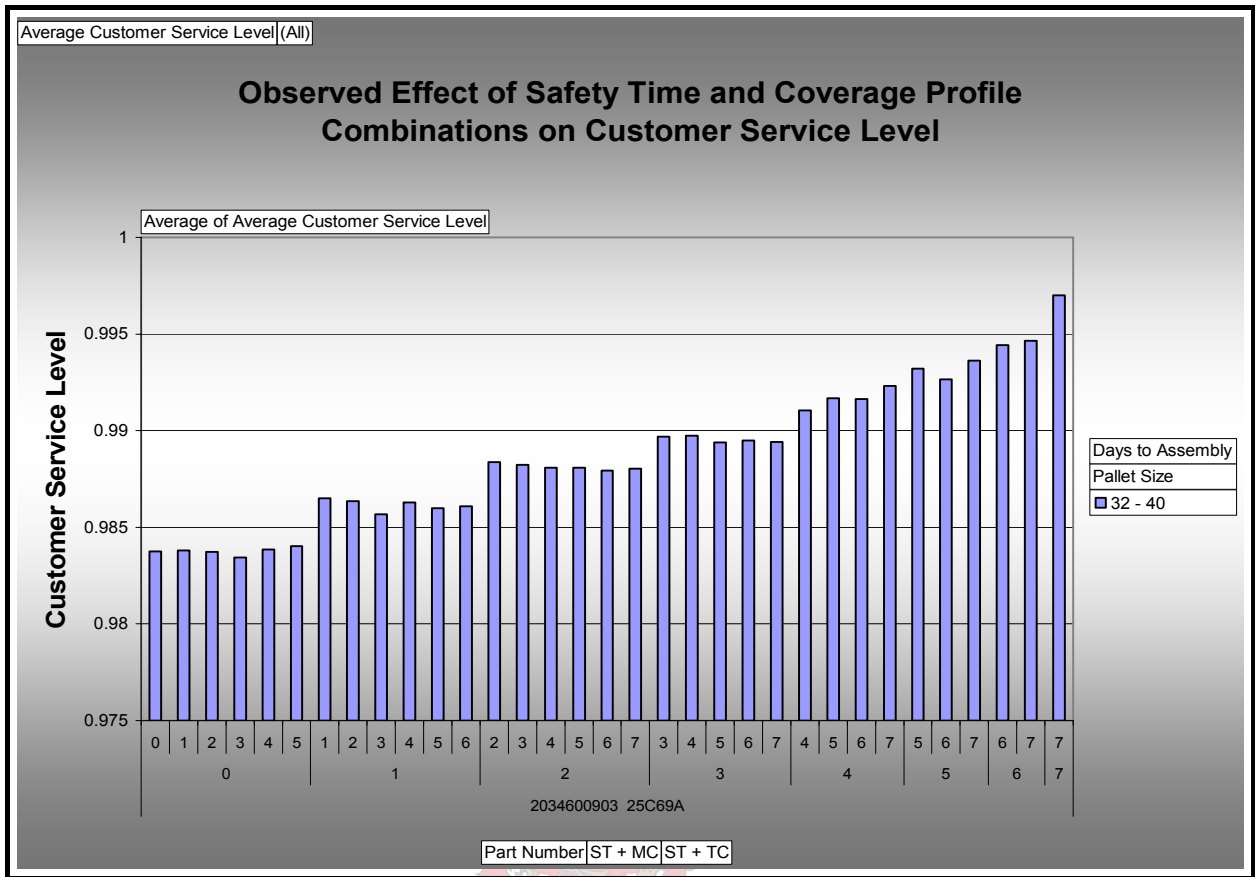


Figure 230: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Service Level. Ultra Low Runners.

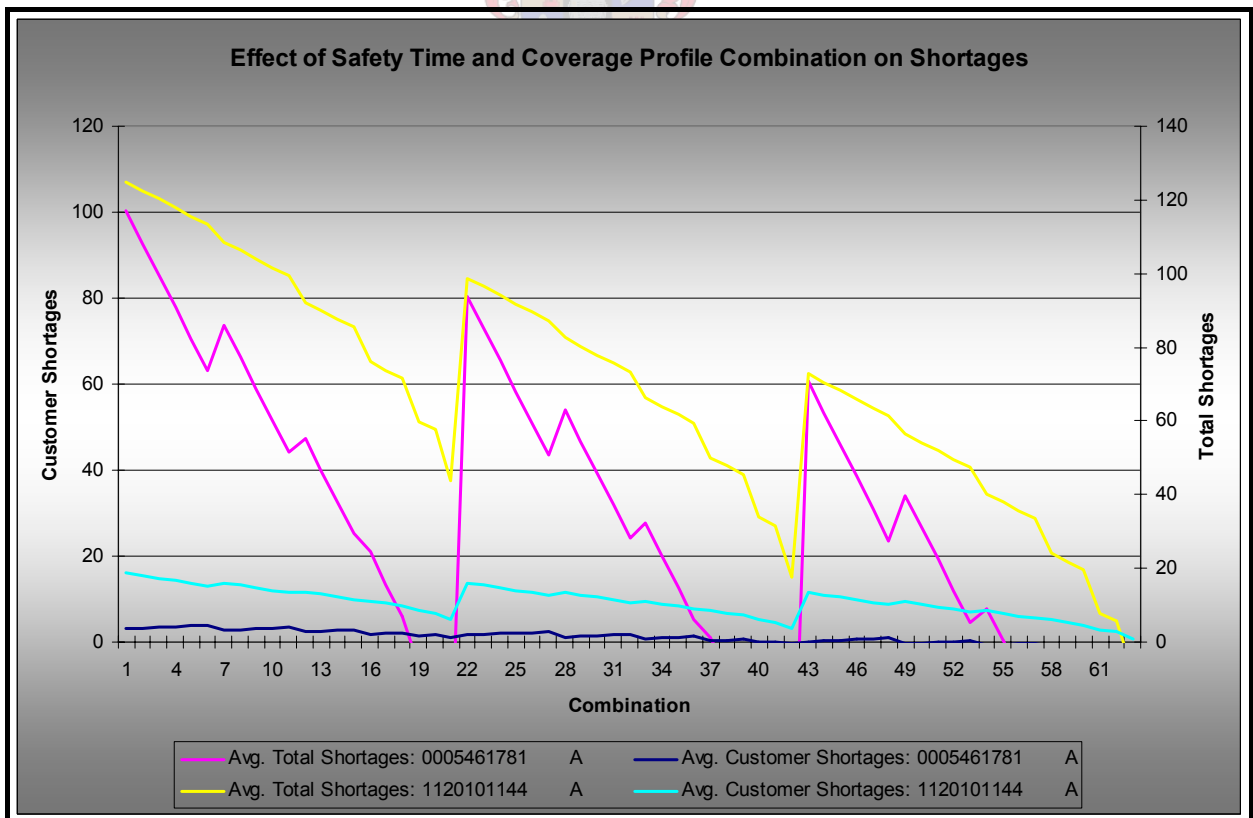


Figure 231: Effect of Safety Time & Coverage Profile Combinations on Shortages. Ultra Low Runners.

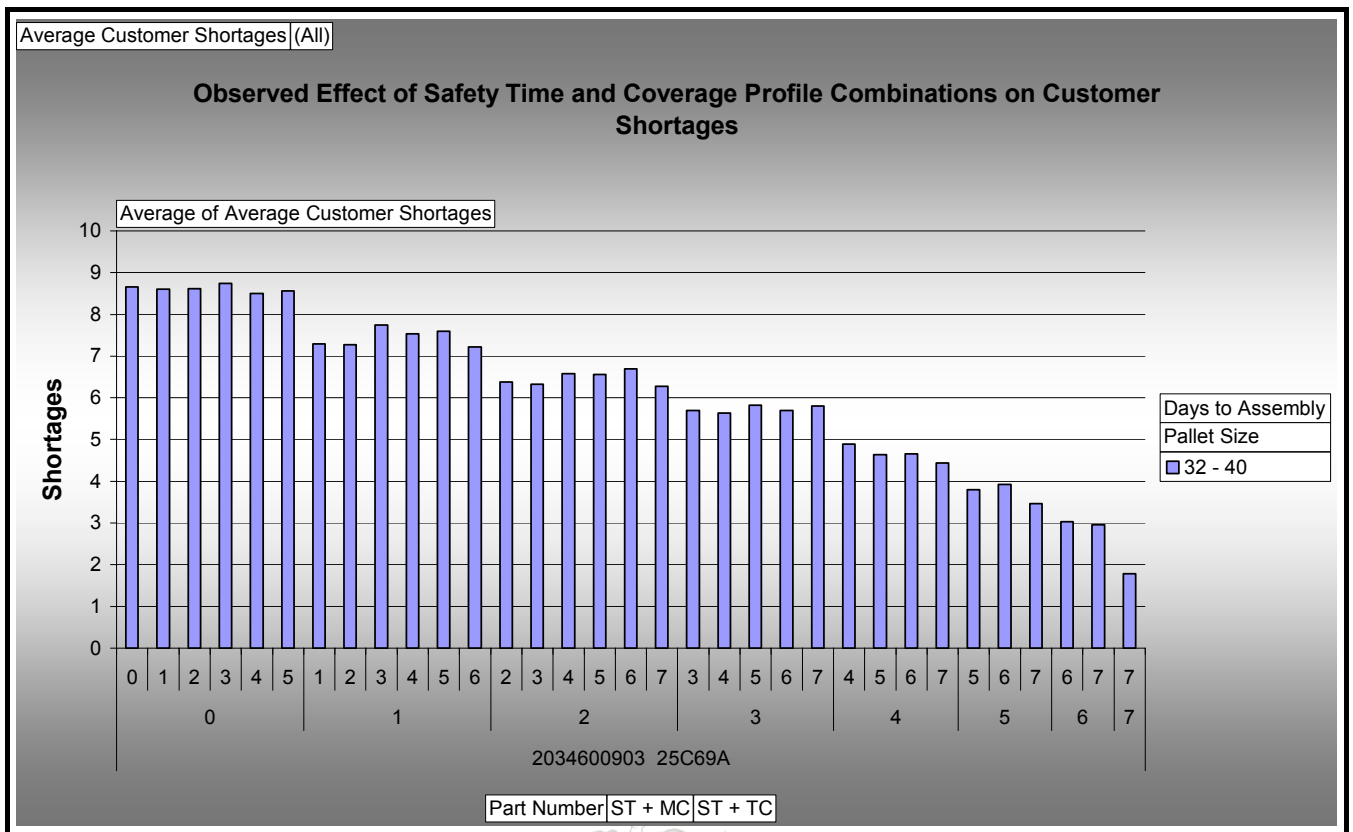


Figure 232: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Shortages. Ultra Low Runners.



Low Runners.



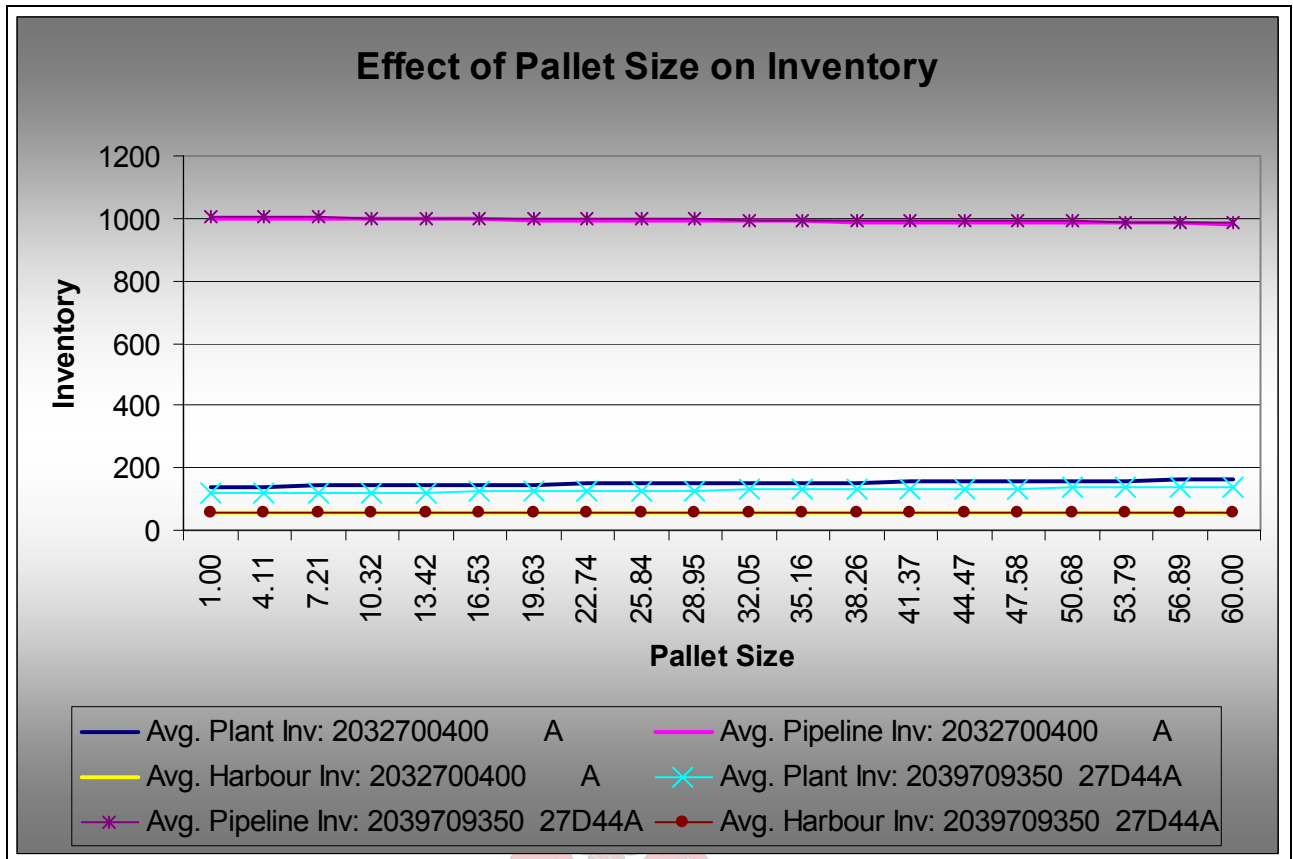


Figure 233: Effect of Palletization on Inventory. Low Runners.

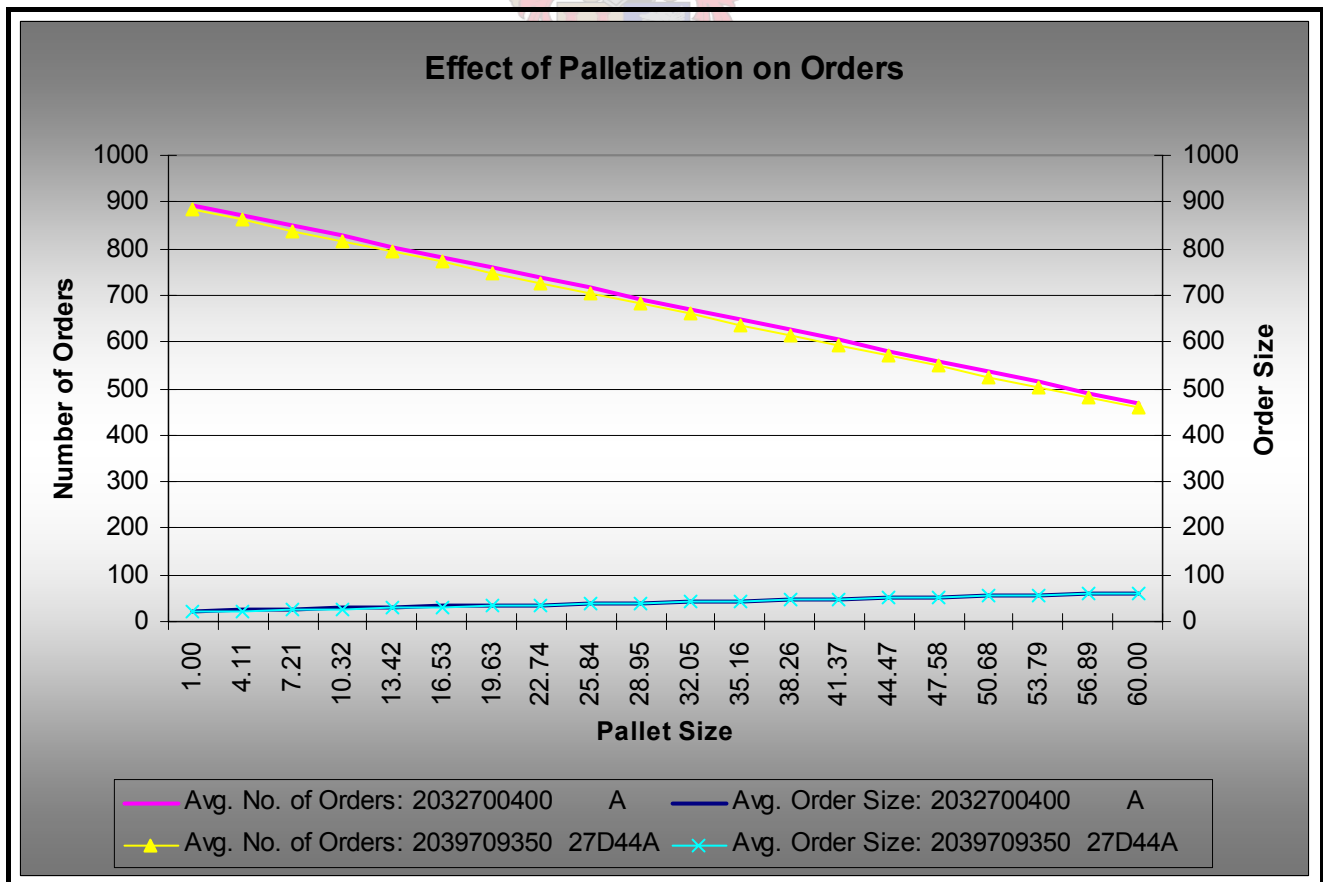


Figure 234: Effect of Palletization on Orders. Low Runners.

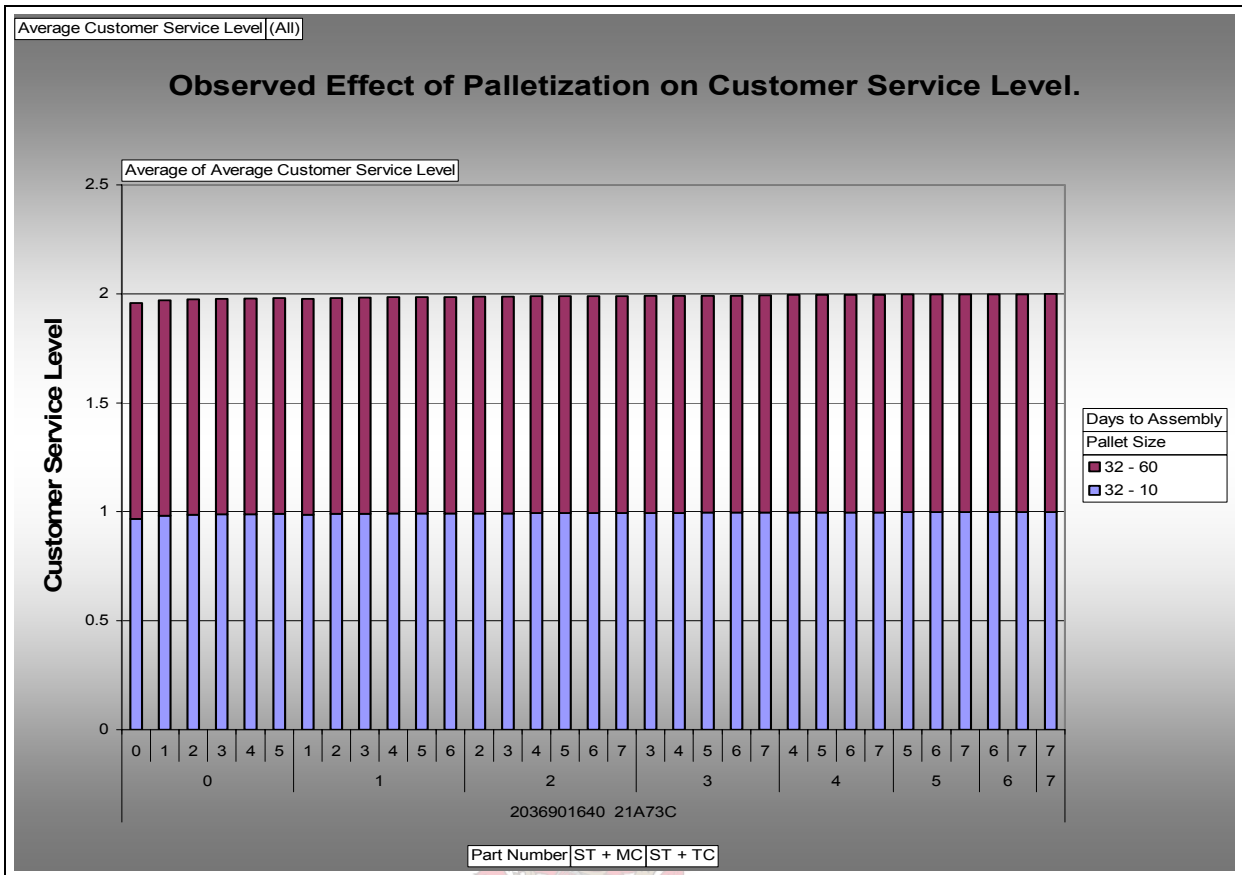


Figure 235: Observed Effect of Palletization on Customer Service Level. Low Runners.

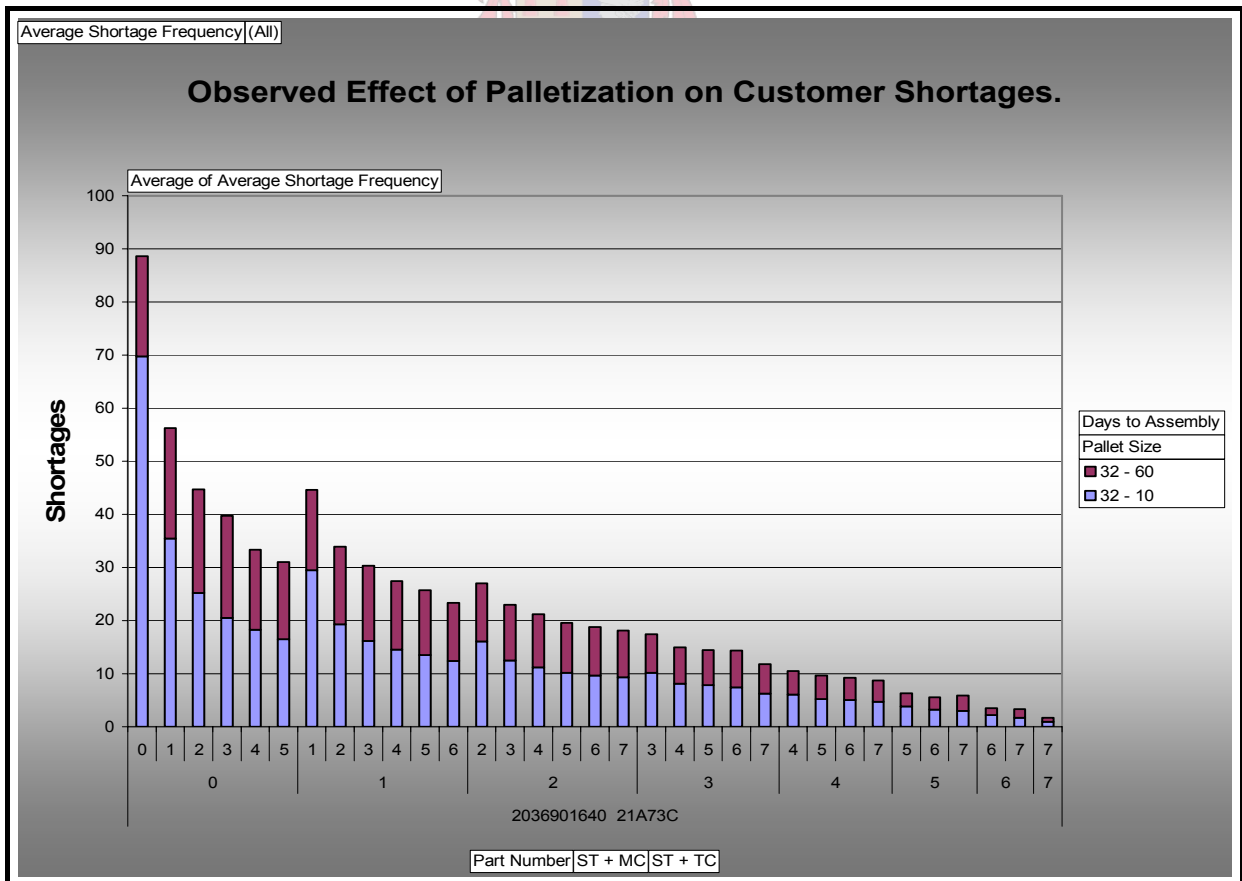


Figure 236: Observed Effect of Palletization Customer Shortages. Low Runners.

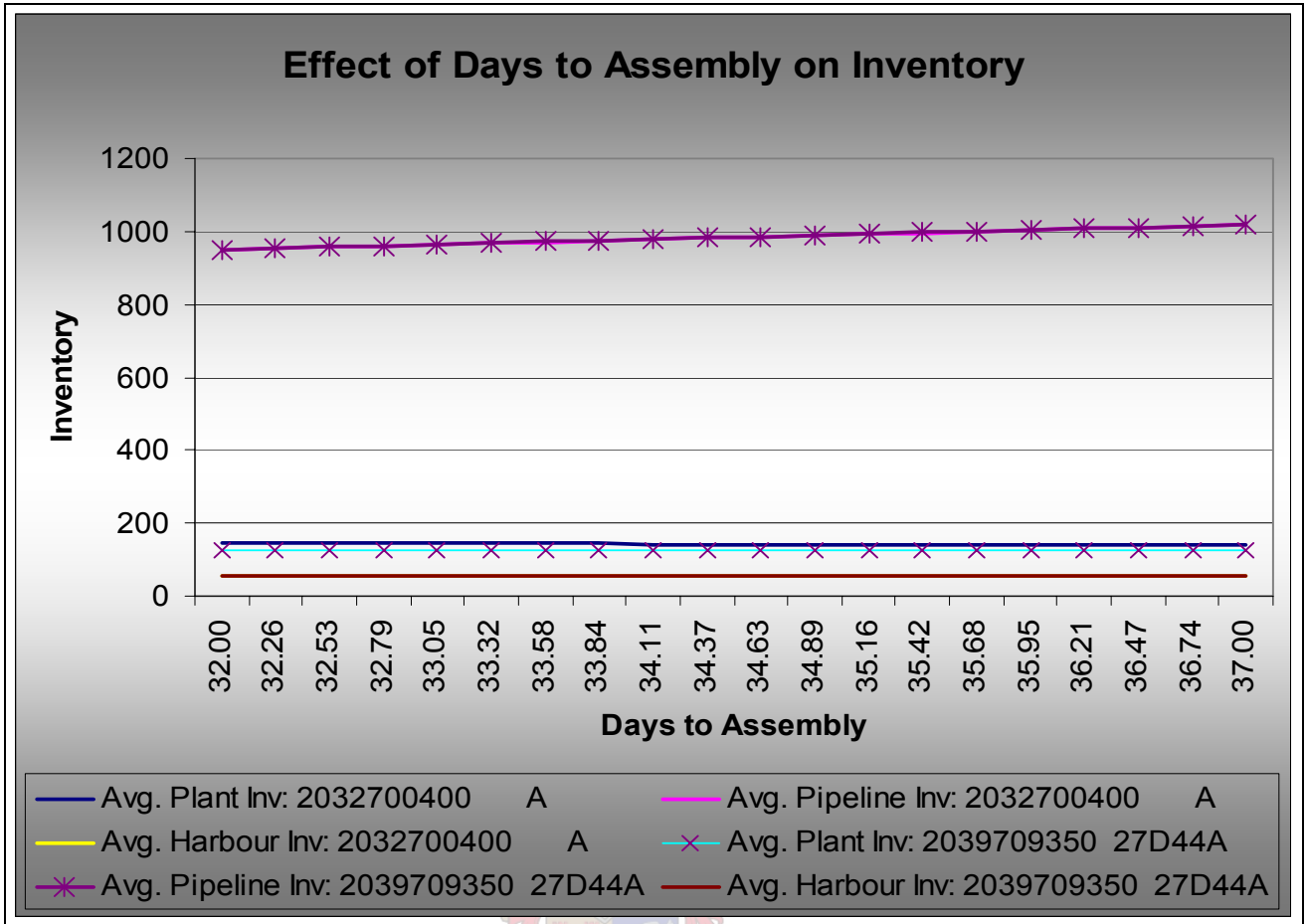


Figure 237: Effect of Days to Assembly on Inventory. Low Runners.

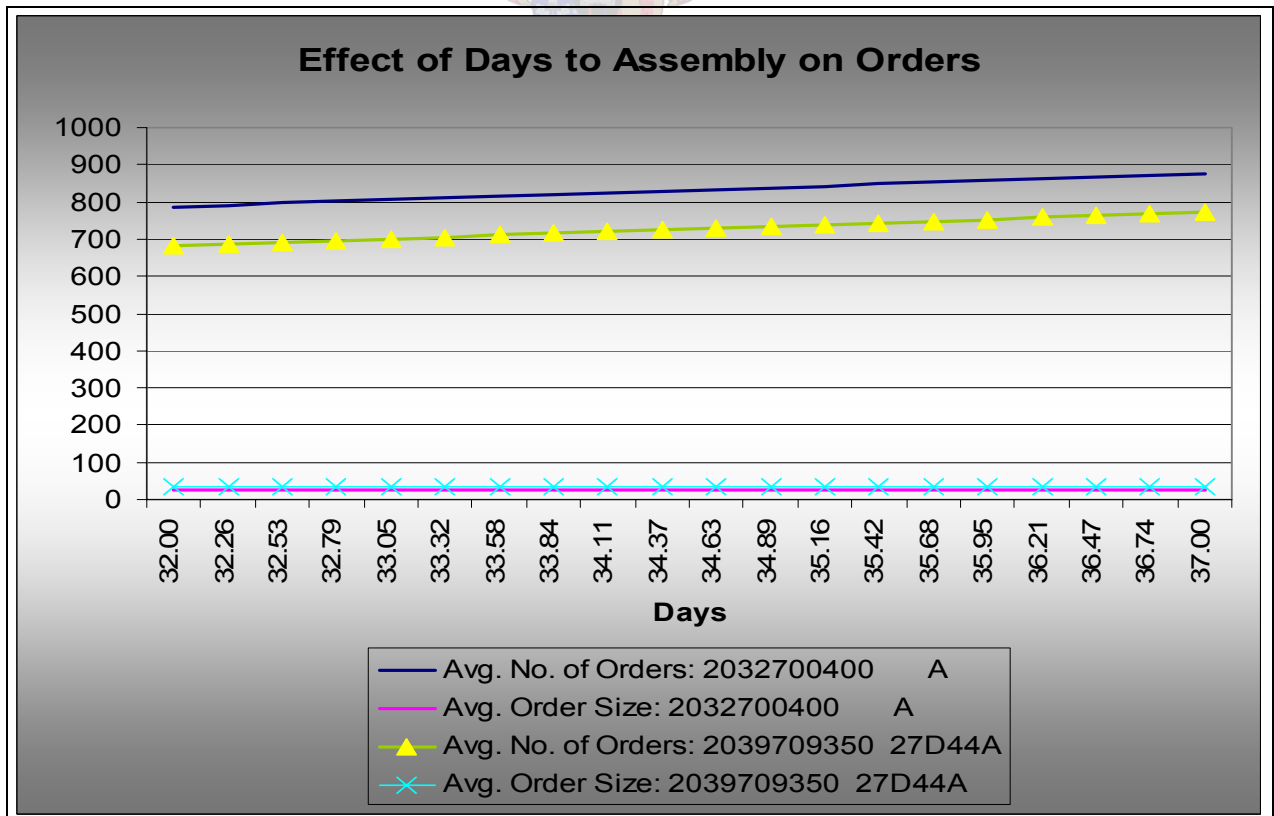


Figure 238: Effect of Days to Assembly on Orders. Low Runners.

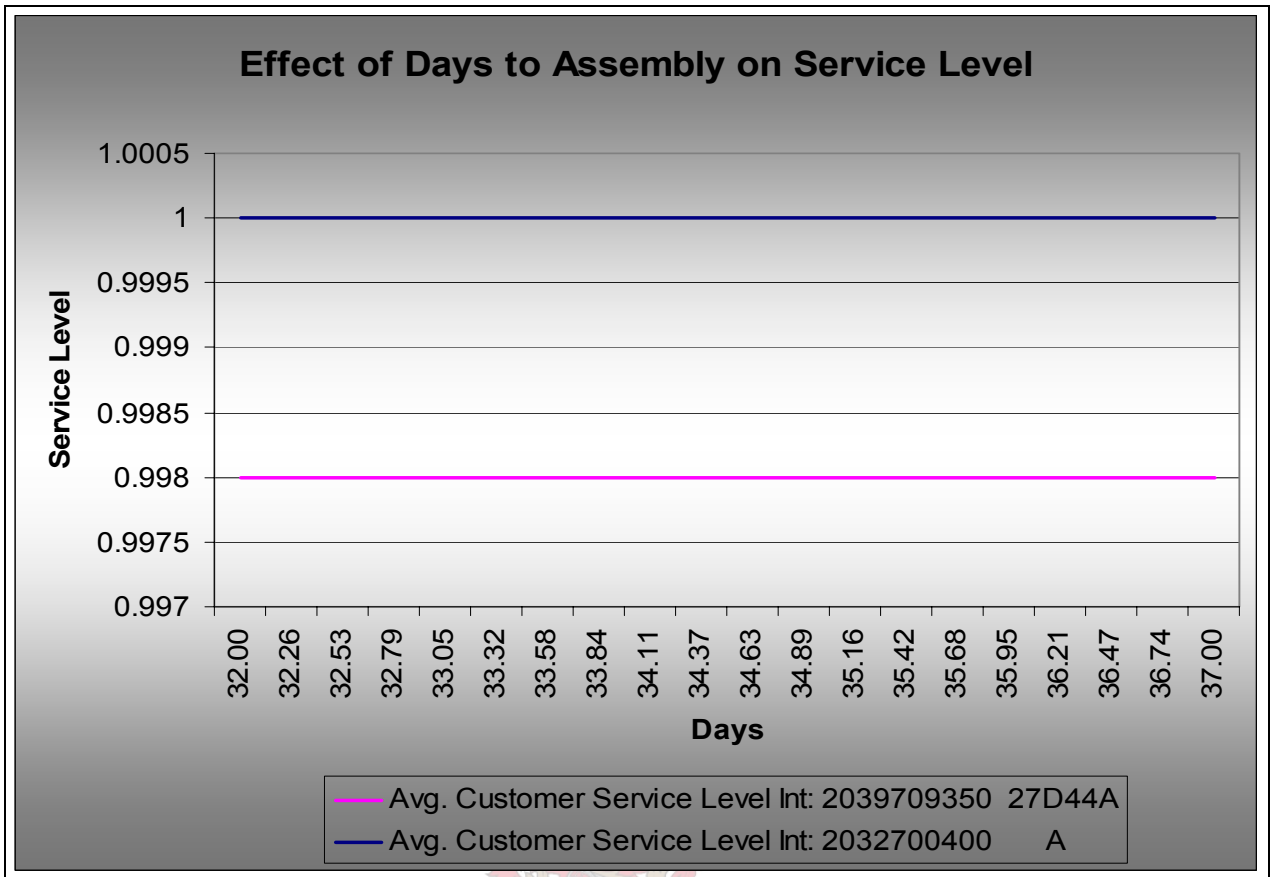


Figure 239: Effect of Days to Assembly on Customer Service Level. Low Runners.

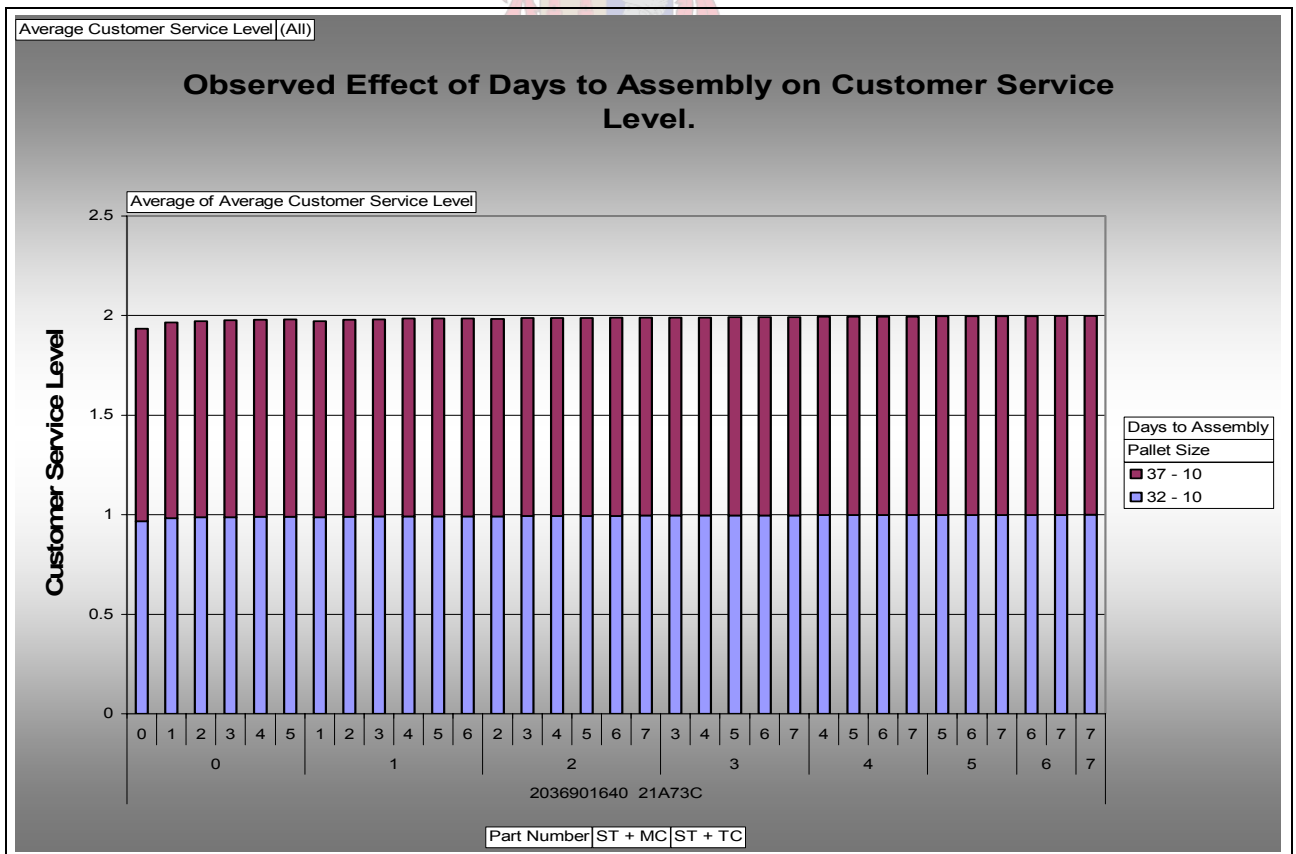


Figure 240: Observed Effect of Days to Assembly on Customer Service Level. Low Runners.

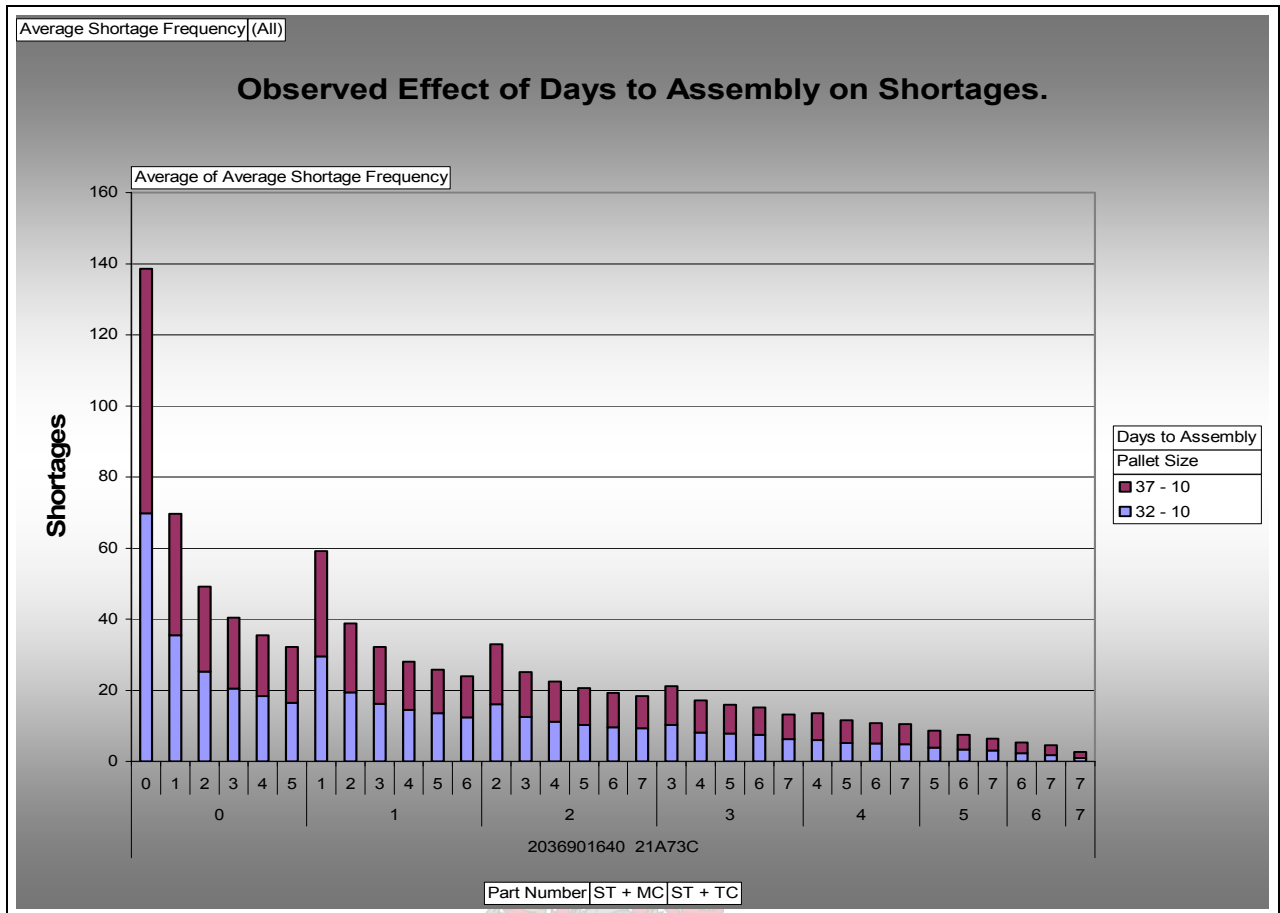


Figure 241: Observed Effect of Days to Assembly on Customer Shortages. Low Runners.

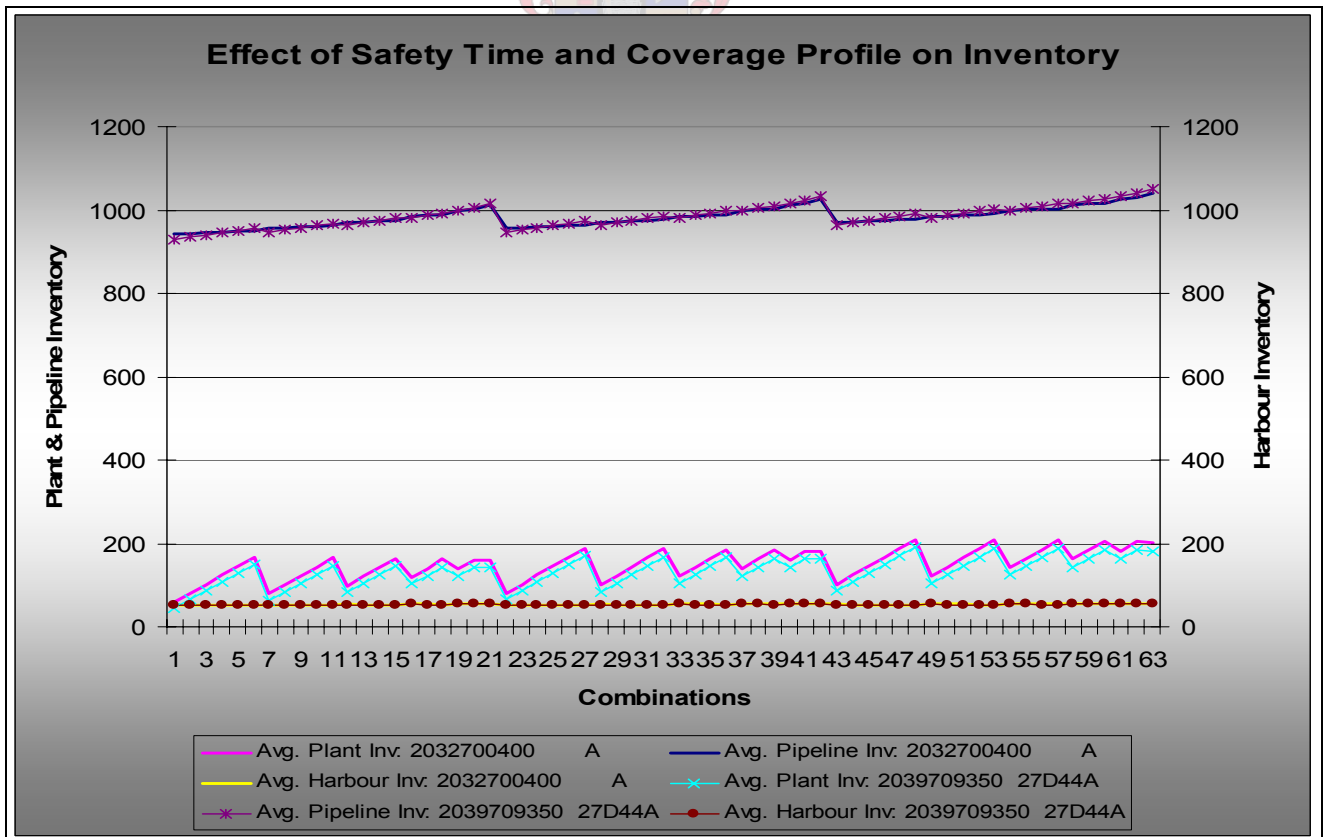


Figure 242: Effect of Safety Time & Coverage Profile on Inventory. Low Runners.

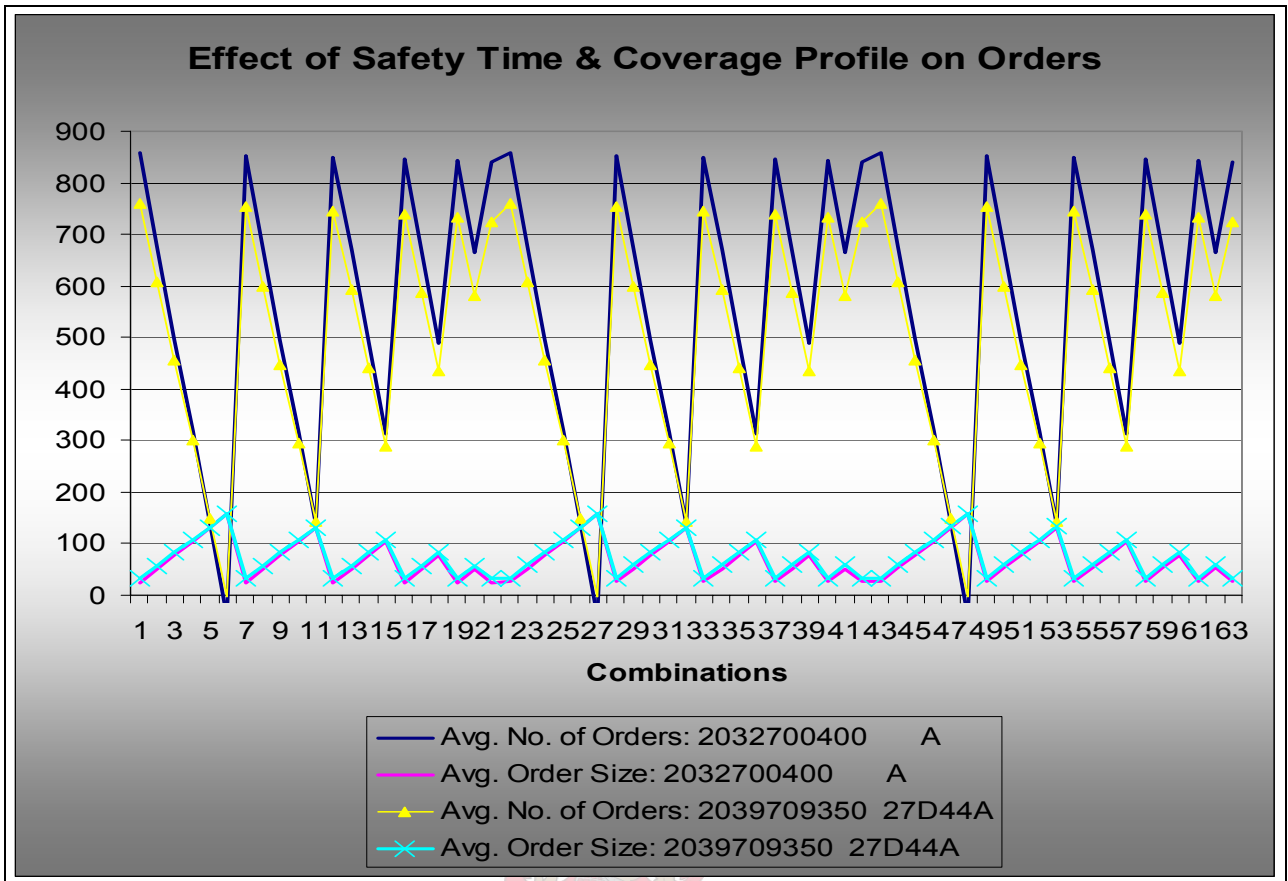


Figure 243: Effect of Safety Time & Coverage Profile on Orders. Low Runners.

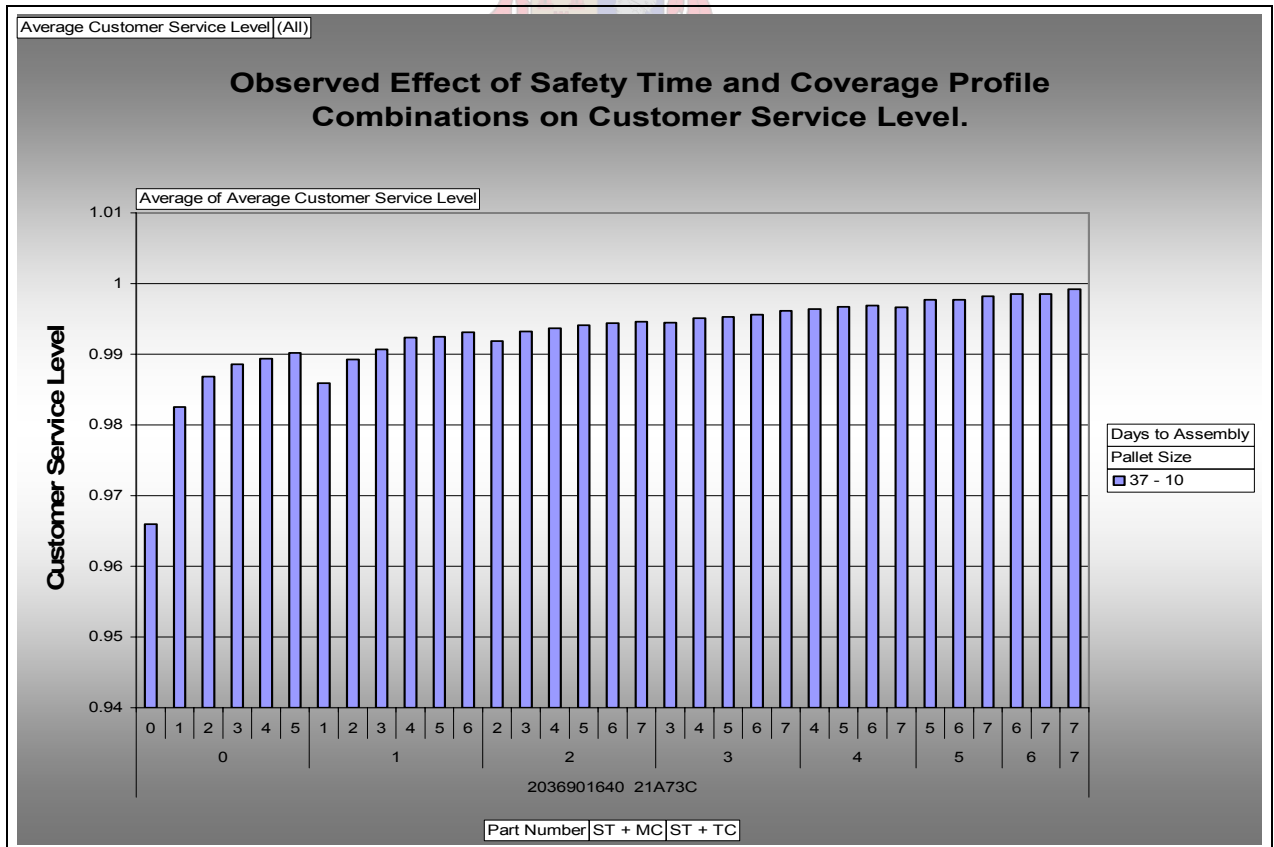


Figure 244: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Service Level. Low Runners.

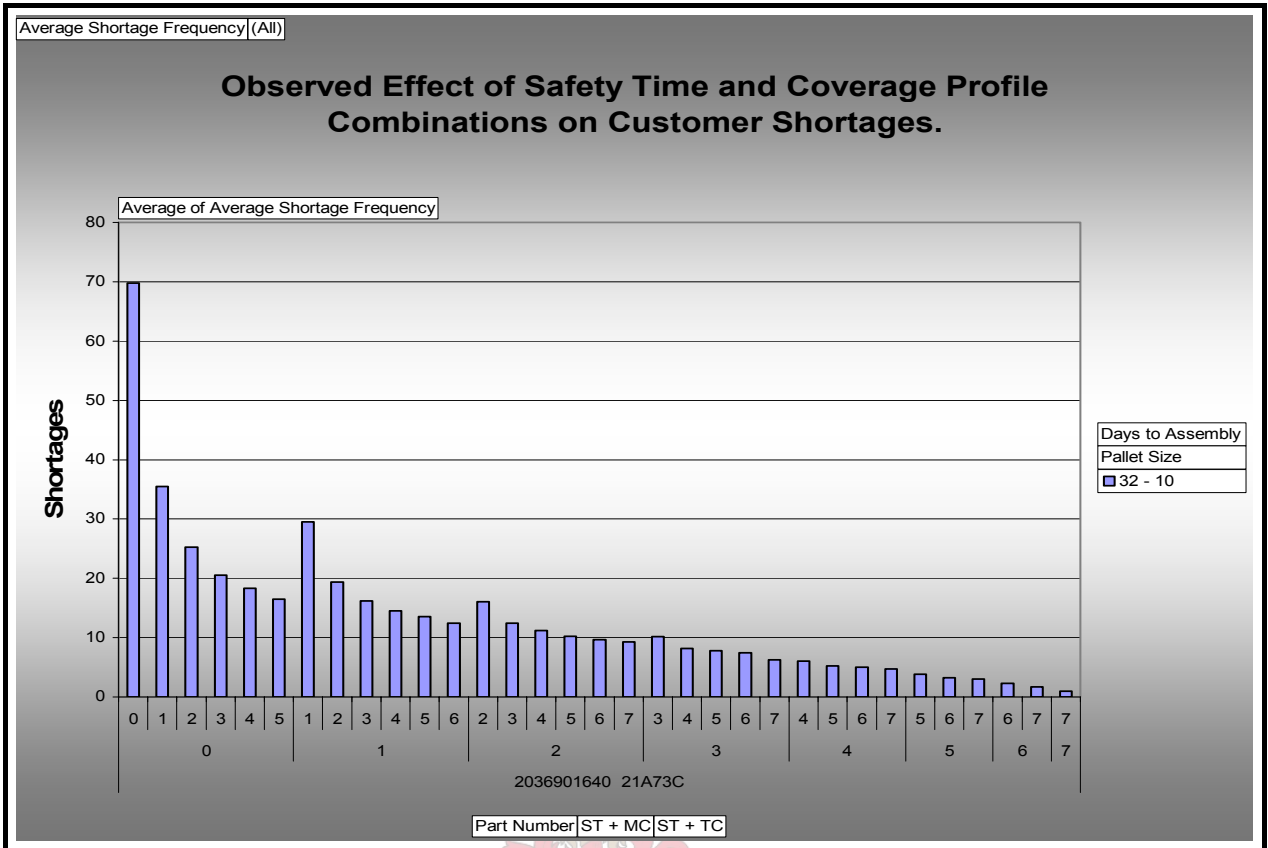


Figure 245: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Shortages. Low Runners.

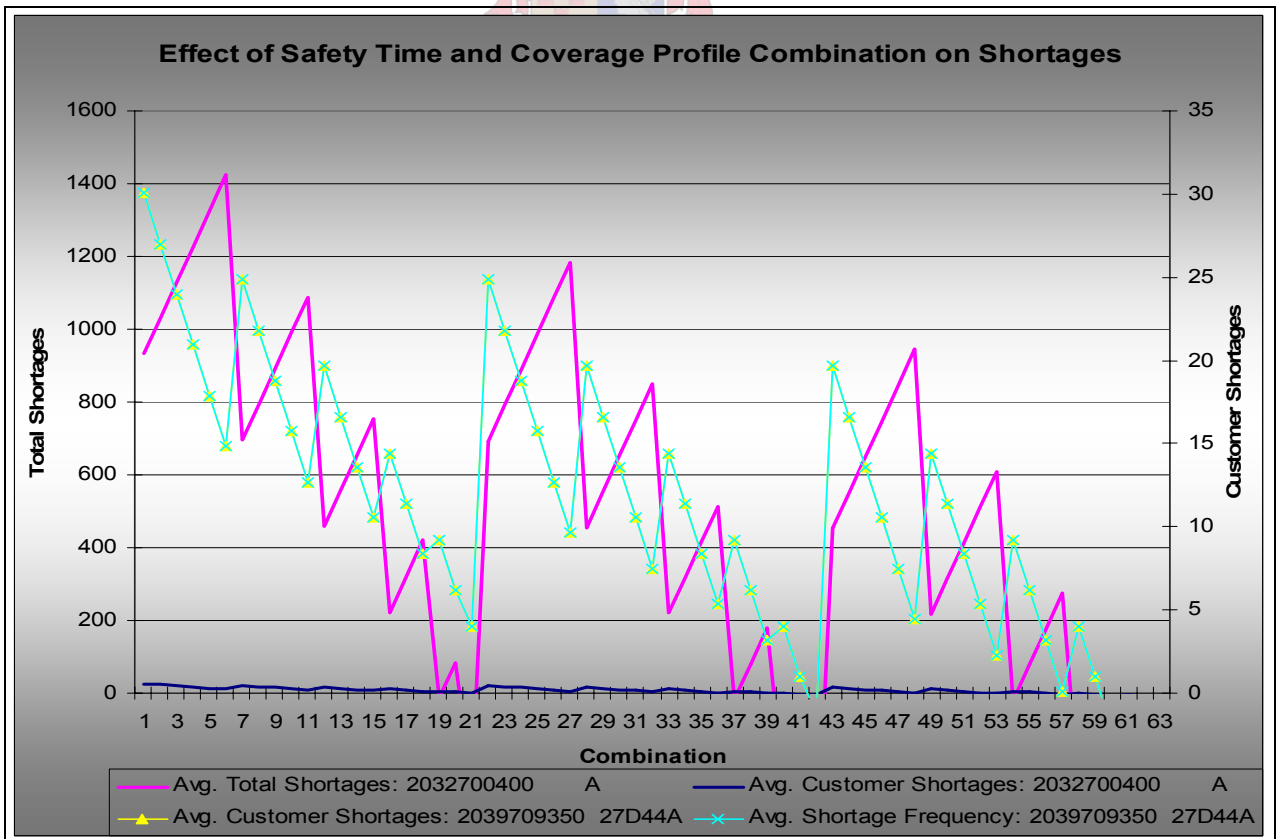


Figure 246: Effect of Safety Time & Coverage Profile Combinations on Shortages. Low Runners.



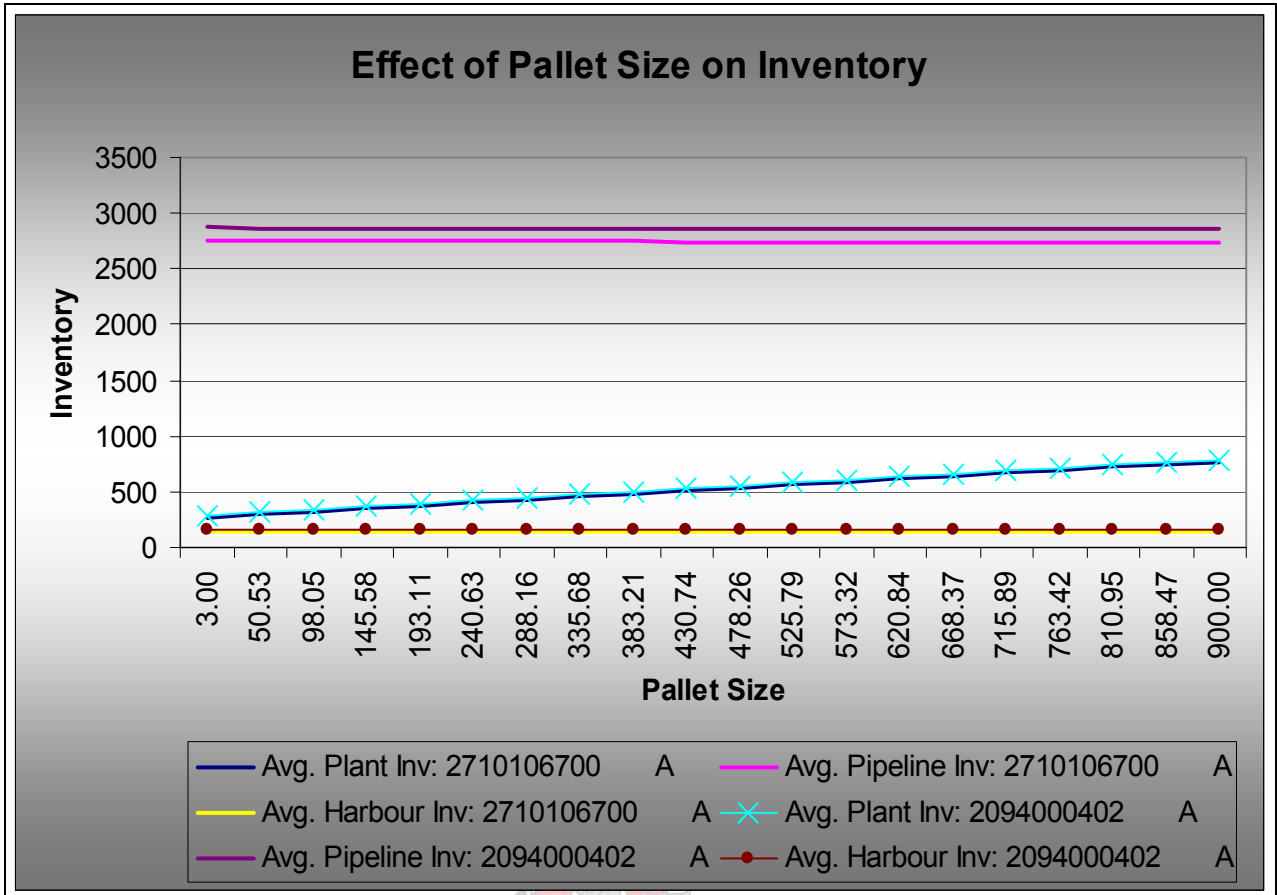


Figure 247: Effect of Palletization on Inventory. Medium Runners.

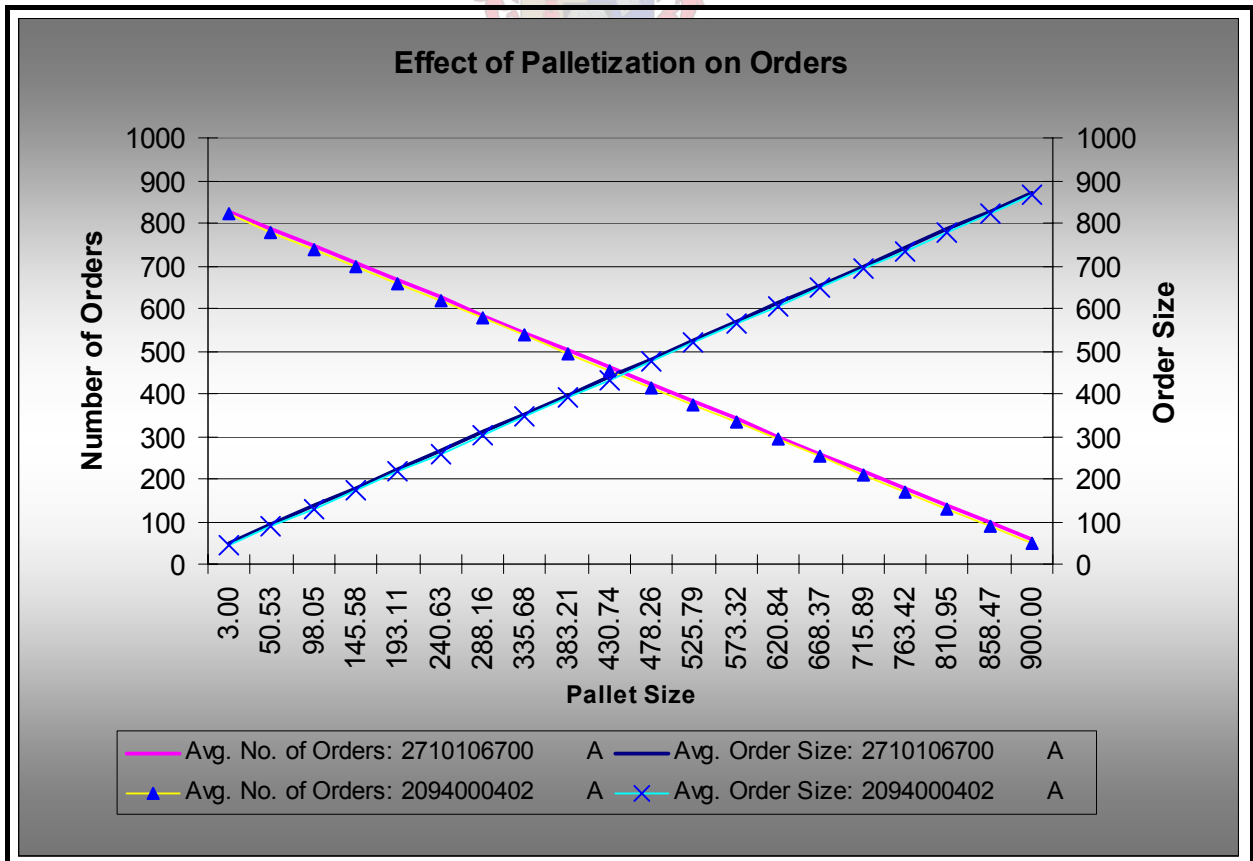


Figure 248: Effect of Palletization on Orders. Medium Runners.

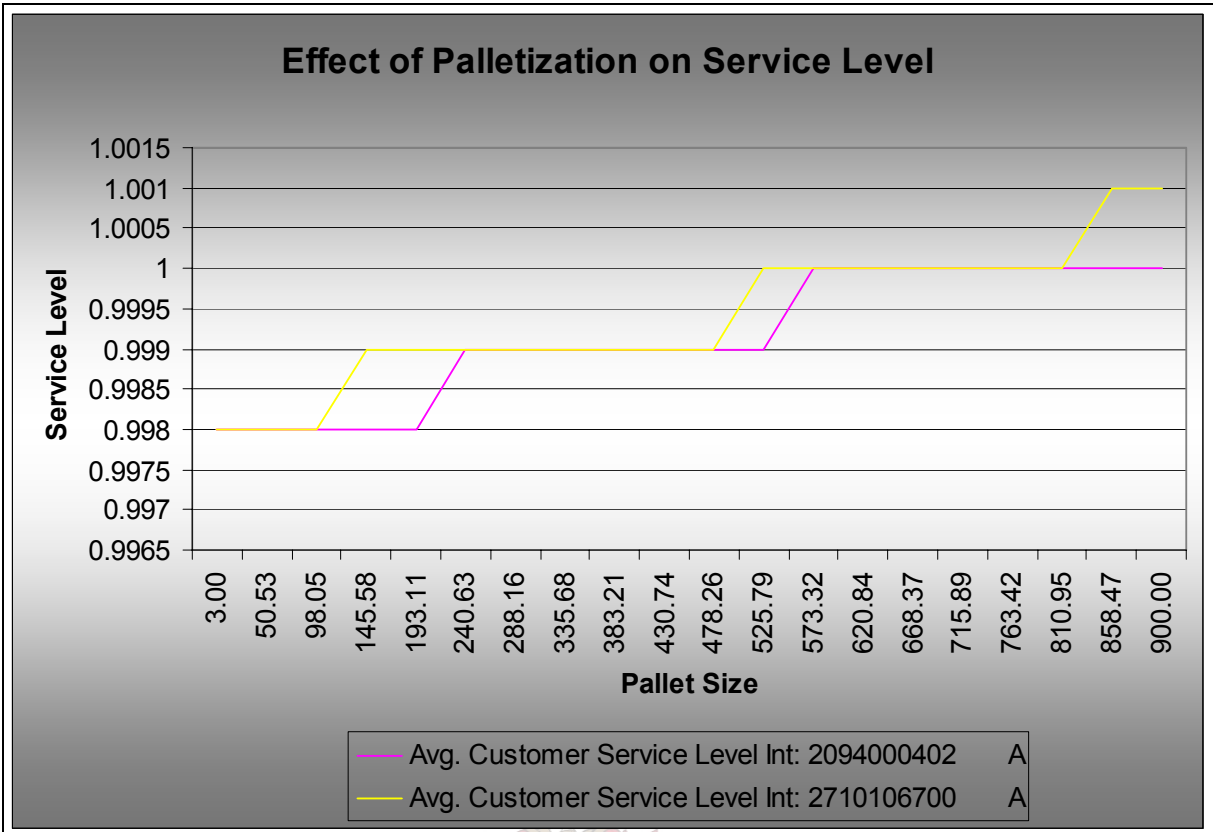


Figure 249: Effect of Palletization on Customer Service Level. Medium Runners.

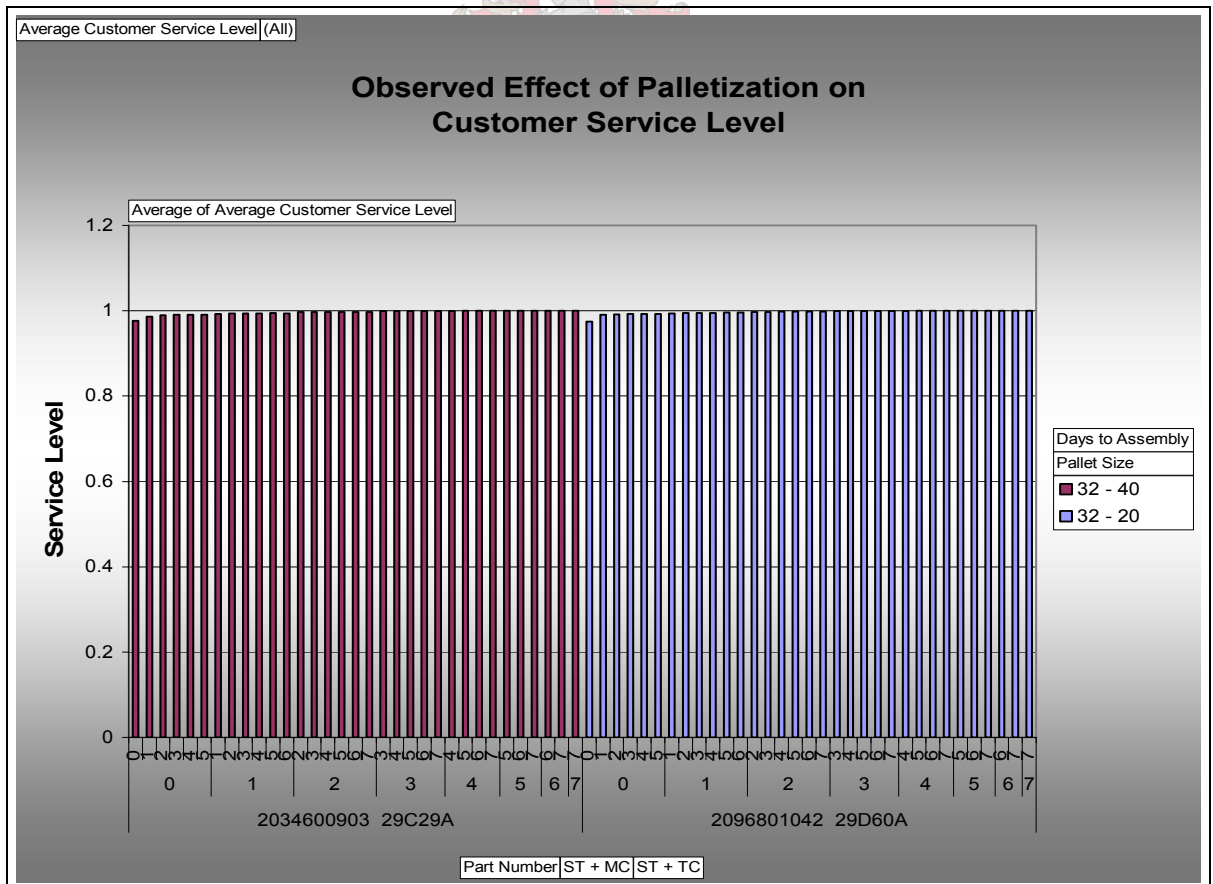


Figure 250: Observed Effect of Palletization on Customer Service Level. Medium Runners.

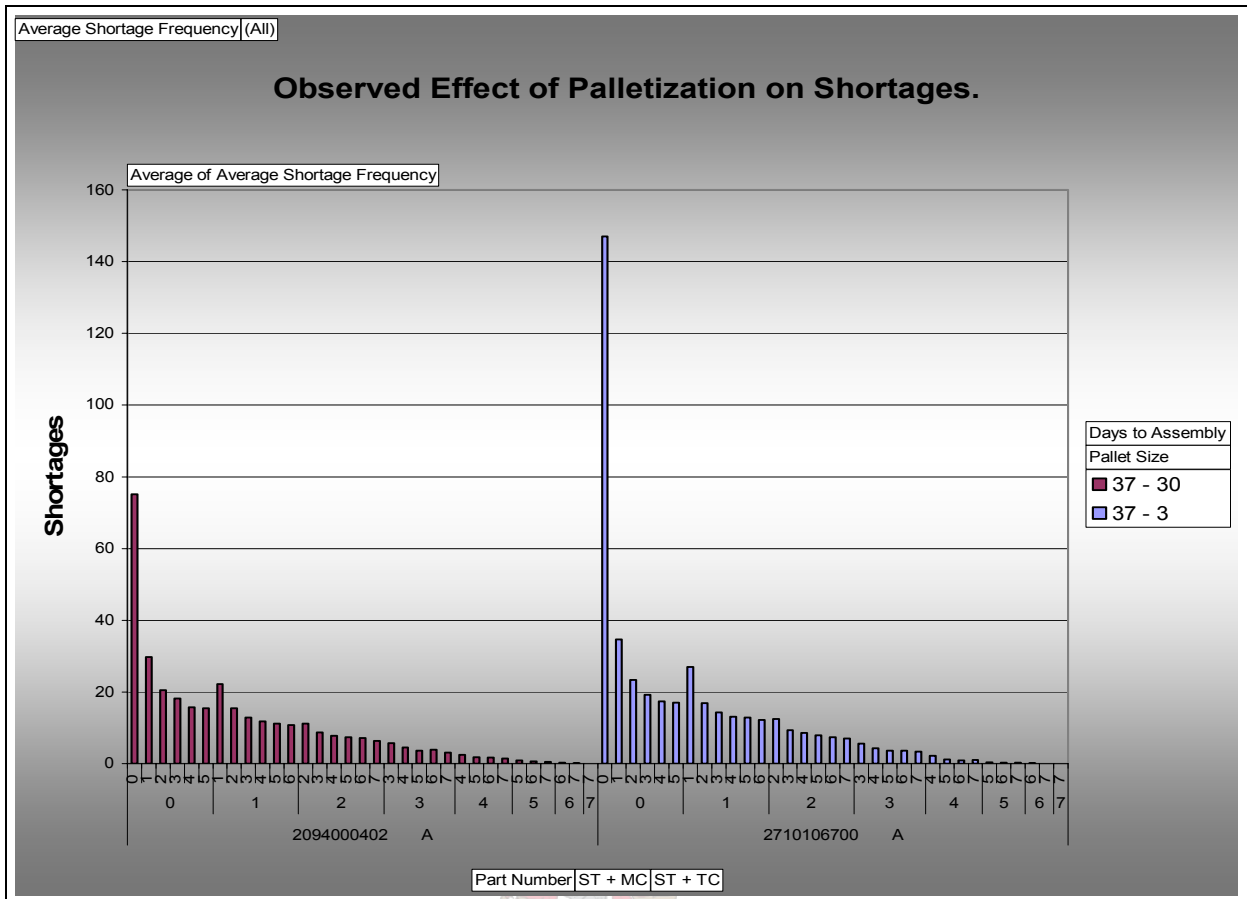


Figure 251: Observed Effect of Palletization on Customer Shortages. Medium Runners.

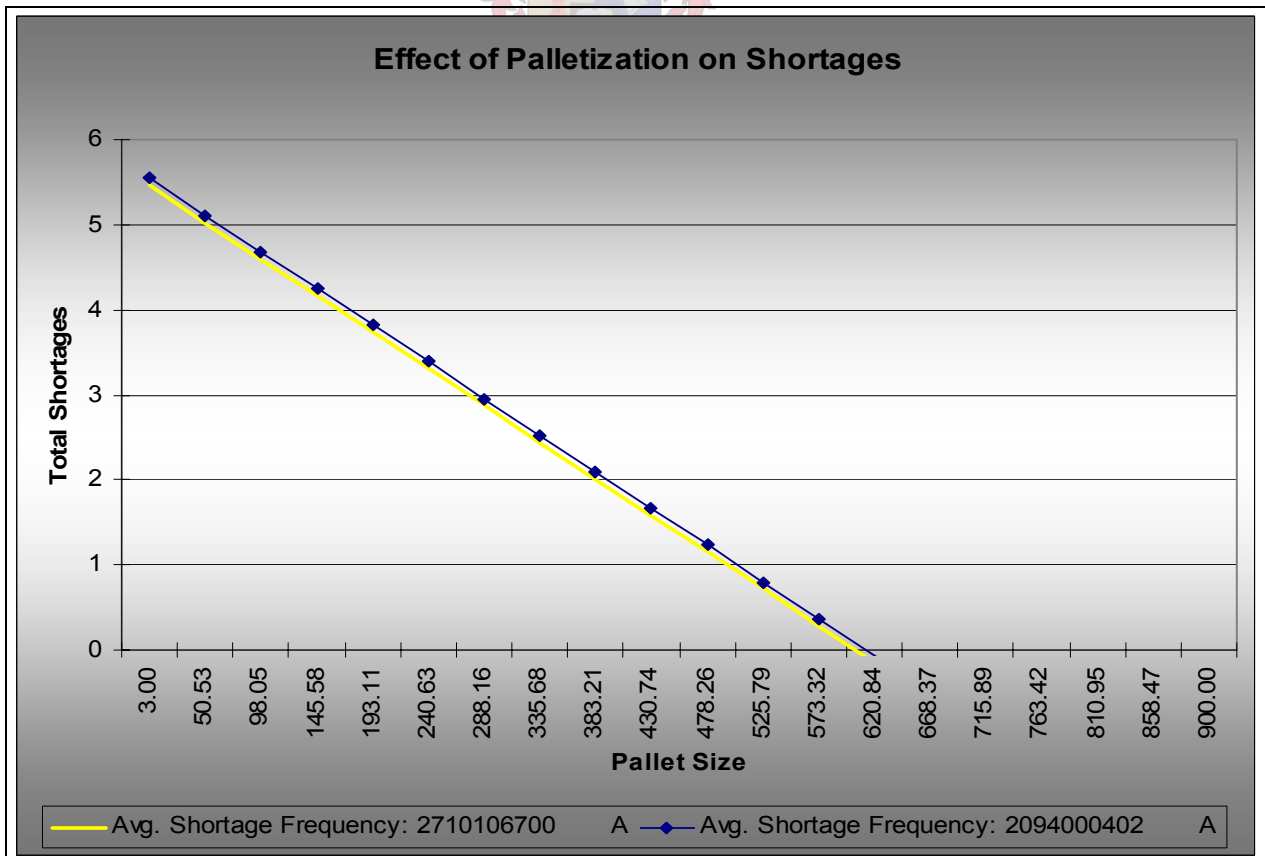


Figure 252: Effect of Palletization on Shortages. Medium Runners.

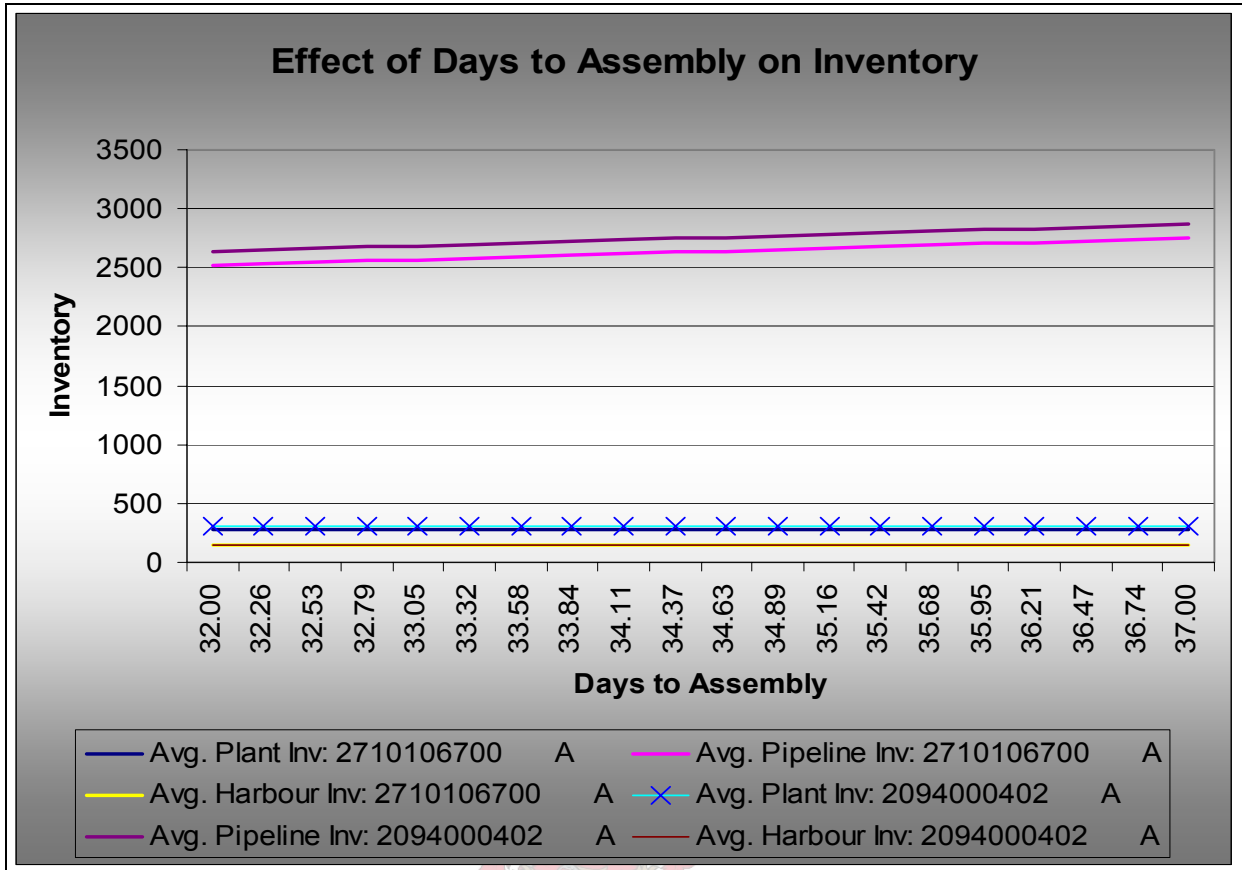


Figure 253: Effect of Days to Assembly on Inventory. Medium Runners.

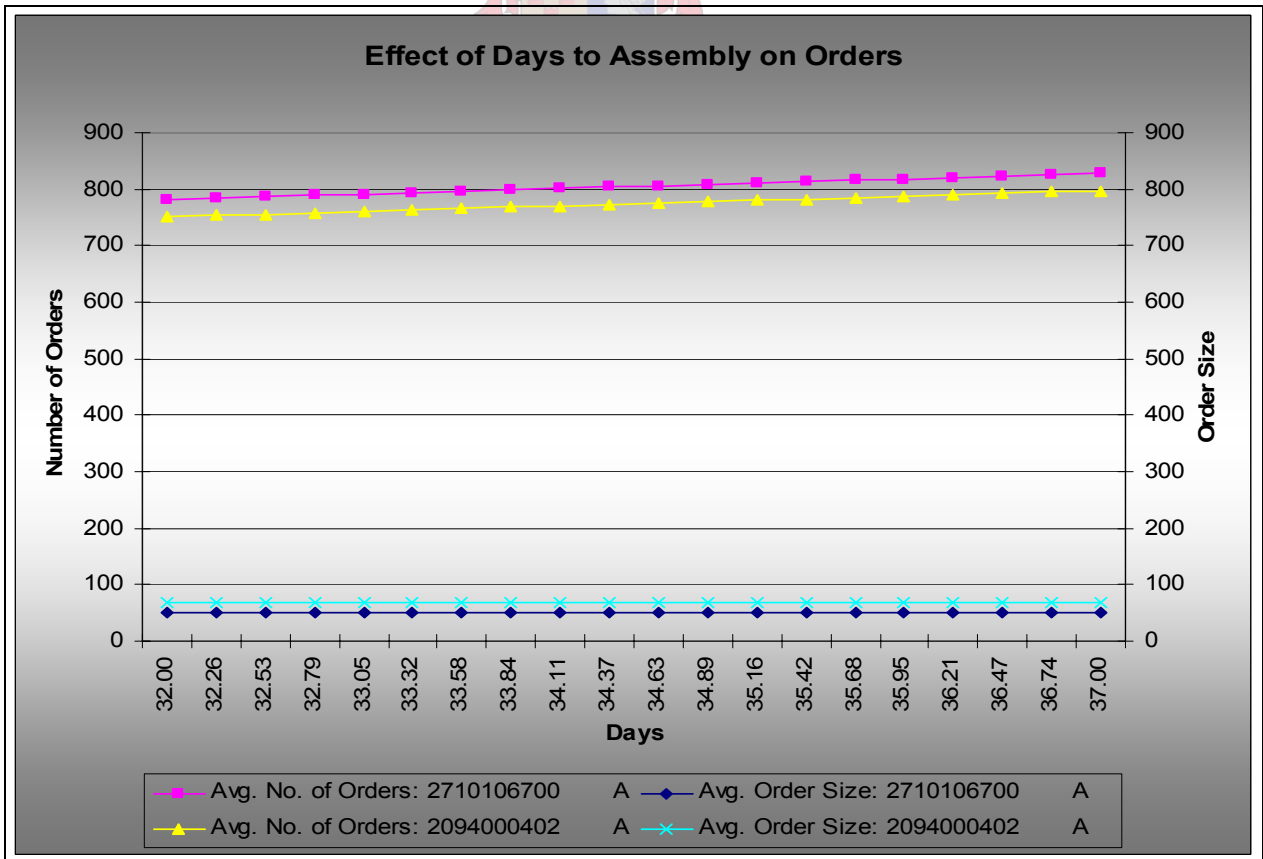


Figure 254: Effect of Days to Assembly on Orders. Medium Runners.

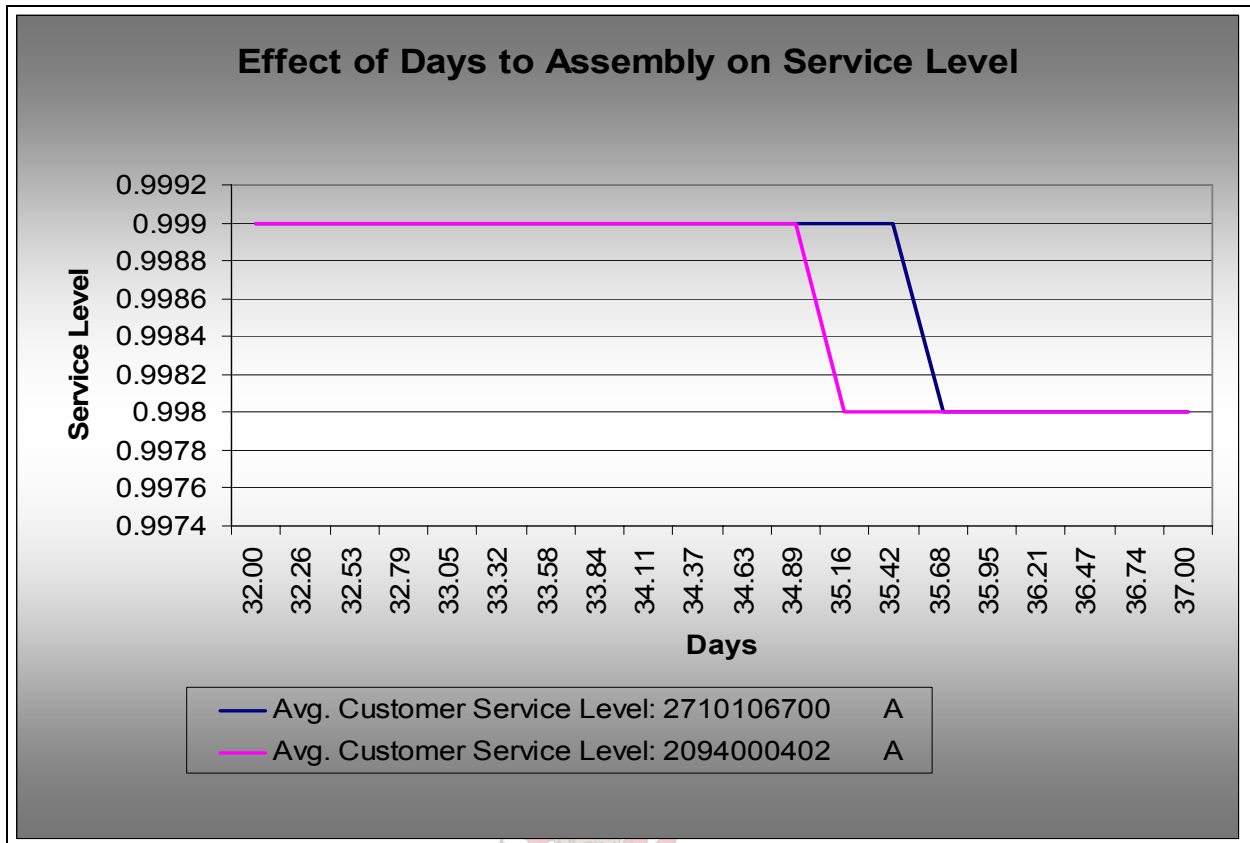


Figure 255: Effect of Days to Assembly on Customer Service Level. Medium Runners.

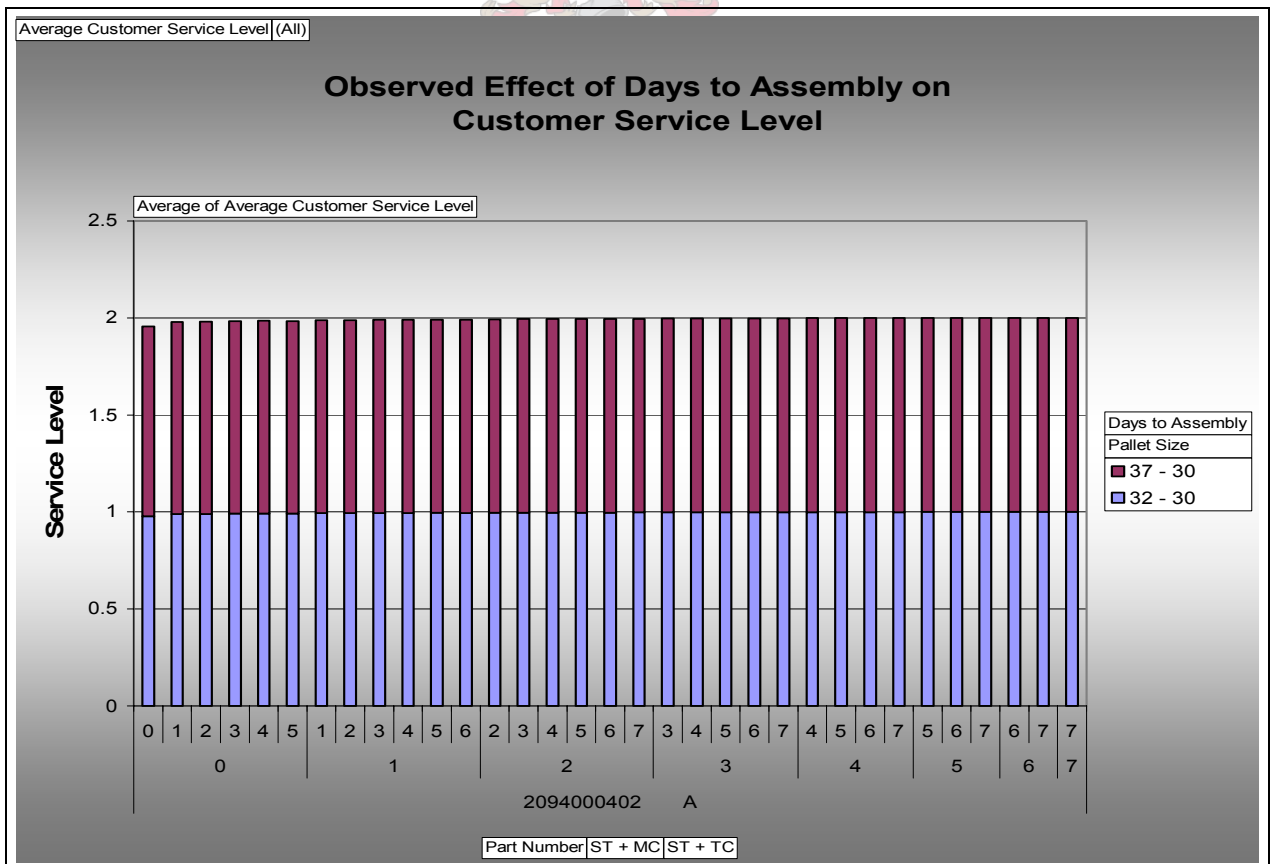


Figure 256: Observed Effect of Days to Assembly on Customer Service Level. Medium Runners.

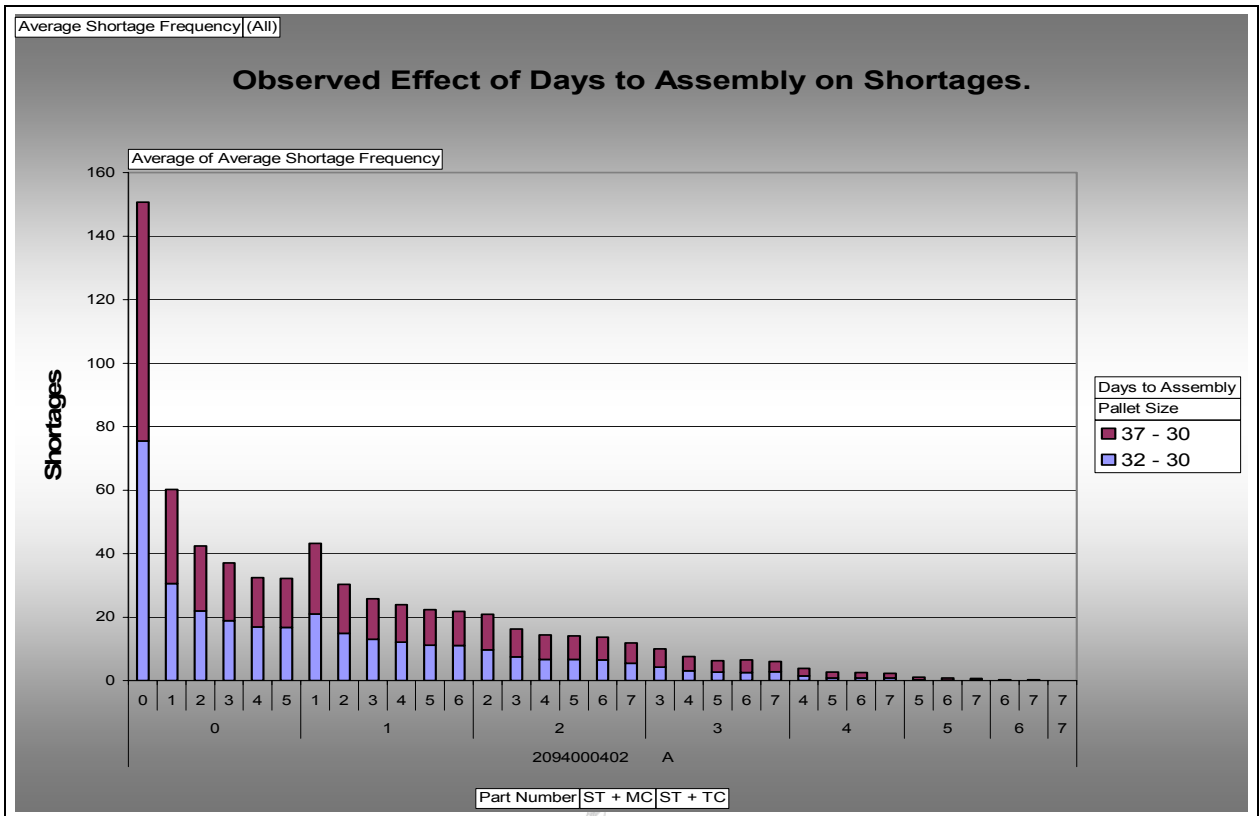


Figure 257: Observed Effect of Days to Assembly on Customer Shortages. Medium Runners.

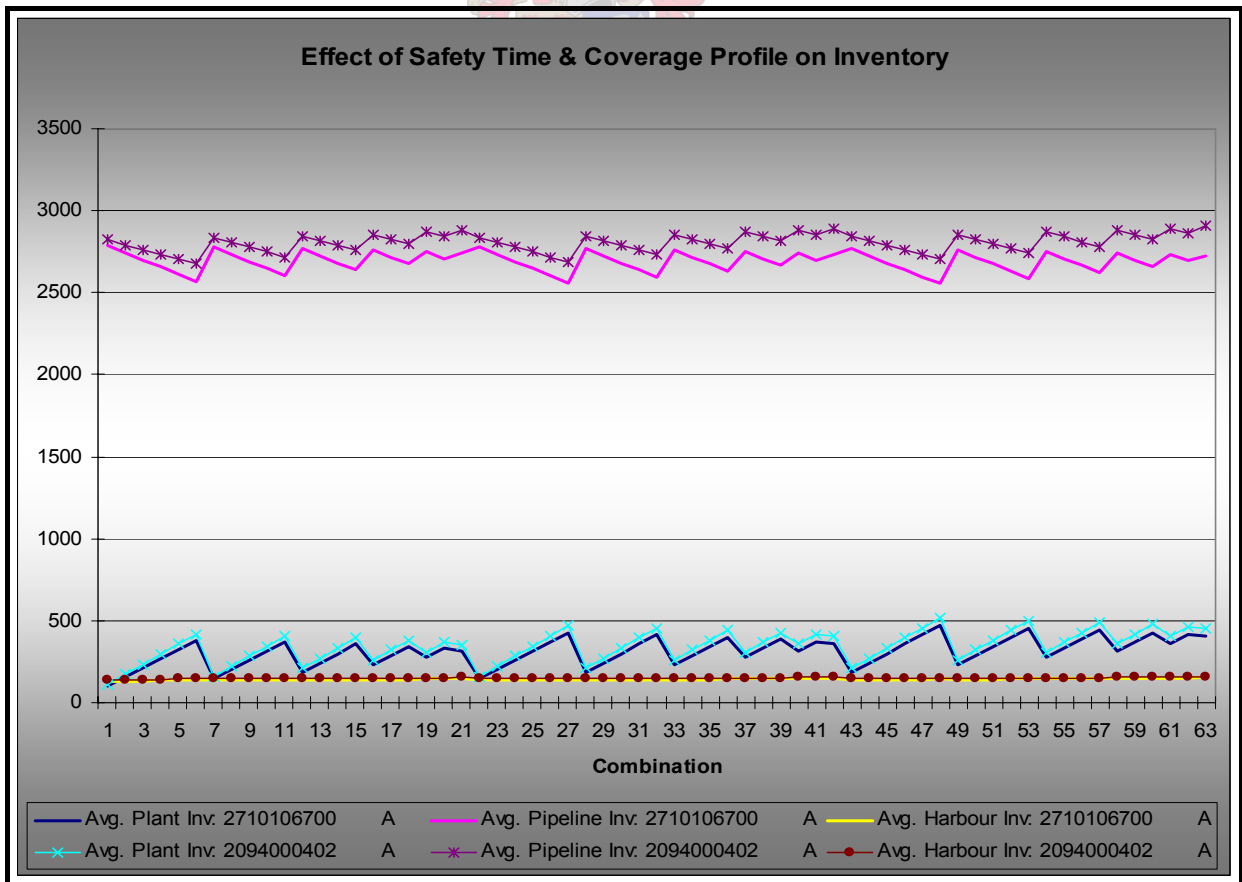


Figure 258: Effect of Safety Time & Coverage Profile Combinations on Inventory. Medium Runners.

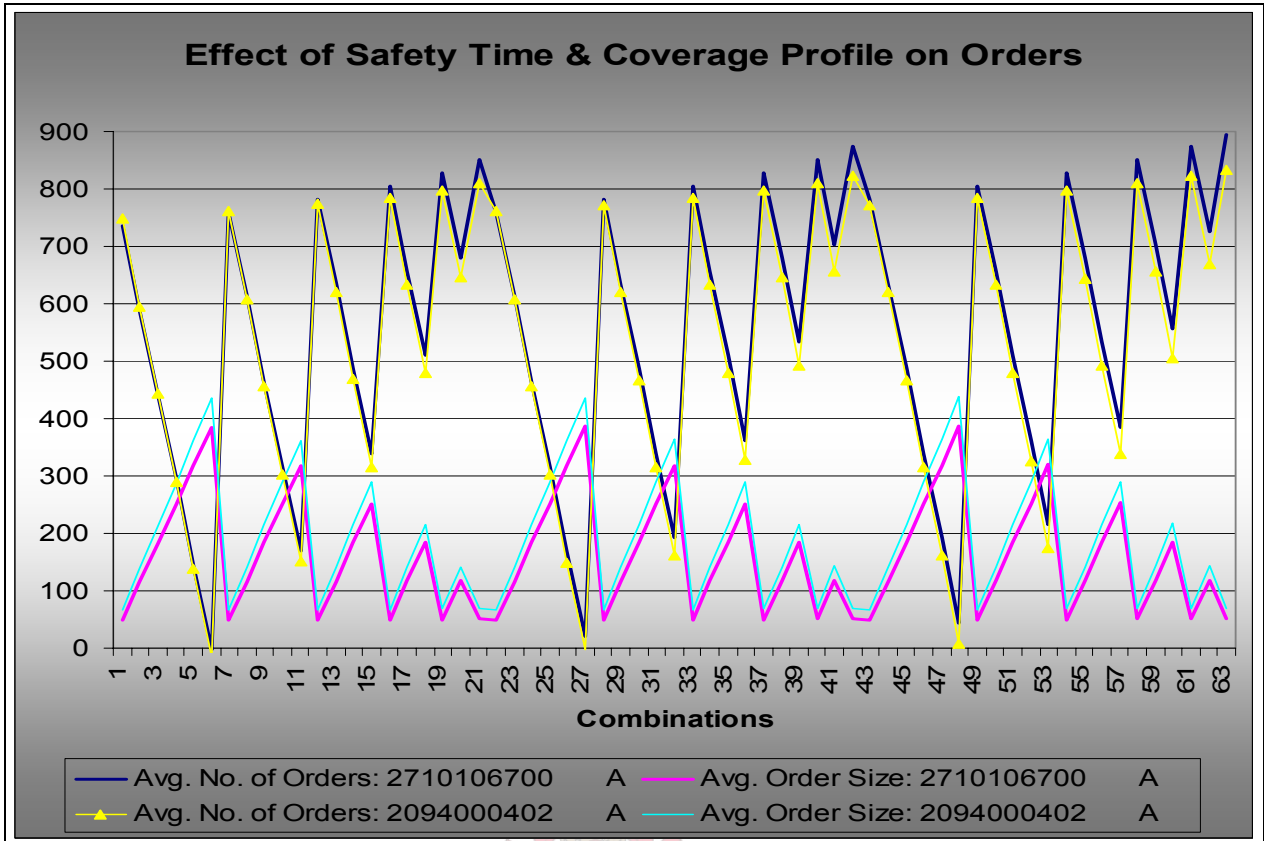


Figure 259: Effect of Safety Time & Coverage Profile Combinations on Orders. Medium Runners.

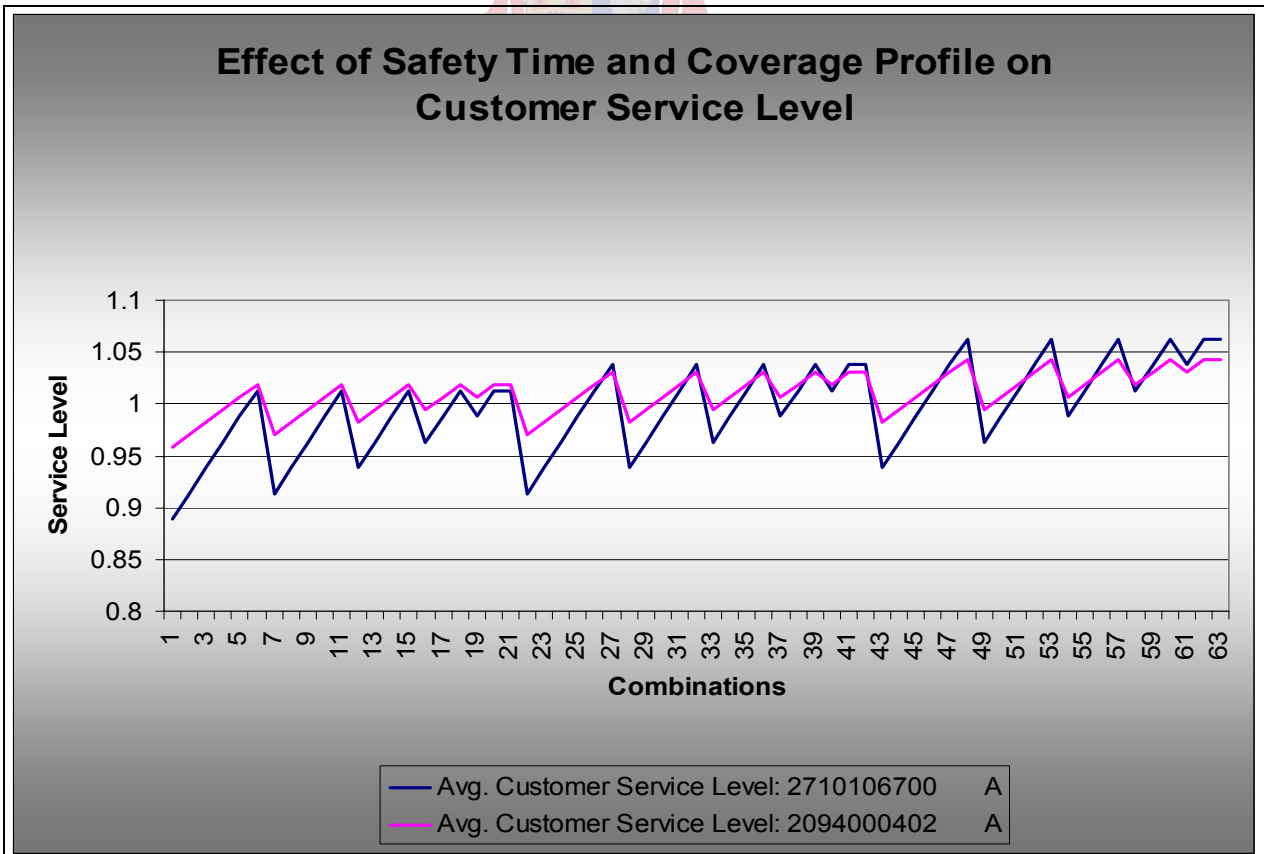


Figure 260: Effect of Safety Time & Coverage Profile Combinations on Customer Service Level. Medium Runners.

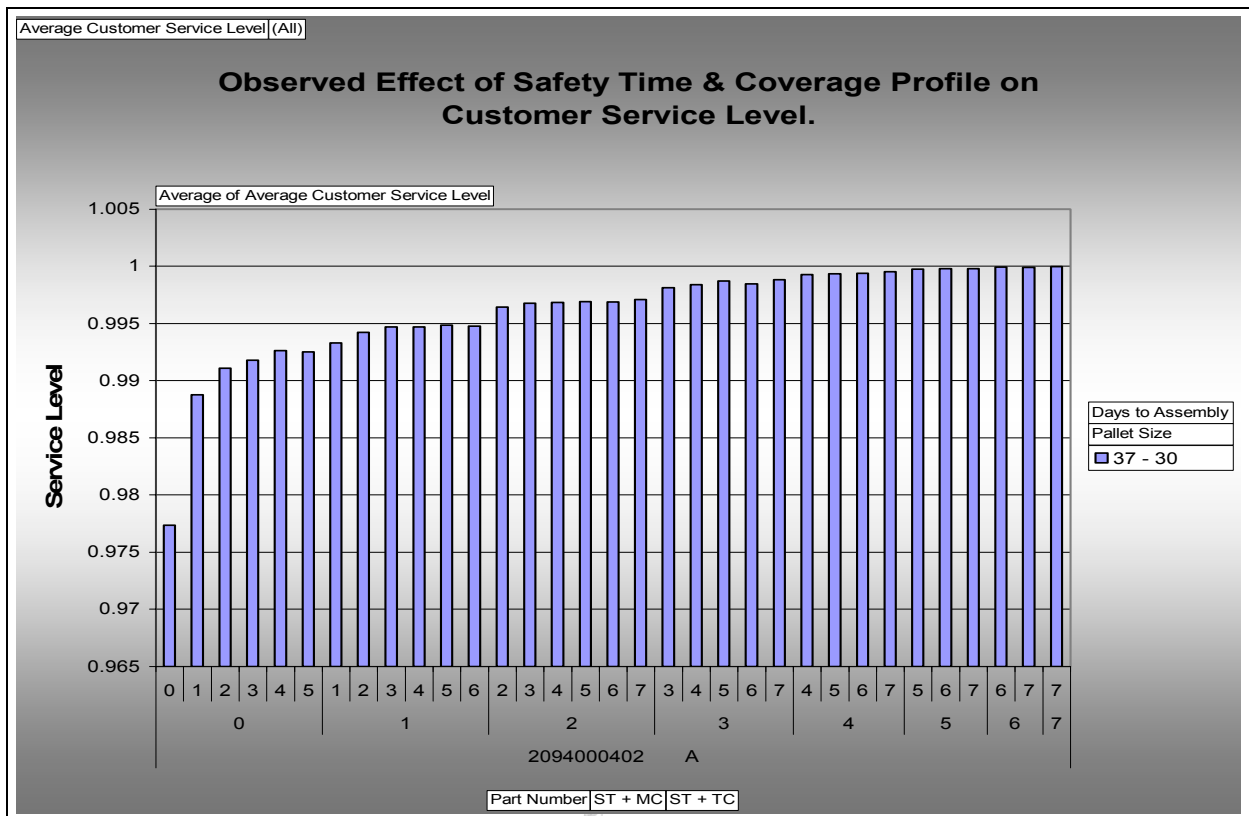


Figure 261: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Service Level. Medium Runners.

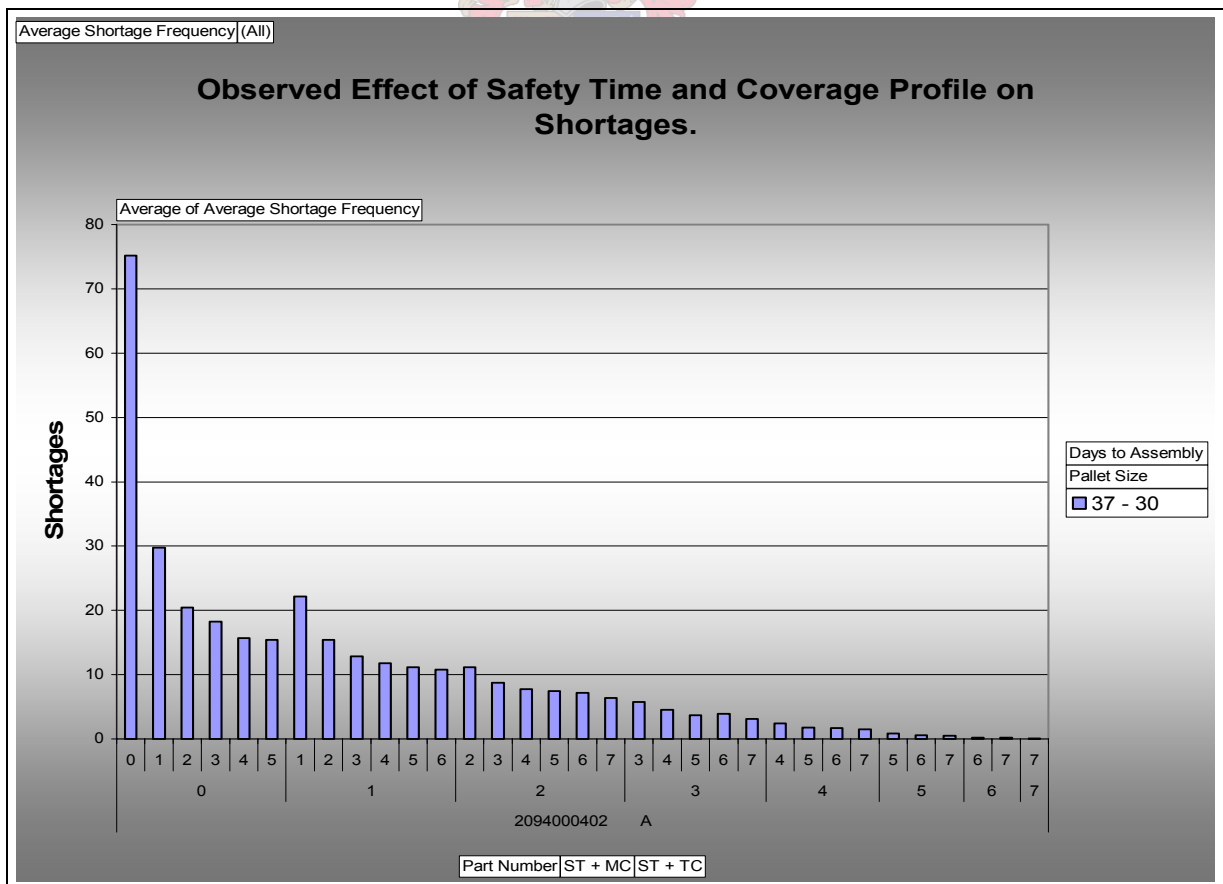


Figure 262: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Shortages. Medium Runners.

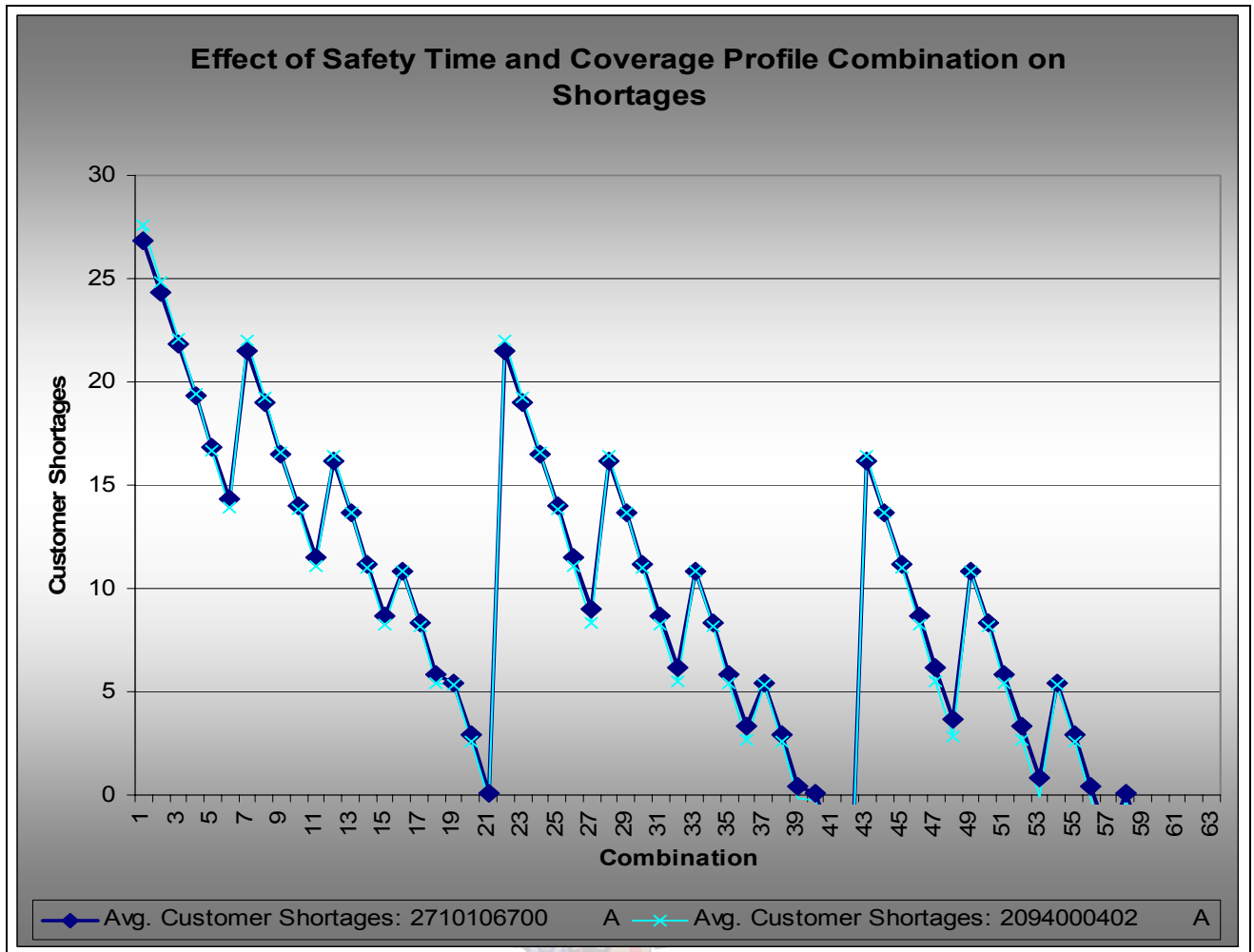


Figure 263: Effect of Safety Time & Coverage Profile Combinations on Shortages. Medium Runners.



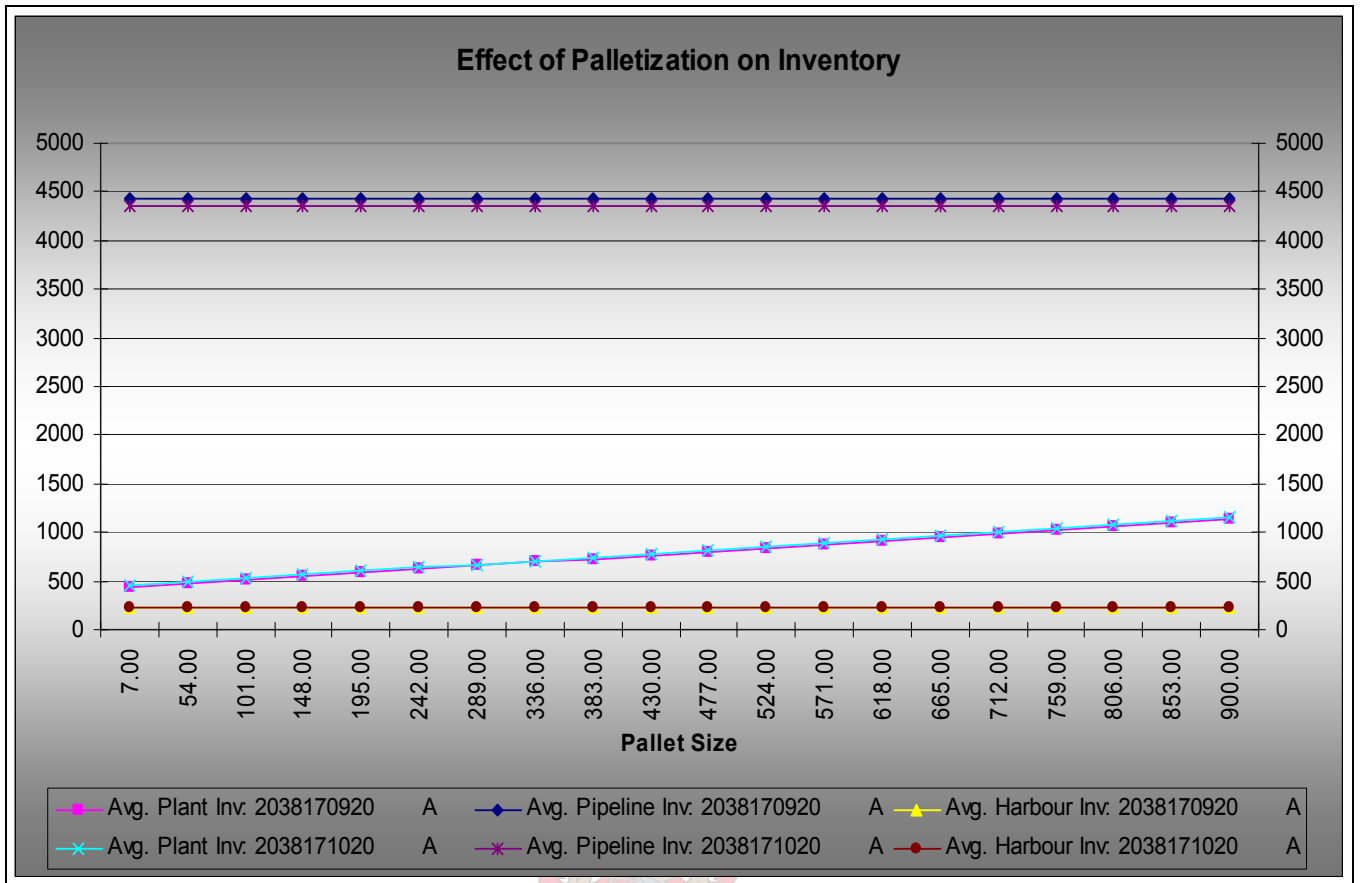


Figure 264: Effect of Palletization on Inventory. High Runners.

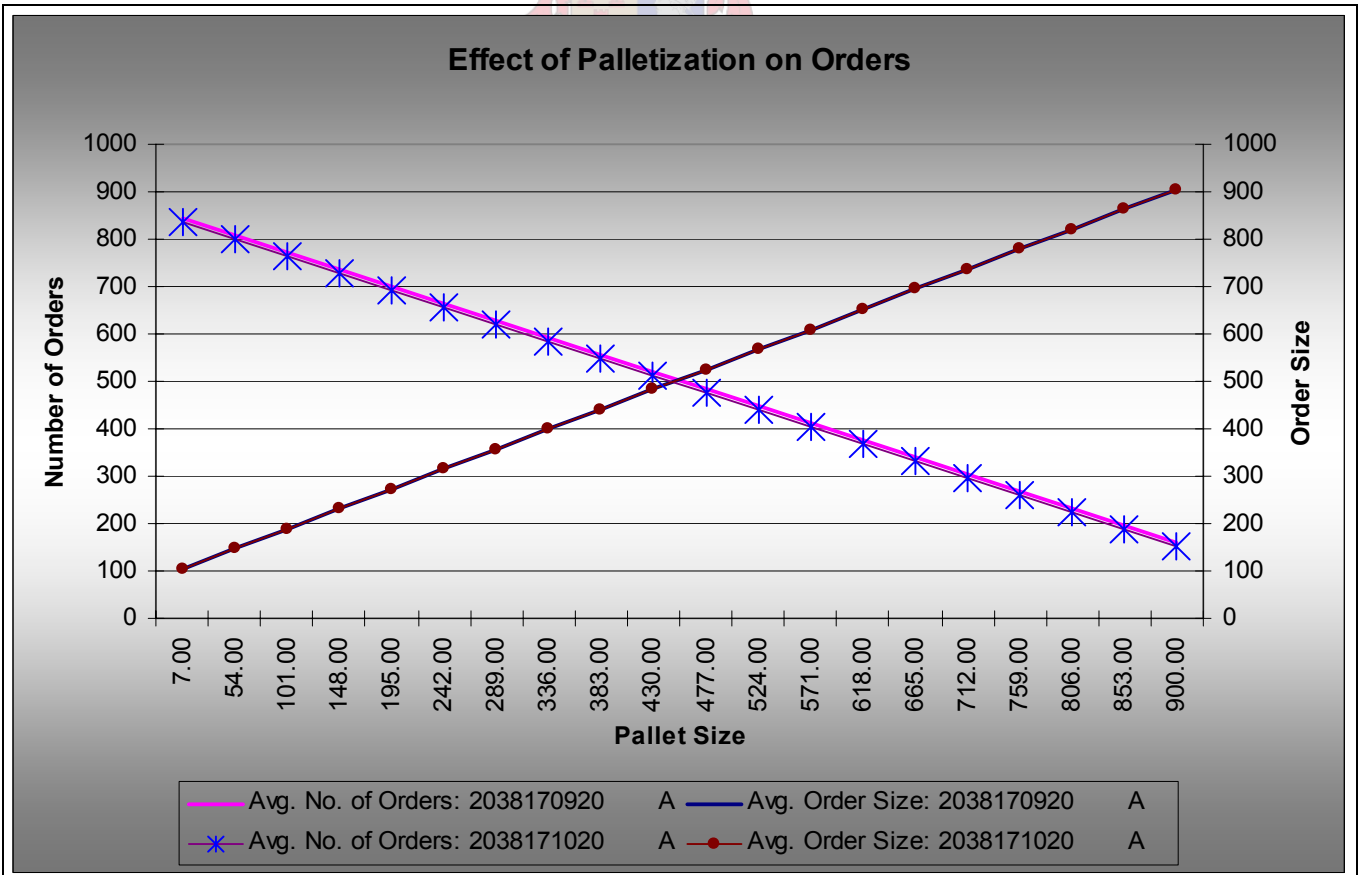


Figure 265: Effect of Palletization on Orders. High Runners.

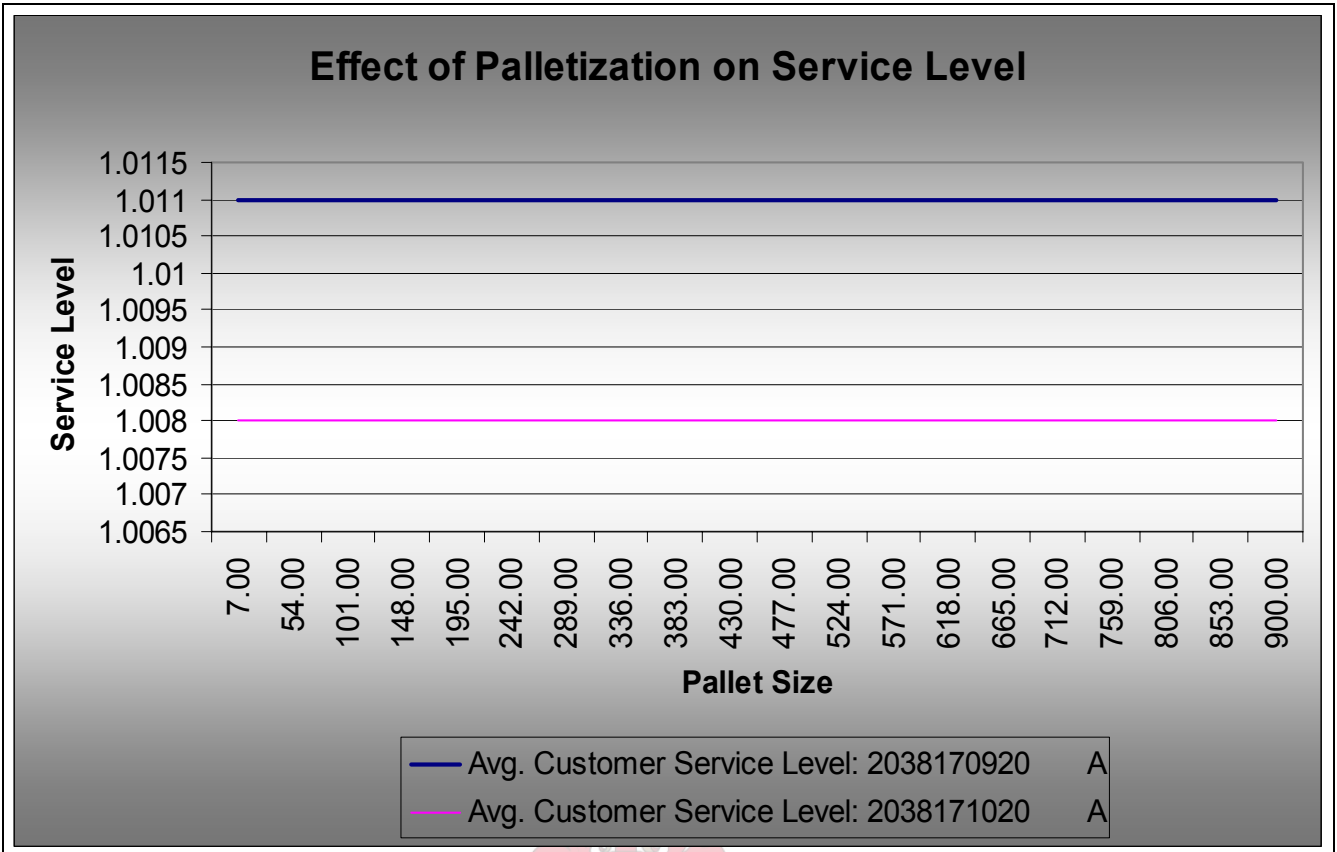


Figure 266: Effect of Palletization on Customer Service Level. High Runners.

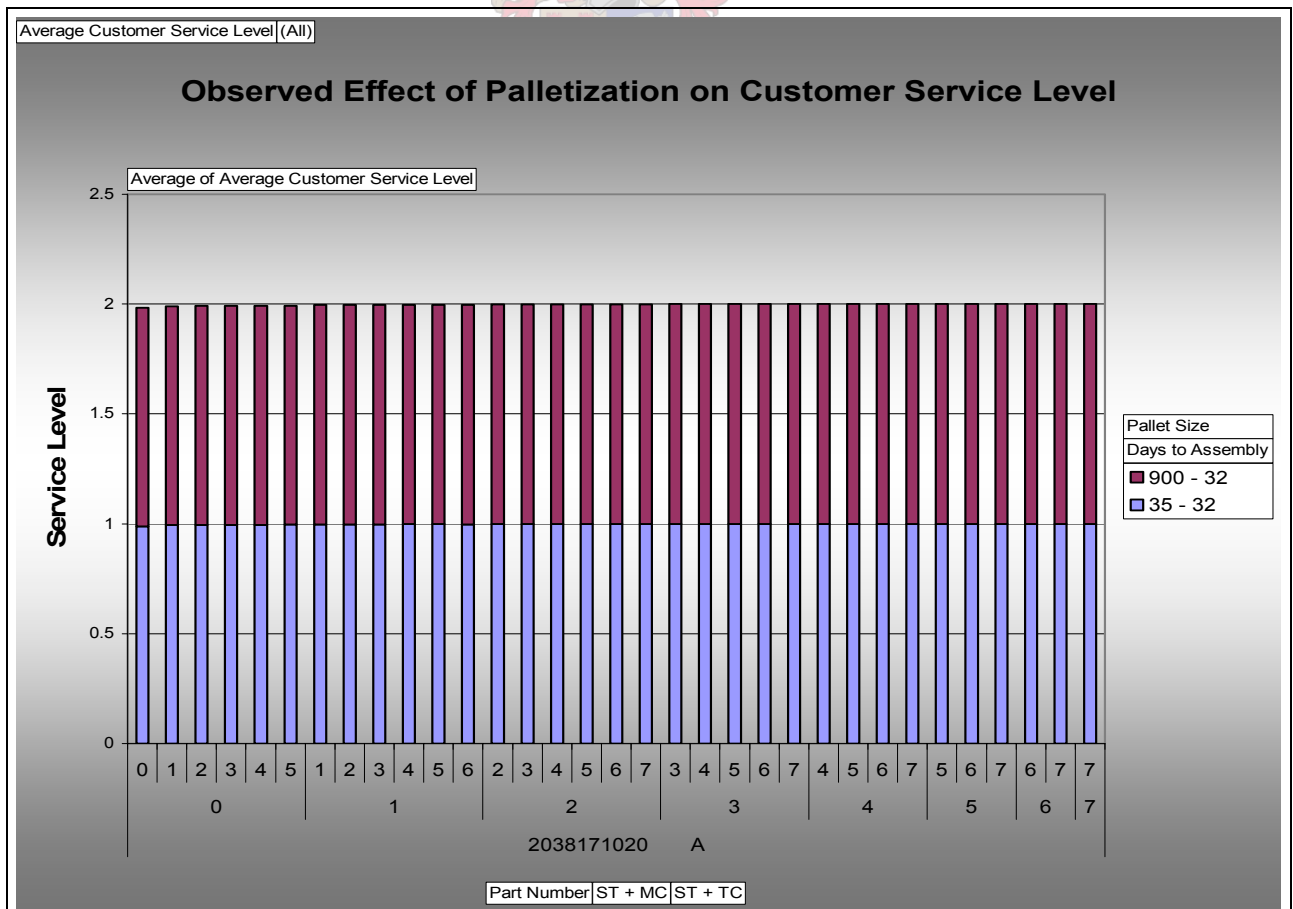


Figure 267: Observed Effect of Palletization on Customer Service Level. High Runners.

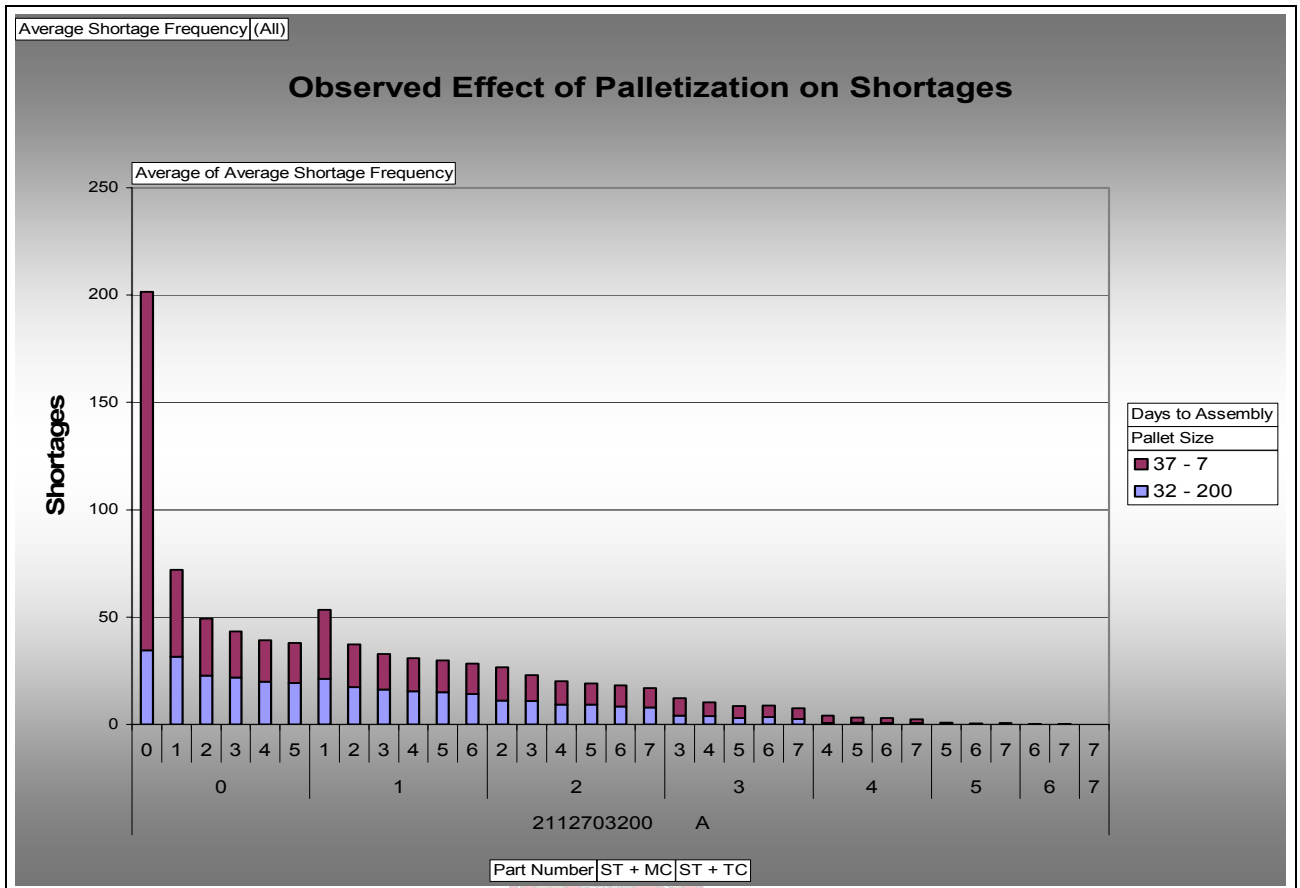


Figure 268: Observed Effect of Palletization on Customer Shortages. High Runners.

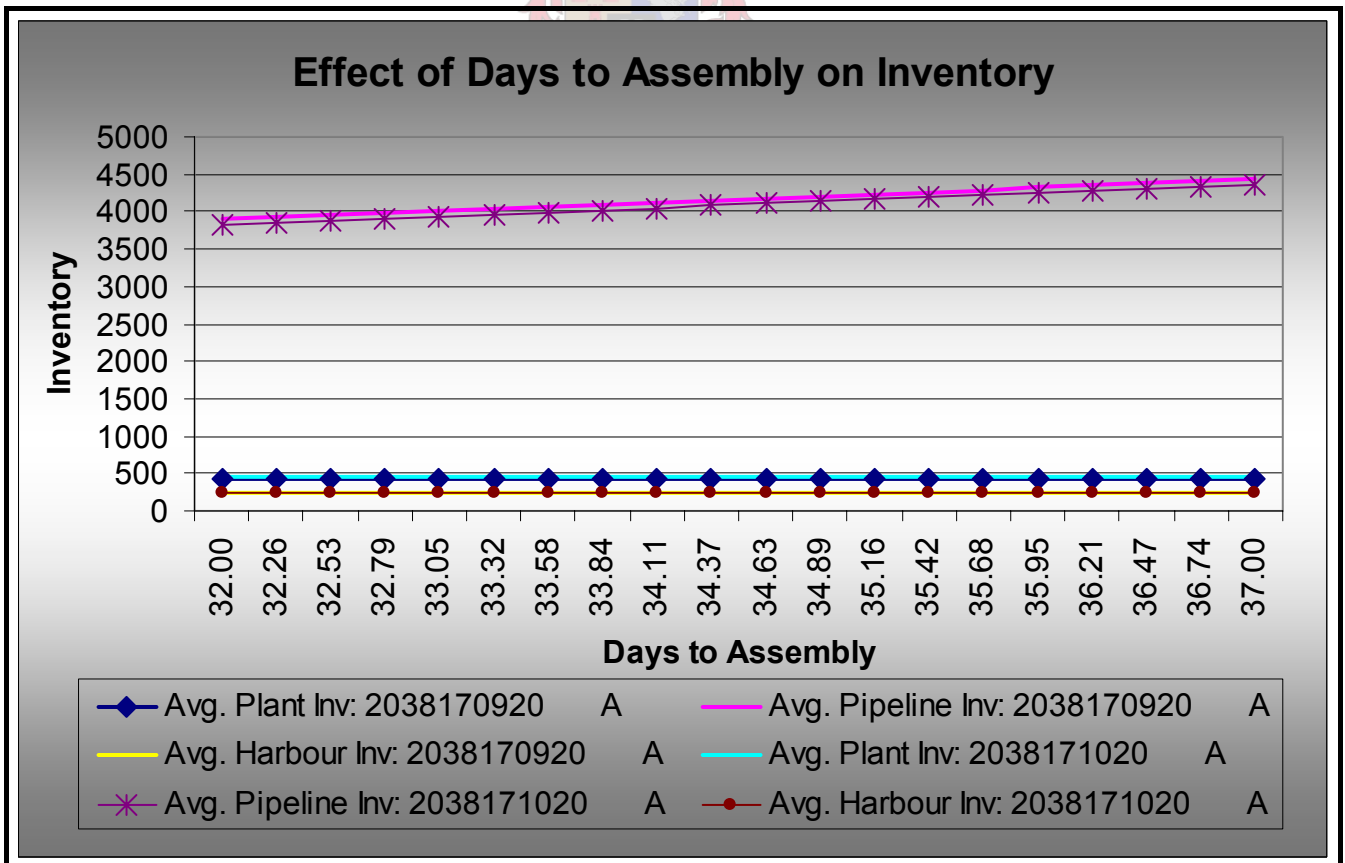


Figure 269: Effect of Days to Assembly on Inventory. High Runners.

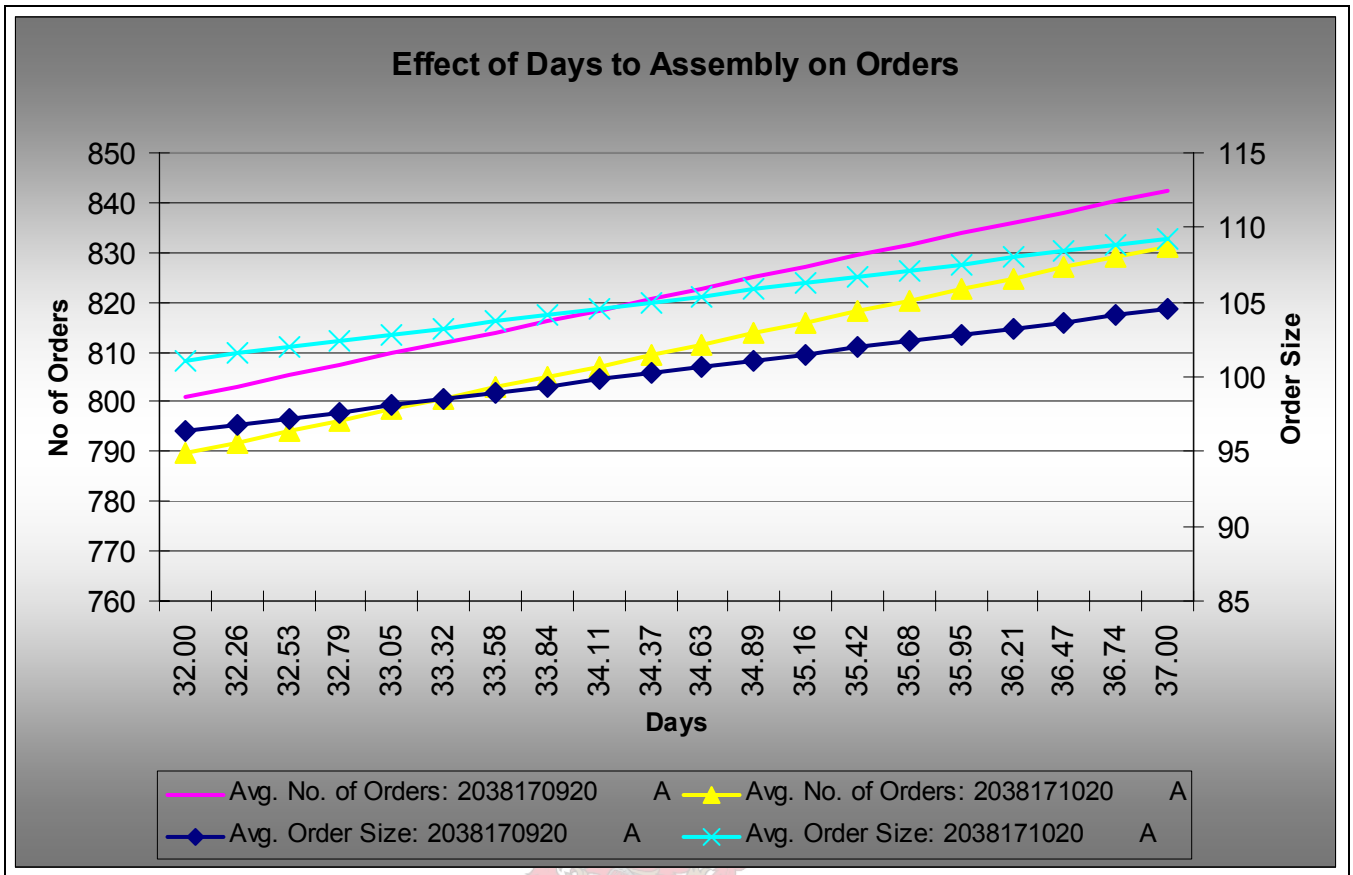


Figure 270: Effect of Days to Assembly on Orders. High Runners.

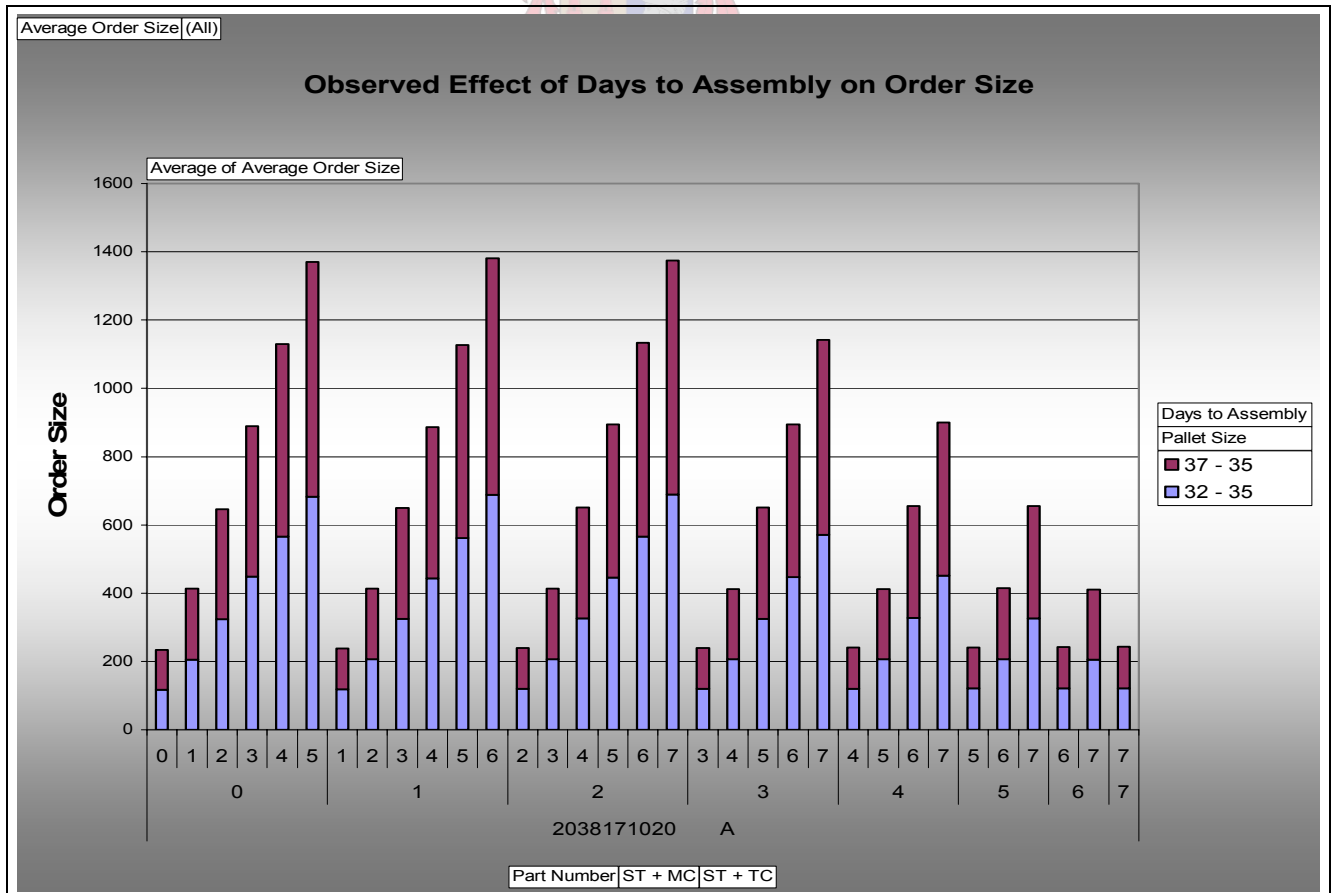


Figure 271: Observed Effect of Days to Assembly on Order Size. High Runners.

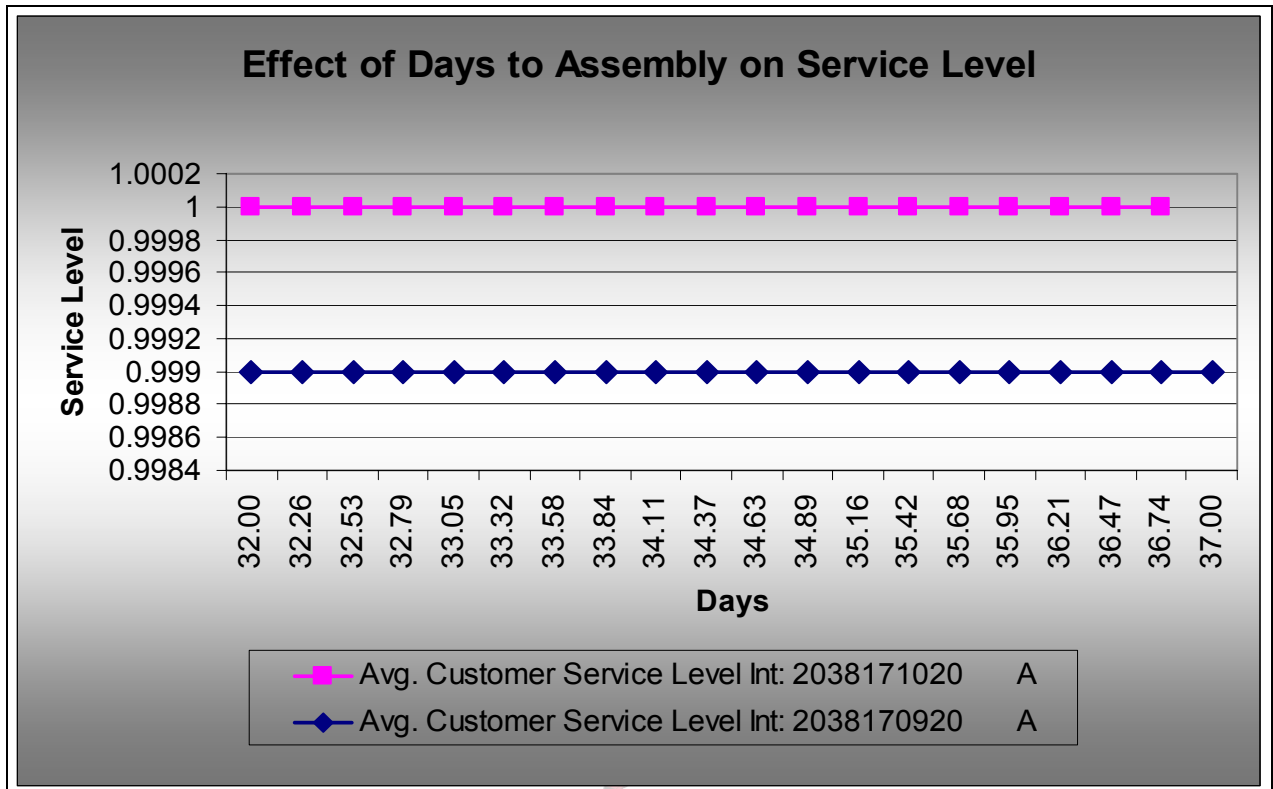


Figure 272: Effect of Days to Assembly on Customer Service Level. High Runners.

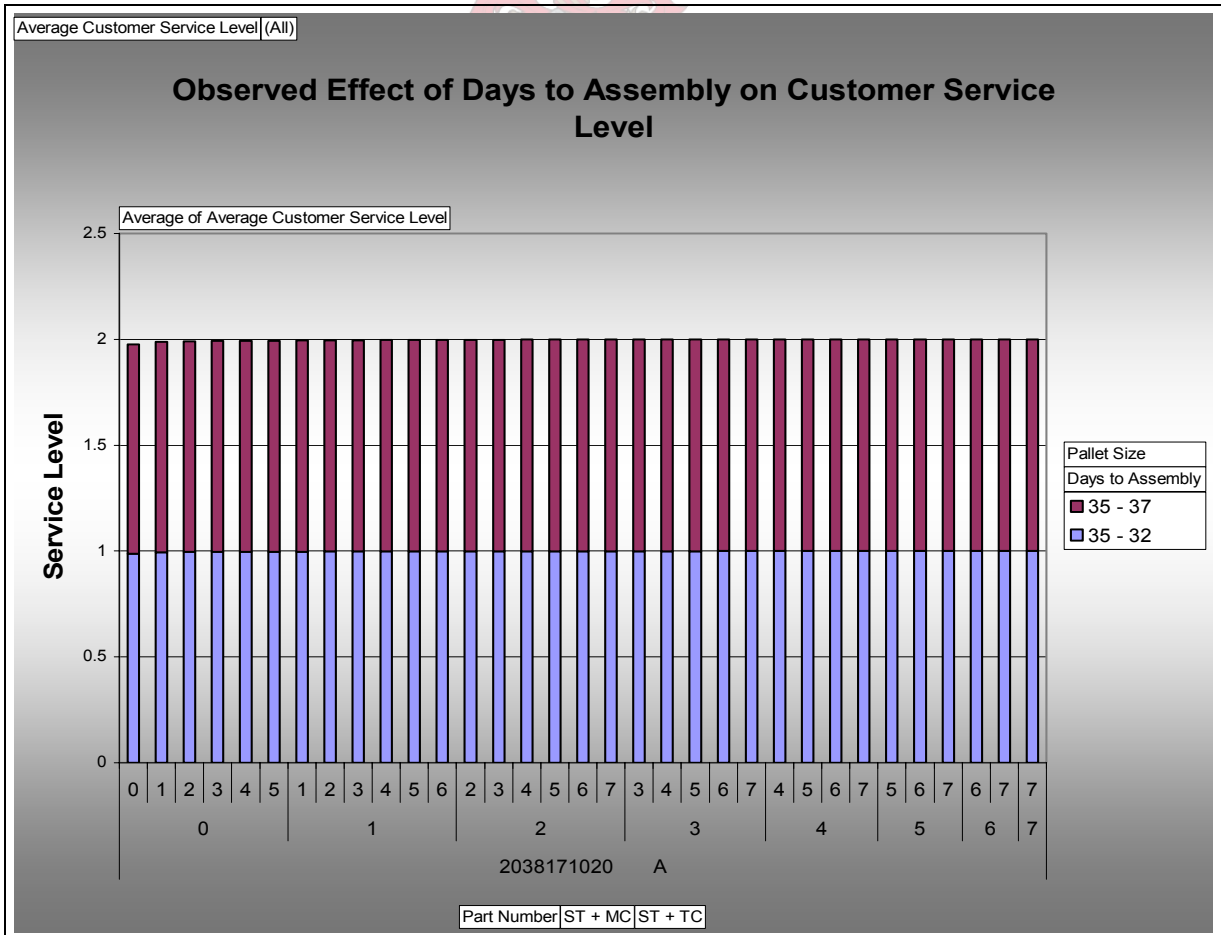


Figure 273: Observed Effect of Days to Assembly on Customer Service Level. High Runners.

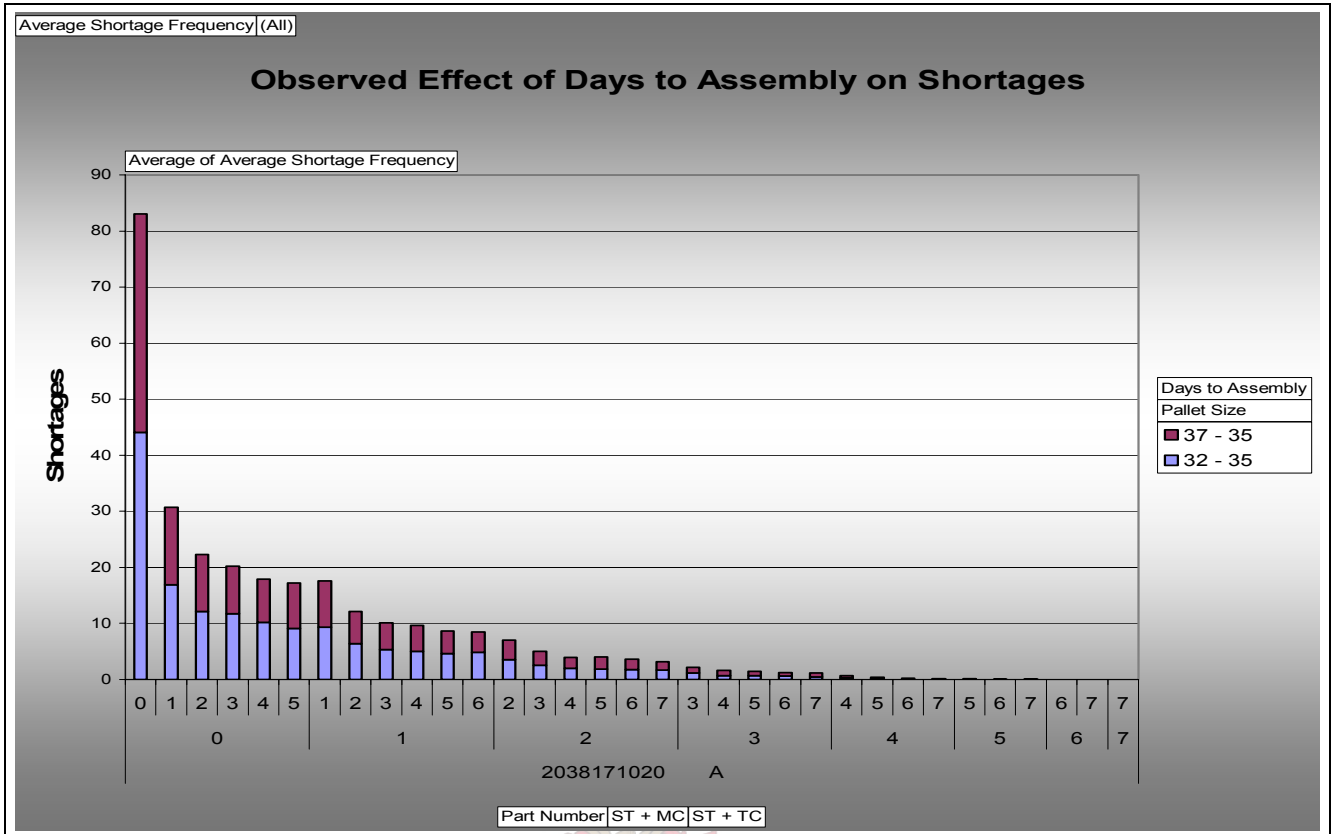


Figure 274: Observed Effect of Days to Assembly on Customer Shortages. High Runners.

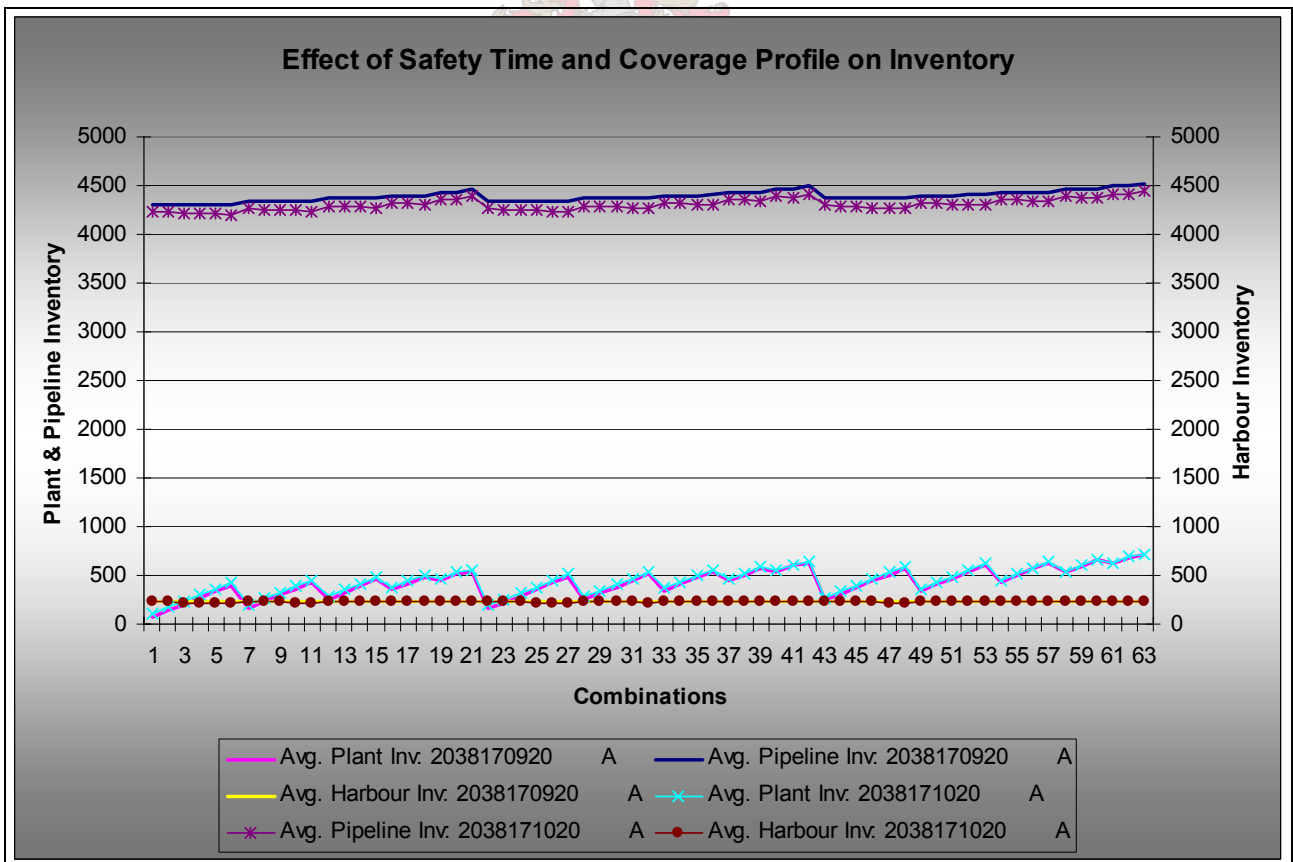


Figure 275: Effect of Safety Time & Coverage Profile Combination on Inventory. High Runners.

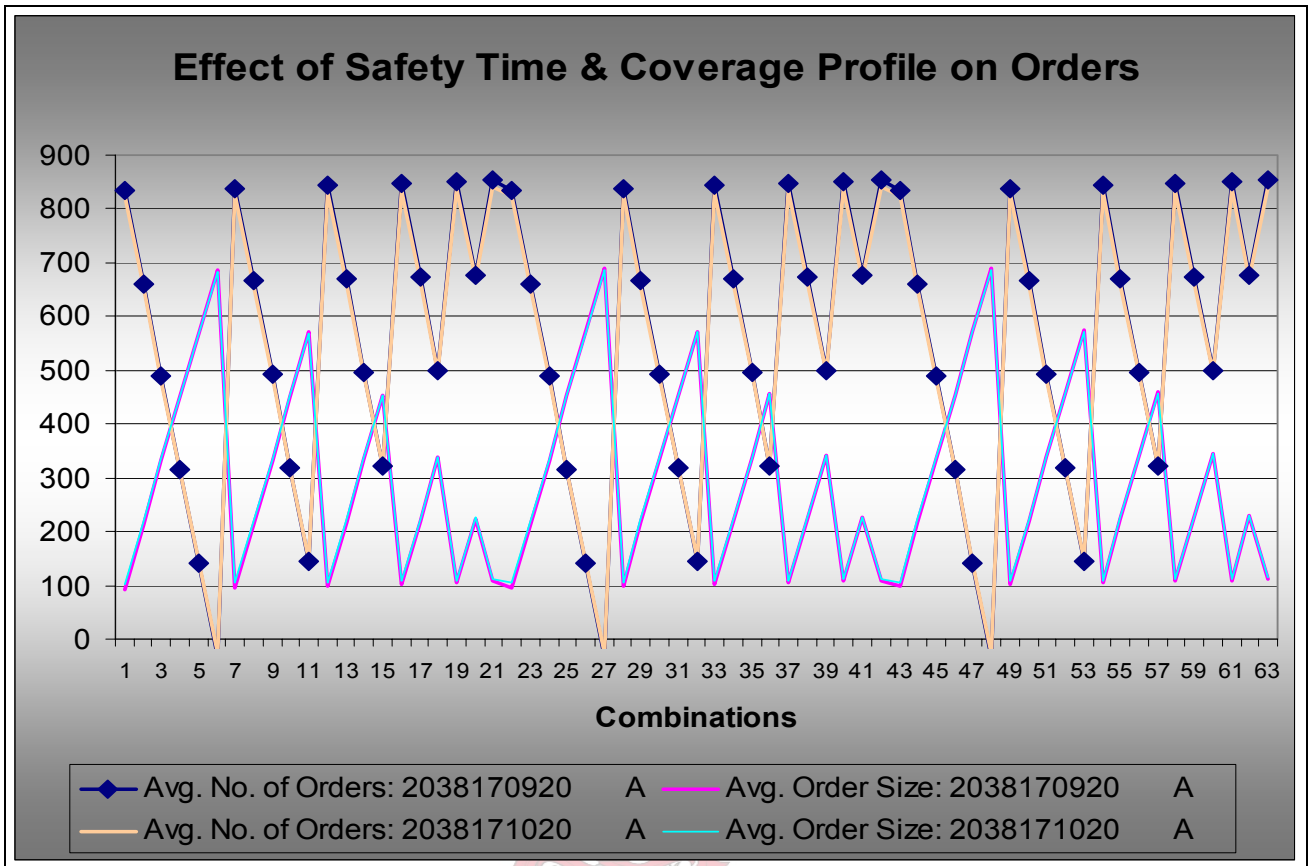


Figure 276: Effect of Safety Time & Coverage Profile on Orders. High Runners.

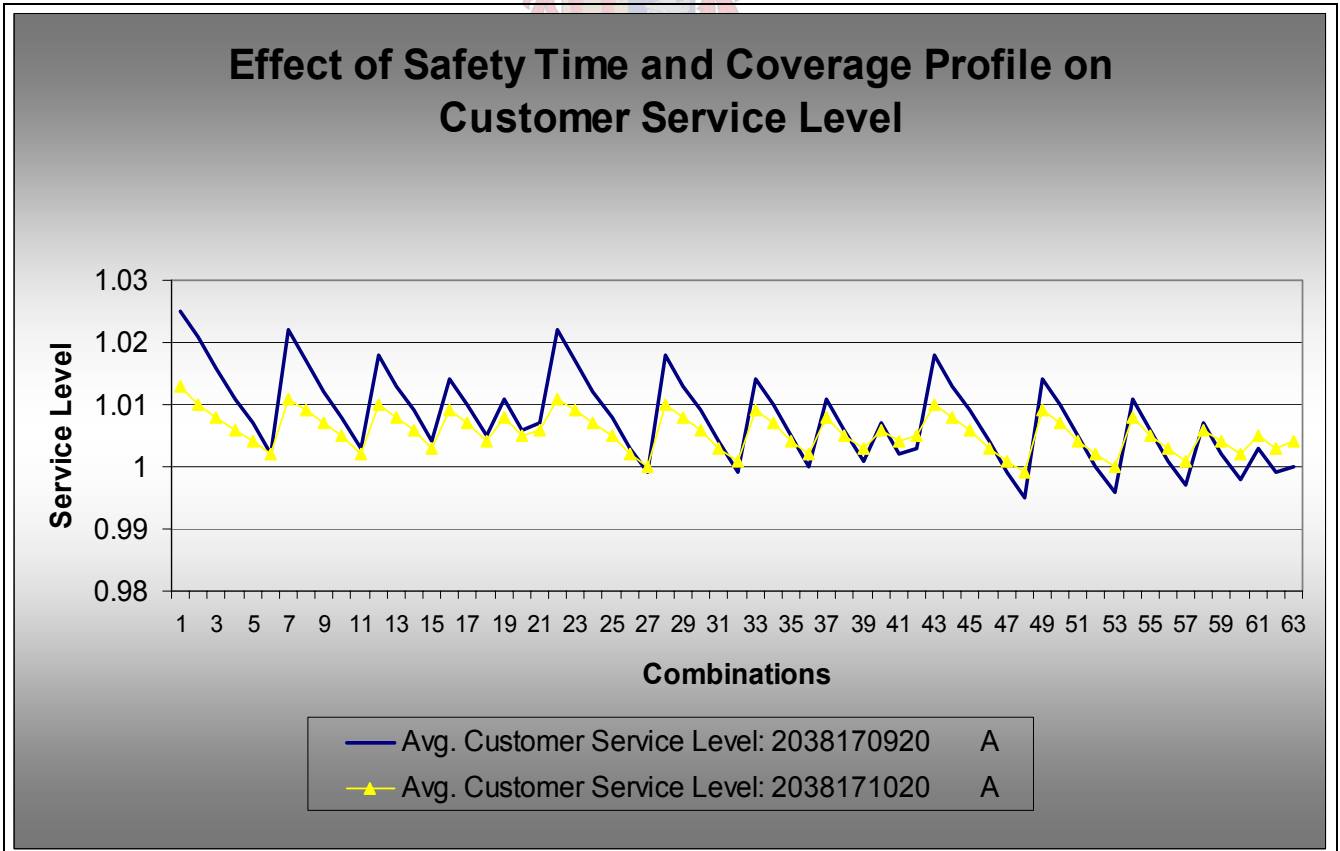


Figure 277: Effect of Safety Time & Coverage Profile on Customer Service Level. High Runners.

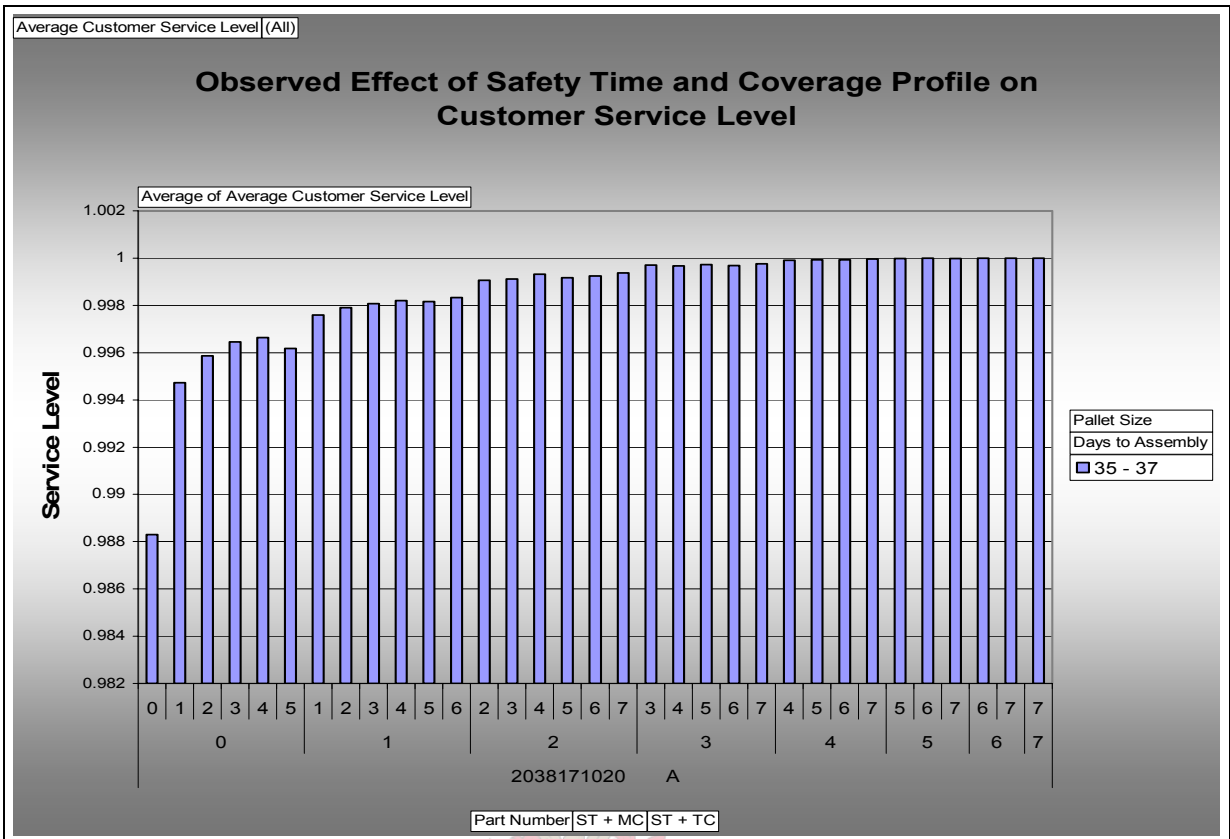


Figure 278: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Service Level. High Runners.

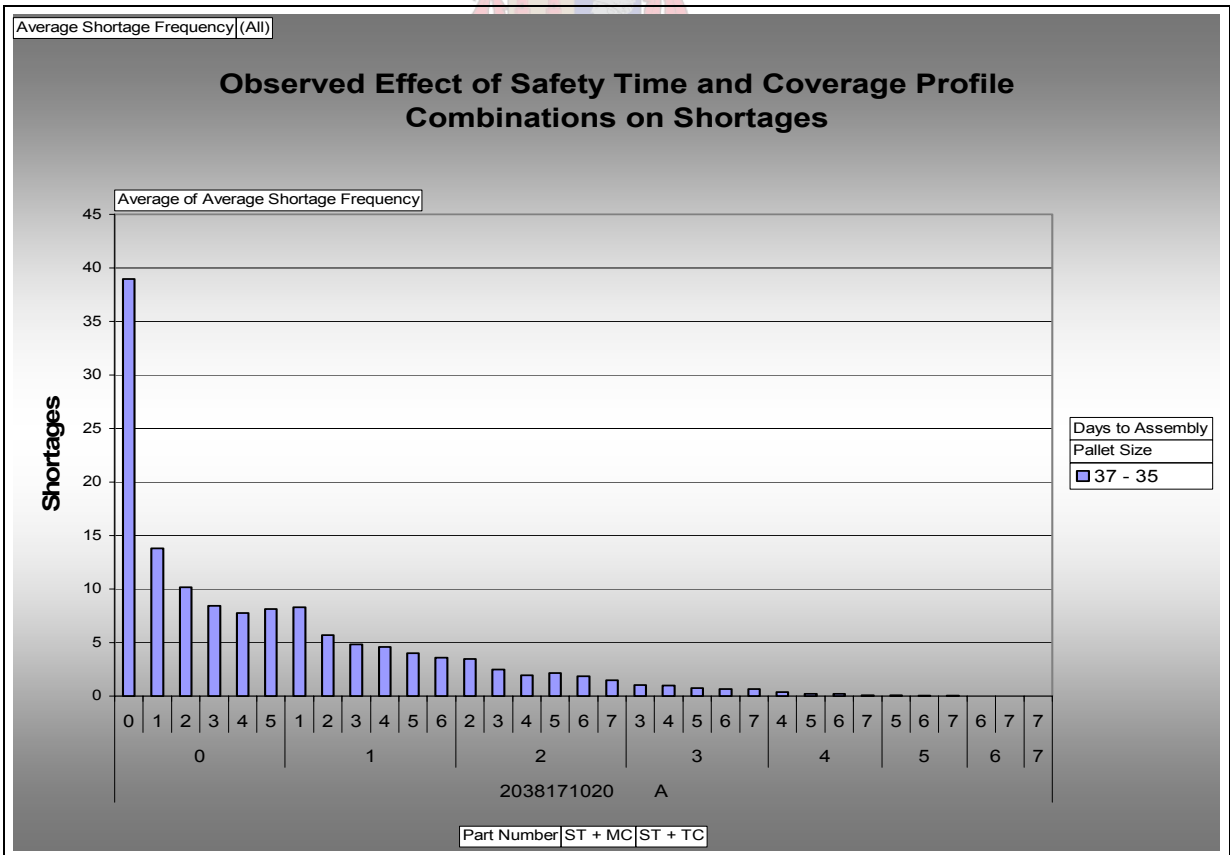
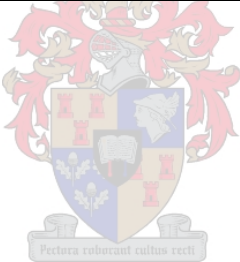


Figure 279: Observed Effect of Safety Time & Coverage Profile Combinations on Customer Shortages. High Runners.

Appendix M Customization Tables



Combination	0005461781 A	1120101144 A	Combination	0005461781 A	1120101144 A
1	32.5248	3.15454	32	27.4346	6.55288
2	32.9473	3.28217	33	25.2319	4.93148
3	33.3967	3.83418	34	26.7056	5.25027
4	32.4029	5.02257	35	24.9958	5.75764
5	32.8566	5.41792	36	25.3663	6.47843
6	33.0573	5.93258	37	25.5134	5.45545
7	29.9706	3.43233	38	24.7881	5.70315
8	29.8809	3.66563	39	25.5223	6.27533
9	28.9492	4.47042	40	24.9618	6.00712
10	30.2903	5.31749	41	25.1825	6.25864
11	29.8542	5.8437	42	25.691	6.7255
12	26.883	3.95762	43	27.2019	4.50387
13	27.9699	4.41235	44	25.5777	5.02425
14	27.4949	4.98125	45	26.1173	5.56053
15	28.1413	5.8333	46	28.4883	6.27445
16	25.7594	4.69477	47	26.9742	6.82871
17	25.9821	4.90504	48	27.2642	7.13105
18	26.2467	5.41702	49	25.5357	5.26123
19	25.0033	5.21511	50	25.5262	5.48176
20	25.5288	5.41554	51	25.1277	6.01082
21	24.8488	5.82412	52	24.9908	6.69515
22	30.125	3.72623	53	25.6052	7.07662
23	29.4701	4.096	54	24.8528	5.69728
24	30.0057	4.93377	55	25.4469	6.1004
25	29.7012	5.65386	56	24.6112	6.48476
26	30.7009	6.1379	57	24.0647	7.13192
27	29.25	6.56754	58	25.5072	6.31815
28	27.3744	4.16414	59	24.1401	6.564
29	27.5078	4.77879	60	24.7723	7.04948
30	28.1125	5.30419	61	24.9407	6.91309
31	27.3213	5.92974	62	25.1359	7.04788
			63	25.7164	7.33745

Table 91: Comparison of Plant Inventories per Combination for Ultra Low Runners

Combination	2039709350 27D44A	2032700400 A	Combination	2039709350 27D44A	2032700400 A
1	30.72	58.68	32	155.95	175.62
2	57.46	82.90	33	92.57	130.05
3	81.00	102.53	34	112.97	148.95
4	105.86	124.29	35	129.40	161.48
5	133.68	146.61	36	143.91	176.88
6	160.88	166.79	37	110.48	153.55
7	51.82	84.02	38	129.63	172.54
8	75.61	104.94	39	142.29	185.74
9	100.18	122.41	40	130.02	177.86
10	122.37	140.75	41	147.76	200.44
11	146.73	159.72	42	153.71	205.68
12	71.07	104.51	43	79.12	113.30
13	95.13	125.22	44	102.29	132.60
14	113.01	142.20	45	120.99	147.84
15	130.59	156.85	46	141.97	164.96
16	89.92	128.78	47	161.39	180.90
17	110.04	146.88	48	180.08	196.41
18	125.93	161.43	49	98.30	132.71
19	107.20	152.32	50	116.40	150.63
20	125.09	171.24	51	133.30	168.63
21	126.04	176.08	52	149.80	178.44
22	56.08	85.86	53	165.91	195.46
23	80.49	107.64	54	114.18	154.30
24	102.78	126.98	55	133.03	171.94
25	124.83	146.10	56	145.06	188.70
26	151.64	162.31	57	157.77	202.07
27	176.34	179.31	58	132.80	177.81
28	75.77	107.48	59	150.86	198.20
29	97.82	129.55	60	163.82	215.82
30	115.85	143.56	61	154.45	204.67
31	136.19	162.24	62	171.71	225.29
			63	180.75	231.56

Table 92: Comparison of Plant Inventories per Combination for Low Runner.

Combination	2710106700	A	2094000402	A	Combination	2710106700	A	2094000402	A
1	60.9151		91.2793		32	382.385		433.074	
2	133.262		164.398		33	209.315		264.502	
3	195.453		237.723		34	256.697		314.977	
4	262.752		315.937		35	303.455		356.991	
5	337.357		390.563		36	338.173		396.813	
6	417.847		471.857		37	246.385		313.643	
7	111.523		150.985		38	290.262		362.582	
8	179.271		219.27		39	322.831		404.361	
9	243.178		291.642		40	295.636		371.943	
10	312.443		357.832		41	345.528		432.348	
11	375.619		421.301		42	357.764		449.096	
12	161.466		199.385		43	178.115		226.514	
13	224.958		262.045		44	236.872		283.027	
14	276.152		317.19		45	294.758		337.967	
15	329.688		373.454		46	342.977		394.771	
16	199.652		248.334		47	395.096		449.978	
17	251.513		301.652		48	442.624		486.081	
18	290.598		352.038		49	218.679		275.301	
19	239.307		305.192		50	272.553		323.325	
20	288.629		352.169		51	309.139		361.604	
21	290.742		376.565		52	351.154		404.509	
22	120.137		164.546		53	388.751		453.55	
23	182.391		229.998		54	257.657		325.778	
24	248.562		295.658		55	301.323		366.866	
25	314.501		362.059		56	330.21		406.617	
26	382.336		426.058		57	367.885		445.574	
27	444.046		491.324		58	301.431		377.346	
28	170.416		217.452		59	348.736		429.337	
29	229.372		271.713		60	387.092		475.183	
30	287.822		325.885		61	362.397		452.977	
31	332.258		375.662		62	418.898		508.711	
					63	436.22		528.249	

Table 93: Comparison of Plant Inventories per Combination for Medium Runners.

Combination	2038170920	A	2038171020	A	Combination	2038170920	A	2038171020	A
1	178.428		205.57		32	693.48		682.233	
2	289.408		308.149		33	470.1		504.749	
3	397.124		395.566		34	548.4		592.281	
4	496.878		498.289		35	612.313		647.977	
5	604.928		593.148		36	669.573		715.752	
6	722.789		675.412		37	558.792		610.935	
7	269.671		302.652		38	641.863		702.006	
8	375.529		390.424		39	708.009		759.829	
9	469.879		472.352		40	673.109		737.108	
10	551.158		548.719		41	751.551		816.166	
11	643.197		617.444		42	785.07		853.897	
12	366.999		404.869		43	389.518		417.894	
13	453.249		476.871		44	487.414		500.993	
14	534.748		545.87		45	554.179		560.491	
15	598.55		607.946		46	629.308		631.373	
16	456.982		511.455		47	716.43		705.77	
17	538.287		575.873		48	774.193		755.68	
18	599.948		643.814		49	476.042		505.696	
19	548.404		609.254		50	565.8		602.557	
20	635.8		693.804		51	620.607		654.471	
21	665.484		729.523		52	692.807		733.287	
22	290.403		321.377		53	766.75		783.769	
23	389.415		404.101		54	574.647		621.12	
24	477.874		479.429		55	652.717		705.743	
25	561.064		556.511		56	711.658		752.311	
26	660.783		631.552		57	781.222		834.467	
27	751.592		708.227		58	684.218		727.296	
28	379.42		405.979		59	758.91		822.517	
29	466.159		490.466		60	823.235		868.429	
30	540.916		561.273		61	785.978		853.504	
31	613.514		623.122		62	878.558		938.439	
					63	917.87		980.028	

Table 94: Comparison of Plant Inventories per Combination for High Runners.

Combination	2710106700	A	2094000402	A	Combination	2710106700	A	2094000402	A
1	60.9		91.3		15	294.8		357.8	
2	111.5		151.0		31	295.6		361.6	
7	120.1		164.4		46	301.3		362.1	
22	133.3		164.5		19	301.4		362.6	
3	161.5		199.4		37	303.5		366.9	
8	170.4		217.5		54	309.1		371.9	
23	178.1		219.3		27	312.4		373.5	
4	179.3		226.5		18	314.5		375.7	
12	182.4		230.0		35	322.8		376.6	
28	195.5		237.7		51	329.7		377.3	
43	199.7		248.3		32	330.2		390.6	
9	209.3		262.0		47	332.3		394.8	
24	218.7		264.5		20	337.4		396.8	
5	225.0		271.7		38	338.2		404.4	
13	229.4		275.3		55	343.0		404.5	
29	236.9		283.0		36	345.5		406.6	
44	239.3		291.6		52	348.7		421.3	
10	243.2		295.7		21	351.2		426.1	
25	246.4		301.7		40	357.8		429.3	
16	248.6		305.2		58	362.4		432.3	
33	251.5		313.6		48	367.9		433.1	
49	256.7		315.0		39	375.6		445.6	
6	257.7		315.9		56	382.3		449.1	
14	262.8		317.2		53	382.4		450.0	
30	272.6		323.3		41	387.1		453.0	
45	276.2		325.8		59	388.8		453.6	
11	287.8		325.9		57	395.1		471.9	
26	288.6		338.0		42	417.8		475.2	
17	290.3		352.0		61	418.9		486.1	
34	290.6		352.2		60	436.2		491.3	
50	290.7		357.0		62	442.6		508.7	
					63	444.0		528.2	

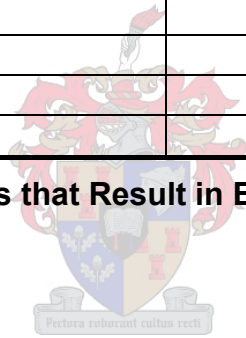
Table 95: Sorted Medium Runner Combinations.

		Safety Time & Coverage Profile Combinations (Safety Time, Min Coverage, Target Coverage)				
		Coded Number	(ST+MC),(ST+TC)	Combo 1	Combo 2	Combo 3
Matching Safety Time & Coverage Profile Values	1	0, 0	0, 0, 0			
	2	0, 1	0, 0, 1			
	3	1, 1	0, 1, 1	1, 0, 0		
	4	0, 2	0, 0, 2			
	5	1, 2	0, 1, 2	1, 0, 1		
	6	0, 3	0, 0, 3			
	7	2, 2	0, 2, 2	1, 1, 1	2, 0, 0	
	8	1, 3	0, 1, 3	1, 0, 2		
	9	0, 4	0, 0, 4			
	10	2, 3	0, 2, 3	1, 1, 2	2, 0, 1	
	11	1, 4	0, 1, 4	1, 0, 3		
	12	0, 5	0, 0, 5			
	13	3, 3	0, 3, 3	1, 2, 2	2, 1, 1	
	14	2, 4	0, 2, 4	1, 1, 3	2, 0, 2	
	15	1, 5	0, 1, 5	1, 0, 4		
	16	3, 4	0, 3, 4	1, 2, 3	2, 1, 2	
	17	2, 5	0, 2, 5	1, 1, 4	2, 0, 3	
	18	1, 6	1, 0, 5			
	19	4, 4	0, 4, 4	1, 3, 3	2, 2, 2	
	20	3, 5	0, 3, 5	1, 2, 4	2, 1, 3	
	21	2, 6	1, 1, 5	2, 0, 4		
	22	4, 5	0, 4, 5	1, 3, 4	2, 2, 3	
	23	3, 6	1, 2, 5	2, 1, 4		
	24	2, 7	2, 0, 5			
	25	5, 5	0, 5, 5	1, 4, 4	2, 3, 3	
	26	4, 6	1, 3, 5	2, 2, 4		
	27	3, 7	2, 1, 5			
	28	5, 6	1, 4, 5	2, 3, 4		
	29	4, 7	2, 2, 5			
	30	6, 6	1, 5, 5	2, 4, 4		
	31	5, 7	2, 3, 5			
	32	6, 7	2, 4, 5			
	33	7, 7	2, 5, 5			

Table 96: Matching Combinations

Category (Safety Time, Minimum Coverage, Target Coverage)					
1	2	3	4	5	6
0, 0, 5	0, 0, 4	0, 0, 3	0, 0, 2	0, 0, 1	0, 0, 0
1, 0, 5	0, 1, 5	0, 1, 4	0, 1, 3	0, 1, 2	0, 1, 1
2, 0, 5	1, 0, 4	0, 2, 5	0, 2, 4	0, 2, 3	0, 2, 2
	1, 1, 5	1, 0, 3	0, 3, 5	0, 3, 4	0, 3, 3
	2, 0, 4	1, 1, 4	1, 0, 2	0, 4, 5	0, 4, 4
	2, 1, 5	1, 2, 5	1, 1, 3	1, 0, 1	0, 5, 5
		2, 0, 3	1, 2, 4	1, 1, 2	1, 0, 0
		2, 1, 4	1, 3, 5	1, 2, 3	1, 1, 1
		2, 2, 5	2, 0, 2	1, 3, 4	1, 2, 2
			2, 1, 3	1, 4, 5	1, 3, 3
			2, 2, 4	2, 0, 1	1, 4, 4
			2, 3, 5	2, 1, 2	1, 5, 5
				2, 2, 3	2, 0, 0
				2, 3, 4	2, 1, 1
				2, 4, 5	2, 2, 2
					2, 3, 3
					2, 4, 4
					2, 5, 5

Table 97: Combinations that Result in Equal Avg. Number of Orders



		Avg. Number of Orders			Avg. Order Size		
		Average	Min	Max	Average	Min	Max
Category (Low Runner)	1	163.43	162.64	164.26	158.00	156.60	158.98
	2	199.08	196.06	200.64	131.03	129.88	131.88
	3	254.40	250.14	258.82	103.31	101.92	104.28
	4	347.81	341.00	356.08	75.91	74.19	77.34
	5	552.96	537.60	570.22	47.93	46.67	48.98
	6	905.53	887.94	934.90	29.31	28.10	30.06
Category (Medium Runner)	1	165.35	162.34	168.52	384.68	383.42	386.73
	2	206.22	202.52	212.58	314.69	312.17	316.20
	3	268.94	262.44	276.10	245.52	241.88	247.73
	4	379.57	369.70	392.56	176.19	172.54	179.16
	5	635.31	606.38	657.66	106.24	103.30	109.16
	6	948.10	932.92	961.22	71.38	68.88	72.08
Category (High Runner)	1	159.85	156.38	163.86	696.38	694.52	698.50
	2	196.87	192.16	199.52	574.82	568.21	581.93
	3	253.41	247.88	258.18	452.23	447.08	455.48
	4	349.24	341.66	359.08	330.90	325.03	336.02
	5	555.89	541.68	567.10	208.95	206.34	212.50
	6	924.03	905.90	945.06	125.98	121.00	128.24

Table 98: Indicators of Avg. Number of Orders and Avg. Order Size Magnitude.

		To																																
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
From	1	0%	41%	189%	75%	262%	112%	454%	109%	150%	560%	389%	184%	567%	639%	449%	661%	725%	206%	684%	738%	508%	779%	505%	235%	806%	538%	233%	579%	244%	599%	268%	284%	295%
	2	-29%	0%	105%	24%	156%	50%	292%	48%	77%	367%	246%	101%	372%	423%	288%	439%	484%	116%	455%	493%	330%	522%	329%	137%	541%	352%	136%	381%	144%	395%	160%	172%	179%
	3	-65%	-51%	0%	-40%	25%	-27%	91%	-28%	-14%	128%	69%	-2%	130%	155%	90%	163%	185%	6%	171%	189%	110%	204%	109%	16%	213%	120%	15%	135%	19%	142%	27%	33%	36%
	4	-43%	-19%	66%	0%	107%	21%	217%	19%	43%	278%	180%	63%	282%	323%	214%	335%	372%	75%	349%	379%	248%	403%	247%	92%	419%	265%	91%	289%	97%	300%	111%	120%	126%
	5	-72%	-61%	-20%	-52%	0%	-42%	53%	-42%	-31%	82%	35%	-22%	84%	104%	51%	110%	128%	-16%	116%	131%	68%	143%	67%	-8%	150%	76%	-8%	88%	-5%	93%	2%	6%	9%
	6	-53%	-33%	37%	-18%	71%	0%	162%	-2%	18%	212%	131%	34%	215%	249%	159%	259%	289%	44%	270%	295%	187%	315%	186%	58%	328%	201%	57%	221%	63%	230%	74%	81%	86%
	7	-82%	-75%	-48%	-68%	-35%	-62%	0%	-62%	-55%	19%	-12%	-49%	20%	33%	-1%	37%	49%	-45%	41%	51%	10%	59%	9%	-40%	63%	15%	-40%	23%	-38%	26%	-34%	-31%	-29%
	8	-52%	-32%	39%	-16%	74%	2%	166%	0%	20%	216%	134%	36%	220%	254%	163%	265%	295%	46%	276%	302%	191%	321%	190%	60%	334%	206%	60%	226%	65%	235%	76%	84%	89%
	9	-60%	-43%	16%	-30%	45%	-15%	122%	-17%	0%	164%	96%	14%	167%	196%	120%	205%	230%	22%	214%	235%	143%	252%	142%	34%	263%	155%	33%	172%	38%	180%	47%	54%	58%
	10	-85%	-79%	-56%	-74%	-45%	-68%	-16%	-68%	-62%	0%	-26%	-57%	1%	12%	-17%	15%	25%	-54%	19%	27%	-8%	33%	-8%	-49%	37%	-3%	-50%	3%	-48%	6%	-44%	-42%	-40%
	11	-80%	-71%	-41%	-64%	-26%	-57%	13%	-57%	-49%	35%	0%	-42%	36%	51%	12%	56%	69%	-37%	60%	71%	24%	80%	24%	-32%	85%	31%	-32%	39%	-30%	43%	-25%	-21%	-19%
	12	-65%	-50%	2%	-39%	27%	-25%	95%	-27%	-12%	132%	72%	0%	135%	160%	93%	168%	190%	8%	176%	195%	114%	209%	113%	18%	219%	125%	17%	139%	21%	146%	29%	35%	39%
	13	-85%	-79%	-57%	-74%	-46%	-68%	-17%	-69%	-63%	-1%	-27%	-57%	0%	11%	-18%	14%	24%	-54%	18%	26%	-9%	32%	-9%	-50%	36%	-4%	-50%	2%	-48%	5%	-45%	-42%	-41%
	14	-86%	-81%	-61%	-76%	-51%	-71%	-25%	-72%	-66%	-11%	-34%	-62%	-10%	0%	-26%	3%	12%	-59%	6%	13%	-18%	19%	-18%	-55%	23%	-14%	-55%	-8%	-53%	-5%	-50%	-48%	-47%
	15	-82%	-74%	-47%	-68%	-34%	-61%	1%	-62%	-54%	20%	-11%	-48%	22%	35%	0%	39%	50%	-44%	43%	53%	11%	60%	10%	-39%	65%	16%	-39%	24%	-37%	27%	-33%	-30%	-28%
	16	-87%	-81%	-62%	-77%	-52%	-72%	-27%	-73%	-67%	-13%	-36%	-63%	-12%	-3%	-28%	0%	8%	-60%	3%	10%	-20%	16%	-20%	-56%	19%	-16%	-56%	-11%	-55%	-8%	-52%	-50%	-48%
	17	-88%	-83%	-65%	-79%	-56%	-74%	-33%	-75%	-70%	-20%	-41%	-66%	-19%	-10%	-33%	-8%	0%	-63%	-5%	2%	-26%	7%	-27%	-59%	10%	-23%	-60%	-18%	-58%	-15%	-55%	-53%	-52%
	18	-67%	-54%	-5%	-43%	19%	-31%	81%	-32%	-18%	116%	60%	-7%	118%	142%	80%	149%	170%	0%	157%	174%	99%	188%	98%	10%	197%	109%	9%	122%	13%	129%	20%	26%	29%
	19	-87%	-82%	-63%	-78%	-54%	-73%	-29%	-73%	-68%	-16%	-38%	-64%	-15%	-6%	-30%	-3%	5%	-61%	0%	7%	-23%	12%	-23%	-57%	16%	-19%	-58%	-13%	-56%	-11%	-53%	-51%	-50%
	20	-88%	-83%	-65%	-79%	-57%	-75%	-34%	-75%	-70%	-21%	-42%	-66%	-20%	-12%	-34%	-9%	-2%	-64%	-6%	0%	-27%	5%	-28%	-60%	8%	-24%	-60%	-19%	-59%	-17%	-56%	-54%	-53%
	21	-84%	-77%	-52%	-71%	-40%	-65%	-9%	-66%	-59%	9%	-20%	-53%	10%	22%	-10%	25%	36%	-50%	29%	38%	0%	45%	0%	-45%	49%	5%	-45%	12%	-43%	15%	-39%	-37%	-35%
	22	-89%	-84%	-67%	-80%	-59%	-76%	-37%	-76%	-72%	-25%	-44%	-68%	-24%	-16%	-38%	-13%	-6%	-65%	-11%	-5%	-31%	0%	-31%	-62%	3%	-27%	-62%	-23%	-61%	-20%	-58%	-56%	-55%
	23	-83%	-77%	-52%	-71%	-40%	-65%	-8%	-66%	-59%	9%	-19%	-53%	10%	22%	-9%	26%	36%	-50%	30%	38%	0%	45%	0%	-45%	50%	5%	-45%	12%	-43%	15%	-39%	-37%	-35%
	24	-70%	-58%	-14%	-48%	8%	-37%	66%	-38%	-25%	97%	46%	-15%	99%	121%	64%	127%	146%	-9%	134%	150%	82%	163%	81%	0%	171%	91%	0%	103%	3%	109%	10%	15%	18%
	25	-89%	-84%	-68%	-81%	-60%	-77%	-39%	-77%	-72%	-27%	-46%	-69%	-26%	-18%	-39%	-16%	-9%	-66%	-13%	-8%	-33%	-3%	-33%	-63%	0%	-30%	-63%	-25%	-62%	-23%	-59%	-58%	-56%
	26	-84%	-78%	-55%	-73%	-43%	-67%	-13%	-67%	-61%	3%	-23%	-55%	5%	16%	-14%	19%	29%	-52%	23%	31%	-5%	38%	-5%	-48%	42%	0%	-48%	6%	-46%	10%	-42%	-40%	-38%
	27	-70%	-58%	-13%	-48%	9%	-36%	66%	-37%	-25%	98%	47%	-15%	100%	122%	65%	128%	148%	-8%	135%	151%	82%	164%	82%	0%	172%	92%	0%	104%	3%	110%	10%	15%	18%
	28	-85%	-79%	-57%	-74%	-47%	-69%	-18%	-69%	-63%	-3%	-28%	-58%	-2%	9%	-19%	12%	21%	-55%	15%	23%	-11%	29%	-11%	-51%	33%	-6%	-51%	0%	-49%	3%	-46%	-43%	-42%
	29	-71%	-59%	-16%	-49%	5%	-38%	61%	-39%	-27%	92%	42%	-17%	94%	115%	59%	121%	140%	-11%	128%	143%	76%	155%	76%	-3%	163%	85%	-3%	97%	0%	103%	7%	11%	15%
	30	-86%	-80%	-59%	-75%	-48%	-70%	-21%	-70%	-64%	-6%	-30%	-59%	-5%	6%	-22%	9%	18%	-56%	12%	20%	-13%	26%	-13%	-52%	30%	-9%	-52%	-3%	-51%	0%	-47%	-45%	-44%
	31	-73%	-62%	-21%	-52%	-2%	-42%	51%	-43%	-32%	79%	33%	-23%	81%	101%	49%	107%	124%	-17%	113%	128%	65%	139%	65%	-9%	146%	73%	-9%	85%	-6%	90%	0%	4%	7%
	32	-74%	-63%	-25%	-54%	-6%	-45%	44%	-46%	-35%	72%	27%	-26%	74%	92%	43%	98%	115%	-20%	104%	118%	58%	129%	58%	-13%	136%	66%	-13%	77%	-10%	82%	-4%	0%	3%
	33	-75%	-64%	-27%	-56%	-8%	-46%	40%	-47%	-37%	67%	24%	-28%	69%	87%	39%	93%	109%	-23%	99%	112%	54%	123%	53%	-15%	130%	62%	-16%	72%	-13%	77%	-7%	-3%	0%

Table 99: Resultant Change in Avg. Plant Inventory for 2032700400 A.

		To																																
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
From	1	0%	119%	280%	221%	494%	331%	737%	299%	454%	1035%	929%	586%	930%	1310%	1144%	1182%	1550%	629%	1120%	1383%	1176%	1345%	1032%	627%	1357%	972%	538%	1040%	504%	1082%	535%	588%	616%
	2	-54%	0%	74%	47%	171%	97%	283%	82%	153%	419%	370%	214%	371%	544%	469%	486%	654%	233%	458%	578%	483%	561%	417%	232%	566%	390%	192%	421%	176%	440%	190%	214%	227%
	3	-74%	-42%	0%	-16%	56%	13%	120%	5%	46%	198%	171%	80%	171%	271%	227%	237%	334%	92%	221%	290%	236%	280%	198%	91%	283%	182%	68%	200%	59%	211%	67%	81%	88%
	4	-69%	-32%	19%	0%	85%	34%	161%	24%	73%	254%	221%	114%	221%	339%	288%	299%	414%	127%	280%	362%	298%	350%	253%	126%	354%	234%	99%	255%	88%	268%	98%	114%	123%
	5	-83%	-63%	-36%	-46%	0%	-27%	41%	-33%	-7%	91%	73%	16%	74%	137%	110%	116%	178%	23%	106%	150%	115%	143%	91%	22%	145%	81%	7%	92%	2%	99%	7%	16%	21%
	6	-77%	-49%	-12%	-26%	38%	0%	94%	-7%	28%	163%	139%	59%	139%	227%	188%	197%	282%	69%	183%	244%	196%	235%	162%	68%	238%	149%	48%	164%	40%	174%	47%	59%	66%
	7	-88%	-74%	-55%	-62%	-29%	-48%	0%	-52%	-34%	36%	23%	-18%	23%	68%	49%	53%	97%	-13%	46%	77%	52%	73%	35%	-13%	74%	28%	-24%	36%	-28%	41%	-24%	-18%	-14%
	8	-75%	-45%	-5%	-20%	49%	8%	110%	0%	39%	184%	158%	72%	158%	253%	212%	221%	313%	83%	206%	271%	220%	262%	183%	82%	265%	169%	60%	185%	51%	196%	59%	72%	79%
	9	-82%	-60%	-31%	-42%	7%	-22%	51%	-28%	0%	105%	86%	24%	86%	155%	125%	131%	198%	32%	120%	168%	130%	161%	104%	31%	163%	94%	15%	106%	9%	113%	15%	24%	29%
	10	-91%	-81%	-66%	-72%	-48%	-62%	-26%	-65%	-51%	0%	-9%	-40%	-9%	24%	10%	13%	45%	-36%	8%	31%	12%	27%	0%	-36%	28%	-6%	-44%	0%	-47%	4%	-44%	-39%	-37%
	11	-90%	-79%	-63%	-69%	-42%	-58%	-19%	-61%	-46%	10%	0%	-33%	0%	37%	21%	25%	60%	-29%	19%	44%	24%	40%	10%	-29%	42%	4%	-38%	11%	-41%	15%	-38%	-33%	-30%
	12	-85%	-68%	-45%	-53%	-13%	-37%	22%	-42%	-19%	65%	50%	0%	50%	106%	81%	87%	141%	6%	78%	116%	86%	111%	65%	6%	112%	56%	-7%	66%	-12%	72%	-7%	0%	4%
	13	-90%	-79%	-63%	-69%	-42%	-58%	-19%	-61%	-46%	10%	0%	-33%	0%	37%	21%	24%	60%	-29%	18%	44%	24%	40%	10%	-29%	41%	4%	-38%	11%	-41%	15%	-38%	-33%	-30%
	14	-93%	-84%	-73%	-77%	-58%	-69%	-41%	-72%	-61%	-20%	-27%	-51%	-27%	0%	-12%	-9%	17%	-48%	-13%	5%	-9%	3%	-20%	-48%	3%	-24%	-55%	-19%	-57%	-16%	-55%	-51%	-49%
	15	-92%	-82%	-69%	-74%	-52%	-65%	-33%	-68%	-55%	-9%	-17%	-45%	-17%	13%	0%	3%	33%	-41%	-2%	19%	3%	16%	-9%	-42%	17%	-14%	-49%	-8%	-51%	-5%	-49%	-45%	-42%
	16	-92%	-83%	-70%	-75%	-54%	-66%	-35%	-69%	-57%	-11%	-20%	-46%	-20%	10%	-3%	0%	29%	-43%	-5%	16%	0%	13%	-12%	-43%	14%	-16%	-50%	-11%	-53%	-8%	-50%	-46%	-44%
	17	-94%	-87%	-77%	-81%	-64%	-74%	-49%	-76%	-66%	-31%	-38%	-58%	-38%	-15%	-25%	-22%	0%	-56%	-26%	-10%	-23%	-12%	-31%	-56%	-12%	-35%	-61%	-31%	-63%	-28%	-61%	-58%	-57%
	18	-86%	-70%	-48%	-56%	-19%	-41%	15%	-45%	-24%	56%	41%	-6%	41%	93%	71%	76%	126%	0%	67%	103%	75%	98%	55%	0%	100%	47%	-12%	56%	-17%	62%	-13%	-6%	-2%
	19	-92%	-82%	-69%	-74%	-51%	-65%	-31%	-67%	-55%	-7%	-16%	-44%	-16%	16%	2%	5%	35%	-40%	0%	22%	5%	18%	-7%	-40%	19%	-12%	-48%	-7%	-51%	-3%	-48%	-44%	-41%
	20	-93%	-85%	-74%	-78%	-60%	-71%	-44%	-73%	-63%	-23%	-31%	-54%	-31%	-5%	-16%	-14%	11%	-51%	-18%	0%	-14%	-3%	-24%	-51%	-2%	-28%	-57%	-23%	-59%	-20%	-57%	-54%	-52%
	21	-92%	-83%	-70%	-75%	-53%	-66%	-34%	-69%	-57%	-11%	-19%	-46%	-19%	10%	-3%	0%	29%	-43%	-4%	16%	0%	13%	-11%	-43%	14%	-16%	-50%	-11%	-53%	-7%	-50%	-46%	-44%
	22	-93%	-85%	-74%	-78%	-59%	-70%	-42%	-72%	-62%	-21%	-29%	-53%	-29%	-2%	-14%	-11%	14%	-50%	-16%	3%	-12%	0%	-22%	-50%	1%	-26%	-56%	-21%	-58%	-18%	-56%	-52%	-50%
	23	-91%	-81%	-66%	-72%	-48%	-62%	-26%	-65%	-51%	0%	-9%	-39%	-9%	25%	10%	13%	46%	-36%	8%	31%	13%	28%	0%	-36%	29%	-5%	-44%	1%	-47%	4%	-44%	-39%	-37%
	24	-86%	-70%	-48%	-56%	-18%	-41%	15%	-45%	-24%	56%	42%	-6%	42%	94%	71%	76%	127%	0%	68%	104%	76%	99%	56%	0%	101%	48%	-12%	57%	-17%	63%	-13%	-5%	-1%
	25	-93%	-85%	-74%	-78%	-59%	-70%	-43%	-73%	-62%	-22%	-29%	-53%	-29%	-3%	-15%	-12%	13%	-50%	-16%	2%	-12%	-1%	-22%	-50%	0%	-26%	-56%	-22%	-59%	-19%	-56%	-53%	-51%
	26	-91%	-80%	-65%	-70%	-45%	-60%	-22%	-63%	-48%	6%	-4%	-36%	-4%	31%	16%	20%	54%	-32%	14%	38%	19%	35%	6%	-32%	36%	0%	-40%	6%	-44%	10%	-41%	-36%	-33%
	27	-84%	-66%	-40%	-50%	-7%	-32%	31%	-37%	-13%	78%	61%	7%	61%	121%	95%	101%	159%	14%	91%	132%	100%	126%	77%	14%	128%	68%	0%	79%	-5%	85%	0%	8%	12%
	28	-91%	-81%	-67%	-72%	-48%	-62%	-27%	-65%	-51%	0%	-10%	-40%	-10%	24%	9%	12%	45%	-36%	7%	30%	12%	27%	-1%	-36%	28%	-6%	-44%	0%	-47%	4%	-44%	-40%	-37%
	29	-83%	-64%	-37%	-47%	-2%	-29%	39%	-34%	-8%	88%	70%	14%	71%	133%	106%	112%	173%	21%	102%	146%	111%	139%	87%	20%	141%	78%	6%	89%	0%	96%	5%	14%	19%
	30	-92%	-81%	-68%	-73%	-50%	-64%	-29%	-66%	-53%	-4%	-13%	-42%	-13%	19%	5%	8%	40%	-38%	3%	25%	8%	22%	-4%	-39%	23%	-9%	-46%	-4%	-49%	0%	-46%	-42%	-39%
	31	-84%	-66%	-40%	-50%	-7%	-32%	32%	-37%	-13%	79%	62%	8%	62%	122%	96%	102%	160%	15%	92%	133%	101%	127%	78%	14%	129%	69%	0%	79%	-5%	86%	0%	8%	13%
	32	-85%	-68%	-45%	-53%	-14%	-37%	22%	-42%	-19%	65%	50%	0%	50%	105%	81%	86%	140%	6%	77%	116%	86%	110%	65%	6%	112%	56%	-7%	66%	-12%	72%	-8%	0%	4%
	33	-86%	-69%	-47%	-55%	-17%	-40%	17%	-44%	-23%	58%	44%	-4%	44%	97%	74%	79%	130%	2%	70%	107%	78%	102%	58%	1%	104%	50%	-11%	59%	-16%	65%	-11%	-4%	0%

Table 100: Resultant Change Avg. Plant Inventory for 2710106700 A.

		To																																
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
From	1	0%	62%	214%	123%	329%	178%	537%	163%	239%	688%	523%	305%	686%	813%	631%	826%	932%	321%	843%	927%	690%	982%	664%	334%	1034%	696%	330%	747%	338%	780%	361%	392%	414%
	2	-38%	0%	94%	37%	164%	72%	293%	62%	109%	386%	284%	150%	385%	463%	351%	471%	536%	160%	481%	533%	387%	567%	371%	168%	599%	391%	165%	422%	170%	443%	184%	204%	217%
	3	-68%	-48%	0%	-29%	37%	-11%	103%	-16%	8%	151%	99%	29%	151%	191%	133%	195%	229%	34%	200%	227%	152%	245%	143%	38%	261%	153%	37%	170%	39%	181%	47%	57%	64%
	4	-55%	-27%	41%	0%	93%	25%	186%	18%	52%	254%	180%	82%	253%	310%	228%	316%	364%	89%	324%	362%	255%	386%	243%	95%	409%	257%	93%	280%	97%	296%	107%	121%	131%
	5	-77%	-62%	-27%	-48%	0%	-35%	48%	-39%	-21%	84%	45%	-6%	83%	113%	70%	116%	141%	-2%	120%	140%	84%	152%	78%	1%	164%	86%	0%	97%	2%	105%	8%	15%	20%
	6	-64%	-42%	13%	-20%	54%	0%	129%	-5%	22%	183%	124%	45%	182%	228%	162%	233%	271%	51%	238%	269%	184%	289%	174%	56%	307%	186%	54%	204%	57%	216%	66%	77%	85%
	7	-84%	-75%	-51%	-65%	-33%	-56%	0%	-59%	-47%	24%	-2%	-36%	24%	43%	15%	45%	62%	-34%	48%	61%	24%	70%	20%	-32%	78%	25%	-33%	33%	-31%	38%	-28%	-23%	-19%
	8	-62%	-38%	19%	-15%	63%	6%	142%	0%	29%	199%	137%	54%	199%	247%	178%	252%	292%	60%	258%	290%	200%	311%	190%	65%	330%	202%	63%	221%	66%	234%	75%	87%	95%
	9	-71%	-52%	-7%	-34%	26%	-18%	88%	-22%	0%	133%	84%	19%	132%	169%	116%	173%	204%	24%	178%	203%	133%	219%	125%	28%	234%	135%	27%	150%	29%	160%	36%	45%	52%
	10	-87%	-79%	-60%	-72%	-46%	-65%	-19%	-67%	-57%	0%	-21%	-49%	0%	16%	-7%	17%	31%	-47%	20%	30%	0%	37%	-3%	-45%	44%	1%	-45%	7%	-44%	12%	-41%	-38%	-35%
	11	-84%	-74%	-50%	-64%	-31%	-55%	2%	-58%	-46%	26%	0%	-35%	26%	47%	17%	49%	66%	-32%	51%	65%	27%	74%	22%	-30%	82%	28%	-31%	36%	-30%	41%	-26%	-21%	-17%
	12	-75%	-60%	-23%	-45%	6%	-31%	57%	-35%	-16%	95%	54%	0%	94%	125%	80%	129%	155%	4%	133%	154%	95%	167%	88%	7%	180%	96%	6%	109%	8%	117%	14%	22%	27%
	13	-87%	-79%	-60%	-72%	-45%	-65%	-19%	-67%	-57%	0%	-21%	-48%	0%	16%	-7%	18%	31%	-46%	20%	31%	0%	38%	-3%	-45%	44%	1%	-45%	8%	-44%	12%	-41%	-37%	-35%
	14	-89%	-82%	-66%	-76%	-53%	-70%	-30%	-71%	-63%	-14%	-32%	-56%	-14%	0%	-20%	1%	13%	-54%	3%	12%	-13%	18%	-16%	-52%	24%	-13%	-53%	-7%	-52%	-4%	-49%	-46%	-44%
	15	-86%	-78%	-57%	-70%	-41%	-62%	-13%	-64%	-54%	8%	-15%	-45%	8%	25%	0%	27%	41%	-42%	29%	41%	8%	48%	4%	-41%	55%	9%	-41%	16%	-40%	20%	-37%	-33%	-30%
	16	-89%	-82%	-66%	-76%	-54%	-70%	-31%	-72%	-63%	-15%	-33%	-56%	-15%	-1%	-21%	0%	11%	-55%	2%	11%	-15%	17%	-18%	-53%	22%	-14%	-54%	-9%	-53%	-5%	-50%	-47%	-44%
	17	-90%	-84%	-70%	-78%	-58%	-73%	-38%	-74%	-67%	-24%	-40%	-61%	-24%	-11%	-29%	-10%	0%	-59%	-9%	0%	-23%	5%	-26%	-58%	10%	-23%	-58%	-18%	-58%	-15%	-55%	-52%	-50%
	18	-76%	-61%	-25%	-47%	2%	-34%	51%	-37%	-20%	87%	48%	-4%	87%	117%	73%	120%	145%	0%	124%	144%	88%	157%	81%	3%	169%	89%	2%	101%	4%	109%	10%	17%	22%
	19	-89%	-83%	-67%	-76%	-55%	-70%	-32%	-72%	-64%	-16%	-34%	-57%	-17%	-3%	-22%	-2%	9%	-55%	0%	9%	-16%	15%	-19%	-54%	20%	-16%	-54%	-10%	-54%	-7%	-51%	-48%	-45%
	20	-90%	-84%	-69%	-78%	-58%	-73%	-38%	-74%	-67%	-23%	-39%	-61%	-23%	-11%	-29%	-10%	0%	-59%	-8%	0%	-23%	5%	-26%	-58%	10%	-23%	-58%	-18%	-57%	-14%	-55%	-52%	-50%
	21	-87%	-79%	-60%	-72%	-46%	-65%	-19%	-67%	-57%	0%	-21%	-49%	0%	16%	-8%	17%	31%	-47%	19%	30%	0%	37%	-3%	-45%	43%	1%	-46%	7%	-45%	11%	-42%	-38%	-35%
	22	-91%	-85%	-71%	-79%	-60%	-74%	-41%	-76%	-69%	-27%	-42%	-63%	-27%	-16%	-32%	-14%	-5%	-61%	-13%	-5%	-27%	0%	-29%	-60%	5%	-26%	-60%	-22%	-60%	-19%	-57%	-54%	-52%
	23	-87%	-79%	-59%	-71%	-44%	-64%	-17%	-66%	-56%	3%	-18%	-47%	3%	20%	-4%	21%	35%	-45%	23%	35%	3%	42%	0%	-43%	48%	4%	-44%	11%	-43%	15%	-40%	-36%	-33%
	24	-77%	-63%	-28%	-49%	-1%	-36%	47%	-39%	-22%	82%	44%	-7%	81%	111%	68%	113%	138%	-3%	117%	137%	82%	149%	76%	0%	161%	83%	-1%	95%	1%	103%	6%	13%	19%
	25	-91%	-86%	-72%	-80%	-62%	-75%	-44%	-77%	-70%	-30%	-45%	-64%	-31%	-19%	-36%	-18%	-9%	-63%	-17%	-9%	-30%	-5%	-33%	-62%	0%	-30%	-62%	-25%	-61%	-22%	-59%	-57%	-55%
	26	-87%	-80%	-61%	-72%	-46%	-65%	-20%	-67%	-57%	-1%	-22%	-49%	-1%	15%	-8%	16%	30%	-47%	18%	29%	-1%	36%	-4%	-45%	42%	0%	-46%	6%	-45%	11%	-42%	-38%	-35%
	27	-77%	-62%	-27%	-48%	0%	-35%	48%	-39%	-21%	83%	45%	-6%	83%	113%	70%	116%	140%	-2%	119%	139%	84%	152%	78%	1%	164%	85%	0%	97%	2%	105%	7%	15%	20%
	28	-88%	-81%	-63%	-74%	-49%	-67%	-25%	-69%	-60%	-7%	-26%	-52%	-7%	8%	-14%	9%	22%	-50%	11%	21%	-7%	28%	-10%	-49%	34%	-6%	-49%	0%	-48%	4%	-45%	-42%	-39%
	29	-77%	-63%	-28%	-49%	-2%	-36%	45%	-40%	-23%	80%	42%	-7%	80%	109%	67%	112%	136%	-4%	115%	135%	80%	147%	74%	-1%	159%	82%	-2%	93%	0%	101%	5%	12%	17%
	30	-89%	-82%	-64%	-75%	-51%	-68%	-28%	-70%	-61%	-10%	-29%	-54%	-11%	4%	-17%	5%	17%	-52%	7%	17%	-10%	23%	-13%	-51%	29%	-10%	-51%	-4%	-50%	0%	-48%	-44%	-42%
	31	-78%	-65%	-32%	-52%	-7%	-40%	38%	-43%	-27%	71%	35%	-12%	70%	98%	58%	101%	124%	-9%	104%	123%	71%	134%	65%	-6%	146%	72%	-7%	83%	-5%	91%	0%	7%	11%
	32	-80%	-67%	-36%	-55%	-13%	-43%	29%	-47%	-31%	60%	27%	-18%	60%	86%	48%	88%	110%	-14%	91%	109%	60%	120%	55%	-12%	130%	62%	-13%	72%	-11%	79%	-6%	0%	4%
	33	-81%	-68%	-39%	-57%	-17%	-46%	24%	-49%	-34%	53%	21%	-21%	53%	78%	42%	80%	101%	-18%	83%	100%	54%	110%	48%	-16%	120%	55%	-16%	65%	-15%	71%	-10%	-4%	0%

Table 101: Resultant Change in Avg. Plant Inventory for 2038170920 A

*Appendix N Definition of Performance
Measures*



Average Inventory:

Avg. Inventory consists of three sub-measures, namely:

1. Avg. Plant Inventory
2. Avg. Harbour Inventory
3. Avg. Pipeline Inventory

Average Plant Inventory (Avg. Plant Inventory)

Description: This measure indicates the average day-end stock in the plant during the simulation period.

Unit of measure: parts per day

Average Harbour Inventory (Avg. Harbour Inventory)

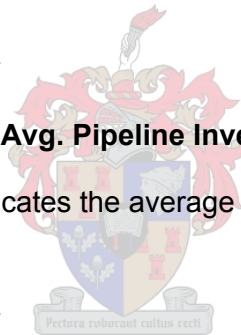
Description: This measure indicates the average daily inventory in the harbour during the simulation period.

Unit of measure: parts per day

Average Pipeline Inventory (Avg. Pipeline Inventory)

Description: This measure indicates the average daily inventory in the Order Pipeline during the simulation period.

Unit of measure: parts per day



Service Level:

Service Level consists of two sub-measures, namely:

1. Avg. Customer Service Level
2. Avg. DCSA Service Level

Average Customer Service Level (Avg. Customer Service Level)

Description:

The author has defined Customer Service Level as: The percentage of the Customer Demand satisfied first time i.e. the demand is satisfied by the Available Stock, without having to emergency freight stock in.

Unit of measure: percent

Average DCSA Service Level (Avg. DCSA Service Level)

Note: This measure was only used when conducting the “Human Intervention” Experiment and worked in conjunction with Avg. Shortage Frequency. It was of no relevance to any other analysis.

Description:

DCSA Service Level is defined as:

The Service Level afforded to DCSA by the SAP - MRP System.

This Service Level differs from Customer Service Level in that DCSA is viewed as being a “Customer” of SAP. DCSA requires the SAP-MRP System to provide a certain level of Plant Stock at all times, based upon the ADR and Coverage Profile. The ability of the SAP-MRP System to abide by these requirements is viewed as being the DCSA Service Level.

The SAP-MRP System computes the required Order Release, based upon the Input Parameters, such that the Coverage Profile is adhered to at the point of receipt for that specific Initial Demand. If the Coverage Profile is not met at the point of receipt then the occurrence is termed as a “Coverage Violation.” In terms of this study, “the point of receipt” is the point at which the stock is required at the assembly line, and **not** the point of receipt at the harbour or warehouse.

Example

The SAP-MRP System releases an order for 50 parts based upon the Initial Demand of 180, Available Stock, Coverage Profile (1, 1, 4), and a Safety Time of 2 days. According to the SAP-MRP System, the Minimum Coverage should be no less than 3 days (Safety Time + Minimum Coverage). However, due to the fluctuating demand the Minimum Coverage is less than 3 days when the Order is received x days later – this is called a Coverage Profile Violation.

Unit of Measure: percent

Orders:

Orders consist of two sub-measures, namely:

1. Avg. Number of Orders
2. Avg. Order Size

Average Number of Orders (Avg. Number of Orders)

Description: This measure indicates the average number of orders released to suppliers during the simulation period. A single order may consist of many pallets.

Unit of measure: orders

Average Order Size (Avg. Order Size)

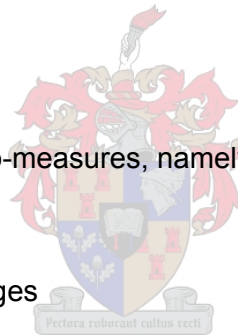
Description: This measure indicates the Avg. Order Size per Order Release during the simulation period. The order size will always be a multiple of the Pallet Size.

Unit of measure: parts

Shortages:

Shortages consist of three sub-measures, namely:

1. Avg. Total Shortages
2. Avg. Customer Shortages
3. Avg. Order Frequency



Average Total Shortages (Avg. Total Shortages)

Description: This measure indicates the average total shortages that occurred during the simulation period. It does not represent the total customer shortages, but is rather a measure of the total number of additional parts that had to be ordered because of a stock-out. The simulation program was designed so that, in the case of a stock-out, an order would be placed such that the Range of Coverage is greater than or equal to the Target Range of Coverage. In other words, an emergency order is calculated in the same way that a normal order is calculated. Therefore, the system creates an order that is greater than the amount required due to the stock-out. This assumption was accepted by DCSA.

This measure was not of serious importance to the analysis, due to the assumption that it was based on i.e. DCSA will not necessarily follow this policy when creating an emergency freight Order Release. Therefore, it did not form part of any decision making process.

Unit of Measure: parts

Average Customer Shortages (Avg. Customer Shortage)

Description: This measure indicates the average customer shortages that occurred during the simulation period. A customer shortage is equated to a line stoppage or stock-out occurrence and is the result of there being not enough parts to satisfy a specific Customer Demand.

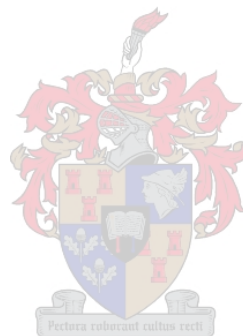
Unit of Measure: parts

Average Shortage Frequency (Avg. Shortage Frequency)

Note: This measure was used in the “Human Intervention” Experiment and, when not used in this context, it equals Avg. Customer Shortages.

Description: This measure indicates the average shortages that occurred during a simulation period. A shortage occurrence was defined as a demand that resulted in a Coverage Profile Violation.

Unit of Measure: parts



*Appendix O Introduction to Simulation
Software*



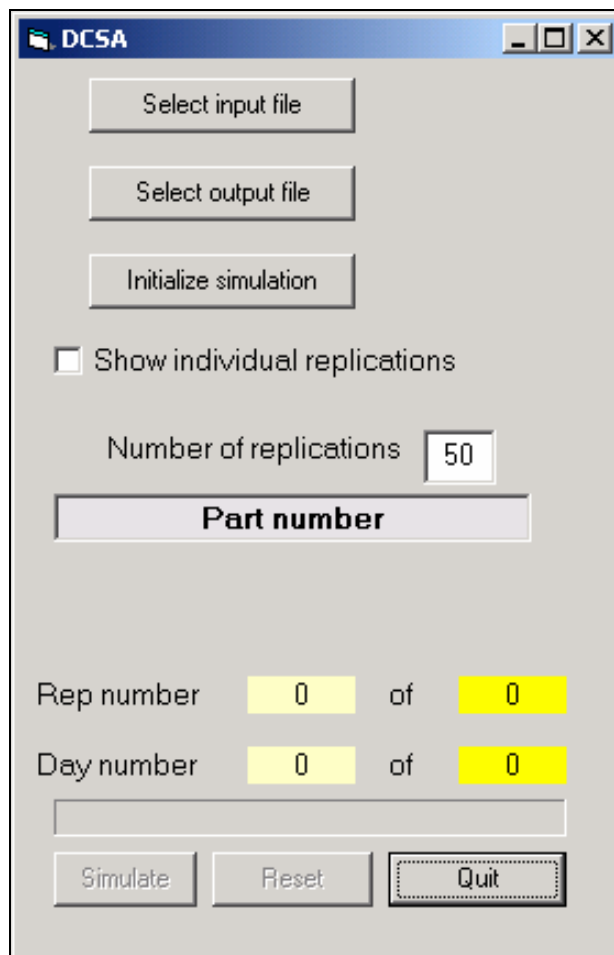
Introduction to the Simulation Software.

This section introduces the simulation software to the reader. It is not a user's guide but merely a basic description of the purpose of each form and the function of each parameter found on the form.

Start-Up Form.

The Start-Up Form, shown below, appears when the simulation program starts up. It is used to select the input and output Excel files with which the program interfaces during the simulation run. The user returns to this form after setting the various Input Parameters on the Initialising form where the Simulate command button is used to execute the program.

Various text boxes are utilised to keep the user informed as to the status of the simulation program.



The screenshot shows a software window titled "DCSA". Inside the window, there are three buttons stacked vertically: "Select input file", "Select output file", and "Initialize simulation". Below these is a checkbox labeled "Show individual replications" which is currently unchecked. Underneath the checkbox is a text box labeled "Number of replications" containing the number "50". A large, light-colored rectangular area is labeled "Part number". At the bottom of the window, there are three buttons: "Simulate", "Reset", and "Quit". The "Quit" button has a dashed border. Above the "Simulate" button, there are two status indicators: "Rep number 0 of 0" and "Day number 0 of 0", where the numbers "0" are highlighted in yellow.

Figure 280: Simulation Start-Up Form.

Initialising Form.

The Initialising Form, Figure 281 on page CCXXIX, is based on the one developed by van Wijck et al. [4]. The left half of the form is used to

- Set the OIMM parameters.
- Select the part for analysis.
- Name the output sheet.
- Set the number of days to be simulated.
- Set Lead-Time if required.

The OIMM component of the program has undergone various changes, which is highlighted in the following section.

Slider Settings

Previously the user was able to adjust the various slider settings. This is no longer possible and the slider settings are automatically adjusted to reflect the correct values associated with a specific part. All the values are calculated according to the 10 Day Option Freeze Environment and are loaded from the Input file when the “Load Settings” command button is clicked. The values differ from those indicated in Table 17 due to the alternate reference points used.

The screenshot shows the 'Initialize parameters' dialog box. It features a top dropdown menu with '2032700400 A'. The 'Operations frame' section includes a timeline with 'Review Interval' (5 Days), 'Option freeze' (12 Days), and 'Assembly Point' (39 Days). Below this, 'Simulation settings' are listed: 'Starting stock' (0 Units), '#Days to simulate' (1000 Days), and 'Prob(Stock-out)' (50%). The 'SAP-MRP Settings' section on the right contains: 'Safety Time (Days)' (2), 'Minimum Coverage (Days)' (1), 'Target Coverage (Days)' (1), 'Coverage Tolerance' (0), 'Minimum Order Quantity' (7), 'Avg. Daily Req Window (Weeks)' (4), and 'Avg. Daily Demand' (27.2670). At the bottom, there are checkboxes for 'Order 1 for 1', 'Maintain Coverage', and 'DOE', along with buttons for 'Close', 'OK', 'Unload', and 'Load Settings'.

Figure 281: Simulation Program Initialising Form.

Review Interval.

The Review Interval is set by default to 5 days to reflect the weekly arrival of the supply ship from Germany.

Lead-Time Command Button.

Should the user wish to override the default Lead-Time of the part under analysis, the “44 and 53 day LT” command buttons are used.

The right half of the form is used to set the SAP-MRP System settings. The reader will already be familiar with the majority of parameter names and the roles they play within the SAP-MRP System. However, a few parameters are new, namely

- Coverage Tolerance
- Average Daily Demand
- Maintain Coverage
- Design of Experiments (DOE)

Coverage Tolerance.

Coverage Tolerance is used in conjunction with the measurement of DCSA Service Level. The user can set a tolerance level that influences the point at which a Profile Violation occurs. The default tolerance is set to zero.

Average Daily Demand.

The Average Daily Demand indicates the average demand of the input data for the part under analysis. The user can refer quickly to this field, to confirm the Usage Category of the currently selected part i.e. High, Medium, or Low Runner.

Maintain Coverage.

This checkbox is used to alert the program that an Order Release should be created to push the stock level up to the Target Coverage level should a Coverage Violation occur.

DOE.

This checkbox must be selected in order to activate the program component that is responsible for automatically changing the Coverage Profile and Safety Time values for the Design of Experiments.

The sheet name field provides for an output sheet in MS-Excel, and is automatically changed per simulation run. This is done to avoid the error that occurs when the same sheet name is used more than once in the same workbook.

The “Load” and “Unload” command buttons are used to load and unload the Part Vital Statistics from the input sheet, into and out of memory, respectively.

Operating the Simulation Software.

The software is operated in four different ways, namely:

1. OIMM (Stand-Alone)
2. SAP-MRP (Stand-Alone)
3. OIMM vs. SAP-MRP
4. DOE

The term “Stand-Alone” is used to indicate that the associated component is operated independently. The user is not required to interface with any additional components

Operating the OIMM in Stand-Alone Mode has been well documented and discussed by van Wijck et al. [4]. Therefore, the author will present an overview of how the software is operated in terms of the last three modes.

SAP-MRP (Stand-Alone).

If the user needs to analyse the effect that a certain SAP-MRP parameter has on a specific measure of interest e.g. Plant Stock, or Order Frequency then he/she would use the software in this mode. Figure 282 on page CCXXXII presents a flow chart diagram of the processes and decisions that a user would have to work through when using the software in this mode.

Prior to starting the simulation program, the user should specify the measure he/she wishes to analyse. Selecting the Input and Output files using the Start-Up Form will do this. Next, the part under analysis should be selected and the Vital Statistics loaded using the “Load” command button. The parameters should then be adjusted to meet the Analysis specifications and execute the simulation program in the Start-Up Form. The simulation results are written to the Excel output file, where the user will decide whether the output results are satisfactory or not. If the results do not meet expectations, then the analysis must be re-designed, otherwise the experiment is terminated.

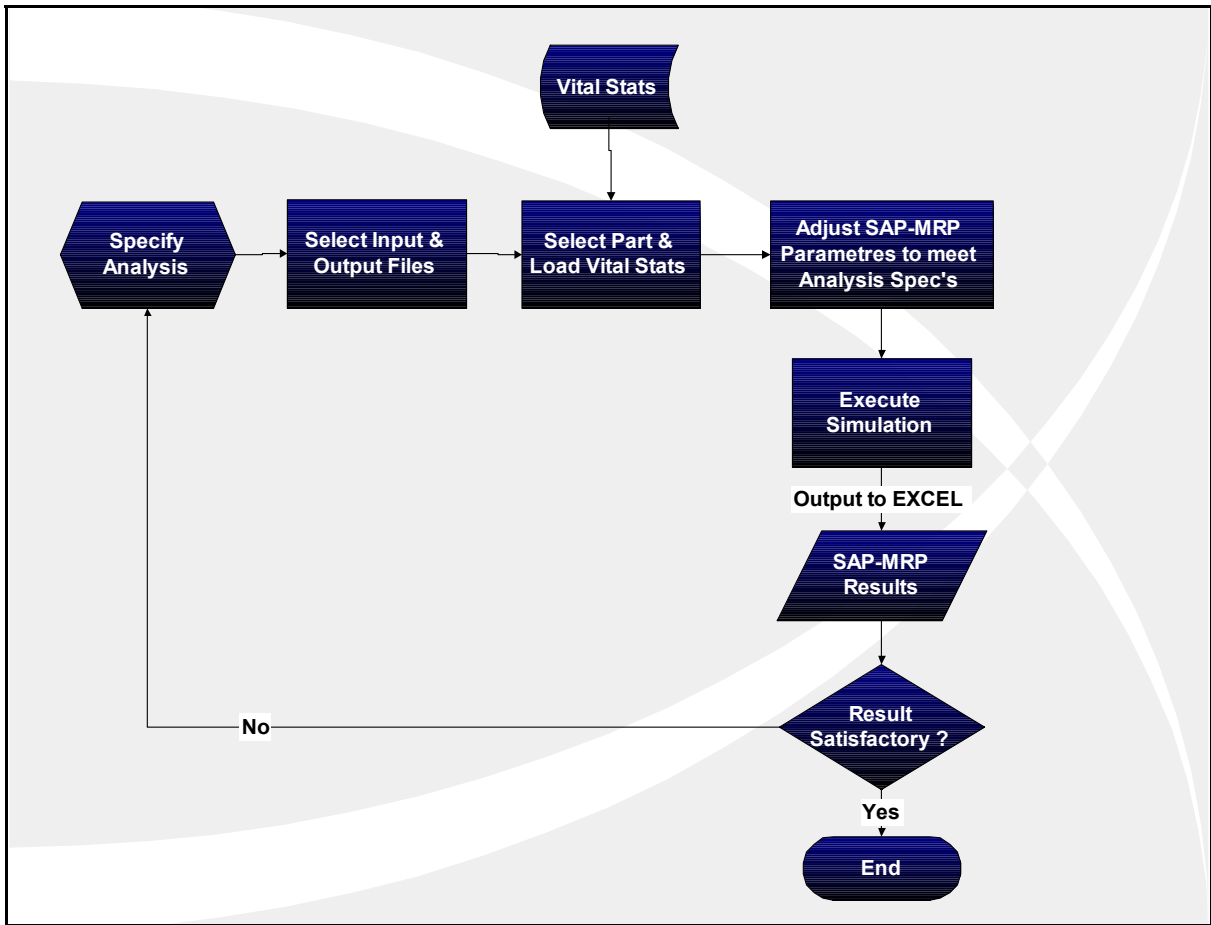


Figure 282: SAP-MRP Stand-Alone Flow Chart.

OIMM vs. SAP-MRP.

Note: This evaluation procedure is included for completeness, although this it was not pursued.

This type of analysis would be used to evaluate the performance of the OIMM System vs. the SAP-MRP System. This was the exact set-up used in this study to compare the OIMM System to the SAP-MRP System.

The OIMM vs. SAP-MRP operation flowchart is shown in Figure 283.

The steps followed here are the same as those followed in the SAP-MRP Stand-Alone Mode. The only exception being, that in this mode the user will adjust the OIMM parameters to meet the Analysis Specifications. The current version allows the user only to adjust the “Probability of Stock-out” parameter.

Typically, the user would already have executed multiple SAP-MRP Stand-Alone simulations before operating the program in this mode. The multiple simulation runs would have given the user “a feel” for the behaviour of the part under analysis and indicated the optimal parameter settings that provide the maximum Avg. Customer Service Level for that part. The user would then vary the “Probability of Stock-out” parameter until a point is reached where the OIMM’s Avg. Customer Service Level is better than, or equal to that of, the SAP-MRP System. It will then be

possible to evaluate which system is superior, in terms of the selected Performance Measure, while still maximising the Avg. Customer Service Level.

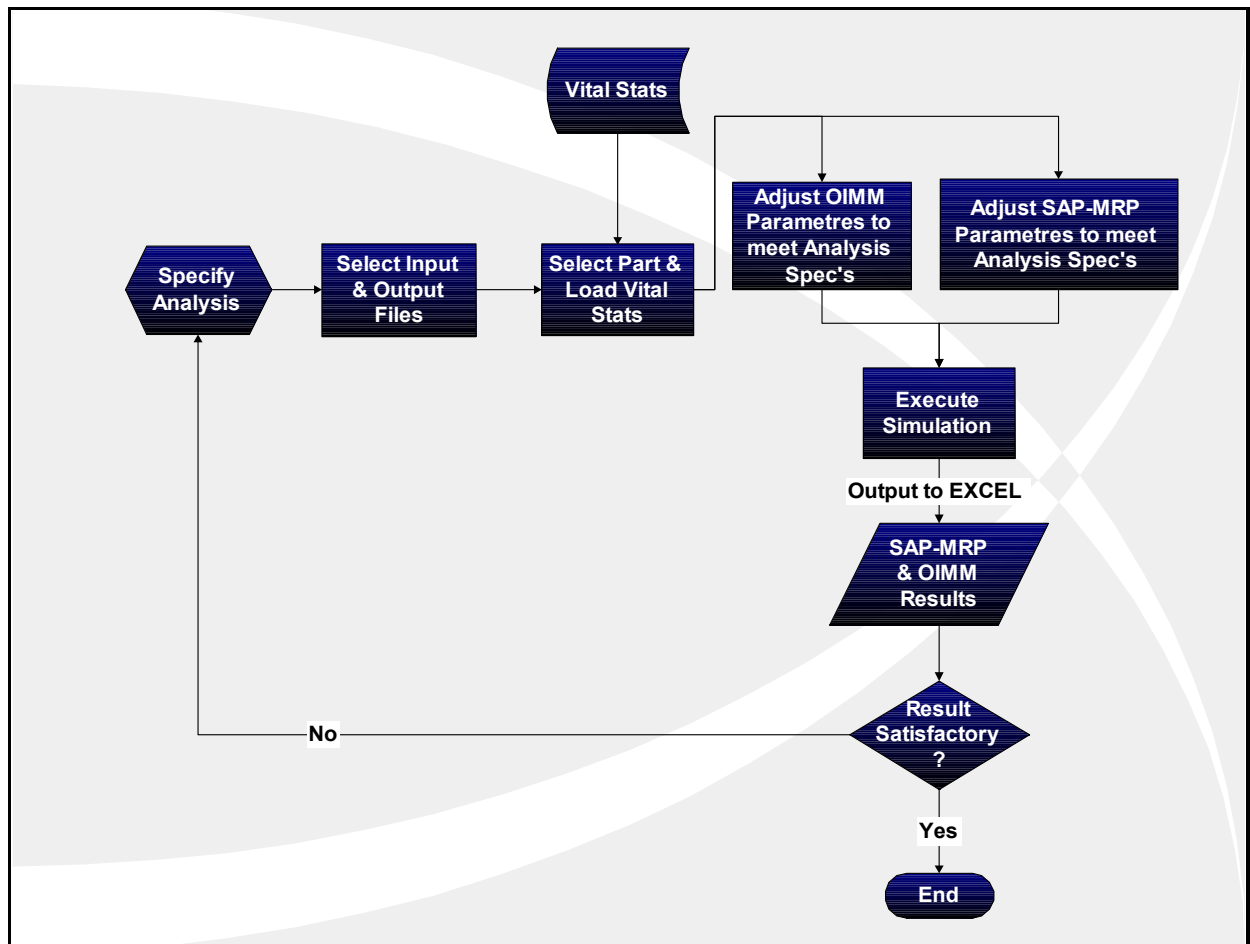


Figure 283: OIMM vs. SAP-MRP Flow Chart.

DOE Mode.

The DOE Mode is a completely automated simulation process.

Figure 284 presents the DOE process flow. The user simply selects a part for analysis, selects the “DOE” checkbox in the Initialising form, and then clicks the “Simulate” command button in the Start-Up Form. The program automatically names each Excel sheet as well as alters the Coverage Profile and Safety Time parameters.

The results of all 63 simulation-runs are then prepared for Regression Analysis, using the Statistica package, by means of an Excel Macro. A snapshot of the output generated by the DOE is seen in Figure 75 on page XL and a snapshot of the data after it has been processed by the Excel Macro is seen in Figure 76 on page XLI.

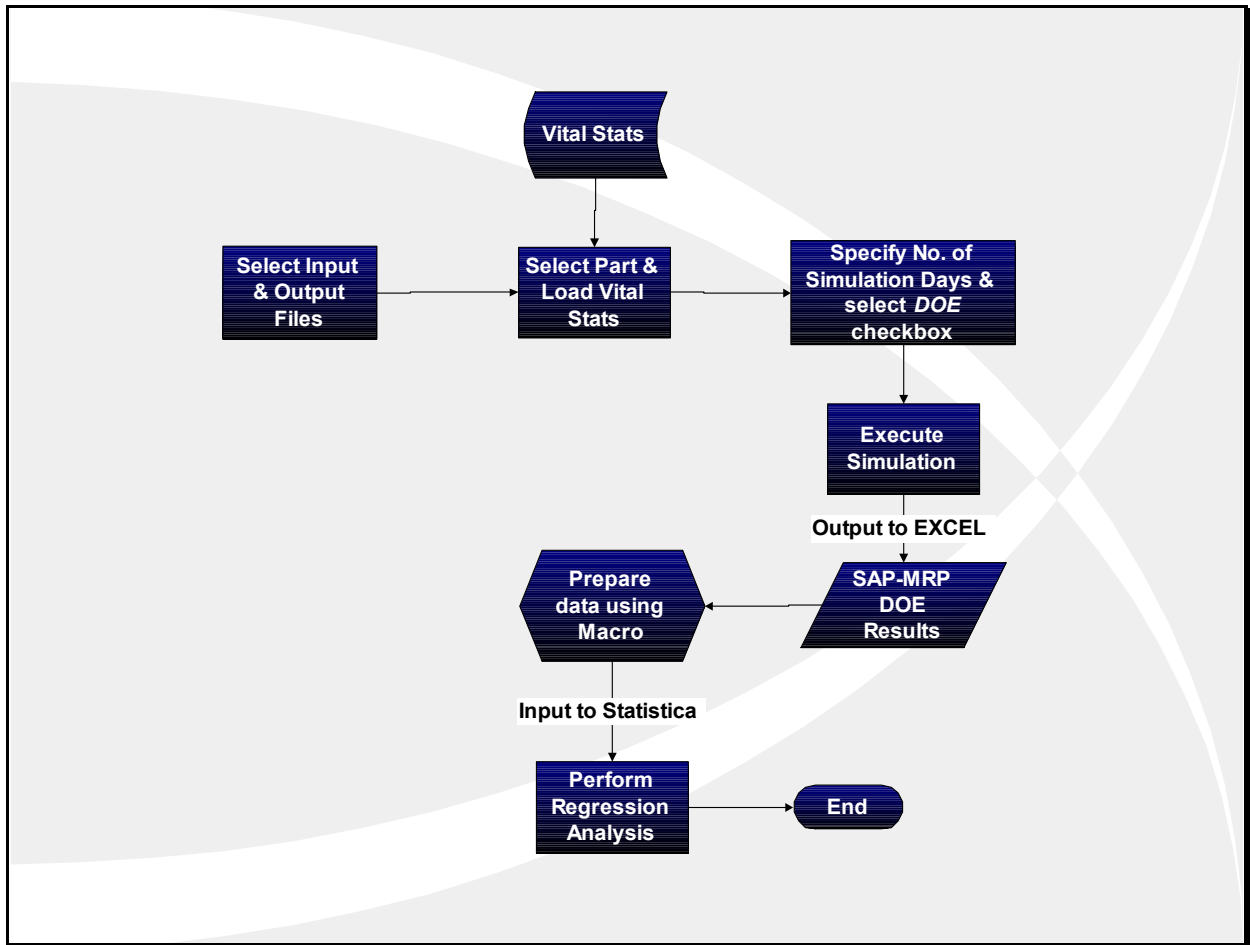


Figure 284: DOE Process Flow Chart.

