Measuring and Modelling of Field Reliability for an Electronic Product.

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Declaration

I declare that this thesis is entirely my own work, except where otherwise stated and has not been previously submitted to any institute or university.

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Abstract

Traditionally field reliability has been measured and predicted by the use of manufacturing data. One of the great challenges that manufacturers of electronic products face is trying to measure accurately how a product is performing in the field. Based on a literature review as well as discussions with an electronics company, it was determined that it was necessary to base field reliability monitoring on field data. The company had a previous reliability issue where a product was performing poorly in the field but by time it was identified and corrective action was taken, it had cost the company millions of dollars. For this company it was important to determine if a product's reliability in the field was performing well or deteriorating.

The relevant literature research was divided into three main fields: Introduction to reliability, field databases in use in industry and finally measuring field data. The field study focused on two products for Company X. The main tools used to measure and model the data were, Rate of occurrence of failures (ROCOF), replacement rate by month trending, replacement index (RI) modelling and control charts. Future prediction was facilitated by the use of the lognormal distribution plot. Product A had a latent defect that only exhibited in the field and wasn't identified until nineteen months after it started shipping from manufacturing site. Product B was a very similar product to Product A however performed very well in the field.

The results showed clearly the Product A did not perform as well as product B. The RI model indicated at a very early stage that there was evidence of wear-out for Product A. The *p* control chart would have indicated six months before the actual investigation happened that there was a problem with this product. The lognormal distribution plot was very accurate in predicting the future reliability of the product. The results show that these techniques can provide a company with a clear indication of field reliability and highlight areas of concern.

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Chapter 1

Introduction to Reliability

1.0 Introduction

Reliability is the trust in a product to perform its tasks over time and has become a keystone in the manufacturing and selling of a product. By knowing the reliability of a product it gives a leading edge to a manufacturer and also a market confidence in the product. Reliability measurement is taking product information and using it to interpret how well or poorly the product is performing.

Reliability measurement came to being during the Second World War. Due to the complexity and reliance on military equipment, the US Department of Defence initiated projects to study the field of reliability. This has developed into the worldwide recognition of Reliability and its prediction as a key tool in developing and monitoring a product through its development and life cycle. Romanchik (2000) describes a situation, "In 1993, for example the failure rate for surface mount microprocessors in General Motors' engine control modules was nearly 450 parts per million (ppm). By 1997, that figure had dropped to less than 15 ppm. The failure rate for surface-mount CMOS (complementary metal oxide semiconductors) linear ICs (integrated circuits) dropped from more than 1,200 ppm in 1993 to approximately 150ppm in 1997". This is attributed to reliability improvements in design and the manufacturing process.

1.1 Importance of Reliability to Manufacturing

Product reliability is critical to the success of any company. Dupow and Blount (1997) states that the impact of reliability is becoming greater and the customer is becoming more and more concerned with quality and thus with cost and reliability. They state that "A reliable product provides safety in terms of functional and should last longer which decreases cost and provides the customer with product satisfaction". To have confidence in a product one needs to know its reliability. The reliability of a product can be tested, measured and predicted. You can test the reliability of a product by putting it through a series of tests to ensure its success rate. Tests can be normal (testing the product as it would function), destructive (to see when it will fail) or accelerated (to ensure its strength). The reliability of a product can be measured by analysing the data from the testing. Finally reliability can be predicted by using the measured data to estimate future failure or success rates.

Reliability testing is explained by Artesyn (2001) as putting a fixed number of the same devices on test for controlled periods of times, however he states that this can be very time consuming and expensive. According to O'Connor (1996) the reliability test programme must cover a range of environmental conditions which the product is likely to endure e.g. temperature, vibration, shock, humidity, power input and power output. However Barnett (2003) feels that this type of testing can lead to extremely long test times.

Reliability can be measured by analysing the data from product testing. There are many metrics in circulation for measurement of reliability, some of which will be discussed in Chapter 3. Examples of these being Mean Time Between Failures

(MTBF), Failure Rates, Replacement Rates, Yields etc. Ryerson (1956) says the mean life or the MTBF has become perhaps the most common figure of merit for general use. While researching this dissertation, it was found that this metric was the most frequently mentioned. The 'Mean Times' metric is used in many different ways and many different forms for example, Wood (2001) makes reference to Mean Time To Failure (MTTF) , Mean Time Between Part Replacement (MTBPR), Mean Time Between Service Call (MTBSC), Mean Time Between Warranty Call (MTBWC) etc. These start to show a link between measuring reliability from test data and from field data. MTTF can represent the mean time between failures in-house where as MTBWC represents field data (Warranty data). Artesyn (2001) sees the Failure rate measurement as the fundamental variable that defines reliability. It is expressed in terms of failures per unit of times. Company X used in-house yields which is also use throughout the manufacturing industry to monitor reliability and represents the percentage of successful parts through a process.

Finally reliability can be predicted using the test data or field data to estimated future failure or success rates. Kerscher (1988) explains that it is desirable to predict the field reliability of potential product designs so that reliability improvements may be identified and acted upon early in the product development cycle. Reliability prediction allows the quantification of the success of a product. It is important to note that prediction isn't always spot on. It can be thwarted by random events but if used correctly it can be a very valuable tool for any industry. There are numerous standards available to help the manufacturer predict the reliability of a product. There has been a lot of analysis done on standards and how they relate to the actual field performance of a product. However in the instance that there is little or incomplete field data, prediction models are very useful. Wood and Elerath (1994) feel that realistic reliability predictions are important for

- Setting reliability goals
- Evaluating design reliability
- Life-cycle cost trade-off studies (More money spent in development may save in service)
- Determining optimal test times
- Service planning

Jones and Hayes (1999) warn that care must be taken when comparing the predicted reliability with that observed in the field, because prediction models can assume a constant hazard rate. This is especially true for Mil Hdbk.

Dupow and Blount (1997) also discuss some concerns with predicting reliability. These are...

- Change of failure rate with respect to age
- Differences in reliability for parts purchased from different vendors
- Effects of specific stresses
- Industry wide reliability improvements
- Effectiveness of repairs
- Effects of management priority on maintenance
- Manufacturing learning curve

However Brombacher (1999) defends reliability prediction by explaining that a problem can be found with the lack of feedback on actual reliability performance as they come late in the product life cycle, therefore companies use prediction tools to compare predicted reliability and product reliability requirements without ever looking in detail at the field performance.

1.2 Reliability Standards

There are numerous reliability standards in circulation to guide the manufacturer in the testing, measurement and prediction of product reliability. These are getting more and more focus. Recently following a huge electricity blackout in the US, Harding (2003) explains that President George W. Bush said he was confident congress would pass new laws introducing "mandatory reliability standards" requiring companies to be responsible for the upkeep of the electricity grid. The most prominent standard organisations governing reliability would be the Military standards and the IEEE (Institute of Electrical and Electronics Engineers) standards; there are others that have published their own standards (e.g. Bellcore and Siemens). There is a lot of discussion around the accuracy of prediction models and how they compare to field data and each other. The following are some of the standards that will be discussed:

- Mil Hdbk-217 was developed to establish and maintain consistent and uniform methods for estimating the inherent reliability of electronic equipment and systems.
- The Bellcore Standard provides reliability models for commercial grade electronic component and is recently better known as the Telcordia method.
- CNETs RDF which is a follow on to CNET 93 and is a comprehensive model similar to Mil Hdbk-217 which provides a detailed stress analysis.
- RAC's PRISM was developed by the Reliability Analysis Center (RAC), for doing MTBF (Mean Time Between Failure) prediction and system reliability analysis.
- HRD4 is the British Telecom Handbook of Reliability Data, and is quite similar in approach to the Mil Hdbk-217. It also provides models for a wide range of components.

- IEEE – 1413 Reliability Prediction Standard was developed to identify the key required elements for an understandable and credible reliability prediction, and to provide its users with sufficient information to select a prediction methodology and to effectively use the results.

It is necessary to critique these standards highlighting comparisons and differences. Mil Hdbk-217 has generated much discussion and controversy during its life and it was found that most standards were compared to it. . Zzyzx Peripherals Inc (2001) compares Mil Hdbk-217 & the Bellcore reliability prediction model and sees them as similar however they do cite some dissimilarities. Some differences being that Mil Hdbk-217 is targeted for military applications and also that it tends to be somewhat pessimistic when used in commercial products. Bellcore has the ability to take into account burn in, field and laboratory testing thus making it more popular with commercial organisations. One problem many manufacturers find with MIL Hdbk-217 is that it assumes a constant Failure rate where as in reality this almost never happens. Jones and Hayes (1999) in their analysis found that the Mil Hdbk-217 had a closer prediction to the failure rate of circuit boards than the Bellcore. Their investigations indicate the two models that gave predictions that were low were Mil Hdbk-217 and Siemens where as the others gave high predictions (Bellcore, CNET and HRD4).
This reinforces Zzyzx Peripherals Inc (2001) theory that Mil Hdbk-217 is more pessimistic than Bellcore.

Other sources agree with Zzyzx Peripherals Inc (2001) theory that the actual rates experienced were higher than what was predicted with MIL Hdbk-217. Black and Martin (1988) stopped using MIL Hdbk-217 default values as they experienced that the failure rate predictions for commercial grade Integrated Circuits were higher than the actual rates experienced by the users. Wood and Elerath (1994) compares Mil Hdbk-217 and Bellcore and concluded that they are both generally much lower than the MTBF experienced in the field yet higher than the MTBF demonstrated during manufacturing burn-in.

There are more standards than Mil Hdbk-217 and Bellcore. Charpenel *et al* (1998) feels that although various prediction methods exist (MIL Hdbk-217, CNET RDF...) that they are limited in terms of the number of failures in a given environment and the determination of actual cause of failures because they are based on empirical failure rate models, developed from curve fits of failed data.

As mentioned briefly earlier in this chapter Jones and Hayes (1999) carried out a comparison between Bellcore, CNET, HRD4, Mil Hdbk-217, the Siemens prediction models and Field Data. HRD4 proved the closest to the field data followed by Siemens, Mil Hdbk-217, Bellcore and CNET respectively.

Foucher *et al* (2002) looks at HRD-5 and PRISM and tells that they are designed to take reliability improvement into account but HRD-5 is insensitive to the component technology. New technologies are conservatively dealt with, although PRISM and CNET latest issues tend to address this problem.

Pecht *et al* (2002) provide a thorough comparison of reliability prediction methodologies. Some of these conclusions are:

1. Mil Hdbk-217 & RAC Prism identifies the sources used to develop the prediction methodology and describe the extent to which the sources are known. Telcordia SR-322 and CNET do not.

2. RACs PRISM, SAEs HDBK, Telcordia SR-322 and CNETs assumptions are used to conduct the prediction according to the methodology identified including those used for the known data where as Mil Hdbk-217 does not.
3. Sources of uncertainty are not identified in Mil Hdbk-217, SAE HDBK, Telcordia SR-322 or CNET. Neither have failure modes, failure mechanisms, or confidence levels been identified.
4. None of the handbook methodologies account for life cycle environmental conditions.
5. The handbook methodologies do not account for materials, geometry and architecture that comprise the parts.
6. Mil Hdbk-217, Telcordia SR-332 and CNET do account for part quality but RACs Prism and SAEs HDBK do not.

The handbooks have some limitations and Pecht *et al* (2002) suggest three sources of data that can be used that do not have these limitations or not as many, these are field data, test data and stress & damage models.

1.3 Use of Field Data in Reliability Analysis

Most methods for measuring and predicting reliability are based on in-house manufacturing data, which is a very valuable source of information. However another source exists that hasn't been used to its full potential, this is field data. As stated by Coit and Dey (1999), reliability engineers and managers require timely, accurate data to assist in the analysis of system designs and to aid decision making. Reliability data from components installed in fielded systems are also considered to be very desirable because they inherently capture the appropriate usages and environmental stresses. Brombacher (1999) proves this as Fig1.1 shows an example of the results of a field study where the reliability field performance of components in a high volume consumer product was compared with the predictions using a number of prediction handbooks, such as the MIL Hdbk-217 and the British Telecom HRD4. This shows the difference between in-house reliability prediction and the actual field performance. It shows that it is not possible to prove a relationship between prediction results and field performance.

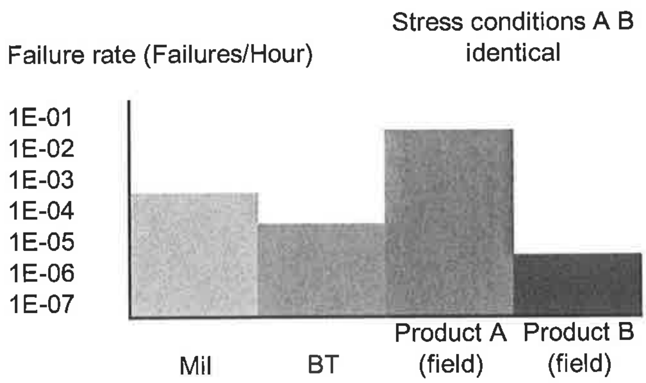

Figure 1.1 Observed differences between predicted and actual failure rates; Brombacher (1999)

Kershcer III (1988) took an example of several electronic assemblies and it found that the failure rate could be approximated by the failure rate function of a Weibull Distribution and it was also found that the Mil Hdbk prediction procedures were useful in estimating the failure rate of that distribution at the characteristic life.

Kerscher III *et al* (1989) went on to investigate the comparison of field data and Mil Hdbk-217 and Weibull. This time however he concludes that Mil Hdbk-217 was not representative of the field reliability however a combination of Mil Hdbk-217 with the Weibull distribution was found to more closely approximate field reliability. This shows how important it is to compare the prediction model to the field data. Brown (2003) also sees combining field data and prediction methods as a viable option. In her study she finds that field data proved valuable in the prediction of reliability. It allowed the model to be modified to improved predictions for the product.

Pirovano and Turconi (1988) suggest that the validity of Mil Hdbk-217 rests on the large amount of experimental data taken into account. More analysis adds to this argument. Bothwell *et al* (1995) compares the MTBF calculated from Mil Hdbk-217, Bellcore and field data. Mil Hdbk-217 predicted 4.09 years; Bellcore predicted 5.65 years however the field data showed a MTBF of 8.26 years. Another source, Brown (2003) compares reliability predictions from PRISM and field data. She found that the PRISM tools revealed predictions that were optimistic in comparison to the observed field performance. For example she took a certain circuit card and predicted failure rates in Failures per million hours (Fpmh), generated from PRISM and compared them to the field failure rate. They found that the PRISM calculation at 13.73 was half the actual Fpmh of 22. This is confirmation enough that predictions can be based on models alone but that the field data provides the invaluable information to help the prediction of future field performance.

Limitations in field data have been discussed by many authors. Baxter and Tortorella (1994) highlights some concerns when using field data and these are incomplete data, Questionable operation time – there may have been down time not recorded, environmental factors and component being a sub part of a bigger system and not being recorded individually.

Artesyn (2001) gives the following limitations for using field data.

- Field failure information tends to be incomplete due to the focus being on fixing the problem not recording it.
- For products it is difficult to assess the actual operating hours.
- Environmental conditions are difficult to calculate
- Failures may not be categorised correctly in the field. There may be precautionary pulls.
- Some failures are as a result of overstress from other failures.
- Takes a long time to build a valid field history.

Incomplete data will give false or misreading reliability results. If correct and available; field data is a valuable source of information for determining the reliability of a product. However it is imperative that the data is looked at and measured in the best way to give the clearest realistic picture of its performance.

1.4 Monitoring Field Reliability for Company X

The difference between predicted reliability and the actual reliability of fielded systems have been discussed. Miller and Moore (1991) term this difference as the "reliability delta" and suggest many reasons for this, some being definitional, operational and environment factors. Broadly speaking the main reason for the difference between predicted reliability and field reliability is that in the field the product is operational for its life and has many different factors affecting it (i.e. environment factors and time). In Company X there is an example of a product with a latent defect that only exhibited itself in the field. Product X was manufactured by the vendor and was then brought in-house for testing and integration into a larger system. The product went through in-house testing specifically designed to stress components however no significant problems were identified. Fig 1.2 shows the in-house yields for this product.

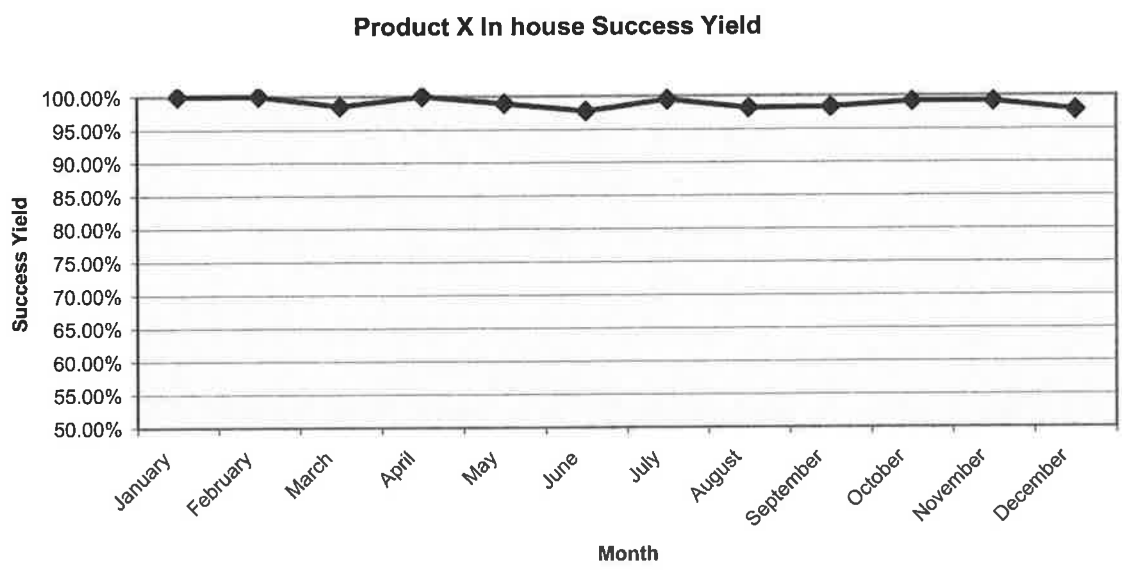

Figure 1.2 In house Yield Rate for Product X

Testing was determined from its design specification and the product passed tests successfully. However during its production a vendor added one stage to the manufacturing process that (unknown to the supplier) would cause latent failures in the part. It took a year from evidence of the field failures to identify the reason for failure. In the mean time it had cost the company millions of dollars. The high replacement rates can clearly be seen in Fig 1.3.

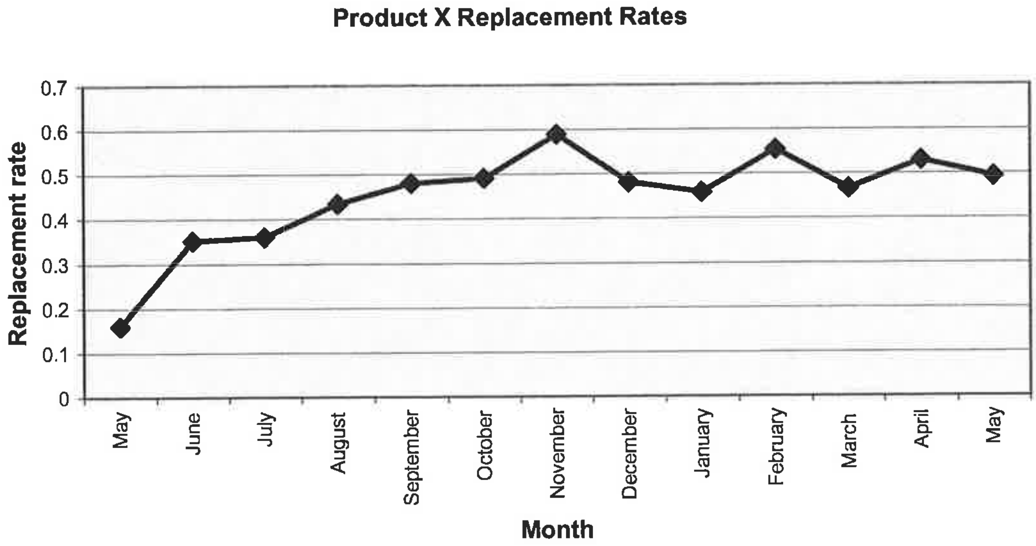

Fig 1.3 Field Replacement Rate/Year of Product X

Figure 1.3 shows that the in-house testing did not unearth this issue. Just to clarify, this product had been strenuously tested in-house to ensure reliability and had gone through numerous stress tests, unfortunately this issue escaped. If the reliability prediction was based on Fig. 1.2 it would not show an accurate view of the field reliability. However if Fig 1.3 was used it would be a much more realistic picture. In short the focus wasn't put on field information where the product was being tested in a variety of ways, primarily by time. When parts began being replaced, investigations were carried out on the returned product. However this took time to recreate and valuable action time was lost in looking into the issue. The impact was not to be known till months after the replacement rate went up. In the mean time defective parts were replaced by more defective parts. By looking at the information that was available from the field it was clear that there was an issue with the product. Fortunately there was access to field information as above but unfortunately this was not the first point of contact. If the field data had been used, the level and severity of the problem would have been clear from the beginning, time wastage could have been minimised and a plan of action could have been prepared. The field retraction and replacement of these product cost Company X $10,792,696. This was the physical cost of solving the issue in the field and doesn't account for other invisible costs such as loss of reputation, customer loyalty, potential sales etc.

1.5 The Cost of Poor Reliability to a Company

One of the primary concerns with predicting reliability on in-house data is that a problem might be hidden in the field by not monitoring the data closely. Not capturing an issue costs a company in many different ways. Costs can be physical but there are hidden costs also associated with poor reliability. The customer has the inconvenience of part replacement, customer service has to come to their product and replace the part with a new one. Though this doesn't sound like it can have a big impact it does grow to affect the customer's perception and trust, this in turn has a big impact. As stated by Daffy (2000) a customer that is not satisfied will do the following:

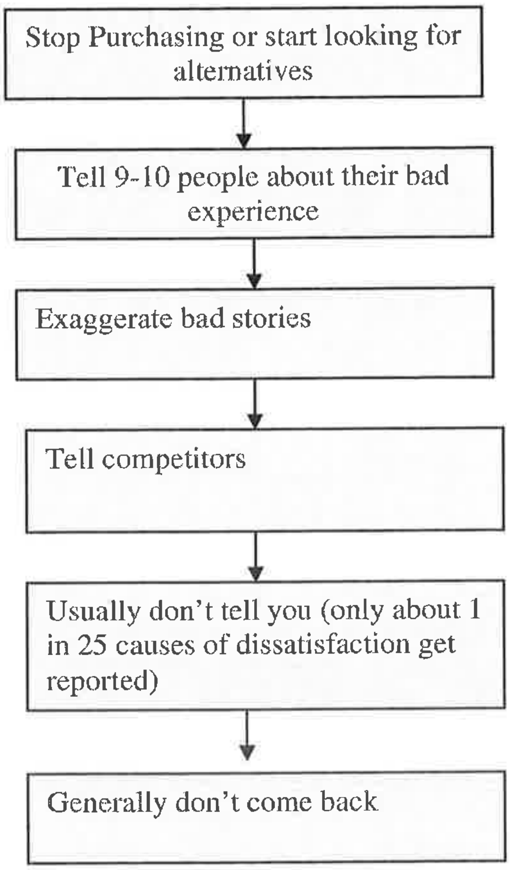

Figure 1.4 Customers reaction to bad reliability

Daffy goes on to say, "Even the best companies occasionally get things wrong. The real measure of a company's service is how it reacts to being told things have gone wrong – and what it then does about it"

As well as the customer this has an impact on the manufacturer, who has to;

1. Provide the replacement part - The cost of the replacement part and its transport to the customer.
2. Provide the customer service to replace the part - Training and providing of a customer service engineer to replace the part.
3. Offer some incentive/discount for customer inconvenience - To ease any discomfort suffered by the customer.
4. Analyse the product on return - Time and cost of analysing the product on its return to identify the reason for the replacement.
5. Produce extra spare parts - On realising the affected population of this issue, extra spare parts have to be generated costing the manufacturer in people and time.
6. Storage of extra spare parts - Once these spare parts are manufactured they have to be stored (which costs money) for when they are needed.
7. Maintain Customer Support and service - When there is a population affected, Customer Support must do their utmost to limit the discomfort to the customer, which again takes time and resources.

This all cumulates to have a big impact on the manufacturer as well as the customer, primarily in areas of cost and time. This eats away at profit, which is the overall goal of any business.

1.6 Conclusion

Reliability is very important to any competitive manufacturer in today's industry. By knowing the reliability of a product and being able to predict future reliability gives a manufacturer extra confidence, safety and control. Numerous standards exist to predict product reliability for a manufacturer and these have their own strengths and weaknesses. One area exists that can be developed to give a more just picture of what will happen in the field, this area is field data. The advantage of field data is that it can highlight problems that only exhibit the field and an example of this was with Company X, where if the field data had been used a costly reliability problem would have been identified sooner. However looking at the in-house data the product looked fine so any prediction based on that wouldn't have highlighted the issue. This issue cost Company X in excess of 10 million Dollars. Outside of the physical costs there are other costs which incorporate customer dissatisfaction, loss of reputation etc. What has been identified here is that Company X needs a field data base that can monitor the field reliability of its commodities and predict future replacement rates.

Thus the next step is to look at Field data, how it is being used by other companies, what data is needed and how it can be retrieved to provide a basis for reliability measurement.

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Chapter 2

Field Data

2.0 Introduction

According to Jones and Hayes (1997), the reliability in the field has to be assessed before any reliability improvement can be made to a product. There is a phenomenal amount of field data available and more and more companies are becoming aware of its importance. Companies are also developing applications to enable users to store and analyse field data. Coit and Dey (1999) explains the principal advantage of field data is that the operational and environmental stresses are those which are of most importance and the most faithful and rigorous laboratory testing will fail to precisely simulate all field conditions.

The general approach to the use of field database will be discussed. However some companies don't have field databases and the only field data they have is on Warranty databases (short term). A warranty database may not have originated for reliability analysis but for financial means to monitor the costs of warranty returns. The data necessary to populate a field database will be discussed. Different users have different needs for a field database and require different fields and information. This will be discussed and a suitable list of data will be compiled to suit the needs of Company X.

Field data does have limitations as discussed earlier in chapter 1 however once identified, these limitations can be controlled and even eliminated. This project does not in any way wish to take away from the benefits of in-house preliminary reliability predictions at the early stages of a product life. However it is advocating the use of Field Data as a source for reliability analysis. It is a valuable foundation of information and will tell a great deal about a products performance, be it good or bad. Cooke and Belford (2002) explains that the "problem of analysing reliability data has become a problem of data compression." Years ago they say that analysts complained about the lack of reliability data. With the advent of computers there is no reason for that today. The problem they state is "know what to collect, how to make sense of the wealth of data that one can gather, and what to do with it."

2.1 The Use of Field Databases

There is a phenomenal amount of field data available and more and more companies are becoming aware of its importance. Also companies are developing applications to enable users to store and analyse field data.

EPRD-97 (1997) - Electronic Parts Reliability Data - is a source of field data provided by the Reliability Analysis Center (RAC). This provides empirical field failure rate data on electronic components. The data was compiled from a wide variety of sources between 1970 and 1996 and the RAC screened the data such that only high quality data is present. This is a valuable source of information for any electronic company to compliment existing reliability prediction methodologies by providing failure rate data in a consistent format on various electronic component types. Another example of this is the Nonelectronic Parts Reliability Data (NPRD –95) document that contains all (non-proprietary) component data that is in the RAC databases.

Many organisations and companies keep their own store of Field Failure information. Pinna (2001) discusses ENEA "Ente Per LE Nouve Technologie, L'Energia E L'ambiente" who maintain a "Fusion component failure rate database (FCFR-DB)". This has been developed to collect data on component failures. ENEA see it as very important to perform probabilistic assessment of fusion devices, to compare to other devices. It helps to predict availability for fusion facilities safety/reliability assessment.

Xu *et al* (1999) analyse field failure data to understand the nature of failures in their products and to identify performance and dependability bottlenecks in such systems.

The data is collected from a networked Windows NT system logs from 503 servers running in a production environment over a four-month period. The reasoning for studying the field data and compiling a store was because characteristics of failures in networked systems were not well understood. The data was collected by the error logging mechanism in the underlying operating system. This data is then analysed to provide Mean time between failure (MTBF), Mean time to repair (MTTR) and availability information. The results idenfitied areas for improvement such as, system maintainability and fast recovery.

Italter is a leading Italian manufacturing company in telecommunications that have experience using a field database. Pirovano and Turconi (1988) explain that a reliability database based on real field experiences is necessary for the following reasons:

- The data could point out anomalous trends and lead to corrective actions
- Confirm the success of corrective actions from design and engineering
- Collect reliability data to validate and adjust prediction models which are used to calculate design reliability parameters
- To have a common reporting base to statistically evaluate reliability characteristics versus specified values.

From this need they developed FREDA which is a methodology and a tool for monitory quality and reliability of equipment and systems in the field. According to Broggi and Salari (1988) this database provides the methodology for management and analysis of field data. It allows improvements to be identified and corrective actions to be carried out – and monitored. It is described as a tool from the field for the improvement and control of product reliability and maintainability, and of the system availability.

Wang *et al* (1999) explains how users and manufacturers of the computerized numerical control (CNC) lathes collect and analyse field failure data and use it to reduce down time and increase availability. The database is specified to contain enough information about the hierarchical structure and field failures that can be used for analysis. Its main tasks are to;

1. Calculate reliability characteristics, such as MTBF
2. Graphical analysis techniques such as cause and effect diagrams
3. Failure mode and effect analysis
4. Fault tree analysis
5. Maintainability analysis
6. Reliability growth analysis
7. Other Reliability prediction analysis

The data collected is the number, product code, product name, model, manufacture date, date of first use etc.

There are also databases designed that allows the user just to enter the field data and it then carries out the analysis. An example of such a database is RACs Prism product "PRISM". It is available as an automated tool as opposed to a standard or handbook. Prism was originally developed by RAC but was been developed further by Relex and is a standard for MTBR prediction and system reliability. According to Dylis and Priore (2001), PRISM was developed for estimating the failure rate of electronic systems and its methodology factors in all available test and field reliability data, as it becomes available on a program to form the best estimate of field reliability.

Gottfried (2002) tells of "Gloria Data Input Tools" as another example of tools produced to facilitate the process of data input of the target region's field data in a uniformed manner. It was felt this would make the data input easier and quicker and can also avoid any inconsistency in the data as much as possible. Any data entered in the database is inputted according to a standard (Multi-Summit Field Manual). This is an access database that allows the entry, editing, saving and reporting of field failures.

2.2 Warranty Databases

Warranty databases can be a source of field data but are not the same as field databases. Hotwire (2001) explains that warranty data may not include all the field data necessary to adequately track reliability. They are designed to track finances and not performance. However it is possible to garner adequate reliability information based on the inputs of the warranty data. Reliasoft (2001) feel that accurate predictions about the quantity of products returned under warranty can provide huge benefits to manufacturing organisations. It can be an early warning signal that there is a problem with a product in the field. They feel that "shipping and warranty return quantities are the minimum data requirements for performing effective warranty data analysis."

Murthy and Djamalundin (2002) feel warranty is very important in the context of new products. They state that "often customers are uncertain about new product performance. Here warranties play an important role in providing product assurance to customers."

Majeske *et al* (1997) investigate warranty data by using automobile warranty data and generate hazard plots to focus on product quality at time of sale. The data is seen as important as "to use warranty claims as the measure of customer satisfaction ties directly with the manufacturer's technique of cost justifying product and process changes based on a projected reduction in warranty expense."

Oleinick (2005) uses warranty data for his reliability analysis. He explains that "warranty data represents real customer usage in real life situation and so will always contain more valid information than laboratory test data". The negative aspects he sees as being that not every failure is reflected in warranty data and also using the warranty data as the failure time may have problems due to delays.

2.3 The Field Data Needed for Reliability Analysis

The Field data needed to analyse the reliability of a product can vary from product to product. In its most basic form, a company ideally requires, a serial number for the product, a date of install and a fail date. However, the more information that is available then the more detailed analysis that can be carried out. Wang *et al* (1999) recommends a total of 19 fields to be filled out for any field maintenance. Different companies and databases have different requirements. Wang *et al* (1999) gives examples of the data collected by the field failure database of CNC lathes. Data fields include:

- Product details – Code, Name
- Manufacturer
- Failure cause
- Failure date
- Repair time
- Repair method
- Repair date etc.

Pinna (2001) discussed the data collected for the ENEA Database. It includes:

- Number of failures
- Numbers of components
- Number of damaged components
- Mean number of failures for single components
- Mean working time for single component
- Global working time
- Global number of demands

- Real global time of component unavailability
- Real mean time of component unavailability
- Real mean time of system unavailability,
- First date of failures
- Last date of failures

Xu *et al* (1999) tells that the data collected for the networked Windows NT systems field failure data includes:

- Server
- Outage start
- Boot time
- Shutdown type
- Outage reason etc

This data is then analysed to provide mean time between failure (MTBF), mean time to repair (MTTR) and Availability measurements

The FREDA database as described by Broggi and Salari (1988) has the following field data collected:

- System site serial number
- Product part number
- Product serial number
- Date of replacement in the field
- Post repair test data

Having studied and discussed other field databases the data required for Company X needs to be identified. Company X component and system level parts are all serialised so this uniquely identifies every part. Other data necessary is the product type, for the electronics industry this may be a drive, a board or a power supply. The dates needed include the ship date, date of install and failure date. Customer information is also important as there may be a trend in a particular customer site due to customer interference. The location of a customer site may identify a specific problem i.e. environmental factor. Company X has a manufacturing site in two locations. This can help in investigating an issue as often one site will have implemented a process or product before the other so it is important to distinguish between manufacturing sites. The failure details are necessary to fully understand the impact to the customer e.g. labour hours, data loss or data unavailability. In summary to allow for detailed investigation of field failures and reliability analysis the following fields are recommended:

- Serial number
- Part number
- Revision
- Ship date
- Customer name
- Order number
- Install date
- Install site details - location
- Fail date
- Data loss (Yes/No)
- Data unavailability (in hours)

- Labour hours (time the engineer is at the customer site)
- Reason for replacement.

There are numerous other fields that can be recorded or pulled to provide greater analysis. This is just a summary of the data available to this project.

2.4 Field Data for Company X

Having discussed the field data that companies use and the field data Company X require, the data must be collected. Company X has a historic data store of field information that needs to be organised and used to its full potential. The quality of this information eliminates many of the limitations associated with the Field Data. The limitations discussed in Chapter 1 will be looked at now and how the data for Company X overcomes them:

1 Field failure information tends to be incomplete due to the focus being on fixing the problem not recording it. – In Company X all field failure information is recorded.

2 For products it is difficult to assess the actual operating hours. – In Company X this can be calculated for most products by using the installation date and failure date.

3 Environmental conditions are difficult to calculate. – For the product being researched in this dissertation, environmental issues play a minimal role.

4 Failures may not be categorised correctly in the field. There may be precautionary pulls. – In Company X the data entered in the field is reviewed and validated before it is published.

5 Some failures are as a result of overstress from other failures. – This is an issue that may affect Company X.

6 Takes a long time to build a valid field history. – Company X has years of field data compiled.

The first step is to look at the data available and how to extract it. This information is available on seven different tables that can be linked together to collect all the information.

Ship Table	Install Table	Site ID	Fails table 1	Fails table 2	Fails table 3	Resellers Returns
Serial Number (ID)	Serial Number (ID)	Site ID (ID)	Serial Number (ID)	Serial Number (ID)	Serial Number (ID)	Serial Number (ID)
Part Number (ID)	Part Number (ID)	Address 1	Part Number (ID)	Part Number (ID)	Part Number (ID)	Part Number (ID)
Customer Name	Install Date	Address 2	Fail Date	Fail Reason	Fail Reason	Fail Date
Sales Order	Install Site	County	Fail Reason			
Ship Date		Country				

Table 2.1 Field data tables for Company X

Points to note are

1. Tables are linked on ID fields
2. There are 3 failure tables to identify 3 different types of failures.
   a. Failures after install
   b. Failures on install
   c. Failures on install for spare or upgrade parts
3. These tables are contained on two different servers. The Ship Table server being on an in-house server and the others on a separate field server. The servers are accessed through networked systems but querying different servers takes more time than querying the same server.

All the data necessary for direct customers can be obtained through all these tables. Extracting it would involve several different steps. Regarding the Reseller information, date of install is not available. This problem can be overcome by the use of the Ship date plus a calculation of average days to install a product. This is the only possible way of overcoming this obstacle.

2.5 Conclusion

Field data despite limitations is a very valuable source of information. Depending on the circumstances, field data collection may be very simple or very difficult. Even if there is no formal field data collection database in place there are other sources for information, primarily warranty costs. There are numerous field databases in circulation as references for companies to analyse and be aware of components reliability. Database tools have been developed for companies to collect, store and measure reliability. Company X has a very valuable source of field information that overcomes many of the limitations generally associated with field data. Having so much information has its limitations in that it is stored on different tables in different servers. It is now necessary to look at the metrics and models available to analyse and measure the field data available to Company X.

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Chapter 3

Metrics and Models for Field Data

3.0 Introduction

The manner in which field data is analysed and reported will largely have to be customized to the requirements of the organisation. An engineer must know the intended audience and what they need to see i.e. managers may want to see the bigger picture whilst engineers and technicians may want to see more detail. Once the field data is available it must be transformed into meaningful data. Metrics are available to measure the reliability of a product though not all may be suitable. Once the data is available it is important to model the data to investigate further any trends or anomalies. In this chapter the different metrics and models will be discussed and critiqued. Current measurement and modelling in Company X will be briefly discussed before new analysis will occur. Sheldon *et al* (1992) describes three broad stages for reliability modelling for software engineering. These are

1. Assessment
2. Model Development
3. Measurement and Estimation

The end result is to predict behaviours and help plan, maintain and upgrade software. This is a good example of how reliability measurement and modelling can impact an organisation.

3.1 Metrics to Measure Field Data

Reliability metrics can be grouped into two main categories explains Wood (2001); Constant rate metrics (exponential distributions) and probability of success metrics (non-exponential distribution). The more common of these two is thought to be the constant rate metrics. He goes on to explain that these cover the middle section of the bathtub curve. This is seen as a disadvantage to some as by assuming a constant failure rate you ignore early life or wear out failure rates. Wood (2001) does give some advantages of these metrics:

- They are good approximations of the reliability behaviour of a product during its "useful life"
- They are the only metrics that can be measured from field data
- They are simple to calculate and easy to explain.

He lists out 9 examples of these metrics.

Constant Rate Metric	Mean Life Equivalent	Definition
Failure Rate	Mean Time Between/Before Failure (MTBF) or Mean Time To Failure (MTTF)	Total failure divided by total population operating time
Failure rate using cycles instead of time	Mean Cycles Between/Before Failure (MCBF) or MCTF	Total failures divided by total population number of cycles
Failure Rate using distance instead of time	Mean Miles Between/Before Failure (MMBF) or MMTF	Total failure divided by total population number of miles
Part Return/Repair Rate	MTBPR (R = return/repair)	Total parts returned/repaired divided by total population operating time
Part Replacement Rate	MTBPR (R = Replacement)	Total parts replaced divided by

		total population operating time
Service or Customer Call Rate	MTBSC	Total service/customer calls divided by total population operating time
Warranty Claim Rate	MTBWC	Total warranty claims divided by warranted population operating time
Service Interruption Rate	MTBSI	Total service interruptions divided by total population operating time
Maintenance Action Rate	MTBMA	Totally maintenance actions divided by total population operating time

Table 3.1 Reliability Metrics; Wood (2001)

The 'Mean time' metric is one of the most common metrics used frequently to measure the reliability of field data. This has been developed and modified to cover a range of processes and products. Ahmed (1996) discusses:

- Mean time between failures (MTBF); used for products that are repairable.
- Mean time to failure (MTTF); used for products that are "one shot items" and are not repairable.
- Mean time to repair (MTTR); this shows the maintainability of the product.

Parr and Larter (1999) look at the standardization of metrics for the Air Force Satellite Control network (AFSCN). The metrics selected to measure the Reliability, Maintainability & Availability were

- Contact Success Rate (sum of the successful contacts divided by the number of contacts)
- Mean Downtime
- Mean Time Between Critical Failures
- Mean Time Between Downing Events (Downing events are events where the system becomes unable to initiate or continue its mission.
- Mission reliability
- Operation Availability

In analysing the stability of a maintenance process, Schneidewind (1999) uses MTTF for long-term analysis. Kumar *et al* (1998), acknowledge that MTBF or its reciprocal – the 'failure rate' – has been used by many customers as a reliability specification without releasing that in most cases it is almost impossible to demonstrate. They list the main drawbacks of MTBF as:

- Being almost impossible to predict if the time to failures distribution is not exponential.
- The methodology used to predict MTBF is based on the exponential distribution and this distribution is used to model failure times primarily because of its mathematical friendliness rather than any scientific reason.

When using the Mean time to failure/replacement/repair etc, it is assumed there is a constant failure rate. James *et al* (2004) explain that this assumption "implies that for an un-failed item, the probability of failing in the next small time interval is independent of the item's age." So if the data indicates that the failure rate is not constant they advise that this metric should not be used. Palmer (2001) feels that the MTBMA metric does not clearly show the risk to an aerospace item's success in terms of performance and cost. He explains that there is a delay in the recognition of the need for a corrective action.

Ahmed (1996) also discusses Failure rate or failure intensity as a measure of product reliability and explains that these measures are the inverse of MTTF and MTBF.

The authors Kumar *et al* (1998) state that the Royal Air force are considering a new reliability metric, maintenance free operating period (MFOP), as the prime reliability and maintainability requirement for their future generation aircraft. It is not a new concept and is essentially the same as the warranty period. It recognises that some components wear out with use, that not all failures are independent of the age of the component as MIL-HDBK-217 and MIL-STD-1388 imply. Todinov (2004) agrees that MFOP is at the heart of a new reliability methodology. It is seen as an alternative method for setting quantitative reliability requirements.

Age-Specific Failure Rate ASFR is a metric that is used to overcome some of the limitations of MTBF measurements. Jackson *et al* (2002) give the equation of:

$$\hat{h}_i = 2 \frac{\hat{q}_i}{1+\hat{P}_i}$$

Where:

$\hat{h}_i$ = Estimated field ASFR in month i

$\hat{P}_i = 1 - \hat{q}_i$

$\hat{q}_i$ = conditional probability of a failure in month i

They list its advantage as:

1. Being able to permit detection of anomalous behaviour of failure rates e.g.,
    a. An increase in ASFR can indicate the premature onset of a wear-out failure mode.
    b. A rapid decrease from a high initial value of ASFR can indicate presence of a supplier-problem with reliability.
2. It provides sharper estimates of warranty costs, enabling better decisions about warranty polices.
3. It provides a more accurate before and after economic analysis of field changes.
4. It provides a more accurate analysis of effect of geographic factors, seasonal factors and customer use environment.

Availability is a metric that Company X finds very useful to measure customer satisfaction. It is the measure of how available a product has been to the customer and is measured as a percentage of the time at the customer site. Ahmed (1996) discusses availability as a measure of products reliability and as a measure to evaluate the time the product is available to the consumer. Moran *et al* (1990) explain that availability depends on the failure rate, repair time, system management, redundancy, system configuration, loading, power failure, etc. These are also the aspects that represent how customers judge a product.

There are many well known metrics for measuring field data, however some engineers have found it necessary to develop their own metric e.g. Tong *et al* (2002) discuss the "Lifetime Performance Index" which was first suggested by Montgomery (1985) when he recommended using the capability index (lifetime performance index) for evaluating the lifetime performance of electronic components. He developed a capability index C_L being defined as follows:

$$C_L = \frac{\mu - L}{\sigma}$$

Where μ denotes the process mean, σ represents the process standard deviation and L is the lower specification limit.

Probability analysis is another measurement of a product's reliability. It can be used on its own or in conjunction with a reliability model e.g. Bayesian Model. Cooke and Bedford (2002) state, "Components subject to demand can be either non-degradable (not subject to maintenance), or degradable (typically maintained). The statistical analysis of the failure data for non-degradable is quite simple; each demand can be modelled as a flip of a coin; assume for each component type that the probability of failure per demand is statistically independent and identical. The probability of observing *r* failure in *n* demands is:

$$\Pr\{r \text{ Failures in } n \text{ trials} | p\} = \binom{n}{r} . p^r . (1-p)^{n-r}$$

Sander *et al* (2003) discuss three commonly used reliability metrics and these are;

1. Field Call Rates (FCR)

2. Warranty Call Rates (WCR)
3. Hazard Function (r(t))

The field call rate is used to monitor the fraction number of field failures of a given product and is used for logistical purposes, for example to estimate the number of spare parts that will be needed in a given location at a certain point in time. Sander *et al* state that the FCR is estimated by:

$$FCR\ (t_1, t_2) = \frac{M(t_2) - M(t_1)}{(t_2 - t_1)N(t_1)}$$

Where:

M(t) = number of failures at time t

N(t) = number of items on the market at time t

t = time since market introduction of the product.

Sander *et al* observes that this does not take into account the age of the item and also is not useful for field predictions and the number of items on the market, as N(t) is difficult to determine.

The Warranty Call Rate (WCR) is useful for companies that are only interested in products under warranty. Its only difference from Field Call Rates (FCR) being that it only takes into account the products under warranty. Sander *et al* explains that this is being used by Philips Audio and is calculated as follows:

$$WCR = \frac{\text{Total number of warranty repairs over the last 12 months}}{\text{Average no. of units under warranty last year, based on monthly figures}} \times 100$$

They point out the weaknesses as being, a sudden change in a given month can be hidden and the metric is susceptible to changes in sales volume.

The third metric discussed by Sander *et al*, is the Hazard Function. It does not relate to the logistics aspect of reliability but to the reliability aspects of the product itself. It is seen to give a good overall impression of the failure behaviour of a product. It is preferable because it helps identify the root causes of failure as it shows if there is a relationship between the age of a product and the instantaneous failure probability.

It is shown as:

$$r(t) = \frac{f(t)}{R(t)}$$

Where:

$f(t)$ = Failure density

R(t) = Reliability or 1 – F(t) (where F(t) = cumulative failure probability)

They see it as beneficial as unlike the FCR or WCR as it takes into account the age of the product and it monitors the "real time" behaviour of the product. If the reliability of a product depends on the period of production, separate hazard functions should be used for the different periods (the hazard function should be updated as soon as new information is available).

Quest Forum (2003), discusses an interesting metric for analysing field data. It looks at Return Index as a measure of the returns of units during the first six months after initial shipment. The One Year Return Rate is the return rate during the first year following the early return Index period. It also discusses the Long Term Return Rate and the Normalized One Year Return Rate. It calculates all these Rates similarly and can be summarised by the following equation. Returns of unit for specified period

$$\text{Return Index} = 100 \times 12 \times \frac{\text{Returns of unit for specified period}}{\text{Total Shipments for specified period}}$$

This gives a rate in percentage form of the returns for the specified period. For example the specified number of shipments will be the same for one month and the returns of units will differ for each month after shipment. This tool may be very useful in analysing reliability data for Company X.

3.2 Modelling of Field data

There are many models currently in use for analysing reliability. These will be discussed and how they are used.

3.2.1 Cusum - Reliability Monitoring/ Analysis

Cox (2003) describes a cusum chart as a graphical technique used to detect changes in a process mean over time with capability of detecting small changes in the mean. O'Connor (1996) explains that the principle behind the cusum chart is that instead of monitoring the measured value of interest, the divergence is plotted (plus or minus from the target value). He goes on to say that it provides a sensitive indication of trends and changes. The target is identified and the measurements are subtracted from the target and this gives the divergence/delta. The delta is then cumulated (Cusum) and plotted against the sample number. Cox (2003) agrees and goes on to say that it can pinpoint the exact time when a production line goes out of control. He sees it as an "effective way to monitor a quantitative measure of a continuously operating manufacturing system". A Cusum chart is categorised in many statistical tools as a control chart as it has control limits to identify when the data has gone out of control.

3.2.2 Control Charts

Batson *et al* (2005) suggests an approach of transforming data and using various control charts to measure "time to first out-of-control signal and persistence of signal after out-of control status begins". The $\overline{X}$ - chart is used for field failure monitoring. At first glance this looked to be a potential measurement for Company X however on investigation it appears the author is graphing failures after 100% of failures. Batson takes the example of 60 motors that are assumed to run until each unit has failed. This is used to generate the normal distribution. For testing the effectives of the proposed control charting three decreasing MTBF scenarios are used and random data is generated. Therefore the control charts are not tested using real time data. If a product is in the field and the manufacturer is "interested in early detection", it is not feasible to wait till all the units have failed and then look back and say that the problem could have been identified at point X or Y. This contradicts the company's need for "more frequent, continuous confirmation of the reliability of the failure-prone unit". This would be very useful looking back at historic data but in real time and identifying current performance this approach would not be suitable.

Oleinick (2005) proposes the use of a *u* chart to monitor the field failure rates of fielded products. The rate is calculated simply by the number of failures in a batch over the production volume of the batch. This he uses as an early warning technique to the manufacturer. He suggest that the failure rate variability can be looked at more deeply by use of the attribute control chart and also states that "One of the assumptions implicit in a control chart is that the underlying process is subject to two kinds of variability: random variation inherent in the process and an intermittent variation that would be assignable to specific causes". The control chart is seen as a signal to differentiate between the steady variability from the assignable causes. To develop this further the author introduced reliability growth as a factor as opposed to the average constant failure rate. This was very successful in his testing and resulted in the reliability-growth-based *u* chart signalling of an out of control point one month sooner than the constant average *u* chart.

3.2.3 Duane - Growth Monitoring

O'Connor (1996) explains that it is common for new products to be less reliable during early development than later in the programme, when improvements have been incorporated as a result of failures observed and corrected. In this way products experience Reliability Growth. He goes on to explain the Duane method applicable for measuring the reliability growth "for a population with a number of failure modes which are progressively corrected, and in which a number of items contribute different running times to the total time." Duane experienced that the cumulative MTBF θ_c (total time divided by the total failures), plotted against total time on a log-log paper gave a straight line. The slope (α) gave and indication of reliability (MFBF) growth, i.e.

$$\text{Log } \theta_c = \text{Log } \theta_o + \alpha (\log T - \log T_o)$$

Where θ_o is the cumulative MTBF at the start of the period T_o. Therefore,

$$\theta_c = \theta_o \left(\frac{T}{T_o} \right)^{\alpha}$$

O'Connor admits that the model is criticised for being empirical and subject to wide variation. It also argues that reliability improvement in development isn't usually progressive but can occur in steps. This model he sees as simple to use and can provide a useful planning and monitoring method for reliability growth. Donovan and Murphy (1999) express concerns with relation to the Duane model. It is felt the model had a number of inherent difficulties, one being the influence of early failures on the slope, the second being the clustering of failures at the latter stages of testing. The 'New Model' was developed to overcome these.

Xie and Ho (1999) see the Duane model as the most well known model for repairable systems. They see its advantages as being:

1. It is highly flexible.
2. Its graphics are easy to interpret.

In this paper Xie and Ho (1999) compare the Duane model to another time series model and comment that as the sample size gets larger the results from the time series models tend to be better. They also conclude that the time series models out performed the traditional Duane model in terms of predictive performance. It is expected that long-term prediction using the Duane model would be rather poor as the model assumes that past history is very representative of the future.

3.2.4 ARIMA

The ARIMA model is based on the time series models. Xie and Ho (1999) see it as considering the times between failures or the number of failures per interval as a time series and applying a time series model to model and analyse the failure behaviour. The ARIMA model is seen as a powerful class of time series model for depicting a wide variety of time series. This includes autoregressive (AR) models and the moving average (MA) models. The AR and MA models can be mixed and provide a third class of general models called ARIMA. It takes the form of

$$X_t = \Phi_0 + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \ldots + \Phi_p X_{t-p} + \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

They go on to state that in practice, the ARIMA model with a p (autoregressive order) and q (the moving average model) value of 1 or 2 should be sufficient. This is especially the case when the data set is small and a complicated model is not appropriate.

3.2.5 New Model

Donovan and Murphy (2001) looked at the Duane model and developed a new model to overcome its limitations. They present the Duane model as:

$\theta_{Du} = \alpha_1 T^{\beta 1}$

In α_1 and β_1 represent the intercept and Duane slope respectively as seen from the following log-log model:

$In(\theta_{Du}) = In\alpha_1 + \beta_1 \, In(T)$

They go on to say that this relationship falls on a straight line when plotted on log-log paper. The new model proposed continues plotting the cumulative MTBF on the *y* axis and cumulative time on the *x* axis. The variance stabilizing transformation theory suggests that for a Poisson process, the transformation equals the square root of the count. Therefore, the transformation of the *x*-axis becomes the square root of the cumulative time. The *y* axis is not transformed and this is any advantage of this model as the cumulative MTBF is plotted directly. The new model looks as follows:

$\theta s_q = \alpha_2 + \beta_2 \oplus `T$

Donovan and Murphy (2002) explain that this model represents an improvement on the Duane model whilst having mathematical similarities to it. Donovan and Murphy (2001) list 5 advantages for the new model over the Duane model:

1. Early failures have a high influence on the Duane model. If it is used to observe growth during testing then the resulting graph is overly affected by those failures occurring early in time. This does not happen with Donovan and Murphy's new model.

2. In the Duane model any failures occurring towards the latter part of the test are inclined to be bunched or clustered together due to the nature of the In(*Cumulative Time*). The new model proposed avoids this.
3. The new model simulations have shown that the latter failures have the greatest influence on the new model and the early failures have little influence on the new model
4. The new model proposed is clear and simple. There is no requirement to transform the *y* axis resulting in the further advantage of reading the cumulative MTBF directly from the graph. It is easier to plot, interpret and visualise.
5. Simulation has shown that the new model provides a better fit to the data when the Duane slope is <0.5. Above this point the Duane model tends to provide a bitter fit to the data. This isn't seen as a drawback as many reliability growth programs have Duane slopes <0.5.

3.2.6 Moltoft

Moltoft (1994) looks at the traditional 'homogenous Poisson process' model (the HPP model) and identifies its inadequacies due to the assumption of a constant failure rate. Bohoris (1996) says that "the renewal process, in which the times between successive failures happen to be exponentially distributed, is a distinctive stochastic failure model called the homogeneous Poisson process. Moltoft looks at field data for an electronic system (with a number of components) in a particular month and calculates a MTBF of 7.5 years with a failure intensity figure of 1.12%/month (with a minimum of 1.03% and max of 1.21%). However when all the monthly rates were calculated over time it was seen that for most months the failure percentages exceeded the confidence limited calculated. This proved that the HPP model was invalid. Moltoft goes on to put forward a new model that he feels overcomes the inadequacies of the traditional model. This is called the 'superimposed renewal process' model or the SRP model. This has been discussed before but Moltoft puts it to the test. Rimestad (1990) says that in the renewal process the times between failures are independent, but from the same distribution. This means that the renewal process is a natural model of a component position, because every time a component fails it is replaced with a new component with the same distribution. Moltoft goes on to explain that the outcome is the value of M(t), which is the mean accumulated number of failures as a function of the operational time. For example, for n components in the system we get:

$$M_n(t) = n\lambda_t + np = \lambda_{\%}t + p_{\%}$$

Where $\lambda_{\%}$ is equal to the failure intensity and $p_{\%}$ is the amount of 'weak systems determined by the intersection of the asymptote with the M(t) axis. There are common patterns for two life periods:

1. Firstly the M(t) graph has a number of complicated time-dependent functions of which Moltoft calls *the transient period*
2. After this the M(t) graph enters a period where it becomes a straight line. Moltoft calls this period *the steady state period.*

Moltoft also states that studies of field reliability information have been carried out at the Institute of Applied Electronics and have shown a common pattern for the M(t) function within an operational life up to seven years. However beyond this the system may have limitations regarding long-term wear-out.

3.2.7 Bayesian - Reliability Probability

There is not always the amount of data needed in the field to make decisions or evaluate reliability on. In situations like this Percy (2002) recommends the Bayesian approach. Examples of situations are where the system or process or product is new or where you have a complex system the reliability of a new subsystem might be unknown until it is in place for some time. Kvam and Miller (2002) also recommend this approach for predicting common cause failures (CCFs). It is seen as a straight forward approach to the prediction problem. Given the density

$f(x|\ \theta)$ of the observed failure counts and the prior distribution $\pi(\theta)$ that characterizes our uncertainty about the parameter, the updated posterior distribution for the unknown parameter θ is computed as:

$$\pi(\theta|x) = \frac{\pi(\theta) f(x|\ \theta)}{\int_{\Theta} \pi(\theta) f(x|\ \theta) d\theta}$$

Where Θ represent the parameter space for θ. The *predictive density* of a new observation Y from $f(x|\ \theta)$ is then defined as:

$$P_{y|x}(y|x) = \int_{\Theta} f(y|\ \theta)\ \pi(\theta|x) d\theta$$

The posterior $\pi(\theta|x)$ serves as a mixing distribution, which combines the updated parameter uncertainty with the original prediction uncertainty.

3.2.8 Weibull Distributions

Another method of reliability analysis is the Weibull probability plots. Patrick D.T. O'Connor (1996) says that this analysis is the most widely used due to the flexibility of the Weibull distribution in describing a number of failure patterns. He goes on to explain that the axes of Weibull probability paper are derived by performing the transformation …

$$R(t) = 1 - F(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]$$

assuming failure free time is 0 (i.e. use the two-parameter Weibull distribution). Therefore

$$\frac{1}{1-F(t)} = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]$$

Hisada and Arizino (2002) explain that it is often used as the lifetime distribution, because some failure modes (e.g., initial, random, and wear-out) are described by their shape parameter. Thus the Weibull distribution is important and has been studied extensively over the years. As well a Weibull, the exponential and lognormal distributions have to be mentioned. Sarawgi and Kurtz (1995) describe these are the most frequently used statistical distributions for modelling different kinds of failures. For their example the lognormal was used as the generic model of a lifetime distribution. This was justified by the fact that the lognormal distribution had been shown to be a valid reliability model for a wide variety of electronic components and systems.

3.2.9 – Warranty and Claims based modelling

A reliability model exists that looks at the warranty claims of a product. Iskandar and Blischke (2003) discuss the Kalbfleisch-Lawless (KL) model that has the purpose of investigating claims patterns, search for trends, predict future claims and estimate field reliability. This model provides information on the pattern of claims and can be used to predict future claims assuming the same basic pattern prevails. It uses an aggregate 2-Dimensional claim's data and is based on estimating age-specific claims rate. On testing, Iskandar and Blischke (2003) identified that when the supplementary data (e.g. usage patterns) is not available, it can lead to errors.

The Gertsbackh-Kordonsky (GK) approach is also discussed by Iskandar *et al* (2003) and is seen as reducing the previous 2-Dimensional model (KL model) to a 1-dimensional formulation and is essentially equivalent under certain conditions.

Iskandar *et al* (2003) discuss the warranty Cost Model as the cost of warranty to the manufactured depending primarily on two factors, the terms of the warranty and the distribution to time to failure of the item. The one and two-dimensional models are discussed. It allows the company to look at its warranty and make decisions on it, for example to upgrade it, shorten it or lengthen it.

3.2.10 Early Detection of Reliability Problems

It is important for a manufacturer to know as soon as possible if there is a reliability problem in the field with a product. Wu and Meeker (2002) explain whilst companies invest vast amounts of money on reliability in design and manufacturing, some face serious reliability in the field due to unanticipated failure modes, harsher than expected environmental conditions, supplier changes or designs not verified properly. They introduce a time to warranty report which monitors the failure data related to its ship month. It graphs by ship month by its 1st, 2nd, 3rd and 4th month in service monitoring a specific failure code. It allowed analysis of the data to pinpoint a specific month of production that related to field reliability problems.

Oleinick (2005) used a similar method to analyse further field data. He used a MOP/MIS (Month of Production/ Months in Service) chart to analyse the field data. The failure data for one production month is graphed by month in service. This showed that the first month in service for the two production months tested, had the highest fraction failed.

3.2.11 Trending graphs

Trending techniques can be used to tell if a product performance is getting better or worse in the field. Bohoris (1996) discusses the rate of occurrence of failures (ROCOF) as an expression of failures per unit time. He describes it as dividing the cumulative number of failures which have occurred by the elapsed operating system time. The Cumulative failures vs. the Cumulative operational time is graphed and results can be interpreted as follows

1. A straight line indicates a constant failure rate
2. A concave up line indicates a deterioration or an increase in ROCOF
3. A concave down line indicated a reliability growth where the time between successive failures is increasing.

Bohoris (1996) concluded that it may not always be valid to fit lifetime distributions to reliability data.

3.2.12 Others

There are other models in use such as the REMM (Reliability Enhancement Methodology and Modelling) model discussed by James *et al* (2004). It was a research project by a UK DTI (Department of Trade and Industry) with the goal to develop a methodology for reliability enhancement and a statistical model for reliability assessment. This model uses a Bayesian approach and the output is expressed in terms of the Survival function, from which other metrics can be derived e.g. Product X has a 43% chance of reaching 16,000 hours without realising a build-related failure.

Mentioned earlier was the ASFR metric and the authors Jackson *et al* (2002) have also developed an improved prediction model for the metric. The distribution is based on the Gaussian distribution. Looking at their data they found that the new prediction model predicted better for the field replaceable unit (FRU) in question.

G Kervarrec *et al* (1999) reviewed the field failures of integrated circuits and proposed a universal predicting reliability model for particular failures. It is seen as an alternative guide to the obsolete MIL-HDBK-217F for predicting reliability calculations. The metric used is Failure rate, based on the CNET RDF93 Handbook and has been modified for the product. Many of these have been calculated out and are used as a model base for other manufacturers or users of integrated circuits.

Exponentially weighted moving average (EWMA) graphs are another method of detecting trends in reliability data over time. Martz and Kvam (1996) use this as a simple, easy to use method to determine if there is any statistically significant trend or pattern over time. The EWMA is seen as more powerful than the shewhart graph in broadly detecting increases in event rate of occurrence.

3.3 Company X Field Data Measurement/Modelling

Currently in Company X the metrics used to monitor field reliability are the replacement rate and the Mean Time Between Part Replacement. The Replacement Rate is calculated using the following calculation:

$$\frac{\#\ \text{Parts replaced}}{\sum \text{operating hours in the field}} * 8760\ \text{(hours per year)} = \text{Replacement rate/yr}$$

This Replacement rate is then converted to MTBPR figure. The MTBPR is used to monitor a products reliability performance in the field and compare it to the expected performance. There is no modelling that would identify a trend or problem developing. When it is known that there is a problem there is no specific analysis tools to identify what caused the problem.

Company X has no model to predict the reliability of a product. This would be very beneficial to anticipate warranty needs, life span and spare part requirements.

3.4 Conclusion

Cooke and Belford (2002) explain that for reliability to be useful it must reveal not only the probability of failure, but also the cause of failure. The next step in the research is to develop a way to predict reliability for Company X, to have method to identify a problem in the field and a method to investigate why a problem has occurred. Reviewing the metrics above the current metric used by Company X of replacement rate is a very accurate and understandable metric. This can be converted to a MTBPR figure which is what the suppliers and customers of Company X deal with. The Return Rate index looks a very valid and easily used metric that could facilitate the closer analysis of reliability for Company X. For modelling the Trend graphing looks a potential option for research. The Cusum and Weibull models will also warrant investigation. Early detection model will be investigated to see if it suits the situation of Company X.

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Chapter 4

Extraction and Analysis of Field Data

4.0 Introduction

The metrics and models used in industry have been discussed. The goals of this chapter is to

- Critique current reporting of reliability in Company X
- Extract the appropriate field data
- Establish away to plot the field data so that trend may be identified.

To establish accurate metrics and models two specific product types will be analysed. One of these electronic parts had poor reliability in the field which was investigated in Oct-05 – to be referred to as Product A. The second performed well – to be referred to as Product B. Their reliability was established based on the Mean time between part replacements (MTBPR) metric. The design goal provided for these products was 400,000hrs. Product A has never reached its goal MTBPR in all its time in the field. Product B on the other hand has never gone below its goal MTBPR. Both products were manufactured by the same supplier and have the same storage capacity. They are both used in the same parent system.

4.1 Field Data Reporting Within Company X

The replacement rate figure is seen by Company X as one of the simplest rate measures based on a population of similar products operating in a given time frame and simply computes the number of replacements divided by the total time the products were operating. It is seen as an easily expressed and easily understandable value. As the rate looks at the total time the products were operating means that a change may not be noticed early enough. If a replacement rate is calculated for June it will take all the failures in that month and the total operational hours for the installed product. As there may be a large population installed in the field a small change in the failures per month may not trigger analysis straight away.

The replacement rate metric is also transformed to a Mean Time Between Part Replacement (MTBPR) by use of the following formula:

$$\text{MTBPR} = \frac{8760}{Replacement\ \ Rate}$$

The figure of 8760 represents the total number of hours in the year. Products A and B were given a MTBPR of 400,000 hours. This equates to a replacement rate of 0.0219 replacements per year. All suppliers give an expected MTBPR figure for their product. Company X then compared the expected MTBPR to the actual MTBPR in the field. Both the replacement rate and MTBPR assume a constant failure rate. Company X has a database based in its site in the U.S. and an MS-Access macro is used to calculate the replacement rates per product on a monthly basis. Currently a field problem is usually noticed by the amount of returns or failure analysis requested by the customer. The field data is not currently used to initiate investigations into the quality or reliability of a product. There needs to be a metric or model that can identify as early as possible that there is a problem in the field.

As well as the replacement rate metric and MTBPR metric a cumulative fraction removal by quarter of installation graph is produced. Although is it grouped by quarter the graph is updated monthly. This is seen in Figure 4.1. Finally in the report all the failures for that month are listed.

The cumulative graph displays the cumulative number of replacements by time, grouped by the quarter of installation. This allows comparison of the different quarters to see if one is showing a higher rate of replacements than the other. Oleinick (2005) agrees with the use of this graph as way to monitor field reliability. He uses warranty claims as the data source to measure the products reliability. The cumulative metric is examined and graphed. Differences in the curves relate to differing field performance. He states that this may be due to

a. The manufacturing process varying from month to month and
b. The components in use are aging, and age can affect reliability.

Figure 4.1 shows an example of the cumulative fraction removal for a product in Company X.

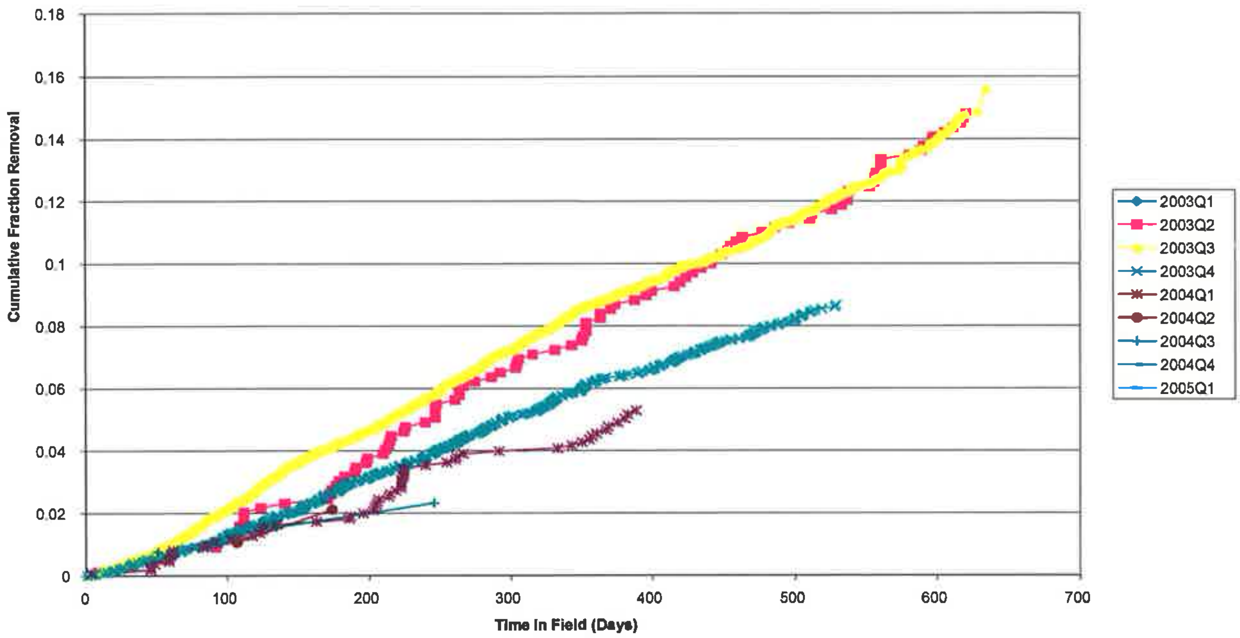

Figure 4.1 Example of Cumulative Fraction Removal for a Product Family

As this graph is grouped by quarter (4 quarters/yr) and the number of installations are in the hundreds of thousands a problem may not be seen early. It does not trigger an immediate reaction. It is hard to tell if there is a spike in replacement rates for one particular quarter of installations. The grouping is by installation quarter so if a particular month is showing a decrease in reliability it may be diluted as part of a quarterly figure. Finally this graph groups similar part numbers together into product families and is not part number specific. Similarly to the doubt over the quarterly grouping, product grouping also means that if one part has decreasing reliability it may not be visible if the other parts in the group are performing well. As an overview of a product family it is a useful graph and can give a big picture on how the month of installations compare to each other.

In Summary Company X produces a monthly report that shows the replacement rate per part number, the cumulative fraction removal by quarter installed grouped into similar parts and finally it lists all of the parts that failed in that month. The data is very important and is reviewed by the engineering departments, nevertheless there are some concerns

1. A trend of increasing or decreasing reliability cannot be easily identified.
2. The MTBPR figure used assumes constant failure rate.
3. A problem may be diluted graphically by the grouping of similar products.
4. A problem may be diluted by graphically grouping months into quarters.
5. It is not possible to predict future reliability performance from the current analysis of the data.

The field metrics and graphs are produced automatically each month by a MS-Access database macro in the U.S. Any other field data or metrics must be extracted manually and analysed from the field tables which reside on servers. The goal of the research to suggest new metrics and methods to identify problems in the field much earlier than is currently available and that can also predict future performance.

4.2 Field Databases and Data Storage

Company X records both in-house process data and field data. Both sets of data are stored on separate databases on separate servers and both are important for analysing field data. The in-house data gives the ship details of a product which is necessary to link with the field activity i.e. a certain population shipped in a certain month showing failures in the field.

All products in Company X have an individual serial number which is related to a part number and revision. If a specific part is a subpart to a bigger system then the parent will also have similar details. All the in-house data pertaining to a part is recorded on a live database. For Company X this system is Oracle. The oracle system tracks the part as it moves through the process recording the following details.

- The Part Details – Part number, Serial number, Revision
- The Nesting Details – What Parent it is nested to
- The Parent Details – Part number, Serial number, Revision
- Transaction History – what stages of the process it has moved through
- Times – the Date and Time it moves through the different stages e.g. start date, test date, nesting date and ship date.

The data is scanned into the oracle database which is installed on every PC by use of a scan gun and a series of steps indicating what is being done. This data is then automatically loaded on the different tables on the overall database which resides in a specific server. The data can range across a number of tables. Examples of these tables are:

- The transaction table
- The history table

- The shipping table
- The quality table (outlining failures)

As every part is uniquely identified by a serial number all these tables can be linked on this unique identifier.

When the product goes to the field it is installed in a customer site. At the site the customer engineer logs the following details in the field database which resides on a second server:

- Serial Number
- Part Number
- Install Date
- Site Details
- Install Success
- Parent Serial Number
- Parent Part Number
- Case Number (each time a engineer logs into a customer system a case number is given to record all actions against)

If there is an issue with a product in the field the customer engineer will go to the site and again record the product specific information but also the call information, which include the following.

- Failure Category
- Corrective Action
- Data Unavailability
- Data Loss

- Date of Failure
- Date of Replacement

This information is stored in a separate table but again the tables are linked on the product specific information such as serial number, parent serial number, site id etc. Examples of field tables in the field are as follows:

- Component Install table
- Parent Install table
- Failure Table
- Install Failures Table
- Call Details
- Customer Information

There is validation in place that a part can't be active on the two servers at the one time. Its "current" location has to be either in-house or in the field. This validation can trigger a warning that the data hasn't been correctly entered by an engineer. For example if a part was not correctly filled out in the field and came back in house it would be caught. All failures are sent back to the company for analysis, so field data is checked and verified to be correct.

4.3 Extraction of field data for reliability analysis for Company X

Field data must be extracted from the existing tables to generate new ways to measure and model the reliability of products. The data must be mined correctly to allow it to be analysed. The tables and servers the data is stored on were discussed earlier in this chapter. To get at the data the primary application used is Microsoft Access. Access allows data to be extracted and manipulated into a useful form for reliability measurement. There are three groups of data that need to be extracted:

a. Ship data
b. Install data
c. Fail data

To get the ship data the shipment table has to be queried which resides on the in-house data server. Figures 4.2 and 4.3 are examples of queries that are run to extract the ship data. The specific part number would be entered in the Part Number field to filter the data return. Other criteria could be specified such as specific customer name or date range etc.

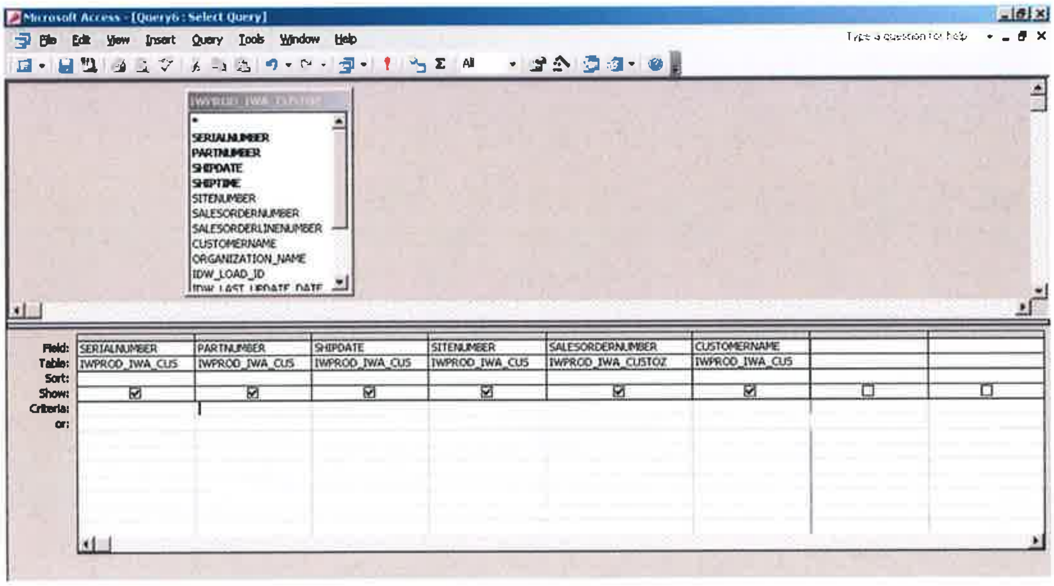

Figure 4.2 Query to pull Ship Data

To link the ship table and the field table to get the corresponding fails the following query is used.

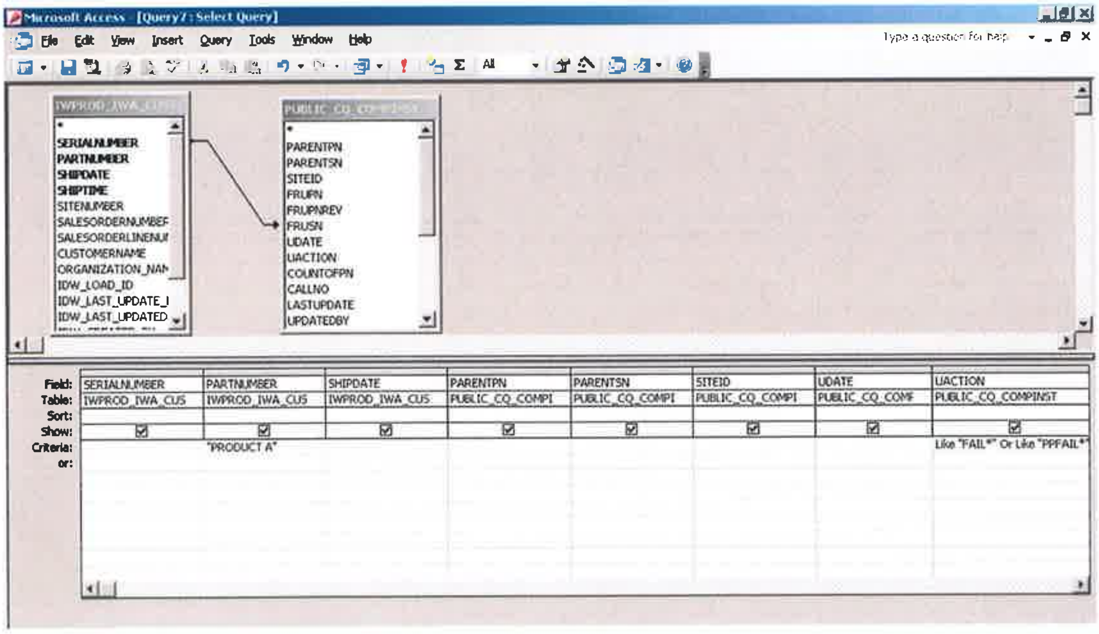

Figure 4.3 Query to link ship data to failure data

Because the field data and the in-house data reside on different servers it may be necessary to generate a local table of the ship data first and then link it to the field data i.e. failure data. Due to the different performance issues on different PCs, local tables may have to be developed on the PC to make data extraction more efficient.

The Figure 4.3 query is looking for all the ship dates for Product A and only the related failures for this product. The link on serial number ensures that the serial number is the unique identifier for a part. The UACTION is specified as "Like "FAIL Or Like "PPFAIL"". The types of actions (UACTIONS) that may be recorded on this table are:

- Install – Installation record of a product that ships to a customer
- Upgrade – The installation record of an upgrade product that ships to a customer (this is being installed in a parent)
- Deinstall – The record that tells when a product is deinstalled from the customer site – as opposed to being failed. A product may be moved from one site to another meaning it has to be powered down and reinstalled in another location. The deinstall record is used here. It is important to be aware of this record and factor it into our analysis of data. This would not represent a failure but would represent a time the product is not functioning in the field.
- Fail – The fail record is when a product fails post installation and is replaced in the field
- PPFail – This record differs from the Fail record in that is happens when the product is being installed. It is referred to as a Plug and Play incident, hence the PP notation before Fail.

To link a part installation record to its corresponding failure or deinstallation record the query outlined in Figure 4.4 is used. This will allow the calculation of the time to failure information. This data needs careful manipulation so that all possible periods of non operation without failure in the field is taken into account. A product in the field may be powered down temporarily for different reasons:

- Maintenance
- Transfer
- A failure of another part in the system

The operational time is calculated so that the replacement rate is as accurate as possible. The query in Figure 4.4 is used to relate an install record and a fail record. The same tables are used however the data filters on the records differ (e.g. looking for the install record and corresponding failure record).

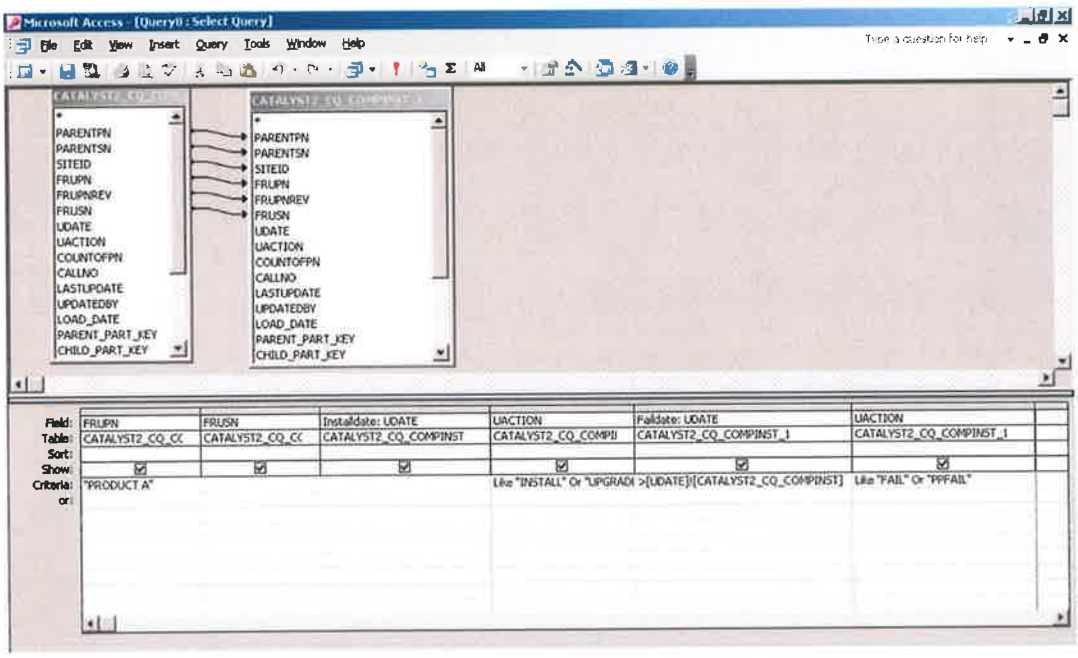

Figure 4.4 Query linking installation data and failure data

Figure 4.4 identifies the failures that are occurring for Product A are being identified. As the same table is used twice in the query, the UDATE field is renamed accordingly as 'Installdate' and 'Faildate'. It is important to ensure (as a data check) that the failure data happens *after* the installation data. It is already known that a product may be installed more than once in the field i.e. relocation. Links are very important to help filter the data. In the Figure 4.4 a link is made on Serial number, Part number, Parent Serial number, Parent part number and Site ID. This ensures that if a product is installed in a parent it can only be failed on that same parent, similarly if it is installed in one site it has to be failed or removed from the same site. This helps validate the records. For example, if a product was installed in parent x, it has to have failed on parent x before it can be installed in parent y. If it subsequently failed on product y the link on serial number makes sure a miscalculation does not occur on the operational time as the time between failures in y to start date in x. Once a product is identified as having failed in the field all the install/deinstall records have be compiled and calculated to give the total operational time in the field. The results of this data extraction will be used in the reliability measurement/modelling and prediction.

4.4 Reliability Models for Company X

Detailed knowledge of database structures allows relevant failure and operational data to be extracted. The next step is the modelling of this data using the best reliability analysis techniques. The following models will be looked at:

- Reliability Trending
  - Rate of Occurrence of Failures
  - Replacement Rate by Month
  - Mean Time Between Part Replacement (MTBPR) by Month
- Reliability Plotting

4.4.1 Trending the Reliability Data by Month

Trending reliability data by month gives an indication of how the product is performing month on month and helps identify a constant decreasing/increasing trend or erratic behaviour.

It is important to trend the correct data. Martz and Kvam (1996) explain that it is important that reliability data analyses the "statistical identification trends and patterns inherent in the data over time".

4.4.1.1 Rate of Occurrence of Failures Trending

Bohoris (1996) discusses the rate of occurrence of failures (ROCOF). For Company X the replacements are looked at so these will represent the failures. To demonstrate the ROCOF graph the cumulative operational time is plotted against the cumulative failures. Figure 4.5 and 4.6 represent the results for Product A and B respectively.

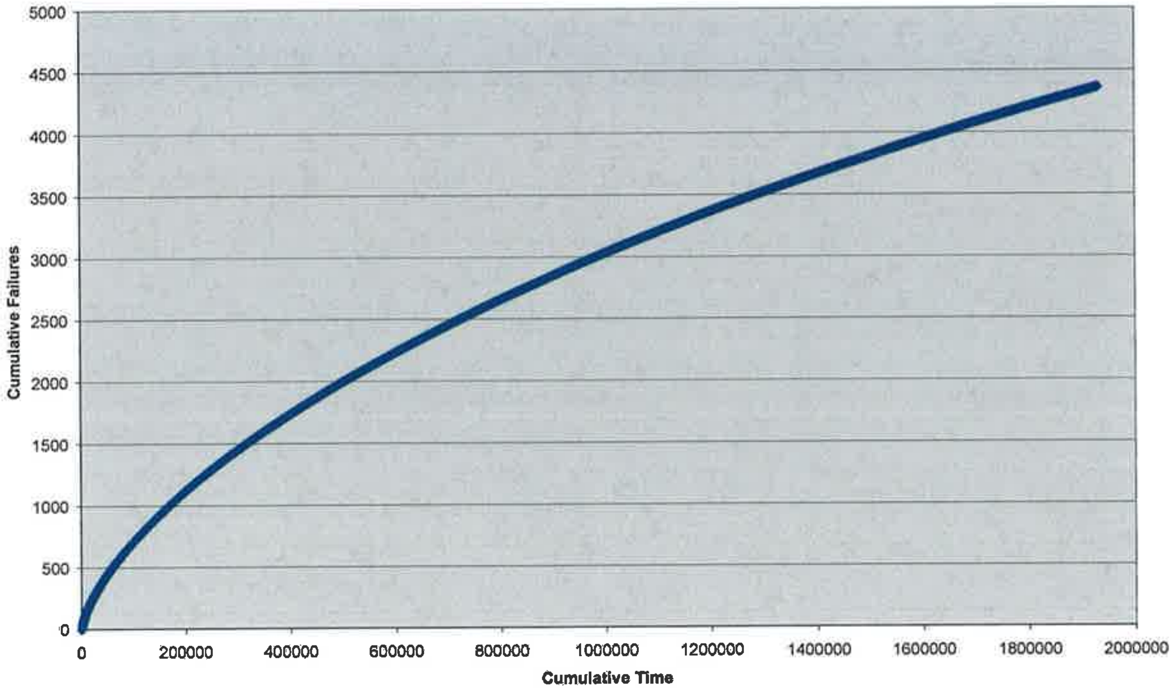

Figure 4.5 Rate of Occurrence of Failures for Product A

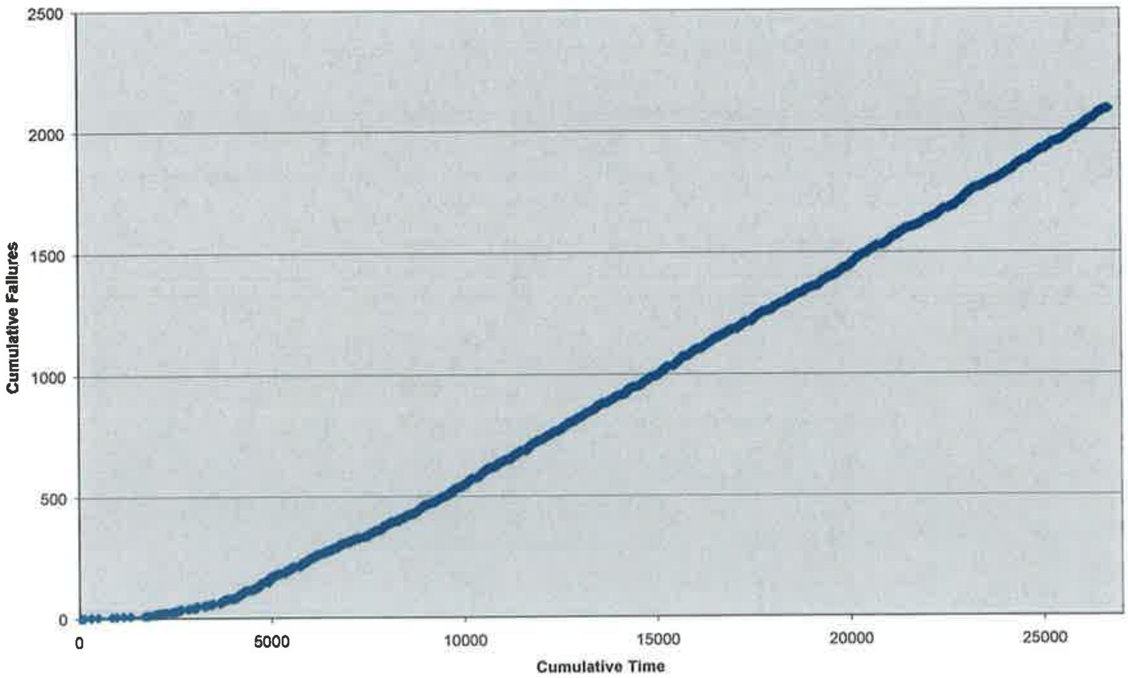

Figure 4.6 Rate of Occurrence of Failures for Product B

Bohoris (1996) also helps in the analysis of these graphs by giving the guidelines discussed in chapter 3 to analysis the curve.

- A concave graph up shows a deterioration in reliability
- A concave graph down shows reliability growth
- A linear effect represents a constant ROCOF

Product A has a concave down graph. It has high number of failures earlier on in life but the product appears to improve. If a product is failing in early life (say in the first 10 months) after this time all the good product will be left and hence an improvement in reliability. The graph shows evidence of early failures. Product B has a more linear graph that shows a relatively constant ROCOF.

4.4.1.2 Replacement Rate Metric Trending

The existing metric reported by Company X of replacements rate can be trended to review the reliability of the product. This is again calculated by the number of products replaced in a month divided by the total operational hours. However when there are large volumes of the product in the field (in some months there is greater than 25,000), a small change in the reliability may be diluted and hidden from the company. For both products a MTBPR of 400,000 hours was the goal performance given by the supplier to the logistics department who plan for spares in the field. This figure equates to a yearly replacement rate of 0.0219. Keeping this in mind also helps in trending. For the products below one is significantly worse than that and one is significantly better. It has to be noted Company X reviews the replacement rate as a numeric value. It has never been graphed over time as per Figure 4.7 and 4.8

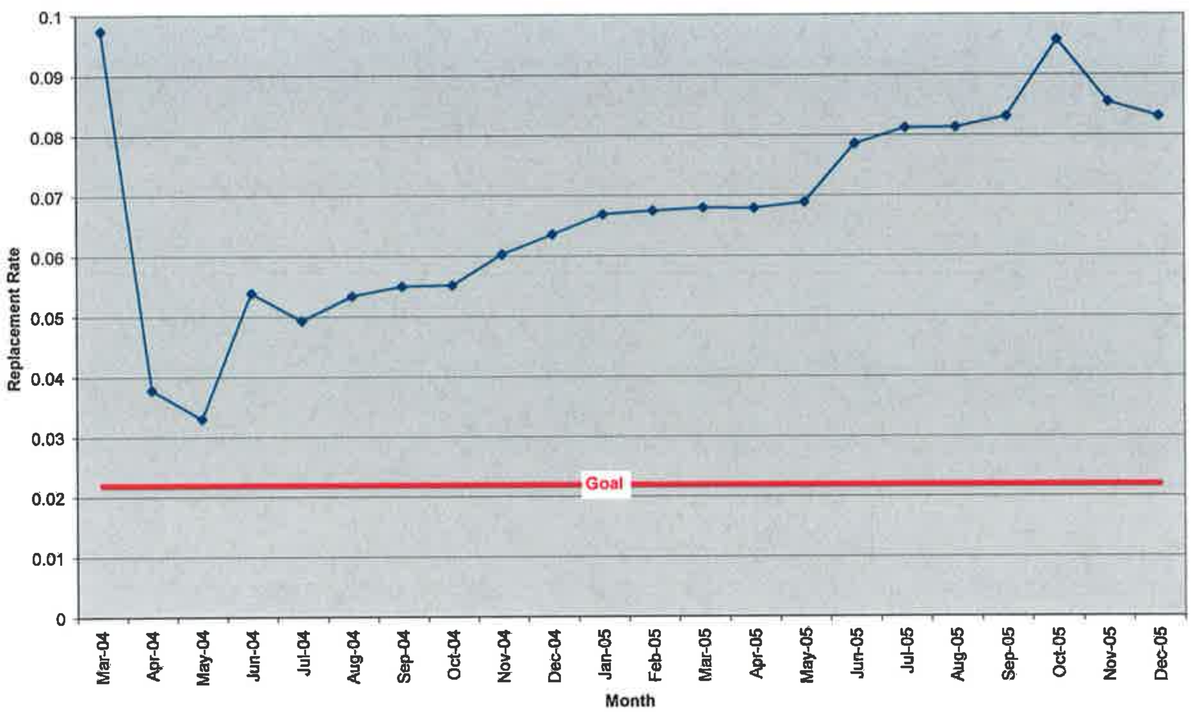

Figure 4.7 The Replacement Rate per Month of Product A

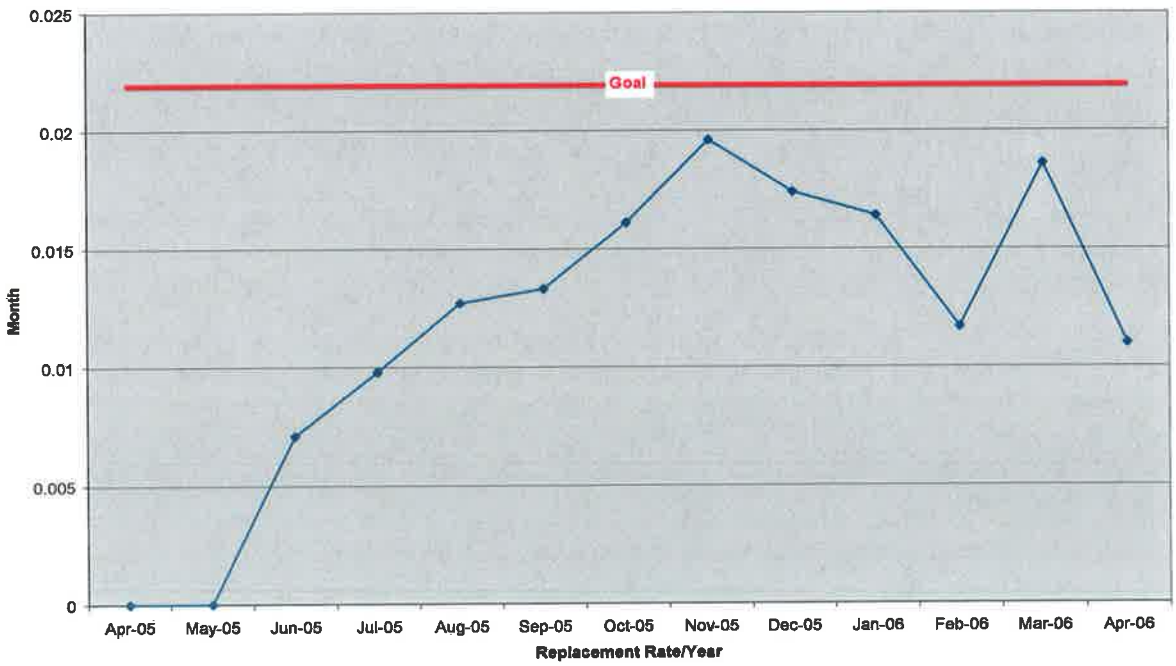

Figure 4.8 The Replacement Rate per Month of Product B

The trending of the replacement rate per month graph gives the following information:

a. Product A has a much higher replacement rate than Product B
b. Product A never reached the goal replacement rate.
c. Product A shows spikes as reliability decreases (replacement rate increases) in Jun-04, Jun-05 and Oct-05
d. Product B had no failures for the first two months of installation in the field (it is visible from Figure 4.8 that the product was shipping for a few months before it was installed).
e. Product B always exceeded the goal replacement rate.

4.4.1.3 Mean Time Between Part Replacement (MTBPR) Trending

The supplier and logistic departments currently report field reliability in terms of MTBPR however no trending or charting is involved. By using the existing replacement rate data it is possible to transpose the data into its MTBPR equivalent. This graph is felt to be more meaningful to the internal users of the data.

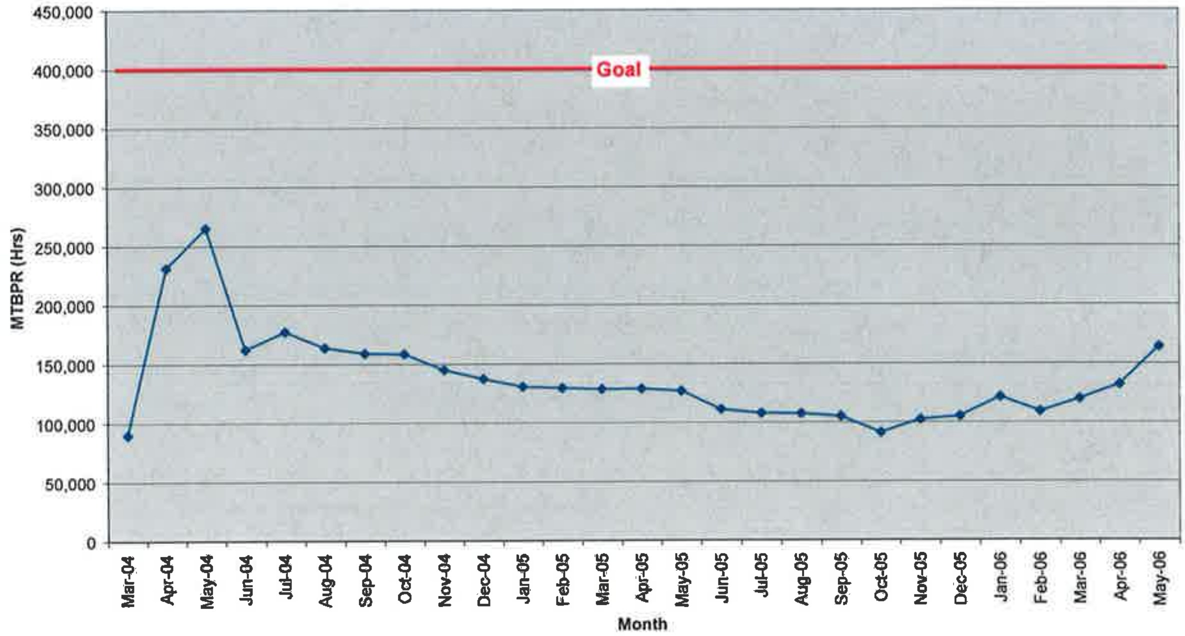

Figure 4.9 Mean Time Between Part Replacement for Product A

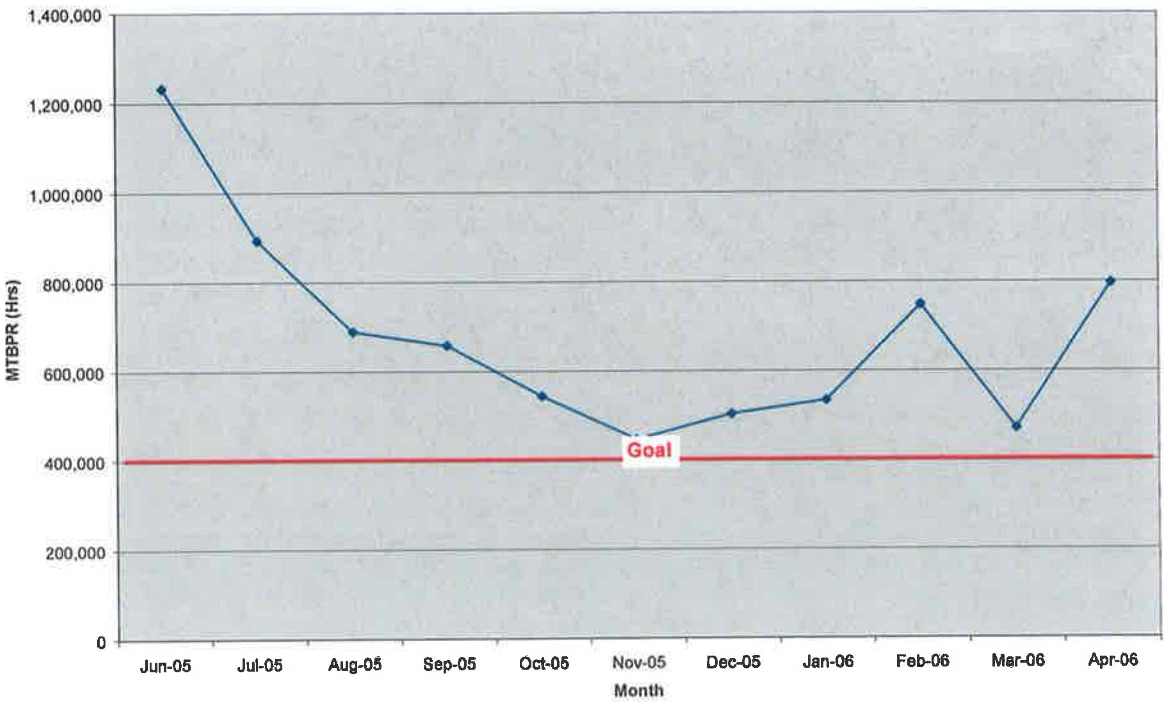

Figure 4.10 Mean Time Between Part Replacement for Product B

By inserting the goal lines again in Figures 4.9 and 4.10, it gives a clear indication of the field performance.

- Product A has never reached the goal MTBPR.
- Product B has never gone under the goal MTBPR.

This analysis shows that the goal MTBPR was totally unrealistic for product A. Trending on MTBPR can drive an investigation into the feasibility of the goal MTBPR figure provided by the supplier.

4.4.2 Reliability Plots

The Minitab statistical software package application is used to generate reliability plots for Product A and B. The data is extracted by failures per month and is then censored to generate the plots. Figure 4.11 and 4.12 represent the Weibull distributions for Product A and B respectively.

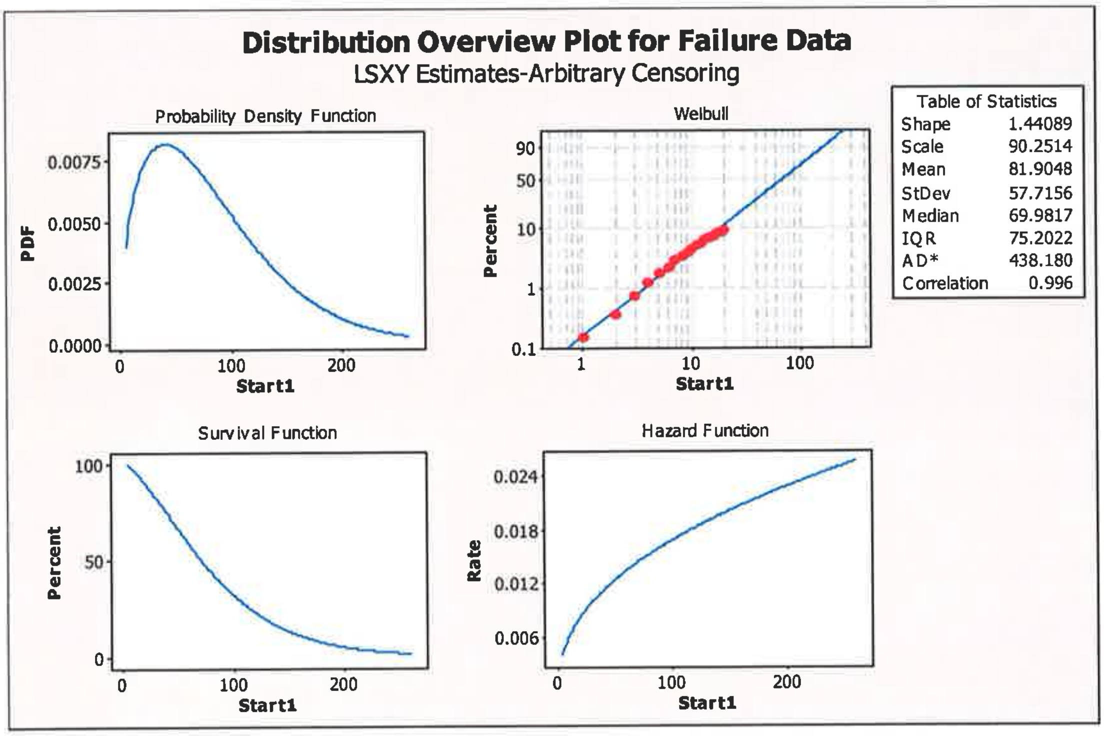

Figure 4.11 Weibull Probability Plot for Product A

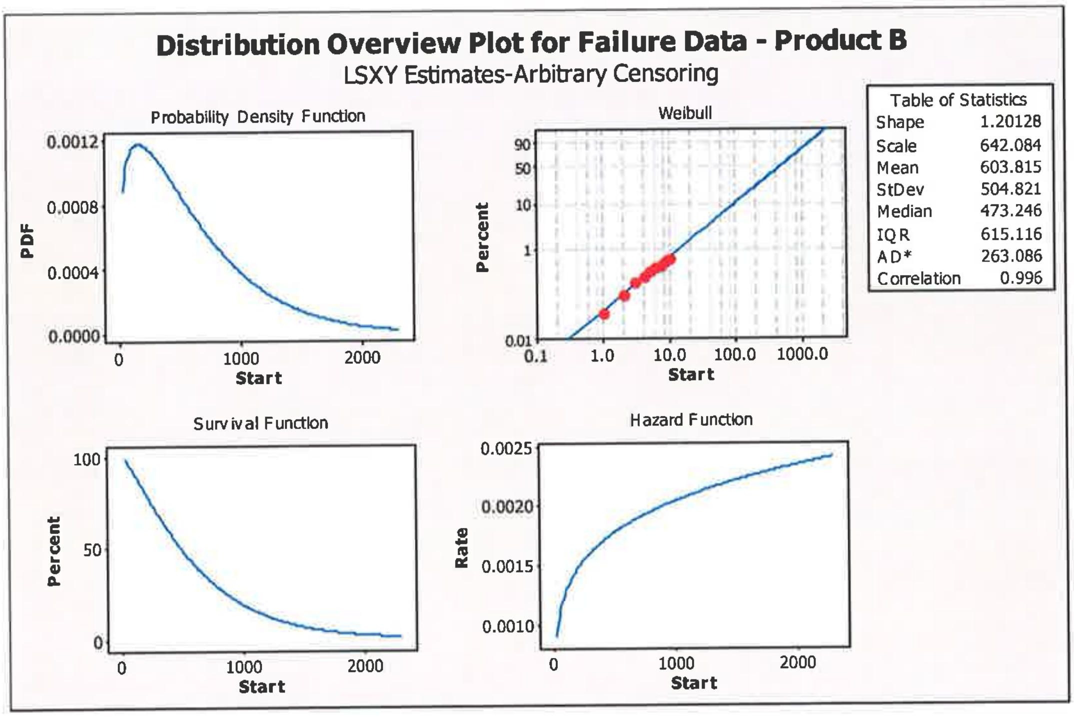

Figure 4.12 Weibull Probability Plot for Product B

These plots take the field failures and plot them against the best fit linear representation. How the data is distributed along the line determines how well it follows the Weibull Distribution. By following the extrapolation of the line it allows the prediction of future failures/performance of the products.

From Figure 4.11 it would appear that there is a curve or a slight shift between month 10 and month 20. To investigate this further the data was broken up into two graphs. Figure 4.13 represents the first ten months of installations. It takes only this data and assumes no knowledge of future failures. This identifies the most appropriate distributional parameters for the first 10 months of a products lifetime. As the shape parameter has a value of 1.76 this indicates that there is some form of wear out evident. A constant failure rate would have a value of 1. Figure 4.14 takes the data after the first ten months and plots them oblivious to the first ten months of data. This exhibits a more constant failure rate with a shape value of 1.15.

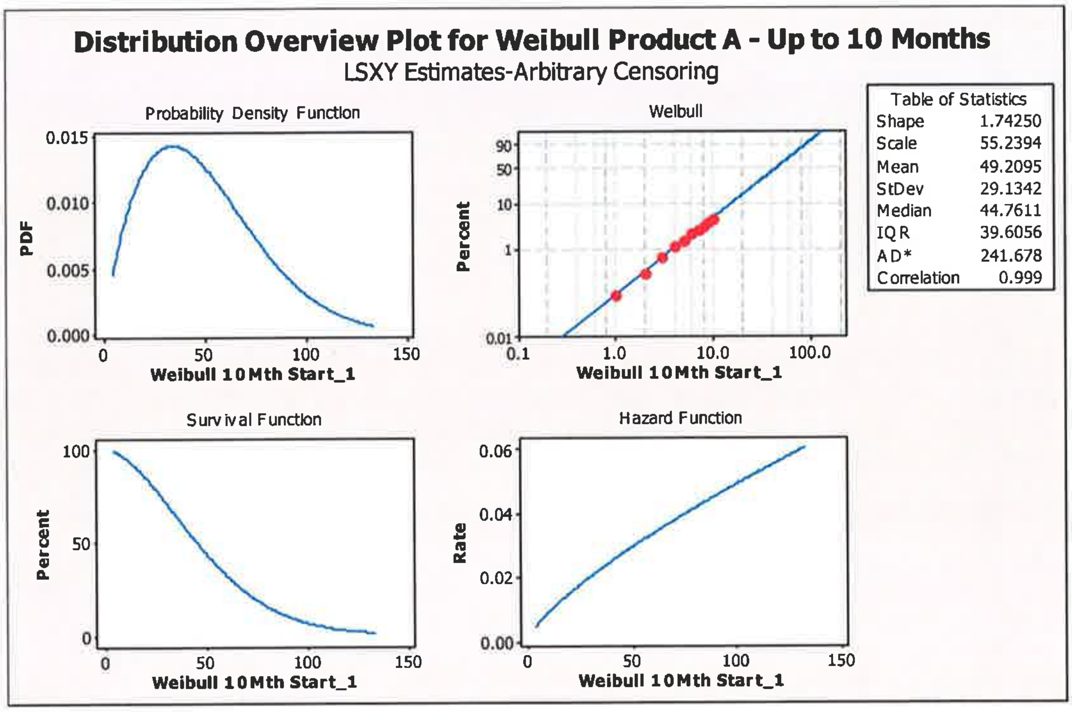

Figure 4.13 Weibull Probability Plot of the First Ten Months for Product A

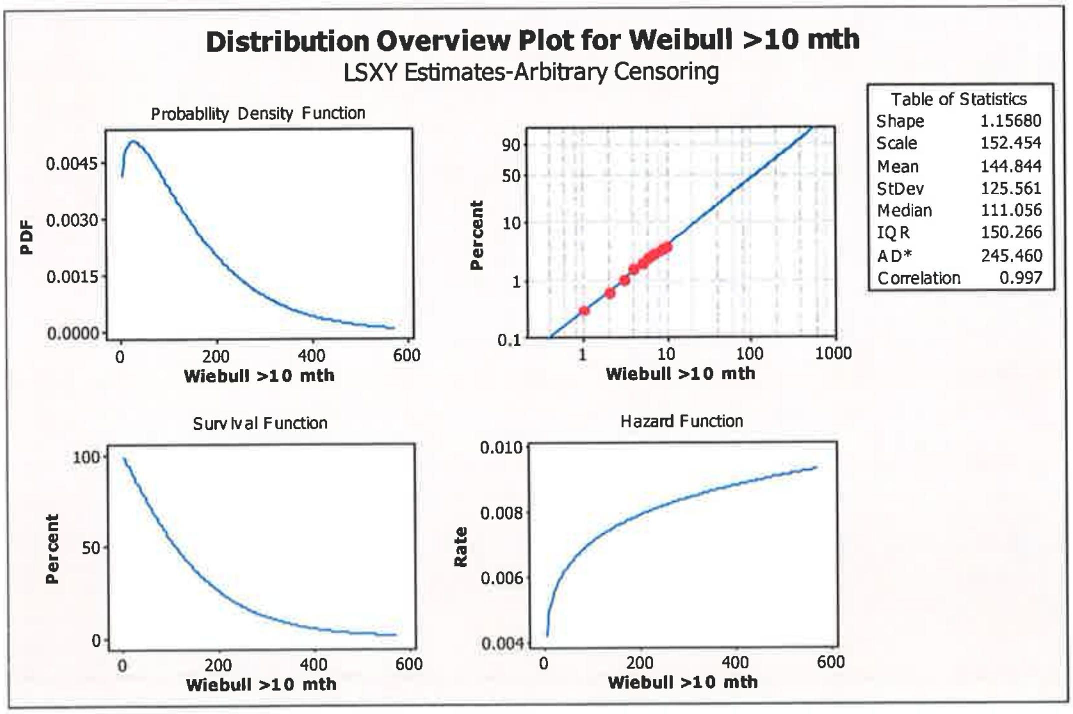

Figure 4.14 Weibull Probability Plot for Post Ten Months for Product A

The only important figure here is the shape parameter for a Weibull plot. The scale parameter is meaningless. The first ten months this figure is 1.7425 and for post ten months it is 1.15680. This indicates that up to ten months the product is experiencing more wear-out than post ten months. After ten months the product appears to be into its useful life period. The component problem that affected this product appears to have worn out by ten months and the good product was left and performed better. This can also be seen by looking at the linear extrapolation of both graphs and comparing them. Figure 4.13 predicts more failures over time than Figure 4.14. The Weibull analysis was very useful in indicating a shift in the field performance of Product A.

4.5 Conclusion

Field reliability is currently reported in Company X on a monthly basis. The replacement rate is reported in numeric form for each product and a cumulative fraction removal graph is plotted by installation quarter for each product family. The graph shows a good overview of how each quarter of installations is performing in the field however as it groups the products into families and groups the installations into quarters, a problem may go unnoticed for some time. The MTBPR figure is used communications between the supplier, the company and the customer. For the research two products were analysed, one developed a latent component issue in the field (Product A) and the second performed well (Product B). Both would have been part of the same product family. A goal MTBPR of 400,000hrs was given for both Product A and B. Product A started shipping to the customer in Mar-04 and in Oct-05 an investigation into its reliability performance was initiated, however it was not highlighted through the existing monthly report. It was necessary to analyse the field data for these two products to see how soon the problem could have been identified by use of different models.

The field data available to the company was analysed and extracted by means of MS-access queries on the different data servers. This provided the pool of information necessary to analyse the performance of the products.

The first analysis looked at was that of trending the data. This allows a manufacturer to see if their product is getting better or worse in the field. The current metrics did not facilitate this. The Rate of Occurrence of Failures was looked at for both Products. As the two products are very similar, one would have expected the graphs to be similar also, however a high rate was seen for Product A in its early life that improved over time. Product B appeared to have a relatively constant failure rate.

The existing metrics of replacement rate and MTBPR were graphed by month which had not been done previously. A goal line was inserted to compare the actually performance to the predicted performance. It showed that for Product A it never reached its goal performance. Product A also has jumps in replacement rates and MTBPR figures that marked decreases in reliability. Product B showed to be performing well in comparison to its goal.

A Weibull reliability plot was used to view the field data for Product A and B. Product A's graph showed a shift after approximately ten months. This was further analysed by looking at two data ranges for Product A, the first ten months censored to ignore future failures and post ten months data. From this analysis it was visible that a difference in the shape parameter was evident. This indicated that Product A experienced wearout in the first 10 months of installation. This corresponded with the ROCOF graph that showed a high rate of failures in the early life of the product.

It is necessary to further analyse the data to pinpoint exactly when the field populations began to deteriorate for Product A.

References

1. Bohoris, G.A. (1996), *'Trend testing in reliability engineering'*, International Journal of Quality & Reliability Management, Vol.13, No. 2, 1996, p45-54.

2. Martz, H.F. & Kvam, P.H. (1996), *'Detecting trends and patterns in reliability data over time using exponentially weighted moving averages'*, Reliability Engineering and System Safety, 51, 1996, p201-207.

Chapter 5

Detection of Reliability Issues and Prediction of Future Performance

5.0 Introduction

Currently in Company X the only way to investigate a field problem is to analyse the field returns by means of failure analysis. This can cause a big delay in identifying a problem as it may take weeks between the first identification of a problem and final conclusion after analysing the returns. It may take months to get product back from some parts of the world and some customers don't return their failures. Not all field returns receive a detailed full failure analysis, a generic analysis is carried out on returns (physically analysis and power up) but only some get full component analysis and testing. If a trend is identified from the number of returns a decision then is made on whether or not to carry out full failure analysis on all returns. It is from this analysis that it is concluded that there is a field problem. If the metrics can trigger an earlier response and point the company in the direction of the problem it would save the company on

a. Time to identify the problem

b. Excessive failure analysis

c. Warranty failures by ensuring that a resolution is put in place quicker

Product A can be seen to have poorer reliability than Product B. Product A had a component problem that only exhibited in the field. This problem was not identified till after Oct-05. The volumes of replacements being returned initiated the investigation.

The goal of this chapter identify suitable models that

1. Detect as early as possible a reliability problem

a. Predict based on field data the future reliability of the product

5.1 Analysis of the Data to Pinpoint where a Problem has Occurred

From the modelling described section 4.4.1. there is a difference visible between Product A and Product B. Now the data must be further analysed to identify what is different. Is it a latent defect affecting all the population or is it a specific 'lot' shipment or installation in the field? As Company X is a global company but has two main manufacturing sites. These are referred to as the domestic site and international site. Together they represent the worldwide population. The domestic site manufactures for the U.S and the international site manufactures for the rest of the world. This researcher is based in the international facility thus it is of interest to investigate if product shipped from the international base differs to the worldwide population. It may be worth while to take this into consideration when analysing the data to see if the problem is due to geography.

- Return Index by Ship Month will be analysed
- Control Charts will be analysed

5.1.1 The Return Index for Each Month of Shipment

Wu and Meeker (2002) discussed an interesting method of looking at the month of shipment and reporting on their subsequent failures. It is used as an early detection method for identifying problems in the field. This matches what is needed for Company X. They look at the month of shipment and monitor the subsequent failures in relation to the ship month.

The rate of replacements are calculated as per Quest Forum (2003) formulas for Return rates and is referred to as a Return Index (RI), this is

$$100 \times 12 \times \frac{\textit{Number of Returns for Time Period based on Shipping Period}}{\textit{Number of Parts Shipped in Shipping Time Period}}$$

The 100 figure represents percentage and the figure 12 represents the twelve months in a year.

For example if 2000 units were shipped in January and twenty were returned in January then the return index for January would be:

$$100 \times 12 \times \frac{20}{2000} = 12\%$$

If thirty units were returned in the second month of operation, this would give February a return index of:

$$100 \times 12 \times \frac{30}{2000} = 18\%$$

For Company X this will be referred to as Replacement Index (RI) as opposed to the Return Index referenced above, to keep in line with previous chapters. Using this data analysis a table was produced for Product A International, Product A Worldwide, Product B International and Product B Worldwide. This analysis involved tabulating the number of shipments per month and their corresponding failures. It was important to subtract failures from the number in the field for each month. For example using the above table the failures for shipments in January meant that for February the number of failures was 20 over 2000 however in March this would change to 30 failures over 1880 (2000 minus the 20 failures in February). The graphs were generated for the worldwide population (Note all graphs so far have been of the worldwide population) and also for the international population. It compares by month of shipment to how product performs in the field. Figure 5.1 and 5.2 show the RI rate for the worldwide and international populations of Product A.

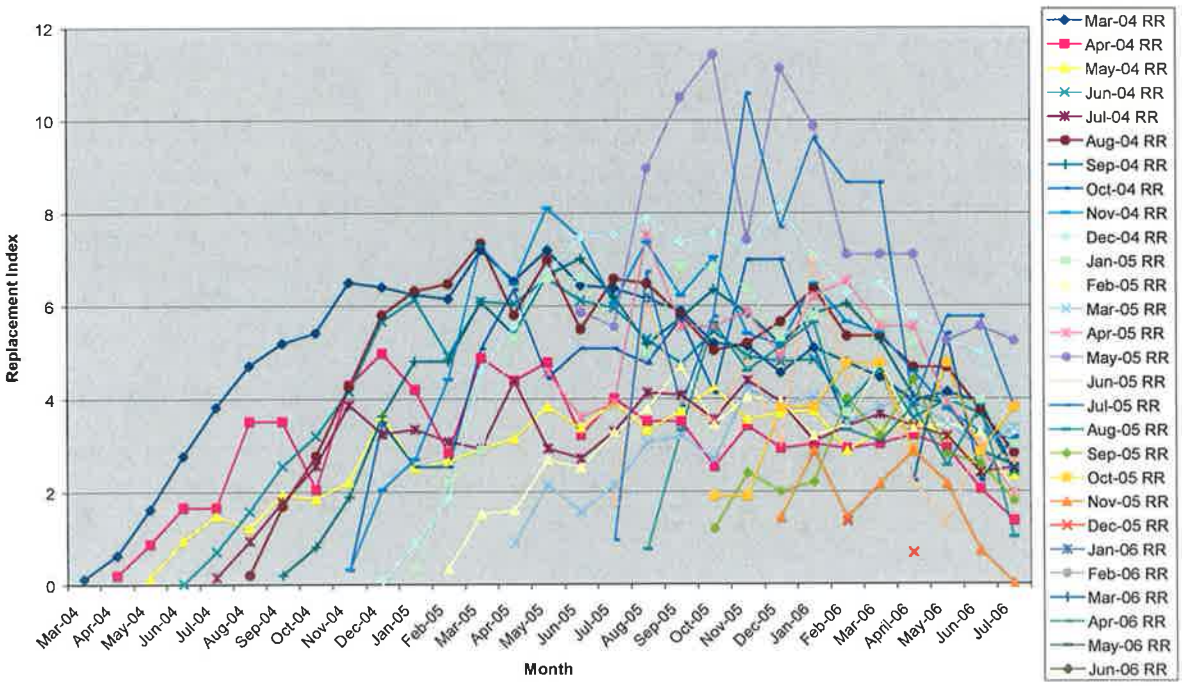

Figure 5.1 Worldwide Replacement Index by Month for Product A

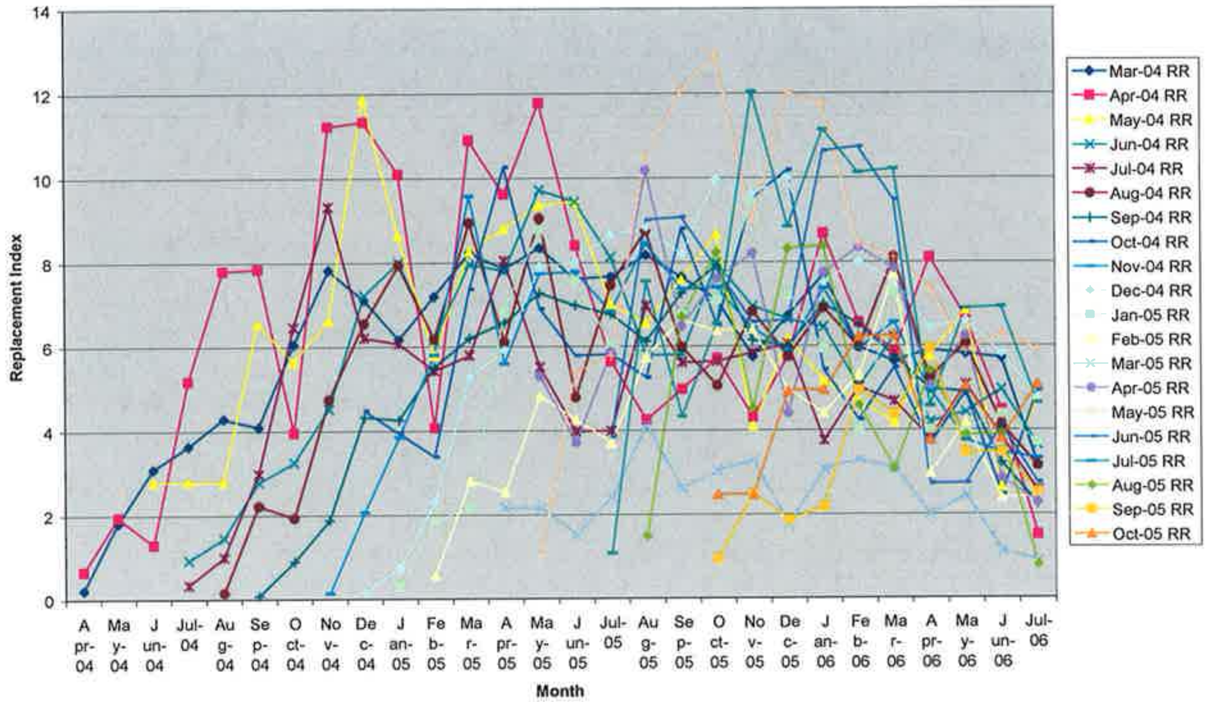

Figure 5.2 International Replacement Index by Month for Product A

It is difficult to interpret these graphs from the amount of series they represent, however some conclusions can be made. For example it appears that international population is seeing a higher RI rate than worldwide for many months. It can also be seen that some months have much higher RI rates than others. For both the worldwide and international populations, May-05 and Jul-05 are the highest rates. This indicates that it is not a geography based problem. It is interesting to compare this to Figure 4.7. These months did not show a significant increase in the replacement rate; however the shipments in May-05 and Jul-05 could be responsible for the sharp increase seen in Figure 4.7 for Jun-05 and Oct-05.

Figure 5.3 and 5.4 show the RI rate for the worldwide and international populations of Product B.

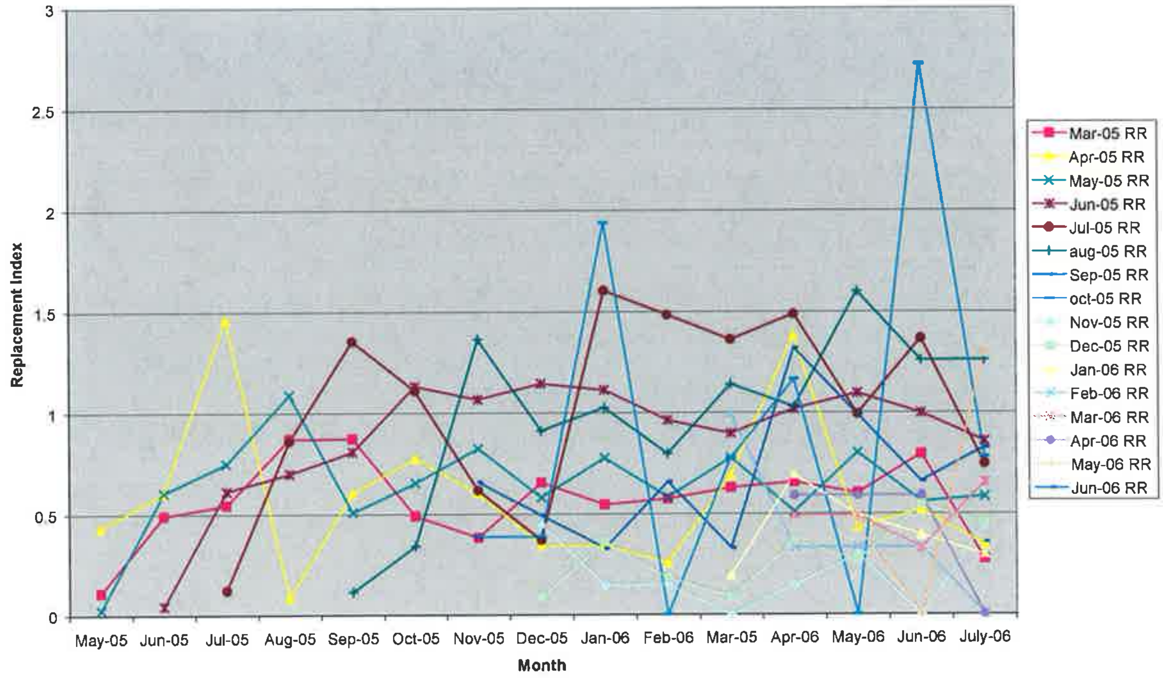

Figure 5.3 Worldwide Replacement Index by Month for Product B

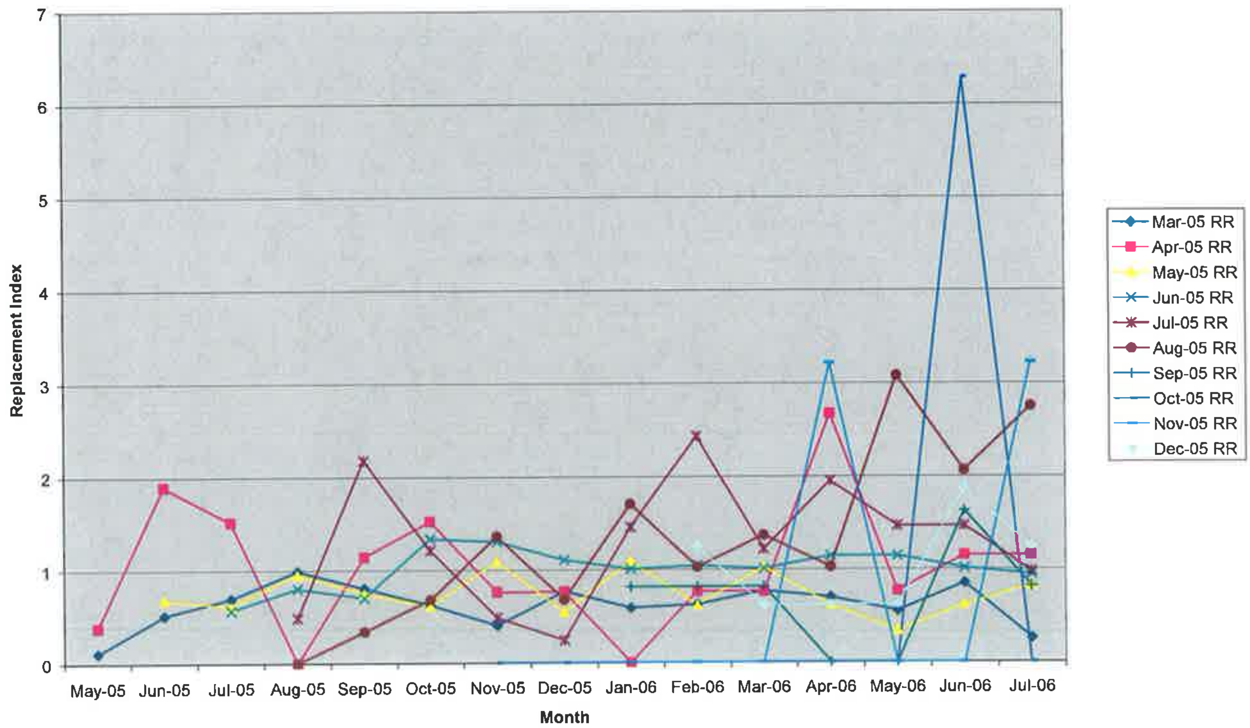

Figure 5.4 International Replacement Index by Month for Product B

From Figures 5.3 and 5.4 more analysis can be made. Both populations have very similar rates however for international some spikes are higher than they are for the worldwide population. This can indicate that it may have not have been seen as strongly (if at all) in the domestic population. It appears that Oct-05 has higher rates than other months.

The difficulty with Figures 5.1 to 5.4 is that it is hard to analyse if there is a trend based on the first, second etc month in the field. The next step is to look at the graphs and chart them by age of month in the field. For example the product shipped in January the first month will be February; the second month will be March. For product shipped in February the first month will be March and the second month will be April etc. Figures 5.5 to 5.8 represent the RI rate by month of shipment for Product A and B and by geography.

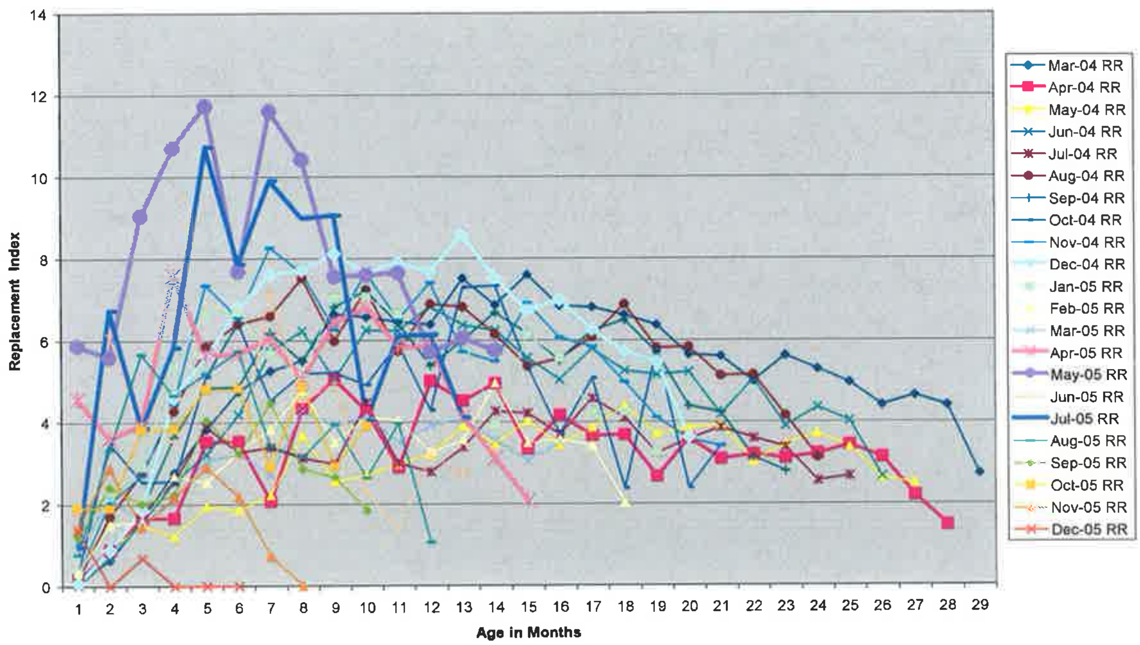

Figure 5.5 Worldwide Replacement Index for Product A Ordered by Month in the Field

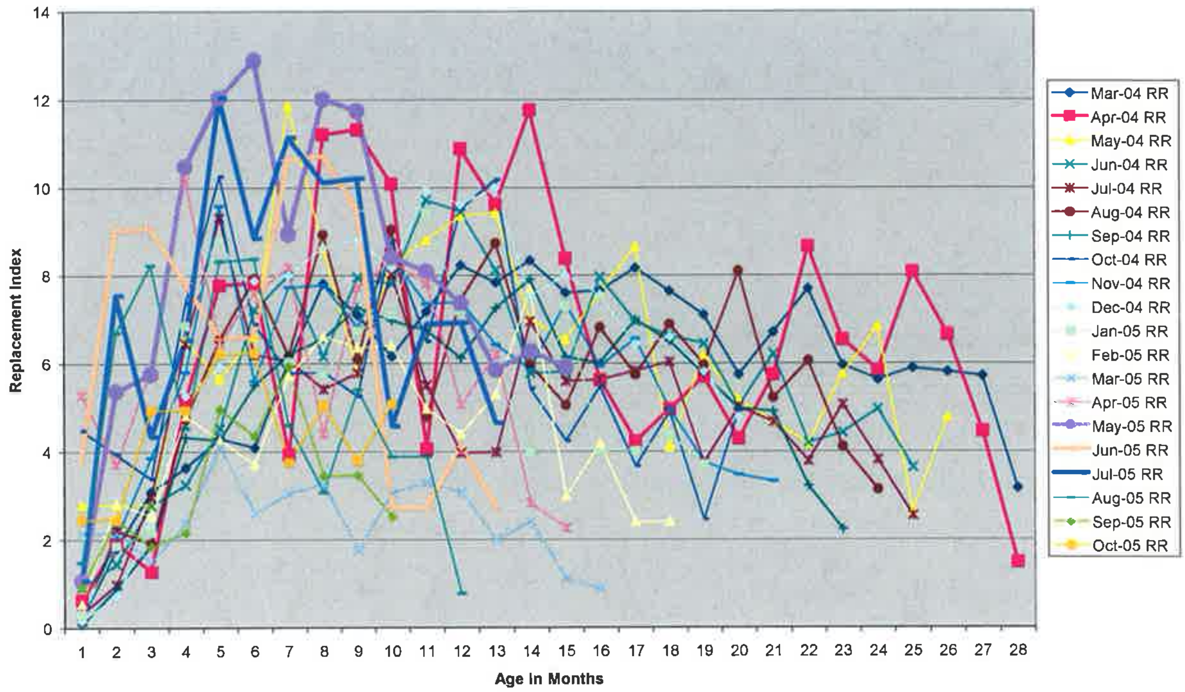

Figure 5.6 International Replacement Index for Product A Ordered by Month in the Field

For Product A both populations show an increase in months May-05 and Jul-05. Interestingly the international Apr-04 rate shows a high rate that isn't seen as strongly in the worldwide population. This may indicate an international only problem. This month can also be compared to Figure 4.8 where a sharp increase in replacement rates was seen for Product A in Jun-04. The most evident trend is that for the first months of install the rate is increasing. It isn't until after approximately ten months that they appear to stabilise. This relates to the Weibull plot in Figure 4.11 and subsequent plots of 4.13 and 4.14 that indicated a difference in the first ten months population and the post ten month population.

Product B populations are compared in Figures 5.7 and 5.8.

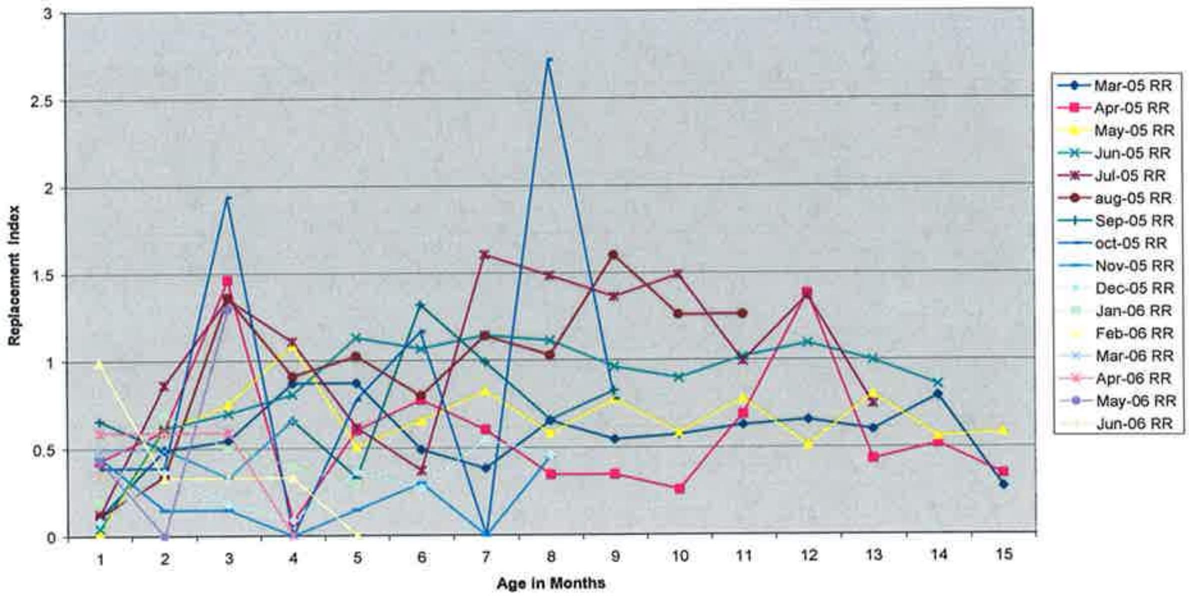

Figure 5.7 Worldwide Replacement Index for Product B Ordered by Month in the Field

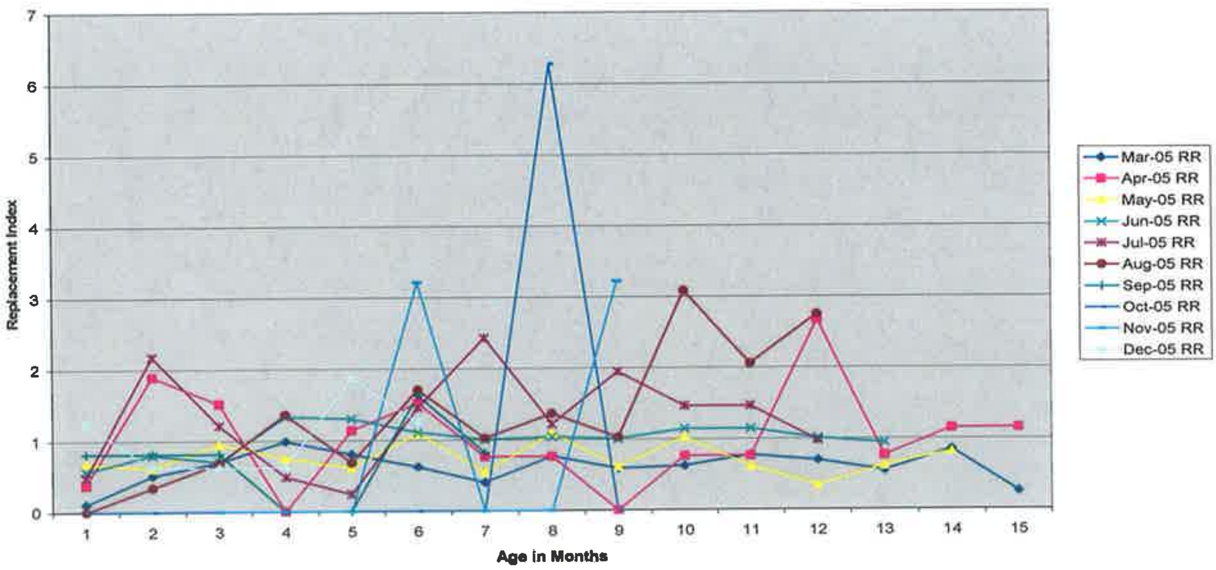

Figure 5.8 International Replacement Index for Product B Ordered by Month in the Field

By representing the data in this way makes it clearer to interpret. The following can be concluded from the analysis of Figures 5-5 to 5.8.

- Product A has a higher Return Rate than Product B this can be seen by comparing all graphs in Figure 5.1 to 5.8.
- Product A shows 2 months in particular that has a very high RI rate. These are months May-05 and Jul-05. The lines have been highlighted in Figures 5.5 and 5.6. This is seen for both International and Worldwide which means that the problem was not process related (wasn't seen by one manufacturing site), it is component related.
- For Product A, the suspect months of May-05 and Jul-05 show that the international population has a slightly higher rate than the worldwide population.
- Product A shows that the first ten months in the field after shipment have the highest rates. This can be seen in Figures 5.5 and 5.6. This can be compared to the Weibull analysis in section 4.4.2.
- The months May-05 and Jul-05 for Product A may be causing the spikes in the replacement rates graph in Figure 4.7. The spikes occur in Jul-05 and Oct-05 but it may be the shipments of May-05 and Jul-05 that cause this.
- Product A's population for Apr-04 shows international has a much higher replacement rate than worldwide. This would indicate that the international population experienced a worse performance than worldwide as the worldwide population includes the international population. This could be further investigated to analyse with the suppliers to understand if the domestic (US) and international product was produced separately or at different times, this

may explain the difference in field performance. This may also be related to the spike seen in the replacement rate graph (Figure 4.7) for Jun-04

- Product B shows a spike for product shipped in Oct-05 after eight months. This spike can be seen in both the worldwide and international population. On analysis the international spike represents two failures so will not be further analysed. In the worldwide population seven failures were seen (five occurred outside of international). It is intriguing how the spikes appear in the same sequence highlighting the closeness of the two populations. The worldwide population sees a spike earlier on in Oct-05's life cycle that is not seen in international which may warrant investigation if the product had questionable reliability.
- Interestingly with Product B the International return rate is greater than the worldwide rate. This is something that may warrant further investigation. However as this product is performing above its goal it is not an immediate priority.

The deterioration in product A was originally seen in Figure 4.7 for product shipped in June 05. The reliability plotting showed that product in the field less than 10 months exhibited wear out more so than product in the field greater than 10 months, which appears to be the useful life period. By using the Figures 5.1 to 5.8 and looking at a shipment month and it subsequent failures it clearly showed early on that there was a problem in the field. The rising RI rates in early life would have triggered investigation sooner. Product A is stress tested so early life failures are not expected. This graph indicates evidence of this and would have initiated analysis into the reasons for it. The population that shipped in May-05 and Jul-05 were of questionable reliability. The

May-05 deterioration visible in this graph was not seen on the replacement rate graph (Figure 4.7) until Jun-05. It is important to note that the actually analysis did not happen till Oct-05 in Company X, when the volumes returning increased significantly.

5.1.2 Control Charts

A further method of analysing the reliability in the field is to look at first month of service after shipment (e.g. the failures for February of product shipped in January). This can be analysed by means of a control chart.

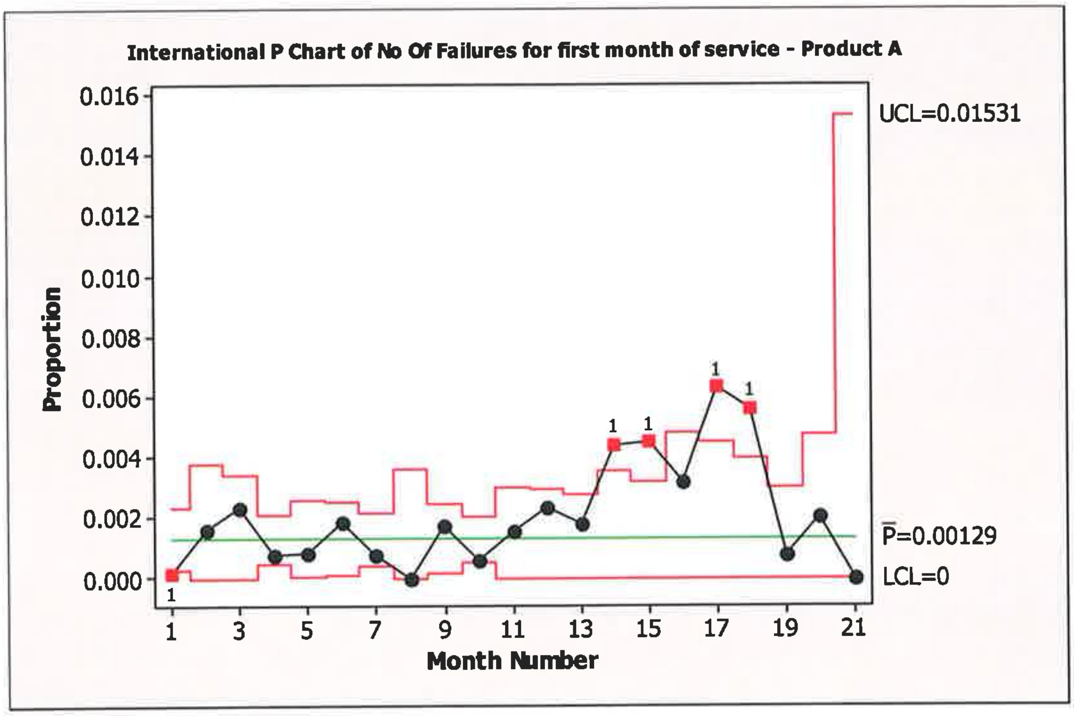

Figure 5.9 International *p* Chart of First Month of Service for Product A

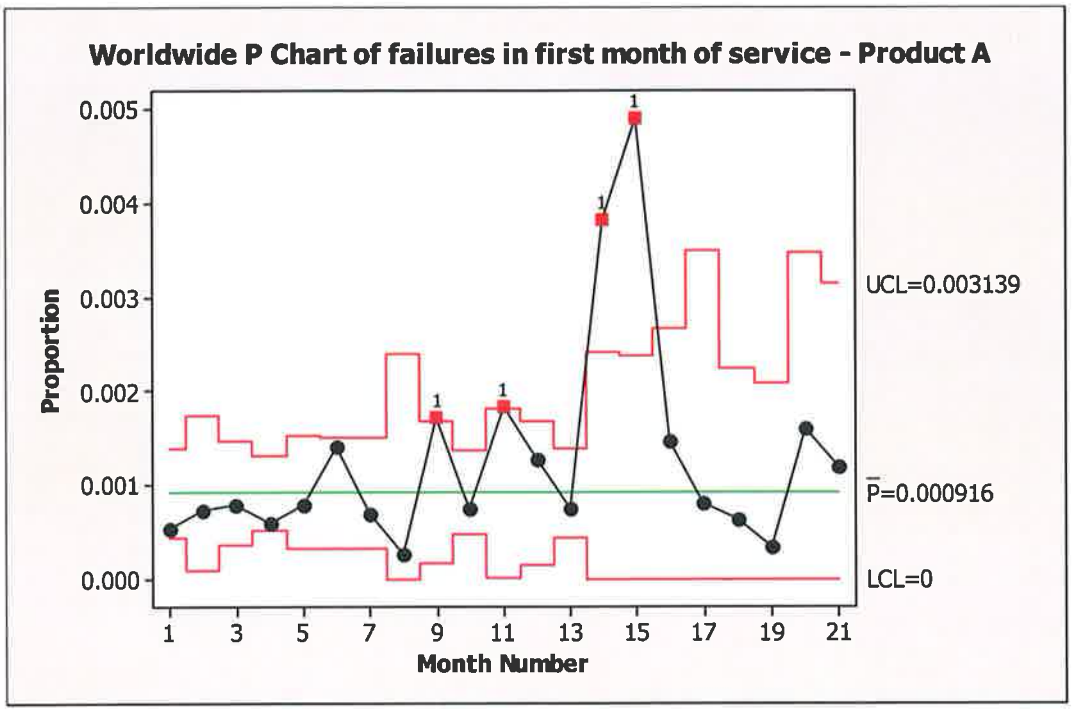

Figure 5.10 Worldwide *p* Chart of First Month of Service for Product A

Product A shows that the worldwide first month of install figures go out of control before the international population. Month 14 and 15 have out of control points for both the international and worldwide population. These months represent Apr-05 and May-05. This is consistent with the increase in the RI rates seen in Figures 5.1 and 5.2. Whilst it is visible from the RI graphs that these months have higher replacement rates than other months, it can be said using the *p* chart that their first month of installation is out of control. In Figures 5.1 & 5.2 it is seen that May-05 and Jul-05 go on to have higher replacement rates than other products in subsequent months. The figures may seem much lower than previously graphed rates however this is just viewing the first month failures over the total number of shipments for that month. This method would give the earliest indication that something has gone out of control.

Product B p charts are represented by Figures 5.11 and 5.12. They show the international and worldwide population.

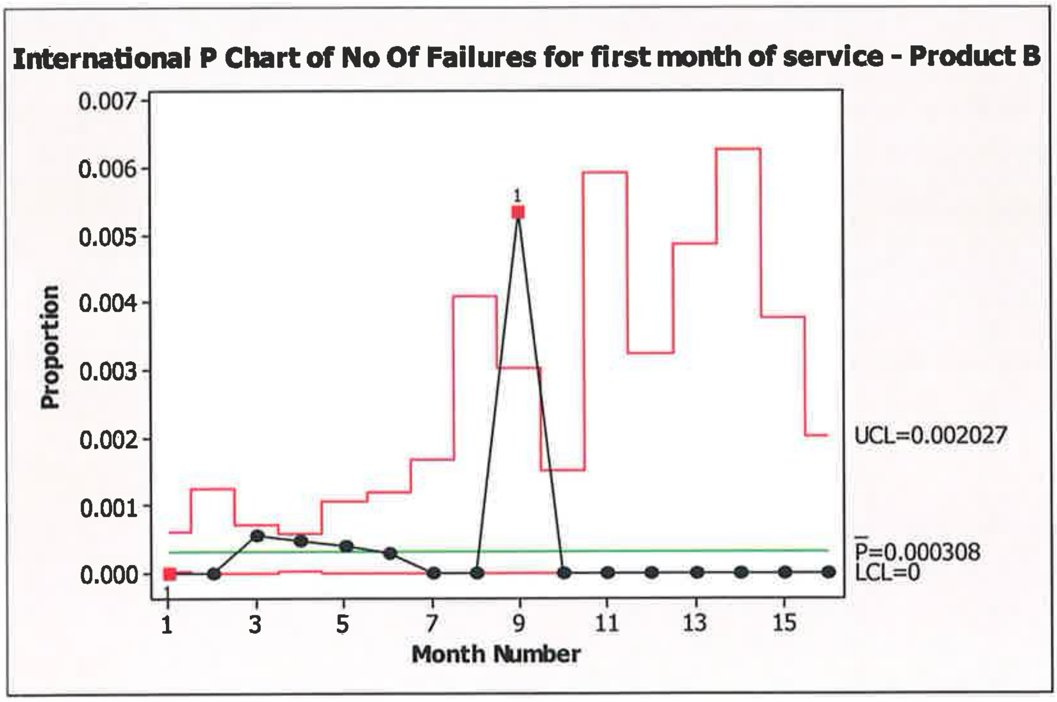

Figure 5.11 International p Chart of First Month of Service for Product B

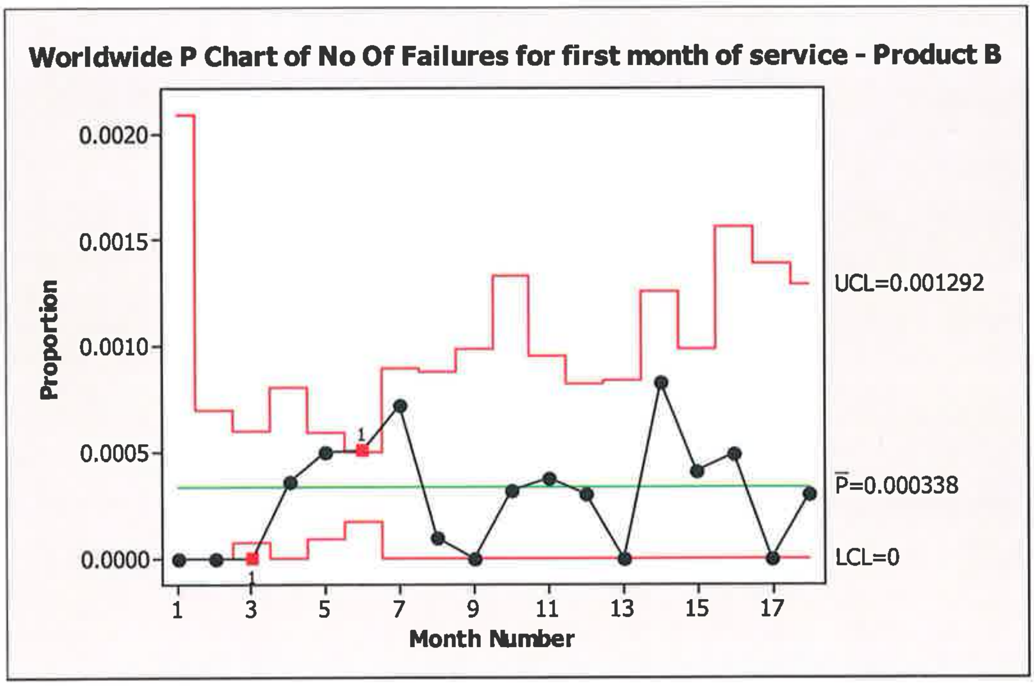

Figure 5.12 Worldwide *p* Chart of First Month of Service for Product A

For Figure 5.11, point 9 shows that it is out of control in the international population. It was necessary to look into the data in more detail and this showed that it represents two failures in the first month of install for the Nov-05 population. It is important to have a signal to trigger an analysis as it allows an insignificant point to be disregarding and an important point to be analysed further. This point was not out of control for the worldwide population because of the extra volume of Product shipped in this month world wide. Nov-05 is represented by point 11 in the worldwide graph as Product B was installed domestically two months before it was installed internationally. Figure 5.12 shows an out of control point at month 6 (Jun-05) for the worldwide population. This was not seen internationally and may warrant further investigation if the product was performing poorly in the field. This month represents the highest number of shipments for the product and the highest number of first month failures.

For Product A the problem would have been identified using the p chart in April-05 however using the replacement rate graph it would have been Jun-05.

Overall both these methods give indications of problems and highlight areas for further analysis. The replacement rate graph by month gives a good indication of how a shipment month performs through its life and comparisons can be made month on month. The p chart can statistically tell if a first month's installation is in control. This can be the first warning signal to trigger analysis. The next step is to investigate using the current reliability can the future performance be predicted.

5.2 Prediction of Product Reliability

Company X has good quality and highly detailed field information. For this reason the field data will be analysed with a view to predicting future failures.

The first step is to analyse what distribution the field data follows. For this purpose Minitab software is used. The data had to be extracted in a time consuming but worthwhile exercise. Once the data was extracted it was necessary to analyse it. Product A was the first product analysed using Minitab. From the analysis it was visible that it fell into a lognormal distribution. Figure 5.13 shows a sample month and how it is lognormally distributed. All months were analysed and showed to be lognormally distributed however just one month is shown here.

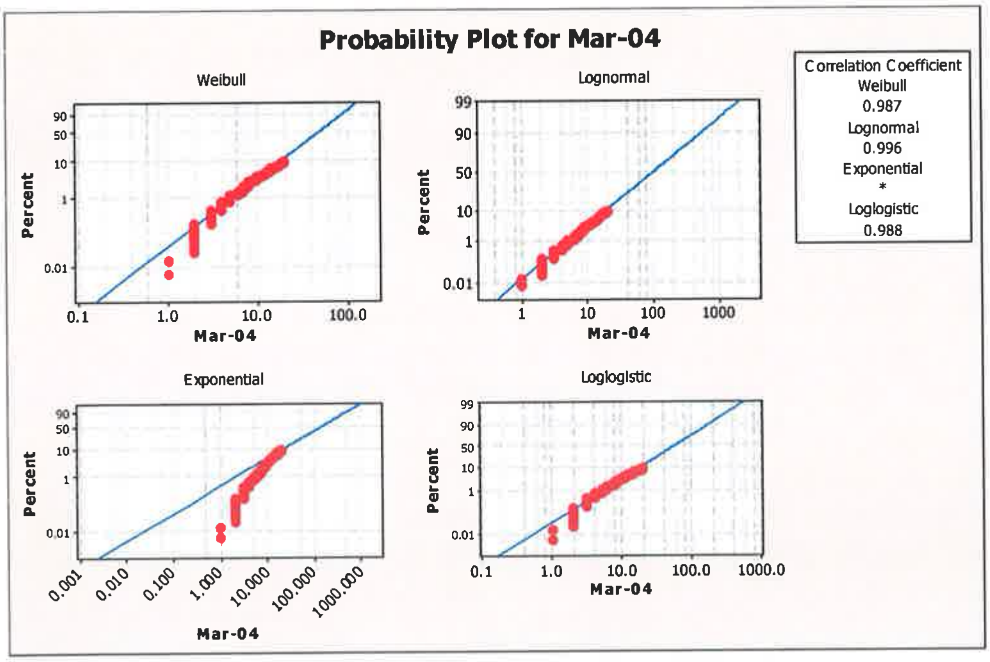

Figure 5.13 Distributions for Product A Month March 04

It can be seen that the lognormal graph is the most accurate is capturing the distribution of the data. It has the highest correlation coefficient. Product B similarly followed the lognormal distribution as can be seen by Figure 5.14. Once again all the months were analysed, this is just one example.

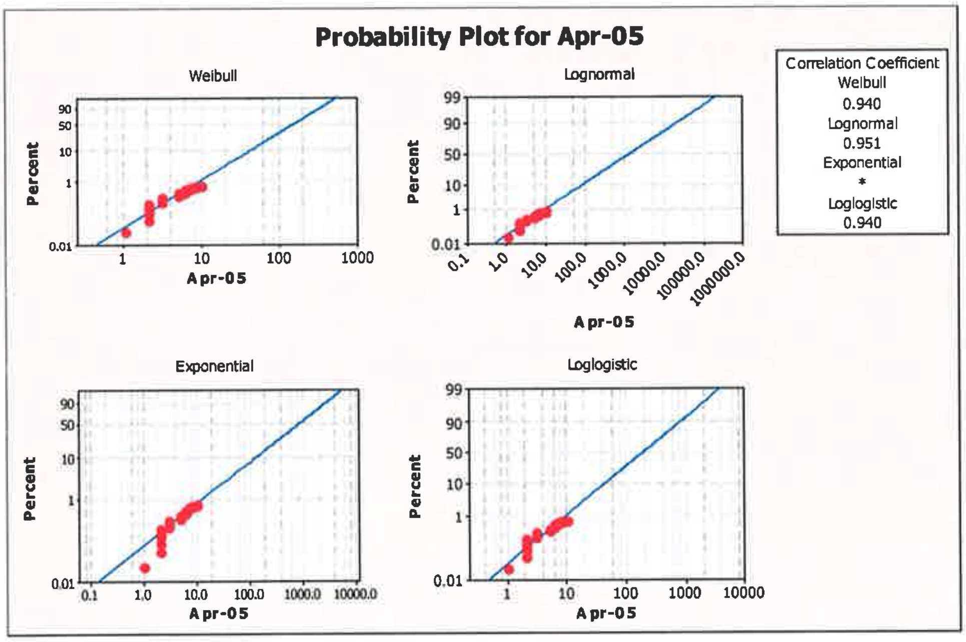

Figure 5.14 Distributions for Product B Month April 05

It can be concluded that this product also follows the lognormal distribution, this indicated again in Figure 5.14 by the correlation coefficient. By knowing this it allows the prediction of future reliability. Taking Product A and looking at all the data for 21 months. It shows it fits a lognormal distribution, see Figure 5.15. This is to be expected when all the months individually were lognormal distributions.

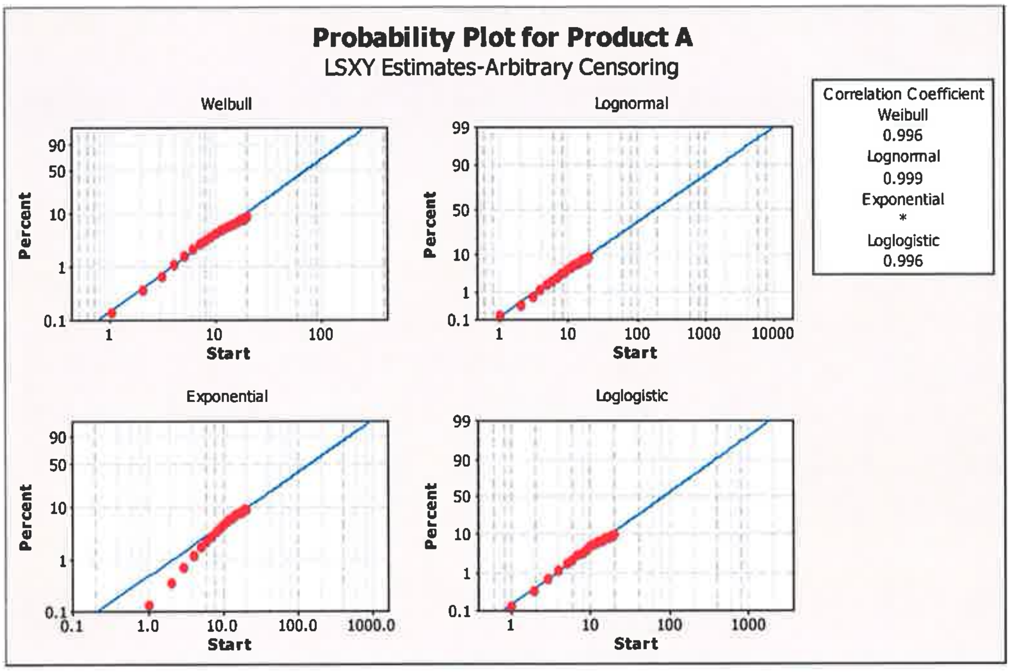

Figure 5.15 Distributions for Product A for Field Data

Next step is to graph specifically the lognormal distribution of all the data. This gives the following graph and also provides the information necessary to predict the future performance of the product in the field.

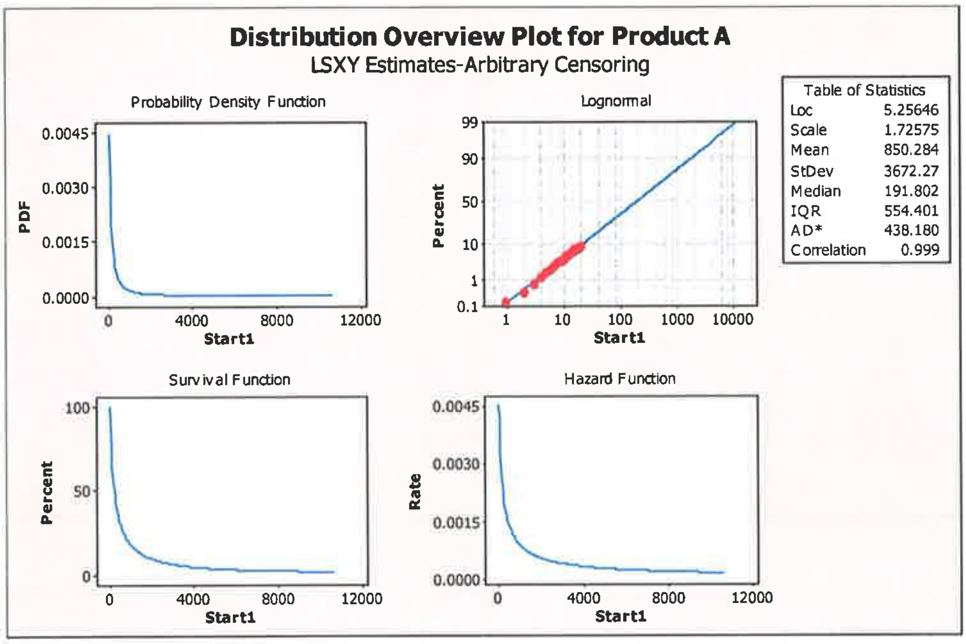

Figure 5.16 Lognormal Distribution for Product A for Field Data

Taking the data Location, Scale, Minitab allows the user to calculate the future performance by using the following lognormal cumulative distribution function (CDF) formula:

$$CDF = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}\sigma t} \exp\left[-\frac{(\ln t-\mu)^2}{2\sigma^2}\right] dt$$

This distribution was censored at 21 months as this is the length of time the data was collected. If the reliability performance at 100 months had to be predicted it could be done using Minitab or Excel. By using the existing data and predicting replacements in 100 months it gives a result of 0.352940 or 35.294%. For this product it can be estimated that based on current performance in 100 months 35.294% of the population will have been replaced. Figure 5.16 also indicates this by following the extrapolated line and connecting 100 months to the corresponding percentage replaced. This technique is very useful and can be based on parts of the data set e.g. one month to predict future month's performance.

If one considers the units shipped in Mar-04 and plots the data as a lognormal distribution, the result is seen in Figure 5.17.

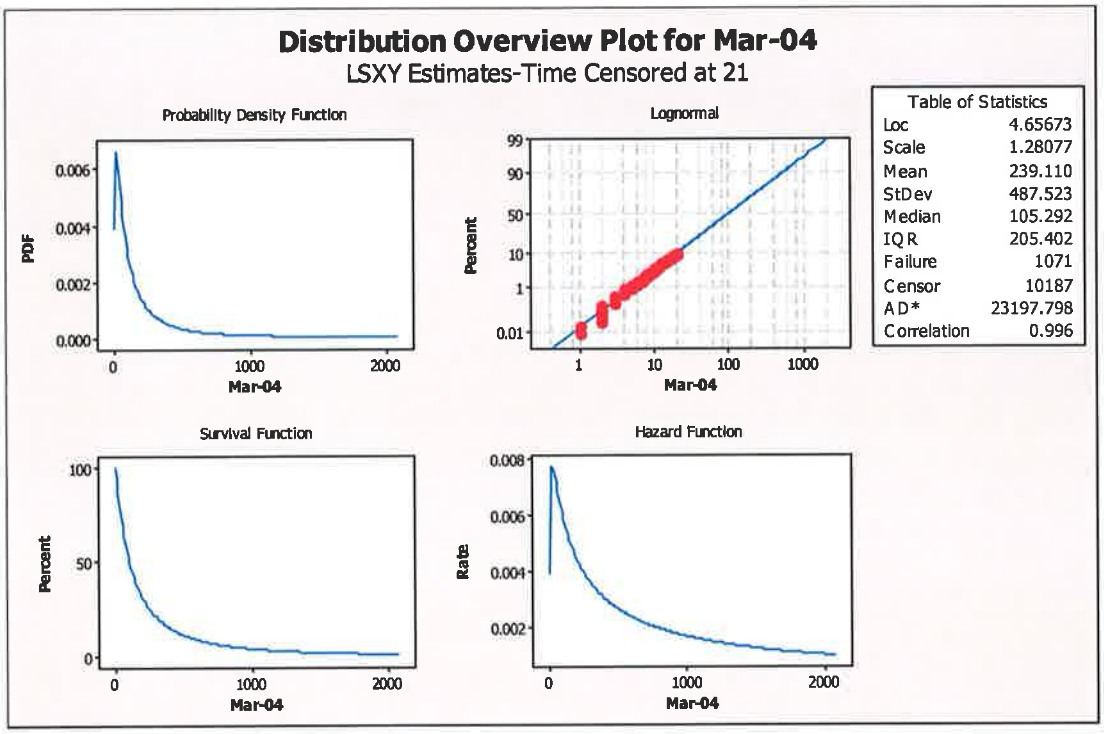

Figure 5.17 Lognormal Distribution of Product A – Mar-04 Shipments

At month 21 it can be estimated from the graph that 10% have been replaced. Looking at the first six months of data for March, it is would be interesting to see if at six months it could have been predicted that 10% would fail by 21 months. This is graphically represented in Figure 5.18. The analysis allows the comparison of what could have been predicted to what actually happened. In fact it validates the technique being used.

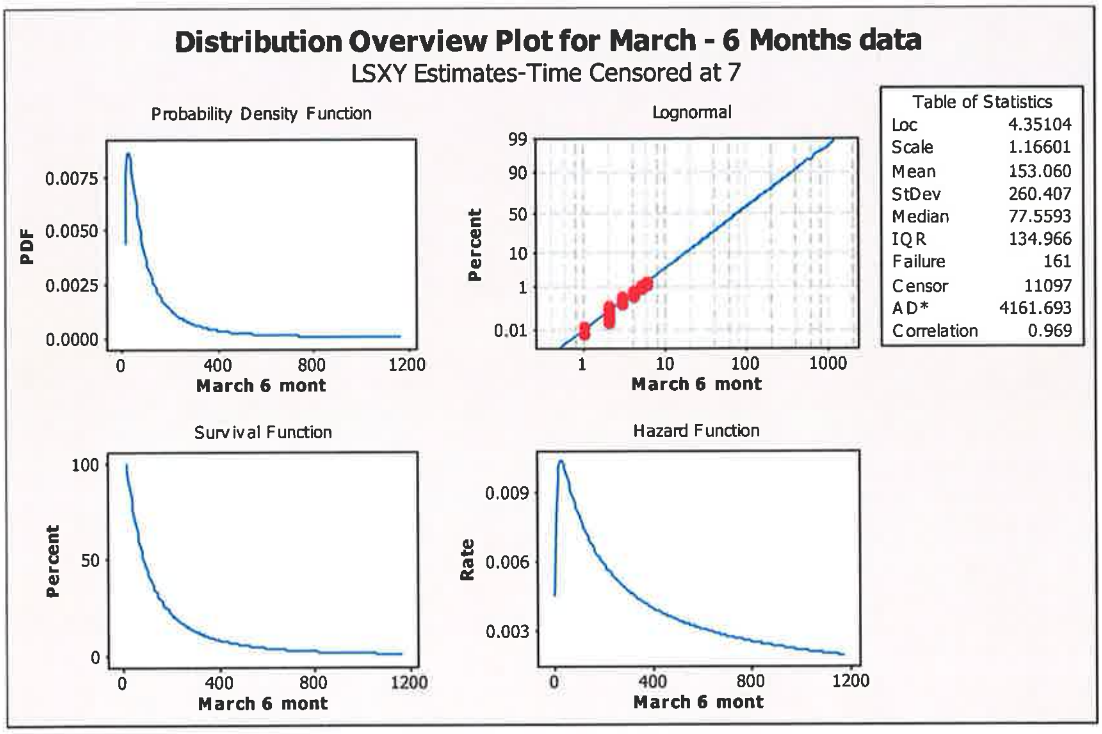

Figure 5.18 Lognormal Distribution of Product A – March Shipments Up to 6 Months

The parameters of this graph are taken and a predication is made for 21 months. This gives a percentage of 12.2547% which is fairly close to the actual value at 21 months. It gives an indication of what the performance would be if it remained the same for the subsequently 14 months. It is worth noticing that based on the first six months data a higher rate of failures was expected than actually occurred. This again relates to the previous analysis, in particular Figures 5.5 and 5.6 that early failures were visible and the product improved in later months.

Close monitoring of reliability performance can provide extremely useful information to a company's logistic department that has to provide field replacements. Being able to tell the logistics department for example "In 10 months 10% of the current population will need replacing" would ensure the company is prepared and can minimize inconvenience to a customer. Up to now logistic demand has been predicted by the goal MTBPR which for Product A was very unrealistic for a number of reasons:

- Assumes a constant failure rate.
- Changes in the field performance largely go unnoticed.

By basing the replacement demand on the above statistics is much more accurate and beneficial to the logistics department.

5.3 Conclusion

The field data of Company X had to be further analysed to see if it was possible to identify what caused the poor reliability and how early could it have been noticed. A very useful method that was adopted here was the Return/Replacement Index (RI), where the number of shipments per month was graphed against their subsequent failures. For Product A it was clearly visible that the replacement index was increasing for the first few months of install and only stabilised after approximately ten months. If this graph had been generated and looked at, it would have indicated a problem in the field in the first couple of months of shipment, as the rate was increasing all the time. This corresponds to the ROCOF analysis in Figure 4.5 and Weibull analysis in Figure 4.11 discussed in Chapter 4. Two month in particular can be seen as having higher rates than the other months. These were shipments in May-05 and Jul-05. This can be related to the replacement rate graph (Figure 4.7) that showed a decrease in reliability in Jun-05 and Oct-05. The shipments from May-05 and Jul-05 were probably responsible for these decreases.

By comparing the worldwide and international populations it was possible to conclude that the problem in the field was not process specific as both populations followed very similar trends. Product A however saw higher rate for the international population than what was seen worldwide. Apr-04 showed to have a very high rate for international and a much smaller rate for the worldwide population. This indicated that product shipped in this month internationally was different to the product shipped domestically. However in general both populations were very similar. The closeness of the two populations confirms the problem to be a component issue and not geographically specific.

Further analysis was carried out by use of the p control chart. For Product A the first out of control points were seen in Apr-05 and May-05 internationally.

Product B analysis confirmed that it performed well in the field. It was very much in control with steady replacement index rates. Certain points discussed through the chapter could be investigated further but as the product was generally performing well the focus was placed on Product A.

As the goal performance for predicted for Product A was grossly overestimated it was necessary to establish a means to predict future performance based on field data. It was identified that the data followed a lognormal distribution. By graphing this using the Minitab statistical software, an extrapolated line was produced that allowed future predictions of the data. This was tested by taking samples of data earlier on in the life of the product and estimating the future (known) performance based on that. By taking earlier months and predicting future performance it showed that the results were reasonably accurate but slightly pessimistic. This corresponds with previous analysis that first ten months in the field for Product A had a higher rate of replacements than post ten months.

In summary, Company X identified a problem with Product A in Oct-05. By using the techniques discussed in this chapter the problem could have been identified much earlier. Using the RI graphs a problem would have been evident in the first few months of service, due to the increasing rate. The shipments in May-05 and Jun-05 would also have initiated investigation as they showed to have much higher rates than the other months. Finally by looking at the p control chart the problem would have been noticed in Apr-05 which would have been six months before it actually was. By using the existing field data it was possible to predict with much greater accuracy the future reliability of Product A.

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Chapter 6

Conclusions and Recommendations

6.0 Conclusions

Traditionally reliability standards were used to predict field performance as companies did not have field data available to them or the data they had was incomplete. Many Reliability standards are in existence, for example; Mil Hdbk-217, Bellcore, CNETs RDF, RACs PRISM, HRD4 and IEEE-1413 Standards. Many papers have been written on these standards and their use in predicting field data. The Bellcore standard showed to be the best of the standards for reliability prediction. However it is concluded that predictions that come from these standards don't compare well with the real field data. Therefore it is important for a company to extract and analyse as much field data as possible.

Field databases were examined to review what data was being used to generate analysis. Some systems recorded data for others to manipulate, for example EPRD-97. Many companies are not proficient in collecting field data however they may have warranty data available to them. From the analysis of different companies certain key measures were identifiable in all the field databases and these were a unique identifier, a start time and an end time to calculate the time in the field. Subsequently the field data accessible to Company X was examined. The analysis found that the data for the company overcame the limitations traditionally associated with field data i.e. incomplete, not timely, can't access operating times etc.

A metric is essential to be able to put a figure on the reliability of a product but it is also very important to be able to say whether or not the reliability of a product is improving or deteriorating. Many metrics were reviewed and the most appropriate ones for Company X were concluded to be the Mean Time Metric, Return Index and Replacement Rate. Models can be used to trend and graphically represent the field reliability of a product. It allows the plotting of product's reliability on a graph to indicate its performance. Many models exist for monitoring field reliability and much has been written about them. These models were researched to identify if they were suitable for use with the field data generated by Company X.

Company X had two products that were investigated; both were very similar and should have performed in the same manner in the field. Product A exhibited poor reliability and as mentioned above this was only noticed in Oct-05. Product B performed well in the field. The existing reporting methods in Company X did not raise awareness to this issue.

For Company X it is very important to be able to visually represent the reliability of the products over time so as to be able to observe if they were getting better or worse. Microsoft Access and SQL were the primary tools used to extract the data to analyse the models. The first model used was based on the Rate of Occurrence of Failures (ROCOF). When the two products were plotted and the following was concluded

- Product A showed a higher rate of failures in its early life.
- Product B had a more constant failure rate.

Another trending method was generated by using the existing replacement rate metric and graphing it over time. The following was concluded from this analysis.

- Product A's reliability had been deteriorating for some time
- Product A had some sharp reliability decreases evident, in particular Jun-05 and Oct-05.
- Product B remained stable throughout its field life.

The popular Weibull plot was also utilised to investigate the reliability of the products. Product A showed a shift in reliability after approximately ten months. This was investigated further and it could be seen in the first 10 months there was evidence of wear-out on a weak component. This improved in the post ten month's population. These results correspond with the ROCOF plot that identified early failures for Product A.

The Replacement Index allowed more detailed analysis as to what caused the reliability deterioration and the following was concluded

- Certain months of Product A's shipments had much higher replacement rates than other months; these were May-05 and Jul-05.
- This was seen in both the worldwide and international graphs, thus indicating it was not an international only problem. It can be concluded from this that the problem was component related and not based on geography.
- The high replacement rates for Product A can be related to the replacement rate graphs where there was decrease in reliability seen in Jun-05 and Oct-05. These months had high RI rates for many months after their introduction in the field.

- A worrying conclusion was that for most of the months of shipment the rate increased for the first few months in the field. If this graph had been used in real-time, the issue would have been highlighted and investigated sooner.

The data was further analysed by using the *p* control chart to compare the first month replacements post shipment. It was concluded that Product A went out of control for international in Apr-05. For this month the worldwide shipments were significantly over the upper control limit. If this control chart had been in use within Company X it would have initiated investigation into the product six months before it actually happened. Product B did have some points out of control however when it was investigated further they represented a small number of replacements that deemed this insignificant and were ignored. Overall, Product B was very much in control and stable in the field.

An accurate method of predicting future performance was seen as a very important aspect of this research. The distributions of the field data for Product A and B were analysed. For both products the lognormal distribution was the best fit and had the highest correlation coefficient. All the data was charted for Product A by Minitab software. An extrapolated line is plotted and provided estimation of future reliability. Another way to predict the future reliability was by using the lognormal cumulative distribution function (CDF) formula. This formula was tested to see how the predicted reliability compared to the actually reliability. The data for Mar-04 was used and was censored after six months and the reliability at twenty one months (which was known) was predicted. The actual percentage replaced at month twenty one was 10% and based on the first six months of data the predicted figure was 12%. It was concluded that this was a very close estimation and again illustrated that the first six months had a higher rate of replacements than subsequent months. If Mar-04 had continued performing the way it was after six months 12% would have been failed at month twenty one however it improved which corresponds with the analyses that shows Product A experienced early life failures.

In conclusion, by using the techniques outlined in this research the problems in the field with Product A could have been identified at least six months earlier. A realistic reliability prediction could also have been made. These combined techniques would have minimised the inconvenience to the customer and expense to the company.

6.1 Recommendations

Field data is a goldmine for companies to monitor field reliability. It needs to be used to its utmost potential. This means that the correct data has to be stored and extracted for analysis.

Company X has a great store of field data however it is also necessary to relate the field data to the ship data (month) this can show correlations that may have been hidden if only the date and install and the fail date were focused on.

It is recommended that Company X would set up an automated database that would generate a monthly report to include the following graphs:

6.1.1 ROCOF Trending

6.1.2 Replacement Rate Trending (including the goal or target line)

6.1.3 Replacement Index Trending

6.1.4 The p control chart for the first month of installation analysis.

It is recommended that each quarter, the performance of the product be predicted using distribution plotting. If there is a suspect or identified performance issue in the field this report may need to become more frequent. This should also be the basis of the logistical demand for field spare units.

There should be a formalised structure to deliver this information to all relevant parties for example:

- Design Engineering
- Supplier Engineering

- Quality Engineering
- Manufacturing Engineering
- Logistics

All the above groups should use this data to investigate a problem and put preventative measures in place. They can also generate an action plan to deal with predicted performances. The Company will benefit greatly by having a structured means to measure, monitor, predict and communicate field reliability.

If the researcher had more time the points noted from the graphs in Chapter 5 would have been analysed further, e.g. the differences between the international and worldwide populations, anomalies in Product B that weren't investigated as the product was performing well etc.

It is recommended that field metrics and models are frequently researched and tested to keep the company as up to date as possible with new techniques.

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