Analysis of Mobile Equipment Maintenance Data

In an Underground Mine

by

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This thesis is dedicated to the memory of my parents, Patrick and Charoline Hall who passed away on May 1, 1988.

Abstract

This thesis focuses on maintenance practices and performance in the context of underground mining. Analytical techniques for evaluation of a mine's maintenance performance using equipment failure and repair time data are presented. The efficacy of these techniques is illustrated through a case study of the mobile equipment in an underground mine operating at high altitude. Data from the case study is analyzed and recommendations for improvement in the maintenance process at the mine are made. Requirements for an effective condition based maintenance program are formulated based on observation of the shortcomings of the oil analysis program in place at the mine. In a similar manner, evaluation of the failure and repair data is used to identify where imprecision of records limits the usefulness of the data.

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Nomenclature

Ag	Silver
B	Boron
Ba	Barium
Ca	Calcium
CBM	Condition based maintenance
Cl	Chlorine
Cr	Chromium
Cu	Copper
D1	Date of current failure
D2	Date of previous failure
EJC	Eimco Jarvis Clark
EU	Effective Utilization
f(t)	Probability density function for failures
Fe	Iron
FFT	Fast Fourier Transform
FMECA	Failure mode effects and criticality analysis
IID	Independent and identically distribution
j	Order number of failure times
K	Potassium
KS	Kolmogorov Smirnov statistical test value
MA	Mechanical Availability

Mg	Magnesium
MH	Maintenance hours
MLE	Maximum Likelihood Estimators
MMIS	Maintenance management information system
Mo	Molybdenum
MTBF	Mean time between failures
MTTR	Mean time to repair
N	Sample size
N	Nitrogen
Na	Sodium
Ni	Nickel
OP	Operating hours
P	Number of parameters estimated for distribution fitted to data
P	Phosphorus
P	Probability
PA	Physical Availability
Pb	Lead
PM	Preventive Maintenance
R	Correlation Coefficient
R(t)	Reliability function providing the probability of survival to time t

RCM	Reliability Centered Maintenance
RTF	Run until Failure
S	Sulfur
SB	Standby hours
Sb	Antimony
SH	Scheduled hours
Si	Silicon
Sn	Tin
t	Time
TBF	Time between failures
Ti	Titanium
TTR	Time to repair
UA	Utilization of Availability
V	Vanadium
Z	Probability of an unsuccessful event
Zn	Zinc
β	Shape parameter for the Weibull distribution
χ^2	Chi Square statistical variable
γ	Location parameter for the Weibull distribution
η	Scale parameter for the Weibull distribution
λ	Instantaneous failure rate
μ	Mean of the lognormal distribution

θ_i Maximum likelihood parameters to be estimated

σ Standard deviation of the lognormal distribution

x_i Independent variable in least squares estimation

y_i Dependent variable in least squares estimation

$\bar{x}$ Mean value of x's

$\bar{y}$ Mean value of y's

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1.0 Introduction

1.1 Maintenance in a Mining Context

Maintenance accounts for 30% to 65% of the overall operating cost budget for a typical mining company and represents the largest portion of the mine's controllable operating costs (Cutifani et al, 1996); (Cambell, 1997). The relative magnitude of this percentage for different mine types and locations is shown in Table 1.1.

Mine Type and Location	Maintenance Costs as % of Operating Cost
Open Pit Chile, Indonesia	>60%
Open Pit Canada, Australia	~45%
Underground Canada	<35%
Smelter Canada, U.S.	~25%

Table 1.1 Maintenance Costs as Percentage of Operating Costs (After Cambell, 1997)

The above, coupled with the fact that industry today is faced with an increasingly complex and demanding marketplace, has led to an increasing interest in methods to reduce maintenance costs.

Although significant effort has gone into developing effective maintenance strategies for industry in general, application of these to the mining industry presents many challenges. These challenges are mainly associated with the specialized equipment in the mining industry, and the susceptibility of this equipment to the mine environment. Some specific contributors to the challenges faced by the mining industry are:

1 A major portion of the equipment used in the mining industry is mobile or semi-mobile.

2 Factors influencing maintenance costs of mobile equipment include,

- Increased failures induced by disassembly and re-assembly of semi-mobile equipment.
- Mobile equipment can fail in inopportune locations that make repair extremely difficult and costly.
- The mobility of the equipment hinders the application of techniques such as continuous condition monitoring.

3 The physical environment under which mining equipment operates is less than ideal. These physical conditions can include: wide temperature ranges, restricted access, poor lighting, vibration and shock, and changing ore characteristics.

4 Logistics can be difficult, depending on the geographical location of the mine: parts and labor can be difficult to obtain in remote locations. Parts requiring very large lead times due to location of the mine can necessitate very high inventory levels.

5 The operating environment of the mine is dynamic, with many unknowns that can affect the life of equipment. Operator practices, varying production demand and changes within the ore characteristics can all have significant influence on the failure patterns of equipment.

Additionally, the increase in mechanization, automation and amalgamation of processes within the mine has further complicated the issue of maintenance (Kumar, 1996).

One company actively pursuing operational effectiveness through continual improvement of maintenance practices is Barrick Gold Corporation. The El Indio mine, located in Chile, is one of their primary focuses. The company is in the process of re-engineering their maintenance philosophy with the initial focus on preventative maintenance and long term objectives to include the implementation of suitable condition based monitoring systems (CBM). To aid in this re-engineering process, an analysis of mobile equipment maintenance data was performed for the period covering January 1996 to March 1997.

1.2 Objectives

The research presented in this thesis represents the culmination of four months of onsite investigation at Barrick Gold's El Indio mine in Chile. The primary focus of this work was the collection and analysis of maintenance data for the underground mobile equipment at El Indio mine. The analysis of such data provides valuable information to assist in optimization of the maintenance function. The objectives of the analysis were:

- Develop a methodology for grouping failure data for each type of equipment such that repair time and failure distributions can be compiled.
- Using the grouped failure data, develop distributions of repair times and time between failures for unplanned maintenance.
- Determine major causes of downtime.

- Demonstrate the potential benefits of using applied statistics to model reliability.
- Develop a methodology for identifying potential areas of improvement.

Results from the above can benchmark the mine with respect to its maintenance practices and provide the necessary baseline for measuring the effects of any changes implemented. Furthermore, this thesis illustrates the usefulness of Pareto Analysis combined with Statistical techniques to identify and prioritize areas where improvement in the maintenance process can be made.

1.3 Scope of Work

Within the constraint of a limited four month period spent at the mine, the analysis was restricted to the following:

- failure data was only analyzed for selected equipment: scoops, trucks and drills.
- The analysis was based on data extracted from the computer based maintenance management software package in use at the mine.
- Detailed statistical analysis was performed on critical equipment as identified by the first level Pareto Analysis.

1.4 Thesis Overview

The organization of this thesis is as follows: Chapter 2 provides a review of current maintenance strategies. Chapter 3 provides a description of El Indio mine. Chapter 4 presents the methodology used for the data analysis. Chapters 5, 6 and 7 present the results obtained and a discussion of their implications. Chapter 8 presents the conclusions derived and recommendations for future work.

2.0 Literature Review

Attainment of an optimal maintenance strategy requires detailed knowledge of the interaction of the factors affecting maintenance. Figure 2.1 presents the interrelation of the factors that need to be considered when contemplating changes to a maintenance process. From this figure we see that maintenance policy is strongly tied to production policy and site conditions. Consequently, to determine the optimum maintenance policy a model would need to account for the effects of both the site and production dependence. In general this is not possible. Normally, the site and production factors are considered as a fixed environment and maintenance strategies are developed from this. This simplification reduces the number of parameters necessary for an analysis, but at the cost of reduced flexibility. For example, the analysis presented later determines specific areas for improvement of the maintenance process however, the net effect of these changes may not be what is anticipated due to the simplifying assumption of fixed operating and site conditions.

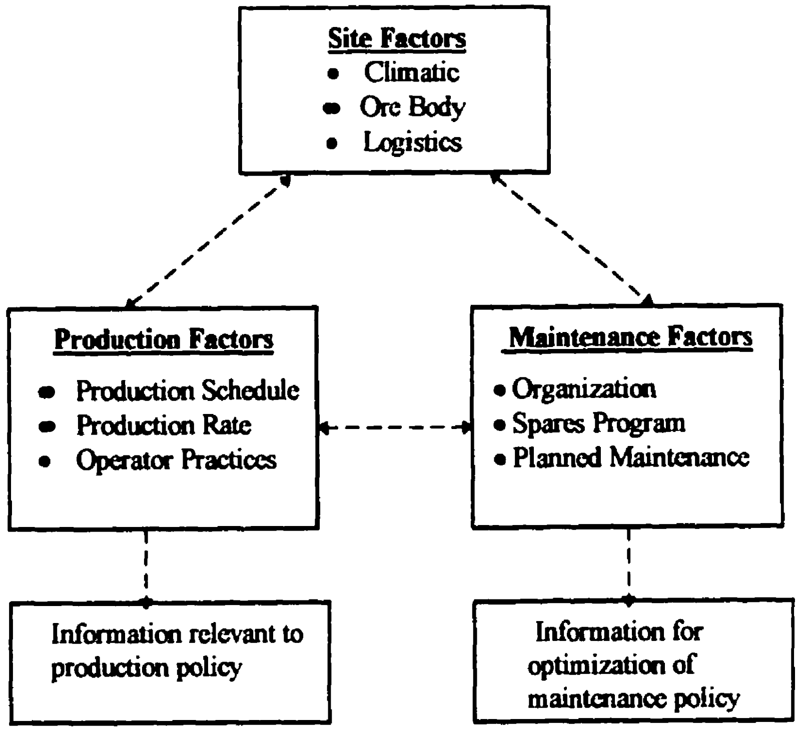


Figure 2.1 Factors Affecting Maintenance Strategies (After Watson, 1968)

There are three basic maintenance strategies which can be applied in practice. These strategies are illustrated in Figure 2.2. In general, a combination of these is used. The exact combination can be determined by an economic analysis of the benefits of the different options.

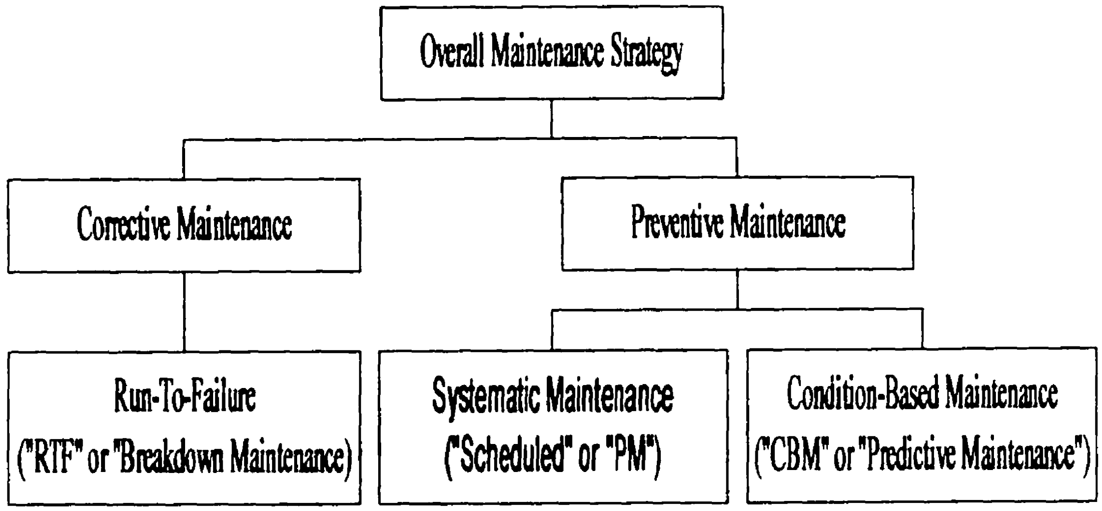


Figure 2.2 Maintenance Strategies

2.1 Run To Failure

The run until failure method, as its name implies, operates a piece of equipment until failure, following which repair or replacement is performed. At first glance, this may appear an ineffective strategy. However, if the consequences to the operation due to the unplanned failure are less than the value added to the operation by changing the component prior to failure, run until failure is a viable option. Unfortunately, most run until failure strategies are not the result of a careful evaluation of the cause and effects of the failure, but instead result from an improper maintenance program. These unplanned failures result in the maintenance department being in a reactive mode. As indicated by Mobley, the cost of an unplanned repair can be in excess of three times that of a planned repair (Mobley, pg 5. 1990). Reasons for this include,

- Extended downtime due to unavailability of parts, or labor.
- Unplanned repairs can result in overtime.
- Unplanned repairs are not executed as efficiently as planned repairs.

2.2 Planned Preventive Maintenance (Scheduled Maintenance)

The excessive costs of unplanned run to failures spawned the second maintenance strategy, planned preventive maintenance. This strategy involves servicing of components at pre-determined intervals. This approach to maintenance is a substantial improvement over the unplanned run until failure approach for most cases. Replacing, or repairing, the components at planned intervals allows effective scheduling of resources to minimize cost and downtime. This strategy is feasible when:

- Equipment is subject to wear out type failures.
- The cost of a preventative replacement is advantageous in comparison to an unplanned replacement.
- A condition based strategy is not an appropriate alternative.

A major obstacle in the effective application of this strategy is determining the optimal replacement/repair time. If the repair is made too early, the components may not have been utilized to full capacity. If the interval is too long the result is an unplanned repair. To complicate matters, most manufacturers recommend preventive maintenance intervals that must be followed to preserve warranty rights. The determination of these intervals by the manufacturer may not be optimum for a particular mining operation, resulting in excessive maintenance costs to the company.

2.3 Condition Based Maintenance

Condition based maintenance (CBM), sometimes called predictive maintenance, involves knowing the condition of equipment in order to schedule maintenance "The axiom of Condition-Based Maintenance is that servicing is permitted only when measurements shows it to be necessary" (Brüel &Kjær, 1989, pg. 6). Using measured parameters and statistical history, maintenance managers can evaluate the probability of failure based on the machine condition. In doing so, they are able to utilize the benefits of planned maintenance and minimize premature replacement of parts. An additional and sometimes overlooked benefit of CBM is its ability to aid in fault diagnosis. Other benefits of CBM are that it:

- Reduces the likelihood of maintenance induced failures by increasing maintenance intervals.
- Lowers inventory levels since parts can be ordered when needed.
- Allows scheduling of maintenance to consider production needs. Thus, reducing lost production due to maintenance downtime (Courrech, 1988).

The growth of CBM in traditional plant environments has led to a wealth of tools being developed to monitor the condition of machines. The most widely accepted monitoring techniques for CBM can be grouped under the categories of: vibration analysis, chemical analysis and temperature monitoring. Within each of these a variety of techniques are utilized. Figure 2.3 shows the common methods used and their applications.

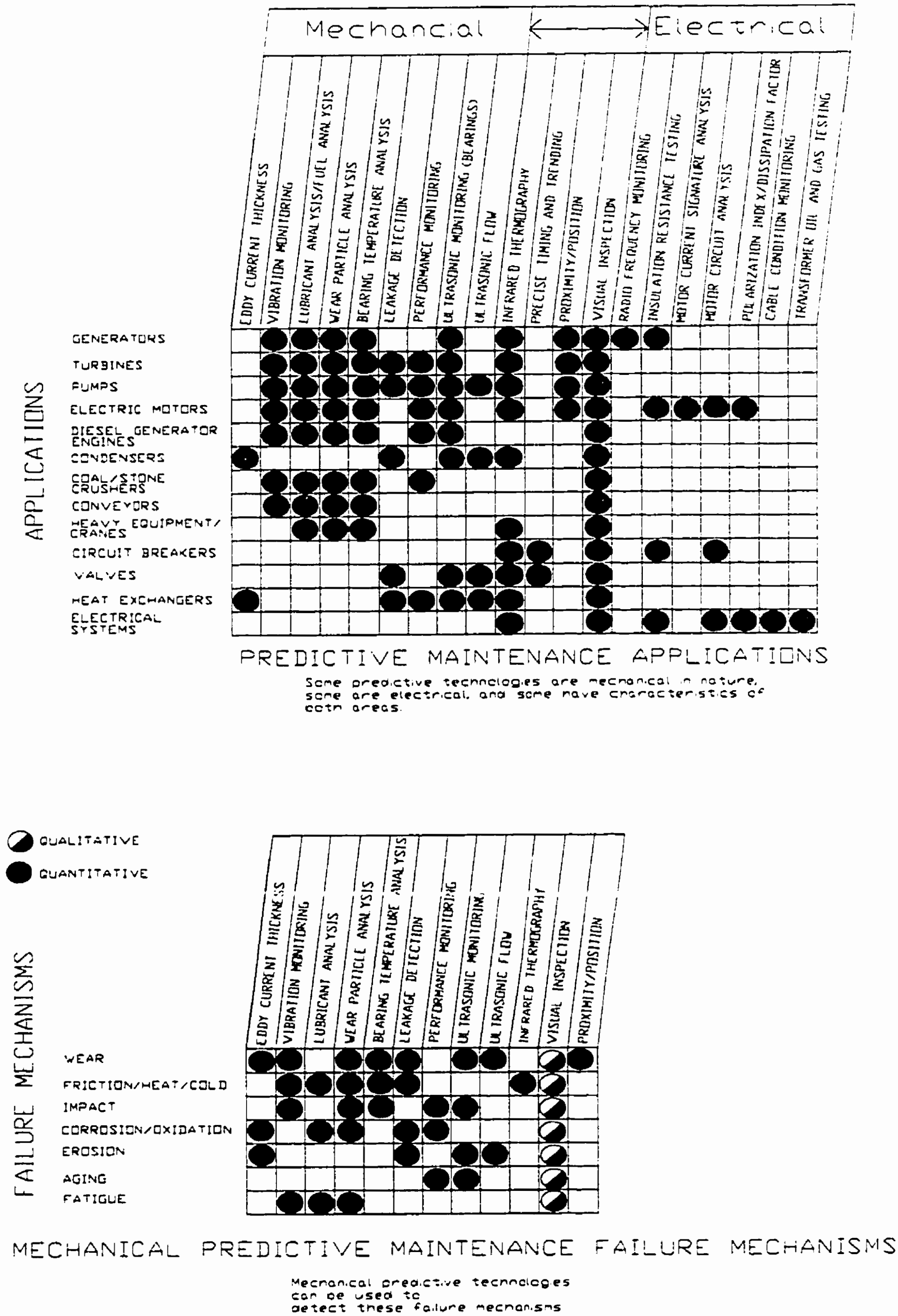


Figure 2.3 Condition Based Maintenance Summary (after Young, 1995)

2.3.1 Vibration Monitoring

Vibration monitoring has two primary objectives: fault detection and fault diagnosis. Fault detection is the process of determining when the machine is running in a condition other than normal. Fault diagnosis is the process of determining what is causing this abnormal operating behavior of the equipment (Burrows, 1996). In using vibration monitoring for fault detection, an assessment of the machine condition is being performed. Based on this assessment, a fault can be detected and repaired, or by suitable data trending a prediction can be made as to when a repair is necessary.

The methods utilized for condition based monitoring using vibration data depend on the type of equipment being monitored and the particular fault. Normally, velocity or acceleration is monitored and the data is displayed in either the time or frequency domain. Many techniques are available for the analysis of vibration data: overall rms level, spectrum analysis using Fast Fourier Transforms (FFT), waterfall plots, crest factor, peak level detection, shock pulse, spike energy, and enveloping (Burrows, 1996).

Most of the current literature on implemented vibration programs for CBM deals with factory environments, where rotary equipment operating in a static environment is monitored. Unfortunately, mobile equipment in the mining industry does not fall into this category. Implementing a vibration monitoring program on a fleet of underground mobile mining equipment faces the challenges discussed in section 1.1 . Nonetheless, this technology has been employed on mobile surface mining equipment with excellent results when used as a predictive and diagnostic tool (Brown et al, 1987);(Burrows, 1996).

A promising new instrument for vibration monitoring of mobile mining equipment is the Mechanic's Stethoscope™ . It is used to monitor and diagnose engine health problems. It is a periodic monitoring system which allows equipment to be tested in the shop under controlled conditions (Fauteux et al, 1995). The monitoring system uses a high speed velocity sensor to measure instantaneous rotational velocity of the crankshaft. Software linked to the sensor is capable of detecting defective engine cylinders and of identifying whether the cylinder has an injection or a compression problem (Johnson et al, 1994) Additionally, the software has the capability to provide online maintenance manuals to assist the mechanic in the diagnoses of faults.

2.3.2 Tribology

> The word Tribology is derived from the Greek word "τριβος" which means rubbing. It is an interdisciplinary science and technology that deals with chemical and physical phenomena that occur at interacting surfaces in relative motion. It encompasses all aspects of the friction, lubrication, and wear of relatively moving mechanical components; and the design and selection of materials for the fabrication of machine parts (Ko, 1997).

The most common method of determining the condition of a machine using tribology is through sampling and analysis of its lubricating oil. Extraction of the oil from a machine for analysis must be done in a manner that ensures the sample is representative of the oil in the machine. For example, sampling downstream from a filter would not provide accurate information about the true condition of the machine. If possible, the sample should be taken immediately downstream from the lubricated surface while the machine is operating under normal conditions and temperatures (Lockwood and Dalley, 1995).

Analysis of the oil sample can be done using: spectrometric metal analysis, ferrography, infrared (IR) spectroscopy, gas chromatography and viscometry. These techniques provide information about the condition of the oil which, with proper interpretation, reveals the machine condition. Proper interpretation of the results from the oil analysis requires knowledge of: the limitations of each test, the composition of the oil and how wear and contamination modify the oil composition. In general, one or more of these tests need to be performed to accurately determine the condition of a machine

2.3.2.1 Spectrometric Analysis

"Spectrometric metal analysis determines the concentration of soluble metals and metal particles up to 10 μm in size. Therefore, it follows mild (benign sliding) rubbing wear and the early stages of fatigue quite well, because in these wear modes the predominant distribution of wear particles is within the detectable (10 μm) range" (Lockwood and Dalley, 1995). The results from a spectrometric analysis are in parts per million (ppm) and provide an overall number for contamination levels in the oil. However, the results are of limited use in diagnosing the type and cause of failure occurring and in the case of rapidly deteriorating components which generate particles >10 μm in size, failure may occur before the analysis reveals it.

2.3.2.2 Ferrography and Particle Counting

"Ferrography provides significantly more information than spectrometric analysis and covers a wider particle size ,<1 to 250 μm range" (Lockwood and Dalley, 1995). Ferrography enables the concentration, shape and size of the metallic particles to be determined. It not only provides information of an impending failure it also allows determination of the particular wear type occurring. The type of wear occurring can be determined with the use of a bichromatic microscope equipped with cameras (Lockwood and Dalley, 1995). The images viewed under the microscope are compared with images that represent known wear types.

A limitation of ferrography and spectrometric analysis is that they primarily identify metallic elements. Non metallic contaminants can arise in mechanical systems through infiltration of dust, sand and cement. A method for identifying all particles is particle counting. Particle counting measures the number of particles per volume of fluid within a given size range. Particle counting can be done using light interruption or laser scanning equipment. A more labor intensive method is the use of filters to collect the particles and then count them using a microscope. Like ferrography, particle counting detects the onset of severe wear. "Problems with particle counting include difficulty in obtaining consistent samples and incorrect counting" (Lockwood and Dalley, 1995).

2.3.2.3 Viscometry and Gas Chromatography

Viscometry is used to measure the viscosity of the lubricant and is of primary importance in evaluating its effectiveness. Gas chromatography is used to determine fuel dilution or water contamination of the oil.

2.3.2.4 Interpretation of Analysis Results

The successful use of oil analysis results requires that they be received before wear has caused a failure and that the results can be used to measure the condition of the machine compared with what it was when the last sample was analyzed. To ensure timely receipt of the analysis results sample turn around time should be kept short.

Interpretation of the results from an oil analysis is best illustrated using the results obtained from an actual sample. Table 2.1 presents the results received for several samples. Table 2.2 provides an insight into what each one of the results may be representative of and possible sources of contaminants. By trending the results obtained from the oil analysis a base line can be established for the appropriate levels of each wear element in the oil. Break down of additives and oxidation of the oil can found by comparing the analysis results to those from an analysis done on new oil. It is important to analyze a sample of new oil with the used sample to ensure that the new oil meets its required specifications. Cases have been found where changes in the oil chemistry by the manufacturer have led to maintenance problems (Kincaid, 1993).

Equip.	FE	CR	MO	AL	CU	PB	SN	NI	V	MN	SI	NA	B	MG	CA	P	ZN	WATER	VISC	Flash
P-44	84	1		6	9	1		0	0		28	26	184		96			yes	25.74	>200
P-44	48	1		4	131	31		0	0		21	29	177		96			nil	21.42	>200
P-44	64	1		17	72	17	0	0	0		21	13	293		105			Trace	17.91	>200
P-44	41	0		5	11	3	6	0	0		20	0	208		131			nil	16.07	>200
P-44	14	0		0	4	0	0	0	0		9	0	103		75			nil	16.28	>200
P-44	26	0		0	7	0	0	0	0		10	1	154		173			nil	16.46	>200

Table 2.1 Sample of Oil Analysis Data (Element in PPM, Viscosity mm^2/s and flashpoint °C)

Elements	Indicates	Sources
Iron (Fe)	wear	cylinders, oxidation, crankshaft, gears
Copper (Cu)	wear and additive	bearings, coolant system
Aluminum (Al)	wear, additive and dirt	bearings, pistons
Chromium (Cr)	wear	Cylinders, rings, gears, crankshafts
Molybdenum (Mo)	wear and additive	rings
Lead (Pb)	wear and fuel	gasoline, grease, paint, bearings
Tin (Sn)	wear	bearings, cooler
Silver (Ag)	wear	bearings
Nickel (Ni)	wear	camshaft, rings, gears
Vanadium (V)	wear	valves, catalysts
Titanium (Ti)	wear and dirt	turbines, springs
Silicon (Si)	dirt	sand, dirt
Sodium (Na)	coolant and additive	coolant system
Boron (B)	coolant and additive	coolant system or sea water
Magnesium (Mg)	additive	bearings, sea water
Calcium (Ca)	additive	
Zinc (Zn)	additive	bearings, coatings
Phosphorus (P)	additive	gears, coolant system
Barium (Ba)	additive	water, grease
Antimony (Sb)	additive	grease
Potassium (K)	coolant	
Sulfur (S)	additive	
Chlorine (Cl)	contaminant and additive	
Nitrogen (N)	additive and fuel oxidant	
Compounds		
Water	Contamination	
Physical Properties		
Viscosity	oxidation or fuel oil	
Total acid number (TAN)	oxidation	

Table 2.2 Relationship between contaminants and sources (Aduvire E et al, 1992) and (Lockwood and Dalley, 1995).

2.3.3 Temperature Monitoring

Monitoring of a machine's temperature can provide valuable insight into its operating condition. Methods for monitoring the temperature of a machine include: thermometers, thermocouples, resistance temperature detectors (RTD's) and thermography. Of these, thermography is the most recent to be used for CBM and the only one that allows non-contact measurement of a machine temperature.

> Thermography is a predictive maintenance technique that can be used to monitor the condition of plant machinery, structures, and systems. It uses instrumentation designed to monitor the emission of infrared energy (i.e. heat) to determine the operating condition. By detecting thermal anomalies - areas that are hotter or colder than they should be - an experienced surveyor can locate and define incipient problems within the plant (Mobley, 1990, pg. 22).

Common instrument types used for measuring thermal energy are: pyrometers, line scanners and thermal imaging devices. Pyrometers use various methods to measure infrared energy, such as total radiation, optical and two color. Regardless of the method used by the pyrometer, it is limited to measuring the temperature at a single spot. Additionally, depending on the distance from the measurement point the background area can have significant effects on the reading. Line scanning provides a one dimensional temperature profile of the part being scanned compared to full imaging devices which provide a two dimensional view of the temperature of a part.

Thermography has been widely used by the electrical industry since high voltage equipment and transmission lines require non-intrusive monitoring because of safety and physical location. However, the use of thermal imaging to find potential problems in mechanical processes is growing. For example, thermal imaging can be used to detect abnormal temperature levels in bearings and gear boxes caused by lubrication or alignment problems (Dumpert,1997). Additionally, thermal imaging has been found to be useful for monitoring: manufacturing processes, refractory and insulation materials, heat leakage from structures, and fire flare ups in waste dumps (Rao et al,1996);(Laird, 1994).

2.4 Statistical Techniques

The application of statistics to analyze maintenance data in the mining industry can lead to opportunities for cost reduction (Mueller, 1995). Figure 2.4 shows the relationship between maintenance costs, lost production cost due to downtime, and the total cost to the operation.

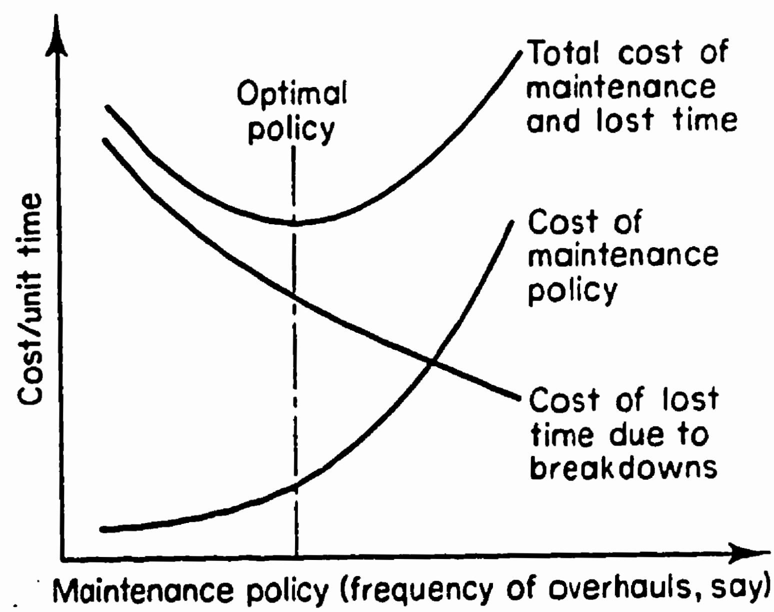


Figure 2.4 Maintenance Cost Relationships (from Jardine, 1973)

Figure 2.5 shows the standard life cycle, or "bathtub", curve for mechanical equipment. By applying statistical techniques to maintenance data it is possible to determine where on the life cycle curve a piece of equipment is operating. This enables determination of equipment reliability and probability of failure. When coupled with cost data for planned replacements and unplanned replacements, reliability data can be used to determine optimal replacement time.

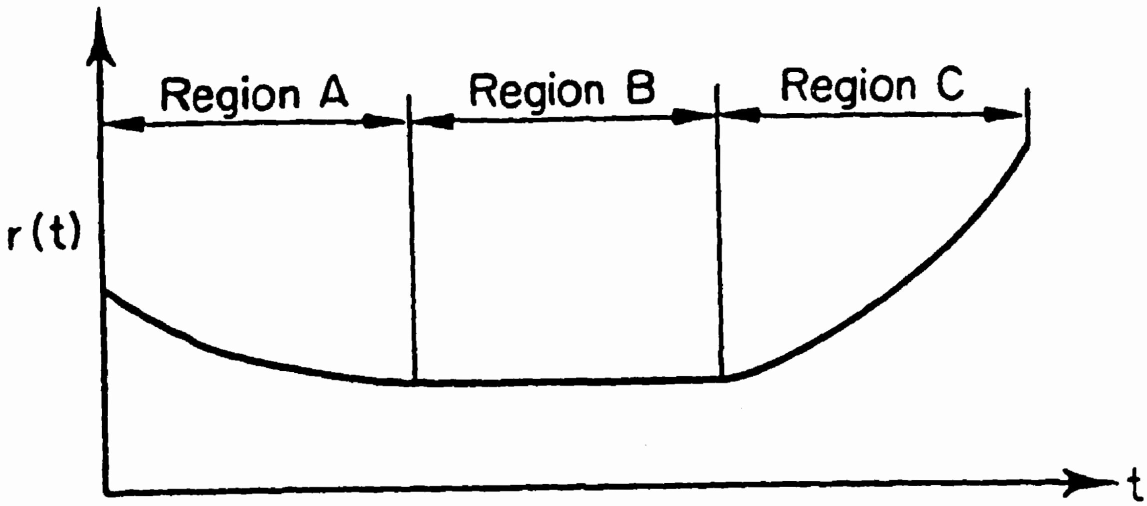


Figure 2.5 Life Cycle Curve (from Jardine, 1973) "A" represents increased failure rate, "B" represents constant failure rate period in life cycle and "C" is near the end of the useful life with the failure rate increasing.

Fitting distributions to the failure and repair times of equipment provides insight into variations amongst components and labor practices. This can help highlight problems such as poor quality parts and improper repairs. Additionally, knowing the probability of failure of components based on data collected from equipment provides a basis for planning of component replacement intervals. Thus, the decision as to when to repair or replace components can be made by the owner using actual data instead of having to rely on manufacturer's recommendations which tend to be conservative.

There are many distributions that have been found to represent the life cycle of equipment. These can generally be divided into two categories, stationary and non-stationary models. Stationary models will be used for the work presented in this thesis. "Stationary models are models where the probability distribution at any time $t_i, t_2 \ldots, t_m$ must be the same as the probability distribution at times $t_{1+k}, t_{2+k} \ldots, t_{m+k}$ where k is an arbitrary shift along the time axis" (Bovas et al 1983, pg. 194). In the context of maintenance the assumption of a stationary process implies that the distribution of failures after a repair is the same after every repair. This implies that the equipment is in exactly the same condition after a repair or part change as it was when new. In reality this is not true due to

- Variation in maintenance practices.
- Replacement components will not be identical. Each will have its own life cycle.
- Some failures may be introduced as a result of the maintenance procedure.

Nevertheless, stationary models are commonly applied to failure data when tests for time variant trends reveal localized trends. Examples of such applications are given by (Paraszcak et al,1994) and (Vagenas et al, 1997). The stationary models that are considered for modeling the failure data in this thesis are the: Weibull, exponential and lognormal distributions. In presenting the functions that represent a distribution the following definitions apply

$f(t)$ probability density distribution for failures.

$R(t)$ Reliability function providing the probability of survival to time t.

$\lambda(t)$ Instantaneous failure rate.

2.4.1 Weibull Distribution

The Weibull distribution is advantageous in that it can be fitted to many life distributions (O'Connor, 1981, pg. 37). The Weibull distribution is given by

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right] \text{ for } t \geq 0 \text{ and } 0 \text{ otherwise} \qquad [1]$$

$$R(t) = \exp\left[-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right] \qquad [2]$$

$$\lambda(t) = \left(\frac{\beta}{\eta}\right)\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \qquad [3]$$

where β is the shape parameter, η scaling parameter and γ is a location parameter. These equations represent the 3 parameter Weibull. For the 2 parameter Weibull, γ is set to zero. The shape parameter β indicates whether the failure rate is increasing, decreasing or constant.

- $\beta > 1$ represents an increasing failure rate.
- $\beta < 1$ represents a decreasing failure rate.
- $\beta = 1$ represents a constant failure rate.

The location parameter is the time that the equipment will run without any failures and has the affect of shifting the distribution along the time axis. "Changing the scaling parameter has the same effect as changing the scale on the abscissa. If η is increased while β and γ are kept the same, the distribution gets stretched out to the right and its height decreases while maintaining its shape and location" (Kececioglu, pg 272, 1991).

2.4.2 Exponential Distribution

The exponential distribution is the simplest and most widely used reliability distribution. Systems whose failures follow the exponential distribution exhibit a constant failure rate. One implication of this is that, for systems operating in the constant failure rate region of their life cycle, planned preventative maintenance does not enhance the reliability of the system. The exponential distribution is given by

$$f(t) = \lambda \exp(-\lambda t) \qquad [4]$$

$$R(t) = \exp(-\lambda t) \qquad [5]$$

$$\lambda(t) = \lambda \quad \text{where } \lambda \text{ is constant} \qquad [6]$$

2.4.3 Lognormal Distribution

"A random variable is lognormally distributed if the logarithm of the random variable is normally distributed" (Kececioglu, 1991, pg. 399). The two-parameter lognormal distribution is given by

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} \exp\left[\frac{-(\ln t - \mu)^2}{2\sigma^2}\right] \qquad [7]$$

$$f(t) \geq 0, t \geq 0, -\infty < \mu, \sigma > 0$$

$$R(t) = 1 - F(t) = \int_t^{\infty} \frac{1}{t\sigma\sqrt{2\pi}} \exp\left[\frac{-(\ln t - \mu)^2}{2\sigma^2}\right] \quad [8]$$

$$\lambda(t) = \frac{f(t)}{R(t)} \quad [9]$$

The parameters μ and σ represent the mean and standard deviation of the natural logarithms of the data. An increase in μ indicates an increase in the mean time between failures and an increase in σ indicates that there is more variation in the TBF. Additionally, μ is the scale parameter and σ is the shape parameter (Kececioglu, 1991, pg. 404).

2.4.4 Tests for Data

Prior to fitting the data with a distribution the underlying assumption of independent and identically distributed failure time should be verified. A common graphical test used to determine if a trend is present in the data is to plot the cumulative time between failures versus the cumulative failure numbers. A straight line indicates lack of a trend in the data. A convex or concave curve indicates a system with a decreasing and increasing failure rate respectively (Ascher et al, pg 74-75, 1984). A test for serial correlation is to plot the ith TBF against i-1:th TBF. If the data are dependent or correlated, the points will lie along a line. It is important that the data should be plotted in the order of occurrence as sorting of the data will induce correlation (Vagenas et al, 1997).

2.4.5 Fitting Failure Distributions

Calculation of the model parameters does not guarantee that the appropriate model has been selected. To ensure that the best model is chosen the parameters are estimated for each candidate model and a comparison of each model is performed to determine which model results in the best fit.

2.4.5.1 Parameter Estimation

The two methods considered for parameter estimation in this work are Maximum Likelihood and Rank Regression. For a continuous function

$$f(x;\theta_1,\theta_2,\ldots\theta_k) \qquad [10]$$

where the θ's represent the parameters to be estimated from a data set of N observation of x. The likelihood function is given by,

$$L(x_1,x_2,\ldots,x_n|\theta_1,\theta_2,\ldots,\theta_k)=\prod_{i=1}^{N} f(x_i;\theta_1,\theta_2\ldots,\theta_k) \qquad [11]$$

the logarithmic likelihood function is given by,

$$\wedge = \ln L = \sum_{1=1}^{N} \ln f(x_i;\theta_1,\theta_2,\ldots\theta_k) \qquad [12]$$

The maximum likelihood estimators (MLE) of the unknown parameters θ are obtained by maximizing L or ∧. Generally, maximizing ∧ is simpler than maximizing L. Maximization can be accomplished by taking the derivative of ∧ with respect to each θ, setting the equations equal to zero and solving them simultaneously (Reliasoft™, 1997). For example, consider the exponential distribution:

$$f(t) = \lambda \exp(-\lambda t) \qquad [13]$$

its likelihood function is given by:

$$L(\lambda; |t_1, t_2, \ldots, t_k) = \prod_{i=1}^{N} f(t_i) \qquad [14]$$

$$= \prod_{i=1}^{N} \lambda e^{-\lambda t_i}$$

$$= \lambda^N e^{-\sum_{i=1}^{N} \lambda t_i}$$

The log likelihood function is,

$$\wedge = N \ln \lambda - \sum_{i=1}^{N} \lambda t_i \qquad [15]$$

$$\frac{\partial \wedge}{\partial \lambda} = \frac{N}{\lambda} - \sum_{i=1}^{N} t_i = 0 \qquad [16]$$

$$\hat{\lambda} = \frac{N}{\sum_{i=1}^{N} t_i} \qquad [17]$$

Thus, for a given data set, equation 17 can be used to estimate the value of λ. A similar approach can be used for the lognormal and Weibull distribution, but the resulting equations require numerical solutions.

An alternate method to estimating the parameters is Rank Regression. Rank Regression is actually a least squares estimate of the parameters of the function. However, since least squares estimation requires values for both the x and y a method is needed for estimating the value of y (in this case y is the probability of failure). One method is to use median ranks. Median ranks are determined from the cumulative binomial distribution given by

$$P = \sum_{k=j}^{N} \binom{N}{k} Z^k (1 - Z)^{N-k} \qquad [18]$$

where, P is the calculated probability of a successful event.

N is the sample size

j is the order number of the failure times, ranked in increasing order.

Z represents the probability of an unsuccessful event.

By setting P to 0.5 and solving equation 18 for Z we determine the median rank with a 50% confidence level. This value is then used as the probability of failure for the j_{th} failure time. This, allows the least squares method to be used to calculate the parameter values for the distribution (Reliasoft™, 1997).

2.4.5.2 Goodness of Fit Tests

Once the parameters have been fitted to the candidate model(s) it is necessary to determine how well they fit the data. Tests that are commonly applied to data include the Chi Square test (χ^2), Kolmogorov-Smirnov test (K-S) and comparison of the correlation coefficient (R).

The Chi Square test involves comparing the number of data that fall into selected classes with the number that would be expected to fall in those classes from the assumed distribution.

$$\chi^2 = \sum_{1}^{N} \frac{(x_i - E_i)^2}{E_i} \qquad [19]$$

where

x_i is the observed quantity in the i_{th} class

E_i is the expected value from the given distribution

χ^2 is the calculated value of Chi Square

N is the number of classes

Equation 19 can be used to calculate the value of Chi Square from the data. This value can be compared to the Chi Square value for N-P (P is the number of parameters estimated) degrees of freedom at a given confidence level. If the calculated value of χ^2 is greater than the tabulated value then the assumed distribution of the data is not supported at the chosen confidence level.

The Kolmogorov-Smirnov test uses a comparison of the ranked value of the data with what the expected value of the ranks would be from the assumed distribution. It looks at the largest absolute difference between the observed and expected rank value and compares this to a tabulated K-S value. If the calculated value is greater than the tabulated value then the assumed distribution of the data is not supported at the chosen confidence level.

The correlation coefficient is a measure of the goodness of fit from the least squares estimate. It is given by:

$$r = \frac{\sum_{1}^{N}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{1}^{N}\left(x_i - \bar{x}\right)^2 \sum_{1}^{N}\left(y_i - \bar{y}\right)^2}} \qquad [20]$$

Generally, values of R greater than .9 indicate a good fit to the data.

2.5 Reliability Centered Maintenance

The goal of reliability centered maintenance (RCM) is to provide the maintenance engineer with a tool that will allow determination of the most cost effective mix of maintenance policies. Effective use of the RCM approach requires that clear goals in terms of the appropriate level of reliability and the acceptable operating standard for the equipment be established (Ing et al, 1996).

Beginning with the knowledge that the reliability of a machine is an inherent function of its design the RCM approach develops a maintenance program to try and attain this level of reliability. Development of the plan includes consideration of the costs associated with maintenance and with failure. These costs include: repair, health and safety, environmental and lost production. To achieve the optimum maintenance program the following steps are performed:

- Failure mode effects and criticality analysis (FMECA) is performed. This involves starting with an analysis of the core functions of a machine and working through the possible failure modes. Once the failure modes have been identified, their effects and their criticality must be determined. The criticality can be based on probability of occurrence and cost, or severity as discussed above.

- Using the identified failure modes and based on their criticality select the appropriate maintenance tasks. These appropriate tasks being: repair on condition, overhaul (traditional preventive maintenance), replace, run to failure and redesign. Details of criteria for acceptance of each of these options are given by Ing (Ing et al, 1996).

Application of RCM in the mining industry has grown slowly. However, some companies have implemented it very successfully. One example is the Hammersley Iron open pit mine in Australia (Knowles, 1994). The fact that RCM provides a structured methodology for arriving at the correct balance between breakdown maintenance, planned interval repair and repair on condition, makes it an attractive technique for mining companies striving to optimize the maintenance process.

2.6 Mine Maintenance Management

Organization and management of the maintenance program can have dramatic effects on its success. A sound technical maintenance program will not reduce maintenance costs if the management structure does not allow proper execution of work and provide clear lines of communication. Figure 2.6 shows the current trend in the mining industry towards a more robust organizational structure for maintenance. The structure shown in this figure allows accountability at each level within the organization by placing a manager in charge of each area with lower level managers who again are given specific responsibilities.

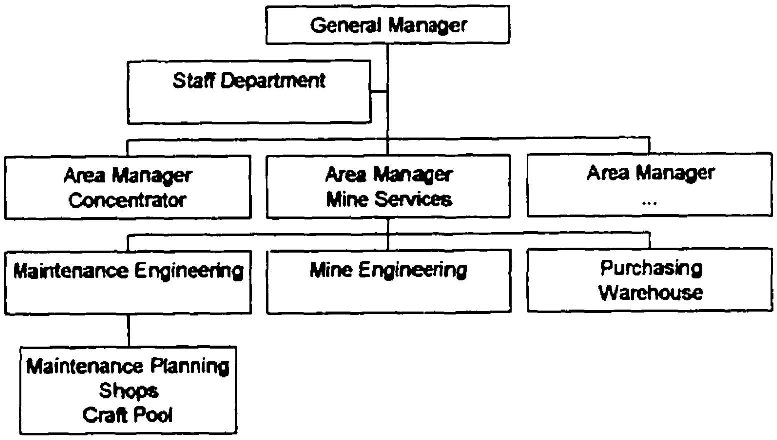


Figure 2.6 Typical Mine Organizational Structure (after Tomlingson,1994)

The use of a craft pool for labor enables the optimization of resources by allowing division of the work between a fixed crew who do the normal day to day work and a resource pool from which resources can be drawn upon as necessary. Normally, the resource pool spends a week in a specific area to assist the fixed crew in clearing any backlog of work. The benefits of having a fixed crew to do the day to day work is that they become familiar with the equipment in their area which allows them to be more efficient (Tomlingson, 1994)

3.0 Background to Case Study: El Indio Mine

> The El Indio Belt is a prolific gold, silver and copper district approximately 175 km long and 10 km wide, located in the Andes Mountains. It lies in a north-south orientation, primarily within central Chile.
>
> Barrick's El Indio property covers 1,300 km^2, making it the largest on the Belt. It is located at a 3,960 m elevation, 380 km north of Santiago and 160 km east of the coastal town of La Serena, the staging area for all supplies and services. The Argentinean border lies a few kilometres to the east. (Dawes, 1996)

The mining operations of Barrick at the El Indio site consist of: two underground mines, Viento and El Indio, and an open pit operation, Tambo. There is a process plant at both the open pit location(6500 t/d) and the underground location (3,150 t/d) (Dawes, 1996). Discussion will be limited to the mobile equipment at El Indio mine.

A brief outline of the departments which provide maintenance services will be given to provide an understanding of how maintenance is accomplished in the mine. This discussion is presented for completeness, and evaluation of the performance of the these departments is beyond the scope of this work.

3.1 Mobile Equipment Fleet

The maintenance history of the following equipment was reviewed for the purpose of this thesis: 11 scoops, 9 trucks, and 7 jumbo drills. Details on manufacturer, model, age and capacity of equipment are given in Table 3.1.

Description	Manufacturer	Model	Year	Capacity	Quantity
Scoop	Eimco Jarvis Clark	EJC-100	1990-1991	2.7 YD^3	7
Scoop	Wagner	ST-2D ST-3.5	1989 1995	2.5 YD^3 2.7 YD^3	2
Scoop	Puma	9000	1994	7 YD^3	2
Truck	Eimco Jarvis Clark	EJC-415	1990-1994	15 ton	4
Truck	Eimco Jarvis Clark	EJC-416	1995	16 ton	3
Truck	Eimco Jarvis Clark	EJC-430	1994	30 ton	2
Drill	Tamrock	H-105	1987-1995	55 kW	5
Drill	Tamrock	H-103	1991 1995	34.5 kW	2
Drill	Gardner Denver	MK-20	1994	55 kW	1

Table 3. 1 Equipment at El Indio

3.2 Organizational Structure and Staffing

The maintenance organizational structure at El Indio is shown in Figure 3.1 . Details for the central maintenance shop are only shown where they directly service the mine's equipment. Table 3.2 shows the maintenance staffing at El Indio mine, Table 3.3 shows the staffing at the central shop associated with servicing heavy equipment (drills, scoops trucks, etc.). It should be noted that the staffing shown for the central shop services all three mines, El Indio, Viento and Tambo.

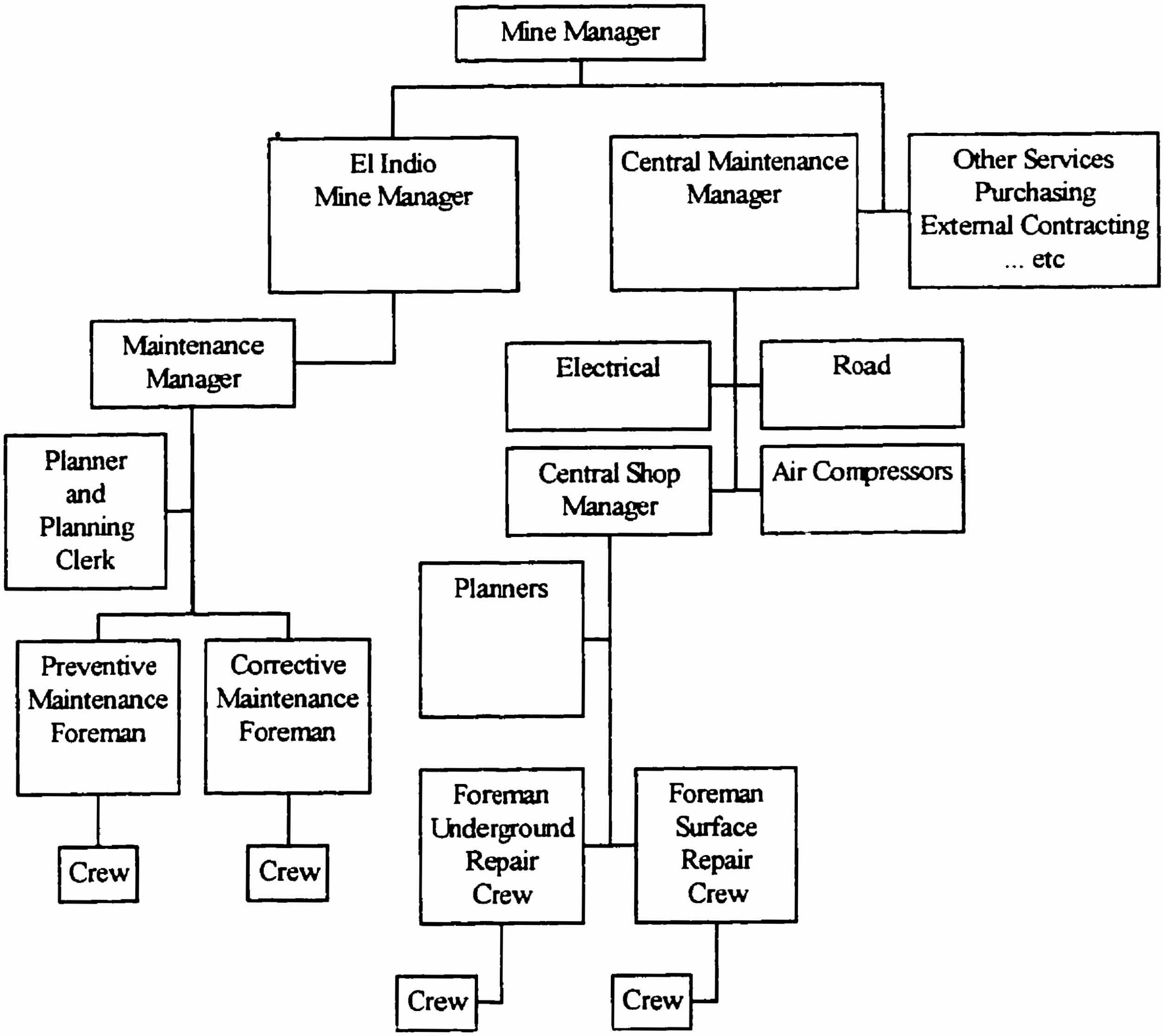


Figure 3.1 Maintenance Organizational Structure for El Indio Mine

Description	**Personnel**
Maintenance Manager	1
Maintenance Foreman	2
Planner	1
Planning Clerk	1
Preventive Maintenance Crew	6
Scoop and Truck Crew	28
Drill and Utility Crew	3
Total	**42**

Table 3.2 Maintenance Staffing at El Indio Mine

Description	Personnel
Manager	1
Shop Supervisor	1
Foreman	2
Planners	3
Mechanics	30
Boilermaker-Welder	2
Total	**39**

Table 3.3 Maintenance Staffing at Central Shop

Examination of Figure 3.1 reveals that the organizational structure differs from that shown in Figure 2.6. The significant differences are:

- No one unit is responsible for the maintenance function for El Indio mine. The mine and the central shop are each responsible for certain aspects of the mine's maintenance. This type of structure leaves room for ambiguity with regards to solution of problems and assignment of responsibility. Both of these can reduce the effectiveness of the maintenance program.
- Support functions - purchasing, external contracting, and warehousing - do not report to anyone responsible for maintenance at a functional level. Consequently, these departments are not directly accountable to the maintenance process. The result being that each function may optimize its process according to the demands of whom they are accountable which may not be optimum for the organization as a whole.
- The central shop has divided its crew foremen into underground and surface equipment. As discussed in section 2.6 the trend is to use crews specialized by

equipment type and supplement the base work force using a craft pool of multi-skilled workers.

3.3 Flow of Work Maintenance Process

The maintenance staff at El Indio mine serves two functions: performance of preventive maintenance every 125 machine operating hours, and repair of failures. If the failure is of a nature such that it cannot be repaired with the mine's resources the equipment is sent to the central shop. Capabilities of the maintenance resource in the mine are discussed in section 3.4.

The central shop's purpose is to provide extended services to the mine. This includes repairing failures which the mine cannot handle and performing one thousand hour maintenance on equipment. This arrangement puts the central shop in the position of being in a reactive mode the majority of the time.

Coordination of the activities between the mine and the central shop is accomplished through weekly planning meetings. Representatives from external services are also present at these meetings due to the fact that for some failures, parts or outside contractors are an issue.

3.4 Shop Capabilities

3.4.1 El Indio Mine Shop

Work done in the mine consists of numerous activities which include: cleaning and painting, oil changes, tire changes, hydraulic hose inspection and repair, electrical troubleshooting and changing of small components, etc. The shop has a small buffer warehouse to store commonly used parts such as, hoses, filters, etc. The shop is limited to doing work that can be turned around quickly since long repairs would prevent staff from dealing with the numerous short time repairs and take up valuable shop space.

3.4.2 Central Shop

Typical repairs that are done at the central shop are:

- Changing: transmission, motors, differentials, bearings, hubs, knuckle joints and brakes.
- Structural repairs.
- Bucket repairs.
- Coolant system repairs.

The central shop does not overhaul engines, transmission, differentials or other components that require precision millwright work. These jobs are sent offsite to be repaired by outside contractors.

3.5 Supporting Services

The departments which directly provide support to the maintenance activities at El Indio mine are:

- The external services department which handles all long term service agreements for component rebuild.
- The purchasing department which buys all consumables and special orders.
- The warehouse whose role is to ensure proper inventory of parts to meet the needs of the mine.

3.6 Data Management

Maintenance data management at the mine utilizes work cards filled out by maintenance personnel on a daily basis. Selected information from these cards is input into the maintenance management software package. The data is entered by the planning clerk in the mine. He enters data for work done at both the mine shop and the central shop. The mine is in the process of changing its maintenance management software from Rushton™ software to Performance Manager™ software.

3.7 Existing CBM

Existing condition based monitoring at the El Indio mine consists of an oil analysis program. Oil samples are obtained from equipment at predetermined intervals and shipped to an offsite laboratory. The laboratory is about 1000 kilometers from the mine and has a 5 day sample turn around time from receipt of sample. Analysis at the laboratory include: viscosity measurement, element concentration, flashpoint determination and contaminate identification. The laboratory sends a report to the mine with the results from the analysis. It does not provide any interpretation of the results. The oil analysis program does not use ferrography or particle counting as discussed in section 2.3.2. Thus, their analysis is not useful in determining the type of wear going on in the equipment. Observations at the mine revealed that samples seemed to be sitting in the maintenance shop for long periods of time before analysis and when the analysis results were received no trending was being done to develop a history of the equipment condition. This is contrary to what is required for effective use and interpretation of results as discussed in section 2.3.2.4. In contrast, decisions were made on an arbitrarily chosen upper limit for contaminants with no consideration of the relative change in contaminant level from one sample to the next. A detailed discussion of the consequences of this will be presented in chapter 7.

4.0 Case Study: Data Analysis

The analysis of the maintenance data at El Indio mine was performed at two levels of detail. The first level analysis was performed to identify problem areas within the maintenance program and identify equipment that might be suitable candidates for a condition based maintenance program. This level relied on a Pareto Analysis for problematic equipment/system identification. The second level analysis involved the use of a statistical approach to gain further insight into the critical items identified from the first level analysis.

Data used for both levels of analysis was extracted from the maintenance information software Rushton™ (Rushton) being used at the El Indio mine. Rushton is a menu driven data base, and the only way to access the data was to have it print generic reports to a file. These generic reports were then imported into Microsoft Access™ and Microsoft Excel™ for analysis.

4.1 Maintenance Indicators

The first indicator used to assess maintenance effectiveness is the mechanical availability of equipment. The maintenance data management software at El Indio mine provides this as a standard report. Table 4.1 shows the level of mechanical availability and several other performance indicators for El Indio mine for 1995 and 1996.

1995

	MA	PA	UA	EU
Trucks	62.1	76.9	49.2	38
Scoops	50.5	68.4	47.3	32
Jumbos	42.7	68	35.2	24

1996

	MA	PA	UA	EU
Trucks	60.8	75.1	51.3	39
Scoops	49.5	66.2	50.1	33
Jumbos	49.3	70.8	40	28

Table 4.1 Equipment Availability at El Indio Mine

A description of the performance indicators is as follows (Lyonnet, 1988, pg 58):

$$MA = \frac{OP}{OP + MH} \quad [21]$$

$$PA = \frac{OP + SB}{SH} \quad [22]$$

$$UA = \frac{OP}{OP + SB} \quad [23]$$

$$EU = \frac{OP}{SH} \quad [24]$$

The relationship amongst operating, standby, maintenance and scheduled hours is shown in Figure 4.1 A written description of the significance of these indices is as follows:

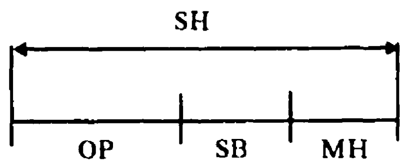


Figure 4.1 Relationship between Hours

MA: Mechanical Availability. This gives an indication of the effectiveness of the maintenance program. If no hours were spent on maintenance this number would be 100% meaning that the equipment was available 100% of the time. In reality this is not attainable due to necessary maintenance such as oil changes, lubrication etc and diminishing returns.

PA: Physical Availability. This gives an indication of how much time the equipment is physically available to do work.

UA: Utilization of Availability. Is a measure of how effective the production operation is at using the equipment when it is physically available.

EU: Effective Utilization. Is an indicator of how much the equipment is being utilized compared to the scheduled production hours.

OP: Operating Hours. The hours that the equipment spends in operation.

SB: Standby Hours. The time that the equipment was ready to operate but was delayed due to non-maintenance issues.

MH: Maintenance Hours. Total hours spent on maintenance, includes preventative maintenance.

SH: Scheduled Hours (based on a 24 hour day) Hours scheduled for production.

The levels of MA shown in Table 4.1 range between 50%and 60% for 1996. These numbers are low and indicate problems with the maintenance process or equipment.

5.0 Data Analysis: Problem Area Identification

The indicators discussed in section 4.1 provide a top level evaluation of both the maintenance and production effectiveness. However, they do not provide any insight into what might be contributing to problem areas. One method used for identifying the most significant contributors to maintenance cost is Pareto Analysis. The usual approach for this type of analysis is to decompose a piece of equipment into suitable systems e.g. hydraulics, motors, drivetrain. Then using recorded failure data and repair and replacement costs for the associated failures, the cumulative percentage cost is plotted as a function of cumulative percentage of failures. What is typically found when this is done is that approximately 80% of the cost is a result of 20% of the failures. This indicates that the maintenance department should focus on these failures. Once specific systems have been identified a Pareto Analysis can then be performed on each system to identify where the problems are arising within the system.

Cost data was not available to do the Pareto Analysis. In its place total down hours were used. To complete the Pareto Analysis for the scoops, trucks and drills it was necessary to make several assumptions regarding the data:

- In some cases, when equipment was noted as being under repair for three or more consecutive days, this downtime was treated as one event. The criteria for determining this were: if it was in for more than 10 hours on any of the three days and if, based on engineering judgment, it seemed reasonable that the type of repair was not the repetitive type.

- For the repairs identified by the above procedure, actual hours were replaced by twice the repair time estimated by Central Maintenance staff. The focus of this analysis was on identifying potential CBM candidates. Consequently, inclusion of repair times that were excessively high due to problems in the maintenance process would bias the results. Twice the estimated hours was used to provide a conservative estimate of what the repair time would be if the maintenance process was working effectively.
- When analyzing the data for avoidable time in the shop, for those dates on which a machine was listed under repair for two or more failure codes, the dominant failure code was used. For example, in the case of overlapping failure records: 700 (Brakes) recorded between 05/03/96-13/03/96 and 110 (Hydraulic Pumps) recorded between 11/03/96-22/03/96 the latter event would be changed to 110-14/03/96- 22/03/96
- Where the downtime was listed against a failure code as 24 hours, it was changed to 20 to reflect the actual shift used at the mine.

The results from the Pareto Analysis for each fleet of equipment are shown graphically in Figures 5.1, 5.2 and 5.3 for scoops, trucks and drill respectively. Tables 5.1, 5.2 and 5.3 show the calculated results. The graphs in these figures are not what was expected. Instead of identifying critical systems that account for significant amounts of downtime, these graphs indicate a near linear relationship between cumulative percent of failures and cumulative percent downtime. The linear relationship between number of failures and downtime indicates that on average the time to repair a piece of equipment is approximately the same regardless of what fails.

A plausible reason for this is that factors other than actual time to repair are contributing to the down time. These factors could include,

- waiting for resources such as parts, labor or shop space,
- excessive time from failure to arrival at the shop,
- low level of equipment utilization resulting in no rush to repair.

Also, shown in Tables 5.1, 5.2 and 5.3 are the average time to repair each system and the average repair time per failure for the fleet. The high average time to repair shown for the miscellaneous category is due to its inclusion of failures caused by accidents and structural failures, which tend to have long downtimes. The average time to repair a failure amongst the fleets ranges from 4.3 to 4.7 hours. The closeness of these values amongst entirely different types of equipment and components tends to support the hypothesis that some factor other than actual repair time is influencing the time to repair.

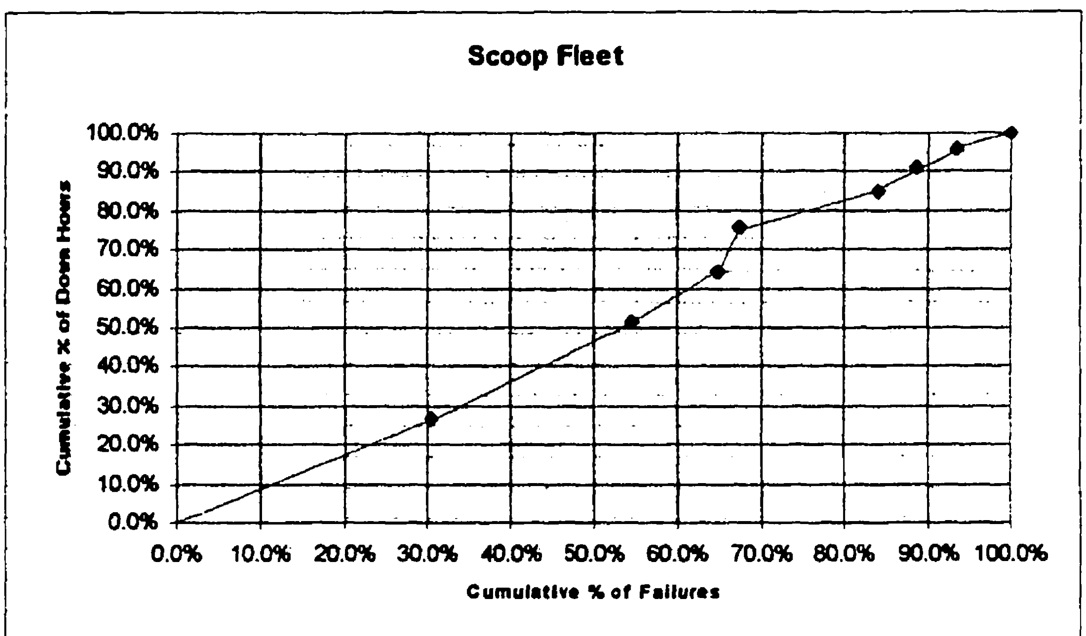


Figure 5.1 Pareto Analysis of Scoop Fleet

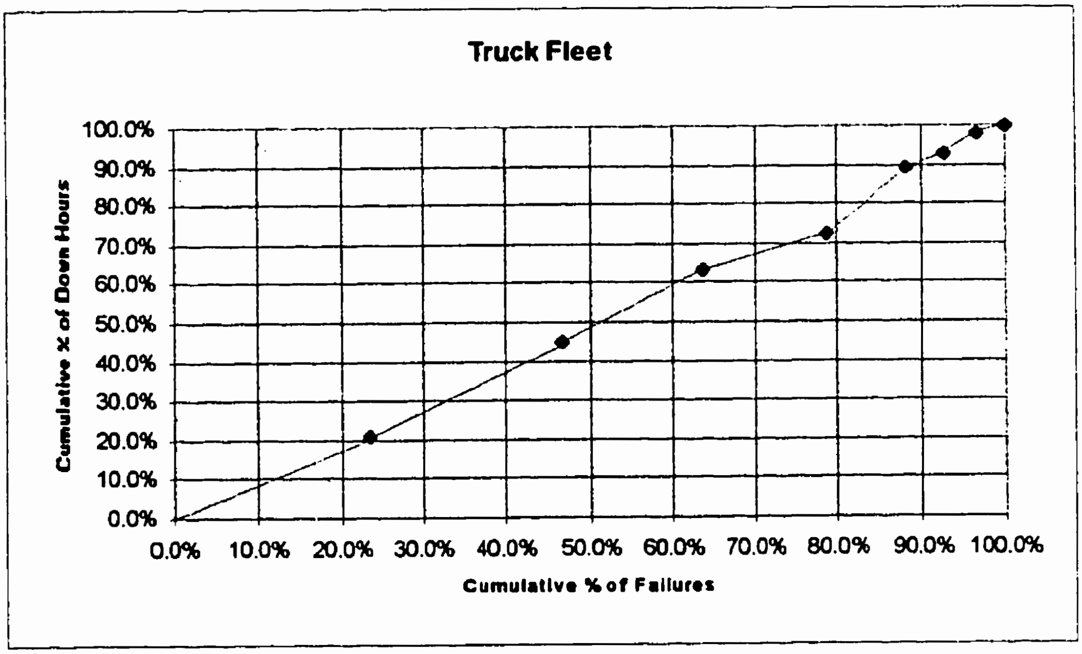


Figure 5.2 Pareto Analysis of Truck Fleet

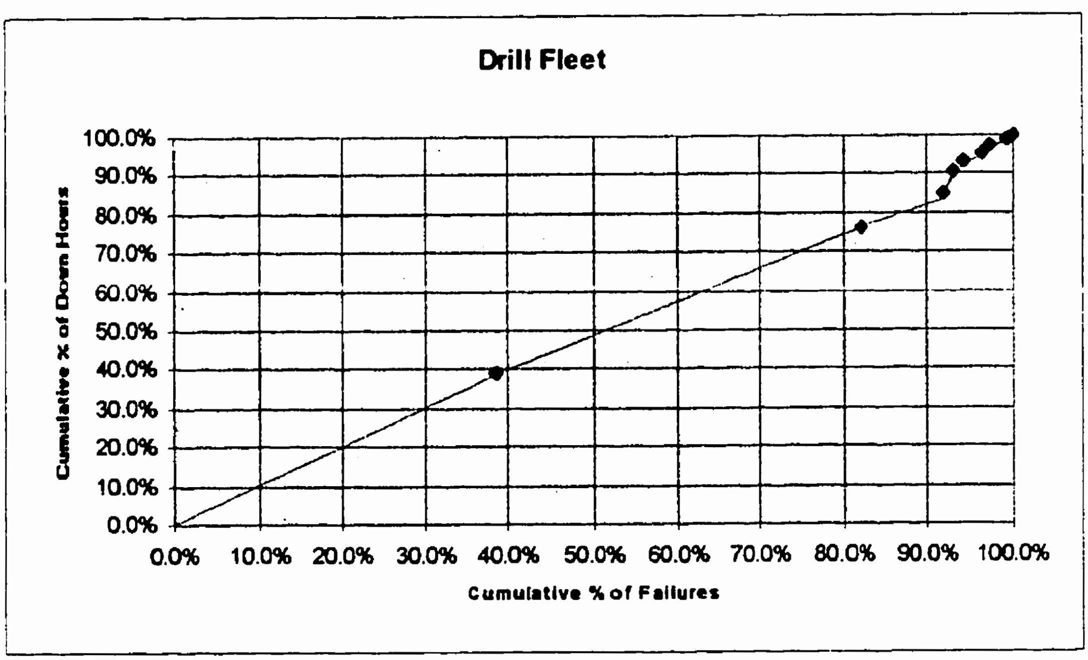


Figure 5.3 Pareto Analysis of Drill Fleet

Description	Hours	Cumulative	%Cum	Failures	Cumulative	%Cum	Average Repair time
Hydraulics	5154	5154	26.9%	1233	1233	30.4%	4.2 Hr
Motors	4699	9852.5	51.5%	980	2213	54.6%	4.8
Drivetrain	2494	12346	64.6%	411	2624	64.7%	6.1
Misc.	2178	14524	75.9%	104	2728	67.3%	20.9
Electrical	1789	16312.5	85.3%	679	3407	84.0%	2.6
Brakes	1149	17461.5	91.3%	187	3594	88.7%	6.1
Structure	847	18308.5	95.7%	196	3790	93.5%	4.3
Wheels and Tires	816	19124.5	100%	264	4054	100%	3.1
Total Fleet	19124			4054			4.7

Table 5.1 Scoop Fleet Pareto Analysis Calculation Results

Description	Hours	Cumulative	%Cum	Failures	Cumulative	%Cum	Average Repair time
Motors	2399.5	2399.5	23.5%	485	485	21.0%	4.9 Hr
Hydraulics	2375.5	4775	46.8%	548	1033	44.8%	4.3
Wheels and Tires	1723	6498	63.7%	421	1454	63.0%	4.1
Drivetrain	1523.5	8021.5	78.7%	222	1676	72.6%	6.9
Electrical	961	8982.5	88.1%	387	2063	89.4%	2.5
Misc.	477.5	9460	92.8%	81	2144	92.9%	5.9
Structure	382.5	9842.5	96.6%	111	2255	97.7%	3.4
Brakes	351.5	10194	100.0%	52	2307	100.0%	6.8
Fleet Total	**10194**			**2307**			**4.4**

Table 5.2 Truck Fleet Pareto Analysis Calculation Results

Description	Hours	Cumulative	%Cum	Failures	Cumulative	%Cum	Average Repair time
Drills	4248	4248	39.1%	966	966	38.5%	4.4
Hydraulics	4046	8294	76.3%	1087	2053	81.9%	3.7
Electrical	978	9272	85.3%	252	2305	91.9%	3.9
Misc.	616	9888	91.0%	25	2330	92.9%	24.6
Brakes	276	10163.5	93.5%	34	2364	94.3%	8.1
Wheels and Tires	230	10393	95.6%	51	2415	96.3%	4.5
Drivetrain	207	10600	97.5%	27	2442	97.4%	7.7
Motors	176	10775.5	99.1%	44	2486	99.2%	4.0
Structure	96	10871.5	100.0%	21	2507	100.0%	4.6
Fleet Total	**10871**			**2507**			**4.3**

Table 5.3 Drill Fleet Pareto Analysis Calculation Results

The Pareto Analysis revealed that at the fleet level repair time was being influenced by outside factors. To further evaluate the maintenance program an evaluation of the estimated repair times versus times to repair was performed Tables 5.4, 5.5 and 5.6 show that for trucks, scoops and drills; 156, 221 and 90 machine days of production were lost due to avoidable downtime. The large discrepancy between the estimated repair times and the times to repair again tends to support the earlier finding that factors other than actual repair times are affecting the time to repair. These hours were determined by obtaining estimates for repair times from the Central Shop Staff and subtracting twice the maximum estimated time from the actual repair times. The value obtained represents an estimate of unproductive non-active maintenance time, this was then multiplied by the utilization of availability (UA) to give an estimate of lost production. Twice the maximum estimated repair time was used to provide a conservative estimate of the downtime and to account for the range of failures contained in each code. A table of repair codes is attached in Appendix A.

Description	2*Estimated time hrs.	# of Failures	Days in shop	Hours	Hours needed to repair	Difference	Hours lost
400	24	11	96	1920	264	1656	850
604	40	5	48	960	200	760	390
410	6	6	27	540	36	504	259
500	20	5	30	600	100	500	257
650	10	6	24	480	60	420	215
310	3	3	17	340	9	331	170
520	16	1	17	340	16	324	166
140	5	4	16	320	20	300	154
110	7	3	14	280	21	259	133
600	30	7	22	440	210	230	118
624	3	1	9	180	3	177	91
610	10	3	10	200	30	170	87
606	16	2	9	180	32	148	76
524	10	2	7	140	20	120	62
130	3	1	5	100	3	97	50
100	5	1	4	80	5	75	38
						Days Lost	**156**

Table 5.4 Maintenance Hours in Excess of Estimated Repair Times for Trucks Jan 96- Mar 97 (Refer to Appendix A for definition of failure codes.)

Code	2*Estimated time hrs.	# Failures	Days in Shop	Hrs.	Hrs Needed to repair	Difference	Hrs. Lost
400	24	24	154	3080	576	2504	1255
430	24	9	57	1140	216	924	463
140	8	10	49	980	80	900	451
500	20	9	43	860	180	680	341
650	10	6	37	740	60	680	341
110	7	5	32	640	35	605	303
700	24	5	36	720	120	600	301
604	40	10	43	860	400	460	230
600	30	4	22	440	120	320	160
100	5	2	13	260	10	250	125
610	10	2	9	180	20	160	80
440	24	2	10	200	48	152	76
606	16	1	8	160	16	144	72
520	18	1	8	160	18	142	71
620	8	1	7	140	8	132	66
310	3	2	6	120	6	114	57
420	4	1	3	60	4	56	28
						Lost Days	**221**

Table 5.5 Maintenance Hours in Excess of Estimated Repair Times for Scoops Jan 96-Mar 97 (Refer to Appendix A for definition of failure codes.)

Code	2*Estimated time hrs.	# Failures	Days in Shop	Hrs.	Hrs. Needed to repair	Difference	Hrs. Lost
110	10	4	67	1340	40	1300	520
100	8	7	35	700	56	644	258
234	14	1	30	600	14	586	234
806	40	6	40	800	240	560	224
850	32	8	30	600	256	344	138
140	6	2	13	260	12	248	99
700	30	2	12	240	60	180	72
250	3	2	7	140	6	134	54
842	32	2	8	160	64	96	38
154	10	1	4	80	10	70	28
520	16	1	4	80	16	64	26
604	20	1	4	80	20	60	24
130	3	1	3	60	3	57	23
210	3	1	3	60	3	57	23
870	6	1	3	60	6	54	22
500	20	1	3	60	20	40	16
						Lost Days	**90**

Table 5.6 Maintenance Hours in Excess of Estimated Repair Times for Drills Jan 96- Mar 97 (Refer to Appendix A for definition of failure codes.)

5.1 Detailed Breakdown of Failures

To gain further insight into what was happening an analysis of total down hours by system and equipment type was performed. Figures 5.4 through 5.9 present a summary of failures by equipment and a summary of the major failure categories by equipment manufacturer. Tables 5.7, 5.8 and 5.9 give a detailed breakdown of the failures by code. A summary of the lost machine days due to maintenance, adjusted as indicated in section 5.0, is 956, 510 and 544 for scoops trucks and drills respectively.

For scoops 617 machine days representing 65% of the total time is due to repair of hydraulics, motors and drivetrains. Examining the breakdown by code given in Table 5.7 for scoops it is evident that:

I. For the hydraulic system: cylinders, oil leaks, valves and pumps account for 4126 of the total hours or 80% of the downtime.

II. For motors: temperature, scrubbers, turbos, motor changes, injector pumps, problems with acceleration, cylinder heads and fuel system valves account for 3963 hours or 85% of the total downtime.

III. For the drivetrain: torque converters, knuckle joints and differentials account for 1979 hours or 79% of the total downtime.

Within the scoop fleet, EJC-100 scoops required significantly more time for maintenance per machine for motor repairs. The Puma scoops required more downtime per machine for hydraulic maintenance.

For trucks, 325 machine days representing 64% of the total time is due to repairs of motors, hydraulics and wheels and tires. Examining the breakdown by code given in Table 5.8 for trucks it is evident that:

I. For motors: oil leaks, cylinder heads, over temperature, turbos, scrubbers and motor changes account for 1872 hours or 76% of the total downtime.

II. For the hydraulic system: valves, hoses, oil leaks and pumps account for 1847 hours or 79% of the total downtime.

Within the truck fleet, 15 ton trucks required more maintenance hours for; motor, hydraulic system and drivetrain repairs.

For drills 415 machine days representing 76% of the total downtime is due to repair of hydraulics and drill specific components. Examining the breakdown by code given in Table 5.9 for drills it is evident that:

I. For Drill Components: bits, chains, heads, booms, advance motors, water pumps and valves account for 3432 hours or 81% of the total downtime.

II. For the Hydraulic System: hoses, valves and oil leaks account for 3027 hours or 75% of the total downtime.

Within the drill fleet The Gardner-Denver drill required the most downtime per machine for maintenance.

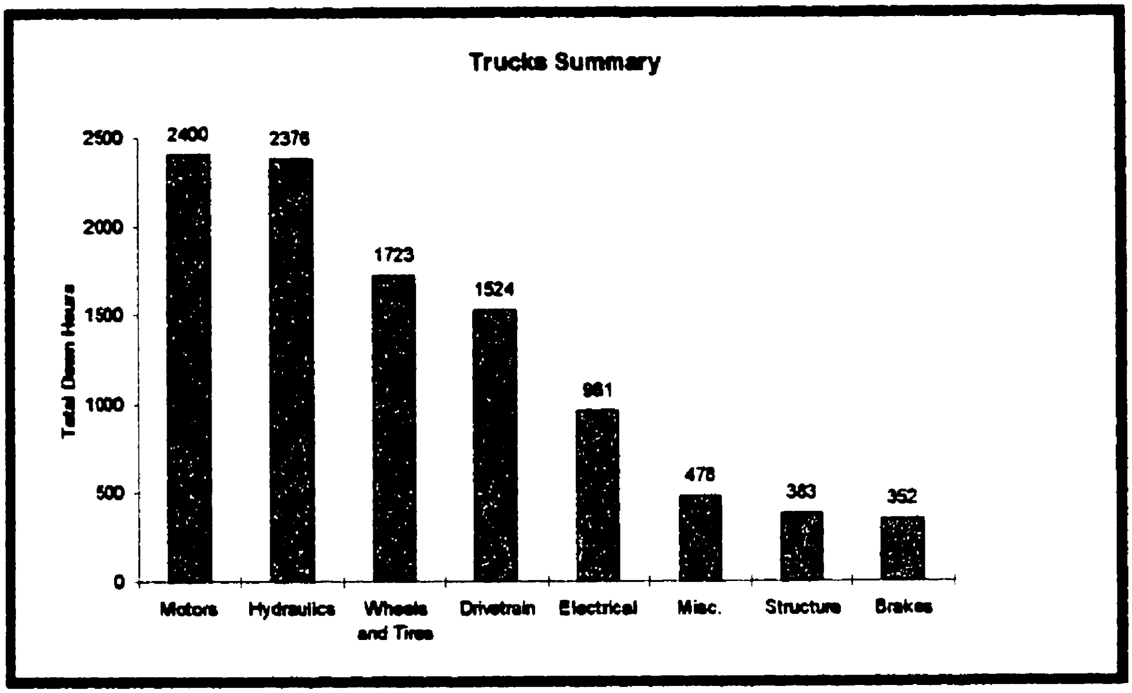


Figure 5.4 Truck Fleet Failures

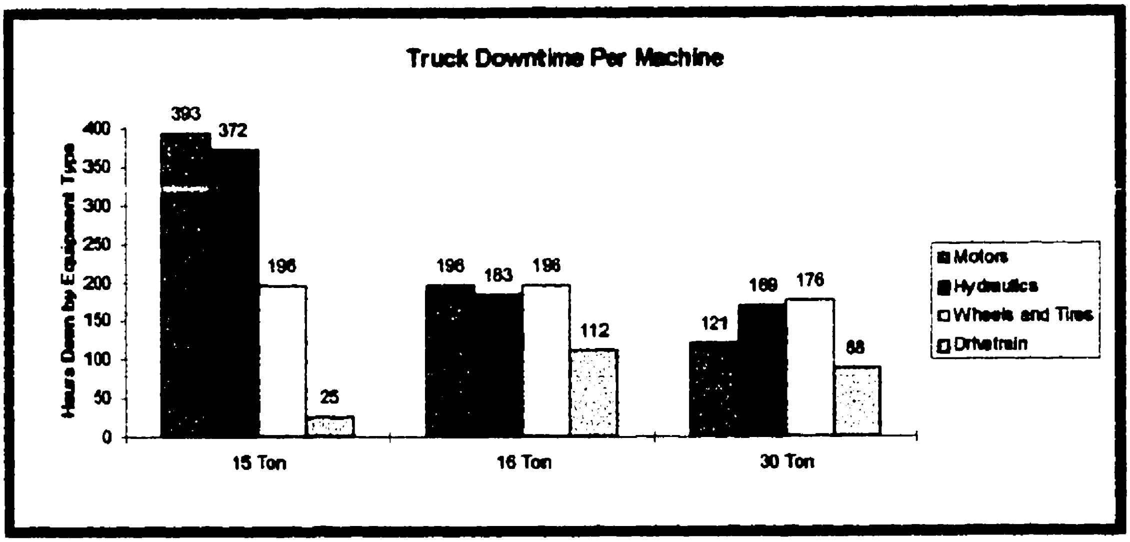


Figure 5.5 Major Truck Failures by Equipment Manufacturer

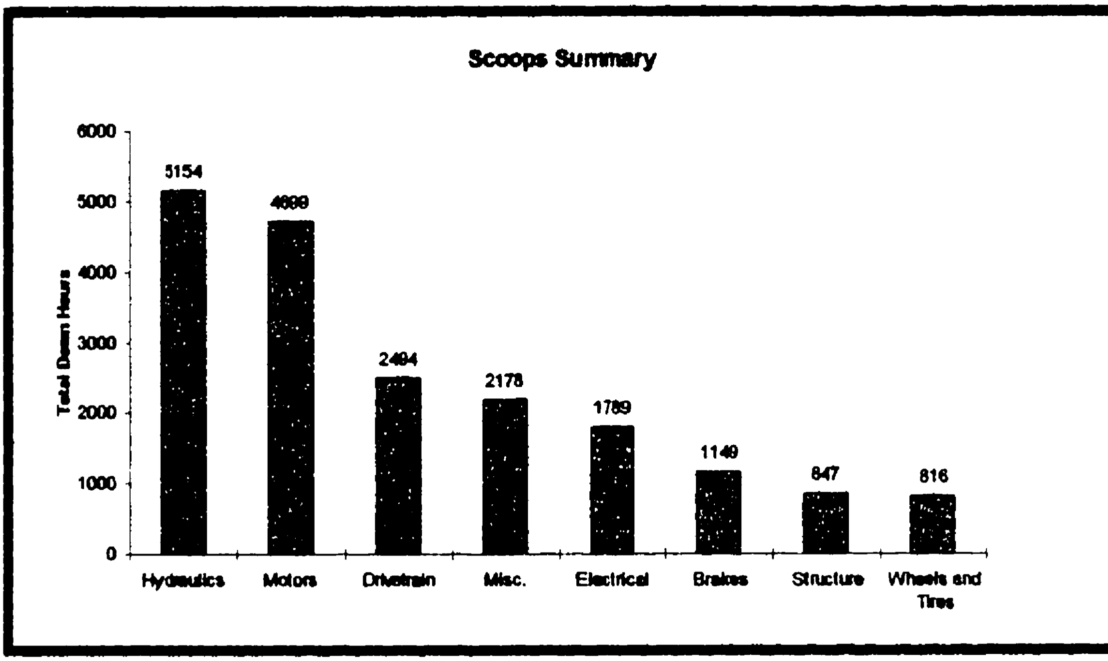


Figure 5.6 Scoop Fleet Failures

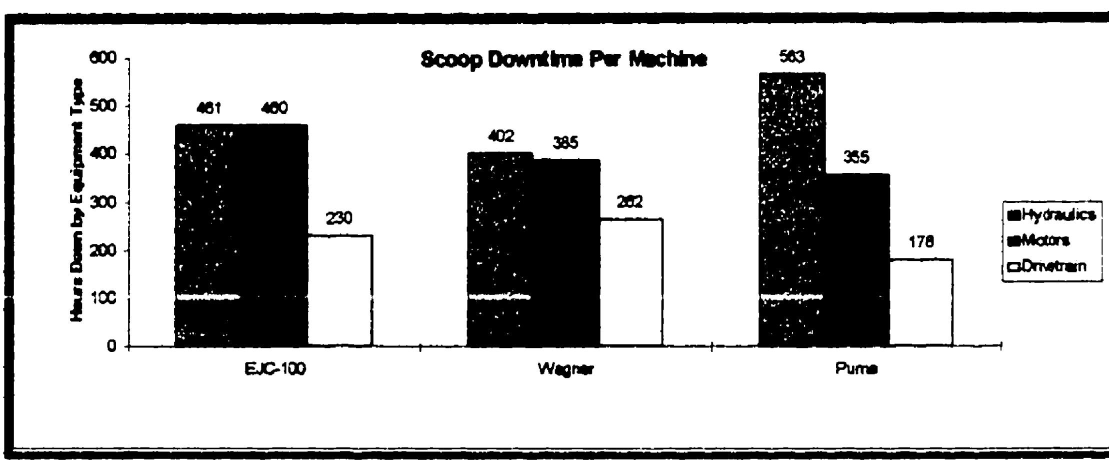


Figure 5.7 Major Scoop Failure by Equipment Manufacturer

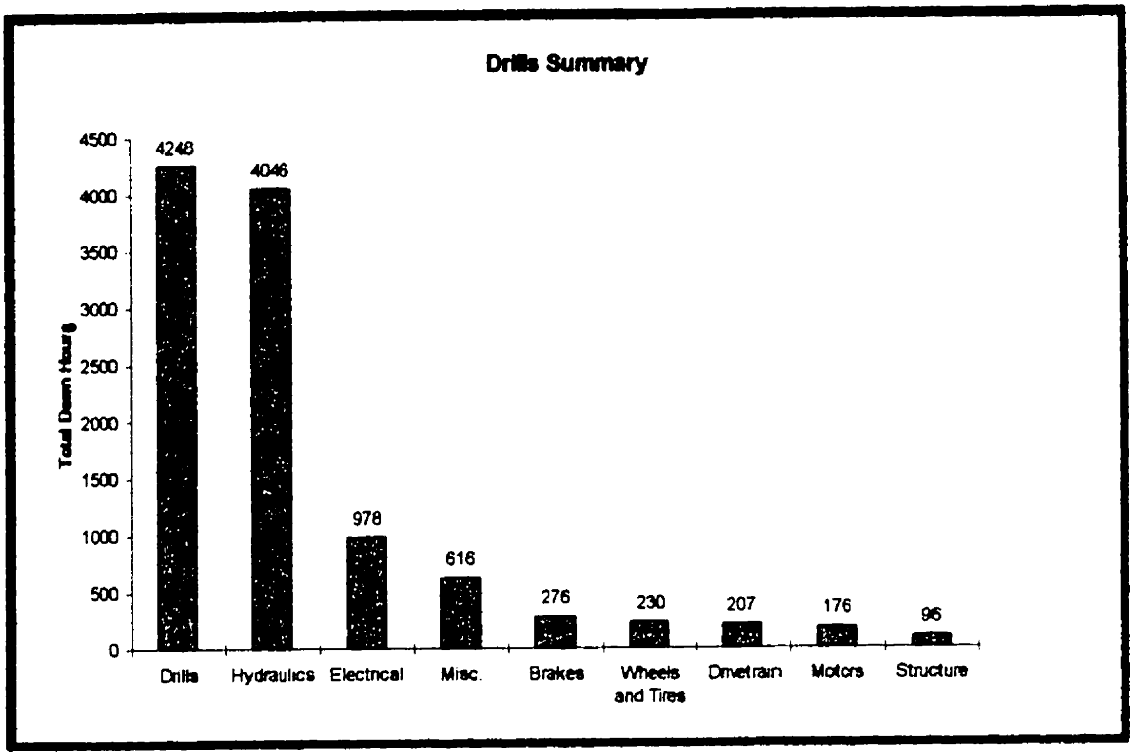


Figure 5.8 Drill Fleet Failures

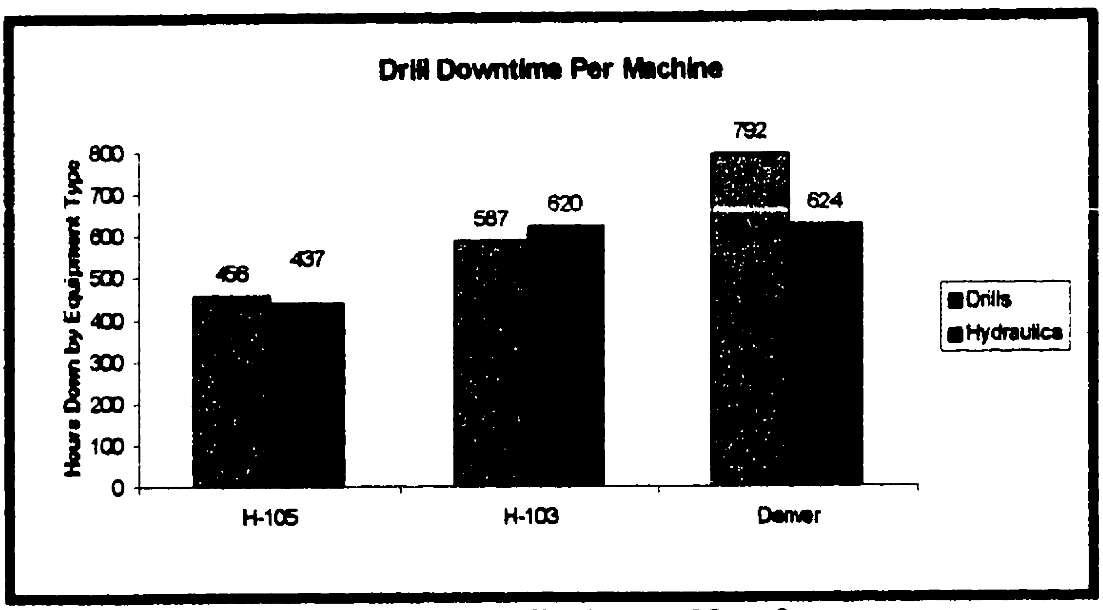


Figure 5.9 Major Drill Failures by Equipment Manufacturer

	Hydraulics			Motors			Drivetrain			Miscellaneous	
Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures
130	1492	326	650	1029	163	400	870	67	102	1447	26
154	1194	371	630	577	287	500	604	184	996	418	3
100	834	192	610	557	74	430	505	53	995	282	72
110	606	96	604	497	22	410	321	67	1000	32	3
140	573	84	620	491	90	440	104	9			
120	197	92	640	409	117	420	91	31			
150	170	54	600	403	31						
152	88	18	624	258	85						
			660	217	43						
			606	93	13						
			622	92	29						
			602	67	18						
			632	12	8						
	Electrical			Brakes			Stucture			Wheels and Tires	
Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures
250	724	256	700	675	98	520	353	90	310	751	240
230	267	102	710	336	66	522	141	38	320	66	24
210	264	80	720	107	17	530	119	15			
240	204	65	702	32	6	510	111	17			
200	126	81				512	82	31			
220	114	67				524	42	5			
232	87	27									
234	4	1									

Table 5.7 Scoop Fleet Failures by Code(Hours modified per section 5.0)

	Motors			Hydraulics			Wheels and Tires			Drivetrain	
Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures
660	403	68	100	544	108	310	1486	384	410	628	101
600	323	19	130	515	143	320	237	37	400	504	43
650	291	51	154	426	138				500	214	48
610	284	31	110	362	53				420	94	23
630	267	151	140	245	32				440	44	4
604	259	10	150	168	44				430	40	2
640	166	57	120	60	23				412	1	1
620	138	36	152	57	7						
624	90	23									
606	72	10									
602	64	11									
622	40	15									
632	6	3									
	Electrical			Miscellaneous			Stucture			Brakes	
Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures	Code	Hrs.	Failures
250	348	129	995	199	72	520	142	51	700	148	21
230	154	75	996	167	3	524	118	16	710	126	20
232	142	27	102	100	3	522	71	26	720	78	11
210	137	48	1000	12	3	512	42	13			
220	131	78				510	7	3			
200	51	30				530	4	2			

Table 5.8 Truck Fleet Failures by Code(Hours modified per section 5.0)

Hydraulics			Drills			Electrical			Miscellaneous		
Code	Hrs	Failures	Code	Hrs	Failures	Code	Hrs	Failures	Code	Hrs	Failures
130	1776	512	850	1290	208	210	362	102	102	258	12
100	634	124	870	626	142	250	324	77	986	200	2
154	617	216	810	468	227	234	120	16	996	158	11
110	362	56	806	432	36	232	60	9			
120	313	122	804	360	86	220	47	28			
140	269	41	866	256	63	200	43	17			
150	76	16	842	217	24	230	24	3			
			800	197	88						
			862	119	25						
			820	100	28						
			802	82	23						
			844	36	4						
			840	30	5						
			846	25	3						
			860	6	1						
			864	4	2						
			830	3	1						

Brakes		Wheels and Tires			Drivetrain			Motors			Stucture		
Hrs	Failures	Code	Hrs	Failures	Code	Hrs	Failures	Code	Hrs	Failures	Code	Hrs	Failures
189	23	310	214	48	500	148	21	604	50	3	520	83	18
49	4	320	16	3	400	54	5	640	26	11	524	8	1
31	5				412	6	1	600	22	2	522	6	2
8	2							630	14	7			
								624	14	5			
								602	13	2			
								622	12	5			
								660	8	3			
								650	7	3			
								620	6	1			
								632	4	1			
								606	1	1			

Table 5.9 Drill Fleet Failures by Code(Hours modified per section 5.0)

5.2 Discussion of Identified Problem Areas

The loss of 156, 221 and 90 machine days of production for trucks, scoops and drills as presented in tables 5.4, 5.5 and 5.6 indicate a high level of excess maintenance time. This high level of unproductive maintenance time is effectively biasing the repair time data such that effects of the actual repair time are hidden, resulting in a near linear relationship between downtime and number of failures. This could be attributed to poor labor productivity or waiting for resources to become available (spare parts, labor and shop space). Another plausible reason is that the low level of effective utilization is a result of an excess of equipment. Consequently, when equipment is down there is no rush to repair it. However, the view expressed by personnel at the mine is that availability of parts is the primary cause of the high level of unproductive maintenance downtime.

From the data it is apparent that for the fleet of equipment studied, motors, hydraulics, drivetrains, wheels and tires and drills account for the majority of the lost machine hours. Within these grouping of components the following is noted:

- The number of hours lost due to motor related failures is in the top two categories for trucks and scoops, but for drills, motors show up as the second lowest hours. The reason for this is that the drills used at the mine are electrically powered and electric motors are less prone to problems than the internal combustion engines on the scoops and trucks.
- The number of hours lost due to hydraulic related failures is in the top two categories for trucks, scoops and drills. For trucks and drills, oil leaks, valves and hoses are the primary causes of downtime within the category of hydraulic system failures. Whereas, for scoops cylinders, oil leaks and valves are the three most significant contributors to downtime. It is expected that cylinders would factor heavily in hydraulic failures for scoops due to the nature of the work performed by the scoops.
- It is interesting to note that for trucks wheels and tires are in the top four contributors to lost hours, yet for scoops wheels and tires are the lowest contributor to lost hours. This is not what is expected since, the scoops are working closest to the muck pile and thus are more apt to run over sharp rock fragments. Additionally, due to the method of filling the bucket by driving into the muck pile the scoop tires have a higher probability of wheel slip which would generally lead to an increased number of failures. A possible explanation for the role reversal of truck and scoop tire failures is that the trucks are

required to travel longer distances as they drive up out of the mine with ore to the plant.

- For scoops and trucks problems with the torque converter are among the top two contributors of lost hours.

6.0 Data Analysis: Evaluation Using Statistical Approach

The statistical analysis of the data presented in this thesis was performed using Weibull++™. This software has the capability of fitting: one and two parameter exponential, two and three parameter Weibull and two parameter lognormal distributions. The program has a built in "wizard" that will select the best fit for the data based on the Chi Square and Kolmogorov Smirnov (KS) goodness of fit tests discussed in section 2.4.5.2 . The user has various options for identifying the types of data being analyzed, censored, uncensored, grouped etc. Additionally, the two methods discussed in section 2.4.5.1 are available for calculating the parameters.

6.1 Treatment of Data

Due to the nature of the data available from the Rushton™ software several assumptions had to be made to fit distributions to it. The primary problem with the data was lack of information concerning Time Between Failures (TBF). The data available from the software contained only the date of the failure, the failure code and the hours to repair (TTR). Consequently, when more than one failure was recorded on the same date it was unclear as to what hours were operated between the failures. To compensate for this lack of information and obtain estimates for the time between failures the following approach was used:

- When more than one failure was recorded on the same day, the sum of the TTR's for all failures occurring on that date was used and the event was treated as one failure. For instances where the sum of the hours equaled 20 or greater, 20 was used since it represents the production operating hours.

- For failures that had multiple TTR's of 20 hours the first TTR less than 20 was included, even if it was against a different code. This was done to avoid a calculated zero TBF.
- Using the TTR as determined above the TBF was calculated using:

$$TBF = [(D_2 - D_1)*20 - TTR)]*EU \qquad [25]$$

Where:

D_2 is the date the failure occurred.

D_1 is the date the previous repair was completed.

20 is to convert days to shift hours.

TTR is the time to repair the previous failure.

EU: is the effective utilization of the equipment as given in section 4.1 equation 24.

- Obvious double entries of times to repair were adjusted. For example, if equipment was in on the same date for the same number of hours for motor overheating and motor change, the TTR hours were only used once.

Using the modified time to repairs will have the following implications:

- The TBF will be a rough approximation and their distribution will be influenced by the TTR distribution which may not represent their true distribution.
- Grouping TTR's on the same day into one event will tend to shift the distribution to the right.
- The estimate for the TBF will be shorter than the actual values.

6.2 Tests for Independence and Identical Distribution

Prior to fitting distributions to the data, tests to validate the assumption of independent and identically distributed data (IID) were performed. Figures 6.1 to 6.4 show samples of results obtained using the graphical techniques for trend and independence testing as discussed in section 2.4.4.

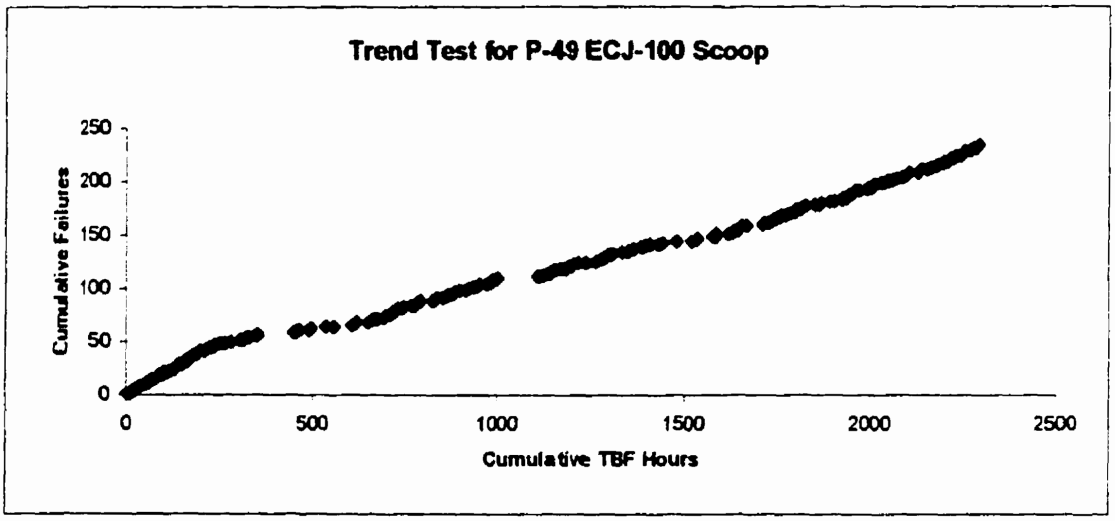


Figure 6.1 Trend Test for P-49

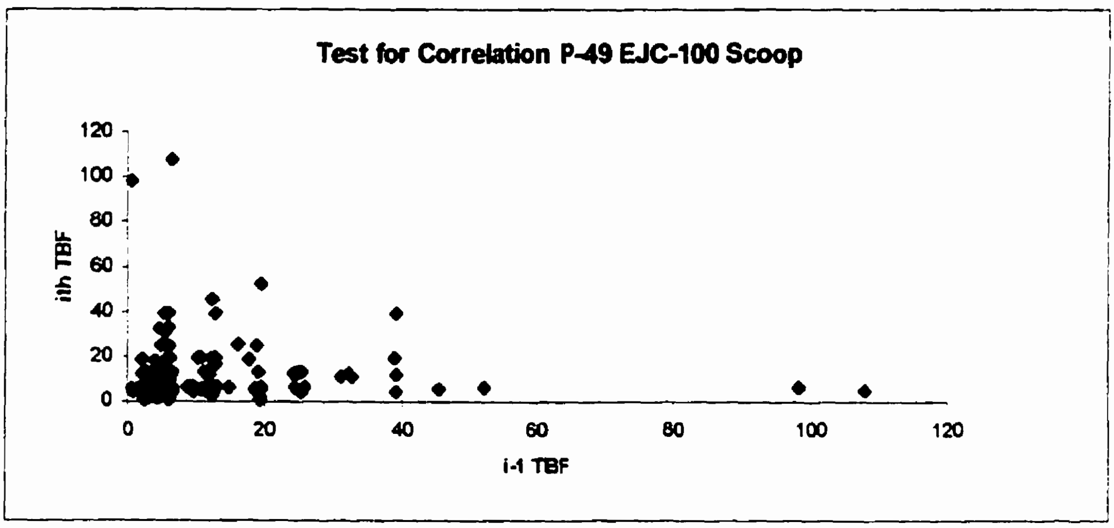


Figure 6.2 Correlation Test for P-49

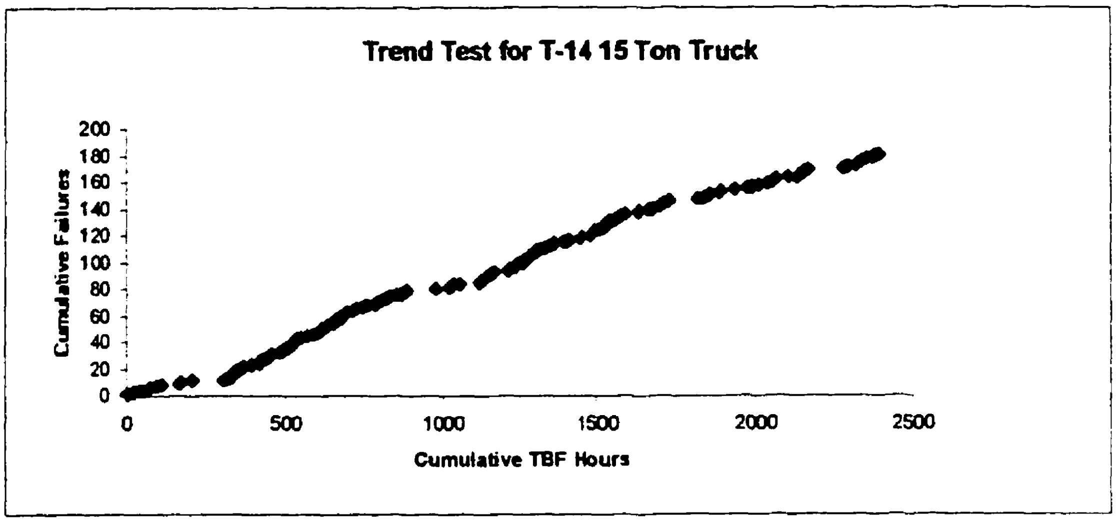


Figure 6.3 Trend Test for T-14

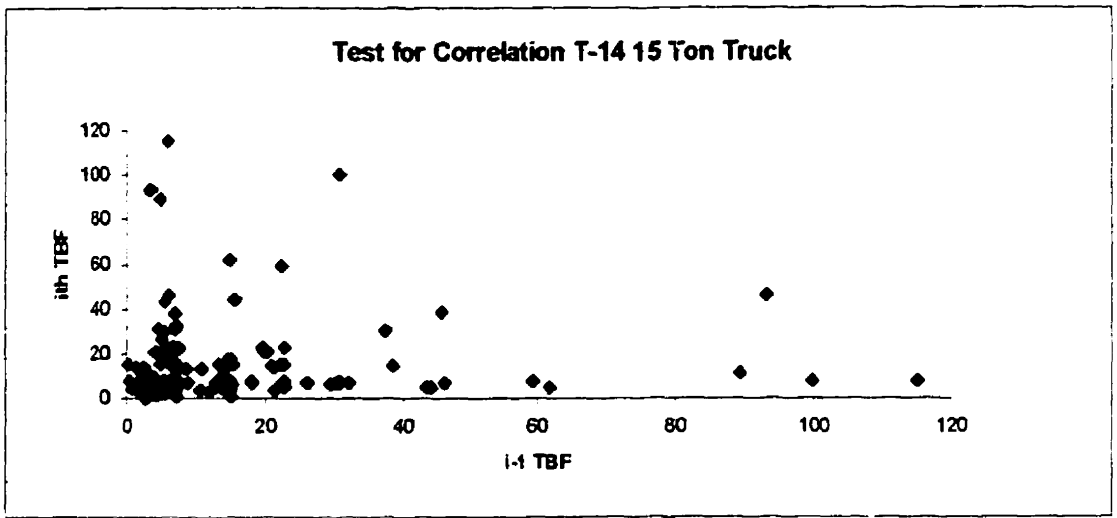


Figure 6.4 Correlation Test for T-14

The trend tests show that there are localized trends in the TBF's. These are indicated by the localized areas of deviation from the linear relationship. For example, between 300 and 350 cumulative TBF hours for P-49 the graph curves upward indicating that for this period of time the failure distribution is non-stationary. These localized trends are evident in all of the trend tests for both scoops and trucks. The test for correlation shows no discernible pattern for all cases. Consequently, the assumption of IID has not been rejected and distributions can be fit to the data using the stationary techniques discussed in section 2.4.

6.3 Distribution of Time Between Failures Entire Machine

Table 6.1 and 6.2 show the parameters obtained for a theoretical distribution fitted to the TBF of the scoops and trucks. The best fit is the lognormal distribution given by equation [7]

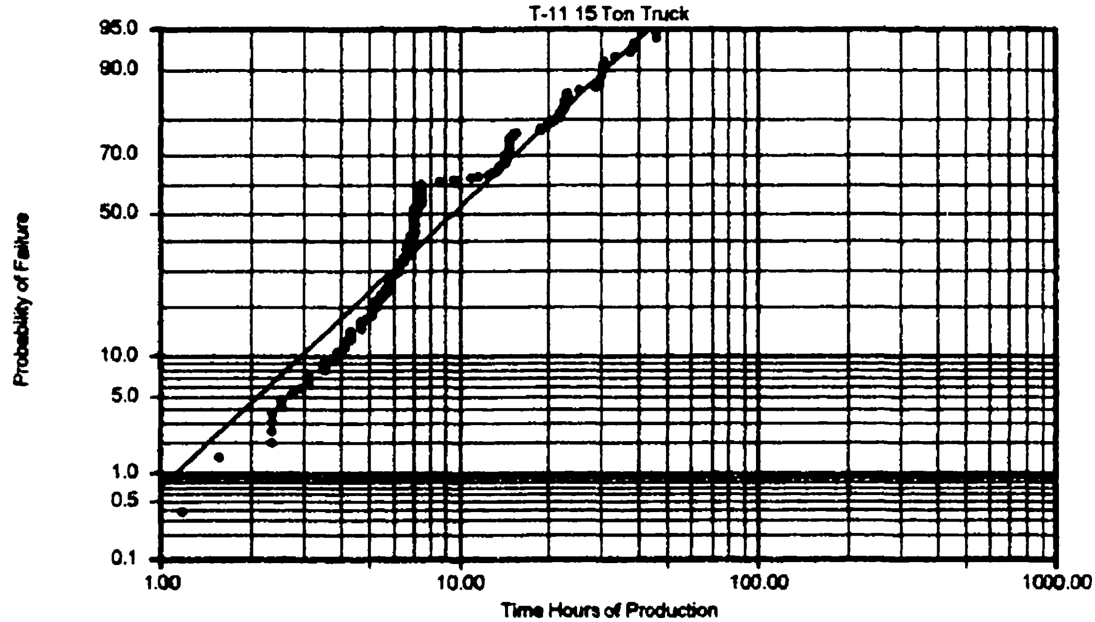
Figures 6.5 and 6.6 show sample plots of the probability of failure, the reliability, the failure rate and the probability density corresponding to the fitted distributions.

	T-10	T-11	T-14	T-15	Fleet
μ	2.2501	2.0616	2.1440	2.1353	2.1418
σ	0.9205	0.8697	0.9446	0.9721	0.9163
MTBF	14.4944	11.4706	13.3316	13.5690	12.9566
N	182	234	181	200	797

Table 6.1 Lognormal distribution parameters for TBF for 15 ton trucks

	P-44	P-45	P-46	P-48	P-49	P-50	P-51	Fleet
μ	2.1237	1.7694	1.9369	1.8145	1.9626	1.9135	1.8163	1.8972
σ	0.9083	0.8332	0.8355	0.7729	0.7680	0.8106	0.8213	0.8162
MTBF	12.6316	8.3021	9.8348	8.2746	9.5593	9.4125	8.6155	9.3026
N	178	242	225	228	234	233	230	1570

Table 6.2 Lognormal distribution parameters for TBF EJC-100 scoops



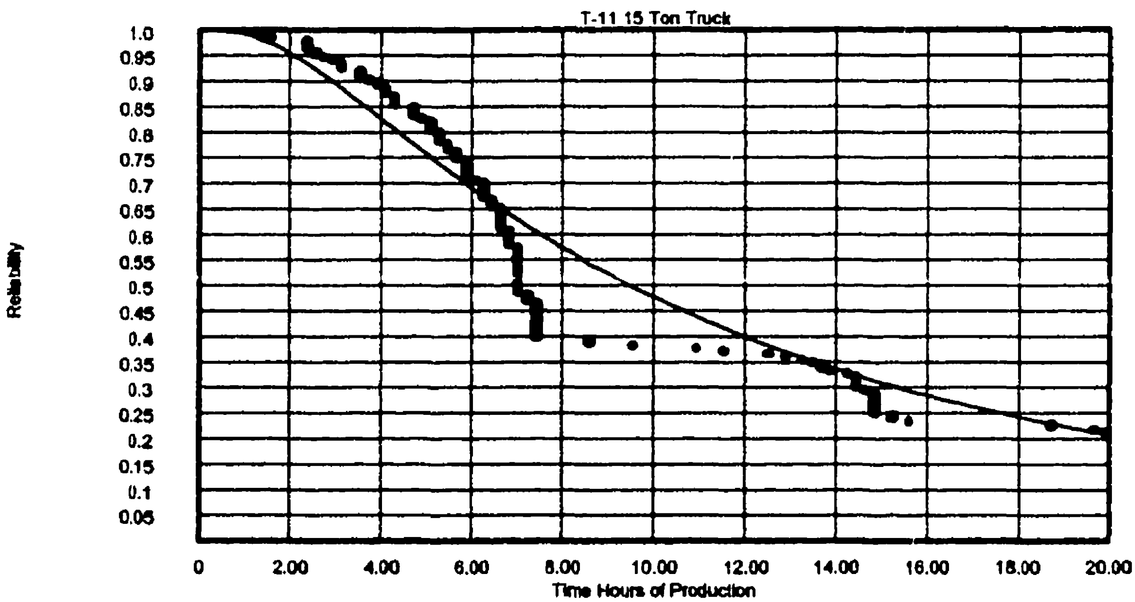
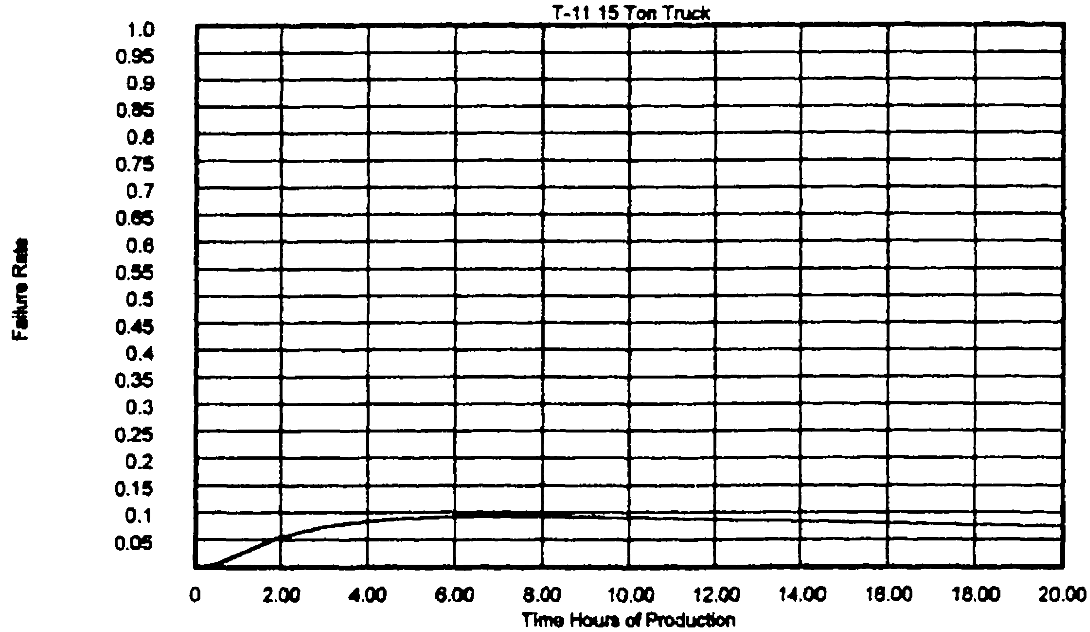


Figure 6.5 Probability of Failure and Reliability Plots for T-11



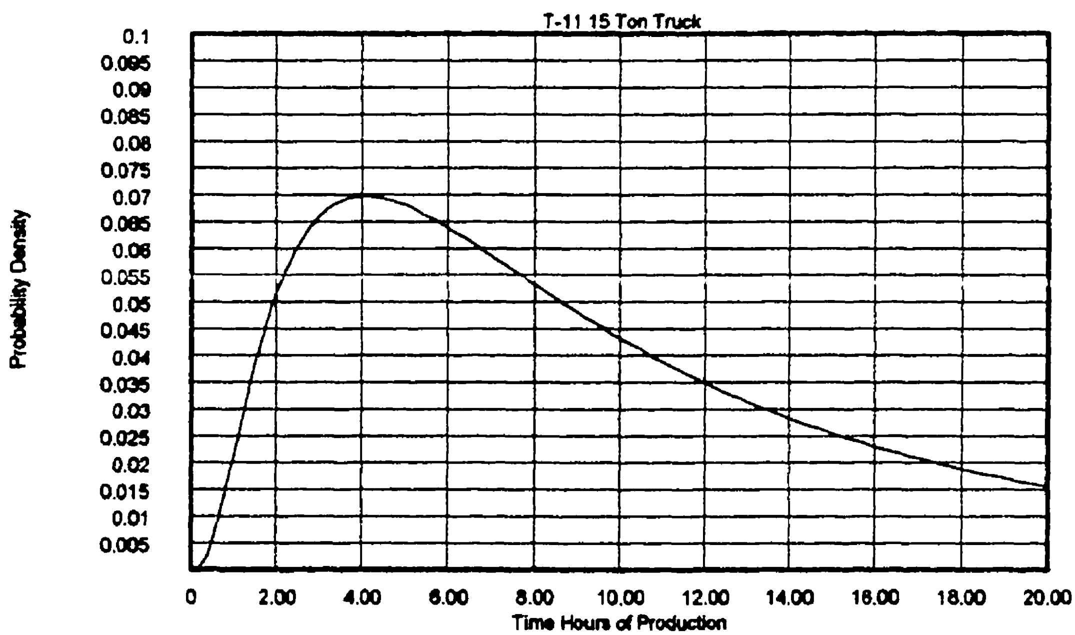


Figure 6.6 Failure Rate and Failure Probability Density Function for T-11

6.4 Distribution for TBF of Truck Components

To investigate the critical components for the trucks indicated in section 5, distribution were fitted to the data for motors, drivetrains and hydraulic systems. The resulting best fit distribution and corresponding parameters are shown in Table 6.3. Testing of the component data for IID showed no correlation, but the hydraulics systems showed evidence of trends.

	Motors	**Drivetrain**	**Hydraulics**
T-10	β=0.7028	β=0.6083	μ=2.9958
	η= 48.6823	η= 103.046	σ=1.4694
	γ= 3.0094	γ= 1.1998	γ= n/a
Mean life (hrs)	m=64.4120	m=153.5262	m=58.8722
Failures	N=50	N=22	N=58
Distribution	Weibull	Weibull	Lognormal
T-11	β=0.8445	β=0.9428	μ=3.2433
	η= 46.7676	η= 57.7742	σ=1.1461
	γ= 0.5997	γ= 0	γ= n/a
Mean life (hrs)	m=51.6889	m=59.3448	m=49.4060
Failures	N=58	N=55	N=72
Distribution	Weibull	Weibull	Lognormal
T-14	β=0.7462	β=0.5560	β=0.6465
	η= 30.6291	η= 51.7540	η= 35.7017
	γ= 1.7409	γ= 2.6799	γ= 3.6753
Mean life (hrs)	m=38.3629	m=89.3401	m=52.7486
Failures	N=50	N=32	N=62
Distribution	Weibull	Weibull	Weibull
T-15	μ=3.3490	β=0.6841	β=0.6236
	σ=1.3570	η=87.2276	η= 34.8861
	γ= n/a	γ= 0.8166	γ= 3.0640
Mean life (hrs)	m=71.5019	m=113.7372	m=53.0729
Failures	N=57	N=29	N=62
Distribution	Lognormal	Weibull	Weibull
Fleet	β=0.8449	β=0.7492	μ=3.1419
	η= 45.9070	η= 69.0348	σ=1.2968
	γ= 0.3881	γ= 0.7596	γ= n/a
Mean life (hrs)	m=50.5221	m=83.0275	m=53.6641
Failures	N=238	N=138	N=254
Distribution	Weibull	Weibull	Lognormal

Table 6.3 Distribution for Truck Components

6.5 Distributions for Time to Repair

Tables 6.4 and 6.6 show the parameters obtained for a theoretical distribution fitted to the TTR for the trucks and scoops respectively, before they were grouped as discussed in section 6.1. Tables 6.5 and 6.7 show the parameters obtained for the scoops and trucks after treatment of the data. For both the original and treated data the best fit is the lognormal distribution given by equation [7]

	T-10	T-11	T-14	T-15	Fleet
μ	1.1245	1.1785	1.1337	1.0750	1.1305
σ	1.0641	0.9875	1.1361	1.1256	1.06625
MTTR	5.4234	5.2914	5.9243	5.5206	5.4679
N	295	367	300	303	1265

Table 6.4 Lognormal distribution parameters for original TTR for 15 ton trucks

	T-10	T-11	T-14	T-15	Fleet
μ	1.4673	1.5783	1.5931	1.4302	1.5192
σ	1.0139	1.0782	1.3003	1.2321	1.1467
N	182	234	181	200	797

Table 6.5 Lognormal distribution parameters for modified TTR for 15 ton trucks

	P-44	P-45	P-46	P-48	P-49	P-50	P-51	Fleet
μ	1.0266	1.0431	1.0357	0.8862	0.8702	0.8970	0.9832	0.9599
σ	1.0121	1.0350	0.9431	0.9591	1.0088	1.0238	0.9985	0.9922
MTTR	4.6403	4.8487	4.3948	3.8426	3.9711	4.1416	4.4004	4.2722
N	294	407	379	414	387	404	419	2704

Table 6.6 Lognormal distribution parameters for original TTR EJC-100 scoops

	P-44	P-45	P-46	P-48	P-49	P-50	P-51	Fleet
μ	1.4415	1.5426	1.5125	1.4826	1.3059	1.3953	1.5506	1.4621
σ	1.1446	1.1483	1.0386	0.9838	1.1217	1.1456	1.1091	1.0894
N	178	242	225	228	234	233	230	1570

Table 6.7 Lognormal distribution parameters for modified TTR EJC-100 scoops

6.6 Discussion of Statistical Results

The results for the individual machine and for the fleet presented in tables 6.1 and 6.2 allow several observations to be made. Looking at the μ parameter for the lognormal function and realizing that this is the mean of the natural logarithm of the data it can be seen that for both scoops and trucks there is no one single piece of equipment whose mean time between failures (MTBF) is dramatically different from that of the fleet. This shows that no one piece of equipment is significantly worse than any other. Additionally, the overall MTBF is extremely low, ranging from 11.5 to

14.5 hours of production for trucks and 8.3 to 12.6 hours for scoops. This low MTBF suggests that equipment may not be repaired properly when it leaves the shop. Other factors that can cause low MTBF are:

- Equipment or its components are not suitably designed for the application.
- The equipment has been improperly selected for the given mining conditions.
- Personnel are operating the equipment in an abusive manner resulting in premature failures.

Table 6.3 lists the distributions fitted to the failure data of the 15 ton trucks for the three critical systems. Among these we see that:

- The best fit distribution for the data for the hydraulic system and motors varies between Weibull and Lognormal. In contrast, the Weibull distribution provides the best fit in all cases for the drivetrain data.
- Within the analysis of the fleet, the MTBF is 51, 54, and 83 operating hours for motors, hydraulics and drivetrains. This ordering implies that motors are more troublesome than hydraulics which are more troublesome than drivetrains. This ranking of mean time between failures confirms what is shown in Figure 5.5 which was obtained by a simple plot of the hours spent in the shop.
- In all cases where the Weibull distribution was found to provide the best fit, β is less than one. This corresponds to a decreasing failure rate which is indicative of infant mortality type failures. Thus, the failures are being induced by improper maintenance procedures or replacement components which are faulty. Plots of the failure rate for the instances where the Lognormal distribution provides the best fit also indicate a decreasing failure rate.

The results for the distributions fit to the original TTR when compared to those for the modified TTR indicate that:

- Modifying the TTRs as discussed in section 6.1 did not change the type of best fit distribution. In all cases the Lognormal distribution provides the best fit distribution.
- As expected, grouping the hours in the shop for more than one failure on the same day resulted in a shift of the distribution to the right. This is indicated by the increase in μ.
- Judging by the reduction in the data set between the original TTR and the modified TTR it appears that the TBF calculated from the modified TTR should be conservative.

From the original data the mean time to repair was found to vary between 5.3 and 5.9 hours for 15 ton trucks and 3.8 and 4.8 hours for scoops. In comparing these numbers with those shown in tables 5.1 and 5.2 which show the mean time to repair as 4.4 and 4.7 hours for trucks and scoops it can be seen that the difference in estimated time to repair each piece of equipment is slightly higher using the original data, as would be expected.

6.7 Effects of Treatment of Data

The discussion in section 6.6 presents valid observations based on the data and the assumptions made in its treatment. However, Figure 6.5 shows obvious points of discontinuity in the data at around 7.8 and 15.6 hours. Although not shown graphically, these discontinuities appear in all of the data sets. The consistency with which these discontinuities occur suggests that they are being induced by the treatment of the data. Recall that due to the lack of records of operating hours between failures it was necessary to estimate the TBF using equation [25], repeated below.

$TBF = [(D_2 - D_1)*20 - TTR]*EU$ where EU =0.39

From this equation it can be seen that for failures one day apart the maximum estimated TBF will be 7.8 hours which corresponds to a zero time to repair. Furthermore for failures occurring two days apart the maximum estimated TBF would be 15.6 hours. Thus, when the difference between D_2 and D_1 changes from one day to two, the TBF jumps from slightly below 7.8 hours to something above. The actual magnitude of the jump is determined by how small the last TTR was on the previous day. This process repeats itself in multiples of 7.8 hours.

Figure 6.6 shows a plot of reliability for Load Haul Dump machines derived by analyzing data presented by Kumar (Kumar, 1990) which exhibits discontinuities at approximately, 8, 19, 38, 55 and 77 hours. In this paper no mention is made of these discontinuities. The discontinuities in the TBF data appear to be occurring at multiples of 19 hours. This highlights a problem with collection of failure data in general, in that a continuous distribution is fit to data recorded at fixed time interval resolutions. For the data presented in this thesis, the cause of the discontinuities has been identified as an artifact of the data treatment. If the data used to fit Figure 6.5 was not being influenced by the data treatment, the data would tend to spread itself out in a manner consistent with its distribution. Thus, the curve fit to the distribution which estimates the least square fit amongst the points actually does a good job of approximating the underlying behavior. Although the exact location of the

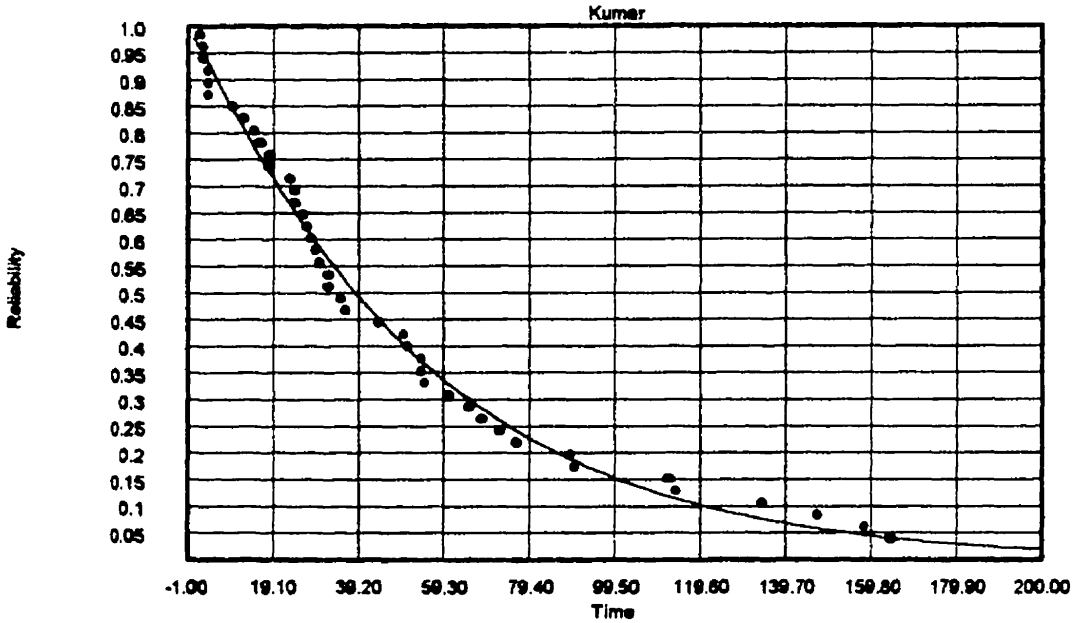


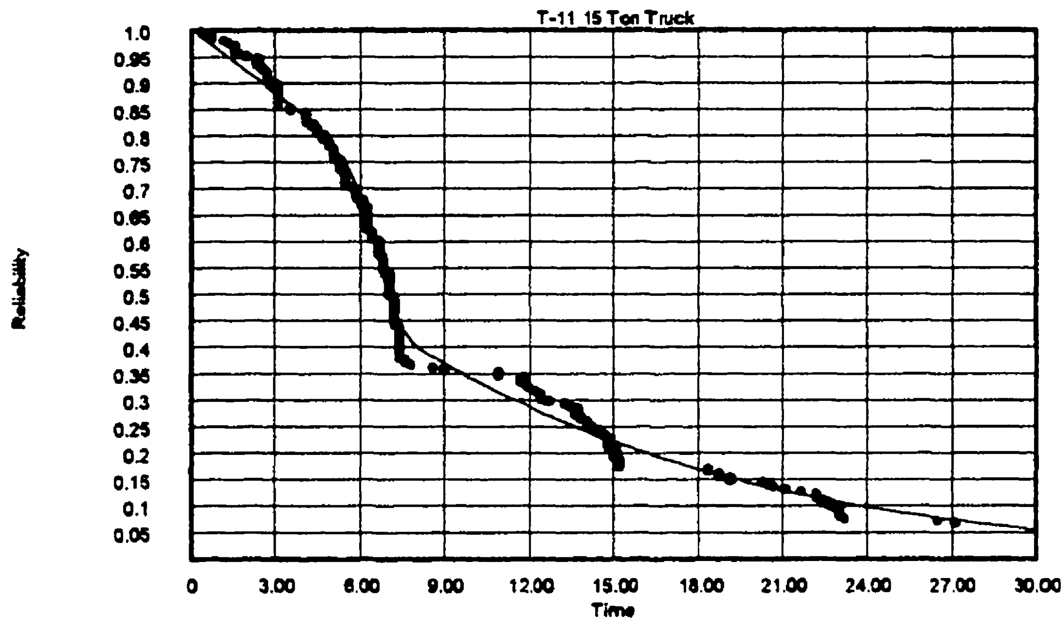
Figure 6.6 Reliability Plot For Load Haul Dump Machines Data from Kumar. (Kumar, 1990)

curve might change slightly, the fitted distribution is consistent with the actual behavior and consequently presents a valid estimate of the reliability of the equipment given the limitations of the data available

If the shape of the distribution fitted to the data as shown in Figure 6.5 was not due to the treatment of the data it could be due to the failure data representing different periods in the life cycle of the equipment. In essence, the data could contain sub-populations which represent a particular stage of the equipment's life. Under these circumstances it would require that a multi-population Weibull distribution be fitted to the data. For illustrative purposes this has been done to the data for truck T-11. Figure 6.7 and 6.8 show the reliability and failure rate graphs for a 2 and 3 population Weibull distribution fitted to the failure data for T-11. From these figures it can be seen that the resulting curves tend to follow the data better. This is particularly apparent in the 3 population failure rate graph which shows the discontinuity in the data. The parameter obtained for these distributions are shown in Table 6.8.

Population	**1** (2 Subsets)	**2** (2 Subsets)	**1** (3 Subsets)	**2** (3 Subsets)	**3** (3 Subsets)
β	9.479	1.1366	2.4309	14.0202	1.6671
η	6.727	13.223	4.3558	6.9890	17.4646

Table 6.8 Multi-Population Weibull Distribution Calculated Parameters for T-11



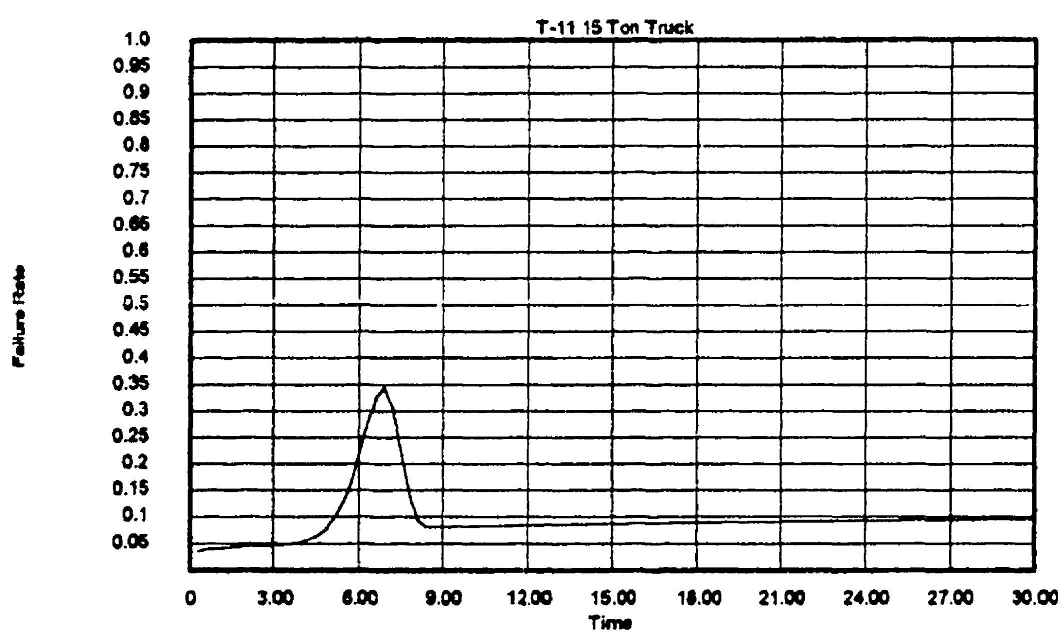
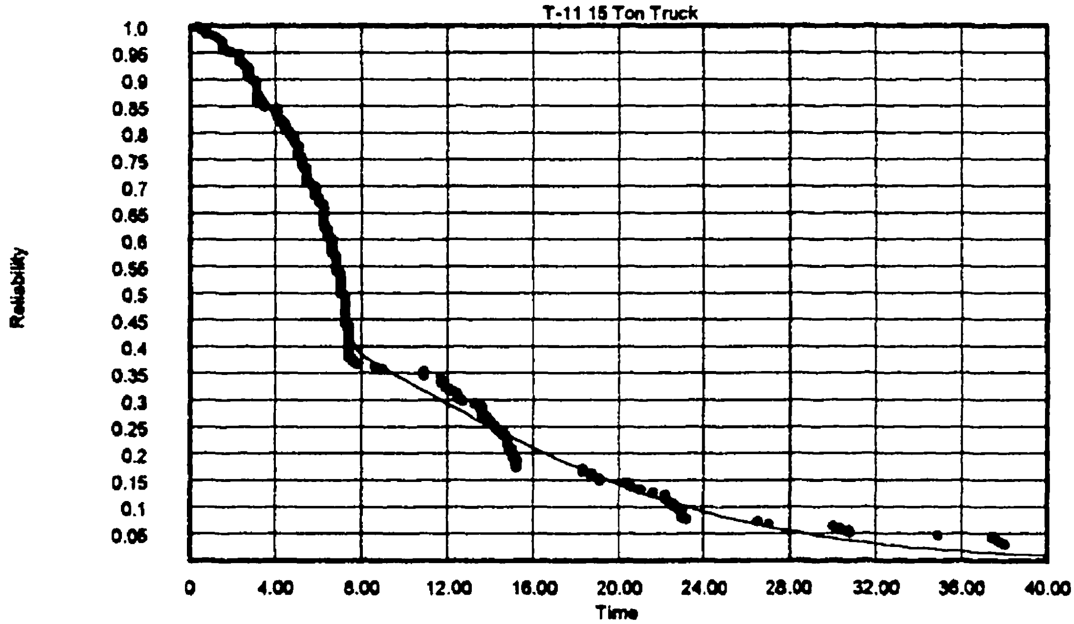


Figure 6.7 Reliability and Failure Rate Plot Obtained Using a 2 Population Mixed Weibull Distribution



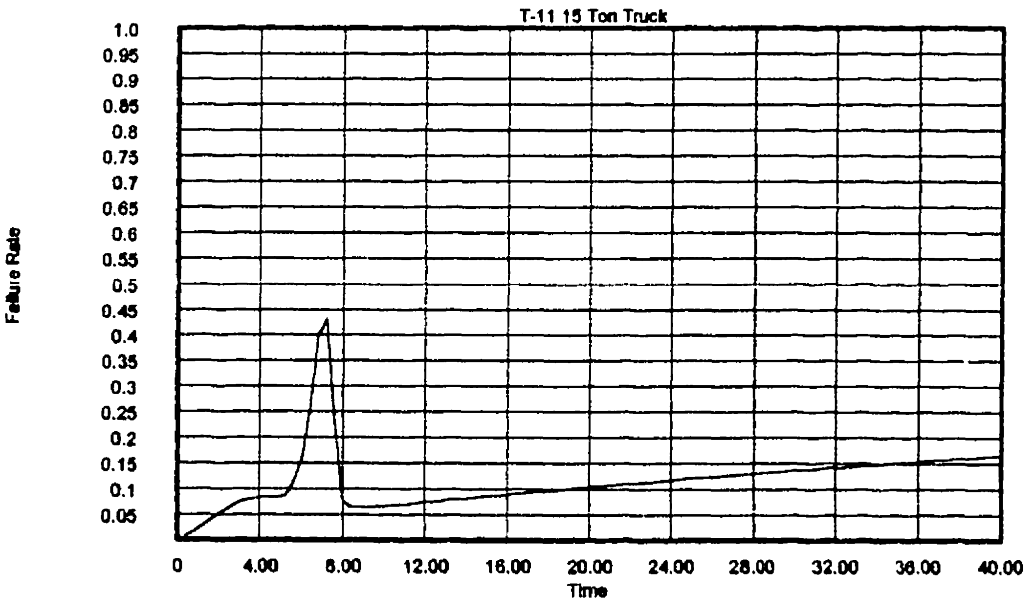


Figure 6.8 Reliability and Failure Rate Plot Obtained Using a 3 Population Mixed Weibull Distribution

7.0 Oil Analysis

To investigate the impact of the existing oil analysis program on maintenance, the results from oil samples from January 1996 until December 1996 were obtained from Esso's laboratory in Antofogasta. From this database the samples specific to the EJC-100 scoops and the 15 tons trucks were extracted. Tables 7.1 and 7.2 show motor failures and the corresponding oil sample history for EJC-100 scoops and 15 ton trucks respectively. Definitions of the symbols used in Tables 7.1 and 7.2 are shown in section 2.3.2 .

To determine if the data in Tables 7.1 and 7.2 could have predicted an incipient motor failure it was necessary to determine prediction criteria. To accomplish this a frequency distribution of each element was plotted and the 90^{th} and 95^{th} percentiles were calculated. The X percentile of a population gives the value of which X percentage of the data fall below. For example, the 95^{th} percentile of copper concentration was calculated to be 71 parts per million (PPM) for EJC-100 scoop motors, which implies that only 5% of the EJC-100 motor results were copper concentrations greater than 71(PPM). As an example, Figure 7.1 shows the distribution of Iron (FE) for EJC-100 scoop motors. All of the frequency distribution plots are included in Appendix B. Based on the shape of the frequency plots and the fact that obvious anomalies were included in the percentile calculations it was decided that the 95^{th} percentile would be used as the cut off. This failure criteria is independent of trending results from previous oil samples. Using the 95^{th} percentile for the cut off for each element measured, the data in Tables 7.1 and 7.2 were analyzed to determine incidences where oil samples revealed abnormal levels of elements prior to engine failure. The results are shown in Table 7.3

According to this table a shorter turn around time and appropriate trending analysis of oil sample data would have indicated at least seven incipient motor failures. Five of these failures resulted in motor changes, (four for EJC-100 scoops and one for 15 ton trucks).

Equip. #	Failure Date	Repair Date	Description	Sample Dates	Arrival at Laboratory	Analaysis Complete	FE	CR	AL	CU	PB	SI	NA	B	CA	Water	VISC
P-44				16-Jan-96	08-Feb-96	13-Feb-96	48	1	4	131	31	21	29	177	96	No	21.42
P-44	17-Feb-96	22-Feb-96	Change Motor	07-Feb-96	14-Mar-96	16-Mar-96	64	1	17	72	17	21	13	293	105	Trace	17.91
P-44	14-Mar-96	16-Mar-96	Over Temperature														
P-44	3-Sep-96	7-Sep-09	Over Temperature	23-Aug-96	05-Sep-96	11-Sep-96	55	2	3	8	7	15	5	131	77	No	19.26
P-45				21-Nov-96	27-Dec-96	10-Jan-97	39	1	21	14	14	11	216	157	55	Yes	45.47
P-45	8-Dec-96	17-Dec-96	Change Motor	04-Dec-96	27-Dec-96	10-Jan-97	23	1	24	11	7	10	216	145	47	Yes	19.27
P-46				02-Jun-96	17-Jul-96	18-Jul-96	36	0	6	9	0	14	2	149	86	No	22.89
P-46	20-Aug-96	3-Sep-96	Change Motor	27-Jun-96	05-Sep-96	11-Sep-96	78	3	12	24	5	27	24	173	120	No	30.82
P-48				06-Mar-96	14-Mar-96	16-Mar-96	28	0	24	8	2	23	86	265	92	Yes	18.72
P-48	6-Apr-96	8-Apr-96	Cylinder Head	16-Mar-96	12-Apr-96	19-Apr-96	31	0	14	9	4	20	76	369	97	No	20.97
P-49	15-Jan-96	17-Jan-96	Cylinder Head	28-Dec-95	15-Jan-96	25-Jan-96	32	0	1	6	2	12	61	176	86	No	18.96
P-49				16-Jan-96	08-Feb-96	13-Feb-96	60	1	15	9	5	20	45	192	98	No	22.89
P-49	12-Feb-96	17-Feb-96	Turbo	31-Jan-96	08-Feb-96	13-Feb-96	103	4	14	129	66	31	42	150	99	Trace	22.45
P-50				21-Dec-95	15-Jan-96	25-Jan-96	44	2	1	20	15	16	15	173	89	No	17.76
P-50	9-Jan-96	11-Jan-96	Change Motor	08-Jan-96	08-Feb-96	13-Feb-96	43	1	1	8	5	11	14	147	81	No	18.32
P-50				19-Nov-96	27-Dec-96	10-Jan-97	36	0	10	24	6	12	113	113	234	Yes	22.60
P-50	4-Dec-96	6-Dec-96	Valves Fuel Sys.	02-Dec-96	27-Dec-96	10-Jan-97	37	2	9	12	6	17	94	164	77	No	20.40
P-51				27-May-96	17-Jul-96	18-Jul-96	14	0	1	4	0	7	2	143	78	No	17.00
P-51	9-Aug-96	14-Aug-96	Change Motor	17-Jul-96	05-Sep-96	11-Sep-96	58	2	4	10	6	13	4	144	90	No	16.4

Table 7.1 EJC-100 scoop motor failures and corresponding oil analysis data (Concentration in PPM)

Equip. #	Failure Date	Repair Date	Description	Sample Dates	Arrival at Laboratory	Analaysis Complete	FE	AL	CU	PB	SI	NA	B	CA	Water	VISC
T-11	31-Jan-96	2-Feb-96	Over Temperature	24-Jan-96	8-Feb-96	13-Feb-96	32	1	8	5	15	8	153	88	Trace	17.86
T-11				4-Jun-96	17-Jul-96	18-Jul-96	19	4	6	0	11	0	146	73	No	17.77
T-11				21-Jun-96	17-Jul-96	18-Jul-96	16	3	6	0	11	0	127	75	No	18.06
T-11	26-Jul-96	28-Jul-96	Cylinder Heads	23-Jul-96	6-Sep-96	11-Sep-96	5	0	4	3	3	2	136	69	No	15.11
T-11				9-Aug-96	6-Sep-96	11-Sep-96	27	8	15	5	20	10	147	75	No	17.66
T-11				11-Sep-96	8-Nov-96	19-Nov-96	15	1	7	3	11	3	146	58	No	15.59
T-11	19-Oct-96	21-Oct-96	Change Motor	15-Oct-96	11-Nov-96	19-Nov-96	38	2	19	16	19	925	179	85	No	16.57
T-14	7-Jan-96	19-Jan-96	Change Motor	3-Jan-96	15-Jan-96	25-Jan-96	25	0	5	3	10	25	154	66	No	15.56
T-14				29-Apr-96	17-May-96	22-May-96	16	0	5	0	13	45	120	84	No	16.79
T-14	26-May-96	7-Jun-96	Motor Air Cond	9-May-96	17-May-96	22-May-96	39	0	16	0	33	151	185	198	No	16.54
T-14				22-Jul-96	6-Sep-96	11-Sep-96	32	2	14	6	14	7	148	85	No	17.60
T-14	31-Aug-96	5-Sep-96	Over Temperature	23-Aug-96	6-Sep-96	11-Sep-96	35	11	18	7	13	195	158	76	No	19.40
T-14				25-Oct-96	11-Nov-96	19-Nov-96	62	1	19	7	13	216	155	66	No	18.52
T-14				8-Nov-96	27-Dec-96	10-Jan-97	73	13	33	15	30	57	159	76	No	19.64
T-14	16-Dec-96	3-Jan-97	Change Motor	26-Nov-96	27-Dec-96	10-Jan-97	134	84	35	21	40	204	171	78	No	28.82
T-15				8-Feb-96	14-Mar-96	16-Mar-96	23	0	5	3	8	1	229	77	No	15.45

Table 7.2 15 ton truck motor failures and corresponding oil analysis data(Concentration in PPM)

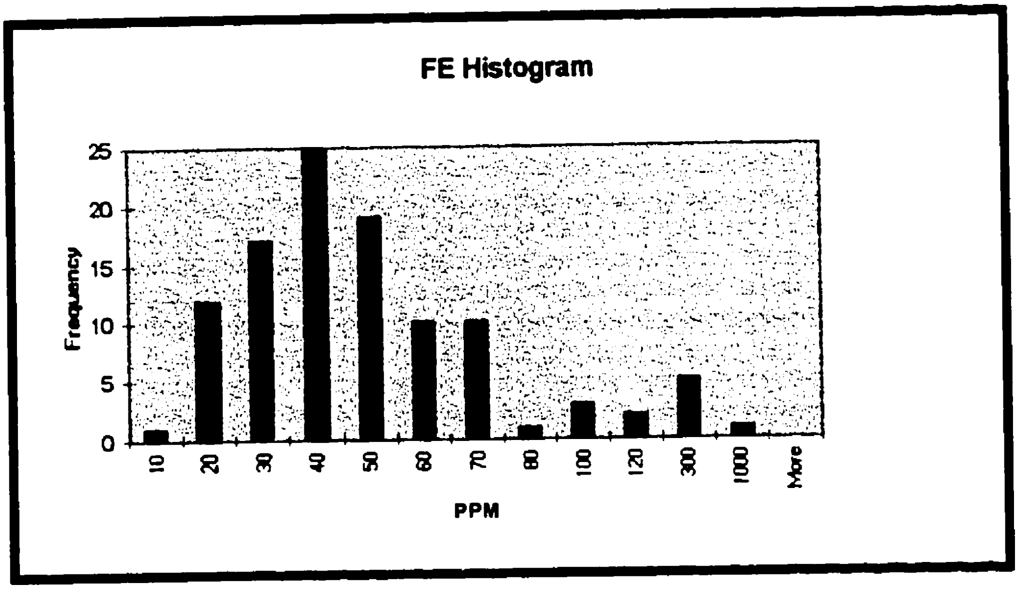


Figure 7.1 Iron (FE) distribution for EJC-100 scoop motors Jan 96 to Dec 96

15 Ton Trucks

								95 percentile	94	12	33	12	30	205	257	171		24
Equip. #	Failure Date	Repair Date	Description	Sample Dates	Arrival at Laboratory	Analaysis Complete	HRS_EQU	HRS_ACE	FE	AL	CU	PB	SI	NA	B	CA	AGUA	VISC
T-14				25-Oct-96	11-Nov-96	19-Nov-96	1489	125						216	155	66	S	
T-14				8-Nov-96	27-Dec-96	10-Jan-97		124						57	159	76	S	
T-14	16-Dec-96	3-Jan-97	Change Motor	26-Nov-96	27-Dec-96	10-Jan-97		115						204	171	78	S	

EJC-100 Scoops

								95 percentile	153	27	71	23	36	214	298	230		28.1
Equip. #	Failure Date	Repair Date	Description	Sample Dates	Arrival at Laboratory	Analaysis Complete	HRS_EQU	HRS_ACE	FE	AL	CU	PB	SI	NA	B	CA	AGUA	VISC
P-44				18-Jan-96	08-Feb-96	13-Feb-96	702	129	48	4			21	29	177	96	S	21.42
P-44	17-Feb-96	22-Feb-96	Change Motor	07-Feb-96	14-Mar-96	16-Mar-96	844	142	64	17		17	21	13	293	105	T	17.91
P-45				21-Nov-96	27-Dec-96	10-Jan-97		119	39	21	14	14	11		157	55		
P-45	8-Dec-96	17-Dec-96	Change Motor	04-Dec-96	27-Dec-96	10-Jan-97		125	23	24	11	7	10		145	47		19.27
P-46				02-Jun-96	17-Jul-96	18-Jul-96	1747	100	36	6	9	0	14	2	149	86	S	22.89
P-46	20-Aug-96	3-Sep-96	Change Motor	27-Jun-96	05-Sep-96	11-Sep-96	2034	102	78	12	24	5	27	24	173	120	S	
P-48				06-Mar-96	14-Mar-96	16-Mar-96	4359	116	28	24	8	2	23	86	265	92		18.72
P-48	6-Apr-96	8-Apr-96	Cylinder Head	16-Mar-96	12-Apr-96	19-Apr-96	4524	140	31	14	9	4	20	76		97	S	20.97
P-49				16-Jan-96	08-Feb-96	13-Feb-96	954	194	60	15	9	5	20	45	192	98	S	22.89
P-49	12-Feb-96	17-Feb-96	Turbo	31-Jan-96	08-Feb-96	13-Feb-96	1129	175	103	14			31	42	150	99	T	22.45
P-50				19-Nov-96	27-Dec-96	10-Jan-97		125	36	10	24	6	12	113	113			22.60
P-50				21-Dec-95	15-Jan-96	25-Jan-96	3773	113	44	1	20	15	16	15	173	89	S	17.76
P-50	9-Jan-96	11-Jan-96	Change Motor	08-Jan-96	08-Feb-96	13-Feb-96	3926	153	43	1	8	5	11	14	147	81	S	18.32

Table 7.3 Failures that could have been predicted (Shaded cells indicate data that would have predicted incipient failures)

7.1 Discussion of Oil Analysis Results

Section 7.0 showed that proper utilization of the existing oil analysis program could have turned 5 unplanned motor repairs into planned repairs. As stated earlier, the cost of an unplanned repair is significantly higher than a planned one. To attain an estimate for the effects these unplanned motor failures had on the mine, an estimate for the cost of lost production due to an unplanned failure was performed. The estimate of lost production was calculated using the data in Tables 7.4 and 7.5 and is based on the following assumptions:

- Planned repair hours are those that were estimated by central maintenance staff assuming availability of labor and parts. Actual average repair hours were obtained from maintenance data.
- Total tons produced were directly proportional to scoop and truck operating hours.
- Ore prices are based on Barrick's 1996 budget values.

Production				**Average Grade**			**Hours Utilized**		**Av. Tons per hr**	
1996 Tons	Au (oz)	Ag (0z)	Cu T.M	Au gm/ton	Ag gm/ton	Cu/ton	Scoop hours	Truck hours	Scoops TPH	Trucks TPH
435,045	139,278	613,369	15,098	9.09	40.04	.0347	211,653	197,764	2.06	2.20

Table 7.4 Production Data for 1996

Production TPH	Ore Prices and Costs per Hour				Maintenance Hours			Cost
	Au(oz)	Ag(oz)	Cu (lb)	Total	Planned repair (A)	Unplanned repair (B)	(B-A)* Utilization	Cost per failure
	$400	$5.25	$1.11					
Scoops 2.06 TPH	$264/hr	$15/hr	$175/hr	$454/hr	20	63	22 (.501)	$9780
Trucks 2.2 TPH	$282/hr	$16/hr	$186/hr	$484/hr	20	116	49 (.513)	$23,840

Table 7.5 Cost difference estimate for unplanned and planned motor failures

Using Tables 7.4 and 7.5 it was possible to estimate the cost of lost production. This was accomplished by dividing the total tons for the year by the total operating hours for scoops and trucks respectively to get an estimate of average hourly production for each. Then using the average grade and price for the year an estimate for the cost of production for scoops and trucks was calculated. This number was then used to estimate the cost of excessive hours in the maintenance shop. The corresponding results shown in Table 7.5 indicate that the estimated extra cost of an unplanned motor repair is $9,780(US) and $23,840 (US) for EJC-100 scoops and 15 ton trucks respectively, considering lost production only. Thus, for the five motor changes that could have been predicted for 1996, the projected value of lost production is $62,960 (US). The actual savings would likely be higher since the ability to predict the incipient failure would enable earlier shutdown and repair, thus mitigating secondary damage to the motor and subsequent costs.

Table 7.6 shows average Deutz motor repair cost for motors overhauled between January 1996 and March 1997. It is difficult to distinguish repair costs for planned versus unplanned motor replacements. Nevertheless, as discussed in section 2.1 the cost of an unplanned failure is typically three times that of a planned failure (Mobley, 1990). This implies that the total cost of the unplanned failures due to improper use of the oil analysis program could be as high as $400,000 US. This number was arrived at by taking the average cost for both motor types and multiplying it by 3 for an unplanned failure, multiplying this result by 5, the number of failures, and adding the cost of lost production given above.

Deutz Motor	**Total Hours For 1996**	**Status of Motors**	**Number of Repairs**	**Average hrs between repairs**	**Repair Cost $US per motor**
F6L413FW	27219	Change	11	2500	21,500
F8L413FW	45695	Change	12	3800	23,500

Table 7.6 Actual Repair Costs for Deutz Motors From January 1996 to date

In analyzing the oil analysis data an attempt was made to determine possible reasons for the failure of the existing program to predict failures it was noted that:

- On average the elapsed time from sample extraction to arrival at the laboratory was 29 days for EJC-100 scoops and 31 days for 15 ton trucks.

- The average elapsed time from sample arrival at the laboratory until the results were sent to the mine was 7 days.
- Through discussion with maintenance personnel at the mine it appears that no trending of the data received from the laboratory was done. When a sample was obtained with abnormal levels the only steps taken were to decrease the time between filter changes. Due to staff turnover it was impossible to find out exactly what criteria was being used to determine abnormal levels.

8.0 Conclusions and Recommendations for Future Work

8.1 Conclusions

8.1.1 Condition Monitoring

The evaluation of the oil analysis program at the mine has indicated that to operate an effective CBM program the following is necessary:

- The turn around time of the data must be short enough to ensure that pending failures can be recognized before they occur.
- To ensure that the data can be used to determine the condition of a machine thought must be given to what indicators need to be extracted from the data and what constitutes abnormal conditions for these indicators.
- Successful CBM requires proper compilation of the data in a manner such that it can be interpreted and alarms generated when abnormal levels of the particular indicator(s) are found.
- Results from the indicators require trending to enable prediction of failures within a reasonable time frame to allow scheduled repair or replacement.

8.1.2 Identification of Problem Areas

- Repair time estimates from maintenance personnel do not accurately reflect actual values observed. Better estimates of repair time could be obtained under a controlled study.

- Equipment downtime tends to be dominated by factors other than actual repair time. These factors could include delays caused by lack of resources- spare parts, labor, shop space- or lack of priority for repairs.
- A Pareto Analysis of failure data is useful for identifying problems within the maintenance process. In the case study presented the Pareto Analysis indicated that downtime was independent of equipment type and component type. This led to the above inference that something other than repair time was dominating the downtime.

8.1.3 Statistical Analysis

- Usefulness of the failure and repair data is compromised by the lack of precision in recording time of failure and associated downtime.
- Assumptions made to compensate for the data's lack of precision lead to artificial segregation of the data sets into distinct populations.
- Fitting of models to the data yielded fairly good results. The fits appear to reflect the equipment behavior more so than the treated data. This is indicated by the smoothing effect the fit curve had in the area of discontinuities.
- The fitted models show reasonable correspondence with the underlying mean time between failure and mean time to repair.

8.2 Future Work

1. An investigation into the costs versus benefits of an improved CBM program at the mine should be performed. This should consider the following:

- Benefits of a faster turn around time for oil samples. This might include investigation into the viability of an onsite laboratory to service all mines on the site.
- The possibility of using additional analysis should be evaluated. This should include consideration of using ferrography on the oil samples to aid in determination of failure causes and the possible implementation of a vibration monitoring program.
- The appropriate methods for interpreting and trending of CBM data should be determined.

2 An investigation into downtime factors should be initiated. This would necessitate a more detailed level of data recording, so that reasons for downtime could be identified. This could include recording downtime in categories like: actual repair time, waiting for parts, waiting for labor and spare equipment (implying low priority on repair). This level of recording could be accomplished by the use of a maintenance management information systems (MMIS) which would require appropriate data entry and training of personnel.

3 A theoretical study could be performed to model the effects of imprecision in the failure and repair data. This would require more precise data which could be obtained from a properly utilized MMIS. Alternatively, precise data could be collected by relying on the operator using a production monitoring system.

- Software simulations could be constructed using the fitted models. These simulations could include cost studies for various levels of equipment availability. They could also be used to run production studies.

- Reliability models could be formulated for these types of equipment from generic component reliability databases. These models could be compared to those identified in this thesis. This would provide an indication of the influence of the mining environment on component and equipment reliability.

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Appendix A

Failure Code Definitions

100	VALVULAS,HIDRAULICO	Hydraulic Valves
1000	REVISION DEL EQUIPO	Revision to Equipment
102	ACCIDENTE DE EQUIPO	Accident
110	BOMBAS,HIDRAULICO	Hydraulic Pumps
120	FITTING,HIDRAULICO	Hydraulic Fittings
130	MANGUERAS,HIDRAULICO	Hydraulic Hoses
140	CILINDROS,HIDRAULICO	Hydraulic Cylinders
150	ACUMULADOR,HIDRAULICO	Hydraulic Accumulator
152	ENFRIADOR,HIDRAULICO	Hydraulic Cooler
154	FUGAS DE ACEITE HIDRAULICO	Hydraulic Oil Leaks
200	LUCES,ELECTRICO	Electric Lights
210	CABLES,ELECTRICO	Electric Cables
220	BATERIA,ELECTRICO	Battery
230	ALTERNADOR,ELECTRICO	Alternator
232	MOTOR DE PARTIDA	Starter
234	MOTOR ELECTRICO	Electric Motor
240	CONTROL REMOTO,ELECTRICO	Remote Control
250	SELENOIDES,BOBINAS,ELECTRICO	Solenoids, Coils
310	NEUMATICO,RODADO	Tires
320	PERNOS,TUERCAS,RODADO	Tire Bolts and Nuts
330	ORUGAS,RODADO	Caterpillar Tracks

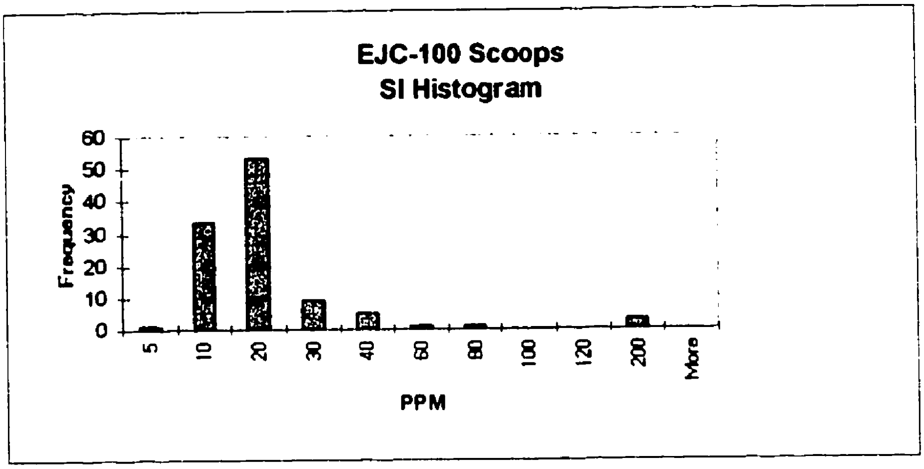
332	RESORTES, RODADO	Springs
400	CONVERTIDOR/TRANSMISION,	Torque Converter
410	CARDAN/CRUCETAS,TRANSMISION	Universal Joint
412	EMBRAGUE, TRANSMISION	Clutch
420	PILLOW BLOCK,TRANSMISION	Bearing
430	DIFERENCIAL,TRANSMISION	Differential
440	MASAS,TRANSMISION	Hubs
500	INSERTO,ROTULAS,PASADOR,TRANSMISION	Knuckle Joint
510	TOLVA,BALDE,CHASIS	Bucket
512	EXTINTORES,CHASIS	Fire Extinguisher
520	TECHO,CARROCERIA,CHASIS	Roof, Body
522	ASIENTO OPERADOR,CHASIS	Operator's Seat
524	ESTANQUE,CHASIS	Tank
530	HORQUILLA,CHASIS	Forks
600	CULATAS,MOTOR	Cylinder Head
602	ENFRIADOR,MOTOR	Motor Air Conditioning
604	CAMBIO MOTOR, MOTOR	Change Motor
606	TURBINA, MOTOR	Motor Turbine
610	TURBOS,MOTOR	Turbo Motor
620	BOMBA INYECTORA,MOTOR	Motor Injector Pump
622	BOMBA CEBADORA,INYECCION	Injector Prime Pump
624	VALVULAS,SISTEMA COMBUSTIBLE	Valves Fuel System

624	VALVULAS,SISTEMA COMBUSTIBLE	Valves Fuel System
630	PTX,FILTROS,MOTOR	Scrubbers
632	CORREAS,MOTOR	Belts
640	ACELERACION,MOTOR	Motor acceleration
650	TEMPERATURA,MOTOR	Motor Temperature
660	FUGAS ACEITE,MOTOR	Oil Leaks Motor
700	FRENO HUMEDO,FRENOS	Brakes
702	BOMBA,FRENOS	Brake Pumps
710	CALIPER,FRENOS	Brake Calipers
720	PEDAL,FRENOS	Brake Pedals
800	CENTRALIZADOR,PERFORACION	Drill Center Device
802	MORDAZAS,PERFORACION	Drill Jaw
804	MOTOR DE AVANCE,PERFORACION	Drill Advance Motor
806	PLUMA, PERFORACION	Drill Boom
810	CULATIN,PERFORACION	Drill Head
820	AGUA,PERFORACION	Drill Water
830	CANDADO,PERFORACION	Lock
840	CABEZAL,PERFORACION	Drill
842	ROTA BOOM,PERFORACION	Boom Rotation
844	CRUDLER,PERFORACION	Drill
846	CHUK,PERFORACION	Drill Chuck
850	PERFORADORA,PERFORACION	Drill Bit

860	SITEMA DE AIRE	Air System
862	COMPRESOR,SISTEMA DE AIRE	Air Compressor
864	VALVULAS,SISTEMA AIRE	Valves Air System
866	BOMBAS,VALVULAS.SISTEMA DE AGUA	Water Pumps and Valves
870	CADENA,PERFORACION	Drill Chain
880	BOOSTER,PERFORACION	Drill Booster
970	MANTENCION EN LINEA (ALPM)	Preventative Maintenance
980	MANTENCION 3000 HORAS(OVER HAUL)	3000 Hr. Service
985	REPARACION EN MAESTRANZA	Repairs in Central Shop
990	MANTENCION 1000 HORAS	1000 hr. Maintenance
995	REPARACION EN MINA	Repairs at Mine
996	REPARACION EN SERVICIO EXTERNO	Outside Repairs

Appendix B

Oil Contaminant Histograms


EJC-100 Scoops
SI Histogram
Frequency
PPM
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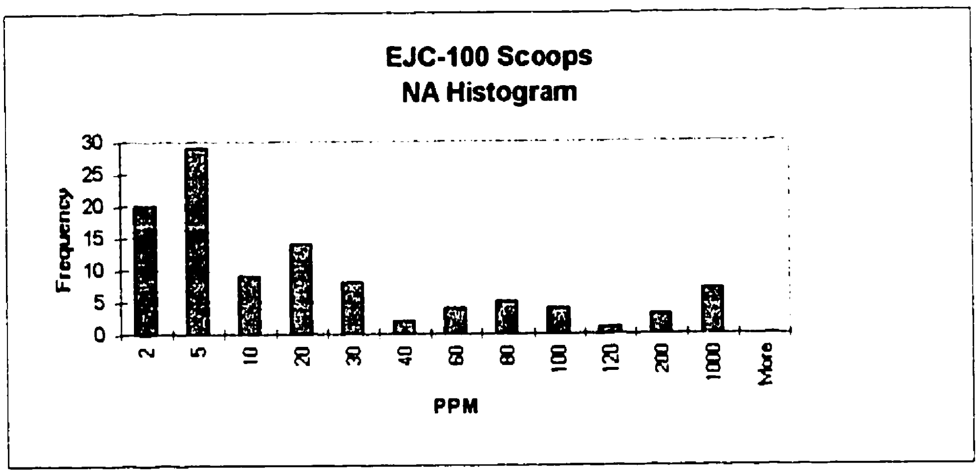
10
20
30
40
50
60
5
10
20
30
40
60
80
100
120
200
More


EJC-100 Scoops
NA Histogram
Frequency
PPM
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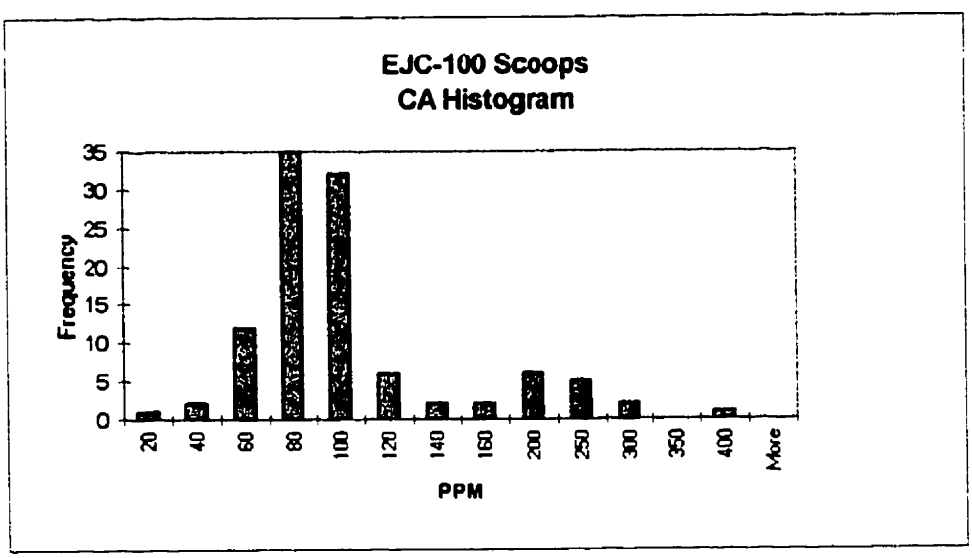
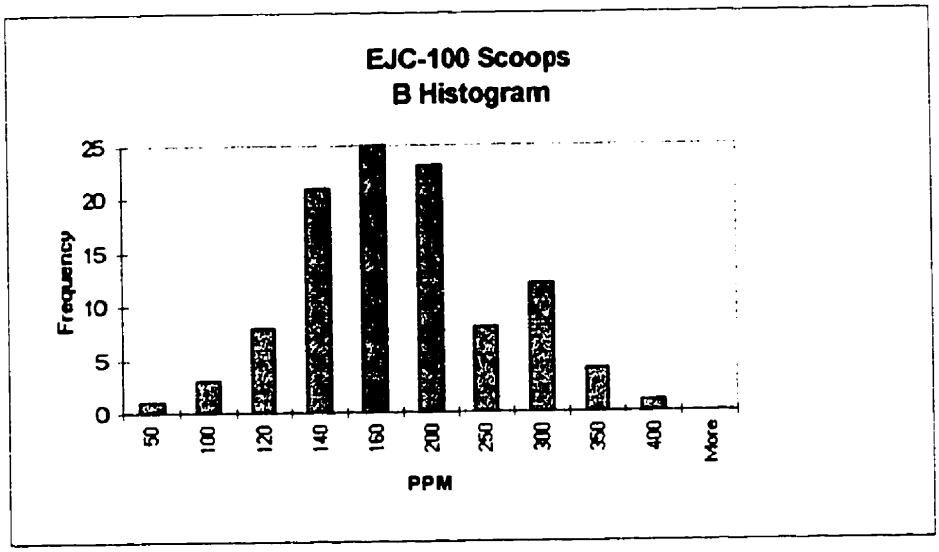
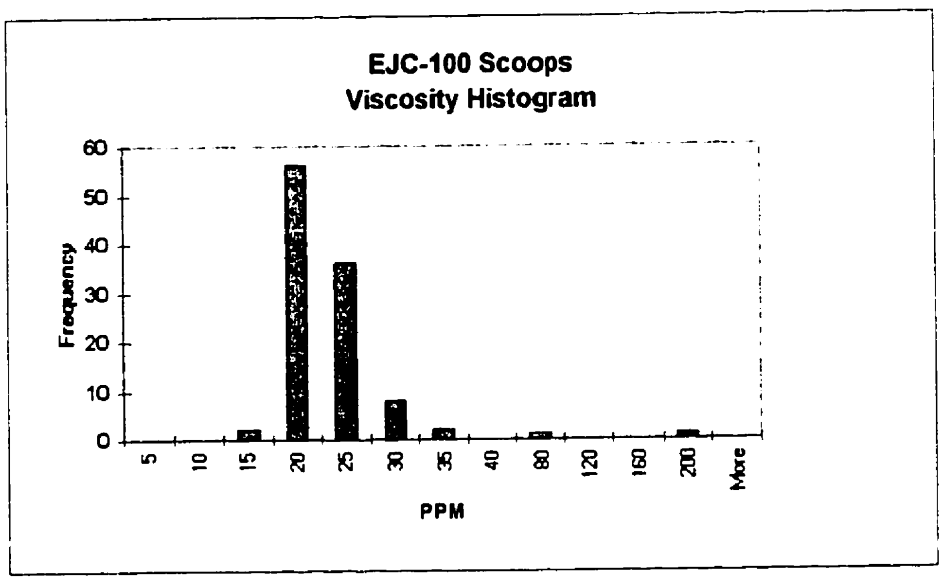
5
10
15
20
25
30
2
5
10
20
30
40
60
80
100
120
200
1000
More


EJC-100 Scoops
CA Histogram
Frequency
PPM
0
5
10
15
20
25
30
35
20
40
60
80
100
120
140
160
200
250
300
350
400
More


EJC-100 Scoops
B Histogram
Frequency
0
5
10
15
20
25
50
100
120
140
160
200
250
300
350
400
More
PPM


EJC-100 Scoops
Viscosity Histogram
Frequency
0
10
20
30
40
50
60
5
10
15
20
25
30
35
40
80
120
160
200
More
PPM