EVALUATION OF EQUIPMENT RELIABILITY, AVAILABILITY AND MAINTAINABILITY IN AN OIL SANDS PROCESSING PLANT

by

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ABSTRACT

The oil sands industry is a developing sector of Canada's economy; one area of focus for oil sands companies is to improve plant maintenance and overall plant availability. Although considerable progress has been made in the improvement of plant maintenance in other industries, oil sands and mining companies in general do not significantly benefit from this due to variable feed supply that impacts plant performance. As well historically for mining maintenance has not been done well.

The work presented in this thesis develops a framework for understanding oil sands processing plant key equipment failures by utilizing data collected over two years at Albian Sands Energy Inc, an operator of an oil sands mine in Alberta, Canada. The data is used to calculate mean time between maintenance for key pieces of oils sand processing equipment. As well various statistical techniques are applied to the data to identify the best maintenance strategies for the site. Finally the efficacy of advanced statistical techniques, such as Power Law modeling, for predicting time to next failure for equipment is demonstrated.

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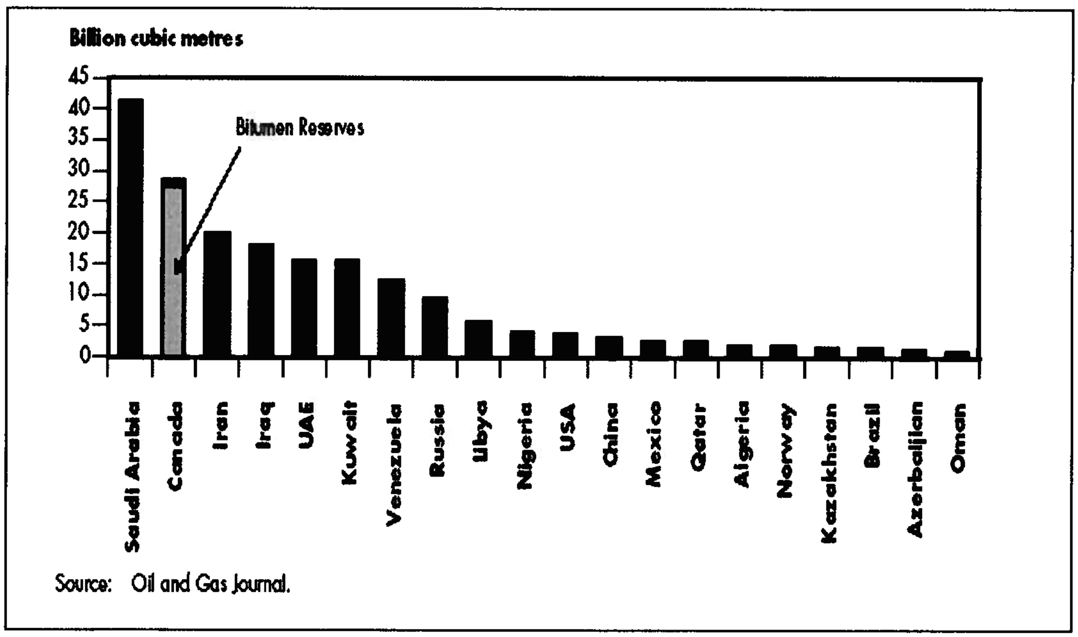
1 INTRODUCTION

1.1 Background

Canada's oil sands are one of the largest known hydrocarbon resources in the world. According to the Oil & Gas Journal and Cambridge Energy Research Associates (2002), Canada's oil sands resources are estimated to contain about 178 billion barrels (28.3 billion cubic meters) of recoverable oil with current technology (National Energy Board of Canada, 2004), which ranks second only to Saudi Arabia, as shown in Figure 1-1.

Figure 1-1 World Oil Reserves – Top 20 (Notional Energy Board, 2004)



Canada's oil sands are found in three different deposits in Alberta: Athabasca, Peace River and Cold Lake. In 2005, Alberta's oil sands production reached 1 million barrels per day – about 45% of Canada's total daily oil production. By 2015, Alberta's oil sands are expected to generate 2 million barrels of crude oil per day to provide more than 67% of Canada's total daily oil production (National Energy Board, 2006).

Oil sands extraction has historically been an unprofitable business because revenues from selling the extracted oil from oil sands could not cover operation costs. In the middle of 2006, the National Energy Board of Canada estimated that the operating costs of new oil sands mining and crude bitumen extraction operation were $9 to $12 per barrel; and the cost of an in-situ SAGD (Steam-Assisted Gravity Drainage) operation was $10 to $14 per barrel for crude bitumen. The employment of huge mining machines and process plants in oil sands mines make capital cost a major part of the total cost. The total cost of crude bitumen production will rise to $18 to $20 per barrel in a new oil sands mining and extraction operation, and $18 to $22 per barrel in a SAGD. The cost of oil sands extraction is not comparable to conventional oil wells, which is about $1 per barrel in the Middle East, and $6 to $9 in the US and Canada. The high oil prices make oil sands extraction a booming industry; however, oil sands extraction is still a high-risk business because of the high operation costs.

The development of oil sands greatly contributes to Canada's economic development. At present, 28 petroleum companies and developers have invested $37 billion in 81 oil sands-related projects; 33,000 "direct, in-direct and conduced jobs" have been created, according to Athabasca Regional Issues Working Group (ARIWG). It is predicted that a total of 240,000 new jobs will be created by 2008. The Alberta government will receive $7.2 billion in taxes annually from oil sands businesses by 2015; the federal corporate and personal tax revenues from the oil sands industry are estimated at $5 billion per year (ARIWG, 2006).

Oil sands process plants are located at remote, cold locations in northern Alberta. The operation and maintenance of the mining process is facing great challenges due to the severe site-working environment (+40 °C to –60 °C), the abrasiveness of ore, the application and configuration of new equipment, and the shortage of workers.

1.2 Importance of Equipment Reliability, Availability, and Maintainability in Plant Production and Maintenance

Oil sands companies are facing great challenges in oil sands production and process plant maintenance. Oil sands production is very different from conventional crude oil production. The process of mining, extracting and upgrading an oil sands resource is complex and involves high operating costs. In addition, being a developing industry, oil sands process plants require many new parts, materials and processes. New technologies are available to improve oil sands production. At the same time, "many of the new technologies are not fully understood; operation systems are becoming increasing complex; and reliability of operation is considerably less than the expected" (Lewis, 2004).

"Industrial plants are under more pressure than ever to produce reliably and predictably" (Matusheski, 1999). In 2003, Syncrude Canada Ltd., an important oil sands company, had two maintenance turnarounds in a single year, even though the annual plant equipment maintenance costs had been in an excess of 450 million dollars before the turnarounds (Anderson, 2005). Maintenance had the greatest impact on production. During 2003, production was reduced by 10%. Operation reliability performance has become an index that investors pay attention to. More and more plants are applying Reliability Centered Maintenance to improve operation and maintenance performance. Suncor Energy Inc, another important oil sands company, began operations in 1967, and its main focus in the early years was to strengthen operational reliability and achieve steady production capacity. In 2006, its production capacity reached 260,000 barrels a day with plans to expand to more than half a million barrels per day by 2010 to 2012 (Fort McMurray Today, 2006). It is recognized that plant equipment reliability, availability and maintainability is an essential factor in achieving good production and business performance.

The reasons that equipment Reliability, Availability and Maintainability (RAM) is important to plant operation are based on the following:

- Production: High equipment reliability, maintainability and availability increase operational availability, reduce downtime, improve operating performance, and increase production capacity.
- Cost: Although initial RAM improvement could be costly, from an equipment life cycle cost consideration, early investment in achieving reliability growth is valuable and reduces the entire life-cycle cost.

- Competitive advantage: A continued effort towards improving plant RAM is a key strategy for business success. RAM improvement involves using new technologies, new materials and new processes, to reduce costs, improve product quality, and ensures competitiveness.
- Environment and Safety. High equipment reliability and maintainability would improve operational safety and reduce equipment-related safety and environmental hazards.

1.3 Research Objectives

This research aims develop an understanding of the key maintenance challenges for processing plants operating in an oil sands environment. This will include quantitative and qualitative assessment of challenges and opportunities

The specific objectives of this research are:

- Identify and quantity the key issues for Reliability, Availability and Maintenance (RAM) improvement in an oil sands operation;
- Identify failure characteristics of oil sands processing equipment. Such as time between failure, time to repair;
- Characterize the RAM performance of key equipment for oil sands processing;
- Enhance the understanding of the dominant influences on equipment RAM in the oil sands environment;
- Develop a method for prediction of pending failures of key equipment.

2 LITERATURE REVIEW

2.1 Reliability, Availability, and Maintainability (RAM)

The primary objective of plant maintenance is to ensure that equipment is running at low cost and high operation efficiency to satisfy plant operational needs. Impressive progress has been made in maintaining plant equipment in an effective manner; however, maintenance costs as a percentage of operating costs in the mining industry have not changed much over the last decade. Ten years ago maintenance costs averaged between 25 to 45% of operating costs (Campbell, 1997), and today they are still the same (Hall, 2007). One could argue the various reasons that account for this, such as increasing equipment size, larger production rates, rising complexity of equipment, higher availability requirement, and so on (Ebrahimi, 2004). The fact remains that maintenance costs still represent an opportunity for increased profitability. Industry professionals and researchers have realized that an important approach to reducing maintenance costs and improving operation efficiency is to improve three related characteristics of operating equipment: Reliability, Availability, and Maintainability (DOD, 2006, Shell Canada 1994, NIST, 2006, Crow, 1994 & 2005, Kumar 1990, Hall, 1997, Barringer, 2004 & 2006).

Reliability, Availability, and Maintainability (RAM) is defined by the U.S. Department of Defense (U.S. DOD, 2005):

Reliability is the probability of an item to perform a required function under stated conditions for a specified period of time.

Availability is a measure of the degree to which an item is in an operable state and can be committed at the start of a mission when the mission is called for at an unknown (random) point in time.

Maintainability is the ability of an item to be retained in, or restored to, a specified condition when maintenance is performed by personnel having specified skill levels, using prescribed procedures and resources, at each prescribed level of maintenance and repair.

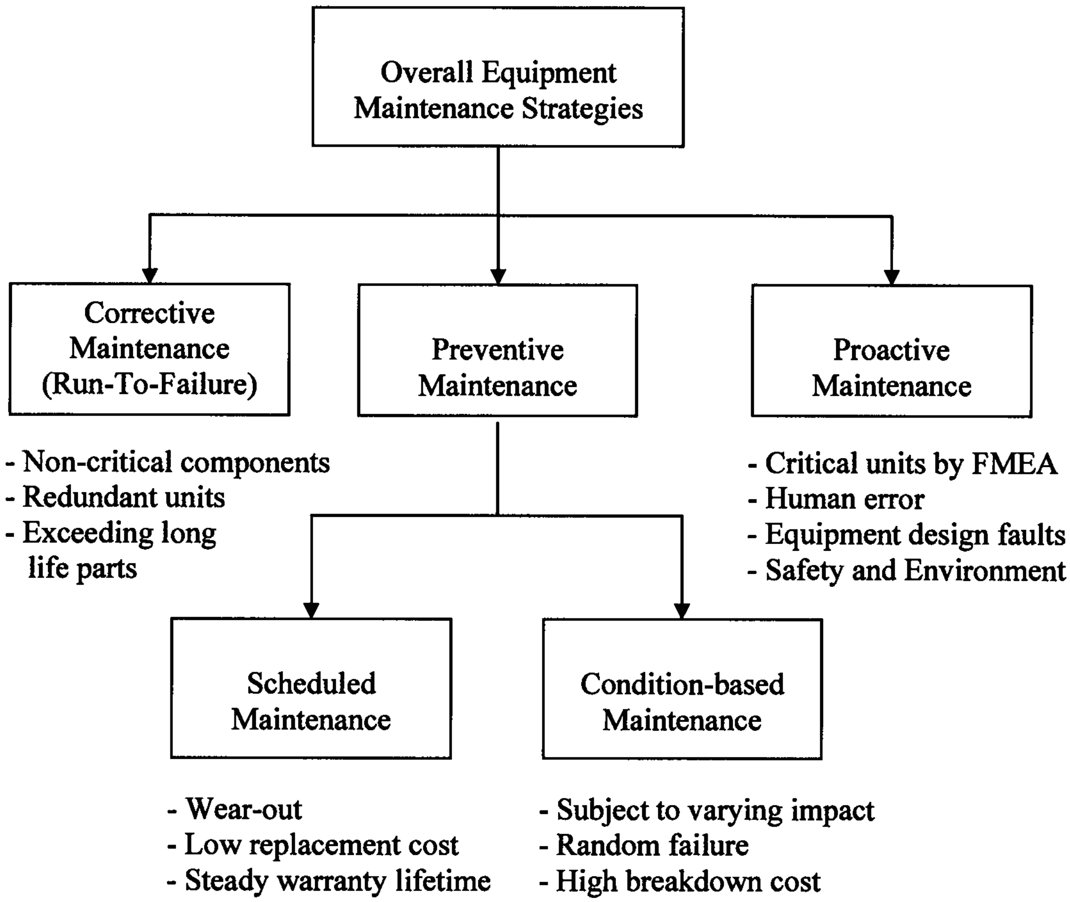
Significant improvements have been made in achieving satisfactory levels of RAM by implementing reliability-centered maintenance strategies in some industries; however, RAM problems always persist. Some problems in oil sands industry may be as follows:

- Confusion in RAM requirements, and setting unrealistical RAM improvement goals
- Lack of RAM data collection and analysis
- Poorly defined priority of RAM improvement actions
- Poor understanding of RAM theory and improvement methods
- Poor management in achieving RAM improvement

Numerous attempts at strategies and philosophies for plant equipment RAM improvements have been put into practice. Figure 2-1 shows the categories of maintenance activities in relation to the equipment repair policy (see Appendix A for details). With respect to a holistic approach to maintenance management, the following management strategies are in practice (see Appendix B for details):

- Reliability-Centred Maintenance
- Total Production Maintenance
- Six Sigma
- Lean Maintenance

Figure 2-1 Overall Equipment Maintenance Strategies (Modified from Hall *et al.*, 1997)

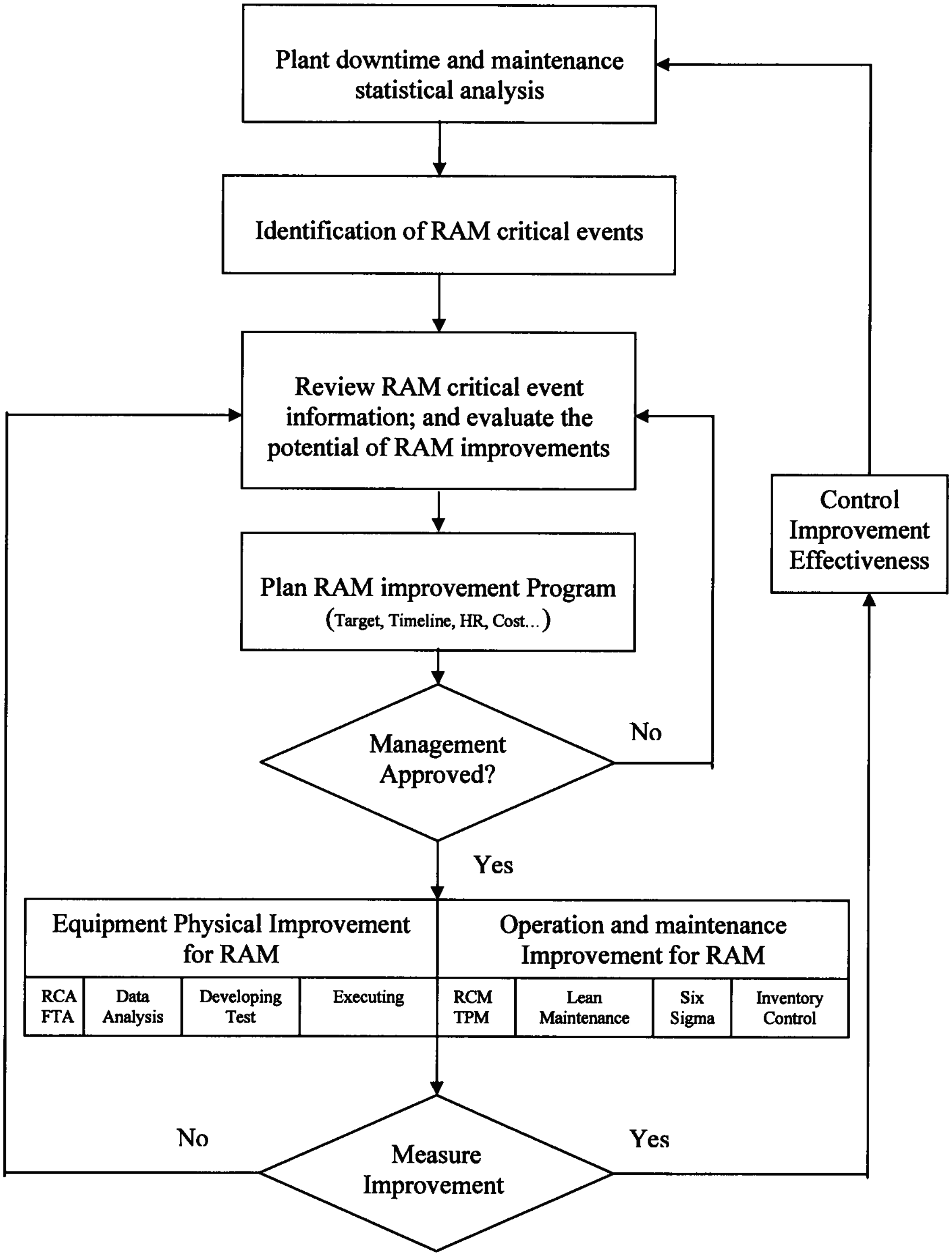


While these maintenance strategies are implemented to improve equipment RAM, equipment RAM analysis must be performed to support maintenance management. To fulfill the requirement of plant maintenance, RAM analysis should be related to the particular program and the facilities (Civil Aviation Advisory Publication, 2001).

Based on the maintenance knowledge literature review (Appendix A, B and C), onsite investigation, and Albian reliability group work experience, it is clear that two primary plant maintenance improvement approaches are equipment physical reliability improvement and maintenance management improvement.

Figure 2-2 illustrates an integrated RAM improvement program workflow for an oil sands plant. The workflow is an Evaluation-Planning-Acting-Modification (EPAM) cycle. It encourages implementation of continuous improvement and fulfills the improvement approaches in plant maintenance. In this workflow, RAM analysis is conducted by the initial downtime and maintenance data analysis to identify where RAM improvement can be made, and to indicate how the improvement is processing so as to facilitate maintenance improvement.

Figure 2-2 RAM Improvement Program Workflow



2.2 RAM Analysis Methods

To analyze RAM, the RAM analysis methods must be selected. Analysis and reporting on plant equipment RAM acts as an information source for plant maintenance effectiveness. Maintenance management and operation may have specific requirements for the RAM analysis; however, the following should be taken into account (Civil Aviation Advisory Publication, 2001):

- Current reliability performance and defects
- Gap between current and the required reliability
- Reliability trend or survival characteristics
- Confidence level for expected improvement results
- Engineering judgment to evaluation results
- Correlation with operation and maintenance

While maintenance data is analyzed to identify equipment RAM information, the general analysis methods can be classified into two categories (Key performance indicator analysis and parametric analysis) with respect to the depth of the analysis and the intended audience.

Key performance indicator (KPI) analysis lists or graphs factors that are treated by simple mathematics, without complex statistical analysis. KPI analysis is widely used in industry practice. It can be quickly and routinely carried out to provide information for management.

Parametric analysis intends to perform statistical analysis to explore the behavior of equipment failure for the use of reliability engineering. In plant maintenance, the time between repairs for complex systems is stochastic because equipment reliability is affected by various factors, such as its design, operation environment, maintenance quality, and the age. This situation is different than non-repairable systems, which is treated as renewal processes in modeling. It is clear that the analysis procedures for non-repairable systems are not suitable for analyzing data from repairable systems (Tobias and Trindade, 1995). Some reliability analysis models for repairable system have been developed (Crow, 1990, 1993; Bain and Engelhardt, 1991). The Power Law model is a widely recognized repairable system statistical analysis model (Kumar, 1990; Tobias and Trindade, 1995; U.S. NIST, 2006). Researchers have used the Power Law model to solve maintenance problems, such as failure prediction, maintenance optimization, and reliability evaluation (Kumar, 1989; Nelson, 1986; Crow, 1990; and Tobias and Trindade, 1995).

2.3 Reliability, Availability, and Maintainability Analysis Techniques

2.3.1 Pareto Analysis

Pareto analysis is a method used to identify the proportion of events that result in the most significant downtime cost (Kumar, 1990). It is based on the Pareto principle, which states that "80% of problems are from 20% of the events". In maintenance analysis, the Pareto method is implemented to determine maintenance priorities according to downtime, maintenance cost, or number of failures. Pareto analysis allows engineers to focus on maintenance events with the best return on effort.

A Pareto histogram is a graphical representation of the results of a Pareto analysis. It lists data in descending order of value, and displays a cumulative percentage curve through the right side of the first bar. The Pareto histogram chart can be used successfully for identification of the events with major downtime or maintenance costs; however, the deficiencies of this method are (Knights, 2001):

- The Pareto histogram analysis is based on downtime (cost, or failure frequency) alone and cannot identify which factors are dominant.
- Frequently occurring failures impact productivity, and are key reliability improvement tasks; however, a Pareto histogram may miss identifying the events with low downtime or maintenance cost and high failure frequency.

Some new methods for Pareto analysis have been developed to implement multi-factors analysis. Boudreau *et al.* (1999) presented an Excel macro to carry out three-dimensional plotting so as to determine the most important factor on the abundance of a species with respect to the three environmental impacts: PH, salinity and oxygen content. Knights (2001) used an x-y dispersion plot of repair time versus numbers of failures to find which factor, failure numbers or downtime, has the dominant impact on equipment availability. Furthermore, Knights developed log scatter plots to classify the unplanned shovel electrical downtime into acute, acute & chronic, and chronic according to repair time and number of failures.

2.3.2 Key Performance Indicators (KPI) Analysis

In practice, the field data are summarized into key performance indicators (KPIs) for providing information on how the equipment is behaving in the operation process. Four basic requirements for the development of KPI are (Reh, 2007):

- KPIs must reflect the organizational goal so as to track the work progress.
- KPIs must be measurable and quantifiable so as to compare and control process improvement.
- The development of KPIs must be based on a long-term consideration.
- The meaning of KPIs should easily be understood by all members of the organization.

KPI analysis has been widely used to identify industrial operation and maintenance targets and measure maintenance effectiveness. (Reh, 2007; Paraszczak *et al.*, 2005) In maintenance performance analysis, KPIs can be broken down into two categories: equipment RAM KPIs and maintenance cost KPIs. These KPIs indicate maintenance goals and detect the progress of maintenance actions and strategy development.

A key performance indicator closed-loop process has been presented by Beck and Oliver (1999) to identify the process of selecting performance indicators, as shown in Figure 2-3. In a logical maintenance system (LMS) developed for a Japanese LNG terminals maintenance, KPI was one of five maintenance efficiency evaluation tools, including RBM (Risk-Based maintenance), RBQC (Risk-Based Quality Control), Long-Term Maintenance Standard, and Asset Management. These evaluation tools are used to approach a PDCA (Plan, Do, Check, and Action) cyclic management system (Aoki, 2006).

Figure 2-3 Key Performance Indicator Closed-Loop Process (Beck and Oliver, 1999)

Figure 2-3 has been removed due to copyright restrictions. The information removed is a closed-loop process, including select KPIs & set targets, Plan & execute, Analyze & identify improvement area, and Evaluate & revise strategy.

2.3.3 Reliability Modeling

An important analysis tool is reliability modeling, which has been widely used for predicting the reliability trend of a component or system. For reliability modeling purposes, systems are classified into two categories: non-repairable and repairable systems (U.S. NIST, 2006).

Non-Repairable System Modeling

Non-repairable systems are those that are replaced when they fail. Lifetime distribution models are used for analyzing such non-repairable components with a single failure mode by identifying the probability of the component surviving in a time interval under certain operating environments. These distributions include:

- Exponential distribution
- Lognormal distribution
- Gamma distribution
- Normal distribution
- Weibull distribution

The Weibull distribution has been widely used for product lifetime analysis (Relisoft, 2006). The advantage of Weibull analysis is "its ability to forecast failures in small samples" (Abernethy, 2002). The three-parameter Weibull probability density function (*pdf*) is expressed by (Relisoft, 2006):

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}}, \quad t>0,\ \beta>0,\ \eta>0$$

where

γ : Location parameter

β: Shape parameter

η : Scale parameter,

The characteristics of these three parameters provide important information for identifying failure behavior:

- The location parameter, γ, indicates the position of Weibull pdf curve along the abscissa.
- The scale parameter, η, estimates a characteristic lifetime. When $t = \eta$, 63.2% of the population is likely to have failed.
- The shape parameter, β, indicates the failure rate characteristic (Abernethy, 2002):

  - $\beta<1$: infant mortality
  - $\beta=1$: random failures
  - $\beta>1$: wear-out failures

Repairable System Modeling

Repairable systems are those that are repaired or restored when they fail during operation. When failure occurs at a certain system age, maintenance is implemented to restore the initial function. These maintenance actions may impact the overall behavior of the system and affect the system function due to variable maintenance resources involved, such as human errors, part quality, and preventive maintenance (Mattes & Zhao, 2005). Consequently, the maintenance effectiveness may be the same as new, better, or worse, so the frequency of failure may be increasing, decreasing, or staying at a constant rate.

An approach is used for modeling "the rate of occurrence of failure (ROCOF)" for a repairable system. The rate is also called "repair rate" (U.S. NIST, 2006). For building a model to simulate the repair rate of a repairable system, "let N(t) be a counting function that keeps track of the cumulative number of failures that a given system has had from time zero to time t; if the N(t) curves for a large number of similar systems are 'averaged', an estimate of M(t) = the expected number of cumulative failures by time for the system defined. The derivative of M (t), m (t), is defined to be the repair rate or ROCOF (U.S., NIST, 2006)."

Most plant equipment is repairable. After repair, the reliability of equipment may be better or worse. An analysis of equipment reliability trends is necessary for maintenance management to identify maintenance needs. According to the Engineering Statistics Handbook of NIST (2006), the rate models used for repairable systems are:

- Homogeneous Poisson Process
- Non-Homogeneous Poisson Process following a Power Law
- Non-Homogeneous Poisson Process following an Exponential Law

If the interarrival times between failures are "independent and identically distributed according to the exponential distribution with parameter λ", the simplest and most useful model for $M(t) = \lambda t$ and the repair rate is the constant $m(t) = \lambda$. Based on this model, the following formulas apply:

The CDF of the waiting time to the next failure:

$$F(t) = 1 - e^{-\lambda t}$$

The probability of N(t), the cumulative number of failures from time 0 to t:

$$P\{N(t) = k\} = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

The expected number of failures by time t:

$$M(t) = \lambda t$$

The repair rate:

$$M'(t) = m(t) = \lambda$$

The mean time between failures:

$$MTBF = 1/\lambda$$

The HPP model has a constant repair rate, $m(t)= \lambda$. If λ is substituted by $\lambda(t)$, HPP model becomes a NHPP with a power intensity function.

If the time to the first failure has a Weibull distribution with shape parameter *b* and characteristic parameter *a*, a model for the expected number of failures in the first hours, M(t), is given by

$$M(t) = at^b \text{ , for } a, b>0$$

The repair rate for this model is

$$m(t) = \lambda(t) = abt^{b-1}, \text{ for } a, b>0$$

If b>1, the failure rate is increasing;

If 0<b<1, the failure rate is decreasing;

If b=1, the model reduces to the HPP constant repair rate model.

This model is called a Power Law model, Duane model or Crow-AMSAA (U.S. Army Materials System Analysis Activity) model.

Under this model, the function

$$MTBF(t) = \frac{1}{\lambda(t)} = \frac{1}{abt^{b-1}} = \frac{T}{Nb}$$

is interpreted as the instantaneous MTBF of the system at time t.

The probability of a given number of failures for the power law process is,

$$P[N(t) = k] = \frac{M(t)^k}{k!} e^{-M(t)} = \frac{a^k t^{bk} e^{-at^b}}{k!}$$

A brief description of Non-Homogeneous Poisson Process following an Exponential Law is

$$m(t) = e^{\alpha + \beta t}$$

If β<0, the repair rate is decreasing; if β>0, the repair rate is improving; and if β= 0, the exponential law reduces to the HPP constant repair rate model. According to the

Engineering Statistics Handbook (NIST, 2006), this model has seldom been used in industrial applications.

Besides the identification of the U.S. National Institute of Standards and Technology using a power law process for repairable system reliability modeling, A U.S. military handbook introduced AMSAA models for reliability growth management of repairable complex weapon systems during their development stages (U.S. DOD, 1981). A recent U.S. military document advised Non-Homogenous Poisson Process and AMSAA models be used in RAM analyses, and put together a reliability modeling selection scheme as shown in Figure 2-4 (U.S. DOD, 2005).

Figure 2-4 Selecting the Appropriate Process Model (U.S., DOD, 2005)

Figure 2-4 has been removed due to copyright restrictions. The information removed is a process to select a reliability analysis model by chronologically ordered Time to system failure and trend test.

2.3.4 Power Law Model Parametric Estimation and Hypothesis Test

The power law process model is a good tool to analyze the effect of successive maintenance actions, and to estimate a quantified deteriorating rate. Several studies have focused on the Power law model parametric estimation and hypothesis test (U.S. DOD, 1981, 2005; U.S. NIST, 2006; Frenkel, 2004; Gaudoin *et al.,* 2003; Crow, 2005; Mettas, 2005; Sun *et al.* 2005; Guo *et al*, 2006).

Parameter Estimation for Power Law Model

If the assumption that a failure rate of $m(t) = \lambda(t) = abt^{b-1}$ in the power law model is appropriate, the unbiased maximum likelihood estimate for b and a is (U.S. DOD, 1981)

$$\hat{b} = \frac{N-2}{\sum_{i=1}^{N-1} \ln(T_N / T_i)}, \qquad \hat{a} = \frac{N}{T_N^{\hat{b}}}$$

where

N= number of observed failures

$T_i = i^{th}$ failure time

Hypothesis Testing Methods for Power Law Process

The methods used to determine whether the model is appropriate to describe the data characteristics and whether the parameter estimation is acceptable are:

- Duane plots
- Goodness of fit tests
- Trend tests

An acceptable graphical estimation for the Power Law model is Duane Plots. Taking logarithms in the expression for the model M(t)= at^b yields

$$\text{Log } M(t) = \text{Log } a + b \text{ Log } t$$

If cumulative number of failures versus cumulative TBM is plotted on log-log paper, the points tend to line up following a straight line if the power law model applies (U.S. NIST, 2006). These "Duane plots" can be easily implemented by Excel functions. When cumulative number of failures against cumulative TBM is plotted on logarithmic scale charts in Excel, the trend line following the power law can be drawn by Excel functions, at the same time the power law equation and R-squared value of this trend line are given. By plotting in Excel, the Power Law model parameter estimation and hypothesis are completed.

A goodness-of-fit test indicates whether it is reasonable to assume that a random sample comes from a specific distribution. Goodness-of-Fit (GOF) tests include (Donadio *et al.*, 2006):

- Chi-square test: for continuous and discrete distributions;
- Kolmogorov-Smirnov test: for continuous distributions based on the empirical distribution function;
- Cramer-von Mises test: for symmetric and right-skewed distributions;
- Anderson-Darling test: for any data-set with any skewness (symmetric distributions, left or right skewed).
- R-squared test.

Based on the coefficient of determination of the regression line in Duane plots, Gaudoin *et al.* (2003) developed critical values of the R-squared GOF test for different sample sizes, and stated "R-squared GOF is simple and powerful for Power law model". The R-squared goodness-of-fit test estimates a significant regression trend so as to answer the PLM hypothesis.

In MIL-HDBK-189, goodness-of-fit tests for the Crow-AMSAA model, namely the power law model, are tested by the use of a Cramer-von Mises test. The Cramer-von Mises statistic is

$$C_M{}^2 = \frac{1}{12M} + \sum_{i=1}^{M}\left[\left(\frac{T_i}{T_N}\right)^{\hat{b}} - \frac{2i-1}{2M}\right]^2$$

where

N=number of observed failures

M=N −1 for AMSAA model

$T_i = i^{th}$ failure arrival time.

If the statistic C_M^2 exceeds the critical value for some specified level of significance α (see Appendix E), the hypothesis is rejected.

Trend tests are used to determine whether the pattern of failures is significantly changing with time. This test can be conducted with a null hypothesis that the system failure pattern is a renewal process, in which the system is restored as "good as new" (Wang and David, 2005), If this hypothesis can be rejected at some appropriate significance level, it can be concluded that some level of reliability improvement or deterioration is occurring. Trend tests that are commonly used include:

- Crow/AMSAA Test
- Laplace Test
- PCNT (pair-wise comparison nonparametric test)

The Crow/AMSAA test is based on the assumption that the repair rate is $m(t) = \lambda(t) = abt^{b-1}$. When b = 1, the repair rate is equal to 1, the process begins to follow a HPP. The test is used to determine whether an estimate of b is significantly different from 1.The maximum likelihood estimate for b is:

$$\hat{b} = \frac{N-2}{\sum_{i=1}^{N-1} \ln(T_N / T_i)}$$

where

N=number of observed failures

$T_i = i^{th}$ failure arrival time

The test statistic is $\frac{2N}{\hat{b}}$. According to MIL-HDBK-189 (U.S. DOD, 1981), it is distributed as a chi-squared random variable. So considering the null hypothesis, the rejection criteria are given by:

Reject H_0, if $\frac{2N}{\hat{b}} < x^2_{2(N-1),1-\alpha/2}$ or $\frac{2N}{\hat{b}} > x^2_{2(N-1),\alpha/2}$.

The Laplace test assumes a system is run until N failures have occurred. Under the HPP assumption, the first N-1 arrival times, designated as $T_1, T_2, \ldots, T_{N-1}$, are uniformly distributed $(0,T_N)$. The test statistic is

$$U = \frac{\sum_{i=1}^{N-1} T_i - (N-1)\frac{T_N}{2}}{T_N\sqrt{\frac{N-1}{12}}}$$

where

N=number of failures

$T_i = i^{th}$ failure arrival time

The Laplace statistic, U, renders the evaluations below (U.S. DOD, 2005):

- If U is approximately equal to zero, it indicates a lack of trend,
- If U is greater than zero, the TBFs are decreasing,
- If U is less than zero, the TBFs are increasing.

For a high (for improvement) or low (for degradation) value the normal distribution can be used to assign a significance interval to the estimate.

2.3.5 Simulation of Power Law Model

A sample PLM simulation is based on the estimated power law equation. The expected number of failures in the first hours in the Power Law model is given by:

$$M(t) = at^b$$

Then,

$$t = \sqrt[b]{\frac{m}{a}}$$

Here,

a, b are the estimated PLM parameters

m is the number of failures

By simulating the expected number of failures, the cumulative TBM is predicted.

However, in plant maintenance, the time to failure for a piece of equipment is a function of many variables, including the failures of different components, the operation condition, and training experience of maintainers. Thus, the probability of failures for repairable systems is neither independent nor identical; the maintenance needs for a repairable system may be a stochastic process (Tobias & Trindade, 1994). To simulate a stochastic process, Tobias (1994) used an approach for simulating a Poisson process described by Ross (1993):

If the repair is a renewal process, the interarrival times are independent and have a distribution F,

$$F = 1 - \exp(-\lambda t)$$

A NHPP has intensity $\lambda(t)$ for $0 \leq t \geq \infty$. For the Power Law model,

$$\lambda(t) = aby^{b-1}$$

Then

$$\int_0^t \lambda(y+\tau)d\tau = \int_0^t ab(y+t)^{b-1}d\tau = a\left[(y+t)^b - y^b\right]$$

So,

$$F_Y(t) = 1 - \exp\left\{-a\left[(y+t)^b - y^b\right]\right\}$$

$$t = \left[y^b - \frac{1}{a}\ln(1-F_Y)\right]^{\frac{1}{b}} - y$$

Substitute the random unit uniform variable 1 – U for F_Y by the inverse transform method,

$$F_Y^{-1}(u) = \left[y^b - \frac{1}{a}\ln(u)\right]^{\frac{1}{b}} - y$$

By generating random unit pseudo-random numbers U_1, U_2, …, to simulate the successive ages Y_1, Y_2,…, using the formula below:

$$Y_i = \left[{Y_{i-1}}^b - \frac{1}{a}\ln(U_i)\right]^{\frac{1}{b}}$$

The simulation results can be used to estimate the probability that a failure for a repairable system will occur at a specific operating hour.

2.4 Literature Review Summary

The literature review has covered the current approaches to measuring, modeling and understanding equipment behaviors using parametric and non-parametric techniques. It has revealed that there have been limited publications on the application of these techniques to the mining industry in general and little if any work has been published on the applicability of these techniques to an oil sands processing plant.

3 CASE STUDY

3.1 Albian Process Plant

The case study presented in this thesis was carried out at Albian Sands Energy (ASE) processing plant. Albian Sands Energy Inc. was created by a joint venture to operate the Muskeg River Mine. The mine sits in the Athabasca oil sands region of northern Alberta, 75 km north of Fort McMurray. The mine contains in excess of 5 billion barrels of mineable bitumen, and at full production, it produces in excess of 155,000 barrels of bitumen per day (ASE, 2006).

The process plant consists of four primary operation areas:

- Mine: the mining operation system uses open pit mining techniques to supply approximately 15,000 tons/hour oil sands to the process plant.

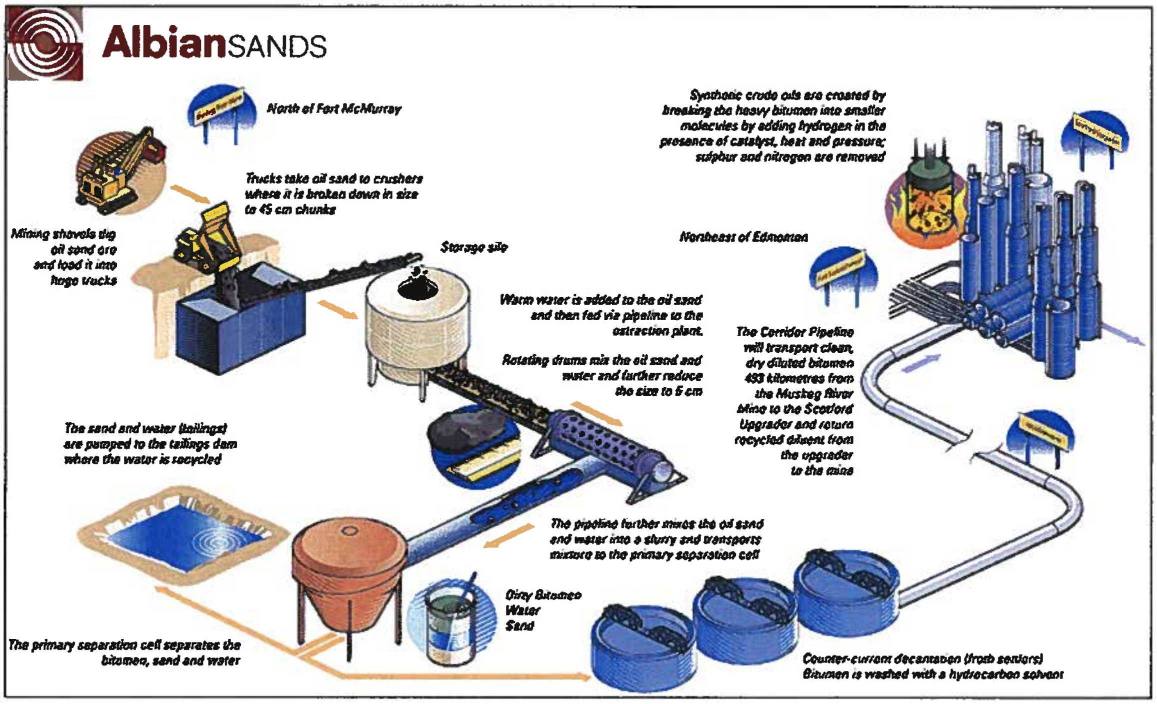
- Ore Preparation: The ore preparation system receives mined oil sand from the haul truck and shovel operation. Crushers are used to reduce the oil sands ore's size. The crushed ore is conveyed to rotary breakers, where warm water is added to liberate the bitumen, and oversized waste rock is rejected. The slurry at a consistent and even feed rate is delivered to the extraction system.

- Extraction: The function of this system is to separate bitumen from the conditioned oil sand feed. The extraction system receives raw feed (oil sands) slurry from the ore preparation area via two conditioned slurry pipelines. Each conditioned slurry line feeds directly into the feed distributor of the Primary Separation Cells of Train 1 & 2, in which the slurry separates into three phases or layers. The upper layer is bitumen-rich froth and is pumped to the froth operation; the middle layer is withdrawn continuously and flown by gravity to the primary flotation cells; the lower layer consists of tailings (mainly fine sand) that are withdrawn and pumped to the tailings treatment area.

- Froth: The froth system removes entrained air from the bitumen froth by cascading it over a shed deck in the presence of steam. The deaerated bitumen is transported by pipeline to the Scotford refining station.

The process is shown in Figure 3-1.

Figure 3-1 Albian Plant Process (ASE, 2005)



At Albian, the maintenance of mining mobile equipment has been subcontracted to equipment vendors. In the process plant, Albian performs the maintenance for ore prep, extraction and froth equipment. An associated reliability and inspection group is set up at ASE to support maintenance teams on plant equipment reliability improvement. The ASE reliability group is engaging in numerous activities to support maintenance. Some of them are:

- Identifying and inspecting important items with respect to maintenance
- Collecting appropriate maintenance data to support maintenance management and operation strategy
- Applying decision logic to critical failure modes

- Implementing root cause failure analysis to improve equipment and system reliability
- Developing design-associated priorities that can facilitate preventive maintenance (PM).

It is suggested by Dabbs (2004) that "specific performance indicators must be established, measured and reported in order to provide operation and maintenance supervision with pertinent and detailed information that they can effectively use to mange their business unit". Unfortunately, until recently existing system at Albian has lots of data but no easy to determine RAM information from it.

3.2 Data Collection and Assumptions

During RAM analysis, two major influences on the results are the accuracy of the data and the selection of analysis models. RAM analysis and evaluation will be effective only if the data are accurate and the model is applicable.

Most modern industrial plants have plant information systems. However, data collection must be specified according to the analysis requirements. It has been determined that the RAM information collection system should be designed to "collect, store, and retrieve the RAM information and to provide the means for displaying the data in a meaningful form (U.S. DOD, 1981)." In addition, the database must be routinely updated and checked to satisfy the requirements for analyzing any new problems. At Albian, RAM Reports are a plant equipment reliability, availability, and maintainability event database, which is integrated into the plant operation shift log. When a downtime event occurs, the downtime is captured by the plant information system, related information is input by the control room operators, and the downtime event information is finally stored in a database, which is accessible for RAM Reports. The data used in this case study is downloaded from this database.

For facilitating the selection of the analysis models, the assumptions of parameter analysis on maintenance efficiency have been classified in terms of "the degree to which the operation of an item is restored by maintenance" in the following ways (Mettas *et al.*, 2004):

- Perfect repair or maintenance: the system is restored "as good as new".
- Minimal repair or maintenance: after implementing maintenance actions, the system operating state is still "as bad as old".
- Imperfect repair or maintenance: the system operating state is between "as good as new" and "as bad as old" after implementing maintenance actions.
- Worse repair or maintenance: maintenance action makes "the operating condition worse than that just prior to failure".

Since the reliability of a repairable system is subject to various impacts, including system design, operating conditions and maintenance quality, time between failures for a repairable system are variable. One purpose of system reliability analysis is to evaluate the reliability trend, with the aim to eliminate the decreasing reliability trend and enhance the increasing trend. To quantify the reliability trend, a non-homogeneous Poisson process model is appropriate. As an important non-homogeneous Poisson process model, the Power Law model has been commonly used in modeling repairable system reliability.

The Power Law model uses failure intervals and number of repairs to identify equipment RAM characteristics. However, due to the implementation of preventive maintenance, some components are replaced before they fail. Some assumptions have to be made so as to understand the limitation of the modeling analysis. The assumptions in this case study are:

- All equipment is repairable;
- Equipment is subjected to imperfect repair and maintenance;
- PM is carried out just before the failure: TBF = TBM; therefore, TBM data can be used in failure modeling analysis.

The TBM data presented in the case study and considered as TBF data is net operating time between maintenances. It is calculated by:

TBM = Time between two maintenances - Standby time between two maintenances - Operational delay time between two maintenances

3.3 Non-Parametric Analysis: Results and Discussion

In the Albian process plant, equipment downtime information is collected and sorted in RAM Reports. RAM Reports have no advanced analysis function yet, so it is necessary to analyze the data in this database to indicate equipment reliability, availability and maintainability information. To analyze the data at a low level, KPI's were calculated and basic graphing was performed. Specifically the following was done.

- Downtime composition: This KPI identifies the major reasons causing plant downtime by summing up downtime by reason. Each unit's downtime is shown in a graph to provide detailed downtime information.
- Mechanical Availability (MA): MA measures the percentage time that a unit is available for production. MA is expressed by

$$MA = \frac{TH - MH}{TH}$$

Where

TH = total hours of the measurement period

MH = maintenance hours in the measurement period

- Pareto analysis: This analysis is used for identifying critical maintenance units according to maintenance hours.
- Time between maintenance and time to repair (TBM & TTR): Time between maintenance is an important index for evaluating equipment reliability; and time to repair is an index of maintainability. TBM and TTR trends can identify whether equipment reliability and maintainability have improved or deteriorated.
- Breakdown repair time: This indicator tracks the breakdown hours of a unit under preventive maintenance (PM), and indicates whether PM procedures are valid in preventing breakdown.
- Maintenance hours per million tons (MH/Mt): This KPI estimates the relationship between maintenance hours and production, and indicates the maintenance effectiveness. It is calculated as

MH/Mt = (Maintenance Hours /(Production Tonnage)

The initial downtime data in the analysis are downloaded from RAM Reports. The downtime reasons in this database are classified as:

- Maintenance: equipment is down for maintenance due to planned maintenance, opportune maintenance, or breakdown.
- Operational: equipment is shut down for operational related reasons.
- False event: this event is not a downtime event.
- Unspecified: this is to capture empty cells.
- Unknown: indicates that no valid reason was put in. It is used to track the operators' effectiveness in inputting data.

Having a database of down time reasons with specific classification for the reason allowed assessment of the equipment history using the non-parametric techniques discussed earlier for Ore Prep, Extraction, and Froth. The analysis was done using data from March 2005 to March 2006. The results are presented next.

3.3.1 Ore Prep Units RAM KPI

Downtime Composition

Table 3-1 summarizes downtime hours in ore prep by reasons. It is noted that identified maintenance caused just 36% of downtime; operational delay caused 20% of downtime, and a significant portion of downtime was classified as Unknown reason downtime, which impacts the accuracy of this analysis.

Table 3-1 Downtime Summary by Reasons for All Equipment in Ore Prep

Downtime Reason	Downtime Hours	Percentage
False Event	70.15	0.49%
Maintenance	5127.47	35.88%
Operational	2976.22	20.83%
Unknown	6109.59	42.75%
UNSPECIFIED	7.08	0.05%

Downtime is also shown in graphic form by units and by month, to provide downtime information in this analysis, as shown in Figure 3-2 and Figure 3-3.

Figure 3-2 Downtime of P421 Crusher Train 1

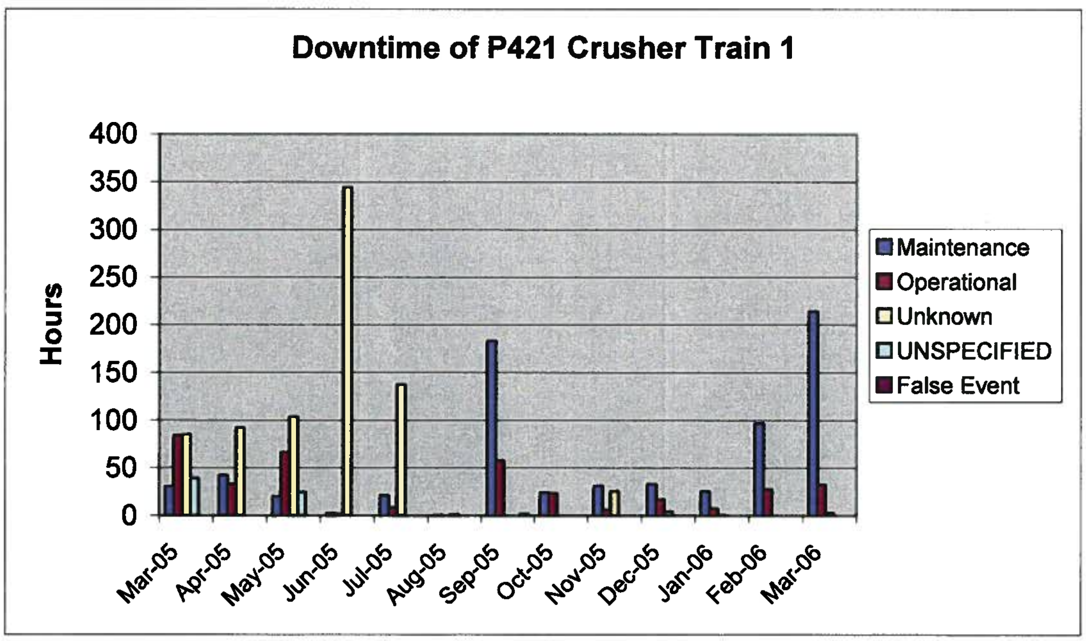
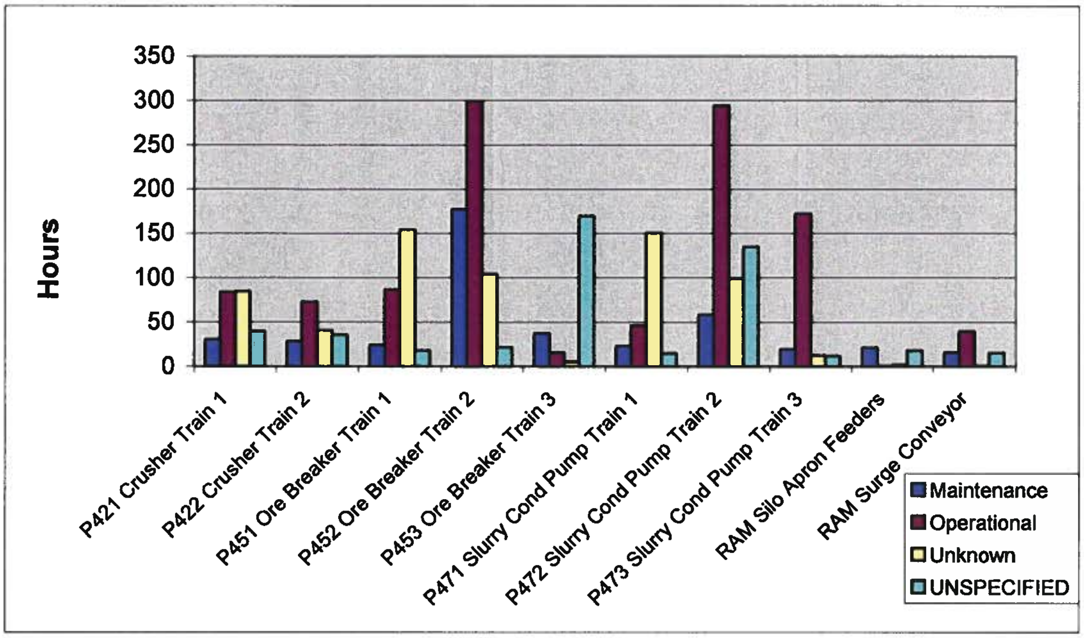


Figure 3-3 Downtime of Ore Prep for 2005 March



Mechanical Availability (MA)

Mechanical availability analysis of each ore prep unit is shown via graphs by unit and by month. It is obvious which unit had low MA in a certain month, or which months had the lowest unit MA. Figure 3-4 and Figure 3-5 show MA of ore prep by month and by unit.

Figure 3-4 MA of Ore Prep Units for March

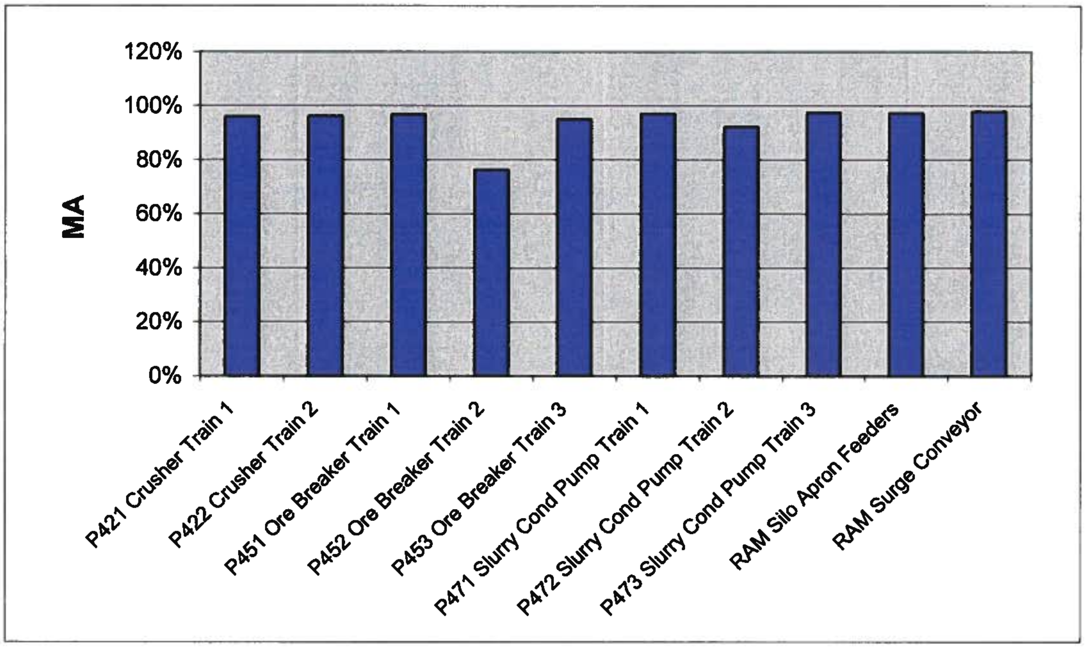
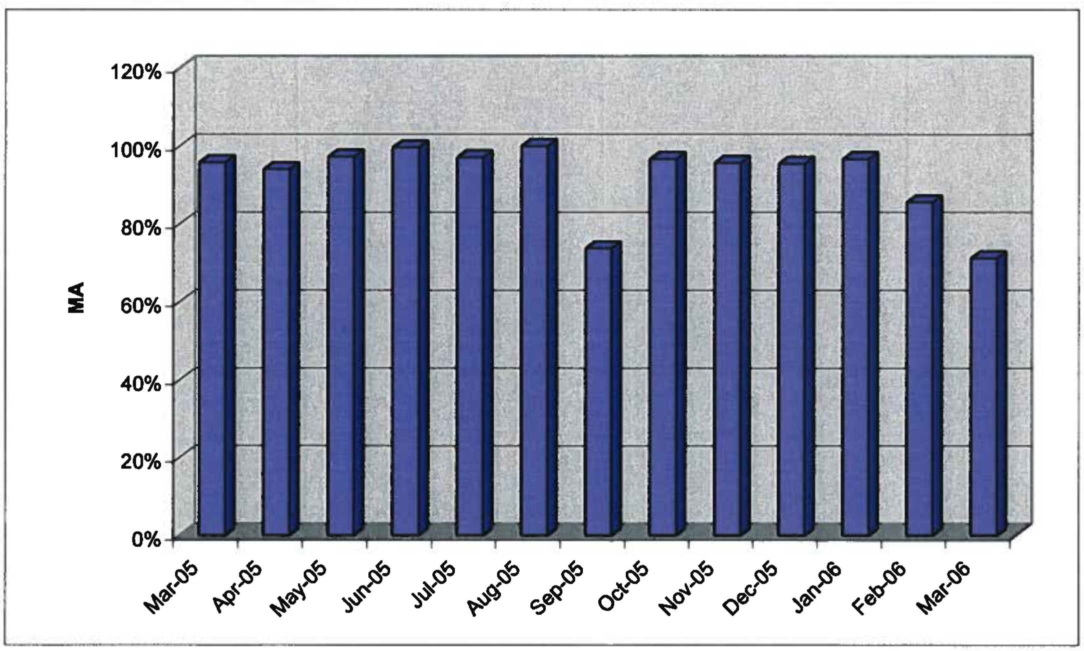


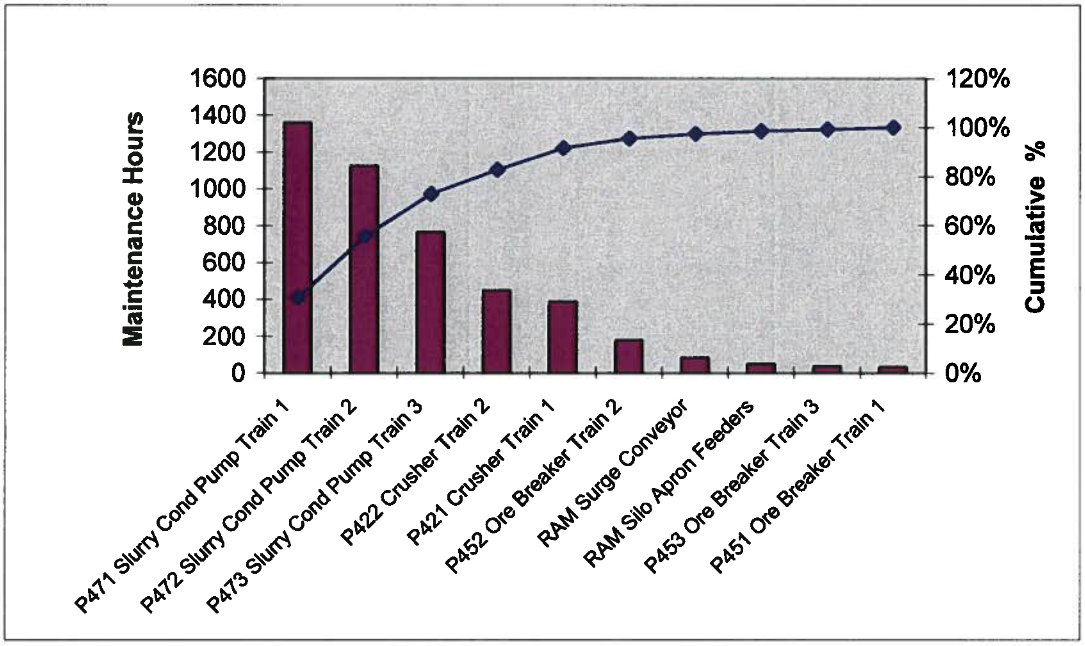
Figure 3-5 MA of P421 Crusher Train 1



Pareto Analysis

Pareto analysis was carried out for identification of major maintenance downtime units. In the Ore Prep area, Pareto analysis shows that the top three units (Slurry condition pump 1, 2 & 3) caused 80% of total Ore Prep downtime (Figure 3-6).

Figure 3-6 Ore Prep Downtime Pareto Analysis



TBM and TTR

The TBM and TTR of Ore Prep units were calculated, and trend lines are drawn using Excel functions. TBM and TTR analysis in Ore Prep show the reliability of some of the equipment is decreasing. The equipment whose TBM trend has significant decreasing is listed below:

- P473 Slurry Condition Pump Train 3 (Figure 3-7)
- P472 Slurry Condition Pump Train 2 (Figure 3-8)
- P471 Slurry Condition Pump Train 1(Figure 3-9)
- RAM Surge Conveyer (Figure 3-10)

Figure 3-7 TBM and TTR of P473 Slurry Condition Pump Train 3

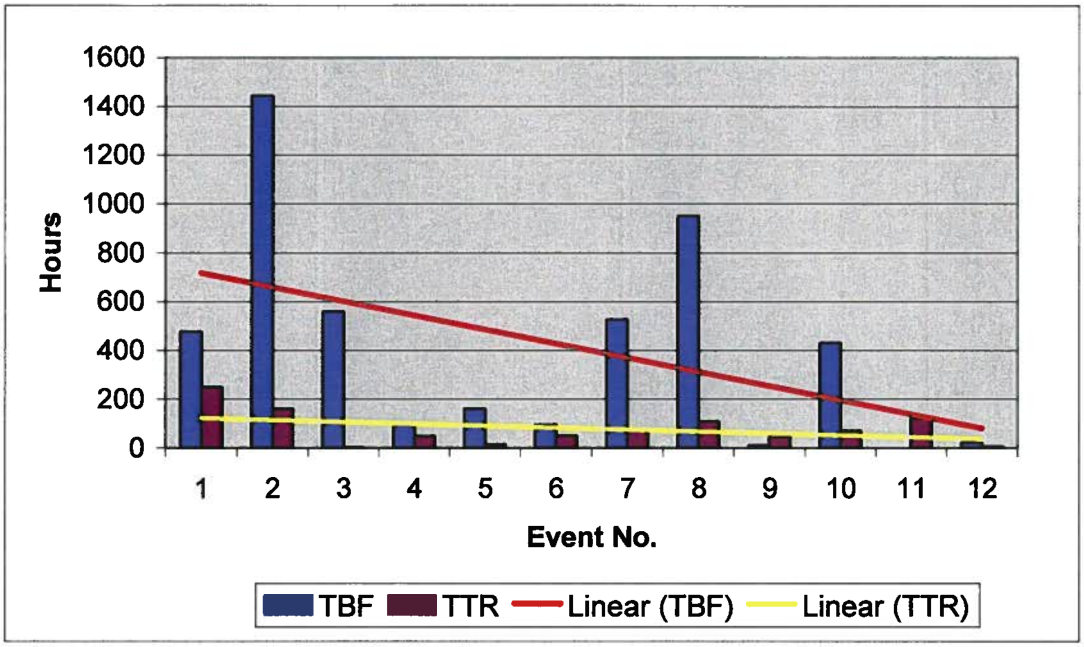


Figure 3-8 TBM and TTR of P473 Slurry Condition Pump Train 2

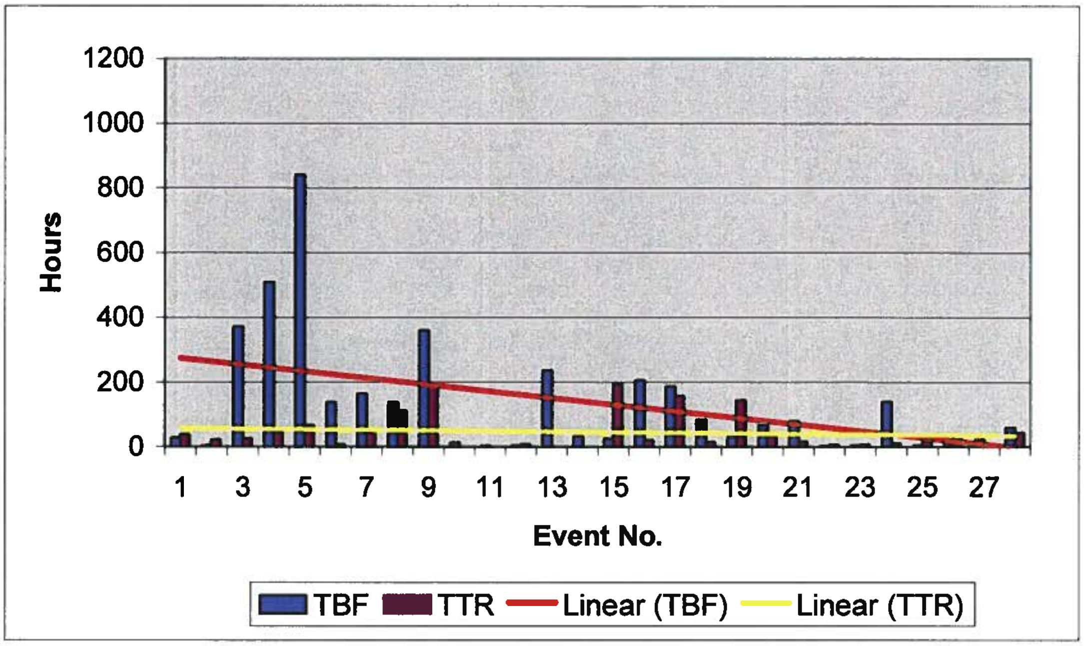


Figure 3-9 TBM and TTR of P471 Slurry Condition Pump Train 1

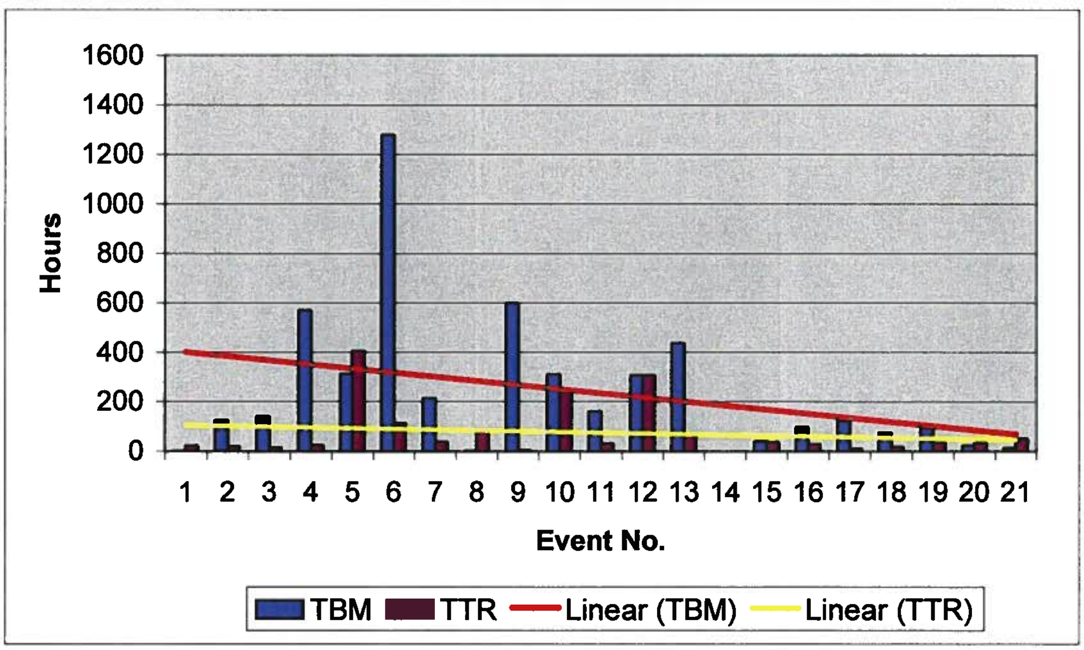
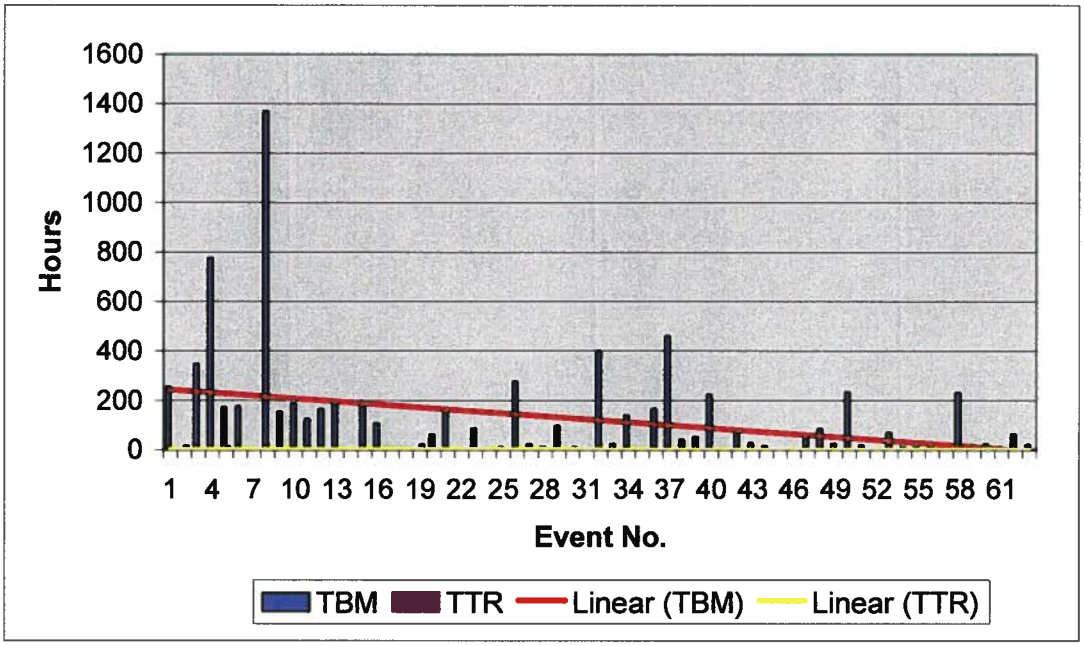


Figure 3-10 TBM and TTR of RAM Surge Conveyor



Breakdown Time

Breakdown time analysis was implemented for the critical units identified by Pareto analysis. Figure 3-11 shows these units had an increasing trend in breakdown hours after October. The slurry condition pump train 2 peaked in November and December, but breakdown time was reduced after January. Train 1 had a continuously increasing trend after December, and the slurry train had significant breakdown hours in January and February 2006. Table 3-2 shows the percentage time the feed was at over-design capacity of 7,000 tons per hour. This may have impacted equipment reliability.

Figure 3-11 Ore Prep Critical Units Breakdown Time Analysis

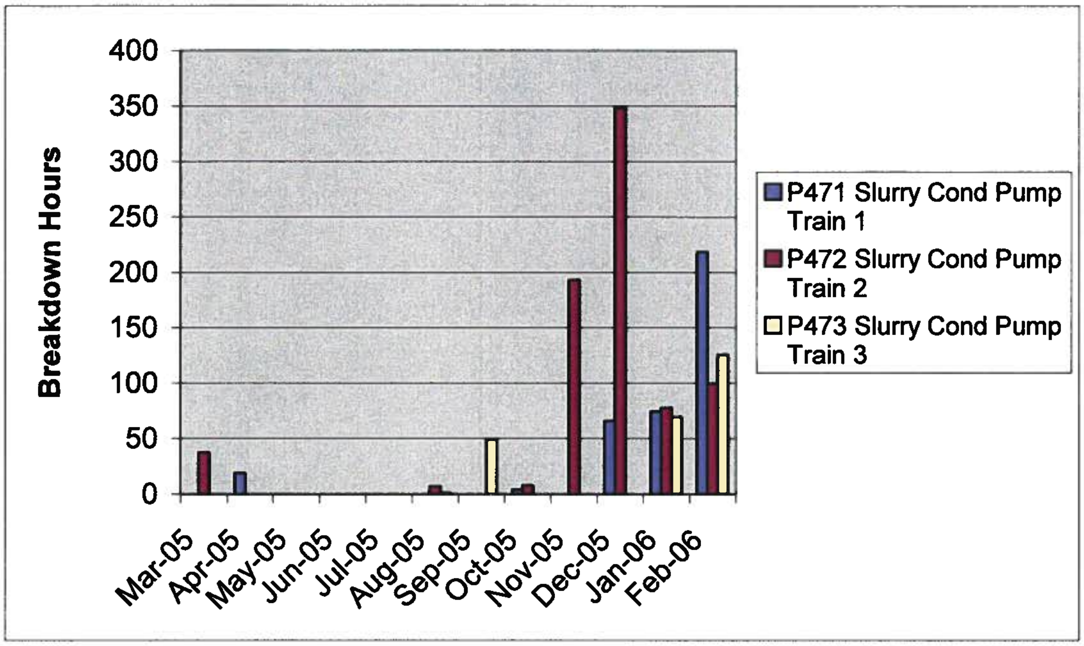


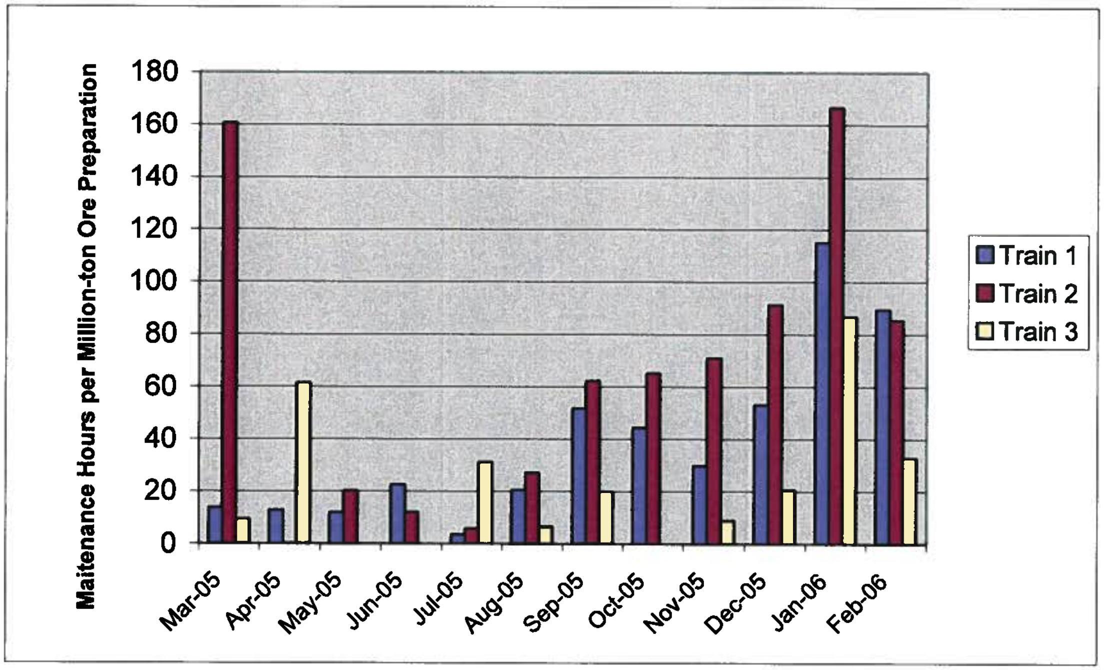
Table 3-2 Percentage of Ore Prep Production at over 7000 tph by time

Data	Train 1	Train 2	Train 3	TOTAL
Jan-05	0.00%	0.00%	0.20%	0.20%
Feb-05	0.08%	0.71%	14.21%	15.00%
Mar-05	0.81%	0.77%	6.98%	8.56%
Apr-05	1.66%	0.50%	5.76%	7.92%
May-05	0.49%	0.28%	7.34%	8.11%
Jun-05	0.28%	0.91%	1.76%	2.95%
Jul-05	1.21%	11.25%	1.29%	13.74%
Aug-05	0.76%	1.27%	2.15%	4.18%
Sep-05	0.85%	2.05%	3.22%	6.12%
Oct-05	6.12%	14.89%	9.79%	30.80%
Nov-05	3.85%	2.19%	11.62%	17.65%
Dec-05	0.96%	7.11%	19.17%	27.24%
Jan-06	1.64%	10.02%	20.04%	31.69%
Feb-06	0.00%	1.01%	2.69%	3.70%

Maintenance hours per million-ton Ore Prep Production Analysis

Maintenance hours per 1 million ton ore production were calculated to estimate the relationship between maintenance hours and production quantity. The maintenance hours per Mt for three ore Prep trains increased, as shown in Figure 3-12. The availability of equipment decreased consequentially.

Figure 3-12 Maintenance Hours per Million-ton Ore Preparation



3.3.2 Extraction Area RAM KPI Analysis

Downtime Composition Analysis

Table 3-3 shows maintenance causes 41% of total downtime, operational downtime is 17% of the total downtime, and Unknown reasons occupied 38% of the total. Unknown reason downtime has a major impact on the accuracy of the results. Figure 3-13 and Figure 3-14 are a part of the results of extraction units' downtime summary by unit and by month.

Table 3-3 Downtime Summary by Reasons for Extraction

Downtime Reason	Downtime Hours	Percentage
False Event	1067.39	3.33%
Maintenance	13190.38	41.10%
Operational	5536.5	17.25%
Unknown	12300.59	38.33%

Figure 3-13 2005 Downtime of P552 PSC2

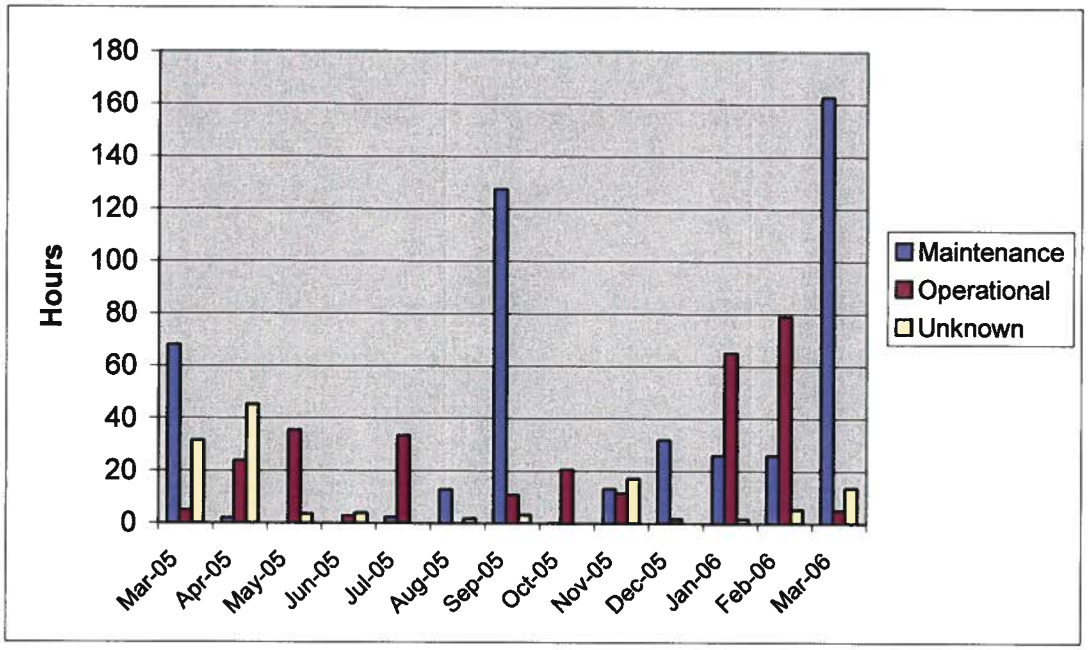
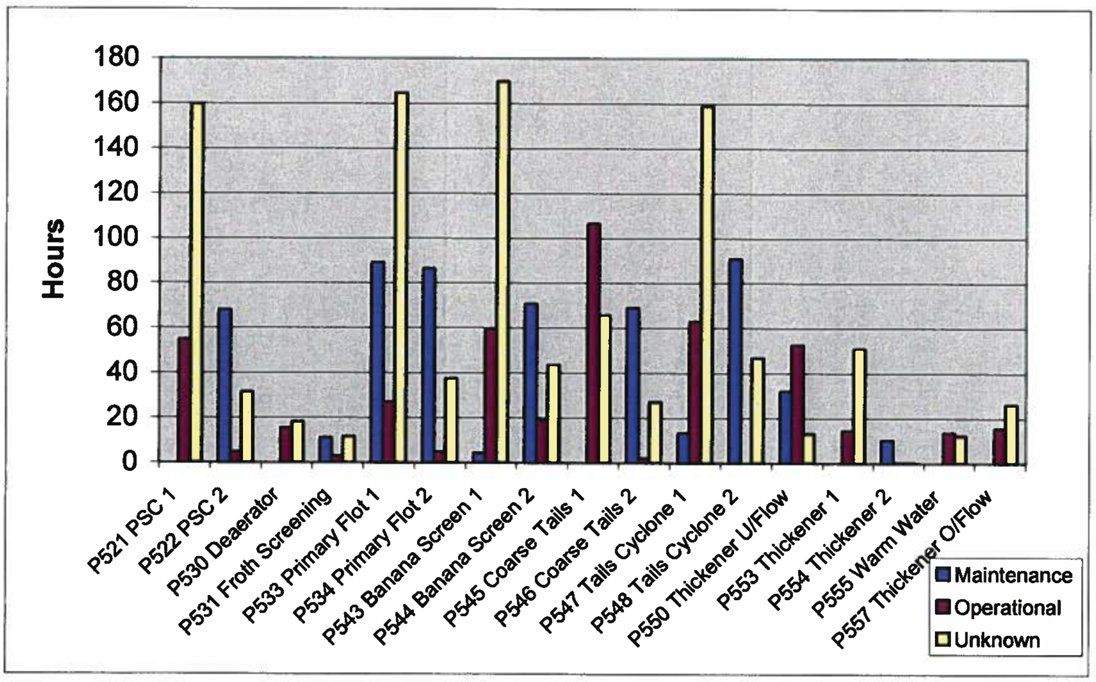


Figure 3-14 Downtime of Extraction for 2005 March



Mechanical Availability Analysis

Mechanical availability of extraction units was assessed by month and by unit from 2005 March to December. The MA charts identified some units with low mechanical availability. Figure 3-13 and Figure 3-16 are examples of extraction units MA by month and by unit.

Figure 3-15 Mechanical Availability of Extraction Units for 2005 April

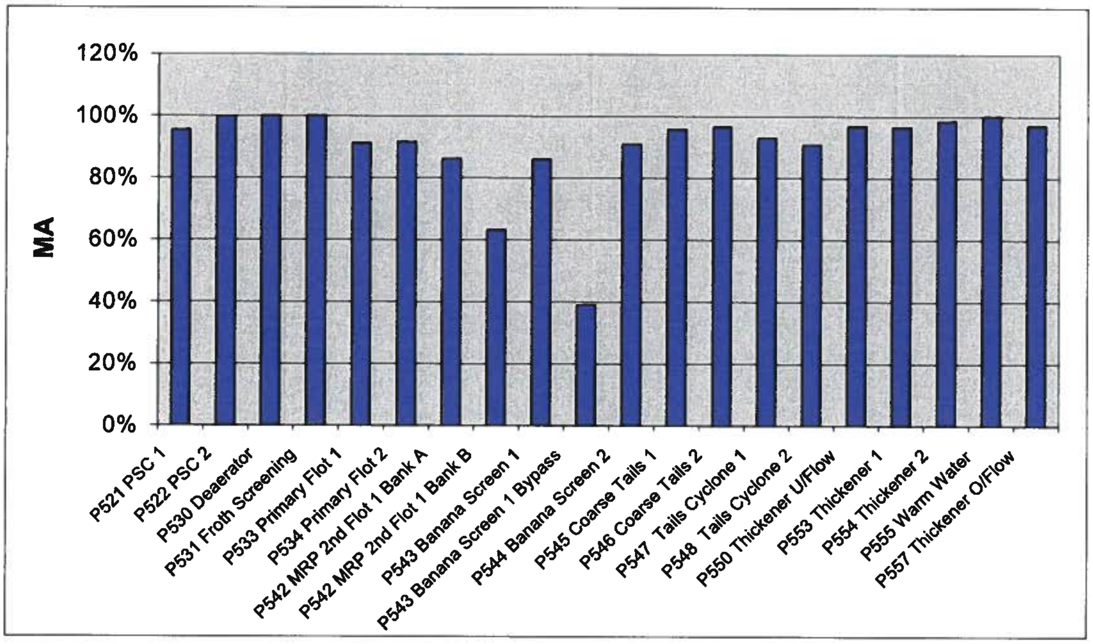
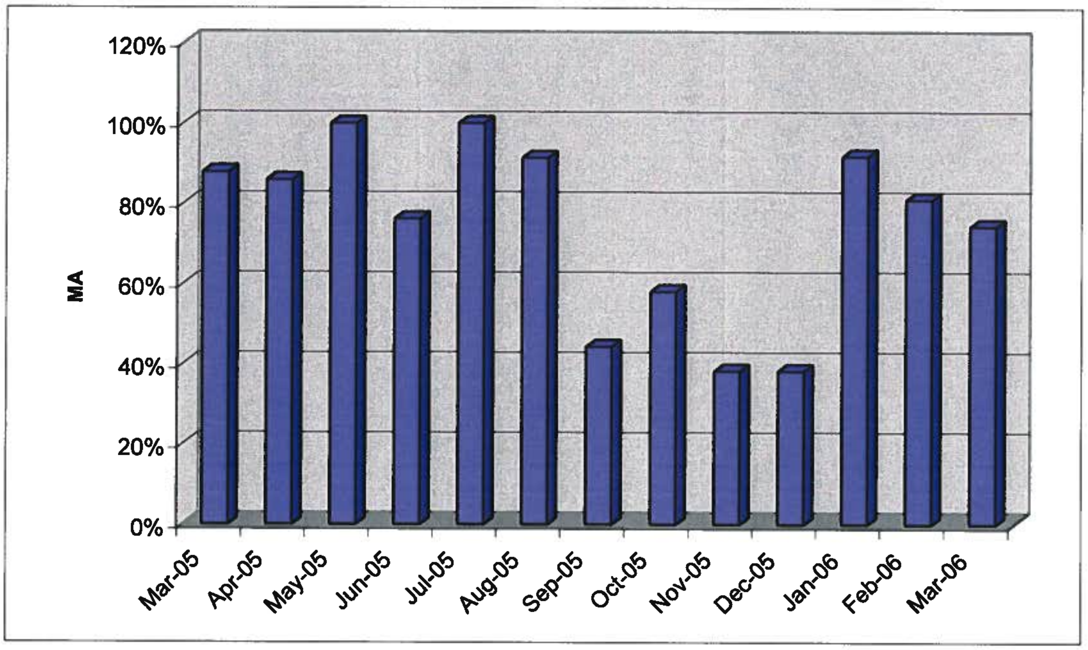


Figure 3-16 Mechanical Availability of P542 MRP Secondary Flot 1 Bank A

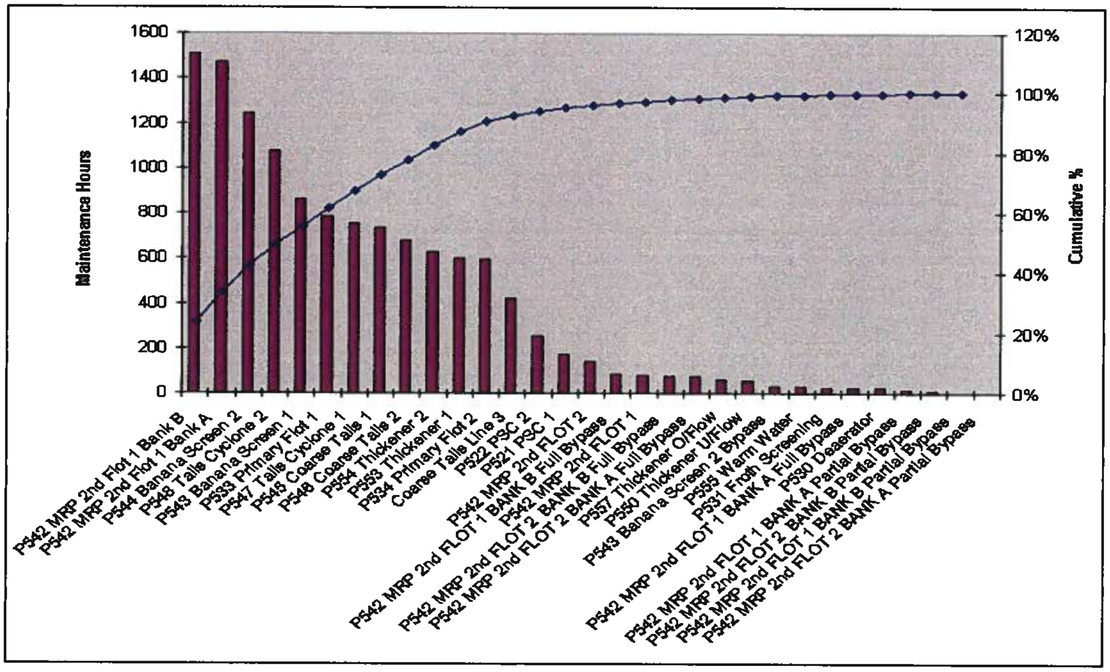


Pareto Analysis

Figure 3-17 shows the Pareto analysis of extraction units' maintenance hours. The Pareto analysis shows that 4 of 31 units caused 40% of total maintenance hours. The 4 critical maintenance units are:

- P542 MRP 2nd Flot 1 Bank B
- P542 MRP 2nd Flot 1 Bank A
- P544 Banana Screen 2
- P548 Tails Cyclone 2

Figure 3-17 Pareto Analysis of Extraction Units



TBM and TTR Results

In extraction, the equipment for which reliability is decreasing based on TBM and TTR chart analysis is:

- P552 PSC 2 (Figure 3-18)
- P552 PSC 1 (Figure 3-19)
- P533 Primary flot 1(Figure 3-20)
- P543 Banana Screen 1(Figure 3-21)

Figure 3-18 TBM and TTR of P552 PSC2

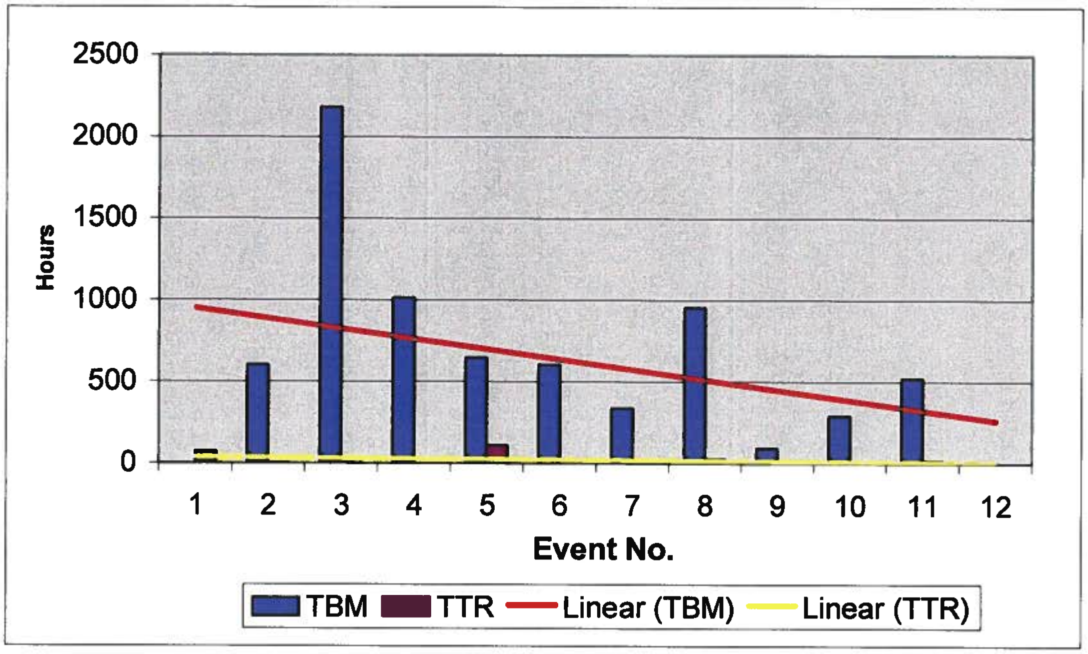


Figure 3-19 TBM and TTR of P521 PSC1

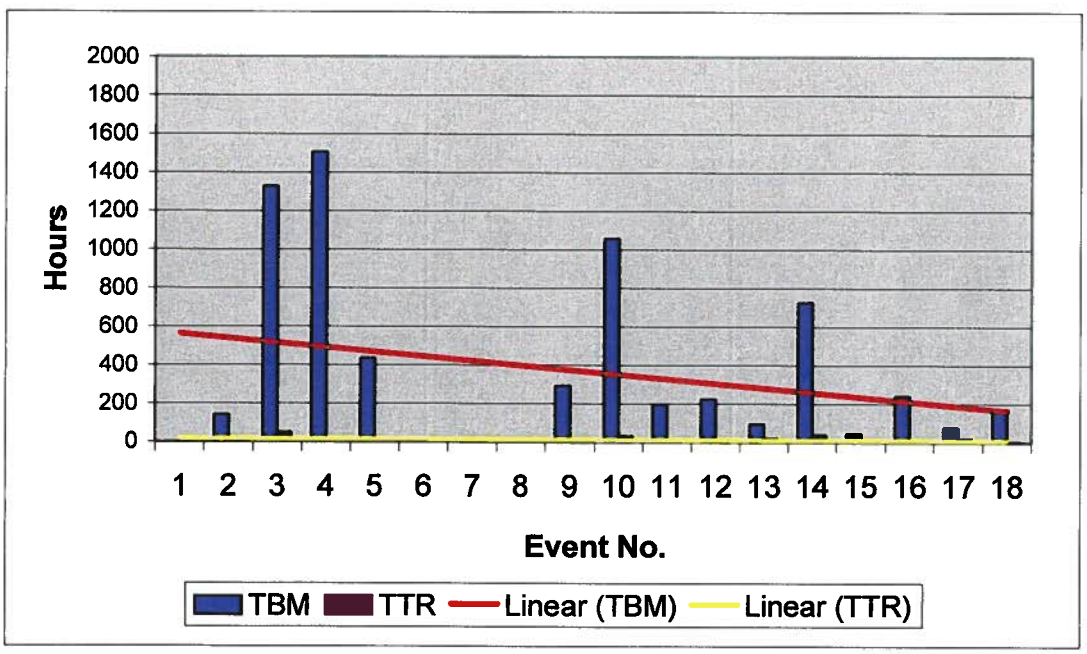


Figure 3-20 TBM and TTR of P553 Primary Flot 1

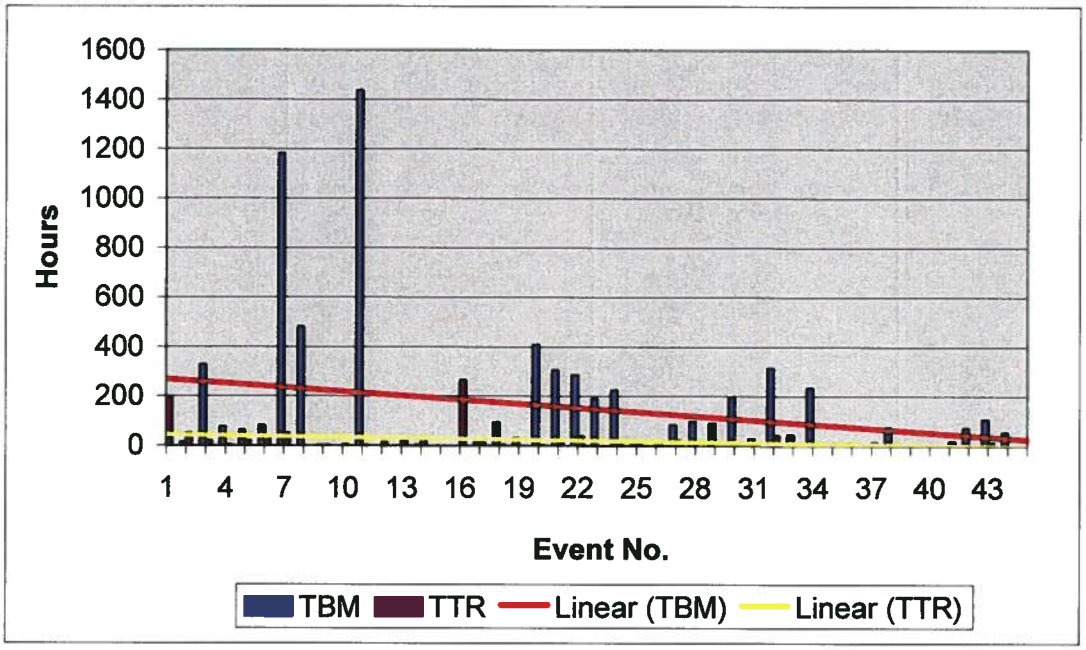
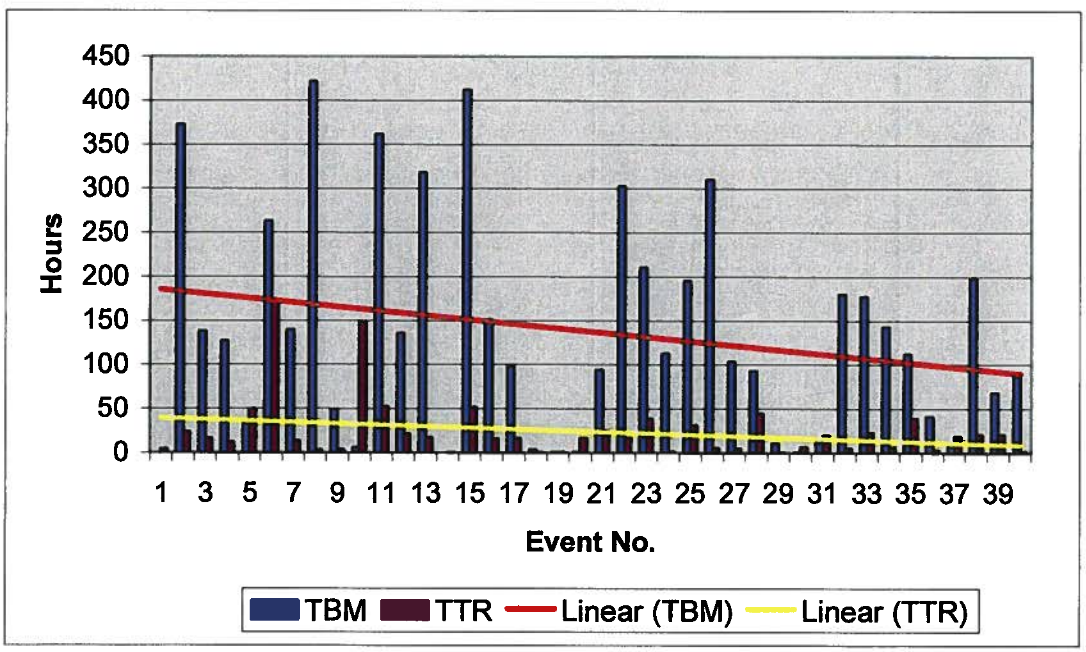


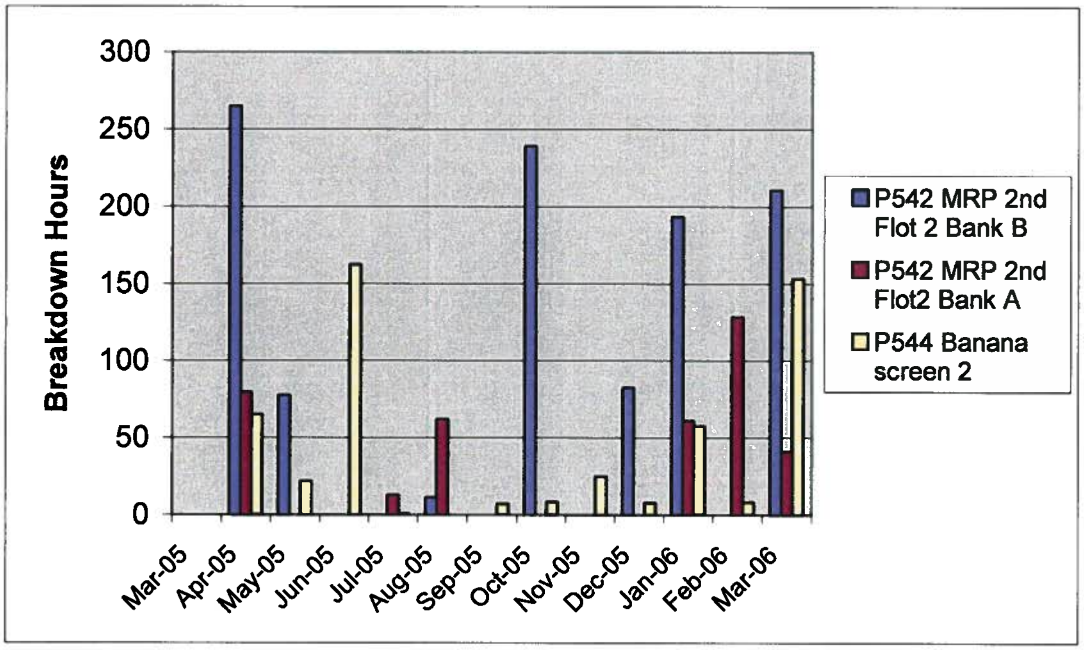
Figure 3-21 TBM and TTR of P543 Banana Screen 1



Breakdown Hours Analysis

Critical unit breakdown hour analysis in Figure 3-22 shows that P542 MRP second Flot 2 bank B had high breakdown risk. It required over 200 hours to repair. P542 MRP second Flot 2 back A and P544 banana screen 2 also had significant breakdowns that caused long repairs.

Figure 3-22 Extraction Critical Unit Breakdown Time



3.3.3 Froth treatment RAM KPI Analysis

Downtime Composition Analysis

Due to comparably high reliability, froth treatment units have 16% of downtime in maintenance, and 52% of downtime is operational delay as shown in Table 3-4. Figure 3-23 and Figure 3-24 shows examples of froth unit downtime hours by unit and by month.

Table 3-4 Downtime Summary by Reasons for Froth Treatment

Downtime Reason	Downtime Hours	Percentage
Maintenance	1416.25	16.32%
Operational	4568.14	52.66%
Unknown	2691.2	31.02%

Figure 3-23 Downtime of RAM Product Tank and Pump 2

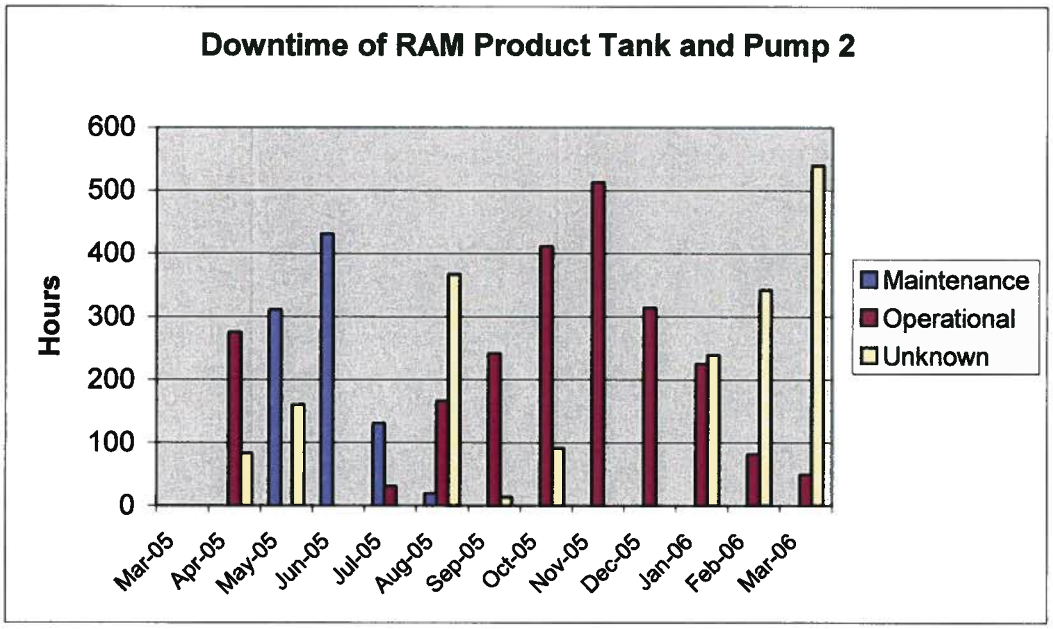
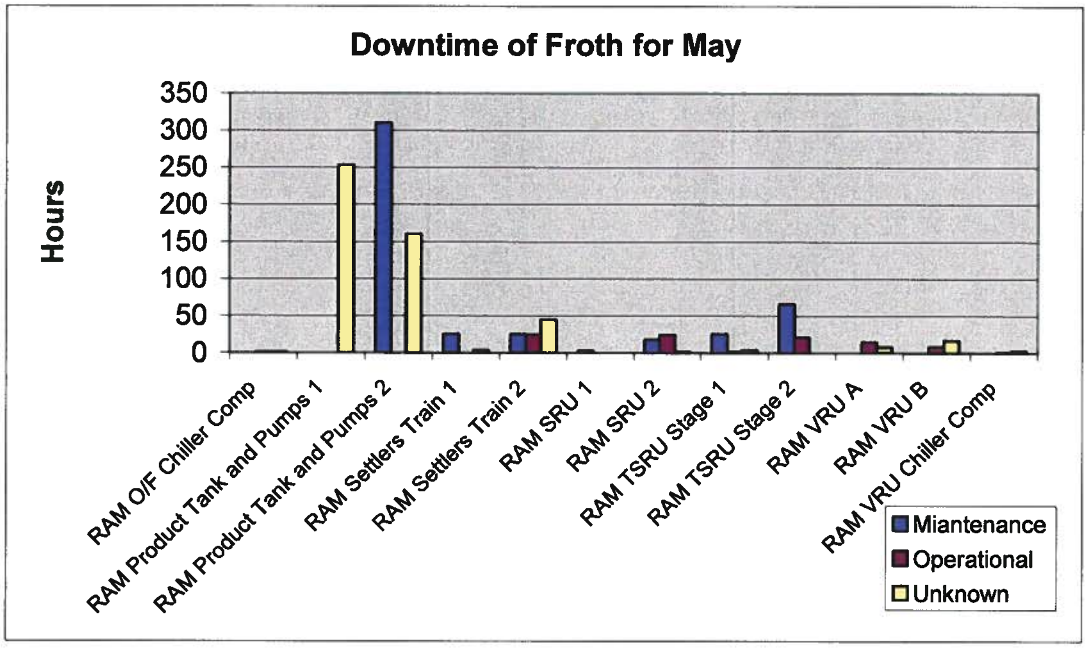


Figure 3-24 2005 Downtime Hours of Froth Units for May



Mechanical Availability Analysis

Froth units have high mechanical availability. The mechanical availability analysis is shown by units and by months, as in Figure 3-25 and Figure 3-26, to monitor the availability of froth units for production.

Figure 3-25 Mechanical Availability of Froth Units for 2005 May

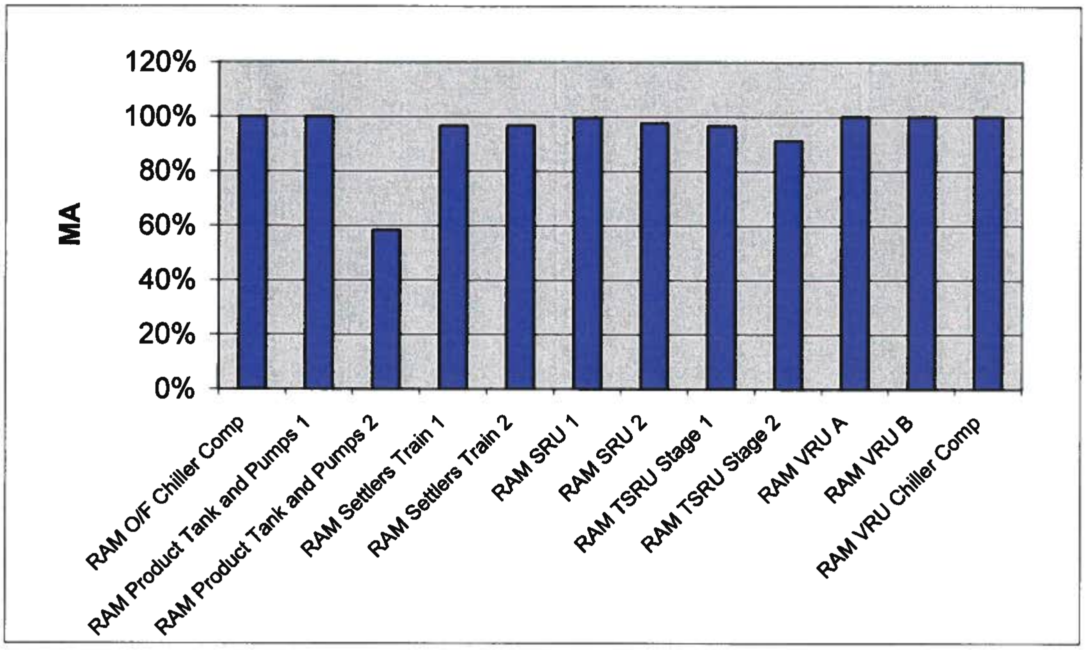
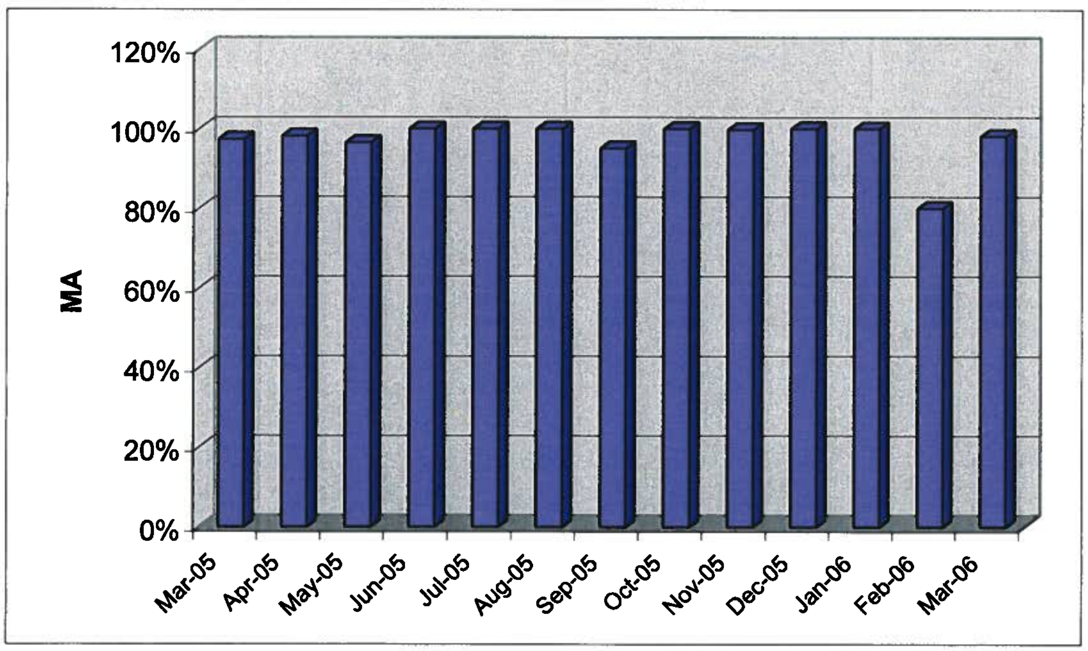


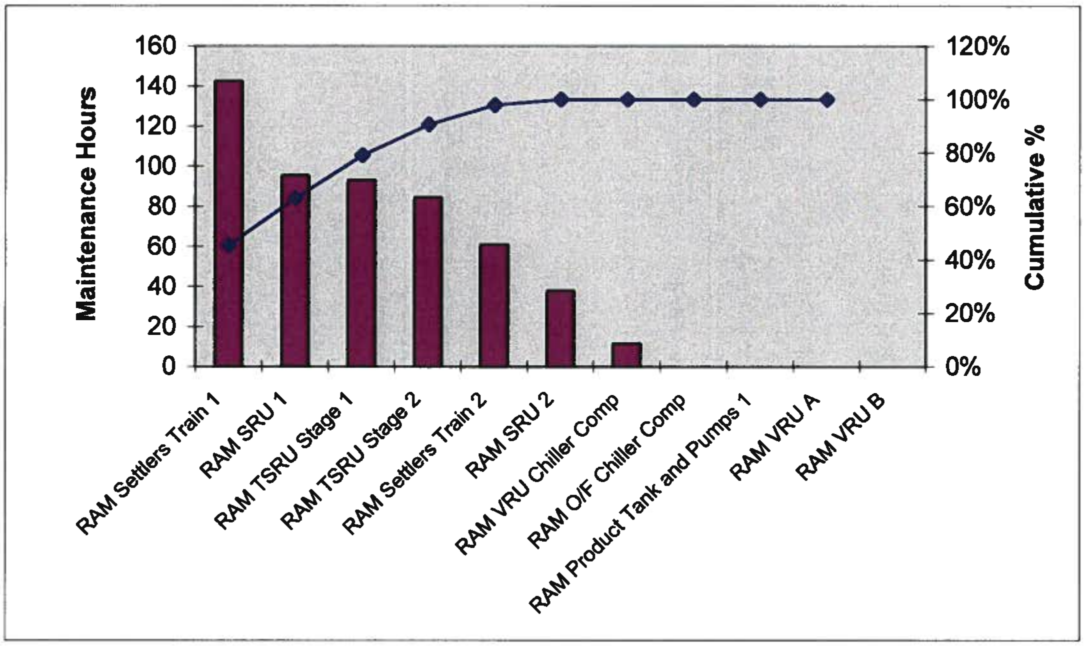
Figure 3-26 Mechanical Availability of RAM TSRU Stage 1



Pareto Analysis

Froth units downtime Pareto analysis identified RAM Settlers Train 1 as a critical maintenance item, which caused 40% of total Froth downtime.

Figure 3-27 Pareto Analysis for Froth Units Downtime



TBM and TTR Analysis

TBM and TTR analysis for Froth units shows the reliability of froth units is increasing, as indicated in Figure 3-28 and Figure 3-29. Due to long maintenance intervals, TBM and TTR in a year do not show reliability information for some froth units.

Figure 3-28 TBM and TTR of RAM TSRU Stage 1

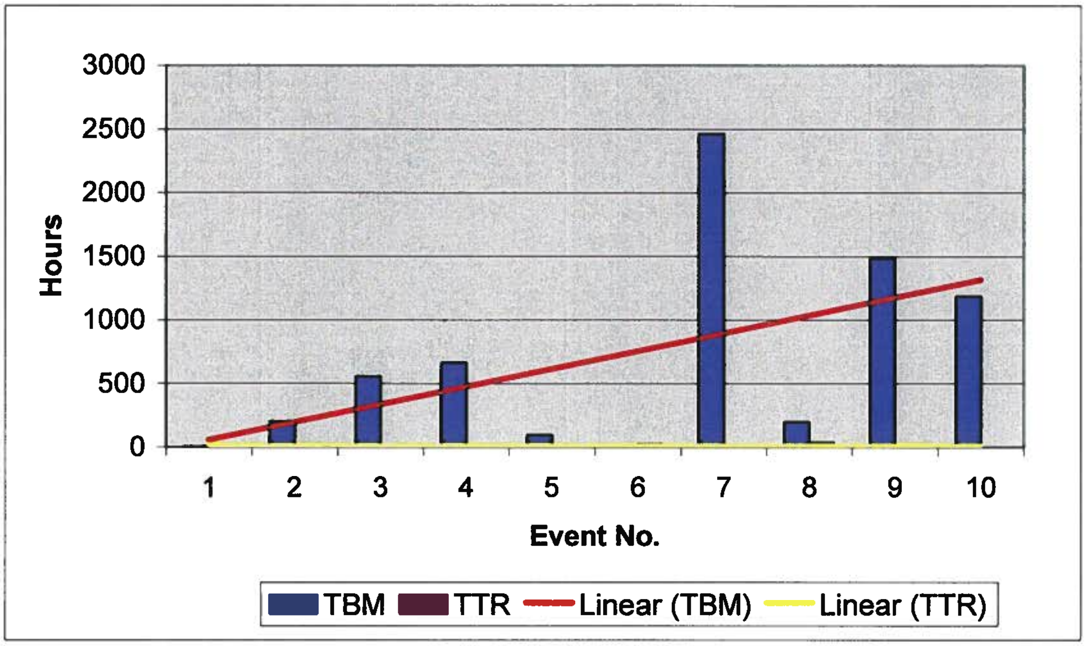
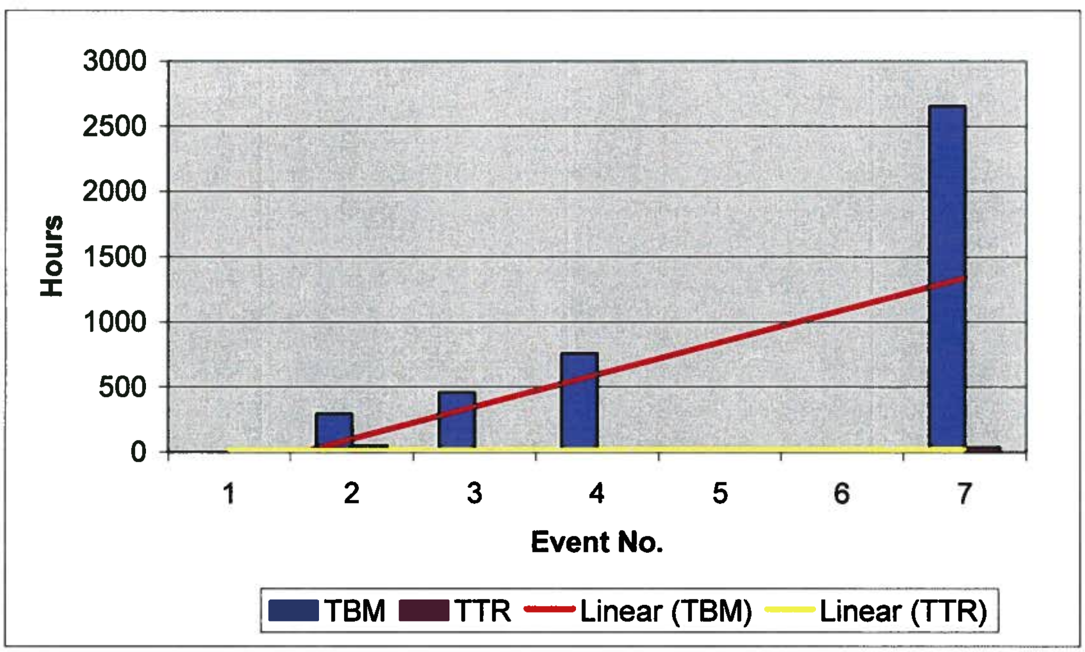


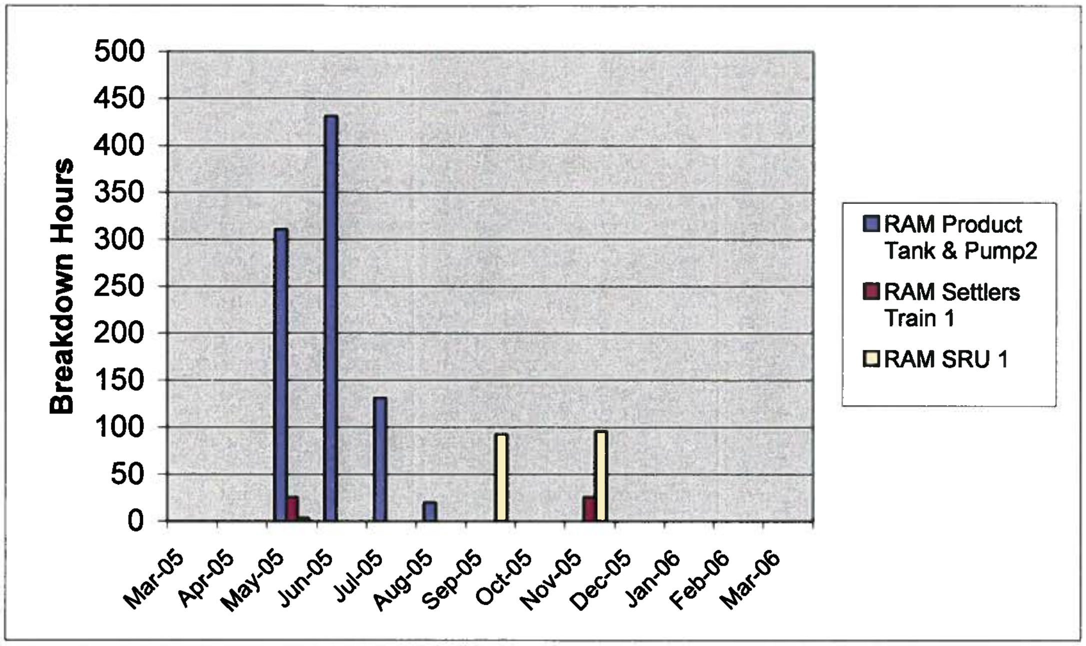
Figure 3-29TBM and TTR of RAM Settlers Train 1



Breakdown Hours Analysis

The RAM product Tank & pump 2 reveal an increasing trend in breakdown repair, as shown in Figure 3-30; however, after September 2005, breakdown was prevented.

Figure 3-30 Breakdown Hours Analysis for Froth Critical Units



3.3.4 Non-Parametric Analysis Results Discussion

The non- parametric analyses have been carried out based on available data. According to the analysis result, the following is noted:

- The downtime composition analysis shows that over 30% of downtime has not been given a reason by the operator, which limits the validity of the analysis results. It also identifies an easy win for the company in encouraging the operators to input the reasons.
- Downtime composition analysis indicates that operational delay is a major part of downtime. Operational delay hours indicate the opportunity cost of the idle equipment. However, given the level of detail of the analysis it is not possible to determine how much of this is due to true operational delays and how much is due to redundant units being on standby. Thus, a more detailed analysis should be performed to determine the amount of operational delay versus standby downtime.
- The Pareto analysis shows that some units have caused a significant part of total plant downtime. These units should have priority for any improvement initiatives.
- Calculation of MA sets a baseline for equipment and allows measurement of the impact of potential changes in practices and procedures. It also allows comparison amongst like equipment and potentially with other oil sands processing plants.
- MTBM indicates the reliability may be decreasing. This would indicate an opportunity to implement different strategies for equipment management.

However this also could be an artifact of the data caused by the high percentage of unknown downtime.

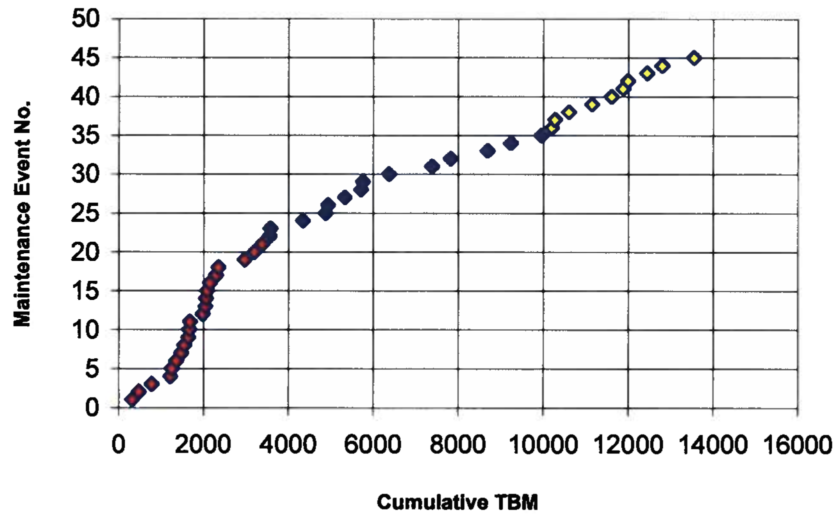
- Maintenance hours per million-ton ore preparation appears to indicate that operating above design capacity has a negative impact on equipment availability. Overload may increase the production in the short-term; however, it causes an increase in maintenance breakdown hours and a decrease in production in the long-term. A stable and uniform loading may provide a better production improvement approach that can ensure equipment reliability and can benefit long-term production.

3.4 Power Law Model Analysis: Results and Discussion

The Pareto analysis has indicated that Slurry pump train 1, 2 & 3 had significant downtime in 2005. For achieving detailed reliability information, the Power Law model analysis is carried out across the cumulative TBM of Slurry pump train 1, 2 & 3 yearly from 2005 to 2007 in this section. The analysis first is to obtain maximum likelihood estimates of the Power Law model parameters. According to the estimated parameters, Graphical trend test, Goodness-of-Fit test, and Laplace trend test are employed to check whether the Power Law model is acceptable. The estimated parameters are further used to understand reliability characteristics, to project the MTBM, and to predict maintenance needs if the Power Law model is accepted.

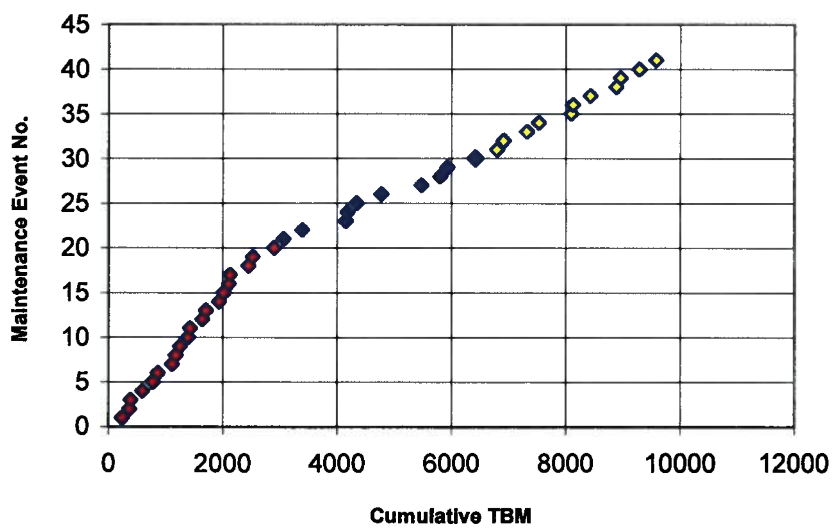
To track the data trend, maintenance event No. versus Cumulative TBM plotting is carried out as shown in Figure 3-31, Figure 3-32, and Figure 3-33. The plots show that maintenance event No. versus cumulative TBM have a yearly trend, which indicates it is appropriate to carry out the analysis by year.

Figure 3-31 Plot of Pump Train 1 Cumulative TBM



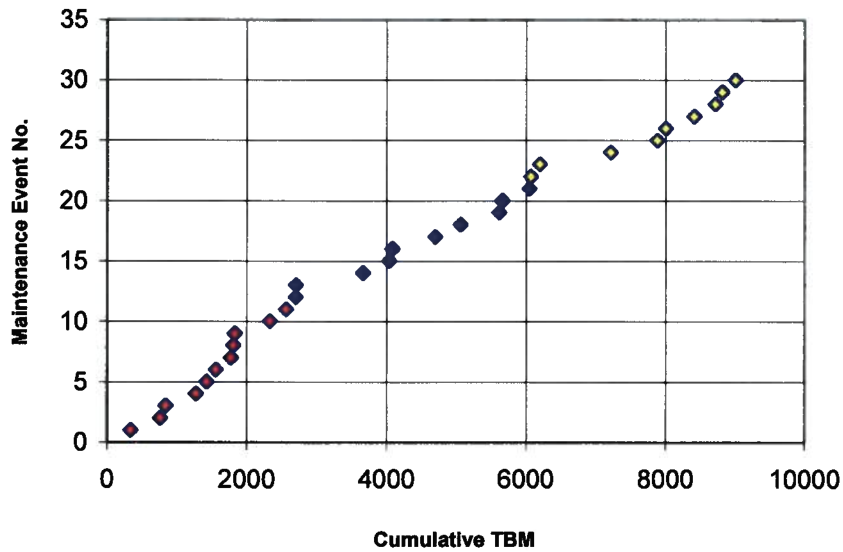
■--- Data point for 2005; ■ --- Data point for 2006; ■ --- Data point for 2007

Figure 3-32 Plot of Pump Train 2 Cumulative TBM



■--- Data point for 2005; ■ --- Data point for 2006; ■ --- Data point for 2007

Figure 3-33 Plot of Pump Train 3 Cumulative TBM



■--- Data point for 2005; ■ --- Data point for 2006; ■ --- Data point for 2007

The PLM parameter estimation results are shown in Table 3-5. The parameters indicate that the TBMs in 2005 were trending down; the TBMs in 2006 had an increasing trend; and the TBM trend in 2007 is approximately renewal. The mean time between maintenance (MTBM) can be used to evaluate the effect of the trend.

Table 3-5 Parameter Estimation Results of Slurry Pump Train Cumulative TBM

Unit Name	PLM Parameter Estimation for 2005 TBM		PLM Parameter Estimation for 2006 TBM		PLM Parameter Estimation for 2007 TBM (the first 6 months)	
	b	*a*	*b*	*a*	*b*	*a*
Slurry Pump Train 1	1.196	0.001269	0.7810	0.01610	0.9160	0.00484
Slurry Pump Train 2	1.021	0.005816	0.8610	0.00885	1.054	0.002251
Slurry Pump Train 3	1.228	0.0007219	0.7531	0.02114	1.0120	0.00272

Table 3-6, Table 3-7 and Table 3-8 show MTBM at the end of each year. They indicate, following the increasing trend of TBM in 2006, the MTBM increased to around 450 at the end of 2006 from 150 at the end of 2005; however, the increasing trend was terminated in 2007. This evaluated the effect of maintenance improvement programs that was implemented in 2006.

Table 3-6 PLM Shape Parameter *b* Values and Indications for 2005 Pump Train Cumulative TBM

2005	*b*	Maintenance Trend	MTBM at the end of 2005
Pump train 1	1.196	Decreasing	130
Pump train 2	1.021	Decreasing/ Renewal	140
Pump train 3	1.228	Decreasing	190

Table 3-7 PLM Shape Parameter *b* Values and Indications for 2006 Pump Train Cumulative TBM

2006	*b*	Maintenance Trend	MTBM at the end of 2006
Pump train 1	0.6768	Increasing	450
Pump train 2	0.7534	Increasing	410
Pump train 3	0.5564	Increasing	460

Table 3-8 PLM Shape Parameter *b* Values and Indications for 2007 Pump Train Cumulative TBM

2007	b	Maintenance Trend	MTBM at the end of 2007
Pump train 1	0.916	Increasing / Renewal	450
Pump train 2	1.054	Decreasing	270
Pump train 3	1.012	Decreasing	330

The hypothesis test results show there is some doubt that the 2005 data fit the Power Law model as the Goodness-of-Fit test for 2005 pump train 1 data indicates a lack of confidence in fitting the model; and the Laplace trend test for the 2005 pump train 2 data demonstrates a contrary trend with the trend that the parameter b indicates, although other tests show the evidences of fitting the Power Law model, as show in Table 3-9. A possible reason for failing to fit the Power Law model is the TBM data for 2005 are not accurate, since downtime reasons were not completely and correctly inputted (there is 30% of unknown downtime in 2005) when the RAM Reports database just started collecting downtime data in 2005; consequently, the inaccuracy of downtime reasons affected the calculation of TBM.

However, Table 3-10 and Table 3-11 show the hypothesis test results for 2006 and 2007 data the Power Law model is accepted for characterizing the data. An important fact is that RAM event information collection has improved by routine data checking since 2006. Thus, the data is more accurate.

Table 3-9 Hypothesis Test Result of 2005 Slurry Pump Train Cumulative TBM

Unit Name	*b*	Hypothesis testing for Statistical Estimation Result				
		Graphical test	Trend test		Goodness-of-Fit test	
		Duane plot test	Laplace test		Cramer-von Mises test	
		Significance (R^2)	Test Statistic	Significance	Test Statistic	Critical Value (α=0.10)
Slurry Pump Train 1	1.196	0.9597	0.2	56.6%	*0.22899* (*Rejected*)	0.172
Slurry Pump Train 2	1.021	0.9849	*-0.3908* (*Rejected*)	65.2%	0.077299	0.171
Slurry Pump Train 3	1.228	0.9737	0.4694	68.1%	0.070325	0.169

Table 3-10 Hypothesis Test Result of 2006 Slurry Pump Train Cumulative TBM

<table>
<tr><th rowspan="4">Unit Name</th><th rowspan="4">b</th><th colspan="5">Hypothesis testing
for Statistical Estimation Result</th></tr>
<tr><th>Graphical test</th><th colspan="2">Trend test</th><th colspan="2">Goodness-of-Fit test</th></tr>
<tr><th>Duane plot test</th><th colspan="2">Laplace Test</th><th colspan="2">Cramer-von Mises test</th></tr>
<tr><th>Significance (R^2)</th><th>Test Statistic</th><th>Significance</th><th>Test Statistic</th><th>Critical Value (α=0.10)</th></tr>
<tr><td>Slurry Pump Train 1</td><td>0.6768</td><td>0.9592</td><td>-0.6</td><td>72.6%</td><td>0.03876</td><td>0.169</td></tr>
<tr><td>Slurry Pump Train 2</td><td>0.7534</td><td>0.9675</td><td>-0.2773</td><td>61.0%</td><td>0.03692</td><td>0.167</td></tr>
<tr><td>Slurry Pump Train 3</td><td>0.5564</td><td>0.8953</td><td>-0.1306</td><td>55.2%</td><td>0.06816</td><td>0.165</td></tr>
</table>

Table 3-11 Hypothesis Test Result of 2007 Slurry Pump Train Cumulative TBM

Unit Name	*b*	Hypothesis testing for Statistical Estimation Result				
		Graphical test	Trend test		Goodness-of-Fit test	
		Duane plot test	Laplace Test		Cramer-von Mises test	
		Significance (R^2)	Test Statistic	Significance	Test Statistic	Critical Value (α=0.10)
Slurry Pump Train 1	0.916	0.976	-0.3616	64.1%	0.06601	0.165
Slurry Pump Train 2	1.054	0.9758	0.1	54.0%	0.02393	0.169
Slurry Pump Train 3	1.012	0.8956	0.4837	68.6%	0.08409	0.167

3.4.1 Simulation Results and Discussion

The simulation is carried out based on the estimated power law equation and the stochastic process PLM simulation method. The estimated PLM equation is able to generate a series of regular cumulative TBMs by giving the expected number of failures.

The first approach using simulation is to attempt to predict the next failure based on previous failure rate of occurrence. For this the simulation was implemented by using the first 6 TBM of 2007 to estimate the PLM parameters, and then to predict the 7th and 8th TBM. Table 3-12 shows the actual data and the simulation results by the estimated PLM equation. From these tables it can be seen that the prediction of the first (Seventh) failure time was reasonably accurate. However, the second (eighth failure time) was not accurate.

Table 3-12 Comparison of the Actual TBM to the Predicted TBM by the Estimated PLM

		Predicted TBM (Hours)	Actual TBM (Hours)
Pump Train 1	7th TBM	344	347
	8th TBM	337	749
Pump Train 2	7th TBM	269	311
	8th TBM	276	455
Pump Train 3	7th TBM	545	410
	8th TBM	512	300

For bounding the next time to maintenance the stochastic process PLM simulation is carried out 100 times to simulate the 7th TBM using the data for the first 6 TBM to estimate PLM parameters from the first 6 TBM of 2007. These results can be used to assign a probability to the time of the next failure occurrence. This allows management to understand the potential risk associated with maintenance decisions. As well, according to the histograms shown in Figure 3-34, Figure 3-35 and Figure 3-36, it appears that the simulation results follow a lognormal distribution.

Figure 3-34 Stochastic Process Simulation Results of Pump Train 1 7th TBM in 2007

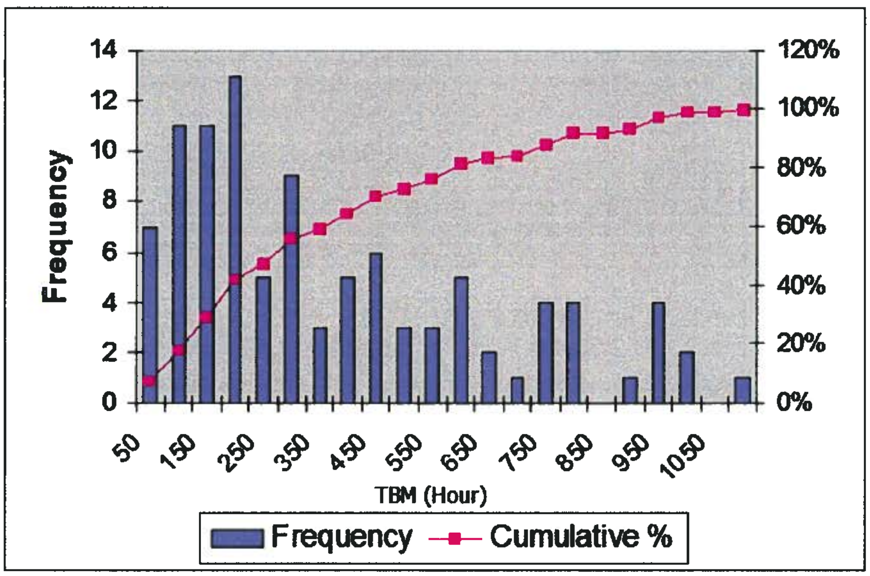


Figure 3-35 Stochastic Process Simulation Results of Pump Train 2 7th TBM in 2007

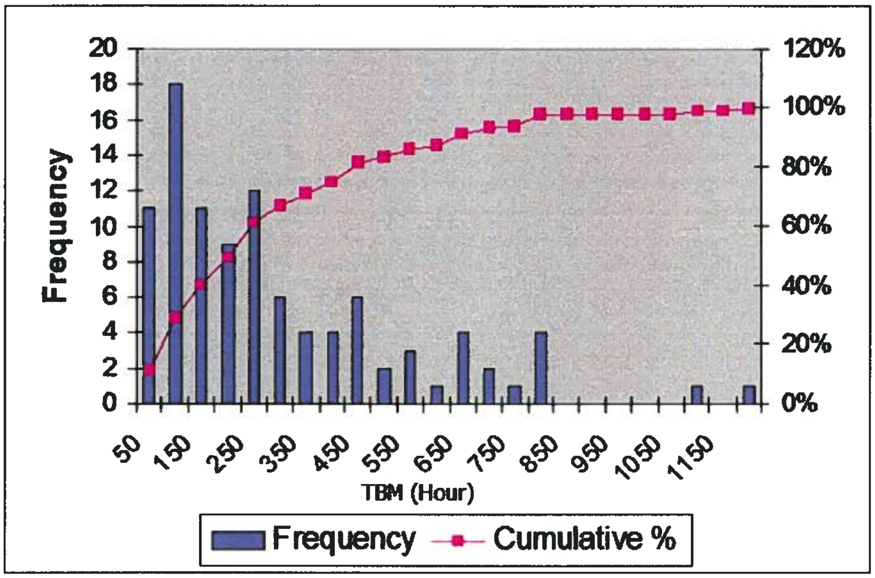
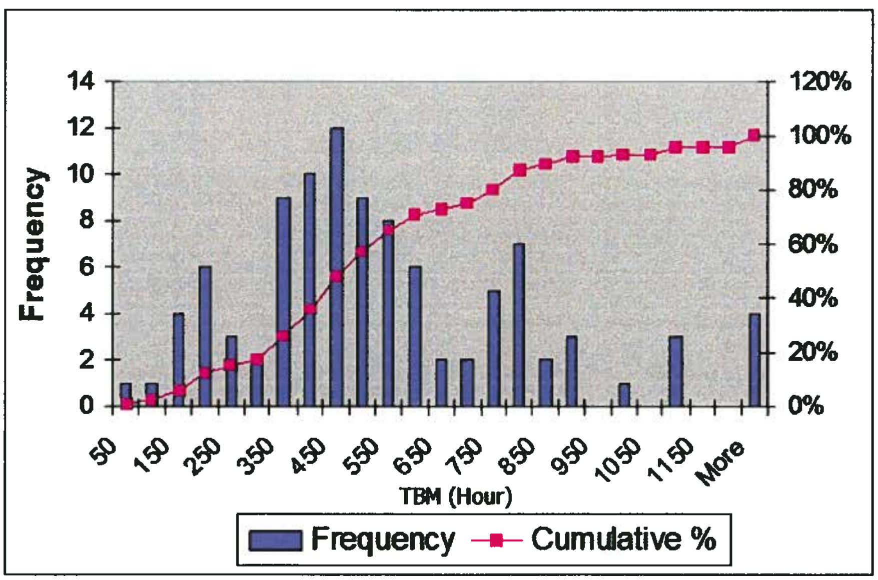


Figure 3-36 Stochastic Process Simulation Results of Pump Train 3 7th TBM in 2007



To check whether the results are lognormal, the logarithm values of the simulation results are shown in a histogram to verify they have a shape of the normal distribution. The histograms show that the logarithm values of the simulation results appear to follow the normal distribution as shown in Figure 3-37, Figure 3-38 and Figure 3-39.

Figure 3-37 Logarithmic Value of Simulated Pump Train 1 7th TBM in 2007

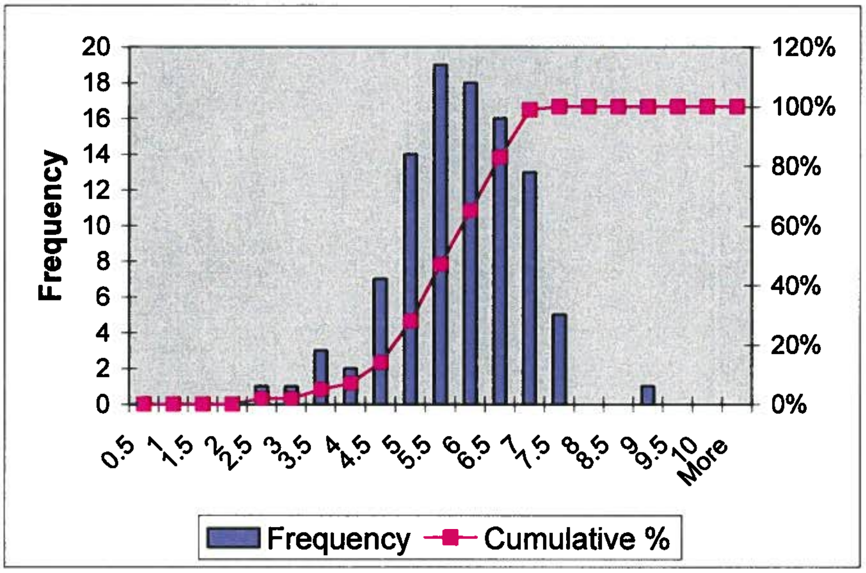


Figure 3-38 Logarithmic Value of Simulated Pump Train 2 7th TBM in 2007

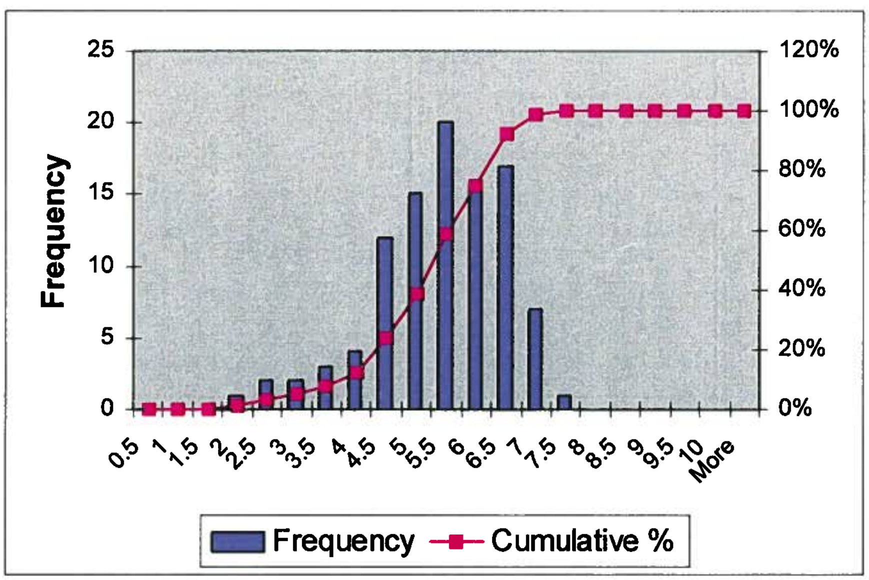
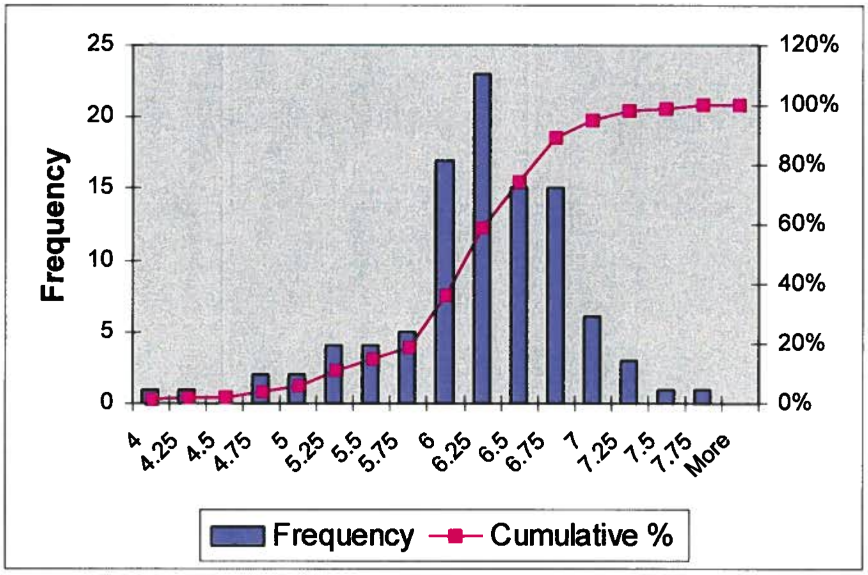


Figure 3-39 Logarithmic Value of Simulated Pump Train 3 7th TBM in 2007



The Chi-Square Goodness-of-Fit Test is employed to further test if the simulation results follow a lognormal distribution. The test results do not reject the hypothesis with a 0.05 significance level as shown in Table 3-13.

Table 3-13 Chi-Square Goodnees-of-Fit Test Results

	Train 1	Train 2	Train 3
Statistic (X^2)	18.2	17	14.7
Critical Value ($X^2_{1-\alpha(\alpha=0.05)}$)	25	26.3	23.7

Based on the estimation above, the final conclusion is that the simulation results are following a lognormal distribution. The probability evaluation can be conducted using the lognormal distribution. Table 3-14 shows the probability evaluation results for the 7th TBM of 2007.

Table 3-14 Probability Evaluation for the 7th TBM for pumps in 2007

Probability	Train 1 (h)	Train 2 (h)	Train 3 (h)
20%	99.6	69.1	251.6
25%	118.3	83.0	281.3
30%	138.1	97.9	311.0
35%	159.3	114.1	341.4
40%	182.4	132.0	372.8
45%	208.0	151.9	406.1
50%	236.7	174.5	441.7
55%	269.4	200.4	480.4
60%	307.2	230.6	523.2
65%	351.8	266.7	571.5
70%	405.9	310.8	627.2
75%	473.6	366.7	693.4
80%	562.4	440.8	775.4
85%	687.1	546.3	883.3
90%	884.0	715.5	1040.6
95%	1284.3	1067.5	1326.8

3.4.2 Discussion of Power Law Model Analysis

- Although the hypothesis tests for the 2005 data show some doubt in fitting the Power Law model due to the inaccurate data, the tests for the 2006 and 2007 data provide evidence that the Power Law model is acceptable for repairable system RAM analysis.
- The Power Law Model provided a reasonable estimate of the next time to maintenance for 2007. However, the accuracy of predictions is impacted by the changes in operational condition and maintenance practices.
- Using a simulation approach with the Power Law process model can lead to probability of time to next failure, which will allow assessment of the risk associated with competing maintenance alternatives.

4 CONCLUSIONS AND RECOMMENDATIONS

This thesis explored plant equipment RAM evaluation and analysis methods to facilitate oil sands plant maintenance improvement. A RAM improvement workflow has been developed to integrate these tools into the work practice. The case study focuses on the first and second steps of this workflow to evaluate equipment RAM using parametric and non-parametric analysis techniques. In general this thesis has contributed to the body of knowledge for equipment maintenance as follows:

- Enhanced the understanding of the reliability, availability and maintainability behaviors of processing equipment in an oil sands plant.
- Developed a RAM improvement workflow process and demonstrated the effectiveness of it,
- Determined baseline mechanical availabilities for key oil sands processing equipment
- Demonstrated the usefulness of the application of the Power Law model to equipment in an oil sands processing plant.

With respect to specific results and conclusions for Albian Sands process plant, based on this analysis the follow can be concluded:

- The downtime composition analysis has shown that over 30% of downtime has not been given a reason by the operator, which limits the validity of the analysis results. It also identifies an easy win for the company in encouraging all workers to cooperate in RAM works

- The Pareto analysis shows that some units have caused a significant part of total plant downtime. These units should have priority for in improvement.
- Calculation of MA has set a baseline for equipment and allows measurement of the impact of potential changes in practices and procedures. It also allows comparison amongst like equipment and potentially with other oil sands processing plants.
- MTBM indicates the reliability may be decreasing this would indicate an opportunity to implement different strategies for equipment management. However this also could be an artifact of the data caused by the high percentage of unknown downtime.
- Maintenance hours per million-ton ore preparation analysis appears to indicate that operating above design capacity has a negative impact on equipment availability. Overload may increase the production in the short-term; however, it causes an increase in maintenance breakdown hours and a decrease in production in the long-term. A stable and uniform loading may provide a better production improvement approach that can ensure equipment reliability and can benefit long-term production.
- The Power Law Model provided a reasonable estimate of the next time to maintenance for 2007. It is believed that using time between failures instead of time between maintenance would lead to a more accurate result.

- Using a simulation approach with the Power Law process model can lead to probability of time to next failure which will allow assessment of the risk associated with competing maintenance alternatives

Some recommendations are:

- The work of this thesis was focused on Albian equipment reliability improvement practice, and the evaluation methods were specifically tailored for available Albian maintenance data. Based on the developed methods, the RAM analysis and reporting should be implemented as a procedure.
- RAM evaluation reporting should be integrated into the management information
- Data collection is still a critical issue in RAM analysis. The inaccuracy of data has caused a lack of confidence in results presented in this thesis. RAM evaluation can not present an accurate RAM report without accurate data resources. Thus Albian should continue to take the necessary steps to ensure that quality data is captured in the database.

5 FURTHER WORK

In this research, some RAM improvement approaches have been identified, and equipment reliability indicators are used. The Power law model parameter analysis is explored in a case study to assist the accomplishment of the first and second steps of analysis in the RAM improvement workflow. However, the remaining contents of the workflow should be implemented as a detailed application study so as to tailor these RAM improvement application techniques at Albian's oil sands process.

In addition, through this research, RAM data collection has been improved; and some RAM analysis techniques are tailored based on Albian maintenance practice. It will assist the Albain maintenance management improvement to continue to work these works and integrity these research experience into Albian maintenance improvement works. Some work that should be implemented in the future are:

- Base on the KPIs used in this research, some Six Sigma techniques could be applied, so that sources of the variation in equipment RAM performance can be identified, quantified, prioritized, and eliminated.
- Power Law model is a tool to evaluate plant equipment reliability. It could be used to track Albian equipment reliability trend and benchmark the maintenance interval so as to avoid a degradation trend in equipment reliability.
- Some standardized analysis procedures must be developed and implemented as soon as possible so as to support maintenance management.

- Maintenance data collection should be considered as a core business function. Good data will assist management decision-making and result in overall improvements to the business.
- Engineers should be trained to use maintenance data analysis for identifying the maintenance problems and tracking reliability improvement.

With good data and management support Albian should build upon the analyses presented in this thesis as follows:

- A more detailed analysis should be performed to determine the amount of operational delay versus standby downtime so as to indicate the opportunity cost of the idle equipment.
- As described previously, the KPI development must reflect the organizational goals. The KPIs developed in this case study provide equipment reliability information. However, each KPI should have a goal value for comparison to identify reliability shortfall and improvement. The exact KPI's needed by Albian management should be developed and implemented into an automatically generated report function in the database.
- Reliability improvement cost analysis is an important part in the reliability improvement decision-making process. Decreasing equipment reliability can result in an increase in maintenance costs. Thus, a cost KPI should be included in the KPI analysis to identify opportunities for maintenance improvements.

- Minimizing human error is important to the improvement of maintenance and equipment reliability. Due to the lack of human error information in the database, human error analysis cannot be implemented in this research. A process should be set up to capture and store human error data into the database so that it can be analyzed.
- This case study explored the application of the power law process in analyzing equipment RAM trend; however, it did not integrate such information to indicate the overall plant RAM information. Further work would include development of a Reliability Block Diagram simulation of the plant RAM using the RAM information.

Appendix A: Equipment Maintenance Strategies

Maintenance data analysis is performed to provide information for maintenance decision-making in RAM improvement. It requires detailed knowledge of maintenance so as to understand the data collection and analysis requirements. Figure 2-2 illustrates common maintenance strategy options. In general, a combination of these maintenance actions is used in maintenance practice. The specific application of each depends on a cost-benefit analysis.

Run-To-Failure Maintenance

Run-to-failure maintenance is the oldest maintenance strategy. Due to the lack of equipment diagnosis or cost considerations, run-to-failure maintenance is used in maintenance practice, and equipment is run until failure. "The consequence of failure may be 3 to 4 times the planned maintenance cost' (Mobley, 1990) because of unplanned downtime, cascading damage to machinery, and overtime expenditure. However, if the consequence of failure under run-to failure maintenance is less than the maintenance cost and risk salvage cost, run-to-failure is still a valid maintenance option (Hall, 1997).

To properly implement run-to-failure maintenance, a corresponding management activity is necessary. For example, inventory level needs to be managed to ensure that spare parts are available when a failure occurs, while at the same time minimizing inventory costs. Continuous life cycle analysis using failure data is an approach to achieve this.

Scheduled Preventive Maintenance

In order to control unplanned downtime that occur under run-to-failure maintenance, scheduled preventive maintenance is applied. In modern factories, a large amount of equipment's maintenance is performed under scheduled preventive maintenance. Scheduled maintenance involves a periodically planned inspection, part replacement or repair, and lubrication and adjustment of a piece of equipment.

A drawback with scheduled maintenance is that it is performed without regard for equipment condition (Dhillon, 2002), and maintenance actions are planned at a set interval to reduce possible failures. Studies show equipment is over-serviced during scheduled preventive maintenance due to frequent replacements and inspections (Kelly, 1997). Recent surveys report that unnecessary or improperly implemented maintenance wastes one-third of all maintenance costs (Invensys, 2005).

An effective scheduled preventive maintenance system relies on maintenance interval optimization. Maintenance history data analysis can be used for setting an optimized PM interval to reduce unnecessary maintenance and breakdown. In addition, "an effective preventive maintenance program needs regular review and updating in order to remain viable and effective, when equipment grows old or operation condition is changed" (University of Michigan, 2005). An equipment maintenance database is essential for improving scheduled preventive maintenance efficiency.

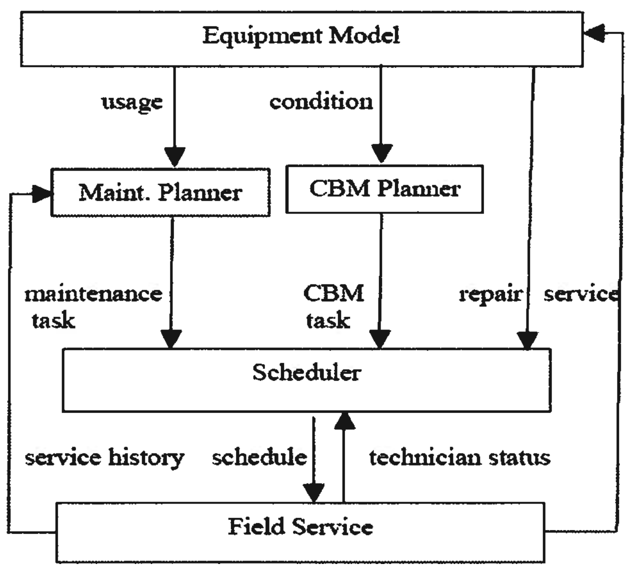
Condition-Based Maintenance (CBM)

In order to reduce the amount of unnecessary maintenance that can occur with scheduled maintenance, condition-based maintenance (CBM) is used for maintaining equipment with high breakdown costs. It has been defined as "maintenance actions based on actual condition obtained from in-situ, non-invasive tests, and operating and condition measurement" (Mitchell, 1998). Condition-based maintenance (CBM) is a maintenance strategy that strives to identify the real equipment operating status with respect to the operating situation, so as to enable more accurate planning of maintenance.

The implementation of CBM relies on techniques, such as vibration monitoring and analysis, thermography, electrical condition monitoring, lubricant and wear particle analysis, passive ultrasonic, and nondestructive testing. Generally, plants select 2 to 3 condition-based parameters to monitor because of high initial costs and the complexity of monitoring techniques. Higgs *et al.* (2004) performed a comprehensive survey on CBM use in the oil and gas, chemical, and manufacturing industries in fifteen countries. Their work found that 77% of respondents agreed that CBM was a predictive approach to maintenance; as well, 46% of respondents agreed that the benefits of CBM were greater than the costs.

A challenge with CBM is how to integrate CBM monitoring parameters for the prediction of failures. Condition monitoring predicts the maintenance needs of a piece of equipment, so that there is enough time for maintenance planning. Simulation and modeling are a technique to complete this task. Some researchers in CBM have focused on condition-based maintenance system modeling. Research in a belt conveyor system in a garment distribution center (Contreras *et al.*, 2002) shows that through integration of CBM monitoring parameters with a simulation model, "the conveyor downtime was reduced by more than 50% and work in process inventory was reduced by more than 65%." Liu (2002) provides an integrated CBM system field service model with integrated equipment condition and field activity to evaluate the benefit of a CBM system, as shown in Figure A - 1.

Figure A - 1 A Generic Field Service Model (Lin, Hsu, and Rajamani, 2002)



Proactive Maintenance

Maintenance is reactively carried out in run-to-failure, scheduled, and condition-based maintenance. Proactive maintenance involves taking active steps to eliminate the potential failures.

Proactive maintenance performs reliability engineering analysis, root cause failure analysis (RCA), failure mode and effect analysis (FMEA), design optimization, operation procedure modification, and risk analysis. The goal of proactive maintenance is to reduce maintenance needs, increase equipment lifetime, and minimize risk. This type of maintenance is carried out in advance to deal with the expected difficulties, such as the failure of critical units, safety and environmental accidents, human error, and design faults.

Appendix B : Maintenance Management Strategies

The production of process plants depends on the reliability of the production equipment. The reliability performance of equipment in turn relies on two factors: inherent reliability and operating condition. On the other hand, it is also influenced by maintenance management, which is responsible for arranging resources to implement maintenance and improve equipment reliability.

Reliability-Centered Maintenance

Reliability-Centered Maintenance was first developed by the airline industry. Tests by the airlines in 1965 showed that scheduled overhaul of complex equipment was not an effective way to improve equipment reliability; many items could not benefit from scheduled maintenance because preventive maintenance actions might threaten a system's reliability due to unnecessary interference and cumulative human errors (Kelly, 1997).

The goal of Reliability-Centered Maintenance is to provide a systematic process to allow maintenance engineers to work on "what has to be accomplished to ensure that equipment is able to continuously meet its reliability requirement in its current operating context" by identifying the following seven questions (Moubray, 1997):

- What are the functions and associated desired standards of performance of the equipment in its present operating context?
- In what ways can it fail to fulfill its functions?
- What causes each functional failure?

- What happens when each failure occured?
- In what way does each failure matter?
- What should be done to predict or prevent each failure?
- What should be done if a suitable proactive action can not be identifyed?

An RCM program is used to implement reliability improvement tools, such as data recording and analysis, condition monitoring, failure mode effects and criticality analysis (FMECA), and root cause failure analysis (RCFA). The use of these tools lead to the determination of the most effective maintenance strategies.

An RCM case study in an Australian mine (Dunn, 1997) showed the overhaul interval of caterpillar Grader engines has been extended from 12,000 hours to 18,000 hours; the large electrical shovel's availability has been improved, and an air compressor trip problem in production drills has been removed by implementing RCM procedures. A strategic resource management consulting company (Strategic Technologies, Inc., 2004) stated that "an oil refinery had a $12,000,000 annual revenue increased" by implementing RCM, and "the planned shutdown in a plant had been reduced 33%."

However, the application of RCM is not always successful. Dhillon (2002) says some causes of the failure may be due to:

- Not enough maintenance analysis conducted,
- Too much emphasis placed on a failure data analysis to force the process,

- The application was too hurried to conduct,
- The maintenance department is individually engaging on the RCM application; other departments do not integrate their own resources in the RCM process.

Total Productive Maintenance

When the fixed-interval scheduled maintenance procedures are applied, equipment often is over-serviced in an attempt to improve RAM. Manufacture maintenance schedules are obeyed with little thought about the realistic maintenance requirement of the equipment (Roberts, 1997); on the other hand, operators that really know the equipment situation do not have enough training and responsibility in equipment inspection and maintenance, so they can not play an active role in its maintenance.

Total Productive Maintenance, a technique originating in Japan, can be adopted to solve these problems. TPM is considered "a people-oriented approach to resolve maintenance and reliability problems at sources" (Kelly, 1999). A simple understanding of TPM is that it encourages operators to participate in maintenance, and transfer a part of maintenance work to operators. Roberts (1997) describes TPM activities as follows:

> "Routine daily maintenance checks, minor adjustments, lubrication, and minor part change out become the responsibility of the operator. Extensive overhauls and major breakdowns are handled by plant maintenance personnel with the operator assisting. Even if outside maintenance or factory experts have to be called in, the equipment operator must play a significant part in the repair process."

An early application of TPM at Toyota Gadei was to reduce the unnecessary maintenance delay, and implement "a small maintenance circle". As a result, the replacement maintenance time of moldings machines was reduced from 49 minutes to 40 seconds at this plant by promoting autonomous maintenance (Kelly, 1997).

Being a maintenance program, TPM still focuses on equipment RAM control. The concept of autonomous maintenance is promoted in TPM to allow operators to monitor and implement maintenance to ensure the accomplishment of the plant production goals. Generally, TPM should be used in maintaining equipment with a constant failure rate. For such kinds of equipment, the major improvements in reliability have been completed; most of the maintenance is routine maintenance, so a part of it can be transferred to the operators.

While autonomous maintenance is implemented, the control of its actions depends on effective evaluation and reporting, which will assist operators and management to improve and integrate maintenance resources. For example, management will know whether the autonomous maintenance is responsive or effective, and whether new maintenance resources need to be added from maintenance analysis.

Six Sigma Theory in Plant Maintenance

The Six Sigma concept has been used by industry as a problem solving model to improve maintenance. It has been demonstrated that Six Sigma is not only a data-driven quality control technique for managing process variations that cause waste, but a methodology for reducing defects based on process improvement (Matchette, 2006).

The main components of the Six Sigma methodology are Define, Measure, Analyze, Improve, and Control (DMAIC). To apply Six Sigma theory to maintenance, DMAIC can be defined as (Milosavljevic and Rall, 2005):

- Defining goals of improvement activity by identifying problems and requirements,
- Measuring the current maintenance performances and resources,
- Analyzing the gap between current practice and the desired goal, to map and arrange resources,
- Improving the maintenance process by engineering, statistics, and management techniques,
- Controling the improvements that have been achieved.

The Six Sigma concept emphasizes improvement of the maintenance process and the control of defects in maintenance actions (VanHilst *et al., 2005*). The goal of Six Sigma maintenance is to provide maintenance with no error. In practice, Six Sigma traces defects and normalizes them so as to improve plant maintenance. A continual improvement in the maintenance process will result in reduced maintenance costs and increased maintenance effectiveness and efficiency.

The implementation of Six Sigma maintenance is not through replacing the existing maintenance management strategy, but through improving the current maintenance management and maintenance process (Quinello, 2004). Six Sigma techniques should be applied based on RCM or TPM to improve maintenance practice. Milosavljevic and Rall (2005) presented a model of a World-Class Maintenance Process (WCMP) by integrating Total Productive Maintenance and Six Sigma maintenance, as shown in Figure B – 1.

Figure B - 1 Model of World-Class Maintenance Process (Milosavljevic and Rall, 2005)

Figure B -1 has been removed due to copyright restrictions. The information removed is 8 steps to achieving a world-class maintenance process.

Lean Maintenance

When management tries to improve plant maintenance, an unexpected result may be the waste of maintenance resources: oversized maintenance teams are set up; equipment is over-serviced and over-inspected; and unused inventory of parts, equipment, and materials are purchased. For eliminating these problems in maintenance management, the Lean concept is introduced into maintenance management. The philosophy of Lean is to avoid actions that do not add value to products and services.

Lean maintenance is based on RCM or TPM, but it emphasizes the improvement of maintenance effectiveness and efficiency. The implementation of lean maintenance eliminates waste from maintenance activities, and controls maintenance resources to actions that can add value to plant production, mainly plant RAM improvement. The achievement of these goals first is to quantify and analyze such resources. For example, lean maintenance is involved in analyzing "setup time, profit goals, cost saving, capacity constraints, production objectives, product mix, and inventory issues" (Johnson, 2005) to optimize these sources and to reduce waste.

Computerized maintenance management systems (CMMS), enterprise asset management systems and Just-In-Time inventory management systems are tools to facilitate the implementation of Lean maintenance. Engineers implement autonomous maintenance to perform Condition-Based-Maintenance using Lean tools as follows (Smith, 2004):

- 5S (Sort, Set in Order, Shine, Standardize, and Sustain) process: a program to improve workplace tidiness, organization, cleanliness, standardization, and discipline, so as to achieve a safer and more productive operation.
- Kaizen (Continuous improvement action): "an on-going, never-ending continual improvement process", to encourage workers to look for every improvement opportunity day by day, and invite other workers to modify their work procedures and implement improvement strategies.
- Lean Performance Indicator (LPI) analysis: mearsure of the effectiveness of lean effort; as a way of monitoring the lean improvement process.
- One-piece Flow: to move parts step-by-step through every workcell, in which all necessary equipment and other parts are available with just-in-time supply to reduce waste.
- Workflow Diagram: to clarify the work process by a graphic representation of the major process steps so as to eliminate disturbances among the process.

Appendix C: Other Maintenance Analysis Techniques

Reliability Block Diagram Simulation

As an important reliability simulation technique, Reliability Block Diagram (RBD) has been recognized as a practical reliability modeling method. For system reliability simulation, components of a system are configured into functional blocks, which may be combined in series, parallel, k-out-of-n parallel, load sharing, or standby configurations, to simulate system function. "RBD is a graphical presentation of a system diagram in reliability-wise or functional logic" (Wang, 2003). Reliability Block Diagram Simulation enables maintenance engineers and managers to study the factors that impact system reliability and performance, and to predict system behavior according to current status or reset configurations.

The advantage of RBD includes the following, as Wang *et al.* (2004) describe:

- It easily models large and complex systems;
- It is easy to construct, modify, and incorporate any system component;
- All reliability indexes can be included;
- It is easy to identify time-based system reliability characteristics.

A proper construction of RBD relies on many facts, such as understanding the system configuration, the adoption of assumption and modeling methods, and the measurement of each component reliability characteristic (Wang *et al.*, 2004). During the construction of RBD, detailed reliability studies on each component are necessary to determine block restrictions, which may include failure and repair distribution, failure mode and effects, operation environment impacts, maintenance strategies, and design configuration. This requires collecting equipment data to provide necessary reliability information that RBD needs.

The RBD technique has been widely used in military equipment systems, industrial and commercial power systems, and in the chemical industry (Wang, 2004; J.A van Luijk, 2003). RBD software has been developed to provide a comprehensive platform for complete system analysis utilizing reliability block diagrams. Van Luijk (2003) investigated RBD software and provided an evaluation as shown in Table C - 1.

Table C - 1 RBD Software Packages and their Characteristics (Luijk, J.A., 2003)

Table C –1 has been removed due to copyright restrictions. The information removed is an evaluation of RBD software, including BlcokSim, SPAR, Titan, MAROS, TARO, Toolkit, AvSim^{+}, SPARC, and Optagon, by model type, Simulation engine, Flow/storge, Spares, Costs, Resources, and Programming.

Life Cycle Cost Analysis

The improvement of equipment RAM can be costly. Life cycle cost analysis provides an approach to estimating costs when planning equipment RAM growth. The total lifetime cost of a piece of equipment includes research and development, construction and installation, operation and maintenance, and disposal. Up to 80% of the total life cycle cost of a product occurs after the product has entered operation (DOD, 2005). A full understanding of the total costs is important for decision-making in equipment RAM improvement.

Since many factors affect equipment life cycle costs, the cost analysis needs to be comprehensive. In the oil and chemical industries, it may include Reliability, Availability and Maintainability (RAM) analysis, economic analysis, and risk analysis (Kawauchi & Rausand, 1999). The implementation of life cycle cost analysis will identify and promote RAM improvement opportunities. For instance, the analysis indicates what caused the high cost, and how much it will be reduced by the improvements. This is a direct driver for RAM improvement.

Kawauchi and Rausand (2002) tailored six basic processes for the oil and chemical industries' Life Cycle cost analysis from IEC, ISO, NORSOK, and SAE documents. The processes are "closely linked" to RAM analysis, and focus on identifying the costs of equipment unavailability. The six processes are below, as shown in Figure C - 1:

- Problem definition

- Evaluation
- Cost profile development
- Data collection
- System modeling
- Cost element definition

Figure C - 1 A LCC Concept Map (Kawauchi and Rausand, 1999)

Figure C - 1 has been removed due to copyright restrictions. The information removed is key points for implementing each process.

Reliability Growth Management

In the oil sands industry, new technologies and materials are constantly put into use. When new equipment is used, the initial reliability is usually lower than expected. In order to identify and correct deficiencies in the equipment, a program is established for achieving equipment reliability growth. A reliability growth program may include the following procedures, as described in <MIL-HDBK-189> (1981):

- Manage reliability growth process
- Identify failure mode root cause
- Test for weakness and improvement effectiveness
- Implement corrective action
- Activate valid reliability improvement

When contractors and plant engineers work together to test and achieve the required reliability, project managers must prepare plant resources, such as finances, labour, and time. This preparation requires foreseeing a reliability growth progress.

To set up a reliability growth program, a growth task or potential must first be identified, as shown in Figure C – 2. The growth potential can be determined from design requirements, maintenance benchmarking, or a reliability database. Then, an idealized growth curve is used to indicate progress.

Figure C - 2 Key Basic Reliability Tasks Out Parameters (Crow, 2005)

Figure C - 2 has been removed due to copyright restrictions. The figure shows how to use an idealized growth curve to identify the relationship between growth potential and reliability development/growth test time.

A parametric equation for the idealized curve of reliability growth has been developed to guide reliability growth management in the U.S. military department (U.S. DOD, 1981). It is estimated as follows:

$$M(t) = M_1(\frac{t}{t_1})^{\alpha}(1-\alpha)^{-1}$$

Where

t = the cumulative test time over the program

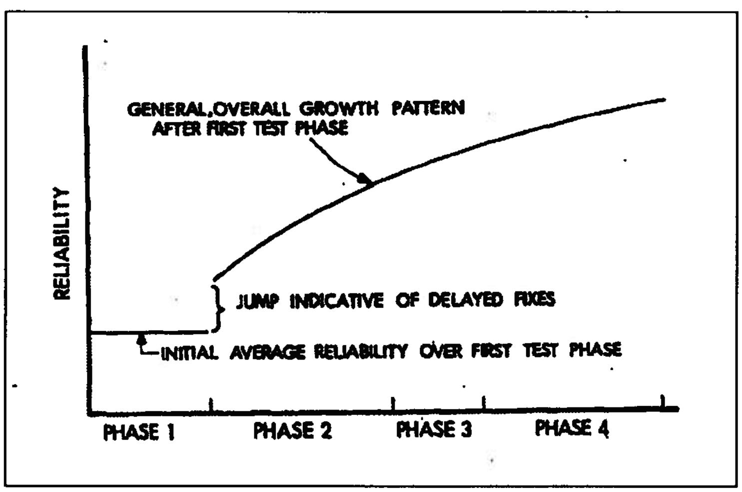
t_1 = the test time for the first test phase

M_1 = the average MTBF over the first test phase

α - = Growth parameter (from similar experiences)

This curve provides an approach to planning reliability growth. An example of an idealized growth curve is shown in Figure C-3.

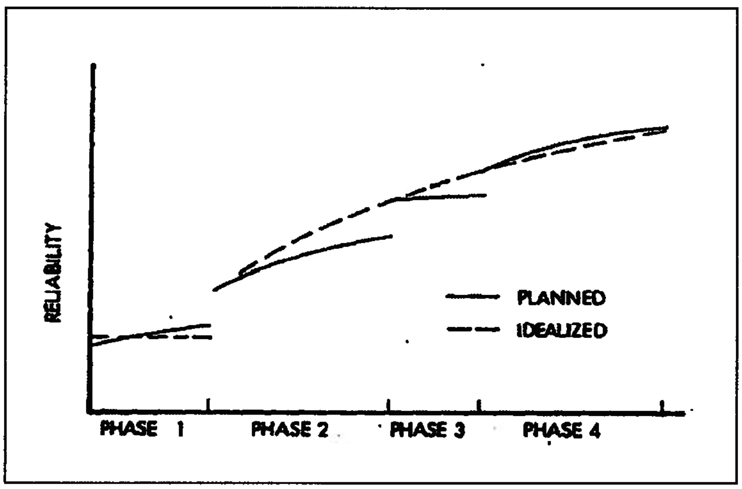
Figure C - 3 An Example of Idealized Growth Curve



Resource: MIL-HDBK-189, 1981

After the general construction of an idealized growth curve, further testing is divided into test phases, as shown in Figure C-4. In the U.S. military department, these test phases may be included in the contract, the contractors implement and detail the reliability procedures, and the program management will track the development of each phase, since the oil sands companies are working with contractors to achieve equipment reliability growth. These procedures provide a valuable guide for the oil sands industry to achieve reliability growth in an efficient and effective way.

Figure C - 4 An Example of Planned Growth Curve



Resource: MIL-HDBK-189, 1981

Human Error Control in Maintenance Operation

During equipment maintenance operation, two major causes of breakdown of equipment are (Kumar, 1992):

- Poorly designed reliability
- Human factors

The improvement of poorly designed reliability can be achieved by redesign, preventive maintenance, predictive testing and inspection, Root Cause Failure Analysis (RCFA), and so on, but human errors should be improved by maintenance quality management and control.

In maintenance analysis, "the contribution of the human error is not negligible in many cases" (Kawauchi & Rausand 1999). Many studies have been developed to reduce human error in maintenance. As Dhillon (2000) summarized, reducing human error in maintenance may be achieve by:

- Ensuring standard work procedures carry through maintenance operations, and implementing maintenance operation quality control.
- Periodically evaluating and updating maintenance procedures.
- Ensuring that management receives regular and structured feedback from maintenance operation.
- Offering checklists to assist maintenance persons in performing routine maintenance operations.
- Double-checking the implementation of maintenance procedures and quality.

When such actions are taken to reduce human error, the effectiveness of improvement actions must be measured. This approach reduces human errors in maintenance, allowing human error information to be properly collected and integrated into a maintenance database, so as to be analyzed as part of the maintenance management function. However, human error is hard to quantify, and the recording of human error is difficult in practice; however, some human reliability quantification techniques have been developed (Kriwan, 1998). These methods of recording and analyzing human error need to be applied in practice.

Appendix D: Time Between Maintenance Data

Table D - 1 Time between Maintenance of Slurry Pump Train 1, 2, & 3 for 2005

No. of Maintenance Events	TBM of Slurry Pump Train 1	TBM of Slurry Pump Train 2	TBM of Slurry Pump Train 3
1	312	236	328
2	160	131	426
3	308	24	79
4	436	205	157
5	38	186	132
6	97	82	217
7	122	249	32
8	74	65	23
9	93	79	
10	21	138	
11	13	32	
12	308	221	
13	53	59	
14	15	230	
15	26	83	
16	73	94	
17	146	13	
18	56	324	
19	613	78	
20	236	372	
21	176		

Table D - 2 Time between Maintenance of Slurry Pump Train 1, 2, & 3 for 2006

No. of Maintenance Events	TBM of Slurry Pump Train 1	TBM of Slurry Pump Train 2	TBM of Slurry Pump Train 3
1	178	160	137
2	20	326	5
3	763	763	959
4	533	27	376
5	62	156	44
6	390	433	618
7	376	698	365
8	44	332	553
9	618	124	45
10	1,013	490	
11	441		
12	866		
13	541		
14	712		
15	257		
16	76		

Table D - 3 Time between Maintenance of Slurry Pump Train 1, 2, & 3 for 2007

No. of Maintenance Events	TBM of Slurry Pump Train 1	TBM of Slurry Pump Train 2	TBM of Slurry Pump Train 3
1	326	381	392
2	541	115	23
3	459	406	129
4	282	203	1012
5	100	570	668
6	457	27	116
7	347	311	410
8	749	455	300
9		68	98
10		327	189
11		297	

Appendix E: Critical Values for Cramer-von Mises

Goodness-of-Fit Test

Table E - 1 Critical Values for Cramer-Von Mises Goodness of Fit Test

M \ α	.20	.15	.10	.05	.01
2	.138	.149	.162	.175	.186
3	.121	.135	.154	.184	.23
4	.121	.134	.155	.191	.28
5	.121	.137	.160	.199	.30
6	.123	.139	.162	.204	.31
7	.124	.140	.165	.208	.32
8	.124	.141	.165	.210	.32
9	.125	.142	.167	.212	.32
10	.125	.142	.167	.212	.32
11	.126	.143	.169	.214	.32
12	.126	.144	.169	.214	.32
13	.126	.144	.169	.214	.33
14	.126	.144	.169	.214	.33
15	.126	.144	.169	.215	.33
16	.127	.145	.171	.216	.33
17	.127	.145	.171	.217	.33
18	.127	.146	.171	.217	.33
19	.127	.146	.171	.217	.33
20	.128	.146	.172	.217	.33
30	.128	.146	.172	.218	.33
60	.128	.147	.173	.220	.33
100	.129	.147	.173	.220	.34

For $M > 100$ use values for $M = 100$.

Sources : MIL-HDBK-189

Appendix F: Stochastic Process Simulation Results

Table F - 1 Stochastic Process Simulation Results for the 7th TBM of Pump Train 1 in 2007

295	240	148	185	311
781	173	55	59	268
88	122	927	747	766
85	523	892	902	276
259	96	714	569	217
919	551	155	228	548
332	465	283	552	37
414	639	747	91	155
725	96	192	283	120
379	26	28	172	425
180	21	126	132	9
63	180	152	146	459
448	9	370	531	964
192	112	778	942	153
41	443	200	751	594
993	218	177	395	292
273	208	114	94	149
193	58	692	148	591
601	192	1201	108	265
59	480	947	108	902

Table F - 2 Stochastic Process Simulation Results for the 7th TBM of Pump Train 2 in 2007

286	328	257	65	175
41	206	59	329	608
98	127	789	587	204
1064	195	241	618	119
749	350	215	298	149
762	16	159	249	780
28	58	621	92	467
54	501	387	113	87
397	80	218	136	276
175	395	84	31	211
103	440	343	90	675
66	408	239	85	183
99	786	427	9	191
384	617	21	133	200
235	67	235	418	547
5	126	36	145	544
14	436	82	248	161
10	1231	135	253	219
406	177	99	128	495
652	272	59	35	92

Table F - 3 Stochastic Process Simulation Results for the 7th TBM of Pump Train 2 in 2007

348	427	410	421	2080
253	1067	759	480	1392
354	752	22	106	417
733	625	368	541	89
193	162	534	188	405
511	176	357	236	199
714	443	978	380	261
575	135	69	446	713
126	111	344	1086	441
791	479	336	435	895
301	797	605	1798	596
1467	1100	900	802	172
524	24	596	345	1771
107	436	410	430	698
664	367	759	89	370
826	714	22	464	1206
703	452	368	1224	170
589	584	756	349	127
159	525	369	534	486
374	892	524	498	502

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KPI analysis has been widely used to identify industrial operation and maintenance targets and measure maintenance effectiveness. (Reh, 2007; Paraszczak *et al.*, 2005) In maintenance performance analysis, KPIs can be broken down into two categories: equipment RAM KPIs and maintenance cost KPIs. These KPIs indicate maintenance goals and detect the progress of maintenance actions and strategy development.

A key performance indicator closed-loop process has been presented by Beck and Oliver (1999) to identify the process of selecting performance indicators, as shown in Figure 2-3. In a logical maintenance system (LMS) developed for a Japanese LNG terminals maintenance, KPI was one of five maintenance efficiency evaluation tools, including RBM (Risk-Based maintenance), RBQC (Risk-Based Quality Control), Long-Term Maintenance Standard, and Asset Management. These evaluation tools are used to approach a PDCA (Plan, Do, Check, and Action) cyclic management system (Aoki, 2006).

Figure 2-3 Key Performance Indicator Closed-Loop Process (Beck and Oliver, 1999)

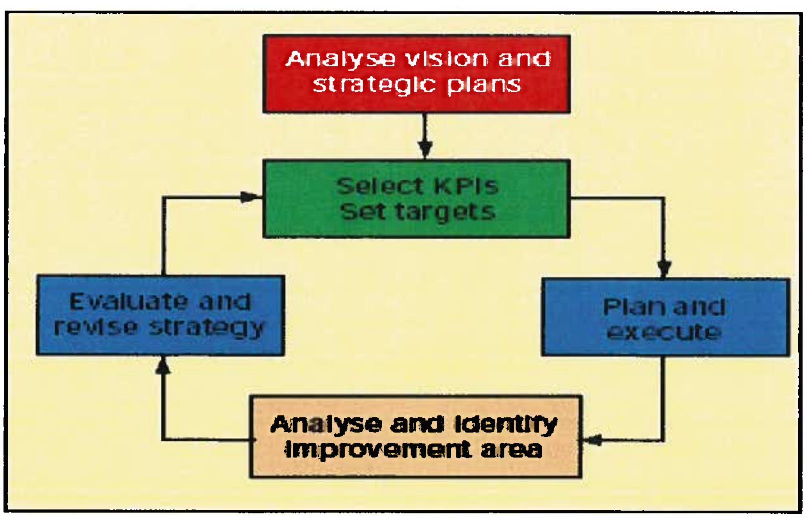
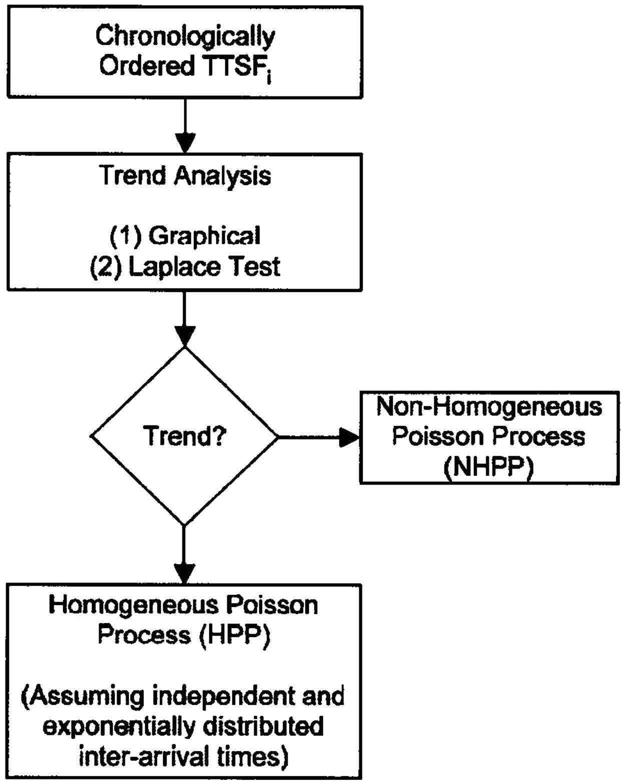


Figure 2-4 Selecting the Appropriate Process Model (U.S. DOD, 2005)



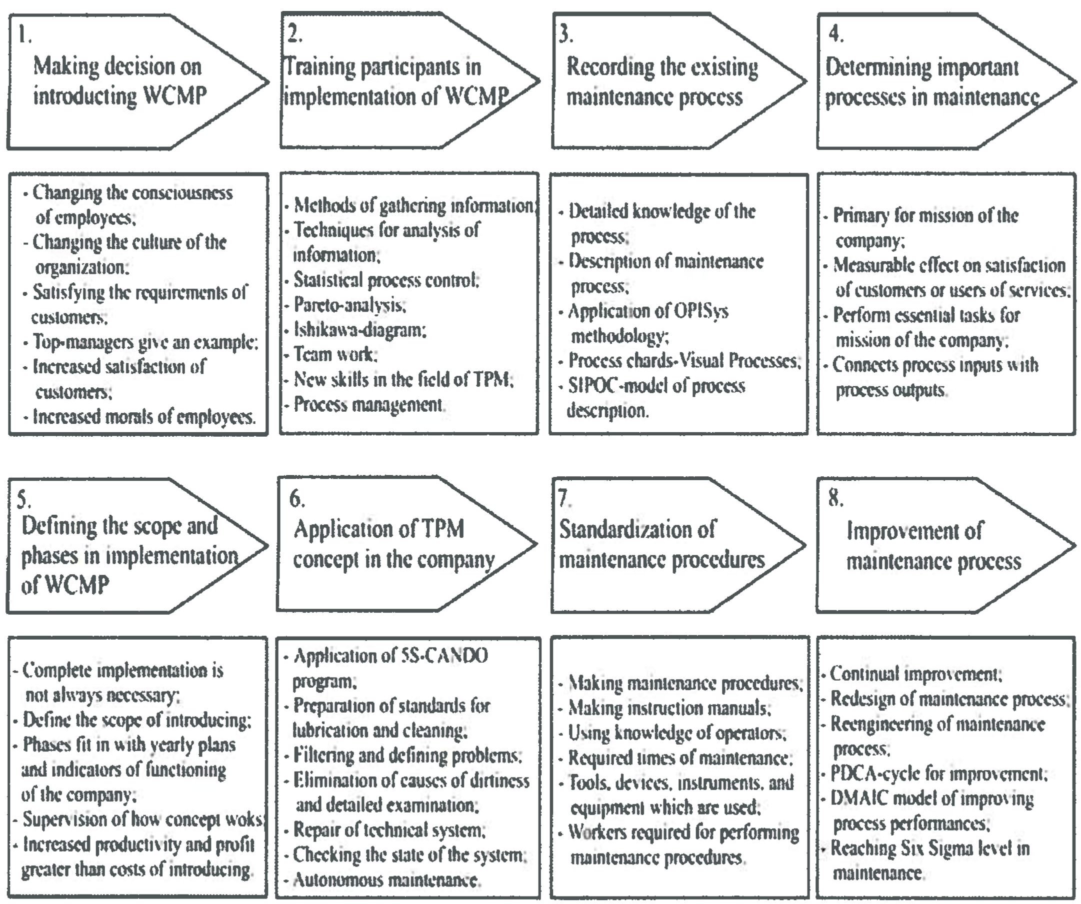
* *TTSF: Time To System Failure*

2.3.4 Power Law Model Parametric Estimation and Hypothesis Test

The power law process model is a good tool to analyze the effect of successive maintenance actions, and to estimate a quantified deteriorating rate. Several studies have focused on the Power law model parametric estimation and hypothesis test (U.S. DOD, 1981, 2005; U.S. NIST, 2006; Frenkel, 2004; Gaudoin *et al.*, 2003; Crow, 2005; Mettas, 2005; Sun *et al.* 2005; Guo *et al*, 2006).

The implementation of Six Sigma maintenance is not through replacing the existing maintenance management strategy, but through improving the current maintenance management and maintenance process (Quinello, 2004). Six Sigma techniques should be applied based on RCM or TPM to improve maintenance practice. Milosavljevic and Rall (2005) presented a model of a World-Class Maintenance Process (WCMP) by integrating Total Productive Maintenance and Six Sigma maintenance, as shown in Figure B – 1.

Figure B - 1 Model of World-Class Maintenance Process (Milosavljevic and Rall, 2005)



operation environment impacts, maintenance strategies, and design configuration. This requires collecting equipment data to provide necessary reliability information that RBD needs.

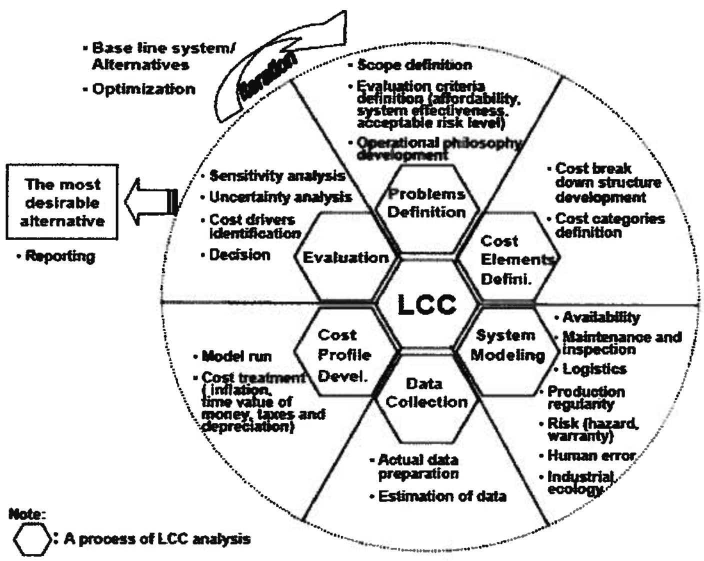
The RBD technique has been widely used in military equipment systems, industrial and commercial power systems, and in the chemical industry (Wang, 2004; Luijk, 2003). RBD software has been developed to provide a comprehensive platform for complete system analysis utilizing reliability block diagrams. Luijk, J.A. (2003) investigated RBD software and provided an evaluation as shown in Table C - 1.

Table C - 1 RBD Software Packages and their Characteristics (Luijk, J.A., 2003)

	Model type	Sim. engine	Flow/ storage?	Spares	Costs	Resources	Programming?
BlockSim	RBD	MC/ AN	+	+	+	+	N
SPAR	RBD	MC	+	+	+	+	Y
Titan	RBD	MC	++	+	+	+	Y
MAROS	RBD	MC	+	+	+	+	N
TARO	RBD	MC	++	+	+	+	N
Toolkit	MKV RBD FT	MC	-	+	+	-	N
AvSim+	RBD FT	MC	+	+	+	+	N
SPARC	RBD	AN	-	-	+	-	N
Optagon	RBD	MC	++	+	+	+	N

- ➢ Evaluation
- ➢ Cost profile development
- ➢ Data collection
- ➢ System modeling
- ➢ Cost element definition

Figure C - 1 A LCC Concept Map (Kawauchi and Rausand, 1999)



Reliability Growth Management

In the oil sands industry, new technologies and materials are constantly put into use. When new equipment is used, the initial reliability is usually lower than expected. In order to identify and correct deficiencies in the equipment, a program is established for achieving equipment reliability growth. A reliability growth program may include the following procedures, as described in <MIL-HDBK-189> (1981):

- Manage reliability growth process
- Identify failure mode root cause
- Test for weakness and improvement effectiveness
- Implement corrective action
- Activate valid reliability improvement

When contractors and plant engineers work together to test and achieve the required reliability, project managers must prepare plant resources, such as finances, labour, and time. This preparation requires foreseeing a reliability growth progress.

To set up a reliability growth program, a growth task or potential must first be identified, as shown in Figure C – 2. The growth potential can be determined from design requirements, maintenance benchmarking, or a reliability database. Then, an idealized growth curve is used to indicate progress.

Figure C - 2 Key Basic Reliability Tasks Out Parameters (Crow, 2005)