UiT THE ARCTIC UNIVERSITY OF NORWAY

Faculty of Science and Technology

RAM Analysis of Mining Equipment and Framework for Data Collection

—

Terje Sneve

EOM-3901 Master's thesis in Energy, Climate and Environment – June 2015

Abstract

In the mining industry, equipment are continuously increasing in size and complexity. At the same time, the demand for available plants and continuous production has never been higher. The performance of equipment depends on the reliability and maintainability performance of the equipment along with the maintenance supportability, operational conditions, and environmental conditions. In order to improve plant availability, fully utilize equipment performance, avoid equipment breakdowns and optimize operation and maintenance (O&M), the concept of reliability, availability and maintainability (RAM) analysis is required. In most industries, the only collected explanatory variables used in RAM analysis have been time to failure (TTF) and time to repair (TTR). For a more precise estimation of the reliability and maintainability characteristics of mining equipment, factors influencing the reliability and maintainability of equipment should be collected and included in the analysis.

In this thesis, the concept of RAM analysis is applied for availability improvement in the mining industry as a quantitative case study. Furthermore, a framework for data collection including influence factors has been developed, which highlights important steps in the data collection process. For including the effects of influence factors in RAM analysis, the Proportional Hazard Model (PHM) with the modified Proportional Repair Model (PRM) are discussed. Finally, a qualitative case study is conducted to demonstrate the application of the framework for data collection for RAM analysis.

The result of the RAM analysis have been used to determine optimum preventive maintenance interval in order to improve availability performance. Furthermore, aspects for improvement of reliability performance and maintainability performance have been assessed in order to improve overall system availability. The framework developed for data collection is considered general enough to cover several industries. However, the framework is especially suited for the mining industry with the use of the PHM and PRM for including influence factors in reliability and maintainability analysis. The work in this thesis, the framework for data collection especially, is considered valuable and necessary as it addresses an area that has received less focus in today's mining industry.

Keywords: RAM, mining, O&M optimization, data collection, influence factors, Proportional hazard model, Proportional repair model

Acknowledgments

This thesis is submitted as a last partial fulfillment of the requirements for the degree of Master of Science and Technology at the Arctic University of Norway (UiT), in the study programme of Energy, Climate and Environment, within the specialization of Technology and Safety in the High North.

I would like to express my sincere gratitude to my supervisor, Prof. Javad Barabady, for guidance and discussions regarding the thesis. In addition, your effort and support with respect to the the study specialization and relevant courses the last two years are much appreciated.

Further, I would like to thank Masoud Naseri for his help, discussions, and suggestions regarding the analysis for the case study in the thesis.

I would like to express my gratitude to Sydvaranger Gruve for their hospitality and financial support during my final year as master student, in addition to providing data and software for the case studies.

Many thanks to my friends and fellow students at the office. Our discussions regarding various aspects of the thesis and the writing process has been vital and decisive for completion of this thesis. It has been a real pleasure getting to know you, and the last 5 years of studying would not have been the same without our ”‘fantastic”’ common sense of humor! A special thanks goes to Martine Espeseth for proofreading my thesis.

Last, to my family, my sincerest gratitude for your continuous support and encouragement throughout my study period.

Terje Sneve,
Tromsø, June 2015

Contents

List of Figures

List of Tables

Abbreviations

CDF	Cumulative Distribution Function
CMMS	Computerized Maintenance Management System
DTCI	Downtime Criticality Index
ETA	Event Tree Analysis
FMEA	Failure Mode and Effects Analysis
FTA	Fault Tree Analysis
IID	Independent and Identically Distributed
ISO	International Organization of Standardization
K-S	Kolmogorov-Smirnov
O&M	Operation and Maintenance
PDF	Probability Density Function
PHM	Proportional Hazard Model
PM	Preventive Maintenance
PRM	Proportional Repair Model
RAM	Reliability, Availability and Maintainability
RBD	Reliability Block Diagram
RM	Reliability and Maintenance
SVG	Sydvaranger Gruve
TTF	Time To Failure
TTR	Time To Repair
$\mathbf{TTR_{res}}$	Time To Restoration
TTS	Time To Support

Nomenclature

A_∞	Steady state availability
A_m	Mean availability
A_o	Operational availability
A_p	Point availability
D_{max}	Maximum of absolute difference between $S_N(t)$ and $Q(t)$
F	Cumulative distribution function
I_R	Reliability importance measure
L	Likelihood function
M	Maintainability
Q	Fitted cumulative distribution for K-S test
R	Reliability
R_S	Reliability of system
R_i	Reliability of component i
S_N	Fraction of data points to the left of $t_i (i = 1, 2, ..., N)$
b	Column vector for PHM or PRM consisting of regression parameters
f	Probability density function
h	Hazard rate
h_0	Baseline hazard rate
m	Renewal density function
r	Repair rate
r_0	Baseline repair rate
z	Row vector for PHM consisting of covariates

z'	Row vector for PRM consisting of covariates
Φ	Cumulative distribution function of the standard normal distribution
β	Failure rate (shape parameter) for the Weibull distribution
η	Scale parameter for the Weibull distribution
λ	Failure rate for the exponential distribution
μ'	Mean of the natural logarithm for the log-normal distribution
ψ	Function incorporating influence factors for PHM and PRM
σ'	Standard deviation of the natural logarithm for the log-normal distribution
θ	Parameter values of MLE

Definitions

Availability
The ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided

[ISO, 2006]

Corrective maintenance
Maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function

[ISO, 2006]

Degraded failure
Failure that does not cease the fundamental function(s), but compromises one or several functions

[ISO, 2006]

Down state/Non-operating state
Internal disabled state of an item characterized either by a fault or by a possible inability to perform a required function during preventive maintenance

[ISO, 2006]

Downtime
Time interval during which an item is in a down state

[ISO, 2006]

Failure
Termination of the ability of an item to perform a required function

[ISO, 2006]

Item
Any part, component, device, subsystem, functional unit, equipment or system that can be individually considered

[CEN, 1998]

Maintainability
The ability of an item under given conditions of use, to be retained in, or restored to, a state in which it can perform a required function, when maintenance is performed under given conditions and using stated procedures and resources

[ISO, 2006]

Maintenance
Combination of all technical and administrative actions, including supervisory actions, intended to retain an item in, or restore it to, a state in which it can perform a required function

[ISO, 2006]

Maintenance supportability
The ability of a maintenance organization of having the right maintenance support at the necessary place to perform the required maintenance activity at a given instant of time or during a given time interval

[CEN, 1998]

Operating time
Time interval during which an item is in operating state

[ISO, 2006]

Preventive maintenance
Maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item

[ISO, 2006]

Reliability
Ability of an item to perform a required function under given conditions for a given time interval

[ISO, 2006]

Required function
Function or combination of functions of an item that is considered necessary to provide a given service

[CEN, 1998]

Up state/Operating state
State when an item is performing a required function

[ISO, 2006]

Chapter 1

Introduction

This chapter presents the background of the topic for this thesis and the thesis problem. Furthermore, it presents the main aim and objectives, research questions, and limitations, before specifying the outline and structure of the thesis.

The reader of this thesis is assumed to have basic knowledge within RAM analysis, probability and statistics, and preferable some knowledge on the mining industry.

1.1 Background

The definition of reliability is the ability of an item to perform a required function under given conditions for a given time interval [ISO, 2006]. In other words, it means that the equipment, system, part, or component are working as supposed to for the period intended. In everyday life and in society today people rely on machines and products now more than ever. Ranging from small electrical products like mobile phones and laptops to heavier machinery like automobiles and airplanes for transportation. In industries like aviation, nuclear, oil and gas as well as the mining industry, the result of operating with unreliable equipment can have catastrophic consequences with respect to health, safety, and environment. These consequences are results of critical equipment breakdowns and system failures. To avoid these breakdowns and failures, the industries have, in recent decades, applied the concept of reliability engineering and reliability analysis.

The field of reliability engineering and reliability analysis rose from the need for more complex and advance weapons and machinery during World War II [Blischke and Murthy, 2003]. Following World War II, the field of reliability engineering spread throughout several industries like aerospace, military defense and electronics, to mention some [Dhillon, 1999]. The field itself grew into specialized application areas, such as mechanical reliability, software reliability, human reliability, and structural reliability [Dhillon, 1999]. The basic reason behind the need for reliability analysis is the natural law that "everything eventually fails". Even the best designed system with components made out of the strongest material will, as time goes by, fail in some manner. That in mind, the field of reliability analysis and reliability engineering is in constant development and the tools and techniques used for analysis are getting increasingly advanced and complex, but at the same time, providing more accurate and precise estimations and results.

For a complete understanding of the performance and condition of equipment the reliability, availability, maintainability, and maintenance supportability should be investigated and modeled. One of the most beneficial analyses to carry out on system level and component level is a RAM analysis. A RAM analysis is aimed to investigate and model the performance of reliability, availability, and maintainability. Here, the aspect of maintenance supportability is defined as part of the maintainability performance. Furthermore, the RAM analysis can be used to reveal the current integrity of the asset, predict future developments, and asset condition and identify the most effective improvement measure for optimization. Perhaps more importantly, the results of the analysis provides a basis for decision-making, especially with respect to design, maintenance strategies, operation, and resource allocation for the assets. The overall goals of a RAM analysis, for a production process, are improvement of the availability performance, achieved by the means of improving the reliability performance and maintainability performance. The analysis is based on historical data, like failure times and repair times along with characteristics of the specific system, like corrective maintenance and preventive maintenance, spare parts, and logistics. As the analysis is based on historical data, there is a need for data collection with sufficient details and information. The focus on achieving high quality data is often insufficient. The data collection can be a costly activity, and the effort of data collection needs to be balanced against the intended uses and benefits [Barabadi et al., 2014]. The result of data collection being costly and benefits being complicated to estimate directly, is less focus and motivation to collect the required data. It is essential to collect accurate data, and data with sufficient information, as any analysis is only as good as the data used.

1.2 Problem statement

Many analyses often only considers TTF and TTR as explanatory variables in the estimation of the reliability and maintainability characteristics. For a precise modeling and prediction of the reliability and maintainability performance, the data have to reflect the operating and environmental conditions which the equipment experiences during operation and maintenance. Problems arise when applying historical TTFs and TTRs from databases for design and operation in new environments, without taking into account the operating and environmental condition the equipment will experience. Assessing these *influence factors* affecting the failure and repair processes is important for an improved understanding of the conditions equipment experiences. It is important to identify the most important influence factors and determine means of collecting the effects of the influence factors during the data collection process [Barabadi et al., 2010].

A study of a stacker belt at the Svea coal mine on Svalbard concluded that the hazard rate could be up to four times as high in the winter period opposed to rest of the year [Furuly et al., 2013]. Predicting a hazard rate lower than the actual hazard rate could lead to earlier expected failures occurring, and thus lead to very undesirable and severe consequences. Predicting a hazard rate higher than the actual hazard rate could lead to the expected failures occurring later, and could lead to unnecessary preventive maintenance and unnecessary cost for the company. The study by Furuly et al. [2013] concluded that changing the maintenance plan during the winter period in order to assess the increased failure rate could lead to increased average time to failure.

There exist databases and standards on reliability and maintenance (RM) data and the data collection method, including the collection planning and collection process. Unfortunately, these standards lack information on data collection with respect to influence factors. Two examples of sources of RM data are the Offshore Reliability Data (OREDA) handbook and the 14224 Standard from the International Organization of Standardization (ISO). The OREDA and ISO 14224 are mainly used for offshore industry but also applicable for other onshore process industries, including the mining industry, which operates with similar equipment. The OREDA handbook and the ISO 14224 standard include accurate failure rates and repair rates for various equipment, after data collection over several years, in addition to special considerations when collecting data. Thus, problems arises when equipment are used in locations other than where the equipment have been used for the data collection in these databases. In unfamiliar locations environmental factors and operational factors will influence the reliability and maintainability of equipment causing the failure rates and repair rates in the existing data bases to be insufficient and inaccurate [Barabadi et al., 2014]. Focus should lie on identifying which factors influence the reliability and maintainability of equipment, furthermore these influence factors needs to be included in the data collection process. Finally, these influence factors should be included when performing analysis with appropriate methods.

1.3 Aim and objectives

The aim of this study is to apply the concept of RAM analysis in the mining industry and suggest a framework for data collection which includes the effects of influence factors on the RAM performance of equipment.

More specifically the objectives of this thesis consists of:

- Review the existing approach for data collection for RAM analysis.
- Apply the concept of RAM analysis as a case study in the mining industry and thus quantitatively analyse the availability performance.
- Suggest a framework for data collection with respect to RAM analysis.

1.4 Research questions

With respect to the thesis problem and main aim and objectives the following three research questions have been identified:

1. How one can improve availability performance by using the result of RAM analysis?
2. How to improve data collection method for RAM analysis?
3. How to include the effects of influence factors in reliability and maintainability analysis?

1.5 Limitations

The limitations for the thesis consists of two parts; the limitations in general for the thesis work and the limitations subjected to the RAM analysis in case study I.

1.5.1 Limitations in general

- Data collected by applying the framework suggested in this thesis will be the data required for RAM analysis. Other analyses could need additional data.
- The concept of including the effects of influence factors in reliability and maintainability analysis is not included in case study I as necessary data was not available. However, the concept and application is discussed.
- Case study I and case study II applies to the mining industry.

1.5.2 Limitations for the analysis in case study I

- Repairable system is studied and subsystems are subject to both corrective and preventive maintenance.
- Data is only from the process plant at Sydvaranger Gruve and is limited to the operating period: 01.08.2013 to 31.12.2014 (1 year and 5 months).
- Failure times are date-based rather than hour-based. Consequently, a small part of the total failures of the subsystems had dates with two or more failures. Whenever this issue occurred one random failure was kept and the other removed from the data set.
- Failure data on the following subsystems was not available: CH024, CH025, CH026 and HO001.
- Cost associated with any downtime or repair is not included in the analysis.

1.6 Outline and structure

Following is an outline of the thesis and a brief chapter content.

Chapter 1: Presents the background and topic of this thesis. The main aim and associated objectives along with research questions and limitations.

Chapter 2: Presents the research approach and methodologies used for achieving the main aim and research objectives along with details on data collection and analysis.

Chapter 3: Presents the literature for the thesis topic. More specific it introduce some basic probability and statistics before RAM performance measures are defined and described. Finally, the concept of importance measures are presented.

Chapter 4: Presents case study I of the thesis. The case study involve applying the concept of RAM analysis to the mining industry.

Chapter 5: Presents a framework for data collection for RAM analysis and case study II of the thesis. The framework includes collecting the effects of influence factors for reliability and maintainability analysis. Further, the chapter discusses two mathematical models for including influence factors in reliability and maintainability analysis. Finally, the chapter presents a case study applied to the mining industry for improvement of data collection.

Chapter 6: Presents a discussion of the defined objectives of the thesis in conjunction with the obtained results. Furthermore, a self-criticism of the study is given and a summation of the main results obtained in chapter 4 and chapter 5. Finally, a conclusion is drawn.

Chapter 7: Presents suggestions for further work within the specific research field and thesis topic before the contribution of the thesis is given.

Chapter 2

Research Approach and Methodology

This chapter explains the research approach and the methodologies used for achieving the research aim and objectives of the thesis. It will highlight important details on the data collection and analysis with respect to sources of data and type of data along with some statistical tests and methods used in case study I.

2.1 Research approach

As stated in the introduction the research problem led to the identification of three research questions. Following, is a brief research approach for each of the research questions.

How can the result of RAM analysis improve system availability performance?

The approach taken to resolve this research problem is by applying the concept of RAM analysis to the mining industry as a case study. The case study concerns collecting and processing historical field data from the mining industry into usable data for statistical analysis, evaluate the data, and carry out methods for RAM analysis.

How to improve data collection method for system RAM analysis?

Developing a framework for RAM data collection that includes collecting the effects of influence factors. The framework for data collection will be a descriptive and illustrative framework divided into three parts; planning for data collection, collecting RAM data, and types of analysis. The framework will be build on previous literature and standards with the addition of influence factors.

In what way can the effects of influence factors be included in RAM analysis?

The concept of a mathematical model with an modified extension for including influence factors in reliability and maintainability analysis will be discussed. Furthermore, a second case study will be conducted for demonstrating the application of the framework for data collection. The case study will illustrate how current downtime reporting systems in the mining industry with a slight modification can be better suited for reliability analysis.

2.2 Data collection

The thesis consist of two case studies both done in cooperation with the mining company Sydvaranger Gruve AS. Following this, is a description of the type and sources of data, for the two case studies.

2.2.1 Case study I

For the RAM analysis, TTF and TTR data are collected. The data is quantitative and based on historical raw data collected over a period of 1 year and 5 months. The data collected is from daily downtime reports and maintenance records, such as work orders created by maintenance personnel. The raw data is secondary data, meaning that someone else besides the analyser collects it for some general purpose [Blaikie, 2003]. In this case, that general purpose of the data collection is for production and maintenance information. After collection, the processing (sorting and classification) of raw data is performed. After processing, the data is in a format that is usable for statistical analysis. The analysis deals with a repairable system, and the data collected is failure and repair times of the subsystems compiling the entire system. The data is limited, and not very suitable for statistical analysis. The analysis in this case study is for that reason more of an analysis to illustrate the methodology of RAM analysis and how the result can be used for improvement with respect to O&M and availability performance.

2.2.2 Case study II

Case study II is concerned with developing a new downtime reporting system for data collection. The design and configuration of the reporting system is based on study literature and in addition discussions with experts at the mining company. The data is hence considered qualitative. Equipment, sub-equipment, equipment codes etc. are collected from the company CMMS or from discussions with maintenance personnel.

2.3 Data evaluation

This section only concerns case study I, the RAM analysis. It describes the approach needed for evaluation of the collected data in order to select appropriate probability and statistical analysis techniques. The main assumption of the data is that the collected data are independent and identically distributed (IID). This assumption needs verification by appropriate statistical tests such as the trend and serial correlation test.

2.3.1 IID assumption

The assumption that the data sets are IID implies that probability distributions can be used to model the subsystems. If the data sets does not fulfill the IID requirement, and probability distributions are used for modeling, then the results and the conclusions of the analysis can be totally wrong [Kumar et al., 1989]. The assumption that the data sets are independent means that one failure is not dependent on the previous one, which implies that the parameters of the chosen distribution do not change with time. The assumption that the data sets are identical means that the different data points follow the same distribution.

A simple illustrative example is a cone toss, where one toss is never dependent on the previous one, neither is the probability of tossing heads or tails changing with time (the probability is the same whether it is the 1st toss or the 100th toss). For that reason, the probability distribution do is time-independent and the different tosses are identical distributed.

Non-homogeneous processes, like the Poisson process, can be used for modeling, instead of probability distributions, in the case where the IID requirement is not fulfilled [Kumar et al., 1989]. The trend test can verify the independent assumption, either analytically or graphically. While the serial correlation test can verify the identical assumption, either analytically or graphically. In case study I, the IID assumption will be checked graphically by the two mentioned tests.

Trend test

In the trend test, the cumulative TTF/TTR is plotted against the cumulative failure number/repair number. If a line drawn through the data points either resembles a concave upwards or concave downwards trend in the data, the system is respectively an improving or deteriorating system. However, if the line drawn through the data points is approximately a straight line, then the data is free from trend, which implies that the data set is identically distributed [Kumar et al., 1989].

Serial correlation test

In the serial correlation test, the (i-1)th TTF/TTR is plotted against the ith TTF/TTR. If the data points are randomly scattered without any clear pattern it implies a data set free from serial correlation, which again implies that the data points in the data set are independent of each other [Kumar et al., 1989].

2.4 Data analysis

This section describes the methods used for data analysis. The system is modeled by TTF and TTR data analysis. Best-fit probability distributions are identified by a *goodness-of-fit* test and parameters for the best fit distribution estimated through the maximum likelihood estimation method.

2.4.1 TTF and TTR data analysis

For a repairable system the analysis is concerned with modeling both the time it takes from a performed repair action (or restoration) to the next system failure (life of the system) and the time it takes to restore the system (repair of the system) back to operating state. The main goal of the TTF and TTR data analysis is to model the failure and repair processes of the different subsystems. This is done by fitting a probability distribution that best represent the failure data, and fitting a distribution that best represent the repair data, and estimating parameters to fit the distributions to the different data sets. For explanation and mathematical expressions on common used life and repair distributions, see Appendix A on probability distributions.

It is common to assess the time between failures for analysis of repairable systems. In this case, the downtime duration, and more specific, the repair duration, is considerable lower than the uptime duration. For that reason the analysis considers the time from restoration to system failure, denoted TTF, and the significant smaller repair duration, denoted TTR.

Goodness-of-fit test

When choosing a probability distribution its goodness-of-fit should be identified by appropriate test. There exist several goodness-of-fit tests suited for different conditions. Some of the most used are the p-value test, the Chi-squared test, Kolmogorov-Smirnov test and Anderson-Darling test [ReliaSoft, 2007]. The principle behind goodness-of-fit tests is to see how far the chosen distribution is from the actual data set, or in other words how well the chosen distribution represent the observed distribution. One goodness-of-fit test often used in RAM analysis is the Kolmogorov-Smirnov (K-S) test. The original K-S test is only applicable for distributions with known parameters. For the case where the parameters are calculated based on the data set itself, a modified K-S test can be used. For more information on the modified K-S test used in the case study, see Appendix B on goodness-of-fit test.

After fitting distributions to the data sets the parameters of the specific distributions needs to be estimated. There are several methods available, like the Rank Regression method, the Maximum Likelihood Estimation (MLE) and the Bayesian Estimation method. In the analysis the MLE method will be used. Appendix C on parameter estimation highlights additional information on the MLE method.

Both the goodness-of-fit test and the parameter estimation by MLE method will be performed by the reliability software Weibull++ version 7 from ReliaSoft.

2.4.2 Monte Carlo Simulation

For a complex repairable system, an analytical expression of the reliability and maintainability is not possible to obtain. The reason is that for a repairable system, the model contains a multitude of probabilistic events, such as failure distributions and repair distribution, along with other characteristics like uncertainties in the maintenance response time, spare part availability and logistics. In these cases, the system is simulated by using discrete event simulation. The simulation technique is Monte Carlo simulation. This technique is aimed at generating random TTFs and TTRs to model the failure and repair processes of each subsystem, to obtain a model for the entire system. The advantage of the simulation technique is that highly complex systems can be modeled. There exist some disadvantages with this simulation technique. One is that there is a lack of repeatability in the results, as each simulation yield new random numbers. In addition, each simulation depends on the number of simulations. This means that a higher number of simulations will yield a more confident result on one hand, but on the other hand, requires more time to run the simulation.

The simulation technique works as the following; the first simulation yields first a random time to first failure, then a random time to first repair, then a random time to second failure, then a random time to second repair, and so on, until the chosen mission time ends. This sequence is repeated based on the number of simulations with each simulation yielding a different sequence. All the different sequences are stored each time. The number of simulations represents the number of different times to first failure, the number of different times to first repair, and so on. The average of all times to first failure is used as the time to first failure. Similar, the average of all times to first repair is used as the repair time for the first repair. The same process applies for the rest of the failures and repairs until the mission end time is reached. If the system consist of several subsystems, this process is repeated for all of the subsystems, which compile the entire system. After all simulations have run, quantities of interest can be estimated, such as point availability, mean availability, point reliability, expected number of failures, among others. The estimates are based on the stored sequences of events, which illustrates how the precision of the estimates depend on the number of simulations. How each random TTF or random TTR is produced is by first generating a random number from 0 to 1, this random number, defined in the interval [0,1], is then used in conjunction with the assigned probability distribution for that subsystem for failure or repair to derive a random TTF or random TTR.

The Monte Carlo simulation will be performed by the use of the reliability software BlockSim version 9 from ReliaSoft.

Chapter 3

Literature Review

This chapter presents the literature for this thesis. Some basic theory within probability and statistics are given for mathematical understanding, before RAM performance measures are defined and described. Finally, the concept of importance measure is described.

3.1 Introduction

The concept of RAM analysis is being increasingly applied in several of today's industries, ranging from the aviation, aerospace, and military industry, to nuclear power, oil and gas, and the mining industry. As the demand of available plants and continuous production increases, the need for reliable and maintainable systems and equipment is essential and necessary. There exist numerous types of reliability analysis in the field of reliability engineering today, from life cycle cost analysis and spare part analysis to reliability-centered maintenance and RAM analysis and others. The common aspect of all these different analyses is that they are applied for improvement of some sort. The improvement can be increased control of asset and equipment condition, increased plant and equipment availability, system failure reduction, better maintenance strategies in addition to several other aspects of improvement. In general, the analysis can be applied for improvement with respect to health, safety and environment or towards production and quality, maintenance, inventory or logistics. Nevertheless, the result of the analysis is some sort of desired improvement with respect to the mentioned aspects. To be more specific, in the oil and gas industry and the mining industry, the RAM analysis is generally applied for decision-making. Identifying and determining the decision which leads to the most effective improvement is essential both with respect to cost and for O&M optimization. The RAM analysis will provide information to management, administration, operation department, and maintenance department about the integrity of the asset, performance indications, as well as implementation of improvement measures.

In order to understand the mathematical definitions of RAM performance measures some basic probability and statistics needs to be addressed. The upcoming sections will present an introductory to some basic probability and statistics, along with definitions and descriptions of RAM before describing the concept of importance measures.

3.2 Probability and statistics

First, consider a random variable X, which can take any value from 0 to ∞, hence is said to be continuous. Now, consider the two functions $f(x)$ and $F(x)$, which is the probability density function (PDF), and the cumulative distribution function (CDF), respectively. Both of these functions are commonly used in probability and statistics, and give a complete description of the probability distribution of a random variable.

3.2.1 Probability density function:

For a continuous random variable X, the PDF of X, is the function $f(x)$, for any number a and b, that satisfy the equation:

$$P(a < X < b) = \int_a^b f(x)dx \tag{3.1}$$

[Walpole et al., 2012]

Which in other words, means that the probability that X is any value between a and b, is the area under the probability density function. As probabilities can not be negative and never greater than 1, the two following properties of the PDF are always true:

$$\int_{-\infty}^{\infty} f(x)dx = 1 \tag{3.2}$$

$$f(x) \geq 0 \tag{3.3}$$

[Walpole et al., 2012]

3.2.2 Cumulative distribution function:

For a random variable X, the CDF is the function $F(x)$, defined by:

$$F(x) = P(X \leq x) = \int_0^x f(x)dx \tag{3.4}$$

[Walpole et al., 2012]

Which in other words, means that the cumulative distribution function is the probability that the value X, is less or equal to x.

The relationship between the PDF and the CDF is that the CDF is the cumulative values of the PDF, meaning that a point on the CDF function curve, is the area under the density function to the left of that point. Further, the PDF is the derivative of the CDF, which provide the following expression on the relationship between the PDF and the CDF:

$$f(x) = \frac{d(F(x))}{dx} \tag{3.5}$$

[Walpole et al., 2012]

3.3 RAM performance measures

Recall that RAM stands for reliability, availability and maintainability. These performance measurements provide the characteristics of the system and the related operation and maintenance conditions. Each can be defined and expressed mathematically in terms of probabilities.

3.3.1 Reliability

Definition

One commonly used definition of reliability is:

> *Ability of an item to perform a required function under given conditions for a given time interval.*

[ISO, 2006]

Reliability can also be defined probabilistic as:

> *The probability that an item (component, subsystem, or system) or process operates properly for a specified amount of time (design life) under stated use conditions (both environmental and operational conditions) without failure.*

[Pohl, 2010]

In mathematical terms, the time to failure T, of an item, is defined as a continuous random variable. The reliability, which is a function of time t, will then be expressed as the probability that the time to failure T, is bigger than the operating time t. This means that the reliability is the probability that the failure has not occurred at time t, and is given by:

$$R(t) = P(T > t) \tag{3.6}$$

[Elsayed, 2012]

where $R(0) = 1$ and $R(t) \geq 0$.

The reliability function can be derived from the cumulative distribution function $F(x)$. In reliability-sense the CDF is the probability that the random time to failure T is less than or equal to the operating time t. The CDF for reliability is denoted $F(t)$, and in combination with the fact that the area under the probability density function is always equal to 1, the reliability function is expressed as:

$$R(t) = P(T > t) = 1 - F(t) \tag{3.7}$$

The relation between the CDF and the PDF is given as:

$$F(t) = \int_0^t f(t)dt \tag{3.8}$$

The reliability function is then obtained as:

$$R(t) = 1 - \int_0^t f(t)dt \tag{3.9}$$

$$R(t) = \int_t^\infty f(t)dt \tag{3.10}$$

[Elsayed, 2012]

where $f(t)$ is the probability density function of the time to failure.

The unreliability, or in other words the probability that the failure has occurred, is then the opposite, and is defined as the probability that the time to failure T, is smaller than or equal to the operating time t. This is the same as the CDF and is expressed as:

$$F(t) = P(T \leq t) \tag{3.11}$$

$$F(t) = \int_0^t f(t)dt \tag{3.12}$$

[Elsayed, 2012]

where $F(0) = 0$, $F(t) \geq 0$, and $f(t)$ is the probability density function of the time to failure.

From the above discussion and the mentioned relationship between the PDF and CDF in equation 3.5, the following expression is obtained for the relationship between the probability density function and the reliability function:

$$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt} \tag{3.13}$$

[Elsayed, 2012]

Some probability distributions model the TTF and the life of items better, and are for that reason called life distributions. Some of the most common life distributions are the Weibull, log-normal and exponential distribution. The normal distribution is also a good representative for modeling, but is not suited for reliability analysis, as its left tail goes to negative infinity. This implies that it can take negative values and negative times to failure make no sense. However, according to both Hamada et al. [2008] and Modarres et al. [2009], the normal distribution can be used as long as it generates a *mean* that is positive, and larger than the *standard deviation* by some factors. In those cases the probability of obtaining negative times to failure is so low that it can be considered negligible [Hamada et al., 2008], [Modarres et al., 2009]. To be on the "safe" side, it is better to omit the use of the normal distribution. Instead, the use of the log-normal distribution is a good substitute, given that the natural logarithm of the times to failure are normally distributed. The log-normal distribution resembles the normal distribution, but without the possibility of obtaining negative times to failure, as the distribution cannot take negative values. The equations and characteristics of the exponential 1-parameter distribution, the Weibull 2-parameter distribution, and the log-normal distribution are listed in Appendix A.

Hazard rate

Another measure of interest in reliability estimations and in the evolution of failures, is the probability of failure of an item in a small interval dt, given that the item has not failed until the time of the beginning of the interval. This probability is given by the product of the small interval dt, and the conditional probability of failure, called the *hazard rate* usually denoted $h(t)$, which is a function of time t [Zio, 2013]. This probability can be expressed as the following:

$$\begin{aligned} h(t)dt &= P(t < T \leq t + dt | T > t) \\ &= \frac{P(t < T \leq t + dt)}{P(T > t)} = \frac{f(t)dt}{R(t)} \end{aligned} \tag{3.14}$$

[Zio, 2013]

where T is the random time to failure variable, t is the operating time, $f(t)$ is the probability density function, $R(t)$ is the reliability function, and the hazard rate h represents the number of failures per unit time t.

The hazard rate defines the lifetime distribution of the units, meaning the statistical probability distribution of the time to (first) failure [ISO, 2006]. Another commonly used notation for the hazard rate is λ. This notation have, in this study, been used for the rate of the exponential distribution, and to avoid confusion, the hazard rate is denoted h. The relation between the hazard rate, probability density function, and reliability function is given as the following:

$$h(t) = \frac{f(t)}{R(t)} \tag{3.15}$$

[Elsayed, 2012]

3.3.2 Availability

Definition

One commonly used definition of availability is:

> *Ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided.*

[ISO, 2006]

Availability can also be defined probabilistic as:

> *The probability that a system or component is performing its required function at a given point in time or over a stated period of time when operated and maintained in a prescribed manner.*

[Ebeling, 1997]

Availabilities can be classified and estimated in various ways. According to [Elsayed, 2012] availabilities can be classified either as 1) time-interval availabilities or 2) downtime availabilities. The time-interval availabilities include point availability, mean availability and steady state availabilities. While downtime availabilities include inherent availability, achieved availability and operational availability. The downtime availabilities are steady state availabilities where different downtimes (repair and maintenance) are considered [Elsayed, 2012]. Hence, they are a subgroup of the steady state availability. In this study only the time interval based availabilities are defined and expressed mathematically along with the operational availability. The operational availability is included as it is the availability which is actually experienced after operation. Next, the different time-interval availabilities along with the operational availability is described.

Point availability

The point availability is the availability at a specific time t and is the probability that the system is available at time t. It can be expressed as:

$$A_p = P(system\ is\ functioning\ at\ time\ t) \tag{3.16}$$

Availability considers both reliability and maintainability of the system. The point availability is therefore the combination of the probability that the system has functioned to time t, which is equal to $R(t)$, and the probability that the system has functioned since the last repair at time u. The probability that the system has functioned since the last repair at time u is given by the expression:

$$\int_0^t R(t-u)m(u)du \tag{3.17}$$

[Elsayed, 2012]

Where $m(u)$ is the renewal density function and $0 < u < t$. Then, the point availability function for time t, is the sum of these two functions given by:

$$A_p(t) = R(t) + \int_0^t R(t-u)m(u)du \tag{3.18}$$

[Elsayed, 2012]

Mean availability

The mean availability is also known as the average uptime availability, and is the mean time the system is functioning. It is given by:

$$A_m = \frac{1}{t}\int_0^t A(t)dt \tag{3.19}$$

[Elsayed, 2012]

Steady state availability

Steady state availability is defined as the availability as time approaches infinity, or after a relatively long operating time t. It is given by:

$$A_\infty = \lim_{t \to \infty} A(t) \tag{3.20}$$

[Elsayed, 2012]

The actual availability is when all downtimes are considered, including corrective and preventive maintenance, along with administrative time, logistics, and so on, and this is only known when the operation is completed. For that reason this availability is described as the operational availability and is given by:

$$A_o = \frac{Uptime}{Total\ time} = \frac{Uptime}{Uptime + Downtime} \tag{3.21}$$

[Smith, 2001]

where *uptime* is the overall time the system or component is operating, *downtime* is the overall time the system or component is not operating, and *uptime + downtime* is the total time period being investigated. This expression can be divided further into the specific uptimes and downtimes, but that is not considered in this study.

3.3.3 Maintainability and maintenance supportability

Maintainability and maintenance supportability addresses the duration of time the item is in a down state/non-operating state. Here, the maintenance supportability performance is considered to be a part of the maintainability performance. Whereas the maintainability describes at which extent the item is repaired back to up state/operating state, the maintenance supportability describes at which extent the resources needed for the repair or maintenance action is provided. More specially the maintainability performance is the intrinsic factors directly related to the build-in characteristics designed to help the maintenance of the item [ISO, 2006]. The maintenance supportability performance is the extrinsic factors like logistics and spare parts designed to support the maintenance actions [ISO, 2006]. For further clarification the term *repair time* is used to define the time it takes to repair the item from a failed state to an operating state, while the term *restoration time* or *downtime* is used to define the time it takes from the item fails to when it is actually operating again.

The definition of maintainability is:

> *Ability of an item under given conditions of use, to be retained in, or restored to, a state in which it can perform a required function, when maintenance is performed under given conditions and using stated procedures and resources.*

[ISO, 2006]

Maintainability can also be defined probabilistic as:

> *The probability that a given active maintenance action, for an item under given conditions of use can be carried out within a stated time interval, when the maintenance is performed under stated conditions and using stated procedures and resources.*

[IEC, 1990]

In mathematical terms, the time to repair T, of an item, is defined as a continuous random variable. This random variable will have a probability density function like the reliability function described in section 3.3.1. However, maintainability addresses the probability that the repair has happened, and therefore the maintainability, which is a function of time t, is expressed as:

$$M(t) = P(T' \leq t) = F'(t) \tag{3.22}$$

[Dhillon, 2008]

where $F'(t)$ is the cumulative distribution function of the time to repair and T' is the random time to repair variable.

In other words maintainability is the probability that the item will be repaired within a time t. Saying that a system or a component has a maintainability of 80 % in one day, will thus mean that there is 80 % probability that the system or component will be restored or repaired within a day. The probability density function for the maintainability is denoted $f'(t)$, then the maintainability function $M(t)$ can be further expressed as:

$$M(t) = \int_0^t f'(t)dt \tag{3.23}$$

[Dhillon, 2008]

where $f'(t)$ is defined to be the probability distribution for the repair time.

The probability distributions for the maintainability function can be the same as for the reliability function, although the most used distributions are the exponential 1-parameter distribution or the log-normal distribution. The reason for not applying other probability distributions is that they often demand background information and thorough understanding of the maintenance actions performed, and the maintenance crew performing the maintenance actions. If the Weibull 2-parameter distribution is chosen for describing the repair process of some system and the shape parameter is positive, it will in reality mean that the maintenance crew performing the maintenance actions are improving with time, on the other hand, if the shape parameter is negative, it means that the maintenance crew performing the maintenance actions are getting worse with time, which is rather unlikely. For that reason, the "'safer"' choice is often to choose the exponential 1-parameter distribution or the log-normal distribution. Since some distributions better represent repair times these distributions are referred to as repair distributions.

Repair rate

Another measure of interest in maintainability estimations is the repair rate. The repair rate is equivalent to the hazard rate presented in section 3.3.1, and is denoted r if constant, and $r(t)$ if a function of time t. The repair rate represent the rate at which an item is restored from a failed state to an operating state. Another often used notation for the repair rate is μ. This notation have, in this study, been used for the mean of the natural logarithm for the log-normal distribution, and to avoid confusion the repair rate is in this study denoted r.

The factors which determine at which rate a component or system is brought back to operating state or working condition, are a combination of the maintenance action itself and the maintenance supportability. The next section will briefly describe the main types of maintenance.

Maintenance

For maintenance actions there exist three basic types, namely corrective maintenance, preventive maintenance, and inspection. In short, the three represent the following:

1. Corrective maintenance is the maintenance actions performed <u>after</u> failure of the item. It is the actions necessary to restore the item back to operating state. The actions are typically repair or replacement of components or subsystems, and is performed randomly as failure times are not possible to know in advance.

2. Preventive maintenance is the maintenance actions performed <u>before</u> failure of the item. It is the actions intended to prevent the failure. The actions can be many but are typically component repairs, lubrication, and overhauls. For preventive maintenance to be necessary and beneficial, two conditions have to be satisfied. Firstly, the system or component have to experience wear-out, implying an increasing failure rate. Secondly, the overall cost of the preventive maintenance actions have to be less than the overall cost of the corrective maintenance actions.

3. Inspections are meant to discover hidden or future failures. The inspection techniques can be many and consist of both visual and non-visual techniques. Common for all inspections is that they do not alter the condition or age of the equipment, as no repair or replacement takes place. An inspection can lead to repair or replacement but in that case the repair is either classified as corrective or preventive maintenance.

These maintenance types can be divided further into subtypes and disciplines. Some of the most common are condition-based maintenance, periodic maintenance, design-out maintenance, and opportunity maintenance. Which subtypes and disciplines that are used in different companies and plants depend on the chosen and prepared maintenance strategy and maintenance plan. It is, however, most common with a combination of all three main maintenance types with associated disciplines, depending on probability of failure and consequence of failure both with respect to health, safety, and environment, production and quality.

The term *maintenance* is considered to be the actual repair time of the component or system, whether corrective maintenance actions or preventive maintenance actions. The term *maintenance supportability* is the excess downtime due to logistic delay, supply delay, waiting time, or administrative time. The maintainability calculation can consider the actual repair time used to bring the item back to operating condition or the restoration time from failure back to operation depending on the desired goal.

3.4 Importance measures

In the mining industry, as well as other industries, it is desirable to identify the most critical subsystem for knowing what subsystem will yield the most effective improvement and knowing where to focus and allocate resources and time. In order to obtain the most critical subsystem the concept of importance measures can be used. Instead of describing it as the critical subsystem, it is perhaps better to describe it as the subsystem of highest importance, as the result of the importance measure calculation will provide the means of allocating resources and time towards the subsystem which will increase reliability or availability the most. By that reason, the calculation of importance measures can be said to be a tool for decision-making in the optimization of O&M.

Birnbaum [1969] was one of the first, if not the first, to derive an expression for the relative importance of the reliability of one component towards the reliability of the entire system. The expression by Birnbaum [1969] is the following:

$$I_R(t) = \frac{\partial R_S(t)}{\partial R_i(t)} \tag{3.24}$$

[Birnbaum, 1969]

The expression gives the relationship between a change in reliability of one component and the associated total change in reliability of the system. Since Birnbaum [1969] first introduced this relative simple derivative, it has been used by mathematics and engineers extensively, and some have used the same principles to derive similar expressions for the availability importance and maintainability importance (see [Barabady and Kumar, 2006]). Even though the expression is simple, it is powerful and very much applicable in several situations. Unfortunately, for a complex repairable system, the expression falls short. For a repairable system, this expression is not applicable, and the reason is that an analytical relation between the system reliability and reliability of the components are too difficult to obtain. For complex systems, modeled through simulation, there are other means available for identifying the subsystem with highest importance. One method is by investigating the relative relationship between component failures or component downtime and how they contribute to the system total.

Chapter 4

Case Study I: Applying RAM Analysis to the Mining Industry

This chapter presents case study I of this thesis. The case study is a RAM analysis, which has been conducted for the process plant at the mining company Sydvaranger Gruve AS. First, a brief introduction to the cooperating company will be given, before the overall process at the plant is described. Furthermore, the scope of analysis is presented. Finally, the analysis is carried out and the results along with suggestions for improvement presented. The chapter aims to answer the research question on how to use the result of RAM analysis to improve system availability performance.

4.1 Introduction

In the mining industry, the availability and production demand are continuously increasing. Dhillon [2008] state that the competitive global economy is forcing mining companies to modernize its operations through increased mechanization and automation. Heavier and more complex machines are put to use every day to increase production rates and increase revenue, and thereby profitability [Dhillon, 2008]. With the demand for higher plant availability comes the need for more reliable equipment, systems, and machinery, and as a consequence an increased maintenance cost for most companies. The overall maintenance cost is especially high for the mining industry, where equipment experience such harsh environments and failure mechanisms, in addition to the fact that the overall mining process is very equipment dependent [Galar et al., 2014]. According to Lewis and Steinberg [2001], the maintenance related cost is approximately 30 to 50 % of the overall mining costs. With such high maintenance cost, focus should be directed at designing equipment and machines as reliable and maintainable as possible. The main goal of this case study is to apply the concept of RAM analysis for improvement of the availability performance. In the mining industry, equipment and systems degrade at a rapid pace. This is a result of the different failure mechanisms they experience, which ranges from shock and impact damages from several hundred kilos rocks, to erosion and other wear mechanisms from high velocity movement of small rock particles. Applying the concept of RAM analysis for O&M and decision-making will lead to a safer and more reliable plant, resulting in higher production and less critical breakdowns and downtime.

4.1.1 Sydvaranger Gruve AS

This case study is conducted in cooperation with the mining company Sydvaranger Gruve AS (SVG). SVG is a mining company located in northern Norway in a town called Kirkenes. The production consist of high-grade iron ore concentrate and the process consist of blasting, cobbing, primary crushing, secondary crushing, primary grinding, secondary grinding, separation, and filtration. The mining company, owned by the Australian company Northern Iron Limited, was established in 2007, and after refurbishment of the old mine and processing plant and processing infrastructure the production started in 2009 [Sydvaranger Gruve AS, 2015]. Today, the product which consist of approximately 68 % iron ore and less than 5 % silica is shipped to the steel industry worldwide [Sydvaranger Gruve AS, 2015].

4.1.2 Processing plant

The mining operations at Sydvaranger Gruve are located in two areas, the mine site in a placed called Bjørnevatn and the processing plant in the town Kirkenes. In Bjørnevatn the ore is blown out from the mountain with explosives, then cobbed and crushed in the primary crushing plant. From Bjørnevatn the primary crushed ore is transported approximately 8 kilometers to the process plant in Kirkenes. There, the ore is first crushed into even smaller ore sizes by one secondary crusher and two tertiary crushers in the secondary crushing plant. From the crushing plant, the ore is transported to the separation plant adjacent to the secondary crushing plant by conveyors. In the separation plant, the ore is grinded by one singular primary ball mill in the primary grinding system. The primary mill and the secondary crusher in the crusher plant are considered to be the most critical systems in the overall process plant (crusher and separation plant). The reason being that those two systems are large and complex mechanical systems, in combination with the absence of redundancy. If the mill or crusher breaks down for some reason, the entire process will eventually stop. For instance, in 2013 the primary mill broke down causing total plant downtime of 28 days. For that reason, the secondary crusher system and the primary mill system are important and critical systems, which needs to be maintained accordingly. That being said, there exist other systems without redundancy in the plant like conveyors and pumps. However, these are smaller and less expensive systems which are easier repaired or replaced. After the primary grinding the gangue (material other than ore which is not considered worthy of producing) is separated from the ore by primary magnetic separators. The process is now a wet process, which means that the material is a slurry consisting of ore, water and other particles like silica. After the primary magnetic separators the ore is grinded even further by 5 smaller secondary ball mills working in parallel in the secondary grinding system. Even though these secondary mills are needed in the process, because they work in parallel, a breakdown of one or two mills are not that critical as the grinding process can continue, even if it is on a reduced level. From the secondary grinding system, the ore is further separated from the gangue by the use of secondary magnetic separators and tertiary magnetic separators. After the last process of magnetic separation the material, which at this point is a slurry containing ore, a small part silica and water is filtrated and dried in the filtration process. The filtration system consist of one large vertical plate pressure filter and three vacuum disc filters. The three vacuum disc filters (in series) work in parallel with the pressure filter, compiling the filtration system. A system failure on the filtration system will only occur when all disc filters and the pressure filter breaks down simultaneously, although the production rate will be reduced accordingly. It is very important that the filtration system is able to dry the concentrate sufficiently. If the concentrate is not dry enough, there will be a too high percentage of liquid content, which could cause the ship to capsize during transportation to the marked. After filtration, the concentrate is transported to several large silos for storage before shipment.

Maintenance in the processing plant

The maintenance for the processing plant is divided into corrective maintenance (CM) and preventive maintenance (PM) where the preventive maintenance consist of both periodic based maintenance and condition based maintenance. The periodic maintenance normally has a higher priority than the condition based maintenance, which means that the process plant has scheduled shuts and preventive maintenance task based on equipment condition are moved to the appropriate shuts. Exceptions are made if the condition of highly critical equipment is so poor that it is likely to break down prior to the shut. In this analysis the preventive maintenance is defined as *scheduled shuts* rather than actual preventive maintenance affecting the system. In the shuts equipment is inspected, checked and tested, and more than often the work done cannot be considered as PM. The shuts are divided into ten minor shuts (24 hours) and two major shuts (7 days) during a year, resulting in one shut each month. In the analysis, the minor shuts are denoted PM 1 and the major shuts are denoted PM 2. The minor shuts are scheduled every month besides the months where the two major shuts are scheduled. The two major shuts are usually scheduled in the months October and March. According to experts at the SVG, the major shuts needs to be scheduled in the mentioned months as the temperature during the winter months (December, January and February), in this part of northern Norway, could drop to below minus 30 degrees causing a shut to be problematic for many reasons. Therefore, to get the optimum interval and at the same time the best conditions for the shut, the major shuts are scheduled in one of the spring months and autumn months. During these shuts all tasks such as cleaning, inspections, and, in some cases, other repairs or replacements, are being executed by several departments in the company including production, mechanical, electrical, and automation, along with the preventive maintenance group.

4.2 Scope of analysis

The first objective of the analysis was to consider the primary mill at Sydvaranger Gruve. As mentioned in section 4.1.2 the primary mill is one of two most critical systems in the process plant. This was the main reason for choosing that system for the analysis. The analysis was supposed to focus only on the primary mill, and to consider operational failures of the parts and components of the mill causing system failure and mill downtime. After discussion with experts at the company, it was decided that such an analysis would most probably be of little use with respect to O&M optimization and availability improvement. The scope was reconsidered, and the second and final scope was to study the primary grinding system at the processing plant. This resulted in considering the surrounding subsystems of the primary mill, including the primary mill itself, and focus on the subsystems causing primary mill downtime. Analysing such a system would hopefully provide a better potential and result for improvement. Whereas the level of the first scope was down on parts and components, the level of the second scope would focus on a larger system composed of several subsystems.

4.2.1 Primary Grinding System

The primary grinding system includes all systems between the crusher system and the secondary grinding system. Although that means auxiliaries such as water, air and power, along with cranes and other additional equipment the analysis was only to consider the specific systems used in the process flow. The defined system with system boundary, reliability block diagram and assumptions are presented in section 4.3.1.

4.3 System RAM analysis

The following sections presents the different steps conducted in the RAM analysis. The different steps are:

- System definition, assumptions, and limitations
- Data analysis
- Data evaluation
- TTF and TTR data analysis

- RAM analysis
- Results, discussion, and suggestions for improvement

4.3.1 System definition

When conducting a system analysis the first step is to define the system. This implies defining what systems to include in the analysis, and at what level of focus the analysis should have with respect to systems, subsystems, assemblies, parts, or components. This can dependent on available data or it depend on what one wish to obtain from the analysis. The system is defined to be the primary grinding system at the process plant and more specific the separation plant. The overall system consist of the following thirteen subsystems:

- CV026 (conveyor)
- CV028 (conveyor)
- CH024 (chute)
- CH025 (chute)
- ML001 (ball mill)
- HO001 (hopper)
- CH026 (chute)
- CV060 (conveyor)
- BN015 (scats bin)
- CV061 (conveyor)
- PP001 (pump)
- PP002 (pump)
- CC001 (cyclone cluster)

Out of these thirteen subsystems the scats bin (BN015) is left out as it is not considered critical in the process flow. The three chutes and the one hopper (CH024, CH025, CH026 and HO001) are included in the system but is considered to be so reliable that they do not fail. This assumption was needed as specific data on those subsystems was not available. The limitations for this analysis is mentioned in section 1.5.2. The lack of available data for the chutes and the one hopper subsystem have resulted in the assumption that they are not subject to failure.

The defined system is better illustrated by a system boundary. Using a flow chart from the process plant and a dashed line containing the subsystems, a system boundary has been established. The system boundary is reported in Figure 4.1.

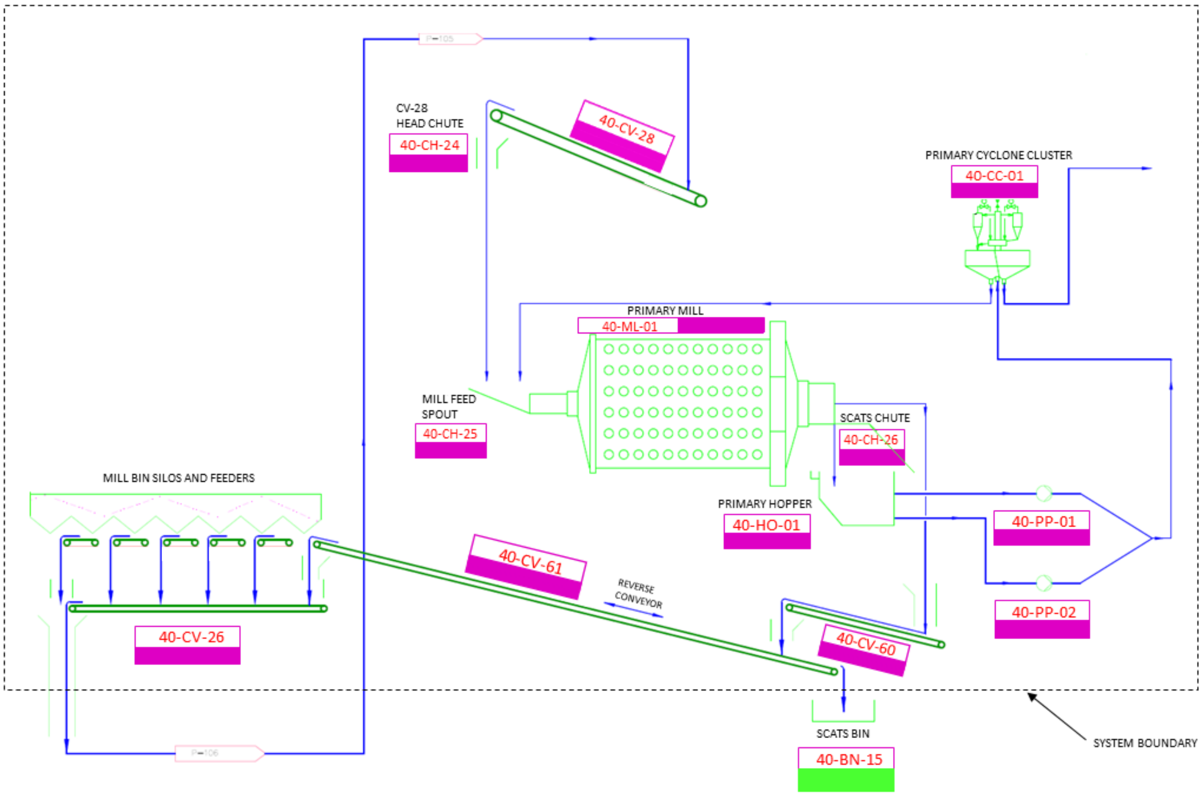


Figure 4.1: System boundary of primary grinding system. Adapted from flow diagram SVG-05–P-000/106 from SVG.

Assumptions for analysis and modeling

The following assumptions have been made for the system and the analysis for simplification and for being able to model the behavior of the system.

- Repair is initiated immediately upon failure.
- Corrective repair actions on all subsystems are assumed to bring the item back to bad-as-old condition.
- Some subsystems experience a decreasing failure rate based on collected failure data. It is assumed that all subsystem receive preventive maintenance. This is a result of mining engineering, which is necessary to keep them operational.
- All preventive maintenance tasks are assumed to bring the subsystems back to bad-as-old condition.
- There are sufficient maintenance personnel to handle simultaneous failures.
- Some subsystems have been assumed to be reliable and not subject to failure, these

subsystems include chutes and hopper subsystems.

- The transition between pump 1 and pump 2 is considered not possible to fail. In addition, pump 1 is the primary pump and pump 2 is the secondary pump.
- The duration of the scheduled shuts for preventive maintenance can in reality vary, however assumed to follow the planned schedule which is 10 stops for 24 hours and two stops for 7 days during one operating year.
- Ore is assumed to always be available. The case where subsystems need to be shut down as a cause of no ore feed is not considered.
- Water, electricity, air, and other auxiliaries are assumed to always be available.

Two assumptions need further clarification and explanation. First, the assumption that pump 1 is the primary pump and pump 2 is the secondary pump implies that when pump 1 fails, pump 2 takes over, but after pump 1 is repaired it is re-activated again (pump 2 only operates when pump 1 is under repair). Secondly, the usual assumption on preventive maintenance actions is that they restore the item back to *good-as-new* condition. However, for this case the data is limited with respect to both failures and the short time period the data is collected from. In addition, the preventive maintenance actions that are performed on the subsystems are not always preventive maintenance tasks which alters the "age" or condition of the subsystems. Often the subsystems, as a consequence of mining engineering, require calibrations, lubrication, checks etc. which bring the system down but do not improve the subsystem in some way. Recall that the preventive maintenance task are in this case defined as scheduled shuts. Furthermore, as will be seen in section 4.3.4, some subsystems reflect a decreasing failure rate, which contradict the concept of preventive maintenance. However, to overcome the mentioned issues and challenges with limiting data and mining engineering requirements, in addition to illustrate how to model and simulate a system, the preventive maintenance actions are included, and are assumed to bring the subsystems back to *bad-as-old* condition.

Reliability Block Diagram

From the system boundary reported in Figure 4.1 and from discussions with experts at the mining company, a reliability block diagram (RBD) for the system has been established. The RBD is reported in Figure 4.2, where the solid dark green blocks are the subsystems subject to failures, and the light green dashed blocks are subsystems not subject to failures. The larger light green box containing pump 1 and pump 2 indicates that these two pumps works in parallel, where pump 1 is the active block indicated by [A], and pump 2 is the standby block indicated by [S:1]. The rest of the subsystems work in series.

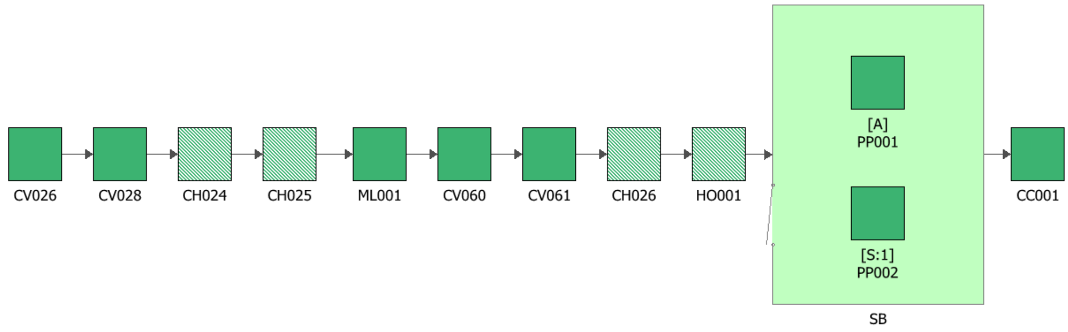


Figure 4.2: Reliability Block Diagram for the primary grinding system.

4.3.2 Data analysis

To get a clearer view of the failures of the subsystems, a bar chart can be used which presents the failure frequency of the different subsystems compared to the total number of failures. The bar chart is reported in Figure 4.3. As Figure 4.3 illustrates, the CV026 subsystem is the one with most failures.

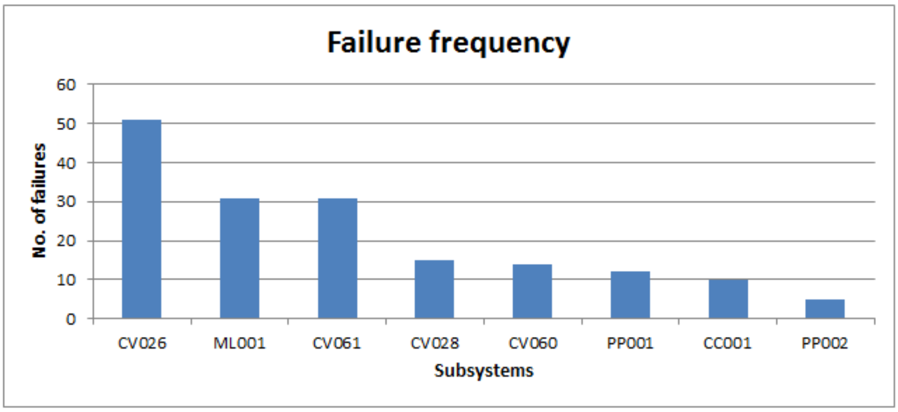


Figure 4.3: Failure frequency of the subsystems in the primary grinding system.

Another way of illustrating the effect of the failures is by using a bar chart of the downtime frequency of the subsystems. In Figure 4.4 the downtime frequency is reported, showing that the ML001 subsystem is the subsystem causing the most downtime on the grinding system. The failure frequency and the downtime frequency can be combined in order to investigate the average downtime per failure for each subsystem. By combining the two graphs it can be found that CV026 subsystem has the highest number of failures of all subsystems, however, only contributing to the fourth most downtime on the grinding system. From that observation it is evident that the reliability performance of this subsystem should be improved, rather than its maintainability performance.

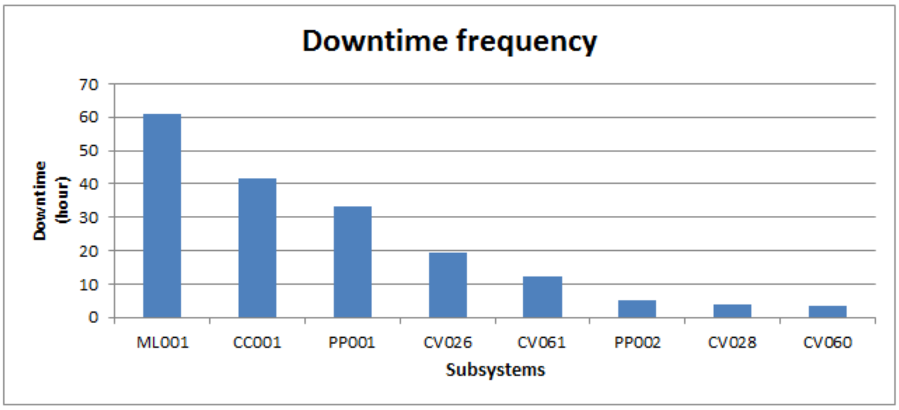


Figure 4.4: Downtime frequency of the subsystems in the primary grinding system.

4.3.3 Data evaluation

To be able to verify the IID assumption the TTFs and TTRs needs to be sorted and arranged chronological, in addition the cumulative TTFs and cumulative TTRs needs to be obtained. Table 4.1 lists a portion of the data set for the ML001 subsystem for illustration.

Table 4.1: Portion of TTF and TTR data set for ML001 subsystem

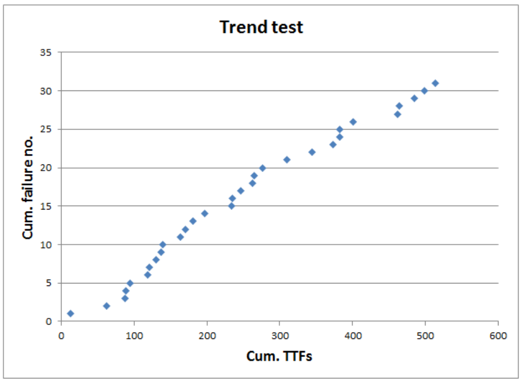
No	TTF (days)	TTR (hours)	Cumulative TTF	Cumulative TTR
1	13	4	13	4
2	49	3	62	7
3	25	3	87	10
4	2	6	89	16
5	5	4	94	20
6	25	12	119	32
7	2	4	121	36
8	9	8	130	44
9	7	3	137	47
10	2	1	139	48
11	25	0,5	164	48,5
12	6	12	170	60,5
13	11	1	181	61,5
14	16	2	197	63,5
15	37	1	234	64,5

IID assumption

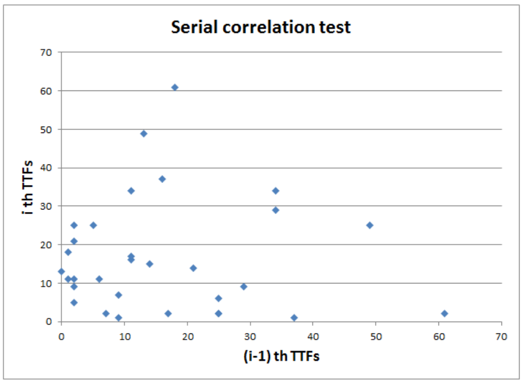
In order to select appropriate statistical approaches for modeling the system, the assumption that the data sets are independent and identically distributed needs to be verified. This is achieved by performing trend tests and serial correlation tests on each of the data sets. Both the trend test and the serial correlation tests have been conducted graphically.

Trend test
In Figure 4.5a the trend test for the TTF data for the ML001 subsystem is reported. As the figure illustrates, the data points indicate an approximately straight line, which implies a data set free of trend, which further implies a identical distributed data set. The same test was performed for the rest of the subsystems (both for TTF and TTR data) which revealed that all data sets are trend free and therefore identical distributed.

Serial correlation test
In Figure 4.5b the serial correlation test for the TTF data for the ML001 subsystem is reported. As the figure illustrates, the data points are randomly scattered and no correlation is found, which results in independent data points in the data set, i.e., no correlation among the data points. The same test was performed for the rest of the subsystems (both for TTF and TTR data), and the same conclusion as for the ML001 subsystem could be drawn for the rest of the subsystems. Overall conclusion is that the IID assumption is valid for all data sets (both for TTF and TTR data).



(a) Scatter plot of the cum. failure number versus the cum. TTFs for ML001 failure times.



(b) Scatter plot of the ith TTF versus the (i-1)th TTF. TTFs for ML001 failure times.

Figure 4.5: Trend test (a) and serial correlation test (b) for TTFs from ML001 subsystem.

4.3.4 TTF and TTR data analysis

In TTF and TTR data analysis the goal is to model the failure and repair processes of each subsystem. This is achieved by determining a probability distribution which best fit the failure data and a probability distribution which best fit the repair data. Then, estimate associated parameters which best represent the data. The next two sections will present the TTF and TTR data analysis for the TTF and TTR data sets.

TTF data

For modeling the failure data for the subsystems, the exponential 1-parameter distribution, the Weibull 2-parameter distribution, and the log-normal distribution have been selected. These three distribution are well known to be appropriate for modeling failures of mechanical systems, as well as having different characteristics to cover a wide area of types of data. To determine the best fitted distribution for the data sets the modified K-S goodness-of-fit test have been used. The parameters for the distributions are estimated using the MLE method. Both for the modified K-S test and for parameter estimation using MLE the reliability software package Weibull++ version 7 has been used. The result of the modified K-S test for the three distributions, the best fitted distribution, and estimated parameters are listed in Table 4.2.

Table 4.2: Goodness-of-fit test for TTF data

Subsystem	K-S test			Best fit	Parameters
	Exponential 2-parameter	Weibull 2-parameter	Log-normal		
CV026	0.9999	0.9978	0.9537	log-normal	σ= 1.1999; μ= 1.1213
CV028	0.4964	0.0229	0.0005	log-normal	σ= 1.4796; μ= 2.6206
ML001	0.0944	0.2838	0.3676	exponential 1-parameter	λ= 0.0603
CV060	0.8733	0.0103	0.0016	log-normal	σ= 1.6515; μ= 2.2419
CV061	0.8318	0.3113	0.3275	Weibull 2-parameter	$\beta = 0.8021$; $\eta = 14.6206$
PP001	0.2674	0.1751	0.0852	log-normal	σ= 1.5613; μ= 2.6669
PP002	0.4723	2.72×10^{-6}	2.13×10^{-7}	log-normal	σ= 2.3060; μ= 2.8691
CC001	0.3026	0.047	0.1739	Weibull 2-parameter	β =0.8000; $\eta = 39.7887$

TTR data

For the repair data only the log-normal distribution has been chosen to model the repair of all subsystems. According to Kline [1984], Zapata et al. [2008], and the Center for Chemical Process Safety [CCPS] [1998], the best distribution to model repair data is the log-normal. Both Kline [1984] and Zapata et al. [2008] conducted studies based on investigating a larger amount of data sets and looking at which distribution fits the majority of the data sets. The authors concluded that the log-normal distribution was the best fit, and in the study of Kline [1984] it was shown that the only distribution which could be used to model the repair of all data sets in the study was in fact the log-normal distribution.

The MLE method has been used to estimate parameters from the log-normal distribution for the different TTR data sets, with the help of the reliability software package Weibull++ version 7. The subsystems with the log-normal distribution and estimated parameters are listed in Table 4.3.

Table 4.3: Log-normal distribution for TTR data with estimated parameters

Subsystem	Distribution	Parameter estimate
CV026	log-normal	$\sigma = 0.6374$, $\mu = 0.6031$
CV028	log-normal	$\sigma = 1.0281$, $\mu = 1.0485$
ML001	log-normal	$\sigma = 1.1324$, $\mu = 1.1541$
CV060	log-normal	$\sigma = 0.8197$, $\mu = 1.0588$
CV061	log-normal	$\sigma = 0.8057$, $\mu = 0.8026$
PP001	log-normal	$\sigma = 1.1507$, $\mu = 1.2106$
PP002	log-normal	$\sigma = 1.3390$, $\mu = 1.6944$
CC001	log-normal	$\sigma = 1.0034$, $\mu = 1.3609$

4.3.5 RAM analysis

In a RAM analysis, the goal is to achieve an improvement of either of the three RAM performance measures. This can be achieved by several methods, techniques, and approaches. Although, when improving the characteristics of reliability or maintainability it will result in improved overall availability. The approach for RAM analysis is to model the defined system based on the model of each subsystem obtained in the TTF and TTR data analysis. In this case, the defined system, with its subsystems and associated distributions and parameters, will be simulated by the use of the reliability software package BlockSim version 9. The software simulate by Monte Carlo simulation. The Monte Carlo simulation method is previously discussed in section 2.4.2.

System simulation

When simulating a system using Monte Carlo simulation it is critical that the number of simulations are sufficient as the confidence of the simulation depends on the number of simulations. In addition, as for this case, it is important that the simulation end time is sufficient for the system to settle and the mean availability to reach a constant value. In this case, the chosen number of simulations are 10 000. That number of simulations should be sufficient, while at the same time be practical to simulate with an ordinary computer, with respect to time needed for simulation. In Table 4.4 the system simulation details are listed.

Table 4.4: System simulation details

Simulation detail	Parameter	Explanation
Simulation period	5 years	For time perspective
Number of simulations	10 000	For simulation confidence
Failure distributions	See Table 4.2	Historical failure data
Repair distributions	See Table 4.3	Historical repair data
CM tasks	When item fails	Continuing production
PM 1	Every month* (constant)	Based on TUM**
PM 2	Twice a year (constant)	Based on TUM**

*Except for the months were preventive maintenance task 2 is assigned.

**TUM, Time Usage Model for plant Operation and Maintenance at SVG.

Analysis and simulation results

This section will present some of the most important results obtained from the simulation for a 5 years simulated operating time. The main results are listed in Table 4.5. After 5 years of simulation, the mean availability approaches nearly a constant value. That value, as can be seen in Table 4.5, is 91.22 %. Furthermore, the expected number of failures is 195.95 and the number of PMs is 59.89.

Additionally, the number of expected failures causes a CM downtime of 974.16 hours during 5 years. The number of PMs causes a PM downtime of 2 869.90 hours. That gives a total maintenance downtime of 3 844.06 hours for 5 years of simulation. The number of downing events and preventive maintenance actions are not a complete value or a whole number as a result of the nature of the Monte Carlo simulation.

The mean availability graph during the simulation is reported in Figure 4.6. As the figure shows, the availability drops at each scheduled PM 1 and PM 2 task. Referring to the discussion on the preventive maintenance tasks and the bad-as-old condition in section 4.3.1, it is established that these scheduled preventive maintenance tasks are

Table 4.5: List of simulation results

Performance measures	Result
Mean availability	91.22%
System uptime	3 844.06 hours
System downtime (CM)	974.16 hours
System downtime (PM)	2 869.90 hours
System downtime (Total)	3 844.06 hours
Expected number of system failures	195.95
Number of PMs	59.89

required as a result of mining engineering concerns, although they reduce the mean availability. For instance, conveyors are brought down and locked for cleaning and inspection at these schedules shuts. However, there is not performed any preventive maintenance on them which alter the "age" or condition of the conveyors.

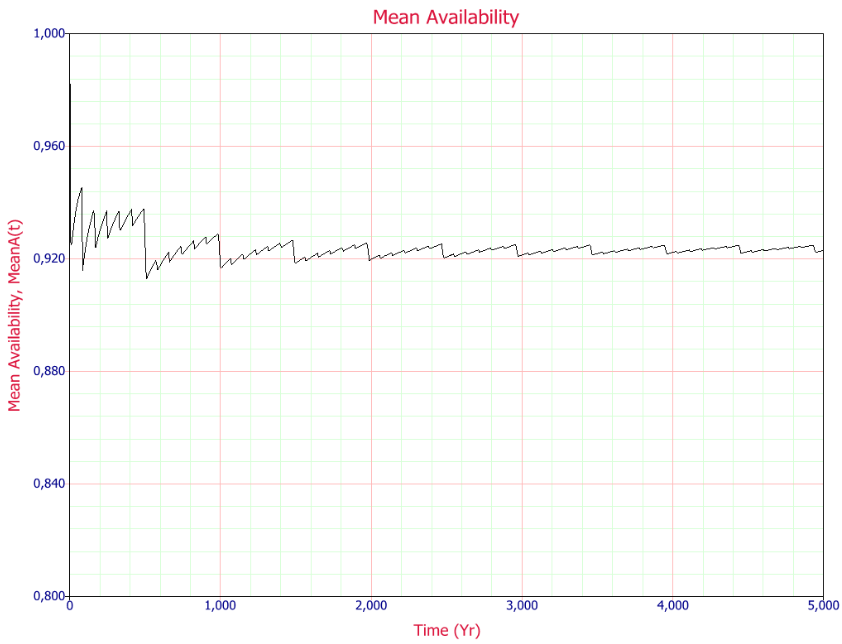


Figure 4.6: Mean availability of the primary grinding system during a simulation period of 5 years.

In Figure 4.7 the point availability during the first year of operation is reported. As can be observed from the figure, the point availability drops to 0 at each preventive maintenance task and remains 0 until the tasks are finished. Furthermore, the relation between the mean availability in Figure 4.6 and the point availability in Figure 4.7 is that the mean availability is simply the area under the point availability curve.

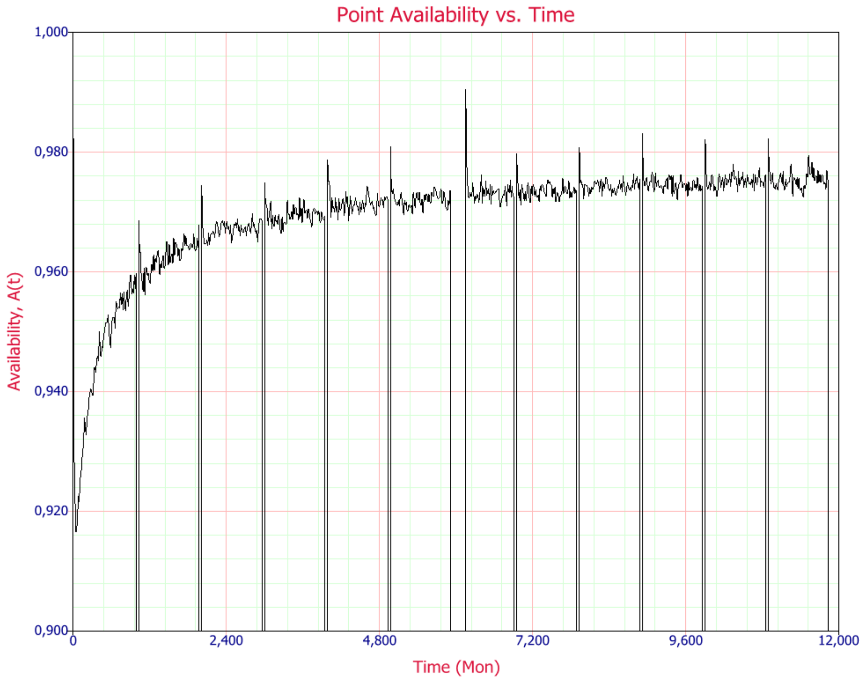


Figure 4.7: Point availability of the primary grinding system during the first year of simulation.

4.4 Discussion and suggestions for improvement

The main aim of system analysis is to improve the system itself or characteristics of the system in order to improve O&M and the availability performance of the system. The production demand in the mining industry is constantly increasing. To meet the demand it is necessary to identify and implement improvement measures in an availability-effective and cost-effective manner for overall availability improvement. There exist several approaches and methods for improvement. In this case study two aspects of improvement will be discussed. The first aspect concerns modifying the interval of preventive maintenance for optimum mean availability. Identifying the optimum, or near optimum, preventive maintenance interval is crucial for meeting today's high production demand. The second aspect of improvement concerns improving the reliability performance and the maintainability performance of the system in order to increase mean availability. This will be achieved by first identifying the most critical subsystem, then improvement measures will be identified and implemented, and the system simulated with the implemented measures. The simulation results from each improvement measure can be compared in order to determine the most effective improvement measure.

4.4.1 Aspect 1: Identifying optimum PM interval

There exist several approaches for identifying optimum PM interval. Some of the most common involve using either cost or safety and reliability. As stated in section 1.5.2, cost is not included in this analysis. Approaches for improvement using reliability is often applied for safety systems and where the consequence of failure is very severe with respect to safety. These approaches have not been considered. In this case the aspect of improvement is to perform a trial and error method for different PM intervals in order to increase mean availability of the system, and thereby identifying the optimum interval. The method involves creating five scenarios where the only varying parameter is the interval of the PM 1 (minor shuts). As a result of mining engineering concerns, the interval of the PM 2 (major shuts) is required to be approximately twice a year and not subject to change. The first scenario evaluated of the five scenarios is the baseline condition of the system with a PM 1 interval of 1 month. The next four scenarios are with PM 1 interval of 2 months, 3 months, 4 months, and 5 months. The results from all five scenarios are listed in Table 4.6.

Table 4.6: Simulation results as the interval of PM 1 changes

PM 1 interval*	Availability (%)	Total downtime	CM downtime	PM downtime	Expected failures
Scenario 1**	91.2236	3 844.06	974.16	2 869.90	195.95
Scenario 2	92.8239	3 143.13	988.24	2 154.89	198.84
Scenario 3	93.3614	2 907.70	991.45	1 916.25	199.58
Scenario 4	93.3595	2 908.55	992.22	1 916.33	199.77
Scenario 5	93.3562	2 909.97	993.37	1 916.60	199.65

*The different scenarios represent the monthly interval of PM 1.

**Scenario 1 is also the baseline system condition.

Based on the results from the simulations where the PM 1 interval changes a graph has been drawn for the PM interval versus the mean availability value. The graph is reported in Figure 4.8.

Three main results needs to be highlighted from the five simulations:

- As both Table 4.6 and Figure 4.8 illustrate, the interval of PM 1 that provides the highest mean availability is the interval of 3 months.
- Table 4.6 can reveal that the CM downtime increases from scenario 1 to scenario 3 but remains nearly the same from scenario 3 to scenario 5.
- Table 4.6 can reveal that the PM downtime decreases from scenario 1 to scenario 3 but remains nearly the same from scenario 3 to scenario 5.

Stating the optimum interval and the behavior of the CM downtime and PM downtime is not adequate in this case. With the characteristics of the model for this system, and

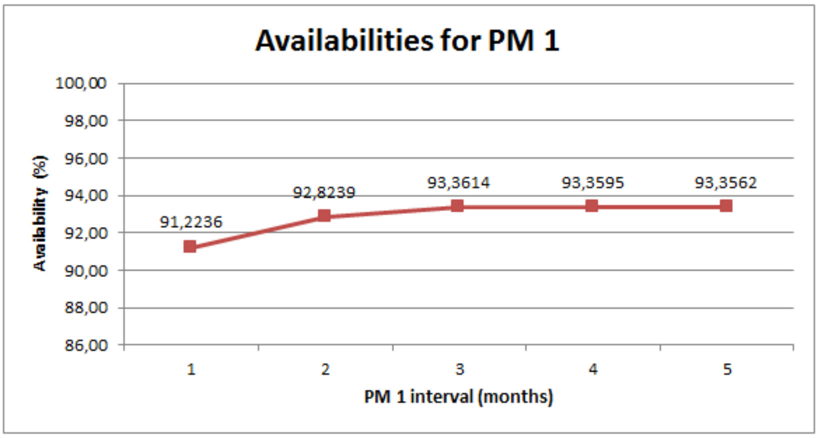


Figure 4.8: Availability of the primary grinding system as the interval of PM 1 changes.

with its associated distributions and parameters, some explanation is needed. From the estimated parameters of the failure rate of the subsystems in Table 4.2, some of the subsystems reflect decreasing failure rates. This imply the subsystems are improving with time. How some subsystems have a decreasing failure rate have an impact on the overall system can be seen by plotting the overall system failure rate. The system failure rate plot is reported in Figure 4.9, and shows that the total system failure rate is also decreasing by time. The PM downtime remains the same from scenario 3 to scenario 5. This can be explained by the fact that increasing the interval of PM 1 from 3 months to 5 months do not increase the overall number of PMs during the simulation. The reason being that PM 2 is scheduled at each 6 month, with a higher priority, which will cancel out PM 1 tasks whenever they overlap. This results in the total number of PMs being identical for both scenario 3, 4 and 5. The CM downtime increases from scenario 1 to scenario 3. This can be explained by the fact that a higher downtime due to PMs for scenario 1 and scenario 2, will result in less uptime, and thereby a lower probability of failure, resulting in lower CM downtime compared to scenario 3, 4 and 5. These explanations on the behavior of the CM downtime and the PM downtime needs to be seen in light with the bad-as-old assumption made on the preventive maintenance tasks, and the fact that the overall system failure rate is decreasing.

In a reliability sense, for a decreasing failure rate imposing PM actions actually do not provide any improvement of the system. As PM actions will bring the system down, it will only impose more downtime and reduce the mean availability. Strictly speaking, removing all preventive maintenance tasks would actually provide the highest availability by time. In industry, this is often not possible, as some subsystems (like mechanical mining equipment in this case) require some different tasks regardless. Some systems need calibration, lubrication, checks etc. These tasks are more associated with mining engineering and do not actually modify the condition or "age" of the equipment some how.

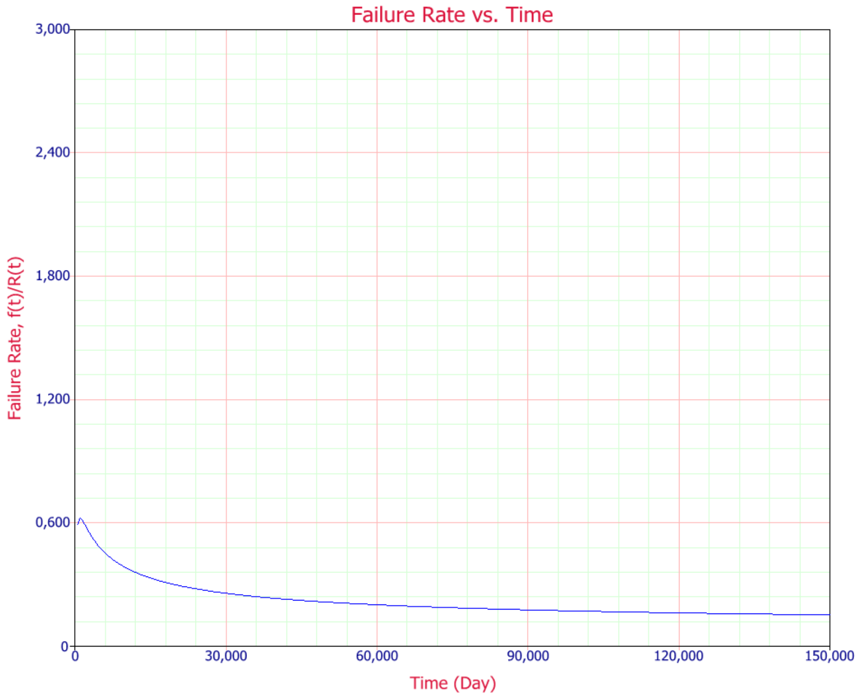


Figure 4.9: System failure rate of the the primary grinding system.

The reason for the decreasing failure rates for some subsystems in this system can be difficult to explain. One reason can be the limiting period of time data is collected from, and thereby the limiting failure data. This limitation results in a model that do not reflect the actual behavior of the system. There is always uncertainty related to modeling complex systems like the defined system in this case study. Being aware of different concerns and in which degree the model reflects the real behavior of the system, is important when assessing the analysis output and results. To overcome and tackle this situation, additional detailed operational data can be used if available. In addition, expert judgment or consultation with maintenance personnel can yield ideas and indications on maintenance intervals whenever operational data is lacking.

4.4.2 Aspect 2: Improving reliability or maintainability

Before determining improvement measures for the reliability and maintainability the most critical subsystem should be identified, as this help in allocating resources most effectively. To identify the most critical subsystem the Downtime Criticality Index (DTCI) from ReliaSoft can be used [ReliaSoft, 2014]. The DTCI is a relative index which considers each blocks downtime contribution to the total system downtime. The DTCI plot for a simulating period of 5 years is reported in Figure 4.10.

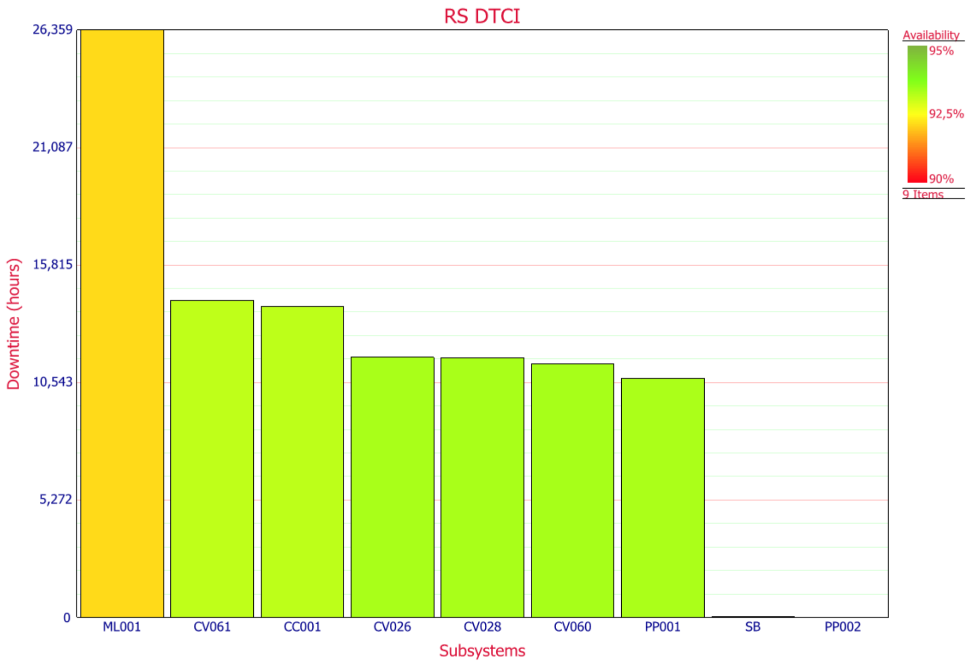


Figure 4.10: DTCI plot of the system illustrating each subsystem downtime to the system total downtime.

As the plot in Figure 4.10 shows the subsystem which contributes to most downtime of the system is the ML001 subsystem. Identifying the most critical subsystem can be beneficial for many reasons. It will help in the decision-making regarding where to allocate resources, and if time is limited it will indicate where the focus should be for optimized improvement. When the most critical subsystem is identified, the reliability performance and maintainability performance of that subsystem can be improved in order to improve overall system availability performance.

Reliability improvement

There are several actions which can be taken in order to improve system reliability performance. More commonly, components can be changed with other components out of a different material, which is more resistant to wear, or the design of the system can be changed in order to increase system reliability. According to the production department at Sydvaranger Gruve, the company is considering the implementation of an additional mill system, similar to ML001. For that reason, it is appropriate to choose this scenario for reliability improvement. An additional subsystem identical to the critical subsystem is implemented for added redundancy to the system. The new mill configuration is that one of the mill subsystems is in active mode, while the other is in standby mode (similar to the pump configuration of pump 1 and pump 2). When the active subsystem fails, the other will be activated and take over, and the failed subsystem will be repaired. In that way, the production rate stays the same as before and the probability of system failure for the mill is highly reduced, as the two subsystems will work in parallel. Which means that unless the active subsystem fails and the new subsystem which takes over fails before the first is repaired, this part of the system will never go down. This addition and implementation results in a modified RBD of the system. The modified RBD is reported in Figure 4.11.

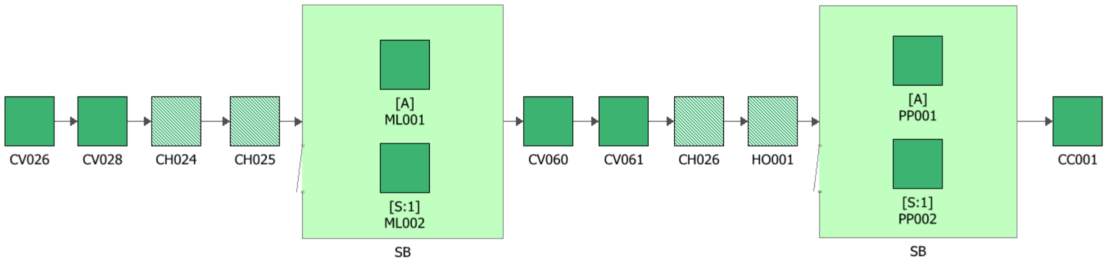


Figure 4.11: Reliability Block Diagram for the primary grinding system with added redundancy.

Improving reliability is often expensive and difficult to achieve in the operating phase of a process plant. As practical issues, such as increased space and production stops, are often needed. The ideal situation would be to assess the reliability in the design phase and then deciding on the best options, although this is rarely the case. As for this case, the mill system is identified as the most critical system for improvement. In reality this system is highly expensive and occupies a larger area of the plant. However, some improvement measures are possible, like using new components which are more resistant to wear, which will last longer. In this case, the option for improvement has been to implement an additional mill working in parallel with the original. Since production and throughput capacity is not considered, instead of both working in parallel simultaneously, one system is active while the other is in standby. This will increase the availability of the total system in some degree. The result from the original configuration compared to the new with the extra mill system is listed in Table 4.7. As can be seen the number of system failures will be halved and the corrective maintenance downtime reduced by approximately 600 hours during the simulation period.

Furthermore, the system reliability will improve with an additional mill, as two mills working in parallel are more redundant than just one single mill. How the system reliability is improved is illustrated by an overlay plot of the point reliability, with one mill in series and two mills in parallel. The overlay plot is reported in Figure 4.12.

The mill is the critical subsystem in the grinding system not only based on the fact that it contributes to most downtime but because it is the system which the primary grinding system is surrounding. The mill is the actual equipment grinding the ore, and without

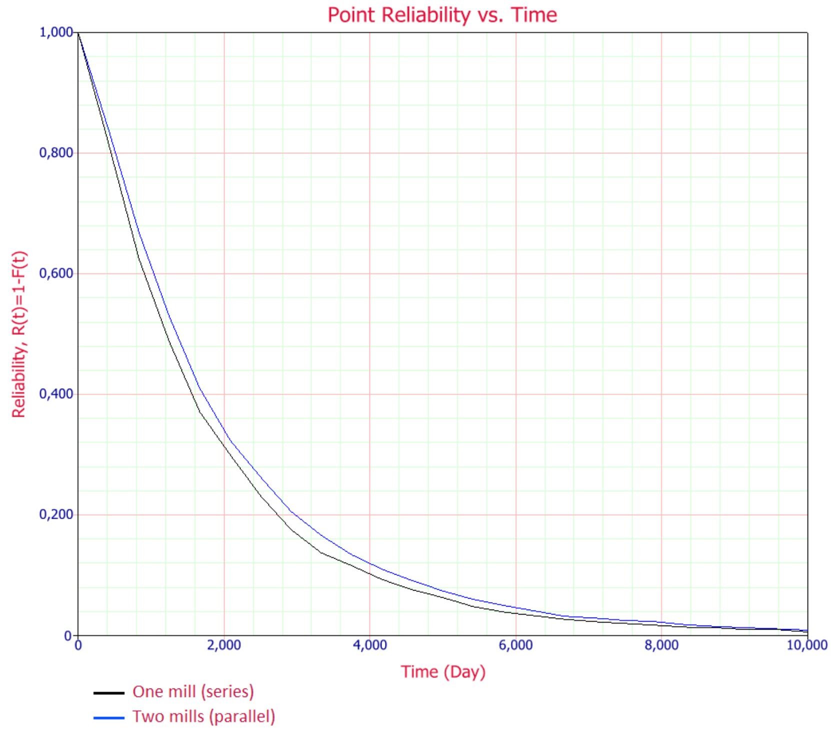


Figure 4.12: Overlay plot of point reliability for one mill (series) and two mills (parallel).

the mill, the grinding system cannot perform its required function. The other subsystems are, of course, important systems, but are considered to be additional systems necessary in the process flow.

The mill is also the main reason for the two major shuts twice a year. The inner surface of the mill shell is covered with lining, which has the purpose of protecting the mill shell, and also to improve the movement of the charge (combination of slurry and mill balls) for optimum grinding and throughput. After the mill has operated for a certain period, the lining is worn-out and needs to be changed (relined). That interval is approximately 6 months for this particularly ball mill. If an additional mill is implemented operating in parallel, then one mill can be down for relining and maintenance, while the other is operating. In that case, the two preventive maintenance task of 7 days duration could be removed and the yearly downtime reduced by 14 days. The result of removing both PM 2 tasks from the maintenance plan is listed in Table 4.8. As can be seen in the table, the availability is increased by 3,2263 % when no PM 2 task is included.

The removal of PM 2 from the maintenance schedule is just an illustration, it is not realistic to totally remove the two major shuts. The reason is because the two major days shuts also include numerous other important maintenance tasks on several equipment

Table 4.7: System availability considering an improved reliability performance of ML001 (1)

Reliability characteristic	Availability (%)	Total downtime	CM downtime	PM downtime	Expected failures
In series	91.2236	3 844.06	974.16	2 869.90	195.95
In parallel*	92.5752	3 252.04	374.62	2 877.41	97.78

*Redundancy added to system by using an identical block as standby.

Table 4.8: System availability considering an improved reliability performance of ML001 (2)

PM 2 characteristic	Availability (%)	Total downtime	CM downtime	PM downtime	Expected failures
Twice a year*	91.2236	3 844.06	974.16	2 869.90	195.95
Once a year**	93.3682	2 904.75	995.22	1 909.53	199.88
No PM 2	94.4499	2 430.93	1 000.33	1 430.61	201.51

*7 days each of total of 14 days.
**5 days once of total of 5 days.

and systems in the plant besides the mill. In other words, just excluding the two major shuts from the operating and maintenance schedule is not realistic. However, a reduction of e.g. two shuts of 14 days total downtime to one shut of 5 days total downtime might be a more realistic scenario. Running the same simulation with one PM 2 task of 5 days duration each year for 5 years yield an availability increase of 2,14 % as seen in Table 4.8.

A final decision of implementing an additional mill must be made while including the acquisition cost (including any structural engineering cost associated with installation), operational and maintenance cost, and the resulting increase in availability, and thereby production.

Maintainability improvement

There are several actions that can be taken in order to improve system maintainability performance. Maintainability improvement measures are often cheaper to implement than reliability improvement measures. Although, those measures can be difficult to obtain and the maintainability improvement measures needs to be very effective in order to improve the overall availability. Training of maintenance personnel, improved accessibility of equipment, better spare part planning and improved logistics are some of the measures which should be considered for maintainability and maintenance support improvement. In this case there is assumed that the effect of maintenance personnel repairs on the mill system are improved in such a manner that the duration of the corrective maintenance actions on average are reduced by 50 %. As a consequence the repair rate for corrective maintenance is reduced for the corrective maintenance actions. System availability based on this assumption is reported in Table 4.9.

Table 4.9: System availability considering an improved maintainability (corrective maintenance) performance of ML001 (1).

Mean	Log-mean	Availability (%)	Total downtime	CM downtime	PM downtime	Expected failures
3.1711	1.1541	91.2236	3 844.06	974.16	2 869.90	195.95
1.5855	0.4608	91.8960	3 549.56	674.21	2 875.35	197.19

As Table 4.9 shows the reduced repair rate of the mill system results in a mean availability increase of nearly 0.7 %. If the training of personnel is cheap and manageable that improvement measure should be considered for improvement. For further illustration it is assumed that as a result of the trained personnel for repair on the mill system the duration of PM 2 is also reduced from 7 days to 5 days. The results are reported in Table 4.10.

Table 4.10: System availability considering an improved maintainability (preventive maintenance) performance of ML001 (2).

PM 2 duration	Availability (%)	Total downtime	CM downtime	PM downtime	Expected failures
7 days	91.2236	3 844.06	974.16	2 869.90	195.95
5 days	92.2988	3 373.12	982.84	2 390.27	197.72

As seen from Table 4.10 if the duration of PM 2 is reduced from 7 days to 5 days the availability is increased to 92.3 %, which is a significant increase in mean availability. This improvement should be considered, as it affects the preventive maintenance duration of the other subsystems as well as the mill. As stated, it is not always possible to achieve this degree of maintainability improvement. However, this simulation illustrate the potential result of such an improvement if obtained.

Summary

Both reliability improvement and maintainability improvement needs to be considered when aiming at improving overall system availability. Increased availability as a result of reliability improvement are often easier to obtain, but as a consequence are often very expensive and can be difficult to implement (space limitations, downtime due to installations, or component replacement etc.). Increased availability as a result of maintainability improvement can be more difficult to obtain, the reason being that an improvement in maintainability needs to be significant in order to achieve increased availability. Although, maintainability improvement often do not affect production in the same way as reliability improvement besides the cases where production needs to shut down for some design change with respect to maintainability improvement (accessibility and visibility for instance).

In this case, the simulation results indicate that the most effective option is to implement an additional mill system working in parallel with the already installed mill. The optimum availability is obtained when PM 2 is removed from the maintenance plan. However, as discussed, this scenario is not realistic, as other maintenance tasks are also performed on other equipment and systems during the major shuts. Thus, a reduction in planned maintenance shuts is possible and needs to be assessed if an additional mill is implemented. However, it is important that the final decision is made based on the result of a cost-benefit analysis.

This analysis is limited with respect to cost not being included. Considerations needs to be done towards what improvement measure will be the most cost-effective one.

The result of this analysis shows that implementing an addition mill is the best option. When considering the complexity, size, and cost of that particular equipment, in addition to other mining engineering concerns like the significant need for increased water and power, it could be of interest to investigate the second and third most critical subsystem instead. This is not considered in this case study, but the DTCI plot in Figure 4.10 can reveal that these two subsystems are CV061 (conveyor) and CC001 (cyclone cluster) respectively. These subsystems are smaller in size, less complex, and easier replaceable than the mill.

Finally, a goal for this case study from the perspective of the cooperating company was to assess the availability of data and quality of data for RAM analysis. For SVG it is recommended that emphasize is put on recording failures in both date and time resulting in hour-based failure data. Furthermore it is recommended that repair actions are recorded consistently on a lower level in the system hierarchy, in addition to put emphasize on the different ways of recording corrective maintenance actions versus preventive maintenance actions. For the corrective maintenance tasks it is recommended that the time the failure is noticed is recorded, time when the failed component is found, waiting time for spare parts, time at which the paperwork is finalized and other administrative delay time, time when the CM task is performed, and time at which the system is operating again. This will lead to a better basis for knowing which part of the downtime is more critical to focus on for improvement. All these recommendations will result in an improved database of RAM data for analysis in the future.

Chapter 5

Framework for Data Collection

This chapter consist of two parts. The first part presents a framework for data collection for RAM analysis and discusses two mathematical models for including the effects of influence factors in reliability and maintainability analysis. The second part is a case study from the process plant at Sydvaranger Gruve aiming to improve the data collection for reliability analysis. This chapter aims to answer the research questions on how to improve data collection for RAM analysis, and how the effects of influence factors can be included in reliability and maintainability analysis.

5.1 Introduction

In industries today, the focus on health, safety, and environment is constantly increasing, and rightly so. A goal of non fatalities, reduced injuries, and no release of toxic substances to the environment is a goal all companies in the process industry should emphasize and strive for. With this focus, in combination with a high production demand, the need for quality risk and reliability analysis is higher than ever. There have been developed several standards and handbooks on risk and reliability analysis as well as data collection for analysis, like the OREDA handbook and the ISO 14224 standard discussed in chapter 1. However, a shortcoming for these sources of data are the lack of focus on collecting data on the factors that influence the reliability and maintainability of equipment [Barabadi et al., 2014]. As discussed in chapter 1, often the only explanatory variables collected are TTFs and TTRs. Collecting data on the effects of influence factors during failures and repairs and how to use the data in analysis are equally important. According to Kumar and Klefsjö [1993], a frequent problem for analysis of reliability data are that the data have been collected under dissimilar conditions (operational or environmental). These conditions should be isolated and their effects or influence estimated [Kumar and Klefsjö, 1993]. According to Barabadi et al. [2014], for a RAM analysis to lead to effective input to the design, operation, and maintenance process the right person (in this case the analyser), needs the required data, in the right standardized format, at the right time. In industry this is rarely the case, and many studies are using field data with many drawbacks [Ansell and Phillips, 1997]. According to Ansell and Phillips [1997] some of the potential causes for insufficient data are:

- Data are collected as a byproduct of the maintenance process and not solely to aid reliability assessors.
- Component histories are fairly complex and are embedded in other process information.
- Data are often aggregated making it difficult to extract the required and desirable data and information on component failures.

[Ansell and Phillips, 1997]

The following framework is a retrieval of important steps from the methodology proposed by Barabadi et al. [2014]. Although, this framework goes further in explaining each step in more detail. Further, this framework include a planning part of the data collection process, in addition to implementing some new aspects considered important for collection of RAM data. Where additional information has been needed the various sources have been referenced accordingly.

In section 5.2 the framework for data collection is presented and in section 5.3 the concept of a mathematical model with a modified extension is discussed. The framework includes collection of the effects of influence factors, and the two mathematical models illustrate the concept of including the effects of influence factors in reliability and maintainability analysis.

5.2 Framework for data collection

The following framework is suggested for RAM data collection considering influence factors. The framework is divided in three parts and will highlight and explain important steps when collecting RAM data, include additional information on the planning process before data collection starts, and list different types of analysis possible to perform with the data collected. In Figure 5.1 a composite view of the framework is illustrated. The next sections will explain the different steps in the framework in more detail.

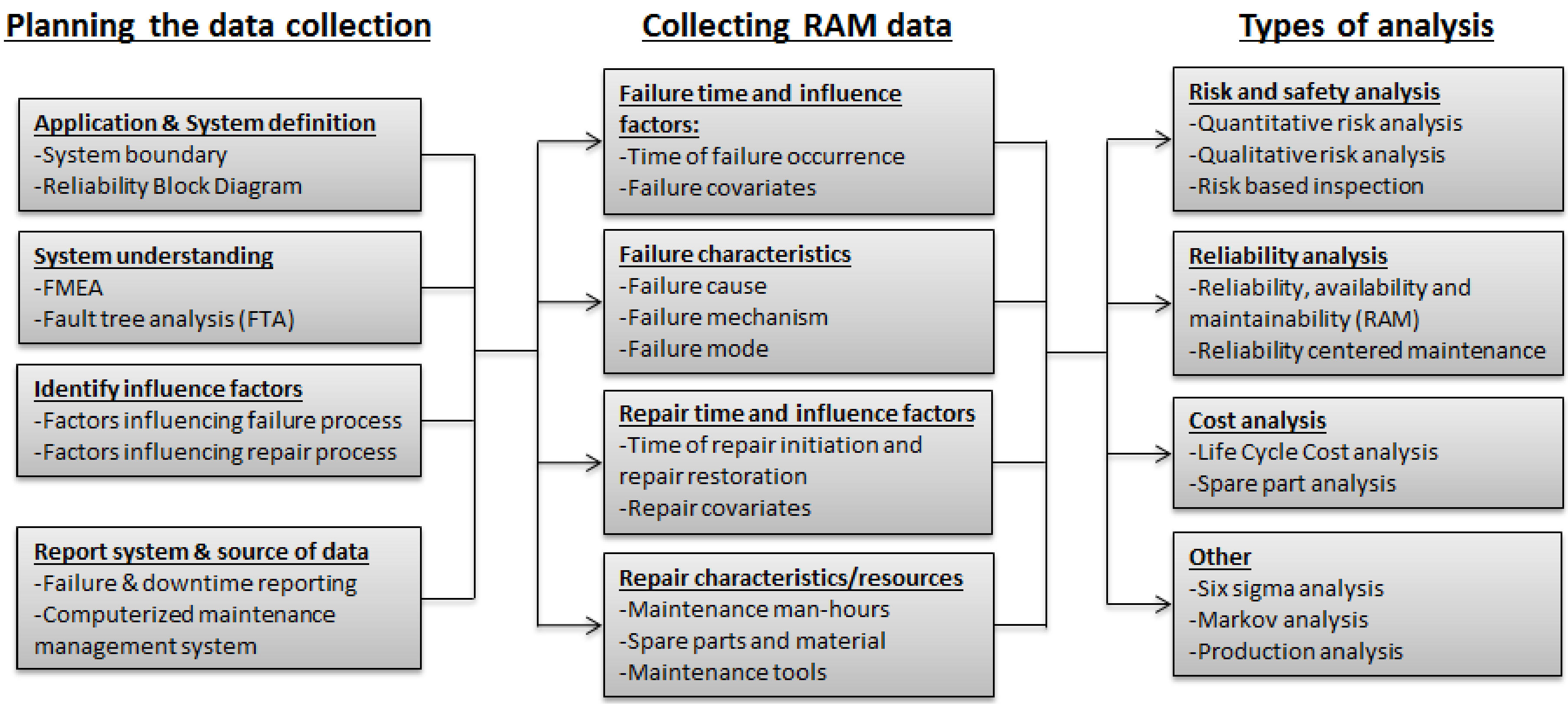


Figure 5.1: Framework for data collection.

5.2.1 Planning the data collection

Before starting the actual data collection, the data collection process should be planned and some preliminary work performed in order to collect optimal data and quality data.

Define application and systems

First, one needs to define and limit the area and application of data collection. In the mining industry, there will often be a mine pit, either underground or open, perhaps a rail road for transportation, a crusher plant, separation plant and possibly a pellet plant. In each location, the equipment types will vary and the operating conditions change. When the area and application for data collection is defined the systems within need to be investigated and defined. Tools and techniques, such as system boundaries and reliability block diagrams, should be used to help define systems and equipment before data collection.

Understanding system

To better understand the systems with respect to operation and failure characteristics, there should be executed a Failure Modes and Effects Analysis (FMEA). An FMEA is an analysis that reveals system failure modes, their causes, and the effects of the failure mode occurrence on the system operation. It provides a basis for identifying potential system failures and unacceptable failure effects and corrective actions to prevent them [Carlson, 2012]. As an FMEA is time consuming and resource demanding it should in the first place be conducted for high-risk and high-priority equipment, systems and components. The different steps in an FMEA can be chronological implemented as the following:

- **Identification.** Identify the component with appropriate numbering.
- **Function/operational condition.** Briefly describe the function of the component with respect to the system and in which state the component has when the system is operating normally.
- **Potential failure mode.** List all the ways the component can fail.
- **Potential effect of failure.** Which effect do the failure have on the system or the end user. (if multiple effects from one failure mode use the most serious).
- **Severity.** Use a defined scale of severity do relatively determine the severity of that particular effect for a specific failure mode.
- **Potential causes.** This should describe the specific reason for the failure and preferably the root cause of the failure.

- **Occurrence.** Rank the likelihood of occurrence of the cause.
- **Controls.** Actions already planned or in place to reduce or eliminate the risk of potential cause of failure.
- **Detection.** Rank the likelihood of detection of the cause.
- **Risk Priority Number (RPN).** Rank the risk of the potential failure mode/-cause by multiplying the severity number, occurrence number and the detection number.
- **Recommended actions.** Task recommended to reduce or eliminate the risk with potential cause of failure.

[Carlson, 2012]

A limitation regarding FMEA is the lack of investigation of the interactions between several failure modes [Carlson, 2012]. For such an analysis of the interactions between failure modes and for further thorough understanding of the system or component a Fault Tree Analysis (FTA) can be conducted to support the FMEA.

Fault Tree Analysis
A FTA analysis is graphical technique applied either qualitative or quantitative. The goal and objective of the FTA is to reveal all causes which can lead to a top event. The fault tree exist of a top event, a failure or unwanted event of some sort, then the different causes which could lead to the failure is identified all the way down to the basic events. The FTA gives a more detailed and deeper understanding of the failure modes and sequence of failures for the top event to occur. The top event can be many different happenings, if the fault tree analysis is used in risk analysis the unwanted event often refers to an event with severe consequences. In the case of the mining industry, the top event can either be related to health or safety, but more often it can be related to system and equipment breakdowns causing downtime and production loss. The FTA is a deductive technique, meaning the top event is first opted, then the different ways the top event can occur is deducted down to lowest level [Modarres, 2006]. The causes leading to the top event are assigned either an OR gate or an AND gate, which are logical operator. If the OR gate is assigned, then only one of the causes are required for the top event to occur, while with the AND gate all the causes are required. If possibilities are assigned to the different causes the probability of the top event occurring can be calculated by the use of cut sets and Boolean algebra [Modarres, 2006]. For more information on FTA and how to use it for risk and reliability analysis see Modarres [2006] and Smith [2001].

Identifying and formulating influence factors

It is vital that the most important influence factors for the defined plant, application, or system is identified. Influence factors can be environmental conditions like varying climate, wind speed, temperature, or operational like operator skill, type of shift or local workers vs commute workers and maintenance personnel skill. The selection of influence factors can be based on experience and suggestions from experts, in combination with potential failure records revealing useful information. Furthermore, the identified influence factors need to be checked for time-dependency. The condition of time-dependency will determine which models to use for the analysis. The effects of influence factors needs to be quantified by numerical variables, called covariates. Preferably, only the influence factors that most probably has an significant impact on the failure and repair processes, should be identified and collected data on during operation and maintenance. In addition, to factors influencing repair, the factors which influence the maintenance supportability (support covariates) should be collected data on [Barabadi et al., 2014]. How to include the effects of influence factors on failures and repairs in reliability and maintainability analysis is presented in section 5.3.

Sources of data

This section describes two of the common sources of data for RAM analysis in the industry. In general, the production and maintenance department will often collect basic RAM data indirectly. The sources are often a downtime reporting system used by the production department, and the CMMS used by both production and maintenance department (although, mostly maintenance). The two next sections briefly highlight what data and information can be found in each of those two sources of data.

Reporting system for failures and downtime events
The production department will often record the time and date when systems or equipment fails. These records can be used to extract raw data, which then can be processed into TTFs for equipment or systems. The recording of downtime events should in addition be used to capture information like failure modes, failure mechanisms and failure causes. If possible, a link should be made between the downtime events and eventual maintenance actions performed to restore the system or equipment back to operating state [ISO, 2006].

Computerized Maintenance Management System (CMMS)
The CMMS contains work orders created for various maintenance tasks on equipment and systems. These work order records can be extracted and processed into TTRs for equipment and systems. However, the CMMS can, and should, also be used to capture man-hours, spare parts, and material used for each repair action. A common fault in many companies is that the CMMS is not fully utilized. A study from the Aitik mine in Sweden identified several faults leading to improper use of the CMMS [Galar et al., 2014]. Continuous improvement on the use of the CMMS and focus on the most important aspects will, with time, provide the RAM database with sufficient and accurate quality data in addition to an improved utilization of the overall use of the CMMS.

5.2.2 Collecting RAM data

After planning the data collection, the data collection can start. The next sections will describe important types of data, which should be collected in order to establish a comprehensive database of RAM data. The steps mentioned in the planning part will benefit the data collection greatly if performed properly.

Failure times and influence factors

When a failure occurs the date and time should be recorded. This is the source for providing TTF when doing analysis. The influence factors on the failure process identified in section 5.2.1 in the planning part should be collected data on continuously during operation, but especially when a failure occurs. This will ensure that the required information (including conditions having an impact on the failure process) at the time of failure is recorded for later use and analysis. When the equipment has been restored back to operating state, the date and time should be recorded. This will provide the total downtime of the equipment. In addition, administrative delay time and time it takes for shutting down and starting up the plant or specific equipment is recorded. Emphasize should be made towards recording the failure down to component level, or at least functional location level. It is also recommended that during preventive maintenance shuts degraded failures are reported if encountered.

Failure characteristics

Failure characteristics which would be beneficial for reliability analysis to collect in the case of a failure are the failure mode, the failure mechanism and the failure cause. Even though this step is recommended, by ISO [2006] among others, it requires that the operator present during the occurrence of failure have some basic technical knowledge on the failure processes of the equipment. Even though the knowledge among operators varies this step is recommended and after a transitional phase the operators will be more used to identifying these failure characteristics when a failure occurs. For more information on typical failure modes, the ISO [2006] standard can be used as guidance. In addition to the failure characteristics described, a code should be assigned to the failure, whether the failure causes downtime or not is irrelevant. This code unique for each failure will be used when creating work orders, in order to connect repair actions to specific failures.

Repair time and influence factors

When a failure occurs a repair is usually necessary to restore the equipment back to operating state. When the repair action is initiated the date and time should be recorded.

During the repair, the influence factors on the repair processes identified in section 5.2.1 in the planning part, should be collected data on. This will ensure that information having an impact on the repair processes and the repair rate is collected. After the repair action is performed, the date and time should be recorded. This will provide the actual time used on repair. The restoration time (total time it takes to restore the equipment back to operating state) is the same as the downtime collected in section 5.2.2.

Repair characteristics and resources

Repair characteristics beneficial to collect for maintainability analysis are typical the resources needed for the repair, i.e: man-hours, spare parts, and material used, in addition to special maintenance tools necessary for the repair action. This should be considered a minimum. In addition, characteristics such as logistics and other reasons for repair delays should be recorded. This will provide a basis for maintenance supportability analysis. Furthermore, it is recommended that operational reports include the profile of production level, plant throughput, and the cost of items (equipment and subsystems). These data, if collected, will provide a basis for cost analyses.

Time operation schedule for data collection

As an addition to the framework, a time schedule for operation has been developed. By combining the composite view of uptime and downtime from Blanchard and Fabrycky [1998] and the schematic picture of the time for collecting RAM data by Barabadi et al. [2014] a schematic time schedule for operation and downtime has been developed. The time schedule is reported in Figure 5.2. This schedule is an illustrative tool showing the relationship between uptime/downtime, the collection of influence factors during the operating cycle, and the statistical RAM data, which is retrieved from the data collection. As Figure 5.2 illustrates, the TTF and TTR are retrieved from the data collection Furthermore, the time to support (TTS) before and after the active maintenance repair is retrieved, which gives a basis for providing the time to restore ($\mathrm{TTR}_{\mathrm{res}}$). The time from a failure occurring to total non-operating state is a transition phase dependent on a combination of the degree of failure and the run down time. The time from non-operating state back to total operating state is a transition phase dependent on the ramp up time [ISO, 2006].

5.2.3 Types of Analysis

This part of the framework is just an informative part on some of the common types of analysis, which can be performed with this framework for data collection and with the

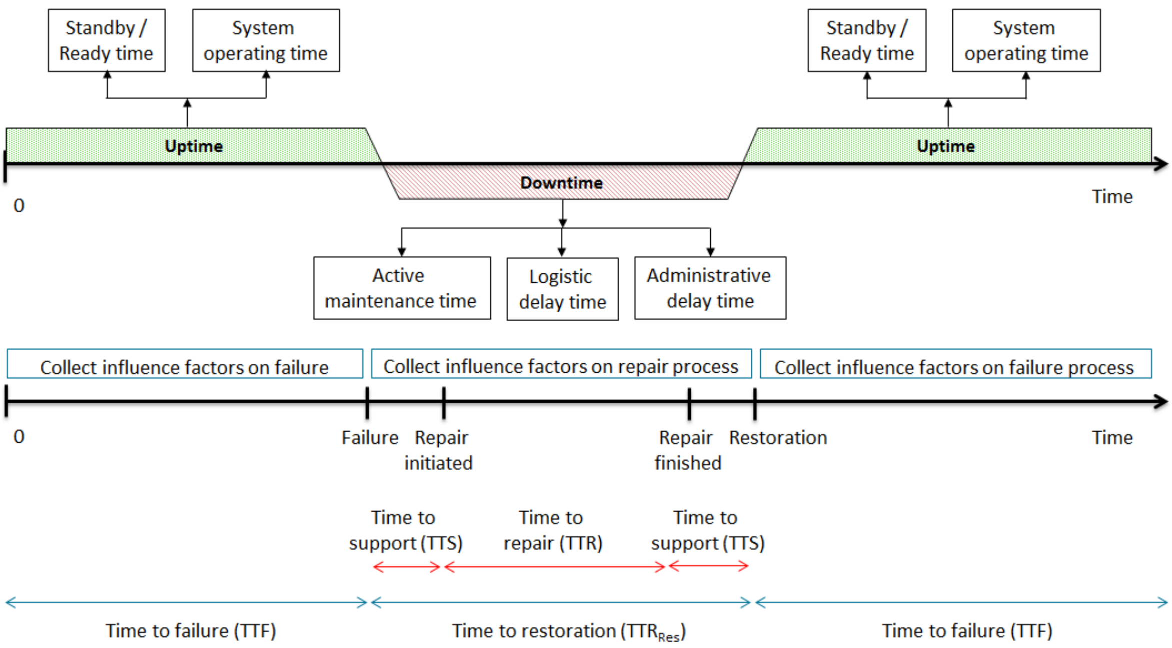


Figure 5.2: Time schedule for operation. Adapted and merged from Blanchard and Fabrycky [1998] and Barabadi et al. [2014].

data collected. The types of analysis are divided into four sections, namely risk and safety analysis, reliability analysis, cost analysis, and other general types of analysis.

Risk analysis

Risk analysis can be conducted both quantitatively and qualitatively. With respect to failure and maintenance, two common analysis are risk based maintenance and risk based inspection. These two analysis are more considered as maintenance strategies, in the sense that they guide the maintenance department how to maintain and inspect their plant, systems, and equipment. Another typical tool used in risk analysis is Event Tree Analysis (ETA).

Event Tree Analysis
The goal and objective of the ETA is to illustrate how an initiating event can lead to several outcomes based on what subsequent events occur (or barriers prevents) after the initiating event has happened. The event tree starts with an initiating event on one side, then going through several events or barriers which either operates successfully or not. If one event or barrier is not operating satisfactory, then this could lead to either a final outcome or the next event or barrier can decide the path further. If probabilities are assigned to the different events and barriers, the probability of the

outcomes can be calculated. For more information on ETA and how to use it for Risk and Reliability analysis see Modarres [2006] and Smith [2001]. Other common risk and safety analysis:

- Safety integrity level
- Environmental- and social-impact assessment
- Failure mode, effects and criticality analysis (similar to FMEA but with criticality included)

[ISO, 2006]

Reliability analysis

RAM and reliability-centered maintenance are two of the most commonly used analysis and strategies in industry today. RAM analysis inform the O&M department, as well as management, about the condition of the plant or assets and act as a guide in the decision-making process. The reliability-centered maintenance is more of a maintenance strategy applied by many companies, in several industries, for allocating maintenance resources most effectively. The main goal for RAM analysis for systems is to increase overall operating availability by improving the reliability or maintainability of the system, subsystems, or components. Reliability-centered maintenance is a tool used to identify preventive maintenance tasks and requirements to ensure that operations takes place safe, cost-effective, and reliable [Carlson, 2012]. The FMEA already conducted in the planning part of this framework will be a key part of the reliability-centered maintenance process, if chosen as a maintenance strategy [Carlson, 2012]. Other common reliability analyses are:

- Root cause analysis
- Weibull lifetime analysis
- Sensitivity analysis

[ISO, 2006]

Cost analysis

Life Cycle Costing is an analysis which is used for decision-making when purchasing products. When purchasing a product it is not only the initial price (acquisition cost) that is of interest. One should also take into account operating and maintenance cost (ownership cost) during the products life time and the cost with disposing (disposal cost) the product afterwards [IEC, 2004]. That life cycle cost can then be compared to the life cycle cost of other products to identify the best option. The life cycle costing analysis is based on the assumption that the technical aspects (such as reliability) of the products compared are approximately identical. Other analysis related to cost are:

- Spare part analysis
- Cost-benefit analysis

[ISO, 2006]

Other types of analysis

In addition to the different types of analysis discussed in previous sections the following analyses could be of interest based on preference.

- Markov Process analysis
- Six sigma
- Production analysis
- Availability analysis

[ISO, 2006] and [Modarres, 2006]

5.3 Proportional hazards model

A method for including the effects of influence factors in reliability analysis is by using the proportional hazards model. In 1972 the statistician David R. Cox suggested the *Cox model*, often referred to as proportional hazard model (PHM) [Cox, 1972]. The model is very applicable and has since 1972 been modified, developed, and extended for the use in medicine, economics, and reliability applications among others [Ansell and Phillips, 1997]. In traditional life modeling the assumption is that all items are identical and that all items experience identical conditions. When this assumption is valid, then the items are independent and identically distributed, with a probability distribution $f(t)$ and a reliability function $R(t)$, where the failure characteristics of the items are best modeled through the hazard function (hazard rate) [Spring and Freitas, 1989]. However, with traditional life modeling and real life field data these mentioned assumptions are often not valid as a result of the following:

- Items are not indistinguishable.
- Conditions vary from item to item.
- Specific parametric model for the underlying hazard rate cannot be specified.

[Spring and Freitas, 1989]

These assumptions are not needed for the PHM model as the only assumption for the PHM model is that the hazard rate it is given by the product of an arbitrary and unspecified baseline hazard rate, $h_0(t)$, which is only dependent on the time, and a positive influence function incorporating one or more influence factors, given by $\psi(z;b)$, which is independent of time [Kumar and Klefsjö, 1993], [Spring and Freitas, 1989]. The PHM is a mathematical model which can be used to incorporate influence factors by treating them as explanatory variables, or more common referred to as covariates. With this assumption on the hazard rate, the hazard function takes the following form:

$$h(t;z) = h_0(t)\psi(z;b) \tag{5.1}$$

[Kumar and Klefsjö, 1993]

where $h(t;z)$ is the resultant hazard rate, z is a row vector consisting of the covariates, and b is a column vector consisting of the regression parameters. The influence factors are conditions which affects the failure processes of equipment. The regression parameter b is a measure of importance or weight of each covariate [Spring and Freitas, 1989]. The baseline hazard rate is considered to be the rate at which the covariates have no effect on the failure pattern (i.e. $z = 0$, which requires $\psi(z;\beta) = 1$).

The term $\psi(z;\beta)$ can have different functional forms. Most commonly the exponential, the logistic, the inverse linear, and the linear form respectively, i.e.:

$$\psi(z;b)_{exponential} = exp(zb) \tag{5.2}$$

$$\psi(z;b)_{logistic} = log(1 + exp(zb)) \tag{5.3}$$

$$\psi(z;b)_{inverse\ linear} = 1/(1 + zb) \tag{5.4}$$

$$\psi(z;b)_{linear} = 1 + zb \tag{5.5}$$

[Kumar and Klefsjö, 1993]

Determining the form of the PHM can be based on a combination of goodness-of-fit tests, experience, and physical reality [Kumar, 1995]. The name of the model comes from the fact that the ratio between any two individual hazard functions is time invariant (i.e., any two hazards are proportional) [Spring and Freitas, 1989]. In other, words if two items are observed at any time t with associated covariates sets z_1 and z_2 the hazard rates will be proportional to each other and can be written $h(t;z_1) \propto h(t;z_2)$ [Kumar and Klefsjö, 1993]. How the effects of covariates influence the hazard rate is better illustrated by the graph reported in Figure 5.3. In Figure 5.3, a negative influence on the hazard rate will cause it to increase, while a positive influence will cause it to decrease as illustrated.

Studies have been conducted where the effects of influence factors have been measured related to the failure rate of systems or components. Furuly et al. [2013] concluded that the failure rate during winter season for a stacker belt in the Svea Coal mine was four

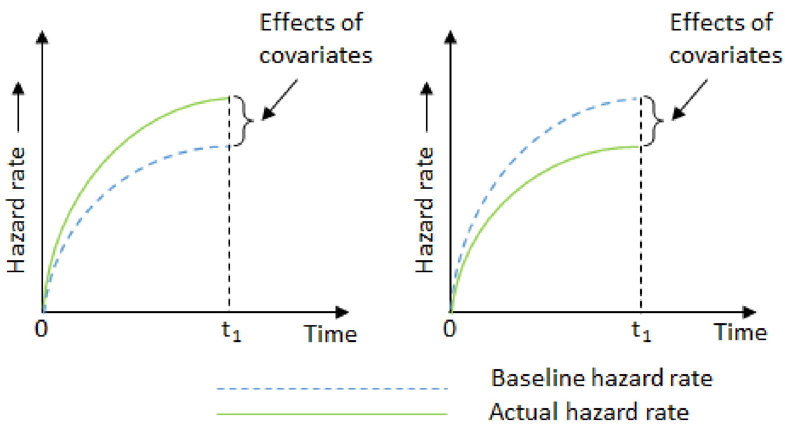


Figure 5.3: Relation between the actual hazard rate and the baseline hazard rate in the presence of influential covariates. Adapted from Kumar and Klefsjö [1993].

times as high as during rest of the year. This study was based on collected historical failure data and data on influence factors during failures treated as covariates with the PHM model. Studies like this can be used to optimize maintenance strategies and maintenance plans, where the influence factors on equipment varies during the operating cycle.

Since D.R. Cox first suggested the proportional hazard model there have been suggested several modified models and extensions of the original model. These modified models take into account other factors, uses different assumptions, or consider other variables. There also exist several case studies where the PHM has been used for modeling. Some of them, as stated by Kumar and Klefsjö [1993], are component failures in a nuclear plant, marine gas turbines, aircraft engines, and components of a mine loader. Recently Gao et al. [2010] developed a modified model called the proportional repair model (PRM) for considering influence factors on maintainability and repair rates.

For a repairable system experiencing both failures and repairs a modified model such as the PRM is needed for also including the factors having an impact on the repair processes. In section 5.3.1, the proportional repair model (modified from the PHM model) suggested by [Gao et al., 2010] is presented.

5.3.1 Proportional repair model

The proportional repair model is a mathematical model which incorporates influence factors on repair processes by treating them as covariates. The PRM is, like the PHM, the product of an arbitrary and unspecified baseline repair rate $r_0(t)$, which is only dependent on the time, and a positive influence function incorporating one or more influence factors given by $\psi(z';b)$, which is independent of time. It is given by:

$$r(t;z') = r_0(t)\psi(z';b) \tag{5.6}$$

[Gao et al., 2010]

where $r(t;z)$ is the resultant hazard rate, z' is a row vector consisting of the covariates, and b is a column vector consisting of the regression parameters. The influence factors are conditions which affects the repair processes of equipment. The baseline repair rate is considered to be the rate at which the covariates have no effect on the repair pattern (i.e. $z' = 0$, which requires $\psi(z';\beta) = 1$). The term $\psi(z';b)$ can have different functional forms. Most commonly the exponential, the logistic, the inverse linear, and the linear form. Respectively given by:

$$\psi(z';b)_{exponential} = exp(zb) \tag{5.7}$$

$$\psi(z';b)_{logistic} = log(1 + exp(zb)) \tag{5.8}$$

$$\psi(z';b)_{inverse\ linear} = 1/(1 + zb) \tag{5.9}$$

$$\psi(z';b)_{linear} = 1 + zb \tag{5.10}$$

[Gao et al., 2010]

Like for the hazard rate the relation between the actual repair rate and the baseline repair rate in the presence of covariates can be illustrated with a graph as reported in Figure 5.4. Although, for the repair rate, a negative influence will cause the rate to decrease and a positive influence will cause the rate to increase (opposite to the hazard rate).

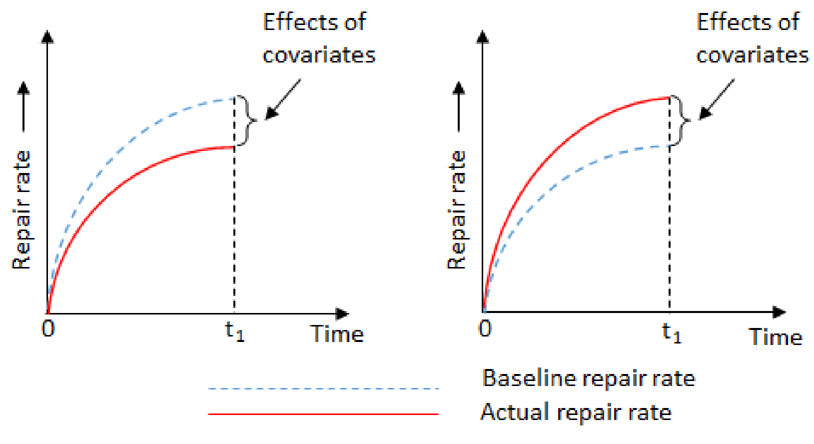


Figure 5.4: Relation between the actual repair rate and the baseline repair rate in the presence of influential covariates. Adapted from Gao et al. [2010].

There have been suggested several modified models from the Cox model, like the PRM from Gao et al. [2010] discussed in this study. When applying the PHM or the PRM, the assumption that the covariates are time-independent needs to be verified. In the cases where the covariates are time-dependent, the proportionality assumption is violated, and other modified models have to be used for modeling. For time-dependent covariates, either an extension of the Cox regression model or a stratified Cox regression model can be used [Barabadi et al., 2011]. Kumar and Westberg [1996] illustrated how to model time-dependent covariates for reliability analysis by using linear regression, and Barabadi et al. [2010] illustrated how to use the stratified Cox model for time-dependent covariates for maintainability analysis.

5.3.2 Influence factors

Factors having an impact on failure processes and repair processes can be many and can vary greatly in influence. For some applications there are only a few influence factors while for other applications there can be several factors, where some affects failure and repair processes more than others. According to Barabadi et al. [2014], the influence factors can be classified into whether they are categorical (e.g. effect of maintenance crew skill), or continuous (e.g temperature, wind, rain etc.), or dichotomous (e.g. whether or not it is raining).

Influence factors for, but not limited to, general plant operation typical for the mining industry, are the following (both for the failure process and the repair process):

Operational

- Operator skill
- Maintenance personnel skill
- Effect of repair
- Material of components
- Accessibility of system or component
- Ore characteristics (type, hardness, content)

Environmental

- Temperature
- Humidity
- Visibility (darkness)
- Wind
- Dust
- Snow/ice
- Rain

5.3.3 Discussion of the PHM and PRM

There are several benefits and reasons for deploying the PHM and PRM. Both models are very flexible, as seen by the many case studies covering several different applications and industries. Special for reliability and maintainability analysis is that these models give more accurate estimation of reliability and maintainability. As a result of using the factors that influence the reliability and maintainability, reduced sample sizes can be used for estimation [Spring and Freitas, 1989]. According to Ansell and Phillips [1997], the PHM model is relative robust to departures from the proportional assumption, which leads to that significant effects of explanatory variables would be obtained even in the cases where the model is not wholly appropriate. This further result in the advantage that the model can be used as an exploratory technique to identify explanatory variables [Ansell and Phillips, 1997]. The aspect of identifying the conditions that have the greatest influence on the reliability of equipment can help with determining which factors to control or improve in order to improve reliability of the system or plant. As a result of the flexibility of the model it can often be extended to a wide range of other reliability estimation situations [Spring and Freitas, 1989]. These aspects mentioned here are all related to reliability and maintainability analysis. In more detail, the PHM can be used for O&M optimization by, for instance, identifying optimum maintenance intervals, as done by Love and Guo [1991]. It can also be used for identifying periods of increased prediction of the failure rate of equipment, to optimize the maintenance strategy based on varying environmental conditions, like the work of Furuly et al. [2013]. Furthermore, the PRM can be used for estimating the maintainability function taking into account influence factors like temperature, shift, location, wind, icing, and rain as done by Barabadi et al. [2010]. Barabadi et al. [2010], in addition, illustrated how the PRM assumption, if not valid, can lead to wrong estimates on the maintainability. This element, of course, also apply to the PHM assumption, and in the cases where the assumptions are not valid, other approaches like the extended Cox model or, the stratified approach can be applied (assuming the covariates can be stratified) [Barabadi et al., 2014].

5.4 Case study II: Data collection for reliability analysis

5.4.1 Introduction

Based on discussions with experts at Sydvaranger Gruve and the suggested framework for data collection, case study II aims at developing a new reporting system including influence factors. The reporting system should be a software program and replace the current manual writing reporting system. The new reporting system is illustrated in Figure 5.5a.

The goal is to develop a new reporting system for downtime events on various equipment and systems causing downtime on either the secondary crusher or the primary mill. The reporting system will hopefully provide more precise and accurate data than the current reporting system. The new developed system will also lead the path towards a better database of RAM data in the future, with respect to higher quality data, additional desired information in the data collection like failure modes, and including influence factors in the data collection.

For the process plant (including crushing, grinding, milling, separation, and filtration) the metallurgists at Sydvaranger Gruve have a main report called *Daily Downtime Breakdown*, where all downtime on equipment causing downtime on the secondary crusher or the primary mill is reported. This report also tell the percentage of planned loss, breakdown loss, availability, and run time of the plant, along with other process information and details. The report is created in MS Excel and can be ran for specific dates which makes it able to compare downtime for different periods during a year or to compare from year to year. The reason for recording the events causing downtime on the secondary crusher and the primary mill is because these two systems are critical in the overall process. To improve and maintain the already high availability of these systems, it is essential to investigate surrounding equipment causing downtime. Surrounding equipment typical causing downtime on the secondary crusher and the primary mill are conveyors, screens, pumps, cyclones, and, of course, the systems themselves. For more information on Sydvaranger Gruve and the overall process of the plant see sections 4.1.1 and 4.1.2.

The *Daily Downtime Breakdown* report at the process plant provides important information regarding downtime events, such as date of the event, duration of the event, the reason for the downtime, and an allocated code based on a time usage model for the company. The allocated code is needed to know which department the downtime came from, whether it is corrective or preventive maintenance downtime, production delay, production standby etc. Before presenting the new developed reporting system, a brief description of the current reporting system in the process plant is given.

SVG

REPORTING OF DOWNTIME

SECONDARY CRUSHER

Reset page | Codes & categories | Send report

Date:	**31.05.2015**				
Time off/Time on:	**OK**	Total downtime (min):	**67**		
All fields completed?	**YES**	Shift:	Day	Afternoon	Night
Number of events:	**3**	Operator controlroom:			

EVENT NO.	SHIFT	TIME OFF (hh:mm, 24h)	TIME ON (hh:mm, 24h)	DOWNTIME (min)	EQUIPMENT	SUB-EQUIPMENT	FAULT DESCRIPTION	EVENT CODE (TUM)	EVENT CODE DESCRIPTION
1	Day	10:05	10:13	8	30SC003	Bearing	Repair of screen bearing		
2	Afternoon	17:33	17:46	13	30CV013	Metal detector	Metal caused conveyor to stop		
3	Night	21:17	22:03	46	30CH008	Other	Repair of hole in chute		

(a) New reporting system including some some plausible events.

SVG

REPORTING OF DOWNTIME

SECONDARY CRUSHER

Reset page | Codes & categories | Send report

Date:	**31.05.2015**				
Time off/Time on:	**OK**	Total downtime (min):	**67**		
All fields completed?	**YES**	Shift:	Day	Afternoon	Night
Number of events:	**3**	Operator controlroom:			

								COVARIATES			
EVENT NO.	SHIFT	TIME OFF (hh:mm, 24h)	TIME ON (hh:mm, 24h)	DOWNTIME (min)	EQUIPMENT	SUB-EQUIPMENT	FAULT DESCRIPTION	DUST LEVEL (0,1)	ORE TYPE (0,1)	EVENT CODE (TUM)	EVENT CODE DESCRIPTION
1	Day	10:05	10:13	8	30SC003	Bearing	Repair of screen bearing	1	1		
2	Afternoon	17:33	17:46	13	30CV013	Metal detector	Metal caused conveyor to stop	0	1		
3	Night	21:17	22:03	46	30CH008	Other	Repair of hole in chute	1	0		

(b) Potential modification of the new reporting system including covariates and some plausible events.

Figure 5.5: Design of new reporting system (a) and modified design of new reporting system (b) for data collection.

5.4.2 Current downtime reporting system

The downtime and information which the metallurgists record in this *Daily Downtime Breakdown* report is based on a manually written report done by the operators in the control room during the three shifts (morning, day and night). This report is a paper log sheet mostly filled with important process parameters necessary to monitor during production and operation. However, at the bottom of that paper log sheet is a section with three columns which is used for downtime reporting. The part of the log sheet used for downtime reporting is illustrated in Figure 5.6 for the secondary crusher (same setup is used for the primary mill). There are some identified disadvantages with reporting by manual writing and those are:

- It is time consuming. The transfer of data from the paper sheet report into the computerized *Daily Downtime Breakdown* report in MS Excel takes time.
- It occur interpretation faults from the metallurgists reading the paper report as a consequence of bad handwriting from operators.
- Insufficient and variable data and information from operator to operator (the precision and accuracy of downtime reporting varies from operator to operator).

CRUSHER DOWNTIME		
Feed OFF	Feed ON	Description of Downtime
:	:	
:	:	
:	:	

Figure 5.6: Part of crusher log sheet used for downtime reporting. Retrieved from SVG.

5.4.3 New downtime reporting system

As a case study for data collection improvement it was decided that instead of manual writing for reporting downtime a reporting system software should be used. The software was chosen to be MS Excel (same software as used for the *Daily Downtime Breakdown* report). There are several advantages and goals hopefully achieved by using a computer software instead of manual writing. Some of the immediate advantages are the reduced time consumption to report downtime and the elimination of interpretation errors as a consequence of bad handwriting. The report system is as mentioned programmed using MS Excel. It is designed to be user-friendly, and at the same time comprehensive enough to provide the necessary and desired information. The report page for the secondary crusher with three plausible example events is reported in Figure 5.5a.

The process of reporting downtime events in the new system are as following (done by control room operator):

1. Implement name of operator in the control room under the right shift.
2. When equipment stops:
    - Report the current shift (morning, day or night) in the column "Shift".
    - Report the time the equipment stopped in the column called "Time off".
    - Report the main equipment in the column "Main equipment".
    - Report the connecting sub-equipment/functional location of the main equipment in the column "Functional location".
    - Write a more detailed description of the fault in the column "Description of fault".
    - The next two columns are left blank to be filled out by the metallurgists. The columns are used to record a time-code for the event and a description of the code (based the time usage model for SVG).
3. When the equipment starts again, report the time the equipment started in the column called "Time on" and the individual downtime (in minutes) and the total downtime (in minutes) are calculated automatically. Repeat step 2 and 3 until 04.00 AM.
4. At 04.00 AM the report is sent to the metallurgists by hitting the "send report" button in the upper right corner of the screen. After sending the report both pages are reset by hitting the button "Reset page" in the upper right corner. Then repeat step 1 to step 4 continuously.

The software program is currently in the test phase. A metallurgist has received knowledge about the program and how it works, and will start implementation with the operator on the day shift for one week. If this test run for one week is successful the program will be implemented and used on all shifts for downtime reporting. The design of the program, the different formulas, macros, and drop-down lists were programmed in a fairly manageable way. The more difficult issue to handle were the large equipment list which were going to be implemented in the reporting system. To do this in a gentle way, the entire equipment list was first extracted from the CMMS, then only relevant equipment for downtime reporting were chosen, and the rest removed, but stored in a separate list. Still, after removing all irrelevant equipment, the equipment list was too long (250–300). This practical issue made it impractical to use an ordinary drop-down list in Excel. To solve this problem, a searchable drop-down list were programmed and implemented in the program. That way, both the drop-down list can be used, but also a search in the list using equipment code (two letters unique for each equipment type), or the area code (10, 20, 30,...,90), or the equipment number (three digit number) can be used to find the equipment in the equipment list which is to be reported downtime on. The program is easy to use as a result of the automatically updated fields and the drop-down lists, where one is searchable. This is essential for the operators to use the program, and feel comfortable with it. Recording the correct equipment with the standardized equipment code is easy when using the searchable drop-down list for the main equipment. To reduce time consumption and unnecessary work macros have been programmed for resetting the pages and sending the report to the metallurgists each day. How the report macro works is that when hitting the "send report" button, a copy of the report page is made and placed in a folder only accessible for the metallurgists responsible for the main downtime breakdown reporting. In that copy, the metallurgist can filter the downtime by type of equipment or area code and sort the downtime from largest to smallest and vice versa. This was programmed after preference from the metallurgists.

Future potential features

In the future some features of the software program can be implemented either because they are necessary or because they are desirable for improvement or additional information. The features can help improve the reporting system with respect to software issues or practical issues, or they can be implemented for improved data collection with respect to reliability analysis. The two next sections will briefly highlight future potential features.

Improvement of reporting system and software program

- If the report is not sent at 04.00 AM, because of different reasons, a macro could be programmed to send the report automatically every 04.00 AM.
- Make the report compatible to be implemented directly into the main *Daily Downtime Breakdown* report. This will demand a format change in the template but should be manageable. This would provide a reduction in the time spent on reporting.
- Program a code that automatically transfer the reported downtime in the program to the main *Daily Downtime Breakdown* report without having to do it manually. This will eliminate the time used to transfer the downtime from the control room to the main report. Although this process will be less time consuming it could lead to loss of data and other errors. For this reason, the transfer of data should be monitored occasionally to justify that the transfer of downtime reports from the program in the control room to the main downtime report works satisfactory.

Improvement with respect to reliability analysis

- The ISO 14224 standard suggest that also failure modes, failure mechanisms and failure causes are recorded while reporting downtime events. In the reporting system this would easily be done by additional columns.
- A link should be made between the downtime events and an eventual repair action. This could be done by adding a column called "'Event code"'. The same event code should be used when creating work orders in the CMMS and thereby connecting the downtime event to a specific maintenance action.
- In addition to what the ISO 14224 standard suggest the reporting of downtime events should also include collecting influence factors for the failure and repair processes. In the reporting system, columns on influence factors can easily be added after they have been identified (influence factors on repair processes are more problematic to collect, however the recording of work orders in the CMMS could be a useful tool).

The ideal with having a reporting system using software and especially MS Excel is that it is very flexible to changes and modifications. The reporting system shown in Figure 5.5b illustrates the original design of the downtime reporting system, based on the previous manual reporting system and discussions with experts (metallurgists) at SVG. However, this reporting system can be modified with respect to collecting RAM data in addition to the already implemented information that production receives from the current template. In section 5.4.3 on improvement for reliability analysis, there are three main additions which would be highly beneficial to implement for this reporting system. These are failure characteristics (failure modes, mechanism, and cause), a link between failure/downtime events and repair actions and last influence factors which has an impact on the failure processes of equipment. Because implementation of new procedures and learning new systems is time consuming, it was decided that the first version and design of the system should not include too many columns to fill out. In Figure 5.5b a new potential design for the system is showned, illustrating how influence factors (covariates) could be implemented at a later stage. The influence factors can vary from application to application, but for the crusher system in this case, the two influence factors *dust* and *ore type* have been identified to be two of the influence factors having most impact on the failure processes of the equipment. In this case, the dust level is divided into whether there is a normal (0) or high (1) amount of dust present in the plant. The ore characteristics are divided into whether the hardness is normal (0) or harder than normal (1), as can be seen in Figure 5.5b.

5.4.4 Results and discussion

Other features, not mentioned here, are possible and even more feasible when the reporting is performed by using some sort of computer software like MS Excel. These mentioned features are not designed into the software program as the metallurgists wanted to test the program before more advanced features were added. There could be that practical issues which prevents the use of the program. These issues can be difficulties with learning how to use the program and software errors, among other issues. If this is the case, it will be unnecessary to use more hours on more advanced features before the program is properly implemented and used.

To summarize the advantages with the new reporting system compared to the previous reporting system and with respect to reliability analysis are (some already mentioned):

- Less time consuming.
- Precise and accurate data.
- Same amount of information at each downtime event.
- Easier to detect and handle recurrent events when also sub-equipment is reported in each event.

Finally, a goal for this case study from the perspective of the cooperating company was to establish and develop a system for data collection with respect to improved data quality. This was achieved mainly by using a software instead of manual writing in addition to changing the reporting from one field called "Description" to three fields respectively called "Equipment", "Functional location", and "Description of fault". The latter providing more options for recording required information.

Regarding improved data collection with respect to reliability analysis the following recommendations are suggested:

- It is recommended that SVG implement the reporting of failure modes. Eventually also failure mechanism and cause of failure are reported.
- Further, it suggested that a link is established between each reported failure/downtime event and the associated potential maintenance action necessary to restore the equipment back operating state.
- It is recommended that influence factors are identified, formulated and collected data on for both failures and repairs.
- Last, it is recommended that profile production levels, plant throughput and cost of items (equipment and subsystems) are collected and stored for later use as they provide the basis for performing cost analysis such as life cycle cost analysis and cost-benefit analysis.

Chapter 6

Discussion, Results and Conclusion

This chapter presents a short summary of the discussion in chapter 4 and chapter 5 based on the defined thesis objectives. Further, a section a self criticism of the study is given and main results obtained in the thesis listed. Finally, a conclusion is drawn.

6.1 Discussion of results and thesis objectives

6.1.1 Existing approach for data collection for RAM analysis

The review discovered shortcomings in the data collection method with respect to the inclusion of influence factors. Mathematical models exist, which can provide improved estimates of the reliability and maintainability characteristics of equipment operating in various operational and environmental conditions. Regardless of the flexibility of these models and the possibility of utilizing smaller sample sizes of data, they do require some data on the failure and repair processes. Today, the sources of data in the oil and gas industry and the mining industry are mainly handbooks, like the OREDA handbook, standards like ISO 14224, and data collected internally by companies. The handbooks and standards available lack information on including the effects influence factors, an issue which should be focused on in the years to come. The sources of data collected internally by companies are mainly downtime reporting logs from production and maintenance records collected from the CMMS from maintenance. These sources of data are not directly suited for RAM analysis. They can provide TTFs and TTRs but other data for statistical analysis are difficult to extract. The reason being that information is not reported and recorded in a proper way. For failures, there should be developed a system and a reporting culture where not only the effects of influence factors are recorded, but the failure mode, failure mechanism, and failure cause additionally.

Identifying recurrent failures due to one specific failure mode will significantly help in root cause analysis of these recurrent system failures.

6.1.2 Applying the concept of RAM analysis as a case study

The case study of applying RAM analysis in the mining industry was conducted for the mining company Sydvaranger Gruve. The case study illustrates how reliability performance and maintainability performance of equipment have an impact on the overall availability. The result of the analysis is somewhat suffering from limiting data with respect to the short time period of data collection, in addition to reduced quality of repair data. For statistical analysis, it is important that the data sets are of sufficient population with respect to time interval and sample size. Regardless of the limiting data the analysis illustrates how identifying optimum interval of preventive maintenance can improve overall system availability. Furthermore, it illustrates how there exist methods for identifying the most critical subsystem and several different aspects of improvement measures which, all should be considered for identifying the most availability-effective and cost-effective improvement.

This analysis with its limited data further support and stress the need for collection of influence factors. In this case, including influence factors would have resulted in more precise reliability and maintainability estimates, causing the analysis not to suffer in the same manner. The limited data in the analysis combined with the suggested framework for data collection also highlight the importance of overall quality data collection. Regarding the analysis, there will always be some uncertainty because of limited data and assumptions made for the model. In addition, the results in RAM analyses are always estimates. With respect to the methods used in the analysis, they are considered robust and powerful methods also used by numerous other authors. Barabady and Kumar [2006] and [Kumar et al., 1989] have applied similar methods on importance measures, goodness-of-fit test, and test for IID. Xie et al. [2003] have applied the method of MLE for parameter estimation.

6.1.3 Framework for data collection for RAM analysis

The framework suggested in this thesis is considered appropriate for several process industries, especially suited for the mining industry. The framework includes the aspect of influence factors and the importance of including them in the data collection process. Furthermore, the planning of the data collection is considered to be of high importance. The quality of the data collection and the quality of data depends on the quality of the planning part of the data collection process. Being aware of what data is required for proper RAM analysis and doing preliminary steps to ensure that the required data is collected are both vital and necessary. In this framework, tools and techniques are presented to help planning the data collection. However, the framework depends on the quality of the utilization of these techniques. A poorly constructed RBD or system boundary will be of no use. The issue of not executing the steps properly is not considered in this thesis, but emphasize should be made towards performing the steps in the best possible way. It is recommended that several disciplines including production and maintenance personnel as well as reliability engineers contribute with input and discussions in the data planning and data collection process.

6.2 Self criticism

- Regarding the analysis in case study I there will always be limitations, assumptions, and obstacles affecting the analysis result and outcome. In this analysis the aspect of scheduled shuts and preventive maintenance could have been assessed with another approach. In addition to the two preventive maintenance tasks, which both were assumed to bring the systems back to bad-as-old condition, a third maintenance task could have been added. That preventive maintenance task would have been individual for each subsystem. The duration would have been minimal but the task would bring the system back to good as new condition. The interval of each task would be based on expert judgment and input from maintenance personnel. That way, the overall model would reflect a more realistic behavior of the system, and its operational conditions and maintenance characteristics.
- Another approach for the analysis concerning the limited data and decreasing failure rates could be to modify the input data used in the analysis. The modification could have led to a model closer to the realistic system.

6.3 Summary of results

With the work, theory, and case studies in this thesis the following results were achieved.

- In case study I: Suggestions for O&M optimization and increased system availability based on a RAM analysis performed as a case study in the mining industry. Aspects for improvement included optimum preventive maintenance interval and improvement of reliability and maintainability performance.
- A framework for data collection with respect to RAM analysis where the effects of influence factors are included was developed.
- For including the effects of influence factors in reliability and maintainability analysis the characteristics of a mathematical model (PHM) was discussed along with the characteristics of a modified extension of the model (PRM).
- In case study II: A downtime reporting system (software) was programmed for higher quality reliability data as a case study in the mining industry. The reporting

system is more suited for additional features, which will if implemented at a later stage, provide a better database of reliability data for analysis for the specific company in the case study. The program in addition illustrates how it can be easily modified for providing vital data for RAM analysis.

6.4 Conclusion

The initial research problem posed in beginning of this thesis was the lack of focus on including influence factors in data collection for reliability and maintainability analysis. Influence factors provide an improved reflection of the conditions that equipment experiences during operation and maintenance, and hence, will give more accurate results if included in analysis. Furthermore, only applying historical TTFs and TTRs from databases for design and operation in new locations, without taking into account the actual conditions the equipment will experience, could lead to inaccurate estimations on the reliability and maintainability characteristics. This is especially a concern for oil and gas operations. The research approach was to apply the concept of RAM analysis to the mining industry and suggest a framework for data collection including influence factors.

Applying the concept of RAM analysis as a case study in the mining industry illustrated the problems with limited failure and repair data. In the case study the only data available for statistical analysis were TTFs and TTRs. The data sets were in addition limited and unsuitable. Including influence factors in analysis by, treating them as covariates and applying the PHM and PRM model, would provided the analysis with a model better reflecting the real behavior of the system. Furthermore, the developed framework for data collection, which is considered detailed and descriptive for real industry practices, includes the aspect of influence factors. There is a concern that industries lack the focus of collecting data for RAM analysis. Data collected are in most cases collected only for a process or maintenance purpose and analyses and studies will suffer from this when using the data. In many cases, the data collection methods for some general purposes, in this case production and maintenance, can be modified for also providing quality RAM data. Case study II illustrated a modified downtime reporting system which both serves as a reporting system for production purposes and reliabiltiy purposes in the mining industry. The discussion of the PHM and PRM model provides a basis for including the effects of influence factors in reliability and maintainability analysis. The main concern still lie within identifying and formulating the influence factors equipment experiences and actually collecting the effects of covariates from the field. It seems the application of various mathematical models have been satisfactory conducted for several real industry situations, as seen by the many existing case studies. These case studies can be used as a guide for both the formulation of influence factors into quantitative numerical covariates, and for applying them in reliability and maintainability estimations, and last for interpretation of the results for O&M improvement.

Chapter 7

Further Work and Contribution

This chapter presents suggestions for further work and research within RAM analysis and data collection for RAM analysis and last a summary of the contribution for the thesis.

7.1 Suggestion for further work and research

Based on the results and discussions in this thesis, the following recommendations for further work are suggested.

- It is suggested on a general basis that the focus on data collection is increased. This implies that initially the data collection process is improved, and then the utilization of powerful mathematical models for analysis is used with the necessary data. In todays industry, analyses often suffers from unnecessary limitations often due to poor available field data and lack of field data. Therefore, there is a necessity of developing standards similar to ISO 14224 which covers issues with including the effects of influence factors.
- A database should be established covering different factors having most impact on equipment reliability performance and maintainability performance for different applications and areas similar to the OREDA database. When operating in remote and new environments, the degradation and wear of equipment changes and failure rates for the same equipment operating in known locations cannot be used as it will lead to improper estimation of the failure rate. In addition, for areas where the operating conditions vary throughout the operating period (month to month, season to season and year to year), the failure rate and repair rate will vary, which should be analysed and considered in the maintenance plan and strategy.
- It is suggested that case studies illustrating the effect of the planning part of the data collection process for the framework suggested in this thesis are conducted.

Such case studies will reveal in what degree proper planning of the data collection affects the data collection process. Further, it will illustrate more in detail what is required with respect to the different steps. For instance, what data can be used in order to establish system boundaries and reliability block diagrams.

- Furthermore, it is suggested that additional case studies on RAM analyses, which includes influence factors, are conducted and carried out similar to the work and case studies by Furuly et al. [2013], Barabadi et al. [2010], and Gao et al. [2010]. Furuly et al. [2013] estimated the effects of temperature for a stacker belt in the Svea Coal mine and concluded that the failure rate could be up to four times as high in the winter season compared to the rest of the year. Barabadi et al. [2010] illustrated, with a case study, how the maintainability estimation is improved with including the effects of influence factors with the PRM model for time in-dependent covariates, and with the stratification approach for time-dependent covariates. Gao et al. [2010] illustrated a case study for including influence factors for reliability and maintainability estimation for equipment on an offshore gas production facility. Furuly et al. [2013], Barabadi et al. [2010] and Gao et al. [2010] have all applied either PHM, PRM, or both, for identification of influence factors having an impact on the failure or repair rate. Furthermore, they have illustrated how the PHM or PRM can be used for planning operation, improving maintenance strategies, and enhancing overall O&M.

7.2 Contribution

This section lists the author's contribution in this thesis.

- Initially, the topic for this thesis is considered to address an area, which has received little focus in the mining industry. The work done in this thesis, with the suggested framework for data collection especially, highlight important areas of data collection, which needs improvement. Furthermore, it is recommended that industry focus on improved data collection and on quality analysis as both aspects are equally important.
- The first case study in this thesis illustrates how RAM analysis can be applied for increased availability, which is an increasing concern and demand in industry today. It further illustrates how an analysis can suffer from limited data, stressing the necessity of including influence factors in both data collection and analysis
- The suggested framework is considered descriptive and illustrative to be used as guidance in the data collection process for the mining industry.
- Finally, the second case study illustrates how data collection process in industry can easily be modified to serve both as a source of data for production and maintenance, as well as for RAM analysis.

Bibliography

Ansell, J. I. and Phillips, M. J. (1997). Practical Aspects of Modelling of Repairable Systems Data Using Proportional Hazards Models. *Reliability Engineering and System Safety*, 58:165–171.

Barabadi, A., Barabady, J., and Gudmestad, O. T. (2014). RAMS Data Collection Under Arctic Conditions. *Reliability Engineering and System Safety*, 135:92–99.

Barabadi, A., Barabady, J., and Markeset, T. (2010). Maintainability Analysis Considering Time-independent and Time-dependent Covariates. *Reliability Engineering and System Safety*, 96:210–217.

Barabadi, A., Barabady, J., and Markeset, T. (2011). A Methodology for Throughput Capacity Analysis of a Production Facility Considering Environment Condition. *Reliability Engineering and System Safety*, 96(12):1637–1646.

Barabady, J. and Kumar, U. (2006). Availability Allocation Through Importance Measures. *International Journal of Quality & Reliability Management*, 24(6):643–657.

Birnbaum, Z. W. (1969). On The Importance of Different Components in a Multicomponent System. Technical Report 54, University of Washington, Department of Mathematics, Seattle, Washington.

Blaikie, N. (2003). *Analyzing Quantitative Data: From Description to Explanation.* London: SAGE Publication Inc.

Blanchard, B. S. and Fabrycky, W. J. (1998). *Systems Engineering and Analysis.* New Jersey: Prentice Hall.

Blischke, W. R. and Murthy, D. (2003). *Case Studies in Reliability and Maintenance.* New Jersey: John Wiley & Sons.

Carlson, C. S. (2012). *Effective FMEAs: Achieving Safe, Reliable, and Economical Products and Processes Using Failure Mode and Effects Analysis.* New York: John Wiley & Sons.

CCPS, Center for Chemical Process Safety. (1998). *Guidelines for Improving Plant*

Reliability Through Data Collection and Analysis. American Institute of Chemical Engineers. New York: John Wiley & Sons.

CEN, European Committee for Standardization. (1998). PrEN 13306 Maintenance Terminology. Brussels: CEN.

Cox, D. R. (1972). Regression Models and Life-tables. *Journal of the Royal Statistical Society, B*, 34(2):187–220.

Dhillon, B. S. (1999). *Design Reliability: Fundamentals and Applications.* Boca Raton: CRC Press.

Dhillon, B. S. (2008). *Mining Equipment Reliability, Maintainability, and Safety.* London: Springer-Verlag.

Ebeling, C. E. (1997). *An Introduction to Reliability and Maintainability Engineering.* New York: McGraw Hill.

Elsayed, E. A. (2012). *Reliability Engineering.* New Jersey: John Wiley & Sons, 2nd edition.

Furuly, S., Barabadi, A., and Barabady, J. (2013). Reliability Analysis of Mining Equipment Considering Operational Environments – A Case Study. *International Journal of Performability Engineering*, 9(3):287–294.

Galar, D., Naeem, H. B., and Schunesson, H. (2014). Fusion of Operations, Event-log and Maintenance Data: A Case Study for Optimising Availability of Mining Shovels. In Drebenstedt, C. and Singhal, R., editors, *Mine Planning and Equipment Selection Proceedings of the 22nd MPES Conference*, pages 1173–1194. Dresden: Springer International Publishing.

Gao, X., Barabady, J., and Markeset, T. (2010). An Approach for Prediction of Petroleum Production Facility Performance Considering Arctic Influence Factors. *Reliability Engineering and System Safety*, 95(8):837–846.

Hamada, M. S., Wilson, A. G., Reese, C. S., and Martz, H. F. (2008). *Bayesian Reliability.* New York: Springer-Verlag.

IEC, International Electrotechnical Commission. (1990). 60050 Dependability and Quality of Service. `http://www.electropedia.org/iev/iev.nsf/display?openform&ievref=191-13-01` [accessed on 20.02.2015]. Geneva: IEC.

IEC, International Electrotechnical Commission. (2004). 60300-3-3 Dependability Management: Application Guide - Life Cycle Costing. 2nd edition. Geneva: IEC.

ISO, International Organization for Standardization. (2006). 14224 Petroleum, Petrochemical and Natural Gas Industries - Collection and Exchange of Reliability and Maintenance Data for Equipment. Geneva: ISO.

Kline, M. B. (1984). Suitability of the Lognormal Distribution for Corrective Maintenance Repair Times. *Reliability Engineering*, 9:65–80.

Kumar, D. (1995). Proportional Hazards Modelling of Repairable Systems. *Quality and Reliability Engineering International*, 11(5):361–369.

Kumar, D. and Klefsjö, B. (1993). Proportional Hazards Model: A Review. *Reliability Engineering and System Safety*, 44(2):177–188.

Kumar, D. and Westberg, U. (1996). Proportional Hazards Modelling of Time Dependent Covariates Using Linear Regression: A Case Study. *IEEE Transactions on Reliability*, 45(3):386–392.

Kumar, U., Klefsjö, B., and Granholm, S. (1989). Reliability Investigation for a Fleet of Load Haul Dump Machines in a Swedish Mine. *Reliability Engineering and System Safety*, 26:341–361.

Lewis, M. W. and Steinberg, L. (2001). Maintenance of Mobile Mine Equipment in the Information Age. *Journal of Quality in Maintenance Engineering*, 7(4):264–274.

Love, C. E. and Guo, R. (1991). Using Proportional Hazard Modelling in Plant Maintenance. *Quality and Reliability Engineering International*, 7:7–17.

Modarres, M. (2006). *Risk Analysis in Engineering.* Boca Raton: CRC Press Taylor and Francis Group.

Modarres, M., Kaminskiy, M., and Kristov, V. (2009). *Reliability Engineering and Risk Analysis: A Practical Guide.* Boca Raton: CRC Press Taylor and Francis Group, Quality and Reliability 2nd edition.

Pohl, E. (2010). *System Reliability.* New Jersey: John Wiley & Sons.

ReliaSoft (2007). How Good Is Your Assumed Distribution's Fit. Reliability Basics Issue 71.

ReliaSoft (2014). Blocksim Version 9 User's Guide. Tucson: ReliaSoft Publishing.

Smith, D. J. (2001). *Reliability, Maintainability and Risk: Practical Methods for Engineers.* Oxford: Butterworth-Heinmann.

Spring, R. V. and Freitas, S. A. (1989). Field Assessment Using the Proportional Hazards Model. *SAS/SUGI Proceedings of the Fourtheen Annual SAS Users Group International Conference*, 14:1313–1317.

Sydvaranger Gruve AS (2015). Homepage of Sydvaranger Gruve: Company profile. `http://www.sydvarangergruve.no/index.php?lang=en`. [accessed on 20.04.2015].

Walpole, R. E., Myers, R. H., Myers, S. L., and Ye, K. (2012). *Probability & Statistics: For Engineers and Scientist.* London: Pearson Education International, 9th edition.

Xie, M., Hong, G. Y., and Wohlin, C. (2003). Modeling and Analysis of Software System Reliability. In Blischke, W. and Murthy, D., editors, *Case Studies in Reliability and Maintenance*. New Jersey: John Wiley & Sons.

Zapata, C. J., Silva, S. C., and Burbano, O. L. (2008). Repair Models of Power Distribution Components. *IEEE*, Transmission and Distribution Conference and Exposition: Latin America:1–6.

Zio, E. (2013). *The Monte Carlo Simulation Method for System Reliability and Risk Analysis*. London: Springer-Verlag.

Appendices

Appendix A

Probability distributions

In the following sections the most commonly used life and repair distributions with their equations and characteristics are described.

Exponential 1-parameter distribution

Because of the simplicity of the exponential distribution it is frequently used in life data analysis, however, it is not always the best fitted distribution for the data and hence could be inappropriate to use. The reason being that the item need to reflect a constant failure rate, which is rarely the case with mechanical systems. The exponential distribution only consists of one parameter, namely the rate parameter λ. Its probability density function $f(t)$, cumulative distribution function $F(t)$ and reliability function $R(t)$ are respectively given by:

$$f(t) = \lambda e^{-\lambda t} \tag{A.1}$$

$$F(t) = 1 - e^{-\lambda t} \tag{A.2}$$

$$R(t) = e^{-\lambda t} \tag{A.3}$$

[Pohl, 2010]

In Figure A.1 a plot illustrates the shape of the exponential 1-parameter probability density function as the rate parameter λ varies from 0.02 to 0.03 to 0.05.

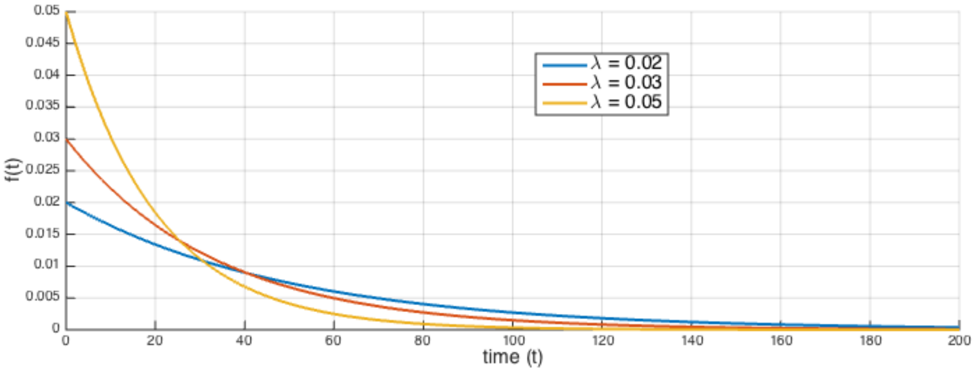


Figure A.1: Exponential 1-parameter probability density function as λ varies.

Weibull 2-parameter distribution

The Weibull 2-parameter distribution is often the most appropriate distribution to use in life data analysis. The distribution changes form depending on its parameters, and can handle both increasing, decreasing, and constant failure rates [CCPS, 1998]. It consists of the two parameters β and η which are the shape parameter and scale parameter respectively. Its probability density function $f(t)$, cumulative distribution function $F(t)$ and reliability function $R(t)$ are respectively given by:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-(\frac{t}{\eta})^{\beta}} \tag{A.4}$$

$$F(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}} \tag{A.5}$$

$$R(t) = e^{-(\frac{t}{\eta})^{\beta}} \tag{A.6}$$

[Pohl, 2010]

In Figure A.2 a plot of the Weibull probability density function is illustrated with the scale parameter η varying from 50 to 100 to 200 and the failure rate β held constant at 3 in all three cases implying an increasing failure rate.

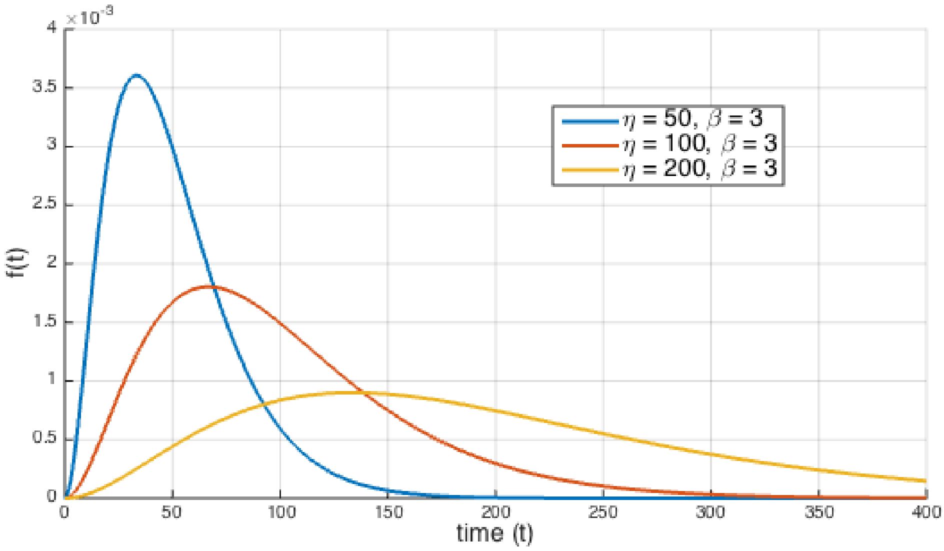


Figure A.2: Weibull 2-parameter probability density function as η varies.

Log-normal distribution

The log-normal distribution is a distribution derived from the well-known normal distribution. The log-normal distribution contains the parameter μ' (mean of the natural logarithms of the times to failure) and σ' (standard deviation of the natural logarithms of the times to failure). Since the log-normal distribution only takes positive values it is appropriate to use as a life distribution eliminating the risk of modeling negative times to failure. When the natural logarithms of the TTFs or TTRs are distributed normally the data follows a log-normal distribution. Its probability density function $f(t)$ is given by:

$$f(t) = \frac{1}{t\sigma'\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{ln(t)-\mu'}{\sigma'})^2} \tag{A.7}$$

[Elsayed, 2012]

Where $f(t) \geq 0$, $t > 0$, $-\infty < \mu' < \infty$ and $\sigma' > 0$.

It is not possible to define a general analytical expression for the cumulative distribution function $F(t)$ for the log-normal distribution. The reason being that the distribution has no closed form [Hamada et al., 2008]. In other words, the cumulative distribution function has to be derived from the specific distribution with known parameters μ' and σ'. That implies that an general analytical expression for the reliability function $R(t)$ is not possible to define either. The expressions obtained for the cumulative distribution function $F(t)$ and reliability function $R(t)$ are respectively:

$$F(t) = \Phi \left(\frac{t' - \mu'}{\sigma'} \right) \tag{A.8}$$

$$R(t) = 1 - \Phi \left(\frac{t' - \mu'}{\sigma'} \right) \tag{A.9}$$

[Hamada et al., 2008]

Where Φ is the standard normal cumulative distribution function:

In Figure A.3 a plot of the log-normal probability density function is illustrated with the mean parameter μ varying from 2 to 4 to 6 and the standard deviation σ held constant at 1.

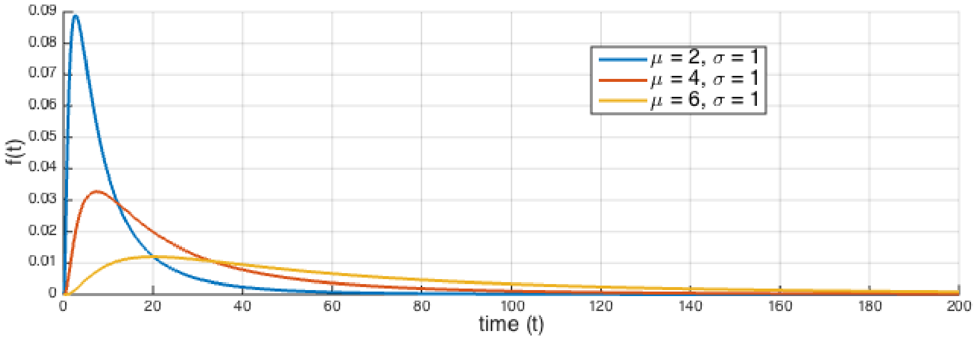


Figure A.3: Log-normal probability density function.

Appendix B

Goodness-of-fit test

This appendix gives a description on the modified Kolmogorov-Smirnov goodness-of-fit test.

Modified Kolmogorov-Smirnov test

For selecting the best fit distribution the Kolmogorov-Smirnov test can be used as a goodness-of-fit test. For the K-S test the parameters of the data sets needs to be known to be able to use it, however, for unknown parameters a modified K-S test can be used. The modified K-S test identifies the difference, or the distance, between the cumulative distribution of the reference distribution and the distribution for the data set and thereby identifies if it is a good fit and with the case of several reference distributions identifies the best fit distribution. Following is a brief description of the modified K-S test.

For a given data set with N failure times (t_1, t_2,..., t_N) a function $S_N(t)$ is defined giving the fraction of data points to the left of a given value $t_i(i = 1, 2, ..., N)$. $S_N(t)$ is constant between consecutive t_i values, and jumps by the same constant $1/N$ value at each t_i.

The modified K-S test uses D_{max}, the maximum of the absolute difference between $S_N(t)$ and the fitted cumulative distribution function, $Q(t)$.

$$D = max|S_N(x) - Q(x)| \tag{B.1}$$

The modified K-S test returns the probability that $D_{CRIT} < D_{max}$. The closer the probability is to 1 the higher difference between the theoretical distribution and the data set.

[ReliaSoft, 2007]

Appendix C

Parameter estimation method

This appendix gives a description on the Maximum Likelihood Estimation method which is a parameter estimation method for probability distributions.

Maximum Likelihood Estimation method

As the name implies the the goal of the MLE method is to maximize the likelihood function. The parameter estimated is the parameter value which produces the largest probability of obtaining the sample. This is achieved by differentiating the likelihood function with respect to the estimator parameter, setting the derivative to zero and solving [Walpole et al., 2012]. Further, the a property with the MLE is that it makes use of the underlying distribution in order to determine an appropriate estimator [Walpole et al., 2012]. A formal definition is:

Given independent observations x_1, x_2,...,x_n from a probability density function $f(\mathbf{x};\hat{\theta})$, the maximum likelihood estimator θ is that which maximizes the likelihood function given by:

$$L(x_1, x_2, \ . \ . \ . \ , x_n; \theta) = f(\mathbf{x}; \theta) = f(x_1, \theta) f(x_2, \theta) \cdots f(x_n, \theta) \tag{C.1}$$

[Walpole et al., 2012]

where θ_1, θ_2, ..., θ_k are k unknown parameters to be estimated for n independent observations x_1, x_2, ..., x_n (where x are either TTF or TTR). The likelihood function is then given by:

$$L(\theta_1, \theta_2, ..., \theta_k | x_1, x_2, ..., x_n) = L = \prod_{i=1}^{n} f(x_i; \theta_1, \theta_2, ..., \theta_k) \ dx \tag{C.2}$$

[Elsayed, 2012]

where $i = 1, 2, ..., n$. Thus the product of the terms dx_1, dx_2,...dx_n do not depend on θ, the equation is rewritten as:

$$L(\theta_1, \theta_2, ..., \theta_k | x_1, x_2, ..., x_n) = L = K \prod_{i=1}^{n} f(x_i; \theta_1, \theta_2, ..., \theta_k) \tag{C.3}$$

[Elsayed, 2012]

The natural logarithm of the likelihood function is often easier to differentiate, hence the natural logarithm of the likelihood function is given by:

$$\Lambda = ln\ L = \sum_{i=1}^{n} ln\ f(x_i; \theta_1, \theta_2, ..., \theta_k) \tag{C.4}$$

[Elsayed, 2012]

The parameter values of $\theta_1, \theta_2, ..., \theta_k$ can then be obtained my maximizing either L or Λ. When maximizing the logarithm of the likelihood function the estimators of $\theta_1, \theta_2, ..., \theta_k$ are the solutions of k equations such that:

$$\frac{\partial \Lambda}{\partial \theta_j} = 0 \tag{C.5}$$

[Elsayed, 2012]

where $j = 1, 2, ..., k$.