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Application of reliability and maintainability analysis in the Svea coal mine

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TEK-3900 Master's thesis in Technology and Safety in the High North

May 2012

PREFACE AND ACKNOWLEDGMENTS

The research work presented in this thesis is a part of a master thesis at the University of Tromsø, at the Faculty of Science and Technology, at the department of Engineering and Safety. It was carried out at the University of Tromsø from September 2011 until May 2012 with fieldtrips to Svalbard. This thesis contains two papers.

The title of the thesis is “Application of reliability and maintainability analysis in Svea coal mine”. It was written in cooperation with Store Norske Kullkompani AS. The thesis is based on two papers which conducts an availability analysis of main conveyors in the coal mine and a reliability analysis considering operational effects of a Stacker. It is assumed that the reader has some knowledge about reliability engineering and mathematics.

I wish to show my gratitude and to thank my supervising Professor Javad Barabady for the in depth teaching of the subject of reliability and availability engineering. I would also thank him for the help during my thesis year for guidance, support and resources needed for the work. I wish to show my appreciation to Associate Professor Abbas Barabadi for the help and guidance in my papers and the thesis. Without this guidance, the contribution of the papers and thesis, it would not be as good as it became. The University of Tromsø has contributed with travelling funding and facilities to use for my master thesis and papers. I wish to thank the institute for enabling me to succeed with my master’s degree.

I would like to thank Store Norske Kullkompani AS for making their data available for me. For the financial support for travelling to their facilities and for making facilities needed at Svea easily available for me. I would also thank my colleges Simen Grenersen and Ernst-Magne Olafson Pedersen for fulfilling discussions and advices.

Simon Furuly

May 2012

Tromsø, Norway

ABSTRACT

The field of reliability engineering is developing, as needed in the industry. This is especially in arctic regions which now are being explored and vast recourses and opportunities are found. The reliability research is limited in the arctic, little knowledge is known about operating in the arctic regions.

This research study will analyze equipment in an arctic region, Svalbard. It calculates the effects of operational conditions and the availability of a conveyor system found in a coal mine in Svalbard. The aim of the thesis is to understand the availability for the system and try to make a practical impact on the operations in the coal mine.

The study has used two types of reliability methods – parametric and non-parametric method. These approaches can be used to find the reliability with and without the operational conditions included in the analysis. Similar for both methods are that they depend heavily on the data available. It seems that the operational conditions data collection is rare or non-existing. The study has produced two papers in order to analyze the main conveyor systems and a Stacker.

It found for one year of operation (2010) that the availability was 96,44%. Although this is a high availability, it was found that the reliability was low. A second analysis was done on the Stacker with consideration of operational conditions. It was found that during the winter season the hazard rate increased by 4,78 times the design conditions. It was also found that if the Stacker's performance operated like the other conveyors, this could save the company more than 3 million dollars. Some improvement measures are discussed for the data collection of failure and covariate data. The result presents an application of reliability and maintainability which seems to be useful for the operations in Svea.

Keywords: Arctic, Covariate, Operational condition, Reliability, Availability, Maintainability, Mining, Proportional Hazard Model, data collection

LIST OF APPENDED PAPERS

Paper I: Furuly, S., Barabady, J. and Barabadi, A., 2012, **Reliability and maintainability analysis of the main conveyor in the Svea coal mine of Norway,** Submitted for publication in the Journal of Mining Science.

Paper II: Furuly, S., Barabady, J. and Barabadi, A., 2012, **Reliability analysis of mining equipment considering covariates effect: A case study**, Submitted for publication in the International Journal of Performability Engineering

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NOTATION AND ABREVIATION

$\lambda(t)$ Failure rate function

$\mu(t)$ Repair rate function

β Shape parameter

η Scale parameter

γ Location parameter

μ Mean of the natural logarithm of TBF/TTR

σ Standard deviation of the natural logarithm TBF/TTR

MTBF Mean Time Between Failure

MTTR Mean Time To Repair

RAM Reliability, Availability, Maintainability

TBF Time Between Failure

TTR Time To Repair

MDT Mean Down Time

Cdf Cumulative density function

Pdf Probability density function

PHM Proportional Hazard Model

iid Independent Identically Distributed

CM Continuous Miner

MB Mine Bolter

SNSK Store Norske Spitsbergen Kullkompani

BASIC DEFINITIONS

Dependability

The collective term used to describe the availability performance and its influencing factors: reliability performance, maintainability performance and maintenance support performance (IEC, 2012).

Reliability

The ability of an item to perform a required function under given conditions for a given time interval (IEC, 2012).

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 (IEC, 2012).

Maintainability

The probability that a failed system is restored to a functioning state, in any given time and in a given environment using the given procedures and resources (IEC, 2012).

Maintenance

The combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required function(IEC, 2012) .

Mean time between failures

The expectation of the time to failure (IEC, 2012).

Mean time to repair

The expectation of the time to restoration (IEC, 2012).

Repairable system

A repairable system for this thesis is defined as a system that fails but is not replaced for every failure.

Covariate

A quantification of factors influencing the reliability characteristics (Kumar et al., 1994).

Failure

The termination of the ability of an item to perform a required function (IEC, 2012).

Fault

The state of an item characterized by inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources (IEC, 2012).

Error

A discrepancy between a computed, observed or measured value or condition and the true, specified or theoretically correct value or condition (IEC, 2012).

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LIST OF EQUATIONS

1 Introduction

This chapter presents the introduction for the reader in order to understand the problem. It covers the background and issues related to the research project. It also presents the objectives, purpose and research questions. Finally some limitations and the structure of the thesis are presented.

1.1 Background

Reliability, maintainability and availability performance of a system have assumed great significance in recent years due to a competitive environment and overall operating and production costs. Today's technological systems, such as aircraft, nuclear power plants, military installations, advanced medical equipment, and mining equipment are characterized by a high level of complexity. The requirements for the availability and reliability of such systems are very high.

Mining history can be traced back many thousand years. The methods and equipment used was inefficient and required many workers for a small amount of goods. Today’s situation is different. Mining equipment is more efficient and the turnover is in the billions. The money spent on equipment and expertise is vast and increasing. This creates a need for improvement of the already efficient process of extracting goods. The expenditure is increasing, and the demand for high quality and quantity of goods is increasing (Dhillon, 2008). The increasing need for energy and to keep expenditure low creates a need to optimize production lines. This process is more complex and challenging than before. There is an expectation that machinery, equipment and technology are supposed to be available at all times, ready for use and have a high performance. In some areas the industry is harder to improve, the cost of improvement work can seem high because the reward is not obvious at first. It may therefore be very hard to increase the reliability or availability of a system in the mining industry (Aven, 2006). The machinery is increasing in complexity and size, which adds to the list of challenges in mining industry.

Economic is important in today’s industry, with the correct use one can gain high reliability which causes the maintenance costs to lower and therefore increase the profit (Barabady et al., 2008). A method to improve this can be to imply an availability and reliability approach in order to increase the availability of the production line. The use of this method can save resources in many aspects, like logistic, unnecessary repairs, more production time etc. By using a reliability analysis the knowledge of a system increases, with this knowledge one is more capable of making decisions when changing the system or operating circumstances (Aven, 2006).

Most mine production lines consist of many subsystems and many components. Each subsystem and component affects to the total availability and reliability of the total production line. Therefore each subsystem and component should be analyzed in order to determine how the component affects the availability and reliability of the overall system. In order to increase the reliability of any machinery it is needed to study it to determine the necessary improvements or modifications that should be executed. When completing these objectives one should be able to improve the production of the mine and increase the availability and reliability of the mine (Dhillon, 2008).

In arctic regions the reliability, availability and maintainability changes due to the climate conditions, also the operation environment can differ greatly from the design conditions. The available data for these climates are of a small scope or badly reported. It is therefore necessary to research the effects of climate conditions on reliability and availability performance of equipment influenced by the arctic conditions (Barabadi et al., 2010; Freitag et al., 1997; Gudmestad et al., 2007).

The effects of operational conditions on reliability, maintainability or availability is not largely researched, however, this knowledge is usually common in the regions exposed to the different operational conditions. A man living in Alaska will know that his car must be taken extra care of, but the calculation and quantification of this is not a widely researched field. This thesis will highlight the approach in order to determine the availability, reliability and understanding the problems with equipment in these perspectives. Mathematics has been used to find the suited distributions for each subsystem in order to determine in what state the equipment is in. A new method for understand the effects of operational conditions (Wind, dust, crew skill, temperature etc.) has been used in order to quantify the effect on the reliability.

1.2 Research problem

The mining equipment are increasing in size and complexity, and this demands a higher level of performance and reliability of such equipment (Dhillon, 2008). According to Blischke and Murthy (2003) the consequences of failure are many and varied; depending on the item and the stakeholders involved, but nearly every failure has an economic impact. A failure in equipment or facility results not only in loss of productivity, but also in loss of quality, timely services to customers, and may even lead to safety and environmental problems which destroy the company image. For example, the consequences of failures can be of such a degree that the system is not profitable and therefore not used, causing loss of potential workplaces and industrial expansion. Therefore, optimizing and improving of the performance of a mine production line is more demanding and complex than ever. In order to improve a system, it needs to be analyzed. Which analyses one uses depends on what result is needed. Improving the systems performance means achieving maximum production that the system can handle. However, there is a cost to improving system. So improvement should be done where it increases the profitability.

A mine production line consists of several subsystems and components. Each subsystem and each component affect the total availability, and reliability performance of the total production line (Dhillon, 2008). Therefore, the performance of each subsystem and component should be analyzed in order to determine how each subsystem and component affects the availability and reliability performance of the whole production line. The result of such an analysis will help to identify the weakest areas of the mine production line and also increase the knowledge about the system. With this knowledge one is more capable of making decisions when changing the system or operating circumstances. Therefore, a focus on a reliability, maintainability and availability analysis is critical for the improvement of the mining equipment performance ensuring that it is available for production as per production schedules.

It should also be mentioned that the mining activities, in general, are carried out in complex and uncertain environments. In such operational environments there are many factors (e.g. ineffective blasting, weather, maintenance strategy, geology etc.) that can directly or indirectly affect the hazard rate or reliability performance of the mining equipment such as reliability and maintainability. Therefore, it is a challenge to analysis the effect of the operational environment condition on the reliability performance of the equipment. According to the literature, the effects of operational conditions on the performance of the equipment are poorly researched. A big issue is that the historical data is poorly recorded if even available. If there is a system for data collection, this is usually for the common data, such as failure occurrence and cause which is not included the operational condition which the failures do occur. The focus on data collection considering operational conditions is not widely known or used.

1.3 Research questions

Based on the research problem described, the following research questions have been formulated:

- How to predict the reliability and maintainability performance of the mining equipment based on the available data?
- How to study and analysis the effect of operational condition on the performance of mining equipment?
- How to improve the method of data collection in the Svea coal mine?

1.4 Purpose and objectives of Research study

The purpose of this research study is to analyze the reliability and maintainability of mining equipment is the Svea coal mine and also discusses and describes the effect of operational condition on the performance of the equipment.

More specifically the objectives of this research are to:

- Analyze reliability, maintainability and availability mining equipment with the available data
- Study and analyze the effect of operational conditions on the performance of mining equipment
- Suggest recommendation for data collection of mining equipment

1.5 Limitation of Research Study

This research is governed by some limitations, which are:

- Due to limitation of the time, the analysis is done only on the main conveyor system.
- Data used from the system is only for the year 2010
- In the case studies and numerical example it is assumed that all influence factor are included in the model

1.6 Structure of Research Study

The structure of the thesis is presented in Figure 1. The first chapter (Introduction) starts with a description of the background and research problem. Thereafter, the aim, research question, limitations and thesis structure are outlined. In the second chapter (Theoretical frame of reference) the theoretical framework will be presented, including aspects of reliability, availability, and maintainability analysis. In the third chapter (Methodology) the chosen research design and different aspects of data collection and data analysis will be presented. Validity and reliability issues of the study will be presented. In the fourth chapter (result and discussion) the general conclusions drawn from the research with a discussion will be presented. The fifth chapter presents conclusions, contribution and further research.

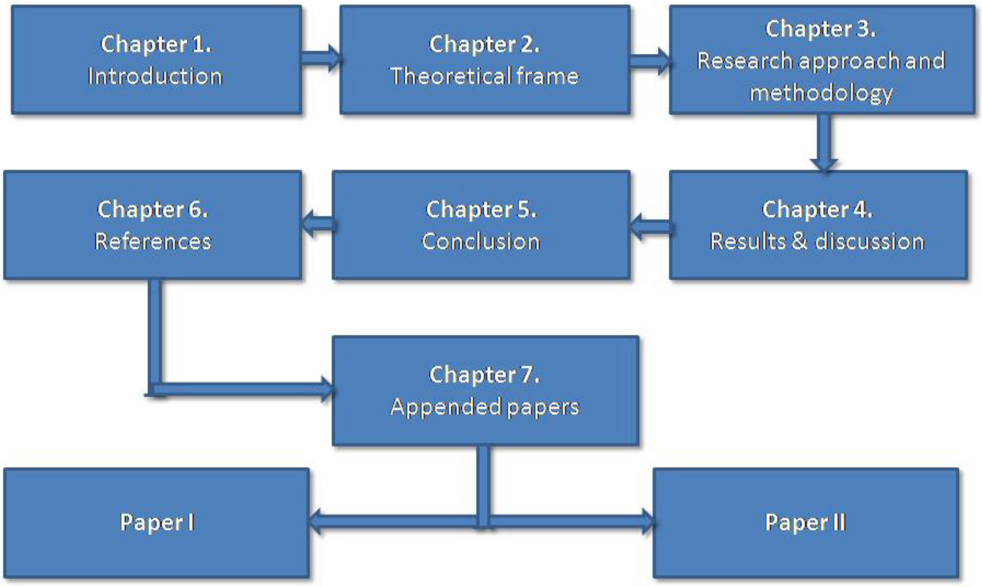


Figure 1 - Structure of thesis

2 Theoretical Frame of Reference

In this chapter some theories of reliability, availability and maintainability will be presented. Areas important for this thesis will be presented.

2.1 Introduction

One of the most important performance measures for repairable system designers and operators is system reliability and availability. Improvement of reliability and availability has been a subject of large number of research and a lot of articles have been published in this area. The availability and reliability are good evaluations of a system performance. Their values depend on the system structure as well as on the components properties. A reliability, availability and maintainability program should be established as part of a project's system engineering program. Establishing such program will help to ensure that the project will be free from reliability and maintainability-related problems that could prevent the accomplishment of health, safety, environment, performance, schedule, and economic goals. Some reasons for reliability and availability programs are:

- In the future the only companies left in the business will be those who know and are able to control the reliability of their products (Kececioglu, 1991)
- For a company to succeed in today's highly competitive and technologically complex environment, it is essential that it knows the reliability, maintainability and availability of its product and is able to control it so it can produce products at an optimum reliability level. The optimum reliability level yields the minimum life cycle cost for the user, as well as minimizes the manufacturer's costs of such a product without compromising the product's reliability and quality (Kececioglu, 1991)
- In today's complex living, where we do practically everything with machinery, automatic equipment, robots, appliances, entertainment centres, and other products both inside and outside the home, we are totally dependent on the successful operation of this equipment, and, if it fails, on its quick restoration to function, hence on their reliability and maintainability. Here is where reliability engineering comes in: to design, develop, manufacture, and deliver these products and the required spare parts to the users in such a way that desirable, high reliability is actually exhibited by all equipment and products during their lifetime with high confidence and at competitive costs (Kececioglu, 1991)

Since failure cannot be prevented entirely, it is important to minimize its probability of occurrence, the impact of failures when they do occur, and the downtime. This is one of the principal roles of reliability, availability and maintainability analysis. Increasing either reliability or maintenance entails costs to the manufacturer, the buyer, or both. There is often a trade-off between the costs. Increasing reliability by improving design, materials and production early on will lead to fewer failures and may decrease maintenance costs later on (Blischke et al., 2003). Lower reliability means increased unscheduled repairs and decreased availability. More stand-by units may increase the system's availability but do not decrease the incidents of system failures (Panagiotou et al., 2000)

2.2 Dependability

The concept of dependability can be defined as "The collective term used to describe the availability performance and it's influencing factors: reliability performance, maintainability performance and maintenance support performance." (IEC, 2012). When calculating the dependability of the system and the capacity performance of the system the production performance of the system can be calculated (Barabadi, 2011). To have an effective dependability analysis the reliability, maintainability and maintenance support performance of the component need to be predicted. There are different terms of dependability, this definition is focused on the research study done for this thesis.

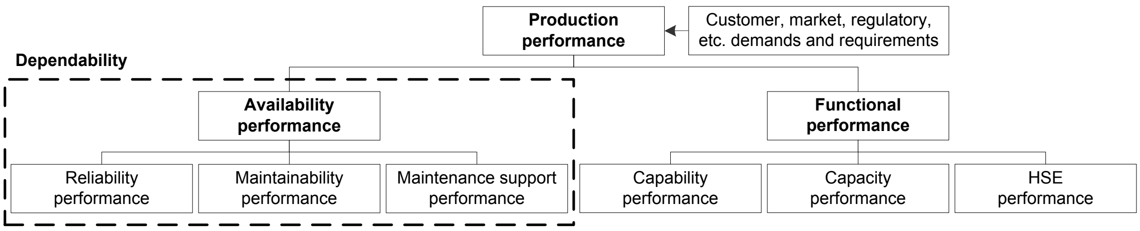


Figure 2 – Dependability concept and the relationship with production performance (Markeset, 2010)

2.2.1 Reliability performance

The formal definition of reliability according to IEV (191-02-06) is "the ability of an item to perform a required function under given conditions for a given time interval".

A keyword is the definition is "required function". It is essential to identify various function of an item. This means, that different reliabilities can be calculated for one component. Because a component can have several functions, one can calculate the reliability for each function. An example of this can be of a valve, it has two functions. It should close when an alarm sounds, and change the flow of fluid depending on what the operator wants it to be. At time 0, the reliability of the valve is 100%. After 100 hours of operating time the reliability is lowered to 95% for fluid control. But for the function of closing for the alarm, it may be 99%.

A second keyword from the definition is "under given conditions". It is essential to identify various foreseeable conditions and operating modes, as well as item (system, equipment, component, etc.) use and misuse in the requirements specification phase of system design. If the same valve in addition was located in the arctic, one could say that the reliability will be lowered to 80% after 100 hours of operating time, due to the effects of operational conditions.

In order to quantify the reliability, some units and terms are needed. Time unit has already been introduced. A common term is to use Mean Time Between Failures (MTBF), which is for a component that can be repaired. Mean Time To Failure (MTTF) is for a component that cannot be repaired, i.e. the failure is total (O'Connor et al., 1996).

The reliability can be measured as the probability that equipment may fail. Therefore data is needed to determine the failure rate of equipment (Leitch, 1995). This demands a need for data. The most common data needed to calculate the reliability is TBF and TTR. In order to take the effects of covariates, we need some data based on different covariates. One should also understand that reliability is relative to the task a component is intended to do. A hammer can for all practical purposes be given a reliability of 100% as they are not know to fail. So for hammering nails the reliability of the hammer after any given time period may be 100%, but for unscrewing a bolt the reliability will be 0% (O'Connor et al., 1996).

For mining industry, the equipment's life is influenced by different factors than other industry. The environment mining equipment is exposed to is different due to most mining is underground. Some causes can be:

- Design inadequacy
- Operational overstress
- Wear, abrasion, erosion
- Corrosion
- Fatigue
- Creep
- Etc.

2.2.2 Maintainability performance

Maintainability can be defined as, "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…" (IEC, 2012). This definition can be hard to use, as it is difficult to determine the ability of an item. A more quantitative definition is also given: "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, 2012).

From these definitions, one could say that maintainability has the purpose of increasing the availability when an item fails. Maintainability is therefore crucial for a repairable system. If the system fails and cannot be restored, it is just as a non-repairable system. In this research study, the time to repair (TTR) is used to define the time period from a halt in the production line, until the production restarts. Figure 3 presents the different operations involved in a failure. In the figure, MDT is defined as TTR for this research work.

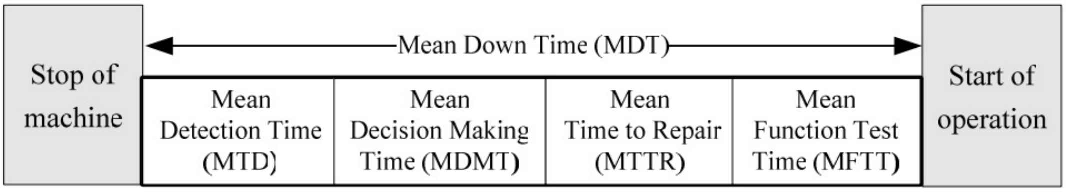


Figure 3 - Mean Down Time (Barabady, 2005)

Maintainability, defined in the broadest sense, can be measured in term of a combination of different maintenance factors. From a system perspective, it is assumed that maintenance can be broken down into the two following categories:

- Corrective maintenance: Corrective maintenance can be defined as: The act of restoring a failed unit to its previously working condition. This type of maintenance cannot be planned, and are therefore usually time consuming for the system and can be very costly. The amount of the corrective maintenance needed depends heavily on the reliability, as the reliability determines the amount of failures (O'Connor et al., 1996).
- Preventive maintenance: The actions which are done in order to prevent a failure from occurring. Depending on what kind of system, this type of maintenance is usually performed when the system is not running or not in use. This type of maintenance needs planning and will therefore be more cost effective and less time consuming on the system. Preventive maintenance can be many different tasks, e.g. lubrication, changing of oil, cleaning, services, change worn parts, calibration etc. (O'Connor et al., 1996).

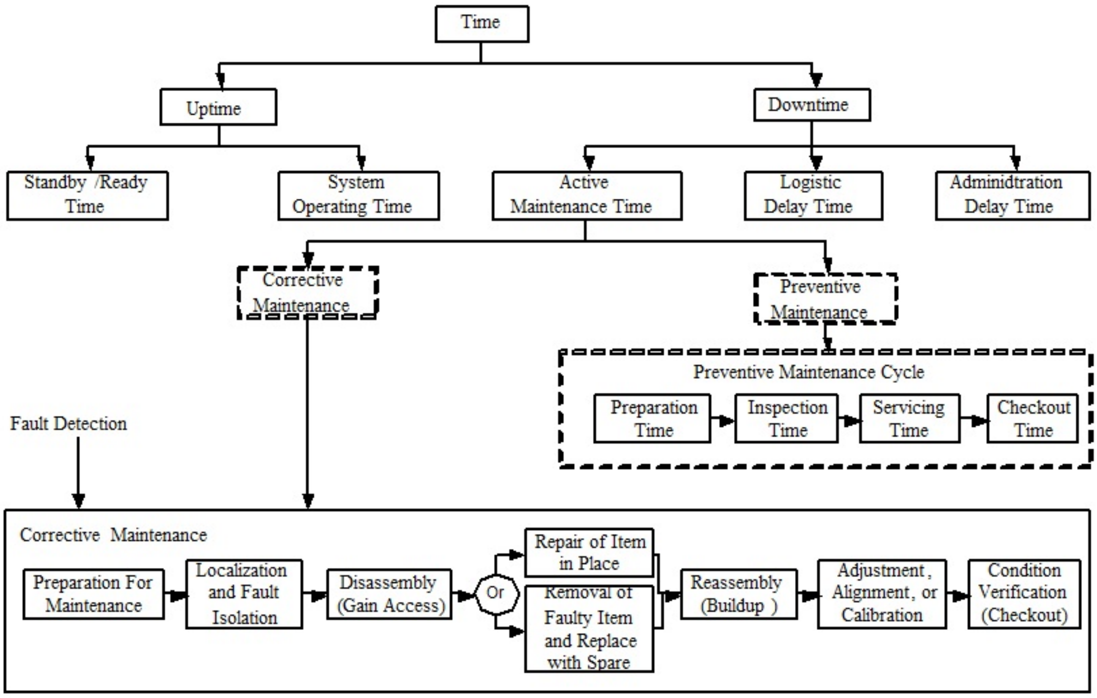


Figure **4** – Composite view of uptime/downtime factors (Blanchard et al., 2006)

2.2.3 Maintenance support performance

Maintenance support performance is defined as: "the ability of a maintenance organization, under given condition, to provide upon demand the resources required to maintain an item, under a given maintenance policy" (IEC, 2012). Defining and developing maintenance procedures, procurement of maintenance tools and facilities, logistics and administration, documentation, and development and training programs for maintenance personnel are some of the essential features of a maintenance support system. Furthermore, for complex, advanced, and integrated production systems, external support is often also needed, for example from the original equipment manufacturer, which can provide expert assistance, field service, spare parts and tools, and training of operation and maintenance personnel. Thus it can be seen that maintenance support performance is part of the wider concept of "product support", which includes support to the product as well as support to the client (Candell et al., 2009; Ghodrati et al., 2005; Markeset et al., 2003). The performance of the maintenance organization may be assessed using organizational performance measurement systems, although delivery performance of external support services should be measured using performance measurement systems focusing on service delivery (Kumar et al., 2007). Here, one link between the technical system and the support system is the Built-in-Test (BIT) system and its integration with the various echelons of the maintenance support systems (Söderholm, 2005).

2.2.4 Availability performance

Availability is defined in MIL-STD-721C (1981) "a measure of the degree to which an item is in the operable and committable state at the start of the mission, when the mission is called for all an unknown (random) time". There are different types of availability, such as point wise, interval and limiting. However, this research study focuses on the steady-state availability. The reason is that this type of availability is the most practical one to use.

- Steady-state availability or limiting availability: the mean of the instantaneous availability under steady-state condition over a given time interval. Under certain condition, for instance constant failure rate and repair rate, the steady-state availability may be expressed by the ratio of the mean up time to the sum of the mean up time and mean down time. Under these conditions, asymptotic and steady-state availability are identical and often simply referred to as availability. The steady system availability (or steady state availability, or limiting availability) of a system, which is defined by (IEC, 2012):

$$A = \lim_{t \to \infty} A(t)$$ Equation 1 – Limiting availability

This quantity is the probability that the system will be available after it has been run for a long time, and is a very significant measure of performance of a repairable system.

Depending on the definitions of uptime and downtime the steady-state availability can be divided into following categories:

Inherent availability: inherent availability is the probability that a system or equipment, when used under stated conditions, is an ideal support environment (i.e., readily available tools, spares, maintenance personnel, etc.), which will operate satisfactorily at any point in time as required (Blanchard, 1998). It excludes preventive or scheduled maintenance action, logistic delay time, and administrative delay time, and is expressed as:

$$A = \lim_{t \to \infty} A(t) = \frac{MTBF}{MTBF + MTTR}$$

Equation 2 – Inherent availability (Leitch, 1995)

Inherent availability is based solely on the failure distribution and repair-time distribution. It can therefore be viewed as an equipment design parameter, and reliability-maintainability trade-off can be based on this interpretation (Blanchard, 1998).

Achieved availability: achieved availability is the probability that a system or equipment, when used under stated conditions is an ideal support environment (i.e., readily available tools, spares, personnel, etc.), which will operate satisfactorily at any point in time. The achieved availability is defined as (Blanchard, 1998):

$$A_i = \frac{MTBM}{MTBM + \overline{M}}$$

Equation 3 – Achieved availability (Leitch, 1995)

where the mean time between maintenance operations (MTBM) includes both unscheduled and preventive maintenance and the mean active maintenance time ($\overline{M}$). If it is performed too frequently, preventive maintenance can have a negative impact on the achieved availability even though it may increase the MTBF. Very short preventive maintenance intervals resulting in frequent downtimes have availability less than the inherent availability. As the preventive maintenance interval increases, the achieved availability will reach a maximum point and then generally approach the inherent availability.

Operational availability: operational availability is the probability that a system or equipment, when used under stated conditions in an actual operational environment, will operate satisfactorily when called upon. The operational availability is defined as (Blanchard, 1998):

$$A_o = \frac{MTBM}{MTBF + MDT}$$

Equation 4 – Operational availability (Leitch, 1995)

where MDT is the mean maintenance down time and includes maintenance time ($\overline{M}$), logistics delay time, and administrative delay time.

2.3 Methodology for reliability analysis

The use of the mathematical techniques in reliability analysis is dating back to about the 1940s, at which time some mathematical techniques which were quite new. They were applied to many operational and strategic problems in World War II. Prior to this period, the concept of reliability was primarily quantitative and subjective, based on intuitive notions. The statistical approaches grew out of the demands of modern technology, and particularly out of the experiences in the Second World War with complex military systems (Barlow et al., 1965). The evaluation of reliability concepts and their industrial application are discussed by (Kececioglu, 2002; Rackwitz, 2001; Villemeur, 1992) provides a review and some prospects of reliability analysis up to that time.

In order to calculate the reliability of the system based on the historical data at the first stage the reliability of its component need to be calculated using an appropriate statically approach and then the relationship between this component need to be model by suitable model. However an effective reliability analysis on system or component level needs all influence factors on life time of the component/system identified and then quantified. On key word in reliability definition is “given conditions”. It is obvious that a component/system may have different reliability under different given conditions. On example of the given condition is surrounding environment and operational environments (e.g., temperature, humidity and dust) (Barabady, 2005). In the Svea mine all equipment inside the mine is closed from environmental effects. However the Stacker is the only equipment which is exposed to environmental conditions and this will be discussed later. Such harsh operational condition has some effect on reliability of the equipment for example (Freitag et al., 1997):

- Lubrications lose their effect, increasing the wear between the materials, which may cause an increase of failure
- Material act different in colder temperatures, materials become more brittle which may cause failures in lower designed loads
- More energy needed by the operator to perform routine repairs and operations
- Higher fuel consumption due to increase in the rolling resistance, higher viscosity of fluids and richer air/fuel mixture
- Degradation of seals, increasing the loss of lubrications and other fluids.

Some other example of given conditions are condition indicating parameters (e.g. vibration and pressure), design modification, the skill of the operator and maintenance crew, the history of the repair activity carried out on the system, etc. All those factors which may have an influence on the reliability characteristics of a system are called covariates. Therefore, it is necessary to consider the effect of covariates both in design phase, when we design, modify and improve production plant to meet the production performance goals and performance criteria. Moreover in operations phase when we observe and measure production plant’s performance, perform preventive maintenance, corrective maintenance and collected data to improve the production performance. Hence the selected statistical approach for reliability analysis under such condition should be able to assess the effect of covariates on reliability performance.

The Reliability performance analysis methods can be broadly categorized in two main groups, namely: parametric and non-parametric methods. In parametric methods the main assumption is that the data come from a type of probability distribution and that interferences are made about the distribution parameters. In the parametric method the lifetime of a system is assumed to have a specific distribution such as lognormal, but in the non-parametric method no specified distribution is assumed for the lifetime of system.

Parametric reliability methods have been very popular since the beginning of reliability analysis of a system (Barlow et al., 1965). When using a parametric approach in order to analysis the historical data, the practitioner attempts to make predictions about the life of component. This is done by fitting a statistical distribution (model) to life data from a representative sample of components. The parameterized distribution for the data set can then be used to estimate important life characteristics of the product such as mean time to failure, probability of failure at a specific time, and the failure rate. Life data analysis requires the practitioner to (Barabadi, 2011):

- Gather life data for the product
- Select a lifetime distribution that will fit the data and model the life of the product
- Estimate the parameters that will fit the distribution to the data
- Generate plots and results that estimate the life characteristics of the product, such as the reliability or mean life

However in parametric method finding appropriate statistical approach for a data set is an important stage. Figure 5 shows the methodology which can be used in order to find the statistical approach for data sets.

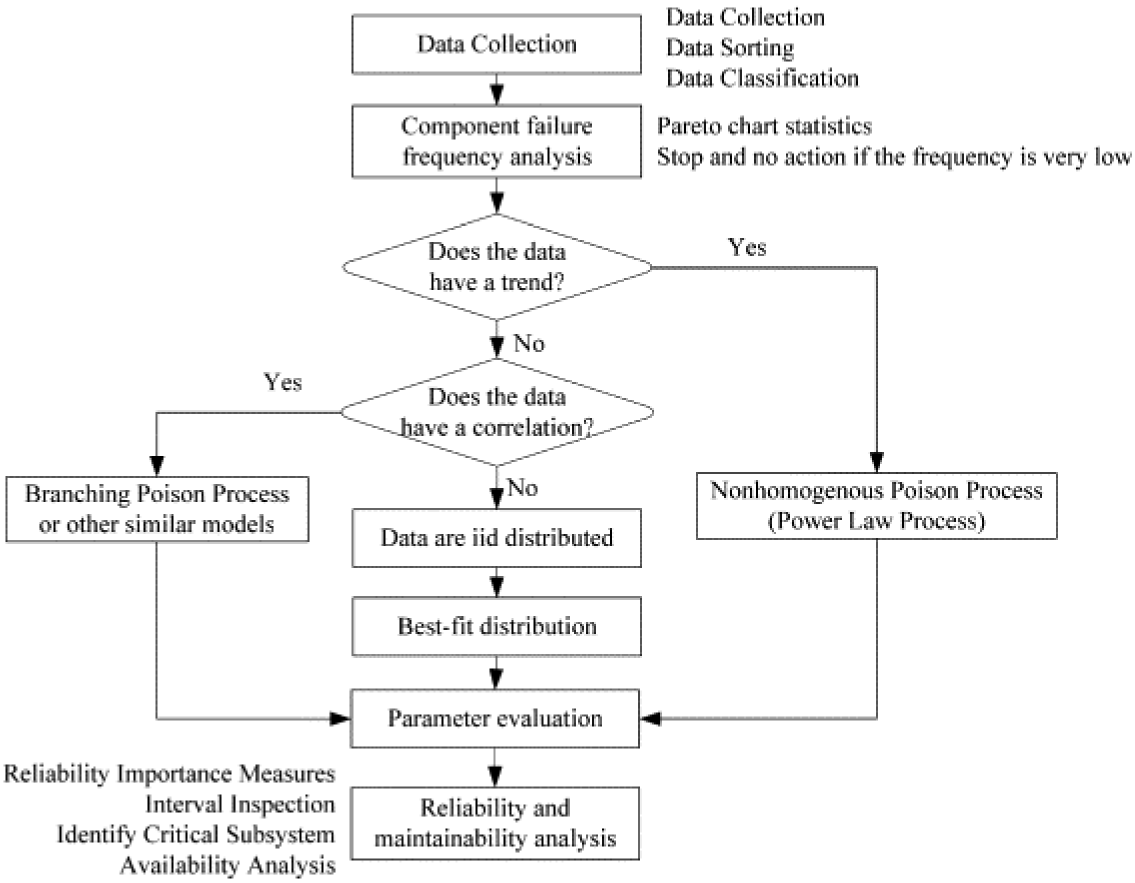


Figure 5 - Methodology for reliability and maintainability analysis (Barabady, 2005)

In the parametric method it must be considered if the historical data does not follow the selected distribution and the assumptions of parametric method are incorrect, parametric methods may be misleading. Furthermore, the majority of the parametric methods consider the operating time as the only variable, meaning that it cannot be used to analysis the effect of operational condition (covariates) on reliability of the components. Restrictions on the fulfilment of assumptions of distribution fitting led to the development of non-parametric reliability models based on the method suggested by. In the situation such as Arctic region when the failure time data involve complex distributions that are largely unknown, or when the number of observations is small, or there is no statistical or experimental evidence about the appropriate distribution shape non-parametric statistics-based models are more suitable.

A major contribution to the concept of non-parametric regression methods for modelling the effects of covariates was made by the method named the Proportional Hazard Model (PHM) (Cox, 1972). The general approach in non-parametric model is that the hazard rate of a component is the product of a baseline hazard and a functional term which describes how the hazard rate changes as a function of influential covariates. The baseline hazard rate is only the function of time and a component will be experience when the effect of covariates is equal to zero.

Applicable models for analysing the covariate effect on reliability performance can broadly be classified as the class of proportional hazards models and the class of accelerated failure time models. In the class of proportional hazards models (e.g. the proportional hazards model, the proportional odds model) assumption is that the effect of the covariates are act multiplicatively on the hazard rate or its transformations. While in the class of accelerated failure time models (e.g. log-logistic model), the effect of the covariates is assumed to act multiplicatively on the failure time or its transformations. (Kumar et al., 1996) reviews some of these methods and proposed a guideline for how to select a suitable model for a given data set.

The PHM is the most common modeling tool used for quantifying the effects of covariates. The purpose for introducing this model is to quantify the operational conditions effect on equipment. The method for using the PHM model was first introduced by Dr. Cox in 1972. During the year several methods which are related or extended to the PHM have been developed, such as stratification approach or extension of PHM. Recently Barabadi et al. (2011) proposed a methodology in order to find the best model for a set of data (Figure 6).

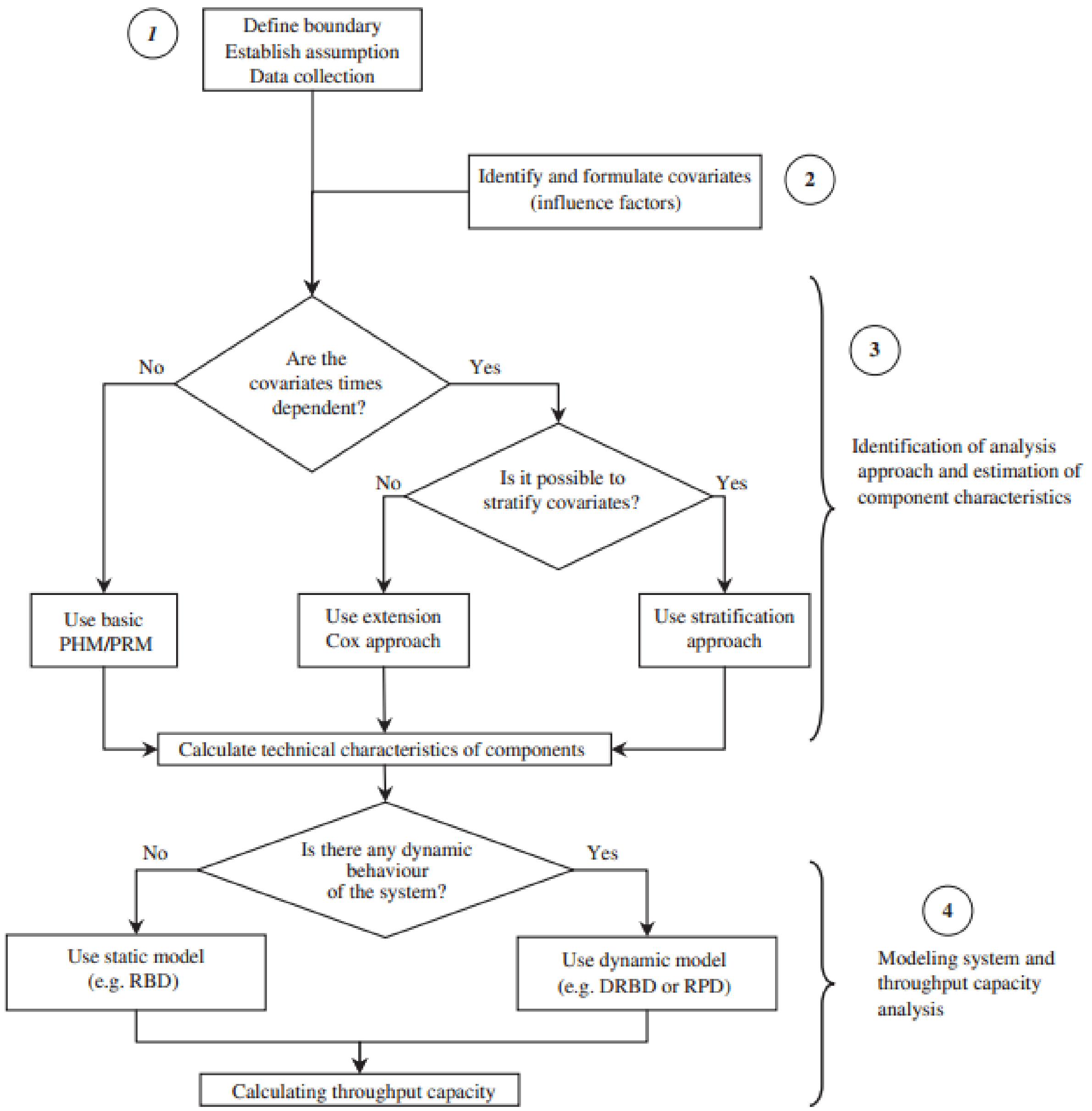


Figure 6 – Performance analysis of equipment considering operational conditions (Barabadi et al., 2011)

There are many methods for RAM improvement, such as (Barabady, 2005; Barabady et al., 2007; International Atomic Energy Agency, 2001). The methods that are used for RAM improvement are closely described and have a good methodology for improvements. It should be noted that all these methods have some similarity. Most methods suggest that whatever improvements that is used, it needs to be a continuous process which does not stop at one cycle. If the cycle is only repeated one time the effects of the improvement will not be as good at it could be if the improvement measures are repeated.

An easy method when reliability analysis is conducted is to use the failure data to identify the failure causes and identify which component is the weaker one. This however is not a complete method for improving RAM for a system.

A reliability analysis in itself should be able to increase the knowledge of the system. The main objectives of a reliability analysis of mining equipment would be to (Barabady, 2005):

- Increase the understanding of failure patterns in the system
- Estimate the characteristics of reliability of equipment in focus
- Identify the critical subsystem which will require improvements or modifications of its operation environment or maintenance routine

Based on the results found in a reliability and availability analysis, it can easily make changes to improve the system. As previously discussed, one can find the most common failure cause. If the time of failure occurs during a special zone and one can improve on the data collection system if one finds that it is not as accurate as can be.

2.3.1 Reliability calculations

In order to predict and calculate the reliability, some failure and reliability functions are used. This chapter contains the equations and functions needed in order to calculate the reliability. From probability and statistics theory, the denotation with a continuous random variable X:

- The probability density function, pdf, as $f(x)$.
- The cumulative density, cdf, as $F(x)$.

The cdf and pdf gives the description of the probability distribution of a random variable (Reliasoft, 2001). The pdf, with a continuous random variable X is a function $f(x)$ such as two numbers, a and b, where $a \leq b$:

$$P(a \leq X \leq b) = \int_a^b f(x)dx$$

Equation 5 – pdf (Leitch, 1995)

This is the probability that X takes the value between a and b, which is the area under the graph between a and b.

One should also know that the sum of the area below the pdf is equal to one, as presented in Equation 6 (Reliasoft, 2002).

$$P(-\infty \leq X \leq \infty) = \int_{-\infty}^{\infty} f(x)dx = 1$$

Equation 6 – Sum of pdf (Leitch, 1995)

The cumulative density function, with a random variable X, is the function $F(X)$, and defined by the number x by:

$$F(X) = P(X \leq x) = \int_{0,-\infty}^{x} f(s)dx$$

Equation 7 – cdf (Leitch, 1995)

Note that the function $F(X)$ depends heavily on the function $f(X)$. The two following figures present the relationship between these two functions.

$$f_i = \frac{\mathrm{n_i}}{\mathrm{N}}$$

Equation 8 - Failure function (Leitch, 1995)

Equation 8 determines the failure proportion between intervals. Time is divided into suitable intervals, f_i is the proportion of failures between i-1 and ith interval. The numbers of failures at the ith interval is n_i. N is the total number of items tested. The total failure at one time will be calculated by Equation 9.

$$F_j = \sum_{k=0}^{j} f_j$$

Equation 9 - Cumulative failure function (Leitch, 1995)

Equation 9 determines the total failure proportions from the start to the jth interval.

$$R(t) = \exp(-\frac{t}{MTBF})$$

Equation 10 – Exponential reliability function(Leitch, 1995)

The reliability can be calculated by Equation 10. Equation 10 is the exponential distributions formula, in paper I, Equation 16 and Equation 17 has been used. For each system, component or subsystem one need to check what kind of distributions fits best. MTBF can be calculated by Equation 11. It should be noted that this equation assumes that the failure rate is constant, as shown in Figure 8 this is for phase II.

$$MTBF = \frac{1}{\lambda}$$

Equation 11 – MTBF (Leitch, 1995)

In order to determine the MTBF one needs λ, which is the failure rate. This can be found in Equation 12**.**

$$\lambda_i = \frac{\mathrm{f_i}}{\mathrm{R_{i-1}}}$$

Equation 12 – Failure rate (Leitch, 1995)

2.3.2 System reliability calculations

In order to determine the systems reliability the reliability of each component should be calculated. By the use of the presented equations and depending on the system this can be used by pre-determined equations that will be adapted to fit the system in focus.

$$R(t) = \prod_{i=1}^{n} x_i$$

Equation 13 - Reliability series system (Nachlas, 2005)

Figure 7 presents an example system. This system contains six components. Three and three components are in a series system and in a parallel system. Equation 13 is used for a system that is in series (component 1-3). The example shown in Figure 7 relates Equation 13 and Equation 14 to a reliability block diagram of a system.

$$R(t) = \coprod_{\mathrm{i}=1}^{\mathrm{n}} x_i$$

Equation 14 - Reliability parallel system(Nachlas, 2005)

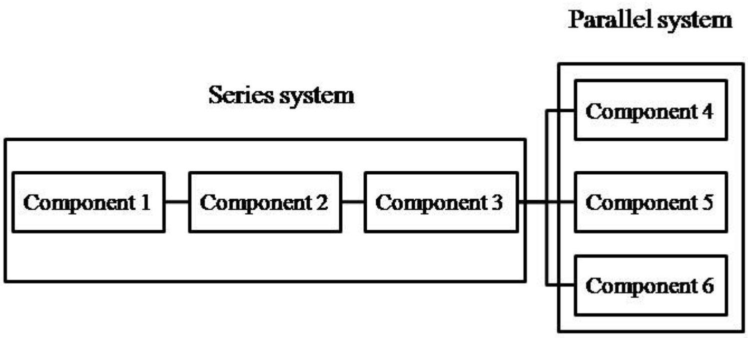


Figure 7 – Components in series and parallel system

Some equations and calculations are needed to use the methods of PHM and non-parametric methods. The PHM equation is covered in paper II. The non-parametric method uses the hazard rate, which is presented in Equation 15.

$$\mathrm{h(x)} = \frac{\mathrm{f(x)}}{\mathrm{S(x)}} = \frac{\mathrm{f(x)}}{1 - \mathrm{F(x)}}$$

Equation 15 – Hazard rate (NIST/SEMATECH, 2003)

2.3.3 Probability distributions

In this research study, two distributions have been used, shown in Equation 16 and Equation 17. The Weibull 3 parameters, has the parameter β which is the shape/slope parameter, η which is the scale parameter, γ that is the location parameter and t which is the time parameter (Reliasoft, 2006a).

$$f(t) = \frac{\beta}{\eta}\left(\frac{\mathrm{t} - \gamma}{\eta}\right)^{\beta - 1} \mathrm{e}^{-(\frac{\mathrm{t}-\gamma}{\eta})^{\beta}}$$

Equation 16 - Weibull 3 parameter (Reliasoft, 2006b)

For the lognormal equation there are two parameters, μ is the mean of the natural logarithm of TBF, σ is the standard deviation of the natural logarithm of TBF (Reliasoft, 2001).

$$f(\ln(t)) = \frac{1}{\sigma\sqrt{2\pi}} e^{-1/2\left(\frac{\ln(t)-\mu}{\sigma}\right)^2}$$

Equation 17 – Lognormal (Reliasoft, 2006a)

2.3.4 Bathtub curve

The Weibull distribution is commonly used in reliability analysis, because of its properties to have many different shapes. It is also used because it can be used if the failure rate is increasing, decreasing or stable (Barabady, 2005).

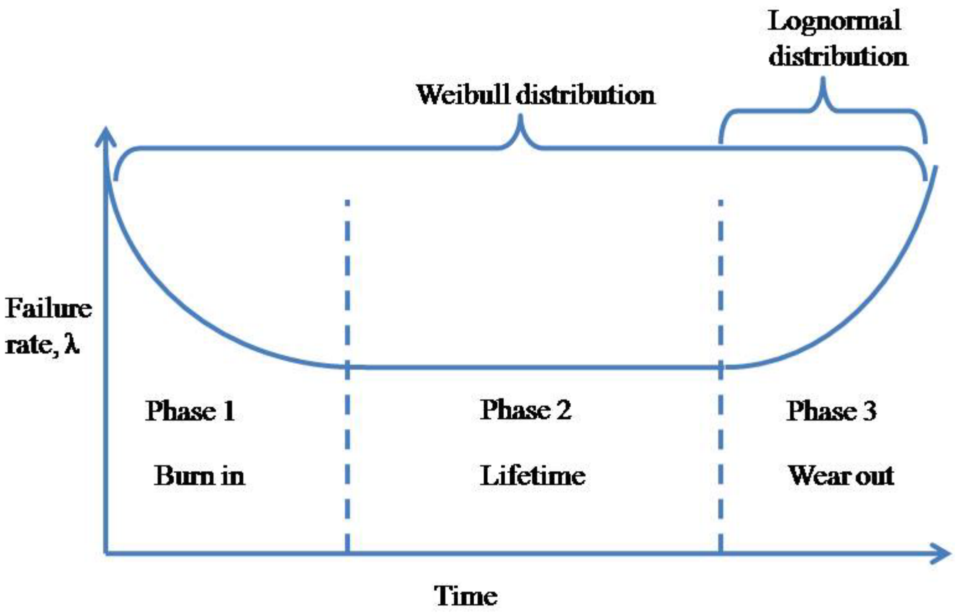


Figure 8 – Bathtub curve

From this curve it is possible to get some information. If the system is in phase 1, the failure rate is decreasing, a sort of burn in period for the system. For phase 2 there is a normal running period, with stable failure rate. Phase 3 is the wear out period of the system. For the Weibull distribution, the parameter β has the properties (Barabady et al., 2005):

- For $0 < \beta < 1$, the failure rate is decreasing with time (Phase 1).
- For $\beta = 1$, the failure rate is constant (Phase 2)
- For $\beta > 1$, the failure rate is increasing with time (Phase 3).

The bathtub curve can also help determine what distributions works for the different phases, for our purpose, it is interesting to see that the lognormal distribution works for the wear out of equipment (NIST/SEMATECH, 2003).

2.4 Information system

Many types of data are relevant to the estimation and prediction of reliability, availability and maintainability. Not all are collected in many instances, and the lack of information is sometimes a serious problem in RAM analysis (Blischke et al., 2003).

If the data and information are found in various places, in various formats, and in various degrees of completeness, it will be hard to get a holistic view of what the data and information system incorporate. The right data has to be available for the right user in the right format at the right time. To improve the physical product, information and data regarding reliability, maintenance, operations, service, market, management focus, etc., need to be available to the correct users (effectiveness). Furthermore, the data needs to be stored in systems that make it easy to retrieve, analyze, and draw conclusions from on a continuous basis (efficiency) (Markeset et al., 2003). In accordance with Markeset and Kumar (2003) some of the factors influencing the management of RAMS data and information system are shown in Figure 9.

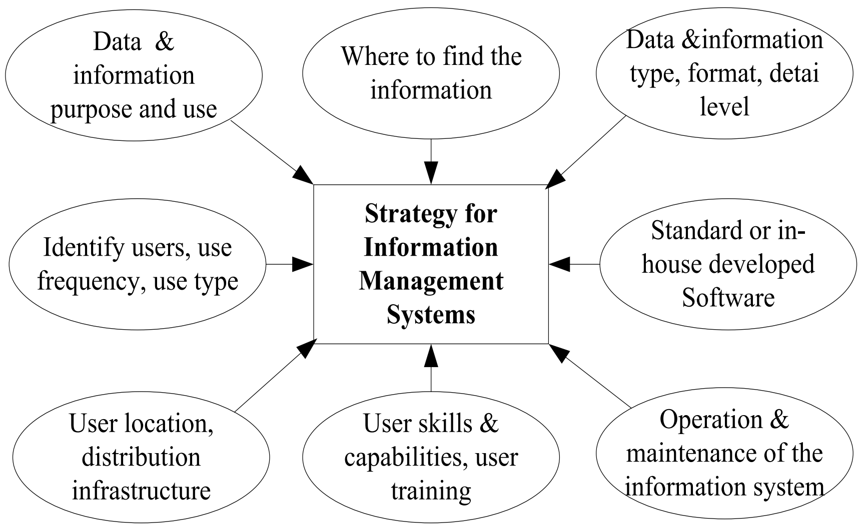


Figure 9 - Factors influencing strategies for Information Management Systems (Markeset et al., 2003)

Right data is data which reflect the real life situation, or operations in mind. The data can be divided in to several categories such as: *i)* technical data which reflect the functional and the functional requirement and in general supplied by the equipment manufacturers, *ii)* maintenance data in the form of the procedure, resources, quality and duration, *iii)* failure and reliability data in the form of censor or complete data and. *iv)* operational and environmental data. In general during the data collection all influence factors on failure process and repair process need to be collected. In general reliability and risk is an function of time/load, condition-indicating parameters (e.g. vibration and pressure), human aspects (e.g. the skill of the operators and maintenance crew) as well as resistance (capacity) of the item, the surrounding environment (e.g. temperature, humidity, dust, etc.), design modifications, the history of the repair activities carried out on the system (e.g. type of repair, number of the repair, etc.), etc. All those factors which may have effect on reliability and risk of an item are referred as covariate. For example some important covariates under the Arctic condition are included, ice, superstructure icing, snow drift, remoteness, environmental conditions (e.g. extreme cold, darkness), human performance and lack of infrastructures.

Data collection is an important part of analysing a system. As we now understand, equipment operating in arctic conditions demands more attention in order to perform as per normal operating conditions. For this reason, data collection is even more important in areas like the arctic, and should therefore have a higher focus than during normal operations.

3 Research approach and methodology

This chapter presents the description of the research purpose, research approach, data collection and processes done in order to conduct a systematically research study.

3.1 Introduction

The term research is widely used and very general, but can be defined as any activity to systematically find out things you did not know. It should contribute to advancing the field in focus. The research methods are the techniques used to carry out the research itself (Walliman, 2011). It can be said that research is the activity of questioning and answering systematically (Dane, 1990).

It is important to choose the right research method as this is crucial to the results and the validity of the research done. Therefore it is necessary to have a good methodology in order to have a systematic research with results that are valid (Walliman, 2011).

This research tries to make a practical impact for a specific case in mind. The study will therefore not only study and analyze, but also suggest improvements measures for the case.

3.2 Research approach and purpose

The research purpose for any researcher is related to what kind of result the research work should produce. A researcher can try to explore, describe, explain, understand, predict, change, evaluate and assess impacts (Blaikie, 2010). This research should formulate and answer questions based on the research. The purpose of this research is to better understand the failures and reliability of mining equipment in the Svea coal mine.

The research approach can affect the research greatly and it is important to formulate the purpose of the study. It is therefore important to know, understand and evaluate which method is the most suitable for a research study.

Table 1 – Different research approach methods (Blaikie, 2010)

	Inductive	Deductive	Retroductive	Abductive
Aim:	To establish descriptions of characteristics and patterns	To test theories, to eliminate false ones and corroborate the survivor	To discover underlying mechanisms to explain observed regularities	To describe and understand social life in term of social factors, meanings and motives
Ontology:	Cautious, dept or subtle realist	Cautious or subtle realist	Depth or subtle realist	Idealist or subtle realist
Epistemology:	Conventionalism	Falsificationism Conventionalism	Neo-realism	Constructionism
Start:	Collect data on characteristics and/or patterns. Produce description	Identify a regularity that needs to be explained Construct a theory and deduce hypotheses	Document and model a regularity and motives Describe context and possible mechanisms	Discover everyday lay concepts, meanings Produce a technical account from lay accounts
Finish:	Relate these to the research questions	Test hypotheses by matching them with data explanation in that context	Establish which mechanism(s) provide(s) the best answer	Develop a theory and elaborate it iteratively

Table 1 presents some of the different types of research methods. There are many more methods, but the most common ones are presented in the table. For this research study, a mix between the inductive, deductive and abductive method has been used. The reason for this is that already stated methods have been used. It includes data collection and data processing. But the research study tries to provide a new view of covariate effect on equipment view.

3.3 Research strategy

It is common to divide research into two categories, qualitative and quantitative research methods. The quantitative is usually said to collect data in the form of numbers, while the quantitative method can also be said to be used whenever qualitative data is converted to numbers (Blaikie, 2010).

The qualitative research method can be used when a researcher collect pictures, gather words, conduct interviews to analyze them from their perspective (Creswell, 2007).

Reliability in a qualitative form is usually not practical for an engineer. Therefore the reliability should be analyzed in a quantitative method to give some practical impact. This research study has collected data to analyze and used methodologies to conclude the results. Therefore there is a mixture of quantitative and qualitative method in this research study.

3.4 Data collection, evaluation and analysis

Data is said to mainly be collected from six sources; documentation, archival records, interviews, direct observation, participant-observation and physical artifacts. For one case study, all six sources may apply (Yin, 2003). When the data is collected from the six sources, we can divide the data into three different categories. i) primary data. This is generated by the researcher for the study. ii) secondary data is raw data collected by someone else. The purpose may differ from the research study.iii) tertiary data is data that already have been analyzed by another researcher. In this case, the raw data may be unavailable for the research (Blaikie, 2010)

The reliability can be measured as the probability that equipment may fail. Therefore data is needed to determine the failure rate of equipment (Leitch, 1995). Data can be collected from different sensors and other means. The most typical ones are:

- Data from sensors on equipment
- Operator or on-board data from equipment
- Historical data or maintenance forms
- Current operational information
- Current maintenance information

The most common data needed to calculate the reliability is TBF and TTR. In order to take the effects of covariates, we need some data based on different covariates.

Historical data from Svea has been collected. This data has been used in the research study. The data can be said to be secondary data, as it is collected in the reports at Svea and changed to fit this study. Fieldtrips to Svea has also been a form of data collection, interviews and discussions with engineers, experts and managers has also contributed as data collection.

3.4.1 Case description

The mine in focus is located in Svalbard and is operated by Store Norske Spitsbergen Kullkompani AS (SNSK). The mine was first opened in 1917, and then owned by the Swedish mining firm AB Spetsbergens Svenska Kolfalt. SNSK bought the mine from this firm in 1934. The mine was operated on and off during the period from 1934 until it was opened for modern mining in 2001.

The mine is located in the Van Mijenfjorden as seen on Figure 10, on the island of Spitsbergen, Svalbard. The methods of transport to the mine are airplane the whole year, boat during summer season and snowmobile during winter.

Figure 10 – Location of the Svea mine

There are approximately 350 workers in Svea. None of these workers are permanently located in Svea. The workers travel in shifts to and from Svea by airplane or snowmobile. In Svea there are living quarters, cantina and all others facilities needed for a short stay. The normal rotation is 1 week on and 1 week off for the workers.

Figure 11 – Svea airport and other facilities

Figure 11 shows the Svea airport, and in front is the workshop, power plant and storage facilities for equipment. In the back there are living quarters, cantina and offices. The road exiting in the bottom of the picture is towards the harbor Kapp Amsterdam.

The production rate at Svea varies from approximately 2 million tons coal to 4 million tons per year. This coal is transported to Kapp Amsterdam using trucks. Then it is loaded to ships. The harbour is closed during winter due to ice covering the fjord. The season for shipping is from July – November. Mainly the coal is used for energy production and sold to Germany.

Mine setup

The entry (adit) to the mine is located in the area of the facilities for the workers and other employees. The tunnel from the entry to the first coal face is approximately 6km. The choice of mining is called longwall mining.

Figure 14 shows the reliability block diagram of Svea. From the block diagram, it can be seen that if the conveyors stop, the whole system will be halted.

The production changes due to the market prices. Svea operates with 2-3 different shifts, were two of these are production shifts. The overlapping of shifts is shown in Figure 12.

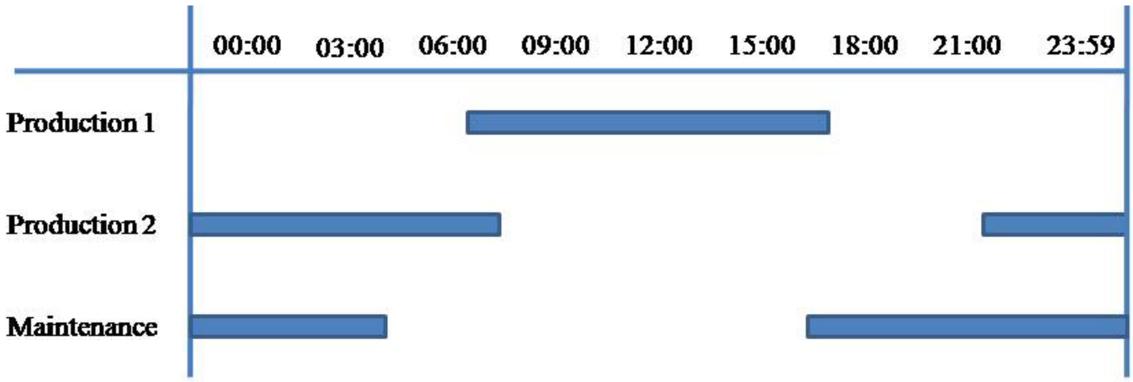


Figure 12 – Shift work Gantt diagram

Cutting machinery

Figure 13 presents the normal method for longwall mining. There is a pre-cut tunnel that the Shearer is moved into. The shearer then works back on forth cutting coal, moving after the coal layer. The pistons as shown in the figure let the rock collapse behind all the equipment. The coal that is cut from the Shearer is transported out of the mine using different types of conveyors.

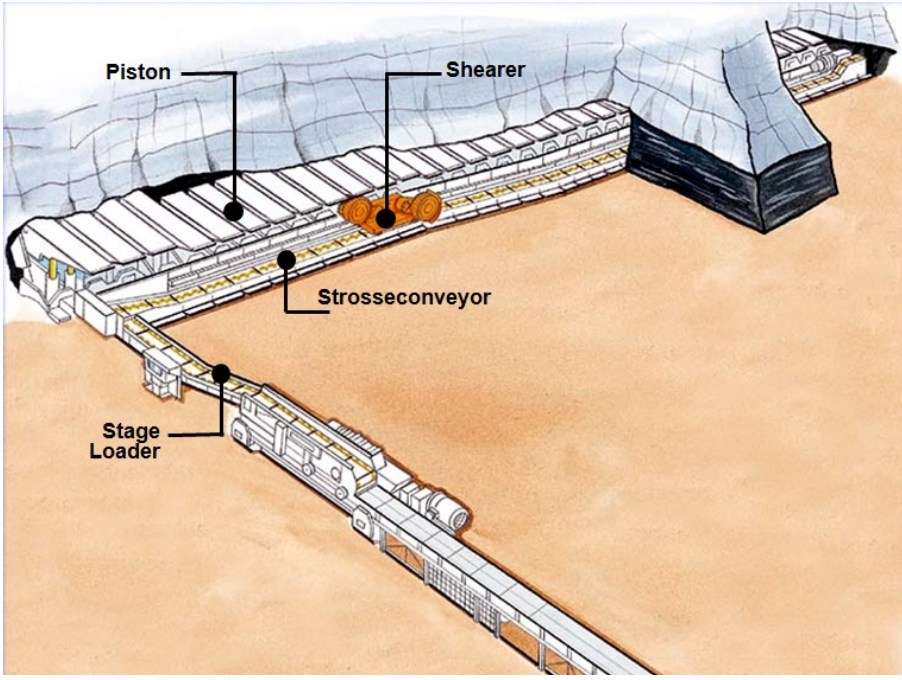


Figure 13 – Longwall mining components

The Mine Bolter (MB) consists of four machines. There are sets of two machines that are the same – Bolters and the Miners. First the two Miners excavate, depending on the rock formation this is between 2-5m. Then the Bolters secure the roof and walls by bolting it in order to not have a fracture in the walls. Then this process is repeated. The main function of the Mine Bolter is to prepare travelling ways or a new face for the shearer.

The continuous miner (CM) has the same purpose and function as the Mine Bolter, the difference is that this is one machine, doing the bolting and mining at the same time.

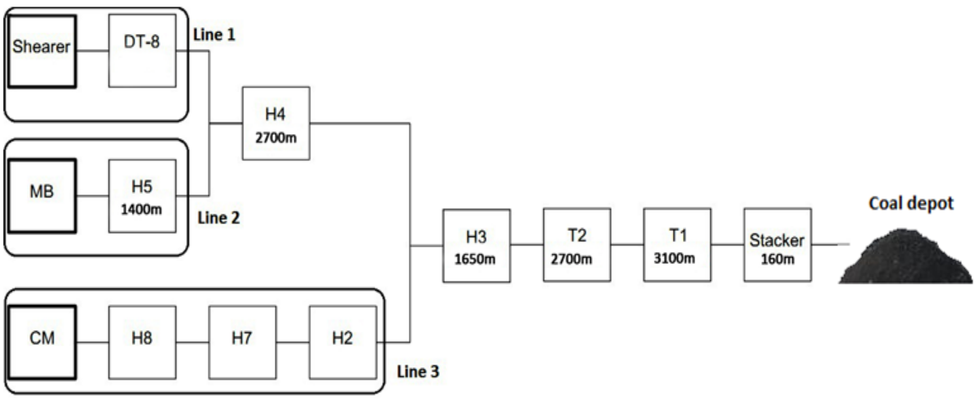


Figure 14 – Reliability block diagram of the Svea coal mine

Figure 14 presents the reliability block diagram. From this figure, we see that there are three production lines in Svea. The functions of each subsystem is presented in Table 2.

Conveyors

As in many other longwall mines there are several conveyors that are changed, moved and serve different purposes. The objective of the conveyor is to transport the coal from cutting machinery, Shearer, MB and CM.

SNSK claim to have enough spare parts at any given time to build a new conveyor system, therefore spare parts are assumed to be available and in storage at all times. The maintenance at Svea is a two part phase that will be discussed more. During down time of the system, maintenance crews take oil samples and do vibration tests and use infrared cameras. This is to make decisions about whether or not they should do maintenance one specific equipment. By these means, one can say that both the maintainability and supportability seems to be in a good nature.

Figure 15 – Mine adit, with the conveyor on top left

The system as shown in Table 2 is operated by a control room outside the mine. The conveyors are operated by an operator that has control of all the units inside the mine. On the MB, CM and shearer there are operators that control the operations, but the control room has data feed from these machines to know the status.

Figure 16 – Conveyor brake

The conveyor system have a capacity of 2000t/hour.

The Stacker, is the last conveyor. The purpose of the Stacker is to stack coal in order to move it outside the mine. This is the only conveyor exposed to the environmental conditions in Svalbard. It is also the shortest conveyor as presented in Table 2.

Figure 17 – The Stacker for the Svea coal mine

Some restrictions had to be made because of the high amount of equipment in the mine. It was therefore decided to focus on the main conveyors in the mine. This decision was made on the discussion with the experts on Svea. The argument is that for every halt in the conveyor, the equipment behind the conveyor has to shut down.

As presented in the reliability block diagram in Figure 14, the Stacker, T1, T2 and H3 can be set as a main line of transportation, as this collects coal from every cutting machine.

Table 2 – Subsystems in Svea

Name	Code	Function	Studied	Length(m)
Shearer	SH	Cutting coal		
Mine Bolter	MB	Development work		
Continuous Miner Machine	CMM	Development work		
Conveyors	DT-8	Transport of coal		
	H5	**Transport of coal**	**X**	**1400**
	H4	**Transport of coal**	**X**	**2700**
	H3	**Transport of coal**	**X**	**1650**
	T2	**Transport of coal**	**X**	**2700**
	T1	**Transport of coal**	**X**	**3100**
	Stacker	**Transport of coal**	**X**	**160**
	H2	Transport of coal		
	H7	Transport of coal		
	H8	Transport of coal		

As previously discussed, the MB is cutting towards a new mining field. Therefore it was decided to include H4 and H5 as these are cutting towards this field. These conveyors, the Stacker, T1, T2, H3, H4 and H5 will continue their production even after Svea is cleared for coal. Therefore these conveyors will be the more static ones, not changing their setup or function for the longest period. Experts at Svea agreed with this reasoning and wanted as well a focus on the conveyors.

Another argument for selecting the conveyors is that production depends heavily on these to function as intended. From this argument one can say that the throughput capacity relies heavily on the conveyors at Svea.

3.4.2 Data collection and evaluation

For this research study, secondary data has been available. The raw data is collected by the company, but processed to fit the research study in this thesis. The different data sorts used are presented in Table 3.

Table 3 – Data used in research

Paper/thesis	Type of data	Covariates	Source
Thesis	Failures, TBF, TTR, failure comments, weather	Temperature	Documentation, Observation, Interview
Paper I	TBF, TTR	-	Documentation, Observation ,Interview
Paper II	TBF	Month of failure, Shift	Documentation, Observation, Interview

SNSK has previously noticed issues with their reliability, in order to quantify this they made systems in order to improve their production and decrease their costs. The result of this process was a meeting each day between the chiefs of operations. This meeting is used to collect the halt data for each day. A small example from the conveyor system is presented in Table 4.

Table 4 – Example form of raw data

Conveyor systems			Total availability [%]		94,70 %
Planned Production [min]:			1140	Halt minutes	60
Shift	Halt [min]	Category	Equipment	Description	
Day	15	Production	T1 0837-2	Blocked shute	
Night	37	Electrical	T1 0837-2	Belt tear	
Day	6	Electrical	H4 0837-7	Belt line	
Day	2	Mechanical	DT-8	Emergency halt	

This is just a small extract from the daily report. This example has a 7x5 table. The daily report is 7x200. The total sum of daily reports for one year gives a great raw data to work with.

In order to analyze the data, the use of different software and programming codes had to be used to change the format of the data. This work is a large deal of the total work amount done for this research study, but will not be highlighted. The results of which this work produced, is shown as an example in Table 5.

Table 5 – Example of processed data

Frequency	Date of failure	Time of	Date of repair	Restored time
1	17.01.2010	06:20	17.01.2010	06:40
2	17.01.2010	12:40	17.01.2010	13:40
3	18.01.2010	09:30	18.01.2010	09:43
4	23.01.2010	09:30	23.01.2010	09:40
5	24.01.2010	04:45	24.01.2010	05:19
6	24.01.2010	09:30	24.01.2010	09:36
7	24.01.2010	14:15	24.01.2010	14:29
8	25.01.2010	06:20	25.01.2010	06:34
9	25.01.2010	12:40	25.01.2010	12:56
10	26.01.2010	04:45	26.01.2010	04:48
11	26.01.2010	09:30	26.01.2010	09:43
12	26.01.2010	14:15	26.01.2010	14:35
13	27.01.2010	06:20	27.01.2010	06:34
14	27.01.2010	12:40	27.01.2010	12:55
15	28.01.2010	09:30	28.01.2010	09:47
16	29.01.2010	06:20	29.01.2010	07:05
17	29.01.2010	12:40	29.01.2010	12:52
18	30.01.2010	06:20	30.01.2010	06:40
19	30.01.2010	12:40	30.01.2010	12:55
20	01.02.2010	06:20	01.02.2010	10:35

For SNSK the terms of failure, fault and error can be defined as:

- Failure: Any action or breakdown that causes an operator or equipment to stop production
- Fault: When the system/component does not manage to complete its intended function or delays production from other equipment
- Error: This is not quantified, but the tolerance for error is high at Svea, as they try to run the system until the maintenance shift is on

3.4.2.1 Identically independent distributed assumption

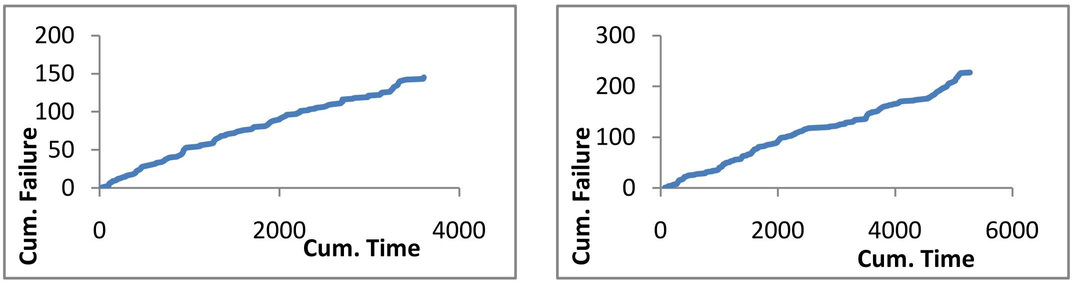
Because of the constant monitoring from operators and the control room in Svea, the data is assumed complete.

The method for calculating reliability depends that some assumptions are made. When using data for a reliability analysis, the analysis uses some assumptions in order to fit the trend of data in a statistical model. Therefore we need to check that the iid assumption is valid for the data set, this is done by testing for trend and correlation of the data (Kumar et al., 1992).

In Figure 5 a step is to check if the data as identically distributed (iid). The cause for this is that the data the data is not related, meaning that one failure does not affect the next failure. It also means that the data obtained is from the same probability distribution. In order to identify if the data is iid or not is critical when doing an analysis. If the data is not iid there should be done another method then the one used in this paper (Barabady, 2005).

Trend test

Trend test for this case study has been performed graphically. It is however possible use an analytic method for investigating if there is a trend or not. When analyzing data it is important to see whether the data has a trend, i.e. if the rate of failures for the system/component is increasing, decreasing or constant (O'Connor et al., 1996). By plotting the cumulative time between failure and number of failure, the graph will show if there is a trend of the failure data. If there is a trend, the line will concave upwards, suggesting an improving system. If the line is concaving downwards it suggests a system that is deteriorating. If the line is linear, one can be sure that there is no trend in the data (Barabady, 2005).



c – Trend test for the TBF of the Stacker d – Trend test for the TBF of the H4

Figure 18 – Trend test of data for H4 and the Stacker

Figure 18 presents two of the six trend tests done, one for each subsystem. However, these show none or little trend in the tests. Therefore, it was concluded that there were no trend in the data.

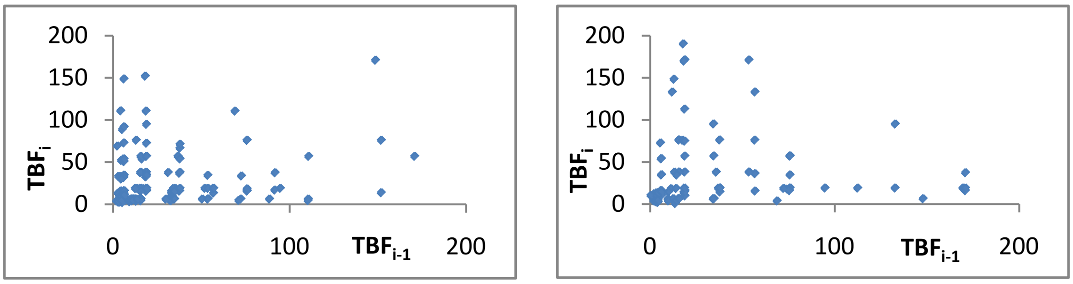
Correlation test

In order to determine if the data correlates, one can use both a graphically method and a analytical method. The analytical method can be used with the graphically, this is because the value the method produces may be difficult to interpret. The same applies for the graphically method (Triola, 2004).

$$\mathrm{CORR}(X,Y) = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})\sum(y-\bar{y})}}$$

Equation 18 – Correlation (Microsoft, 2011)

The correlation tests objective is to determine if there is a relationship between two variables. In statistics this is called the correlation (Triola, 2004). The graphically method is done by plotting the two variables the TBF_i as X value, and TBF_{i-1} as Y value. In order to determine if the data correlates, one can view the scatter plot. If there seems to be no collection of the data in groups or as a linear line, one can be sure that the data does not correlate. To confirm and be certain that there is no correlation one can use Equation 18. The correlation coefficient varies between -1 and 1. If the coefficient is positive, this indicates that the data are positively correlated, that the regression line is positive. If the coefficient is 0 the data is not correlative (O'Connor et al., 1996). Table 6 presents the calculated correlation.



a – Correlation test for TBF of the Stacker b – Correlation test for TBF of the H4

Figure 19 – Correlation test of data for H4 and the Stacker

Figure 19 presents some of the correlation tests of the Stacker and conveyor H4. These tests and the tests of other conveyors showed that there is no correlation between the failures of the equipment.

Table 6 - Correlation coefficient of conveyors

	Stacker	T1	T2	H3	H4	H5
Correlation coefficient	0,10	-0,02	0,06	0,00	0,24	0,38

Based on the tests it was concluded that the data had no correlation and no trend. It was therefore possible to continue with the reliability and maintainability analysis.

3.4.3 Time dependency of covariates

One problem the research study should focus on is the covariates effect on equipment. Due to the lack of covariate data, it was decided to use shift and time of failure (month). In order to use the PHM, an assumption has to be checked. This assumption is if the covariate data is time dependent or time in-dependent. The method is graphically. The graph of log minus log plot yields parallel curves when the data is time-independent. The result is shown in Figure 20.

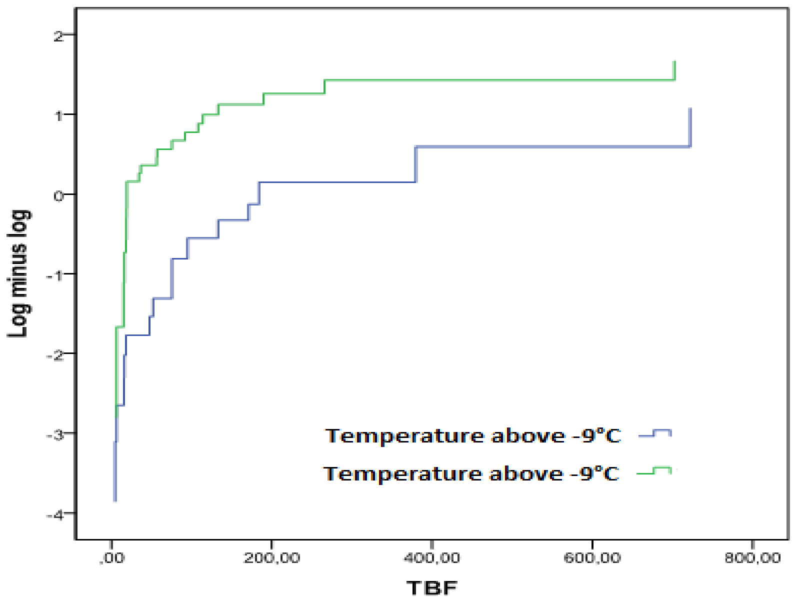


Figure 20 – LML plot of data

This shows that the covariate can be assumed time-independent. The result of this is that the PHM can be used.

3.4.4 Data analysis

As a part of the methodology in Figure 5, the best fit distribution should be found. This step is used in order to determine the characteristics of the failures and repairs of each conveyor. Different distributions were tested with the statistical program, Reliasoft Weibull++ 7. The result of the data analysis is presented in Table 7 and Table 8.

The DESV value is a ranking of distributions. The value of DESV is based on a ranking system from different regressions approaches that fit the distributions. It was decided, that for Weibull 3 parameters were gamma is smaller than one, it should not be considered.

Table 7 – Best-fit distribution for TBF data

Sub-system	DESV- Decision weight ranking					Best-Fit	MTBF (hours)	Parameters
	Exponential 1 Parameter	Exponential 2 Parameter	Log-normal	Weibull 2 parameter	Weibull 3 parameter			
Stacker	470	430	180	300	120	Weibull 3 parameter	149,16	Beta= 0.57; Eta = 89.72 Gamma=4.44
T1	390	400	120	360	180	Lognormal	37,26	LMean= 2.91: LStd = 1.9
T2	440	400	100	360	200	Lognormal	52,59	LMean= 2.97: LStd = 1.4
H3	390	400	150	360	150	Weibull 3 parameter	39,96	Beta= 0.67; Eta = 28.76 Gamma=1.86
H4	390	400	100	360	200	Lognormal	25,97	LMean= 2.68: LStd = 1.08
H5	420	480	170	300	130	Weibull 3 parameter	132,36	Beta= 0.56; Eta = 78.75 Gamma=1.85

Table 8 – Best-fit distribution for TTR data

Sub-system	DESV- Decision weight ranking					Best-Fit	MTTR (hours)	Parameters
	Exponential 1 Parameter	Exponential 2 Parameter	Log-normal	Weibull 2 parameter	Weibull 3 parameter			
Stacker	420	480	200	300	100	Lognormal	0.54	LMean= -1.47: LStd =1.31.31.3
T1	390	400	120	360	180	Lognormal	0.33	LMean= -1.8: LStd =1.161.16
T2	390	480	100	330	200	Lognormal	0.49	LMean= -1.59: LStd =1.3 1.3
H3	390	450	100	360	200	Lognormal	0.17	LMean= -2.2: LStd = 0.94
H4	390	430	150	330	150	Lognormal	0.27	LMean= -2.08: LStd = 1.24
H5	390	450	360	300	200	Lognormal	0.12	LMean= -2.52: LStd = 0.85

3.4.5 Covariate analysis

In order to find the effect of covariates on the Stacker, the PHM was used. The results found that shift had no or little effect on the equipments reliability. However, when we checked for the effects of temperature, the effect was significantly. The results are found in Table 9.

Table 9 – Results of PHM

Step	Covariates	β	SE	Wald	Sig.	Exp(β)
Step 1	Jan.	0.72	0.365	3.897	0.048	2.1
Step 2	Jan.	0.967	0.39	6.143	0.013	2.6
	Feb.	1.062	0.439	5.859	0.015	2.9
Step 3	Jan.	1.639	0.487	11.33	0.001	5.1
	Feb.	1.747	0.529	10.898	0.001	5.8
	Des.	1.43	0.469	9.306	0.002	4.2

The results found that January, February and December had a big influence on the Stacker. It was decided to manage the months into seasons, as this is more manageable to use for practical matters. The categories were made like it:

- Winter – January, February and December
- Fall – October, November and September
- Summer – May, June, July and August
- Spring - March, April

The results then found what is presented in Table 10.

Table 10 – Results of PHM with categories

Step	Covariates	β	SE	Wald	Sig.	Exp(β)
Step 1	Winter	1.565	0.415	14.206	0.0	4.78

These results found that the winter season affects the hazard rate by 4.78 times the design conditions.

3.5 Research validity and Reliability

According to (Yin, 2003), by the term, high reliability of research means that another researcher will be able to achieve the same results as in the study. The methodology used should have a good overview and structure to it, so that the same procedures are done every time. For this study, the source of data is not available for the public, and can therefore be hard to replicate. However, the methods used are easily available and can be remanufactured by a new data set.

Research validity can be thought of as how well the study results compare with the real life scenario (Yin, 2003). The results presented to Store Norske Spitsbergen Kullkompani seem to be in the same tendency that they thought some of the results would be in. It could therefore be said that the study has a high internal validity because the findings of the study are relevant and logically connected to the emitting theory

4 Results and discussion

This chapter describes and presents the findings of the present research, which was conducted to answer the stated research problem. The area of discussion will be focused on the area of research objectives.

This research study has produced two papers which are appended. The papers along with the thesis are made in order to answer the research questions properly. Table 11 represents the answering of the research questions for the papers and thesis. Three X is the highest ranking, while – is the lowest.

Table 11 – Research questions related to papers and thesis

Paper/Thesis	RQ – 1	RQ – 2	RQ – 3
Thesis	XX	XX	XXX
Paper I	XXX	-	X
Paper II	X	XXX	X

4.1 Reliability and availability analysis of mining equipment

The first objective of the research study is to perform a reliability and availability analysis of the six main conveyors in the Svea coal mine. The reason for this is to. i) increase the understanding of failure and repair patterns in the main conveyor system, ii) estimate the reliability and maintainability characteristics of the main conveyor system, and iii) identify the critical subsystem which will require improvements or modifications of its operating environment or maintenance routines.

In order to complete this objective, a methodology has been used as presented in Figure 5, in chapter 2. After data collection, sorting and classification, the second step of the analysis is component failure frequency analysis. Based on this, the failure causes and their frequency was obtained. The failure causes from the data was sorted so that the number of occurrences for each general failure could be presented in a Pareto diagram, as presented in Figure 21 and Figure 22.

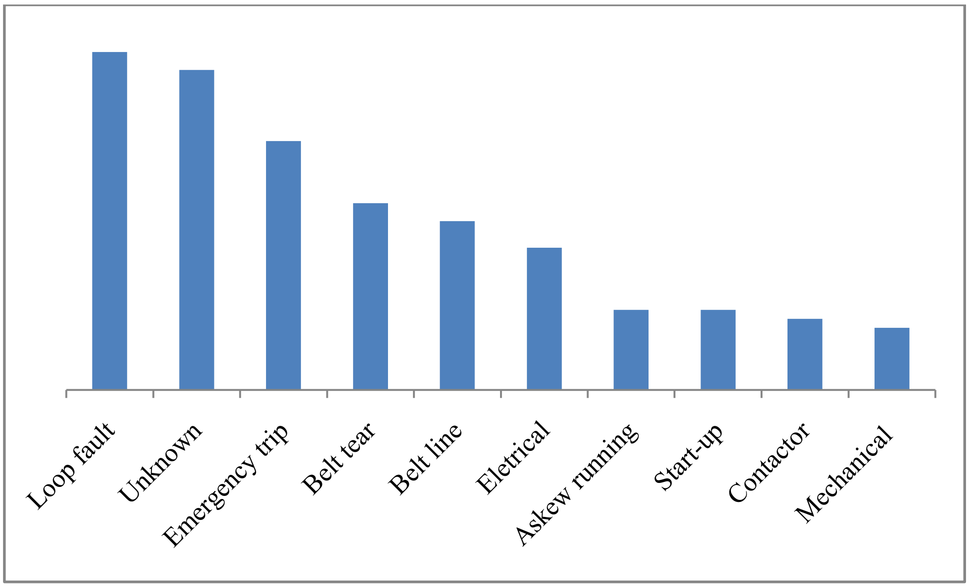


Figure 21 – Pareto diagram of failure causes for the conveyor H4

As H4 had the highest number of frequency, a Pareto diagram was made for this and for the main conveyor system.

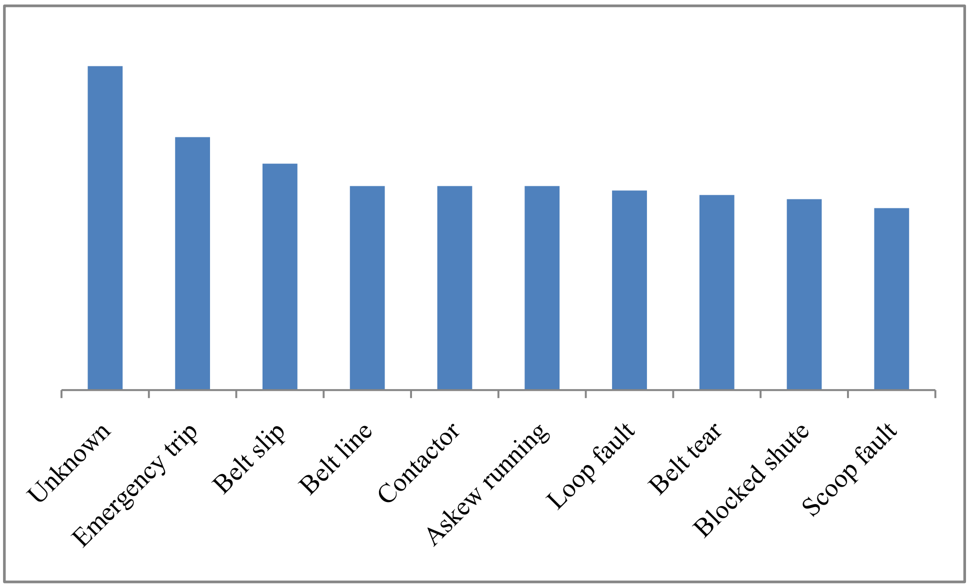


Figure 22 – Pareto diagram of failure causes for the main conveyors

It is not easy to define a single cause as the reason for most of the failures. It should be noticed, that the unknown cause ranks very high. This means that many failures that occur may go unreported. The consequence of this may be that many unnecessary repairs are done on equipment that may be easy to fix. This issue will be discussed more in the data collection chapter.

The result of the data analysis shows that for tree conveyors, Stacker, H3 and H5 the best-fit distribution is Weibull. The value of β is below 1 for all these distributions. This suggests that the conveyors are still in a run in phase and that the failure rate is decreasing.

The conveyors have however been used for a long period, but there may be some explanation to this:

- Due to the high frequency of maintenance work, this can decrease the failure rate
- There may be a wear in as the conveyors have constantly been moved and changed

The result of the Pareto chart in Paper I, figure 2 shows that the conveyor H4 is the cause of most failures. However, as the Table 12 shows, it should be considered that the lengths of the conveyors are different. For example, the Stacker has the lowest number of failures, but the length of this conveyor is 160 meters, which is around 15% of the length of H4. If one compares lengths with failures, one can see from Table 12 that the Stacker is the weakest conveyor. A ratio was made from the lengths divided on frequency of failure.

Table 12 – Length per failure of conveyors

Conveyor	Length [m]	No. Failures	Length per failure [m/failure]
Stacker	160	44	3,64
T1	3100	162	19,14
T2	2700	121	22,31
H3	1650	135	12,22
H4	2700	227	11,89
H5	1400	46	30,43

If SNSK were to improve the failure per meter of the Stacker from 3.63 to 10, the number of failures for 2010 will be 16, and in fact it is 44. The average down time is approximately 30 minutes. If SNSK were to improve the failure of the Stacker from 44 to 16 failures, this will increase the production with 840 minutes. The sales of coal for Svea in 2010 was 1.507 billion USD, by increasing the productivity by 840 minutes SNSK could have made 3.16 million USD more (Store Norske, 2010). Table 12 also suggests that H4 is not the conveyor that should be focus on, as the length compared with failure ratio is the second lowest.

4.2 Effect of the operational conditions

The second objective of the research study is to study and analyze the effect of operational conditions on the reliability performance of mining equipment in Svea.

Figure 6, in chapter 2. In order to study the effect of operational conditions on the Stacker, the methodology presents the following steps:

- Definition of boundaries, assumptions, and data collection.
- Identification and formulation of covariates.

- Identification of an analysis approach and estimation of component characteristics.
- System modeling and throughput capacity analysis

These steps are done and presented in paper II. The results of the study found the hazard rate of the stacker should be written as:

$$h(t,z) = h_0(t)\, exp(1{,}565 z_{20})$$

Equation 19 – Hazard rate for the Stacker during winter season

Based on this equation, it can be concluded that during winter the hazard rate is 4.78 times higher than the hazard rate in the rest of the year. An interesting point of view is that the PHM analysis did not directly include temperature, as the covariate was month of failure. Figure 23 presents a result from a different analysis done. This only plotted temperature based on month with frequency of failures. This figure validates the results of the PHM, as one can see, the failures increase rapidly during winter season (December, January and February).

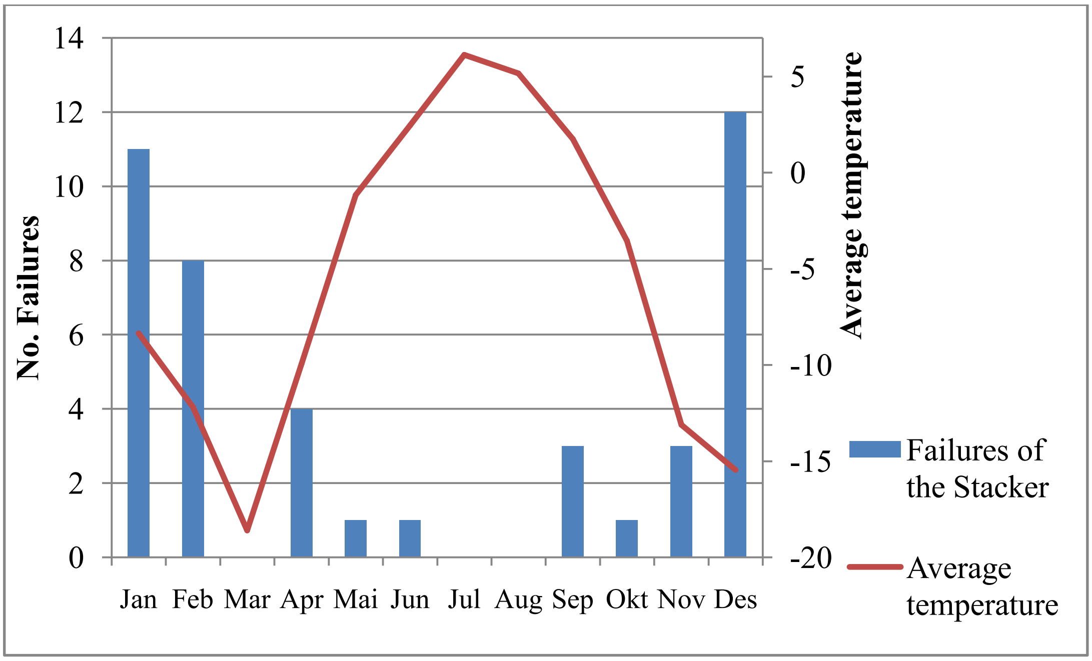


Figure 23 – Frequency of failure with temperature

One should note that in March the shearer was moved, and in July and August there were a summer vacation.

4.3 Data collection

The third objective of the research study is to review the data collection system of the mine and improve it based on the results of this study. Data collection is essential to the methodologies used in this research study. Therefore, the data collection should be focused on as this dictates much of which type of results one can give and the accuracy of the results.

The system for data collection in Svea is adequately. However, some improvements can be done in order to improve the profitability of the system greatly. The regular availability analysis needs some basis information. Most commonly this is the TBF and TTR data, which is recorded in the collection system. The system lacks an accurate time of failure. This analysis is therefore made an assumption that the failures are distributed throughout the day of failure, as date is the only recorded time of failure. This research study found that the hazard rate changed significantly during the winter season. The operational condition in Svea is not recorded. This results presents a finding of which should be considered. One could use standards such as ISO 14224, all tough made for gas and oil production, this can be a basis for building a improved system of data collection in Svea.

In order to improve the Stacker, or other equipment, some collection of covariate data should be collected. We have seen that operational conditions can as seen from the results affect the system greatly. The Stacker is the only conveyor located above ground and is therefore exposed to environmental effects. But it would be interesting to research the effects of covariates below ground, measurements of dust, vibration, rock etc.

5 Conclusion

The aim of this chapter is to present the main conclusions and contribution of this research study. It also suggests future research.

5.1 Conclusions

Based on the previously discussed chapters, it can be concluded that the research produced the following results:

- Data collection of Svea
- Availability analysis of the main conveyors in Svea
- Reliability analysis considering environmental effects of the Stacker in Svea
- Suggestion of measures to improve data collection in Svea

Based on the results and discussion, the following can be concluded for the main conveyors in Svea:

- The availability is high, even with a high frequency of failures, the repair time is low keeping the availability high
- With the high frequency of failures, the reliability is low which needs improvement
- The time of failure for the Stacker is heavily dependent on the season (Winter, Summer, Spring or Fall)
- Improvement of the data collection should be done

It may seem like the bulk of maintenance is done as correctively, as known, this maintenance is unscheduled and unplanned. It may therefore be a high cost related to the high frequency of failure. Maintenance costs may by lowered by increasing the preventive work for the conveyors. With these conclusions it could make an argument that a considerable amount of money can be saved by improving the reliability more as there is many repair operations. From the discussion that by improving the Stacker to the same level as the other conveyors, a considerable amount of money can be saved.

The effects of operational conditions were found to be significant for the Stacker. This should be improved. Generally there are two options for improving the Stacker, increase the maintenance of the work during winter season or winterize the Stacker. A mix of these can also be used. However, the cost of improvement should be considered for the decision.

Data collection in Svea should improve in order to make a more accurate analysis. The available data is good enough to do an analysis, but the accuracy of the analysis may be inaccurate. An argument for this statement is the fact that the unknown cause of failure ranks high both in components and in system reports. Also, the fact that sometimes the time of failure is not recorded should be included in the reports. An interesting subject to research and for the company should be to collect covariate data for the Stacker and other equipment in the mine. In order to study the operational conditions effect on the performance of equipment, the result of such an analysis can contribute to make better decision making with respect to operations and maintenance planning and optimization of the equipment.

5.2 Research Contribution

This research study has contributed with:

- Better understanding of the effects harsh arctic climate has on equipment
- The use of the PHM in a case study
- The effects of time independent covariates on a Stacker in Svea
- A reliability case study and a PHM case study, representing the need for better data collection of covariates
- A thesis that can be used for educational purposes
- A thesis that can assist engineers, managers and experts to predict the reliability and factors affecting it

5.3 Suggestion for Further Research

With the papers presented and the work done in this thesis, the following points for future research are presented:

- Development of methodology for practically using the PHM to improve the systems reliability and availability
- Study the effect of cold climate over a longer time period on the Stacker
- Investigation of covariates that affect the system in Svea
- Improvement of the data collection system in Svea
- Improvement of covariate data collection in the Svea area
- Understand how the failure of the Stacker affects the conveyors and subsystem further inside the mine. There is a start-up procedure that will delay the start of the systems after a failure

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Appended papers

Paper I

Reliability analysis of conveyors: a case study of the main conveyors in the Svea coal mine

Furuly, S., Barabady, J. and Barabadi, A.. Submitted for publication in the Journal of Mining Science.

Reliability and maintainability analysis of the main conveyor in the Svea coal mine of Norway

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Abstract

Reliability and maintainability of mining industry is more in focus than ever, the mining systems are becoming more complex and the equipment more expensive to repair or modify. Unplanned failures can result in significant costs, especially when the machinery is hard to repair or spare parts are far away. This paper presents a case study describing a reliability and maintainability analysis of the main conveyor system of the Svea coal mine located in Svalbard, Norway. The conveyor system includes several separate conveyors. In this study, the main six conveyors of the whole system were selected for the analysis. The failure and repair data of the conveyors were collected for the whole year of 2010 using maintenance and daily reports. The date was analyzed and the result shows that the availability of six conveyers are 96.44% for one year of operation. However, reliability of these conveyers needs to be improved.

Keywords: Reliability, Maintainability, Availability, Conveyor, Coal Mine

1. Introduction

The history of mining can be traced back several thousands of years, the methods and equipment used were inefficient, required many workers and the gain was small amounts of goods. In modern times there are millions of employees, and the turnover of the mining industry is in the billions, the amount of money spent on equipment is also very high, and the demand for high quality and production has increased. The mining equipment are increasing in size and complexity, and this demands a higher level of performance and reliability of the mining equipment[1]. Therefore, the optimizing of a mine production line is more demanding and complex than ever. Furthermore, there is an expectation that mining equipment and technology are supposed to be available at all times, ready for use and have a high level of reliability and availability performance. A mine production line consists of several subsystems and components. Each subsystem and each component affect the total availability, and reliability performance of the total production line[1].Therefore, the performance of each subsystem and component should be analyzed in order to determine how each subsystem and component affects the availability and reliability performance of the whole production line. The result of such an analysis will help to identify the weakest areas of the mine production line and also increase the knowledge about the system. With this knowledge one is more capable of making decisions when changing the system or operating circumstances. Therefore, a focus on a reliability, maintainability and availability analysis is critical for the improvement of the mining equipment performance ensuring that it is available for production as per production schedules. Hence , several studies have been performed to determine the reliability of mining machines such as load haul-dump (LHD) machines [2, 3],longwall face equipment[4], and crushing plants [5] in an underground mine. Reliability and maintainability assessments of repairable mining machines have been reported in some papers[5-7]. The results of these studies show that reliability and maintainability analyses are very useful for planning and deciding maintenance intervals as well as improving mining equipment. The aim of this paper is to perform a reliability and availability analysis of the six main conveyors of the Svea coal mine in Svalbard, Norway, in order to: i) increase the understanding of failure and repair patterns in the main conveyor system, ii) estimate the reliability and maintainability characteristics of the main conveyor system, and iii) identify the critical subsystem which will require improvements or modifications of its operating environment or maintenance routines.

The paper is organized as follows: Chapter two contains an explanation of the system, information about the system and practical information relevant to the analysis. Chapter three deals with the methodology used in order to define the reliability and availability of the system. The data collection, evaluation and processing are all included. Chapter four presents the data and results from the analysis. Finally, chapter five concludes the paper.

2. Case description

The mine in focus is located in Svalbard and is operated by Store Norske Spitsbergen Kullkompani (SNSK) AS. Therefore, there is a significant time span from the order of spare parts until they are received. The company extracts coal from a mine called Svea. The mine was first opened in 1917, later closed and reopened in 1999 for modern mining. The method of mining is the mechanized longwall method, which includes several subsystems such as a drum shearer, armored face conveyors, mine bolters etc. The throughput capacity of the mine is related to the reliability and maintainability of different operating subsystems of the mechanized longwall method. Figure 1shows the reliability block diagram of the mine.

The mine has three different production lines. The first line of the production is the mechanized longwall mining method, and the longwall shearer has a face of 250m. The second line is a Mine Bolter (MB), which prepares new fields for the shearer. The third line of production is continuous mining, which utilizes a Continuous Miner Machine (CMM) with a large rotating steel drum. In this mine, the mine bolter (MB) cutting machine is making a tunnel towards a possible new mining field. The names and codes of the different subsystems and equipment of the mine are presented in Table.

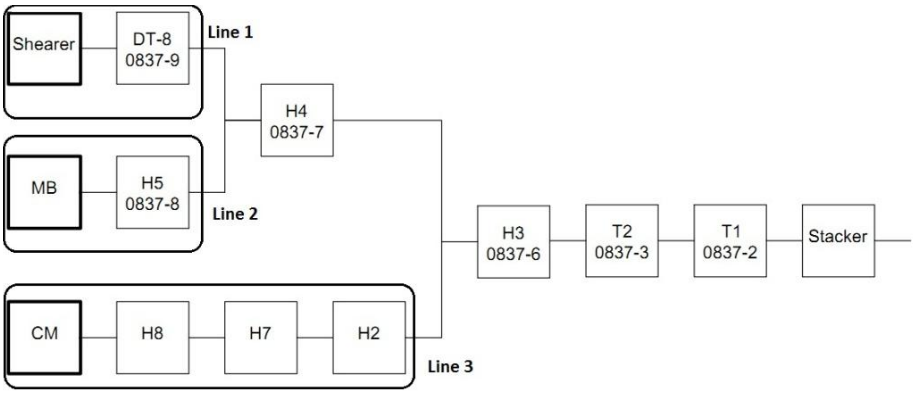


Figure 1. Reliability Block Diagram of the Svea coal mine

The preliminary analysis of the failure data of the mine shows that the number of failures of the conveyor subsystem is higher than the failures of other subsystems of the mine. Therefore, in the first step, it was decided to apply the concept of reliability analysis for the conveyor. The conveyor subsystem of the mine can be divided into several conveyors, which may be changed, moved and serve different purposes. For this study, it was decided to narrow the reliability analysis of the conveyor subsystem of the mine to the part that will be operated for the longest period of time, namely the Stacker, T1, T2, H3, H4 and H5. The selected conveyors will also be the most static ones, not moving in the mine to follow other equipment. These conveyors will also be used for mining in another section of the mine in the future.

Table 1 - Subsystems of the mechanized longwall method used in the SNSK mine

Name	Code	Function	Studied	Length(m)
Shearer	SH	Cutting coal		
Mine Bolter	MB	Development work		
Continuous Miner Machine	CMM	Development work		
Conveyors	DT-8	Transport of coal		
	H5	Transport of coal	X	1400
	H4	Transport of coal	X	2700
	H3	Transport of coal	X	1650
	T2	Transport of coal	X	2700
	T1	Transport of coal	X	3100
	Stacker	Transport of coal	X	160
	H2	Transport of coal		
	H7	Transport of coal		
	H8	Transport of coal		

The mine is worked in two shifts, and during non-production periods of the mine, maintenance crews take oil samples, do vibration tests and use infrared cameras to make decisions about whether or not they should do preventive maintenance. The system, as shown in Figure 1, is operated from a control room outside of the mine. The conveyors are operated by an operator that controls all the units inside the mine. On the MB, CMM and shearer there are operators that control the operations, but the control room has data fed from these machines to know the status. In order to calculate the reliability and maintainability characteristics of the main conveyors, it is assumed that:

1. the system is repairable
2. the system is subjected to repair and maintenance
3. the time to repair includes all waiting and logistic time
4. the repaired components are as good as new

3. Methodology and data collection

3.1 Methodology

The formal definition of reliability according to[8]is “the ability of an item to perform required functions under given conditions for a given time interval”. The reliability and maintainability characteristics of the mining equipment can be determined by the analysis of time between failures (TBF) and time to repair (TTR) data sets. In this paper, the methodology which is used for the reliability and maintainability analysis of the conveyors of the SNSK includes the following steps:

1. understanding of the system and identification and coding of subsystems and faults
2. collection, sorting and classification of TBF and TTR data for each conveyor
3. data analysis for verification of the identically and independently distributed assumptions
4. fitting a theoretical probability distribution to the TBF and TTR data set of each conveyor
5. estimation of the reliability and maintainability parameters of each conveyor with a best-fit distribution
6. identification of critical subsystems

3.2 Data collection, sorting and classification

Data are essential in order to determine the reliability and maintainability performance of a system. The data used in this study have been collected, sorted and classified for a period of 1 year, 2010, for the conveyors of the SNSK mine using daily reports, operation and maintenance cards, and discussions with the experts in the mine. In the mine, there is every day a meeting between the chiefs of operations where halts are discussed and reported in a form. When processing the data some assumptions had to be made. The first one was that every failure that is reported in the form is considered as a failure for the analysis. The form contains the systems and subsystems affected, TTR and a failure comment. Sometimes, the form does not report the time of day that the failure occurred. Therefore, the assumption was made that the failures were distributed throughout the day. An example of the information of the 20 first failures and repairs of the Stacker conveyor is shown in Table.

Table 2 - Examples of TBF and TTR data for the Stacker

Frequency	Date of failure	Time of failure	Date of repair	Restored time
1	17.01.2010	06:20	17.01.2010	06:40
2	17.01.2010	12:40	17.01.2010	13:40
3	18.01.2010	09:30	18.01.2010	09:43
4	23.01.2010	09:30	23.01.2010	09:40
5	24.01.2010	04:45	24.01.2010	05:19
6	24.01.2010	09:30	24.01.2010	09:36
7	24.01.2010	14:15	24.01.2010	14:29
8	25.01.2010	06:20	25.01.2010	06:34
9	25.01.2010	12:40	25.01.2010	12:56
10	26.01.2010	04:45	26.01.2010	04:48
11	26.01.2010	09:30	26.01.2010	09:43
12	26.01.2010	14:15	26.01.2010	14:35
13	27.01.2010	06:20	27.01.2010	06:34
14	27.01.2010	12:40	27.01.2010	12:55
15	28.01.2010	09:30	28.01.2010	09:47
16	29.01.2010	06:20	29.01.2010	07:05
17	29.01.2010	12:40	29.01.2010	12:52
18	30.01.2010	06:20	30.01.2010	06:40
19	30.01.2010	12:40	30.01.2010	12:55
20	01.02.2010	06:20	01.02.2010	10:35

Depending on the market, the mine may produce in two shifts or one shift. Each shift lasts 9.5 hours. If it is necessary, the preventive maintenance is done during the period without production. For SNSK a failure is defined as any event that causes an operator or the equipment to stop production. SNSK claims to run the system as long as possible in order to use the scheduled downtime to do maintenance if they know there is an error in the system.

From the historical data, a Pareto diagram of failures was made, as shown in Figure 2. From this figure it seems that the conveyor H4 is the cause of most failures. However, as the Table 1 shows, it should be considered that the lengths of the conveyors are different. For example, the Stacker has the lowest number of failures, but the length of this conveyor is 160 meters, which is around 15% of the length of H4.

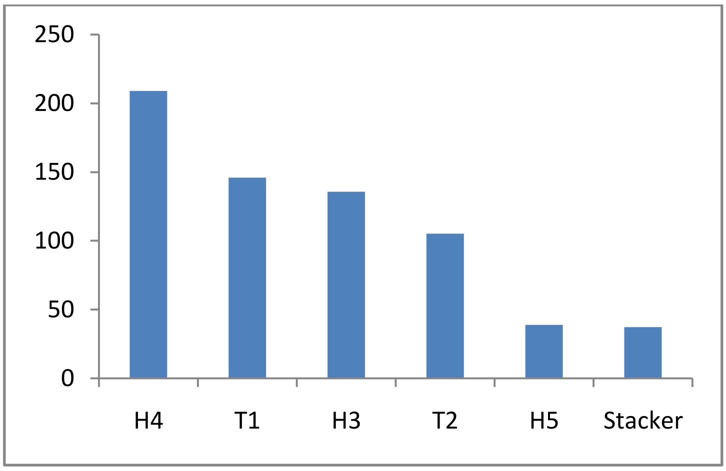
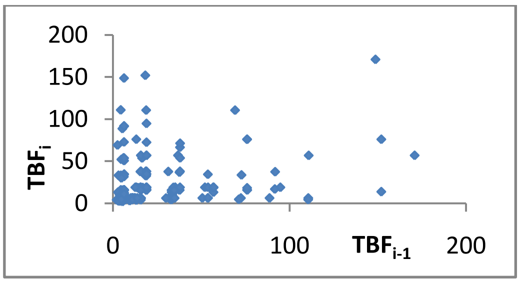


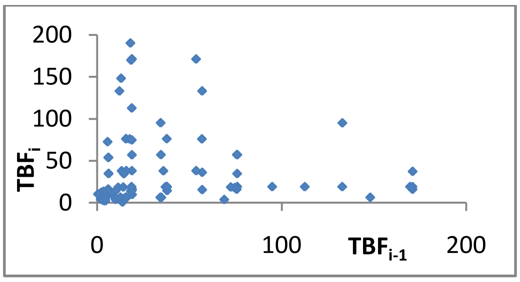
Figure 2. Frequency of failure for the conveyors of the mine

3.3 Data evaluation

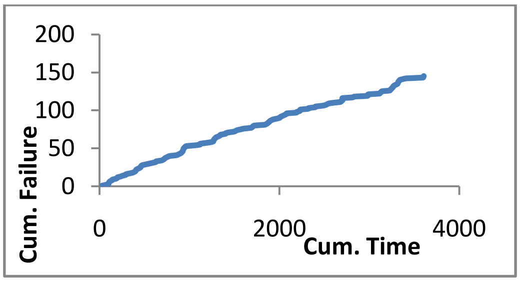
The next step after the data collection, sorting and processing is to validate the assumption that the data are identically and independently distributed (iid) for each conveyor. Two common methods used to validate the iid assumption are the trend test and the serial correlation test. If the assumption that the data are independent is not valid, then classical statistical techniques for a reliability analysis may not be appropriate, therefore a non-stationary model such as non-homogenous Poisson process (NHPP) must be fitted [5]. A trend test involves plotting the cumulative failure number against the cumulative time between failures, and if the data fit a linear line, the assumption of identical distribution is valid. The serial correlation test is a plot of data pairs (TBF_i, TBF_{i-1}) for i = 1, 2... n, where n is the total number of failures. If the TBF data sets are dependent or correlated, the points should lie along a line or a curve. Trend tests and serial correlation tests were carried out on TBF and TTF data sets of each conveyor. In these tests, weak or non-absolute trends were found for all data sets, and the results of the serial correlation test show that all data sets are independent. Therefore, the iid assumptions are justified for the TBF and TTR data of the conveyors. Due to paucity of space, the trend tests and the serial correlation tests of the H4 and the Stacker, for example, are shown in Figure 3.



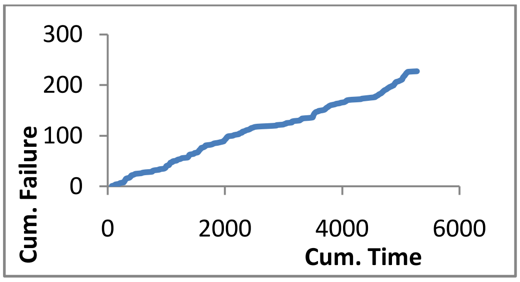
a – Correlation test for TBF of the Stacker



b – Correlation test for TBF of the H4



c – Trend test for the TBF of the Stacker



d – Trend test for the TBF of the H4

Figure 3.Serial correlation and trend tests for TBF data of the H4 and the Stacker

4. Data analysis

The TBF and TTR data are further analyzed to determine the accurate characteristics of the failure and repair time distributions of each conveyor to estimate reliability. Therefore, different types of statistical distributions were examined, and their parameters were estimated by using Reliasofts Weibull++ 7 software. Table 3 and Table 4 show the best-fit distributions for the TBF and TTR of each conveyor respectively. The decision weight ranking (DESV) is used to decide what distribution gives the best fit. The DESV ranks the different distributions by multiplying the best regression fit, this is the DESV number. It was also decided that if the Weibull 3 parameter was the best-fit distribution for a set of data with the gamma parameter less than one, it should not be considered for the analysis.

Table 3. Best-fit distribution for TBF data

Sub-system	DESV- Decision weight ranking					Best-Fit	MTBF (hours)	Parameters
	Exponential 1 Parameter	Exponential 2 Parameter	Log-normal	Weibull 2 parameter	Weibull 3 parameter			
Stacker	470	430	180	300	120	Weibull 3 parameter	149,16	Beta= 0.57; Eta = 89.72 Gamma=4.44
T1	390	400	120	360	180	Lognormal	37,26	LMean= 2.91: LStd = 1.9
T2	440	400	100	360	200	Lognormal	52,59	LMean= 2.97: LStd = 1.4
H3	390	400	150	360	150	Weibull 3 parameter	39,96	Beta= 0.67; Eta = 28.76 Gamma=1.86
H4	390	400	100	360	200	Lognormal	25,97	LMean= 2.68: LStd = 1.08
H5	420	480	170	300	130	Weibull 3 parameter	132,36	Beta= 0.56; Eta = 78.75 Gamma=1.85

Table 4. Best-fit distribution for TTR data

Sub-system	DESV- Decision weight ranking					Best-Fit	MTTR (hours)	Parameters
	Exponential 1 Parameter	Exponential 2 Parameter	Log-normal	Weibull 2 parameter	Weibull 3 parameter			
Stacker	420	480	200	300	100	Lognormal	0.54	LMean= -1.47: LStd =1.31.31.3
T1	390	400	120	360	180	Lognormal	0.33	LMean= -1.8: LStd =1.161.16
T2	390	480	100	330	200	Lognormal	0.49	LMean= -1.59: LStd =1.3 1.3
H3	390	450	100	360	200	Lognormal	0.17	LMean= -2.2: LStd = 0.94
H4	390	430	150	330	150	Lognormal	0.27	LMean= -2.08: LStd = 1.24
H5	390	450	360	300	200	Lognormal	0.12	LMean= -2.52: LStd = 0.85

The theoretical reliabilities for each conveyor at the end of different time intervals were computed with the parameters of the best-fit distribution using Weibull++ 7 software package. The results of the analysis are shown in Table 5.

Table 5. Reliability of each conveyor at the end of different time intervals

Time (hours)	Stacker	T1	T2	H3	H4	H5
10	0.8149	0.6951	0.6826	0.6506	0.6355	0.7537
20	0.692	0.4713	0.4931	0.4797	0.3828	0.6455
30	0.6135	0.3399	0.38	0.3732	0.2498	0.5735
100	0.3546	0.0771	0.1229	0.103	0.0363	0.3331

Table 5 shows the reliability of each component with respect to different operation times. For example, H4 has the lowest level of reliability for different times of operation. In order to improve the reliability of each conveyor, a preventive maintenance strategy can be used. Therefore, Table 56suggests different preventive maintenance time intervals according to different levels of desired reliability, such as 0.70, 0.80 and 0.90. For example, in order to achieve 0.80 reliability for the Stacker, maintenance must be done before 10.9 hours of operation, otherwise the reliability of the Stacker will be less than 0.80. However, the cost should be considered in the decision.

Table 6 – Reliability based time intervals for preventive maintenance

Reliability	Stacker	T1	T2	H3	H4	H5
R(t)=90%	6.1767	3.9949	3.2116	2.8534	3.6593	3.1814
R(t)=80%	10.9079	6.743	5.9667	4.9138	5.8726	7.1283
R(t)=70%	19.1578	9.8353	9.3265	8.0182	8.2596	14.323

The total number of failures and breakdown hours and the availability of each conveyor are calculated and tabulated in Table 7.It shows that the availability of all conveyors is more than 99% after one year of operation. Therefore, for improvement of the system, it is more important to focus on the reliability of each conveyor and reduce the number of failures.

Table 7. Frequency of failure, MTTR and availability of components

Subsystem	Frequency	MTTR(minutes)	Availability	Failure %
Stacker	44	0.54	0.9964	6 %
T1	162	0.33	0.9916	22 %
T2	121	0.49	0.9909	16 %
H3	135	0.17	0.9958	18 %
H4	227	0.27	0.99	31 %
H5	46	0.12	0.9992	6 %

5. Conclusions

Reliability and maintainability analyses should always be an integral part of mining engineering and management for the effective utilization of mining equipment. One should take the subsystem with low level of reliability seriously and consider for example making changes to the maintenance policy of such subsystem for improvement. The result of the analysis shows, in general that the reliability of the main converter system is low and the H4 has the lowest level of reliability with mean time to failure equal to 25.97hours. However, despises the low reliability the conveyors system, it has a high availability. This can be explained by this fact that the maintainability of the conveyers is high. The lowest maintainability is related to the Stacker which is located outside the mine. It is seem that the operation condition may have significant effect on the maintainability of the Stacker which needs to investigate more.

Acknowledgements: The authors wish to acknowledge the contribution of engineers and managers of the Svea coal mine for the data collection discussions as well as for the financial support for traveling to the mine and the facilities that were used there.

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Paper II

Reliability analysis of mining equipment considering covariates effect-A case study

Furuly, S., Barabady, J. and Barabadi, A., Submitted for publication in the International Journal of Performability Engineering

Reliability analysis of mining equipment considering operational environments- A case study

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Abstract: The failure of the complex, sophisticated and so expensive mining equipment may have a lot of consequences on production costs, safety and the environment. Hence, the reliability analysis is required to predicate the failure time and hazard rate of mining equipment. Mining activities, in general, are carried out in complex and uncertain environments. In such operational environments there are many factors (e.g. ineffective blasting, weather, maintenance strategy, geology etc.) that can directly or indirectly affect the hazard rate or reliability performance of the mining equipment. Therefore, the statistical approach for reliability analysis must be selected in such a way as to be able to quantify the effects of the all those influence factors. In this paper the application of a Proportional Hazard Model (PHM) in order to quantify the effects of climate conditions on the hazard rate of the Stacker belt in The Svea coal mine – in Svalbard, Norway –are discussed. The result of the study shows that the hazard rate of the Stacker belt in winter can be four times more than the rest of the year, which needs to be considered in the maintenance plan of the mine.

Key words: *Reliability performance, operational environments, proportional hazard model, Stacker*

1. Introduction

In the mining industry there are millions of employees, and the turnover of the mining industry is in the billions. Furthermore machines used in mining are increasing in size, automation and complexity and becoming more expensive. Hence, there is an expectation that mining machinery is supposed to be available at all times, ready for use and have a high level of reliability. Hence, any factors (e.g. production plans, climate conditions, geology, failure in equipment, maintenance, equipment operators) which can affect the reliability and availability performance of mining machinery need to be identified and quantified. Machinery based in harsh climate conditions is known to have a lower reliability performance. However, the calculation and quantification of the climate conditions has not been widely researched in reliability analyses. The main challenge in quantifying such effective factors is to find the appropriate statistical approach that can incorporate all such influence factors [1, 2].

At present, the most commonly used models for the reliability analyses of a system where the times between the failures are independent and identically distributed, are the Homogenous Poisson Process and the Renewal Process. Furthermore, if the data from a repairable system indicate any form of trend due to deterioration or improvement of the system, the Power Low Process model may be appropriate[3]. These models consider the Time between Failures (TBF) as the only variable of interest. Hence, when the other influence factors have significant effects on reliability these models are not suitable. From a statistical point of view all influence factors on reliability performance of an item are refereed to covariates. Parametric and non-parametric regression models such as PHM and accelerated failure time models can be used to incorporate the covariates effect[4, 5]. The PHM, originally, is processing the reliability of the data without making any specific assumption about the functional form of the baseline hazard rate. Hence, the PHM has been used in diverse areas in the reliability engineering when there is no clear theoretical reason for positing a particular distribution for baseline hazard rates [6-10].

The aim of this paper is to analysis the effect of operational environment condition on the reliability performance of Stacker belt of Svea coal mine. The Svea coal mine is located on Svalbard- the northern part of Norway- and is operated by Store Norske Spitsbergen Kullkompani (SNSK) AS. The method of mining of SNSK is the mechanized longwall method, which includes several subsystems such as drum shearer, armoured

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face conveyor, mine bolter, etc. Longwall mining is an underground operation. However the Stacker belt as a part of the transportation system of the mine is located outside of the mine where it will be subjected to the climate condition effects. Hence, it is necessary to investigate the climate condition effect on the reliability performance of the Stacker belt, which is the subject of this paper. The paper is organized as follows. In section 2, the adapted methodology for the reliability analysis of the Stacker which is based on the PHM is discussed briefly. In section 3, the reliability performance of the Stacker will be calculated using the PHM, and section 4 provides the conclusions.

2. Methodology

The PHM was introduced in 1972 by D. R. Cox in order to estimate the effects of different covariates influencing the hazard rate of a system[9]. It was primarily applied in the biomedical field. The assumption imposed by the PHM is that the hazard rate of a system is the product of a baseline hazard rate, $h_0(t)$, which depends on time only, and a positive functional term, ψ(βz), which describes how the hazard rate changes as a function of the influence factors or covariates. The PHM in the form of a failure function is represented as[12]:

$$h(t,z) = h_0(t)\psi(\beta z) \qquad (1)$$

where z is a row vector consisting of the covariates and β is a column vector consisting of the regression parameters. The covariate z is associated with the system, and β is the unknown parameter of the model, defining the effects of the covariates. The baseline hazard rate represents the hazard rate which an item will experience when all covariates are equal to zero, $z=0$, and requires ψ(βz)=1. The regression vector β can be estimated by maximizing the marginal, partial or maximum likelihood function. See ref. [3] for more information about these methods.However, the PHM can only handle the effect of time-independent covariates. In recent years, some methods such as the Stratification approach and extension of the PHM, which are derived from the PHM, have been developed to analysis the effect of time-dependent covariates on the reliability performance of a system [13]. Recently, Barabadi et al. (2011)proposed a methodology in order to estimate the effect of covariates on reliability performance of a system based on the PHM and its extension[1] which will be used for this case study. The proposed methodology is based on the following main steps:

- Definition of boundaries, assumptions, and data collection.
- Identification and formulation of covariates.
- Identification of an analysis approach and estimation of component characteristics.
- System modeling and throughput capacity analysis

3. Reliability performance analysis of the Svea coal mine

The Svea coal mine was first opened in 1917, later closed and reopened in 1999 for modern mining.. The normal routine for work shifts is: Shift A from 07:30 to 17:30, Shift M from 17:00 to 03:30 and Shift B from 21:30 to 08:00, where shifts A and B are production shifts, while shift M is a maintenance shift. During production, SNSK tries to postpone (if possible) maintenance to the maintenance shift. During the maintenance shift, maintenance crews take oil samples, do vibration tests and use infrared cameras to make decisions about whether or not they should do preventive maintenance. Depending on the market and the price of coal the planned running period can be varied from 19 or 9.5 hours per day. The system is operated from a control room outside of the mine.

Svea has three different production lines (Figure 1). In production line 1, the coal will be cut by the Shearer, and the coal will be carried out of the mine by the conveyors (DT-8, H4, H3, T2, T1 and the Stacker).In production line 2, the Mine bolter (MB) is making a tunnel towards a possible new mining field; the mine bolter consists of four machines, i.e. two cutters and two bolters. The process is that the cutters cut 1-10 meters and let the bolters secure the roof and walls before the process are repeated. The continuous miner (CM) in production line 3 which is preparing a new face for the shearer is also connected to the main conveyor system as well. As mentioned the Stacker is the only part of the production line of the Svea that is exposed to the climate conditions. The function of the Stacker is to stack the coal outside the mine. Hence, the Stacker needs to raise the coal. Thereafter, from the stockpile the coal will be carried out to the main docks, and then it will be exported to different countries in Europe. The failure data from the Stacker are taken for this study.

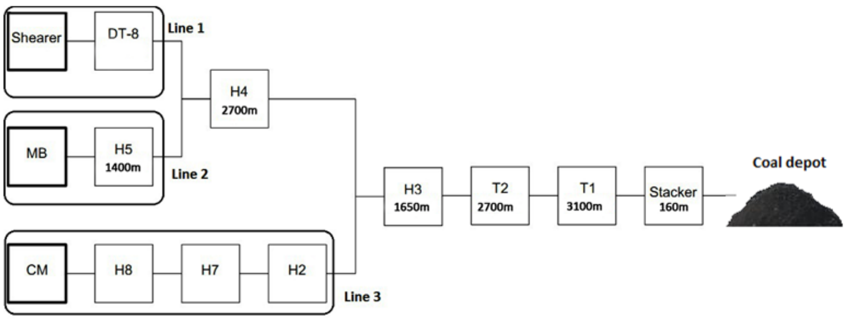

Figure 1 - Reliability block diagram of the Svea production line

3.1 Defining boundaries, establishing assumptions and collecting data

The preliminary analysis of failure data of the mine shows that approximately 6% of the failure in the conveyor line is related to the Stacker. The TBF data set of the Stacker have been collected, sorted and classified for a period of 1 year, 2010, for the main conveyors of Svea. The main sources for data include daily reports, operation and maintenance cards and discussions with the experts in the mine. Although the Stacker consists of several components, the failure data of these components have not been collected in Svea, and all failure data are recorded as failures of the Stacker. Hence, in this analysis the Stacker is considered as a component, and the items which build up the Stacker are out of the boundary. The result of the primary analysis shows that the data are identically and independently distributed. However, in order to calculate the reliability characteristics of the Stacker considering the climate conditions, it is assumed that:

1. The system is repairable.
2. The system is subjected to repair and maintenance.
3. The repaired components are as good as new.

3.2 Identification and formulation of covariates

The Svea coal mine is located on Svalbard at approximately 78 degrees north. The mean temperature for Svea in 2010 was -5.37 degrees Celsius, and on one occasion it dropped to -29.2 degrees Celsius. Such low temperature can change the properties of the material and cause an increased hazard rate. For example, low temperatures have a direct effect on lubricants, making them less effective and thus increasing the wear of the moving parts of the Stacker. Also, there are reports of ice and snow blocking the conveyors causing the belts to halt for removal of ice and snow. According to the discussions with experts on the mine and considering the available data such as temperatures from the Svea Airport, months of failure and shifts of failure are considered as the covariates in this study. Furthermore, a binary code is used to formulate the covariates. The months of the failures were considered to be associated with binary covariates from z_{01} to z_{12} respectively from January to December. For the particular time to failure, only one of these covariates will be equal to one to indicate the month in which the failure has occurred. For example, if the failure occurs in January, then z_{01}=1 and z_{02} till z_{12} will be equal to zero. In order to formulate the shift of failure they were considered as binary covariates z_{13} where, z_{13}=1 represents shift A and 0 represents shift B. An example of the information of 10 failures of the Stacker is shown in Table 1. The first row of Table 1 shows that the Stacker has failed after 47.5 hours and from the covariates column it can be found that the failure has occurred in January on shift B.

3.3 Identification of analysis approach and estimation of component characteristics

Identification of analysis approach

As mentioned above, in order to select the appropriate model at the first stage, the time-dependency of the covariate must be checked. Graphical methods and numerical methods can be used to check the time-dependency of the covariates. In general, graphical methods are based on the partitioning of TBF data sets with respect to arbitrary time intervals, or stratification (grouping) of TBF data based on different levels of desired covariates. If the covariates are time-independent, the log minus log survival plot (LML) or the log cumulative failure plot versus time graphs for different selected groups yields parallel curves[1-3].Through the graphical method the LML plot is more recommended. Hence, in this study the LML plot is selected for checking the time-dependency of the covariates. The TBF data set have been grouped based on different time intervals and levels of different covariates. Figure 2 shows the LML plot when the data are grouped based on the temperature above and below -9°C. The result of the analysis shows that the LML plot for such different groups can be considered as a parallel curve which means that the covariates are time-independent. Therefore, the PHM can be considered as a suitable model for the data analysis.

Table 1: Example of TBF and covariates data for Stacker

TBF (hr.)	TTR (hr.)	Covariates												
		z_{01}	z_{02}	z_{03}	z_{04}	z_{05}	z_{06}	z_{07}	z_{08}	z_{09}	z_{10}	z_{11}	z_{12}	z_{13}
47.5	1.25	1	0	0	0	0	0	0	0	0	0	0	0	0
17.5	0.25	1	0	0	0	0	0	0	0	0	0	0	0	1
75.5	0.25	1	0	0	0	0	0	0	0	0	0	0	0	1
75.5	0.9	1	0	0	0	0	0	0	0	0	0	0	0	1
184.5	3.3	1	0	0	0	0	0	0	0	0	0	0	0	0
114	0.1	0	1	0	0	0	0	0	0	0	0	0	0	1
16	0.1	0	1	0	0	0	0	0	0	0	0	0	0	1
6	0.8	0	1	0	0	0	0	0	0	0	0	0	0	1
378	0.5	1	0	0	0	0	0	0	0	0	1	0	0	1
18	0.4	1	0	0	0	0	0	0	0	0	0	0	1	1

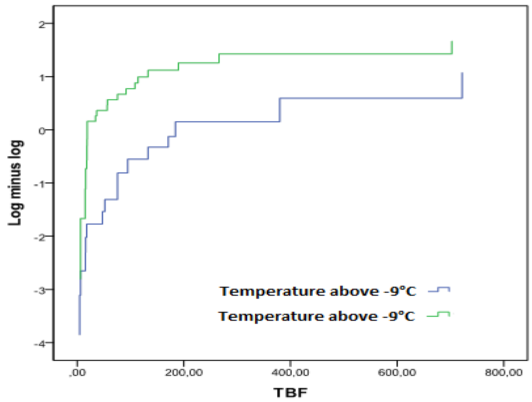

Figure 2: An LML plot of the Stacker based on temperatures above and below -9°C

As mentioned the PHM, originally, has no assumption about the shape of the baseline hazard rate. Under this assumption the PHM is categorized under the non-parametric regression models. However, the PHM has this ability to define a parametric distribution such as the Weibull distribution for baseline hazard rates, known as parametric PHM[1]. Moreover, different functional forms of $\varphi(\beta z)$ can be used. However the exponential form for $\varphi(\beta z)$ is the most widely used because of its generality and simplicity, with regard to the exponential form for $\varphi(\beta z)$ the hazard rate can be written as[1]:

$$h(t,z) = h_0(t)\,exp(\beta z) = h_0(t)\exp\left(\sum_{j=1}^{n} \beta_j z_j\right) \qquad (2)$$

In this study we used the non-parametric PHM and exponential form to model the covariate function $\varphi(\beta z)$.

Estimation of component characteristics

In this study calculations were carried out using the software SPSS. In commercial software such as SPSS, there are two stepwise methods to select a good set of independent variables (covariates),i.e. the forward and backward stepwise. The forward stepwise starts with no variables in the model, trying out the variables one by one, and including them if they are statistically significant. The backward stepwise starts with estimating the parameters for the full model, which include all eligible variables, and it continues with testing them one by one for statistical significance, deleting any that are not significant. The stepwise methods can use the Wald statistic, the likelihood ratio, or a conditional algorithm for variable removal. For both stepwise methods, the score statistic is used to select variables for entry into the model.

In this study the regression coefficient, β was estimated calculating the Wald statistic and its p-value tests using the forward stepwise and the significance of each β. The Wald statistic is calculated by squaring the ratio of the estimate of β to its standard deviation. Normally a p-value of 10% is considered as the upper limit to check the significance of covariates. In this study we consider the 5% as the upper limit. The result of the analysis is shown inTable 2. This analysis indicated that only the effects of Jan. (z_{01}), Feb. (z_{02}) and Dec. (z_{12}) are significant on the hazard rate of Stacker. This analysis showed that the hazard rate of the Stacker in January, February and December will be reduced by the factors equal to 5.1, 5.7 and 4.2 respectively. And based on the result of the analysis the hazard rate for Stacker can be:

$$h(t,z) = h_0(t)\,exp(1{,}639z_{01} + 1{,}747z_{02} + 1{,}43z_{12}) \qquad (3)$$

Table 2: Covariates and their significance in equation

Step	Covariates	β	SE	Wald	Sig.	Exp(β)
Step 1	Jan.	0.72	0.365	3.897	0.048	2.1
Step 2	Jan.	0.967	0.39	6.143	0.013	2.6
	Feb.	1.062	0.439	5.859	0.015	2.9
Step 3	Jan.	1.639	0.487	11.33	0.001	5.1
	Feb.	1.747	0.529	10.898	0.001	5.8
	Des.	1.43	0.469	9.306	0.002	4.2

Table 2 shows that the effects of January, February and December (as the covariates with significant effect) in Svea are not very different. Furthermore, the monthly reporting of the hazard rate is not the most convenient way in order to make changes in the maintenance policy or spare part planning. Hence, based on the result of the analysis the covariate can be defined based on the season of failure, where January, February and December are considered to be the winter season (z_{20}), March, April, October and September to be fall (z_{21}) and May, June, July and August to be summer (z_{22}). The new covariates are formulated by a binary code to show the season of the failure. However, in order to obtain the reliability of the Stacker based on the new defined covariates, the time dependency of new covariates needs to be checked. Using the LML plot, the result of the analysis showed that the new covariates are time-independent. Hence, the PHM can be used for reliability analysis considering the new covariates. Table 3 shows the result of the reliability analysis of the Stacker considering the season of failure as covariates.

Table 3- Covariates and their significance in equation

Step	Covariates	β	SE	Wald	Sig.	Exp(β)

Step 1	Winter	1.565	0.415	14.206	0.0	4.78

Table 3 shows that the only covariate which has significant effects on hazard rate of the Stacker is the winter season. Hence, based on the new analysis the hazard rate of the Stacker can be written as:

$$h(t,z) = h_0(t)\, exp(1{,}565 z_{20}) \qquad (4)$$

Based on equation no. 4, it can be concluded that during winter the hazard rate is 4.78 times higher than the hazard rate in the rest of the year. The PHM has high sensitivity to the omission and the way that the covariate is formulated and any wrong definition of covariate may lead to the wrong result in the reliability estimation. Therefore, it needs to be checked if there is a difference between the failure rates of the Stacker belt when the time of failure as a covariate in defined in two different ways based on month of failure (z_{01} to z_{12}) and season of failure (z_{20} toz_{22}) as mentioned before. The comparison of the hazard function and cumulative hazard for two different way of definition of covariates can be found in Figure 3. It shows that the hazard rates in both cases are equal until 250 hours, and after that the estimated hazard rate based on season of failure is less than the hazard rate based on the month of failure.

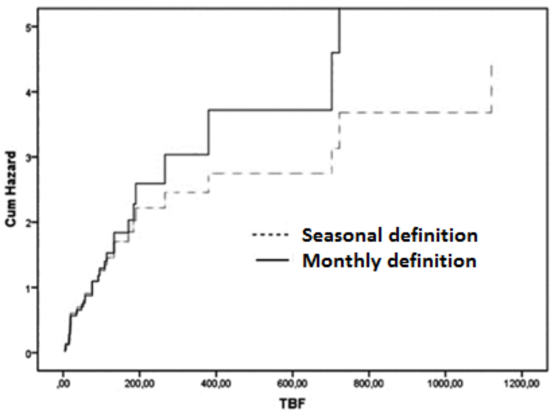

Figure 3 - Hazard function of seasonal and monthly covariates

However, because most of the failures occur before 250 hours it can be said that both ways of definitions of the covariate give the same result. Hence, the seasonal definition of covariate is more applicable and can be used for production planning instead of the monthly definition. Any production planning, maintenance strategy selection or spare part planning for Svea must consider that the hazard rate of the Stacker in winter is 4.781 times higher than the rest of the year.

4. Conclusion

The reliability performance analysis of the Stacker belt shows that the hazard rate of the Stacker increases drastically in winter. Furthermore the shifts of failure have no effect on the hazard rate. For a better performance of the Stacker, it may be concluded that the maintenance strategy needs to be changed in winter which may increase the average time to failure. Further investigation needs to find the reason for the increase of the hazard rate of the Stacker during the winter. To have an effective reliability performance analysis it is very important to collect and explore all the influence factors on the failure mechanism of the components. Furthermore, the formulation of the influence factor must reflect the way which they may affect the failure mechanism. By identifying all influence factors and through the proper definition of these influence factors the PHM can be used for analysing the effects of influence factors on the reliability performance of the components including the mining equipment.

Acknowledgements: The authors wish to acknowledge the contribution of engineers and managers of the Svea coal mine for collecting data for this research study and for helping with discussions as well as for their financial support during the research work.

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