FACULTY OF ENGINEERING

Failure prediction of critical mine machinery

JA JACOBS

orcid.org 0000-0003-0010-1808

Thesis accepted in fulfilment of the requirements for the degree *Doctor of Philosophy* in *Mechanical Engineering* at the North-West University

Supervisor: Dr. HG Brand

Graduation: June 2021

Student number: 24153435

PREFACE

This thesis was assembled and presented in article format. A new practical failure prediction methodology was developed. Three articles, given in the appendices, were constructed from the prediction methodology. The three articles describe the application of a newly developed methodology to three systems, namely mine dewatering pumps, compressors and scraper winch systems. The articles follow a logical flow, indicating the methodology development and application thereof. The authors and all relevant parties provided permission for the use of the articles as part of this doctoral degree.

ACKNOWLEDGEMENTS

I would like to express my gratitude to and acknowledge the following, whose guidance and contributions were critical in achieving this successful thesis:

- God, for always being by my side and always proving me wrong with His greater plan for me. Also, for providing me with a healthy mind and knowledge to have completed this thesis.
- My parents, Rudolf Jacobs and Lizette Jacobs, for their unconditional love and guidance. Thank you for being my emotional filling station and for providing me with continuous support during all the highs and lows.
- My siblings, Rudolf Jacobs and Margorie Jacobs. Thank you for your love, support and understanding during this period.
- My mentor, Marc Mathews, for his expert inputs on the research and write-up of the articles and cover document. Your guidance was crucial to the success of this thesis.
- My co-authors, Hendrik Brand, Charl Cilliers, Kristy Nell, and Jean van Laar, for their invaluable contributions in the write-up of the third article.
- My colleagues at ETA Operations. Also, a special thanks to William Shaw for his friendship and support.
- ETA Operations (Pty) Ltd, Enermanage, and its sister companies for the resources, time and financial assistance to complete this study.

ABSTRACT

Title: Failure prediction of critical mine machinery

Author: Johannes Abraham Jacobs

Supervisor: Dr. Hendrik Gideon Brand

Degree: PhD (Eng.) in Mechanical Engineering, Article Format

Keywords: Pump failure prediction, Compressor failure prediction, Scraper winch failure prediction, Reliability engineering, Reliability improvement, Weibull analysis

The South African mining industry is under immense economic pressure and has been following a negative trend over the last 30 years. It is thus imperative to regain a position at the front end of technological advances in the global market. Today's engineering systems have become increasingly complex to be designed and built while the demand for reliability continues. Various studies have involved reliability analyses in industrial fields based on the evolution of the failure rate of equipment. Proper maintenance strategies are required to achieve maximum reliability.

Both maintenance and reliability have roots in each other's territory. Ultimately, optimising maintenance methods will yield increased system reliability. Typically, maintenance strategies in the mining industry are reactive and cyclic, which can lead to failure creep. These strategies can be improved using a proactive approach, which requires forecasting models. Examples of forecasting models include the Weibull models and the Crow-AMSAA (NHPP) model, which can be represented stochastically by the Weibull process.

Weibull distributions have proven to successfully model failure patterns for various product failure mechanisms, with the most common being the standard two-parameter model. The Crow-AMSAA model is designed for use on systems where the analysis of the reliability growth process is essential. These models have been widely used in the reliability engineering environment, but has not yet been implemented on equipment operating on a deep-level mine in South Africa.

A new practical method was developed for predicting equipment failure using a unique combination of these models, conditional and quantile analyses. The method was applied to mine dewatering pumps, compressors and scraper winches. For each of these components, the base method was adapted to maintain compatibility with the different data set types. The methodology, application and results were documented as three separate articles, which are summarised below.

Mine dewatering pumps – Article I (Appendix B). A new failure prediction methodology was developed and validated on four pumps, operating at different depths. The Weibull analysis was applied to previously installed pumps and successfully predicted the failures of newly installed pumps. Furthermore, the results showed a quadratic relationship between the characteristic life and operating depth of a dewatering pump. Significantly, this correlation quantifies all the factors that contribute to the service life of a dewatering pump.

Mine compressors – Article II (Appendix C). The base methodology was modified to be more generic and applicable to highly reliable equipment. The new methodology was applied to multiple compressors operating at different compressor houses. Furthermore, the results were validated using the leave-one-out cross-validation method. The model successfully predicted the next component breakdown based on the current survival age of each compressor, which yielded an overall average prediction accuracy of 92%.

Mine scraper winches – Article III (Appendix D). The methodology was integrated with the Crow-AMSAA (NHPP) model to predict the number of failures. The ability of the Crow-AMSAA (NHPP) model to make accurate predictions on multi-failure mode systems was leveraged to adjust parameters within the base methodology to predict the actual failure times. An average failure prediction accuracy of 94% was achieved.

THESIS OVERVIEW

The layout of this thesis follows a logical flow pattern consisting of a holistic overview of the current issues faced in the mining industry to a final need for the study. The primary objective of this study is to highlight the importance of system reliability optimisation and to explore the possible maintenance strategies. Fundamentally, reliability is rooted in failure prediction; hence, a failure prediction model was developed, which presents a solution to this problem.

CHAPTER 1: INTRODUCTION

This chapter gives a holistic overview of the current challenges faced in the mining industry. Emphasis is given to the importance of system reliability improvements and how they can be achieved. Furthermore, the chapter presents the novel contributions and indicates the current operations in industry, the limitations, and solutions to address these issues. Ultimately, this yields the need for the study, which is also described in this section.

CHAPTER 2: LITERATURE SURVEY

The literature survey follows the inverted triangle research principle. This section starts with a broad overview of the life cycle and reliability of equipment. Thereafter, the importance of and need for assessing reliability are highlighted. Following this, literature is provided on the development of models involving reliability, how they are constructed and applied.

In addition, a brief overview is provided on the failure prediction method, which was studied more extensively in the appended articles. Finally, research was conducted on critical mine machinery, with emphasis on the functional and economic impact on mining operations. The research highlighted the need for failure prediction, which led to the formulation of the research questions for the appended articles.

CHAPTER 3: PUBLICATIONS SUMMARY

This section provides a summary of each research article. The articles are discussed briefly and the highlights and novelty of each are given.

CHAPTER 4: CONCLUSION

In this chapter, a summary and conclusion are provided with regards to the final results and novel contributions. Furthermore, from the results obtained from the articles, future research is presented.

LIST OF PAPERS

This thesis was compiled and assembled based on an article format structure. It consists of three articles, which are indicated with Roman numerals throughout the document.

I. Jacobs, J.A., Mathews, M.J. & Kleingeld, M. Failure prediction of mine de-watering pumps. *J Fail. Anal. and Preven*. 18, 927–938 (2018).
Available online: https://doi.org/10.1007/s11668-018-0488-3

II. Jacobs, J.A., Mathews, M.J. & Kleingeld, M. Failure prediction of mine compressors. *J Fail. Anal. and Preven*. 19, 976–985 (2019).
Available online: https://doi.org/10.1007/s11668-019-00684-0

III. Jacobs, J.A., Brand, H.G., Cilliers, C., Campbell, K., Mathews, M.J. & Van Laar, J.H. Failure prediction of mine scraper winches. *In Press*.

The technical integrity of each paper was the responsibility of the student, J.A. Jacobs. The co-authors, Dr M.J. Mathews, Dr M. Kleingeld, Dr H.G. Brand, Dr C. Cilliers, Dr K. Nell (Campbell), and Dr J.H. van Laar, provided permission to submit the articles as part of this thesis. Appendix A contains the permissions of all authors and relevant parties.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

CDF	Cumulative distribution function
CMMS	Computerised maintenance management systems
Crow-AMSAA	Crow-Army Material System Analysis Activity
CVM	Cramér–Von Mises
EMF	Electromotive force
GOF	Goodness of fit
LCC	Life cycle cost
LOOCV	Leave-one-out cross-validation
MLE	Maximum likelihood estimation
MTBF	Mean time between failures
NHPP	Non-homogeneous Poisson process
OSL	Observed significance level
PDF	Probability density function
SCADA	Supervisory Control and Data Acquisition
TTF	Time to failure

1. INTRODUCTION

1.1 BACKGROUND

The economic contribution of the South African mining industry has been following a negative trend over the last 30 years [1]. The mining sector's contribution to the overall gross domestic product of South Africa has reduced from 22% in 1980 to 6.8% in 2017 [1], [2]. Rapidly rising costs, controllable or not, keep eroding profitability in this sector [2]. It is thus imperative for mines to regain a position at the front end of technological advances to stay competitive in the global market.

With globalisation, competitiveness is regarded as one of the most important elements that yield high probable market success [3]. Consequently, the mining industry must be subjected to modernisation. Six programmes were set in motion in 2017, which include mechanisation and real-time information management systems [4]. Mechanisation is expected to enable profitable gold-mining operations well beyond the year 2045, see Figure 1 below [4].

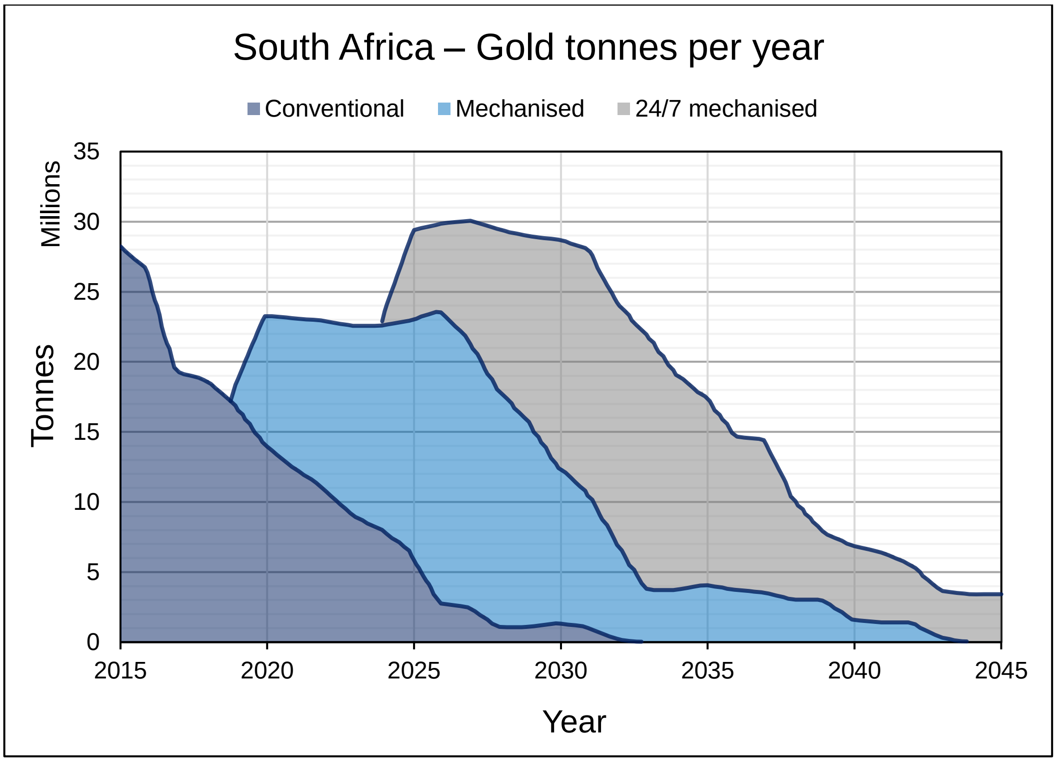


Figure 1: Estimated benefits of using fully mechanised mining techniques, operating 24/7 [4]

It is evident that mechanisation and automation will contribute considerably to the productivity of the mining sector. However, unexpected equipment failures and imperfect planned or routine maintenance can possibly impede maximum equipment utilisation, which will require a significant amount of extra capital investment [5].

Mining equipment capital costs for a given operation typically depend on the size of the mining company and the number of shafts in operation. Essentially, these large investments require optimum equipment usage such that operating costs are minimised [6].

Maintenance is one of the primary contributors that consume a significant proportion of the operational costs in the mining industry. These costs account for approximately 30% to 50% of direct mining costs [7]. Conventional maintenance strategies such as preventive and planned maintenance are scheduled periodically based on the planner's experience and historical failure data [8].

Ultimately, these strategies can result in failure creep, which will result in decreasing reliability [9], [10], [11]. Improving equipment reliability extends longevity at the least cost, which is achieved by using a reliability-centred maintenance strategy [12]. Successful implementation thereof requires an understanding of equipment failure and how it occurs [12].

The definition of failure, which is generally defined as a complete refurbishment, can also be an event that deviates from normal operation. Therefore, it is entirely up to the person conducting the analysis [12]. Regardless of the definition, failure is difficult to quantify and it is further challenging to predict a probable time of occurrence because reliability always involves uncertainty as the time of failures are unknown although the probability of failure exists [13].

Therefore, if failures cannot be averted, the total costs of keeping the equipment in reliable condition are influenced as a result thereof [12]. Costs involving unplanned equipment failure can be 300% more than the maintenance cost that could have avoided the failures, see Figure 2 [12]. It is thus vital to prioritise a proactive maintenance programme over a breakdown maintenance programme to reduce the potential for personnel injury and increase equipment availability [14].

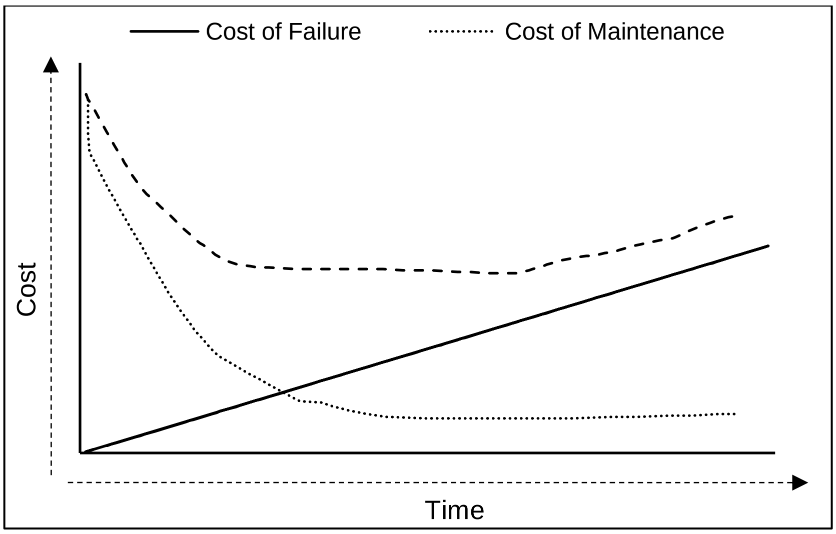


Figure 2: Total equipment costs in relation to maintenance and failure costs

A combination of condition-based models can be used to attempt failure prediction [15]. These models typically require a significant amount of field data, which is sometimes challenging in the mining industry. In most cases, only high-level data can be obtained, ultimately inducing the adoption of simplified models. Such models include the Weibull models and the Crow-Army Materiel Systems Analysis Activity (Crow-AMSAA) Non-homogeneous Poisson Process (NHPP) model, both of which are well known for representing lifetime distributions in the reliability engineering environment [16], [17].

WEIBULL DISTRIBUTION

Weibull formulated the Weibull distribution in 1937 there after he delivered his hallmark American paper on this subject in 1951. According to Weibull, the application of this distribution could be adapted to a wide range of problems. However, during this time, the reaction to his paper was extremely negative – varying from scepticism to outright rejection [16].

However, Shainin and Johnson, pioneers in this field, applied and improved the technique. Ultimately, the United States Air Force recognised Weibull's work and funded the research until 1975. Consequently, the Weibull analysis is now regarded as the leading method in the world for fitting and analysing life data [16].

One of the primary advantages of the Weibull analysis is its ability to provide reasonably accurate failure analysis and forecasts with extremely small data samples [16]. Depending on the data set, it is described by either the standard Weibull, the three-parameter Weibull or the mixed Weibull distribution [18].

The first indication on the nature of how the data set is distributed can be illustrated quickly by the Weibull probability plot on a log-log scale. It is, however, important to ensure that the data can indeed be described by the Weibull distribution. To achieve this, the data set must further undergo a goodness-of-fit (GOF) test, with the Anderson–Darling GOF test being used most widely.

Ultimately, if the data set follows a straight line and the GOF test is conducted successfully, the Weibull analysis can be implemented. From this, multiple Weibull-related functions can be used in conjunction with quantile analysis to attempt failure prediction.

CROW-AMSAA (NHPP)

In 1964 Duane published an article that described the failure data of different systems during their development programmes. It was found that the log-log plot of the cumulative mean time between failures (MTBF) versus the cumulative operating time followed a straight line. Based on this observation, Duane developed a two-parameter model to predict the expected reliability growth in an equipment development programme [19], [20].

Following this research, Crow noted in 1974 that the Duane model can be represented stochastically by the Weibull process. This allowed for statistical procedures to be used in the application of this model in reliability growth. Consequently, this method is presently known as the Crow-AMSAA (NHPP) model [20], [21].

The Crow-AMSAA (NHPP) model mainly involves reliability growth plots and modelling repairable systems, which are useful for mixed failure modes [22]. To apply the Crow-AMSAA (NHPP) model successfully, however, requires the historical failure events to be dependent and not identically distributed, which typically involves human interaction [20], [23].

With the data set in the correct format, the maximum likelihood estimation is used to estimate the Crow-AMSAA (NHPP) parameters. Afterwards, the Cramér–Von Mises (CVM) GOF test must be applied to the data set with confidence bounds using the Fisher Matrix. Thereafter, the final model is integrated into existing maintenance strategies to produce a proactive framework. Consequently, equipment reliability can be improved and operational costs can be reduced. Therefore, it is important to simplify the process of failure prediction and to produce a generic failure prediction model that can adapt to limited data sets.

1.2 STUDY MOTIVATION

The current economic state of the mining industry is following a downward trend. Rapidly rising costs, controllable or not, keep eroding the profitability in this sector. The mining industry is extremely competitive by nature; therefore, it must stay ahead of the competition. Furthermore, due to the increase in equipment complexity in design, operation and maintenance, the need for maximum reliability continues. It is thus imperative to delve into the reliability engineering world and apply techniques studied and developed over the last 70 years.

Proper maintenance strategies are required to achieve maximum system reliability. Predictive or proactive maintenance strategies have the ability to do so, but these strategies are currently lacking in the mining sector due to various factors. Presently, condition monitoring is being used widely in the mining industry but lacks forecasting capabilities. It is, therefore, essential to use the available tools in conjunction with the extensive reliability research to produce a more reliable system.

It is evident from literature that a need exists to improve current maintenance strategies and to maximise system reliability. Therefore, a unique combination of Weibull models, conditional distributions, quantile analysis, and the Crow-AMSAA (NHPP) model was used to develop a simplified, yet comprehensive failure prediction model. This model can be integrated into existing maintenance strategies to produce a proactive framework.

1.3 NOVEL CONTRIBUTIONS

The research conducted in this thesis adds beneficial impact to the current maintenance strategies to produce a proactive framework. For each article, the results are described in terms of what it means for the industry and its contribution.

1.3.1 Current maintenance strategies (How is maintenance done?)

Currently, maintenance strategies are primarily driven by condition monitoring and cyclic planning by maintenance planners. Therefore, maintenance is scheduled periodically based on the planner’s experience and historical failure data. This data is processed into work orders that are displayed and managed by a computerised maintenance management system. Consequently, unplanned maintenance is conducted on a reactive basis as equipment fails, is repaired, and is put in back into service.

1.3.2 Limitations (Why are the current methods insufficient?)

Although current maintenance strategies provide the ability to manage equipment repairs periodically and reactively, unplanned failures are unaccounted for. As a result, equipment reliability is neglected and cannot be optimised accordingly. More so, these methods lack forecasting capabilities and, evidently, are incapable of optimising system reliability.

In addition, the lack of proper and descriptive equipment failure information is prominent in the mining industry, with some data samples containing only running hours or the date of failure. This limits the capability of condition-based models to make predictions, as they require a lot of field data that represents a high number of dimensions. As a result, there is no practical method for evaluating and modelling simplistic data sets in context of failure prediction.

1.3.3 Solution (What is needed?)

There is a need for assessing and optimising equipment reliability. Literature has shown that reliability engineering tools, which have been studied extensively in other industries, can be used in the mining industry. Most importantly, finding the right combination of these models can provide the ability to leverage each individual characteristic to simplify a complex problem, which opens the possibility to make accurate predictions with limited data. Therefore, introducing these tools into the current maintenance strategies in the mining industry can produce a proactive framework capable of optimising system reliability. Most importantly, these tools mainly involve failure prediction, which is, therefore, the main focus of solving this problem by uniquely combining them.

1.3.4 Contributions (How is it solved?)

In Article I, a practical and generic failure prediction model was developed from a unique combination of reliability engineering tools based on small data samples in context of unplanned failures of mine dewatering pumps. This model was validated on four different pumps operating on four different levels underground. The highlights from Article I include:

1.	A unique combination of reliability engineering tools was used to develop a generic and practical failure prediction model. This model is extremely flexible; therefore, it is applicable to any equipment or machinery in the mining industry that adheres to the model constraints.
2.	The novel failure prediction model can be used to determine the optimum replacement time of a dewatering pump in context of the current failure pattern.
3.	A unique correlation between the pump operating depth and its characteristic life was formulated from the failure prediction model outputs.

In Article II, the newly developed failure prediction model was adapted to be applicable to highly reliable systems, which in this case was a typical mine compressor. A unique adjustment algorithm was integrated into the existing model to enable dynamic parameter adjustment based on the current compressor age and failure patterns. This model was applied to four different compressors operating at two different compressor houses. The highlights from Article II include:

4.	The novel failure prediction model can be used to predict the next component breakdown based on the current survival age of the compressor.
5.	A unique correlation between the number of compressor start-ups and its characteristic life was formulated from the failure prediction model outputs.

In Article III, the newly developed failure prediction model was improved by introducing multi-failure mode handling. This was achieved by leveraging the ability of the Crow-AMSAA (NHPP) model to predict the number of failures (NOF) of repairable systems. The model was applied to a scraper winch system and its sub-components. The highlight from Article III includes:

6. The novel failure prediction model can be used to predict sub-component failure, which enables the optimisation of spare part allocation and smarter asset management.

2. LITERATURE SURVEY

2.1 PREAMBLE

The literature survey is structured to highlight the significance of each research question, which is satisfied by the novel contributions of the appended articles.

Firstly, a brief overview of equipment life cycle is provided to highlight the need for assessing reliability within this context. Secondly, prominence is given to correlation between failure prediction and how it can be used to improve current maintenance strategies through reliability models.

Secondly, literature is provided on mine dewatering systems, compressed air systems, and scraper winch systems with emphasis on their sub-components, which include mine dewatering pumps, compressors and scraper winches. For each of these sub-components, research was conducted on both their functional and economic impact on mining operations to highlight the importance of failure prediction.

Ultimately, a generic failure prediction model was developed from literature, which can be applied to any equipment adhering to the model constraints. This model can be integrated into existing maintenance strategies to produce a proactive framework.

Article I *(Appendix B) presents the application of this model on mine dewatering pumps.*
Article II *(Appendix C) presents the application of this model on mine compressors.*
Article III *(Appendix D) presents the application of this model on mine scraper winches.*

2.2 EQUIPMENT LIFE CYCLE AND RELIABILITY

The life cycle of equipment exemplifies various time-connected phases that it goes through, from creation to disposal [24]. During this life cycle, various elements contribute to the total costs of maintaining running status. These costs include but are not limited to: installation and commissioning, operation, support, maintenance and disposal [24]. The sum of all these costs is defined as the life cycle cost (LCC), see Figure 3.

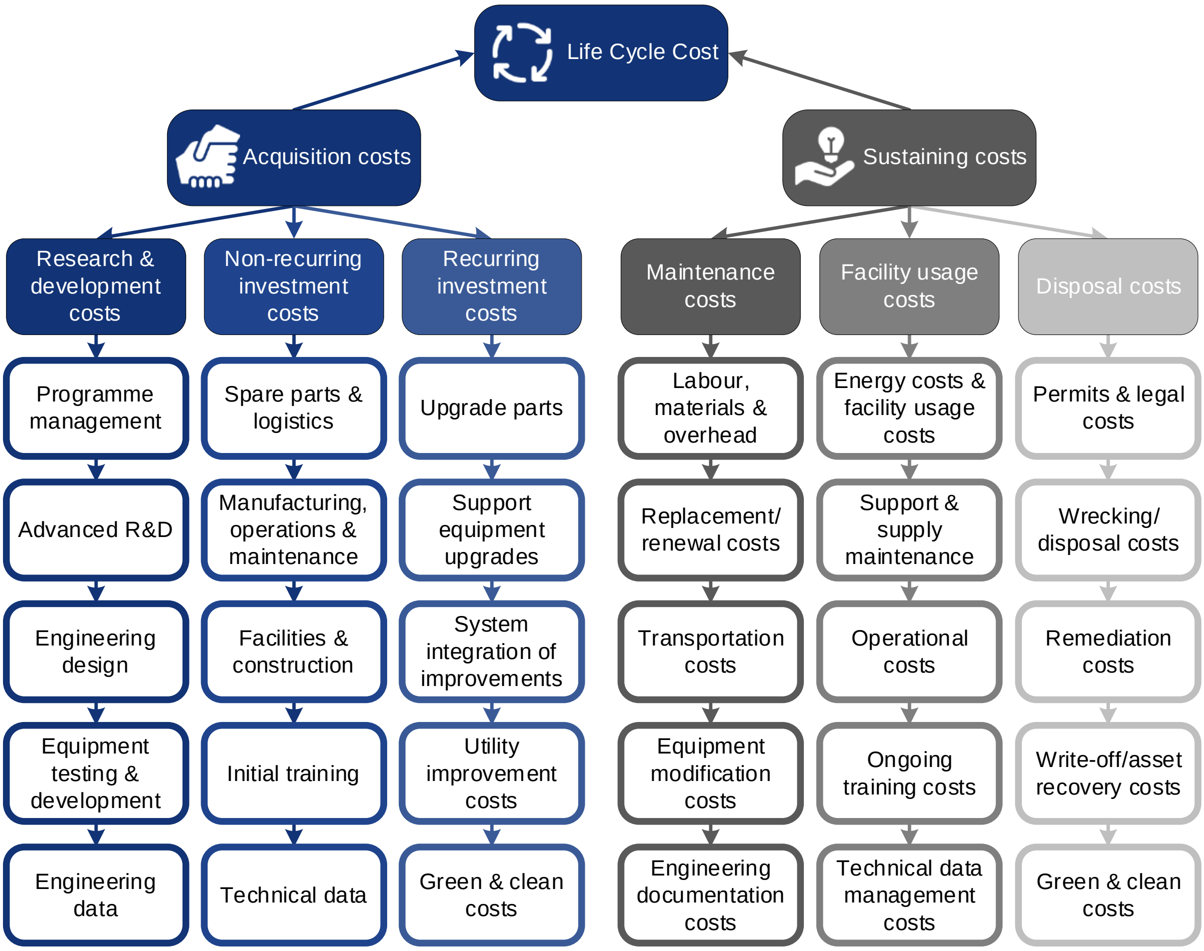


Figure 3: Detailed LCC requirements (adapted from [25])

Comparing LCCs yields smarter decision-making on the lowest long-term cost of ownership using a single estimator, which is called the net present value [25]. The net present value requires information about when and how much maintenance/replacement costs will be incurred [25]. To obtain this information, time and modes for equipment failure are required through reliability technology, which has been developed over the past 70 years [25].

Using actual failure and repair time data through reliability models gives system availability, reliability, maintainability and other operating system details [25]. These system concepts are the foundation on which the lifetime of a component is characterised [26]. Ultimately, costs and trade-offs are constructed from this information to improve decision-making [27].

2.3 NEED FOR ASSESSING RELIABILITY

Knowledge about time to failure is obtained through reliability technology [28]. Reliability engineering has the ability to provide both theoretical and practical tools [29]. These tools can ultimately specify the probability and capability of parts, components, products, and systems to perform their required functions in specific environments [29]. Today's engineering systems have become increasingly complex to be designed and built while the demand for reliability continues [30].

Various studies have involved reliability analyses in industrial fields based on the evolution of the failure rate [26]. Evidently, this tool is crucial for equipment behaviour characterisation in different lifetime phases [26]. Due to the lack of proper maintenance records and failure data, most equipment must be analysed using small samples [28]. Fortunately, practical reliability tools, Weibull models and the Crow-AMSAA model can be used to provide reasonably accurate failure analysis and forecasts [17], [28], [31].

Proper maintenance strategies are required to achieve maximum reliability. Both maintenance and reliability have roots in each other's territory [28]. Ultimately, optimising maintenance methods will yield increased system reliability. One method for strategically optimising the maintenance and operation is measuring the system mean time between failures [32]. Furthermore, using predictive maintenance has proven to be effective and beneficial for achieving adequate system reliability [33].

[1]Predictive maintenance strategies primarily involve condition monitoring, which includes vibration analysis, oil analysis, acoustic analysis, motor current signature analysis, and infrared thermography [33]. In conjunction with forecasting models, current predictive maintenance strategies can be remodelled into a proactive framework. Furthermore, these models have to align well with random failure patterns [34], [35].

As mentioned, to attempt failure prediction, condition-based models require a lot of field data, consequently, resulting in reliability models to make predictions with data that represent a higher number of dimensions. In the mining industry, obtaining this level of data is mostly not possible. Furthermore, using a unique combination of existing reliability engineering techniques to simplify a complex problem, while maintaining an acceptable level of accuracy has not yet been achieved.

[1] Paragraph excerpted from Articles

Therefore, a unique combination of these models was used in the development of a new practical failure prediction model [36], which include;

- **Standard Weibull models** – very efficient in handling single failure modes and make accurate predictions with small data samples.
- **Conditional Weibull distributions and derivatives thereof** – provides the ability to make future predictions based on the current age of the equipment considering the minimum achievable reliability.
- **Quantile analyses** – provided that failure patterns change over time, quantile analysis makes it possible to identify shifts in data distributions, which enables proactive parameter adjustment to enable the model to follow changing failure patterns.
- **Crow-AMSAA (NHPP) model** - mainly involves reliability growth plots and modelling repairable systems. The reliability growth plots are useful for mixed failure modes. Furthermore, this model is ideal for historical failure events, which typically involves human interaction.

Considering that each of these reliability tools have been studied extensively in their separate applications, the combination thereof on a single application, have been overlooked. In this study, this was achieved by combining these tools such that their individual characteristics could be leveraged to simplify a complex problem with limited data.

The growing international competitiveness has increased the need for all engineers and designers to ensure a high level of reliability and quality [30]. It is therefore essential to use the available tools in conjunction with the extensive reliability research to produce a more reliable system.

Research question 1:

Considering the lack of proper data and maintenance records, can reliability engineering tools be used to optimise existing maintenance strategies of critical mine machinery?

2.4 MINE DEWATERING SYSTEMS

A typical deep-level mine requires a water reticulation network to supply water to critical mining equipment, which includes rock drills, dust suppression systems and underground cooling equipment, to name a few [37]. Although these components typically have different demand requirements, they jointly contribute to the total water consumption of the mine. The total water consumption has an approximate proportional relationship regarding the production performance, see Figure 4 [38]. It is thus imperative to maintain a proper supply of water to the production mining blocks.

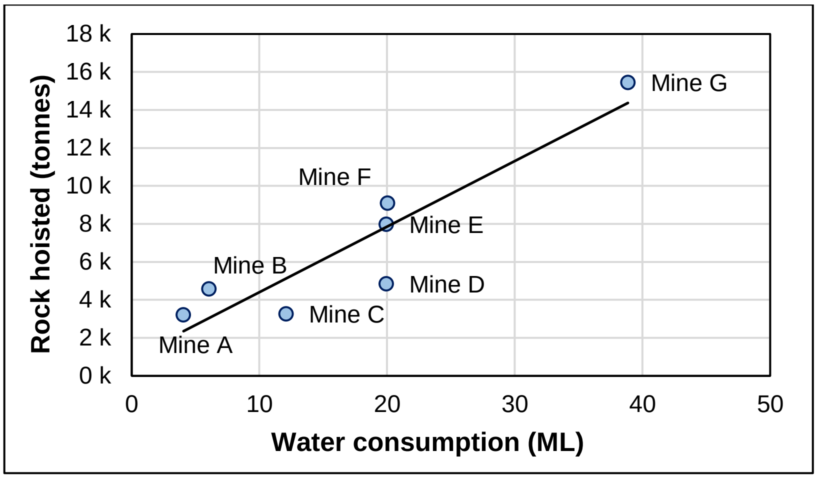


Figure 4: Water consumption vs. mine production (adapted from [39]**)**

Various methods exist for supplying water to different areas within a mine. Firstly, the water is gravity-fed from surface to an underground dam with arbitrary depth. The distance between underground dams on different levels can reach depths in excess of 800 m [39]. Due to the extensive mining depths, the water pressure in the pipe network can reach significant figures [40]. To mitigate this problem, various components such as cascading dams, Pelton turbines or pressure-release valves are added to the dewatering system [40].

Ultimately, after all service, cooling and fissure water has accumulated, it needs to be removed from underground. The waste water can be corrosive and sometimes contain high contents of suspended solids [41]. Consequently, this water is not suitable to be pumped and must be sent through some kind of extraction process. Underground settlers, which are widely used in extraction processes, are used to separate the mud particles from the water [39], [42].

As the water enters the settler, flocculant is added, which promotes the clumping of particles and causes the mud to sink to the bottom [39]. The clear, cleaner water at the surface of the settler is channelled to an underground clear water dam [39]. These dams come in many different shapes and sizes. However, due to specific pump suction pressure requirements, high, cylindrical-type dams are typically used [37]. A pumping station on the delivery side of these dams extracts the water in a cascading manner back to surface, see Figure 5.

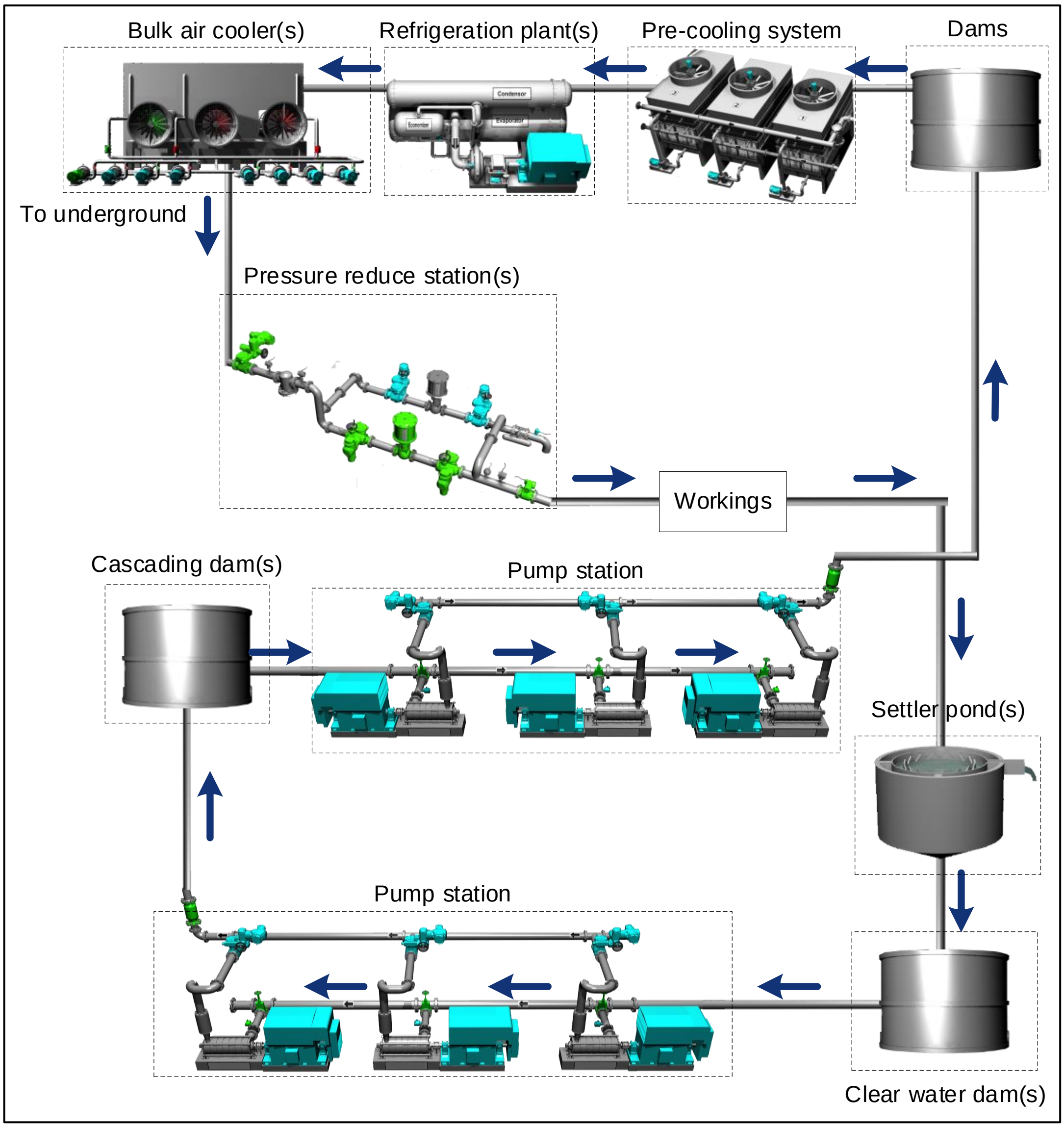


Figure 5: Typical mine water reticulation network

The number and size of pumps and pumping stations depend on the mine depth and dewatering requirements. The pumps must pump water from below the surface at pumping heads in excess of 800 m [39], [43]. Multistage centrifugal pumps are used due to the excessive pumping heads [37].

[2]These multistage centrifugal pumps are exposed to extreme operating conditions, which result in unacceptably short service lives [41]. Demanding conditions cause the pump to build up pressure as a result of suction or delivery valves not operating correctly [44]. This causes premature balance disc failure and balance disc wear ring replacements [41].

[2] Paragraph excerpted from Articles

Generally, centrifugal pumps rank first in failure incidents and maintenance costs [45]. The maintenance costs typically contribute 21% to the total pump LCC, see Figure 6 [45]. Unexpected downtime and the consequent loss of production is a significant element in the total LCC and can rival the energy costs and replacement parts costs in its impact [46], [47].

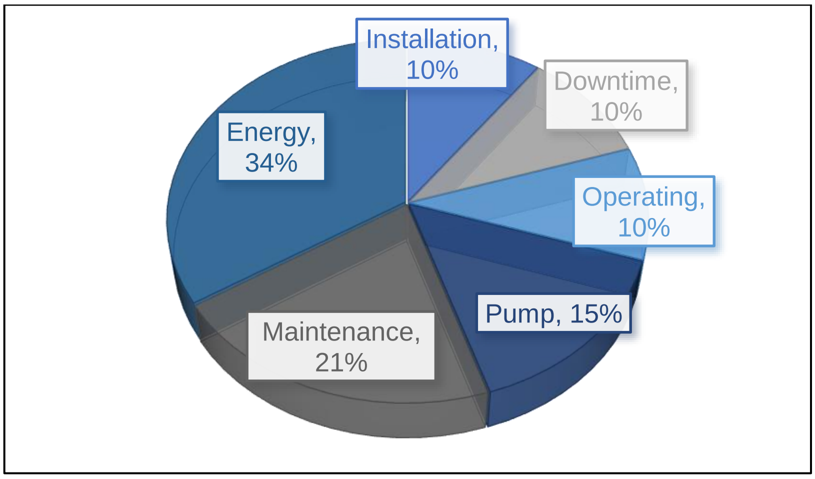


Figure 6: Typical pump LCC breakdown (adapted from [45]**)**

The LCC of repairable equipment depends on its reliability and availability [48]. Repairable equipment, in this case dewatering pumps, is typically replaced or restored upon failure. The reason and timing to repair a failure depend on a pump's reliability and maintainability [48]. Since these failures are random and unexpected due to rigorous operating conditions, they have a direct impact on the LCC [48].

The replacement of major pump components, regardless of the cause of failure, is often a significant contributor to the LCC of a pump [49]. A typical rotating assembly replacement can equate to 70% of the total replacement cost [49]. Various condition monitoring techniques are used to protect a pump against premature failure and/or to optimise pump system efficiency [50]. However, these techniques lack failure forecasting capabilities; reliability tools are required for predicting failures and finding cost-effective alternatives [51].

Research question 2:

Will a novel failure prediction model be able to provide the optimum pump replacement time in context of the LCC with small data samples?

2.5 MINE COMPRESSED AIR SYSTEMS

[3]A typical deep-level mine requires a compressed air network to supply compressed air to critical mining equipment. This network can either function as a standalone or ring-feed system [52]. A standalone system typically comprises a single compressor house containing a combination of different compressors. A ring-feed system is a bit more complex and comprises multiple compressor houses – each containing a combination of different compressors [52].

Regardless of the compressed air network configuration, it is imperative for these systems to maintain a continuous supply of compressed air. The primary compressed air consumers are typically distributed from surface to the deepest level underground. Surface consumers are mainly processing plants, which require an average pressure between 420 kPa and 500 kPa [53]. However, some of the plants have standalone compressors that can be isolated from the main compressed air supply network through simple valve control.

Nevertheless, the largest compressed air consumers are located underground. The underground compressed air pipe network is a convoluted system consisting of many sub-components, including amongst others, rock drills, loading boxes, loaders, hoppers, refuge bays, and agitation systems [53]. The pipe network used to distribute the compressed air to the different components is typically up to eight kilometres away from the surface compressed air connection [54]. Figure 7 illustrates a typical compressed air network.

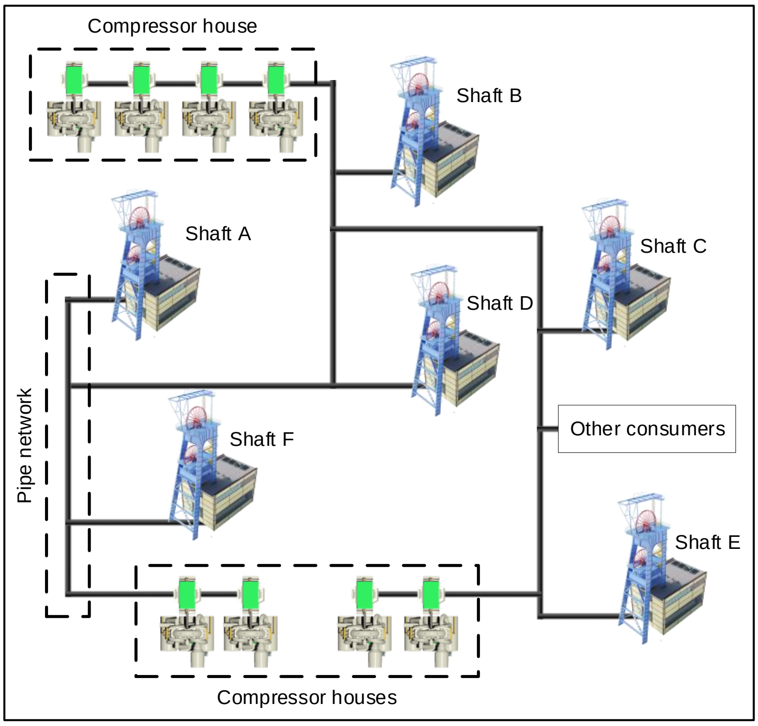


Figure 7: Typical ring-feed compressed air reticulation network

[3] Paragraph excerpted from Articles

Due to the extreme distances and many other factors, these networks are regarded as one of the most inefficient and energy intensive systems [54], [55]. The overall efficiency can be as low as 2% when taking all possible leaks, pipe losses, drill efficiency and the compressor efficiency into account [55]. Figure 8 illustrates the top view of a typical deep-level mine in which each tunnel is equipped with compressed air infrastructure.

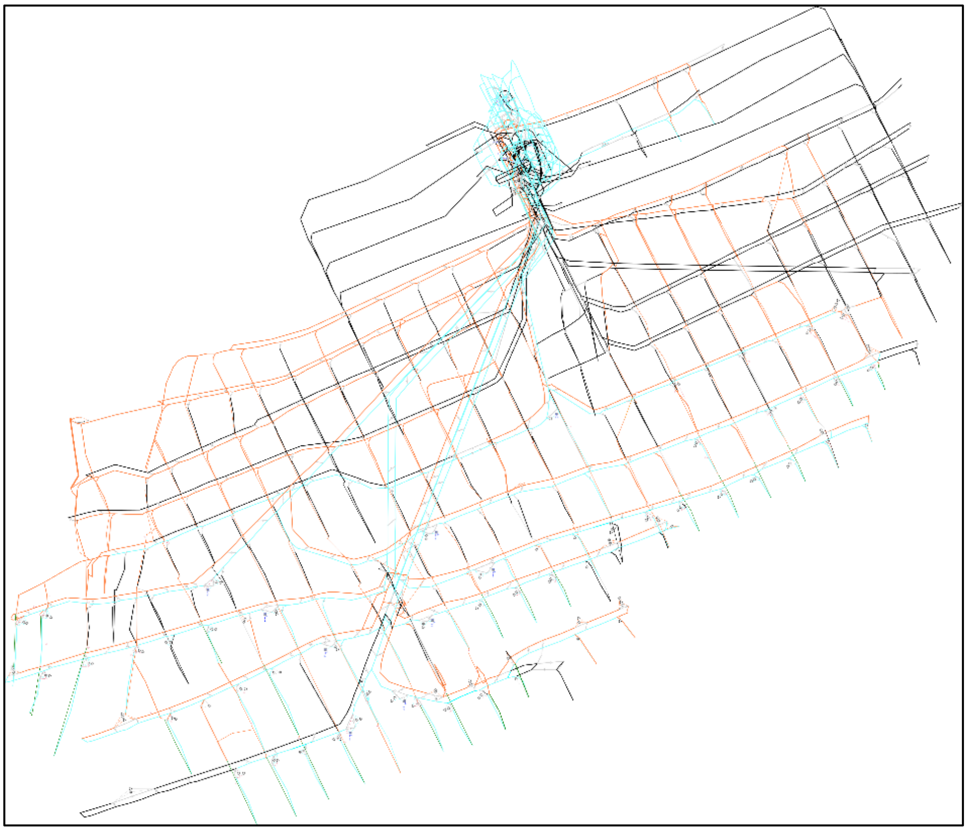


Figure 8: Typical deep-level mine underground reticulation network – Top view

Mine compressors are commonly classified as either positive displacement or dynamic compressors [54]. The mine compressors assessed in this study are all dynamic integrally geared centrifugal compressors, see Figure 9.

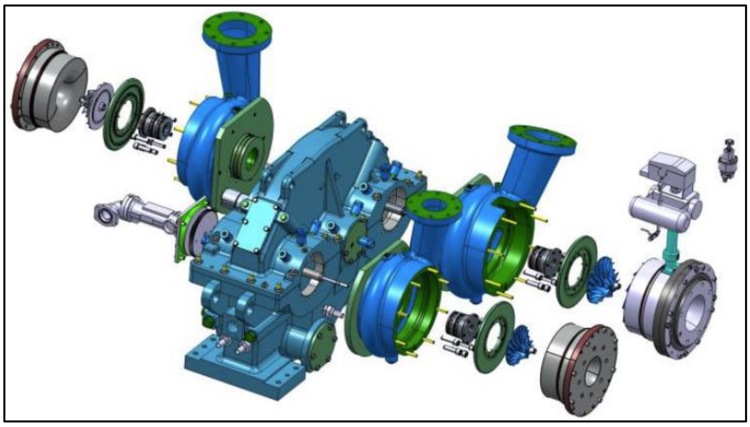


Figure 9: Multistage integrally geared centrifugal compressor (adapted from [56]**)**

Integrally geared centrifugal compressors can achieve high efficiencies but are subjected to complicated mechanical interactions [56]. The configuration of these compressors is either single stage or multistage [56]. Integrally geared centrifugal compressors have been used in a wide range of applications in the process industry, which include compressors operating purely on air and countless other gases [56].

On a mine, compressors are required to operate continuously over a long period [57]. Evidently, these compressors are regarded as critical machinery and are both expensive and highly reliable. In some cases, compressors have operated successfully for more than 40 years without any complete loss of the system [13]. However, with any system it is essential to avoid the cost of unplanned component failures. Overhauling such a compressor costs between $150 000 and $200 000, depending on the nature and size of failure [13]. Figure 10 shows the LCC distribution of a typical centrifugal compressor.

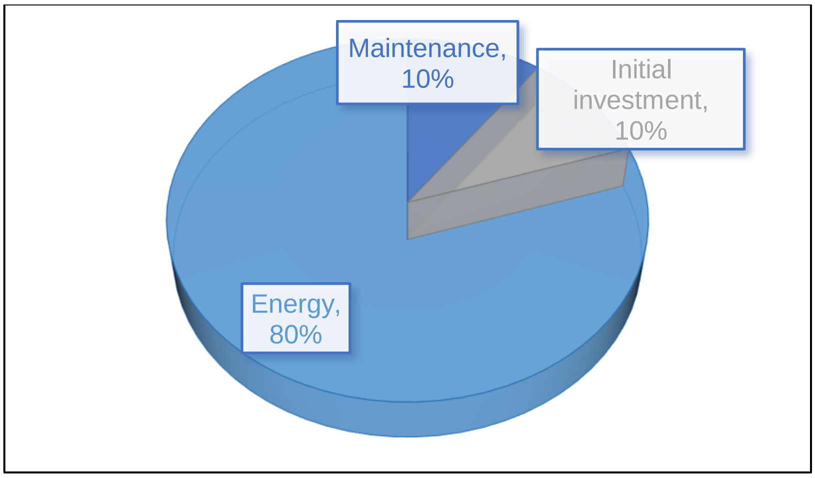


Figure 10: Typical centrifugal compressor LCC breakdown (adapted from [58]**)**

Due to integrally geared centrifugal compressors being extremely reliable, the energy consumed by these machines is the biggest contributor to the total LCC, refer to Figure 10 [58]. Although the energy costs are more than the other costs involved, avoiding equipment failure is still an issue. Unplanned downtime can result in massive system implications and most probably yield substantial loss in production.

Research question 3:

Can a novel failure prediction model be used to determine the next component breakdown based on the current age of the compressor to ensure the lowest possible LCC based on the current failure pattern?

2.6 MINE SCRAPER WINCH SYSTEMS

In the conventional narrow reef-mining environment, the ore-bearing rock movement process consists of three stages: rock face to strike gully; strike gully to centre gully; and centre gully to ore pass [59]. Stoping operations generally take place at dips between 20° and 45° [60]. More so, ore-bearing rock lying in this zone typically has no natural tendency to move. Therefore, mechanically aided cleaning methods are required, which primarily involve scraper winches.

This is the most widely used method in conventional mining and will remain the primary cleaning method despite the introduction of mechanisation [59]. Furthermore, using scraper winches is a cost-effective and practical cleaning method that requires low capital expenditure and maintenance costs [61]. Figure 11 shows a simplified layout of a conventional narrow reef-mining environment using a scraper winch system.

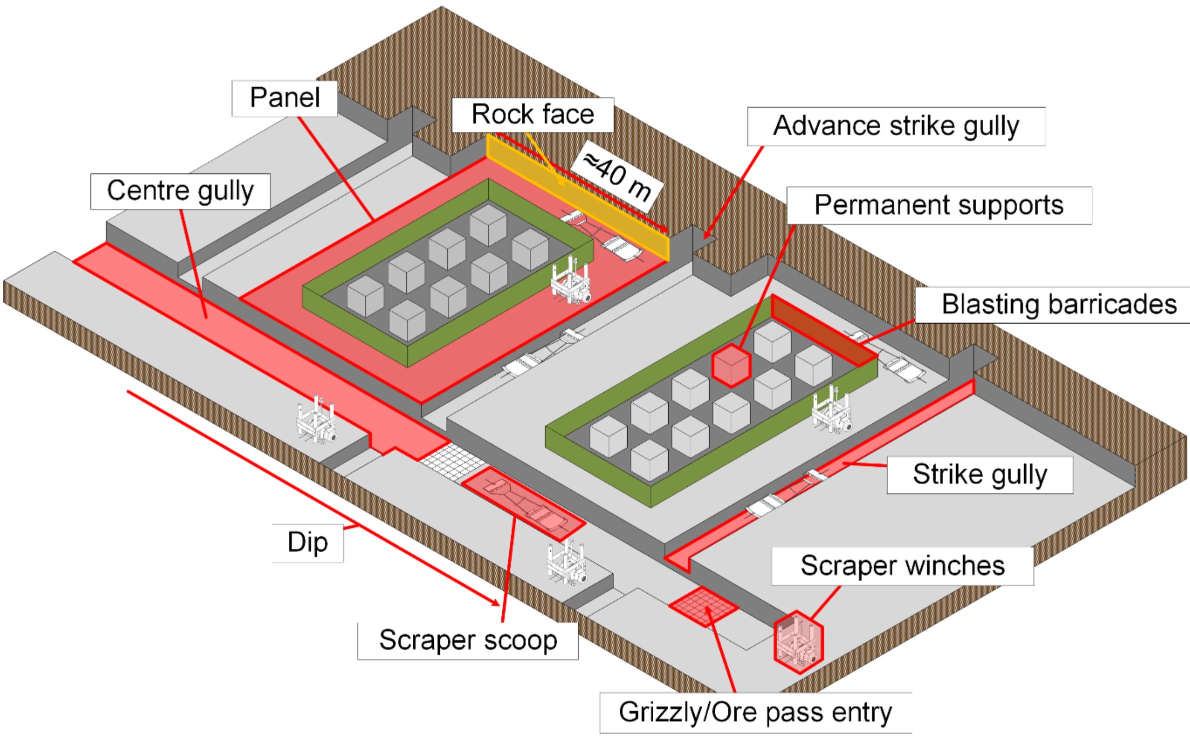


Figure 11: Conventional stope layout depicting a scraper winch system (adapted from [59]**)**

Figure 11 shows that rock faces are commonly divided into panels of approximately 40 m in length, with the strike gullies separating the different panels. Ore-bearing rock is broken from the face by drilling and blasting and is confined to the immediate area. The blasted ore-bearing rock is scraped into the strike gullies. From there, other scraper winches move it away from the face to the centre gully and, finally, to the ore passes.

It usually takes a full shift to clear the bulk of the broken rock. Interruption or delay can prevent the completion of sequential operations before blasting time, which can lead to a missed shift and ultimately production loss [62]. Therefore, the scraper winch system is one of the most important components in the ore-extraction process.

Large gold-mining operations with multiple active shafts have up to 1000 scraper winches in operation at any one time [63]. Considering this and the fact that scraper winches do not last more than four to six months, potential production losses are evident. Therefore, if unplanned failures occur and the underground ore storage cannot be controlled between acceptable limits, up to three full working shifts can be lost [63], [64]. Figure 12 shows a typical scraper winch.

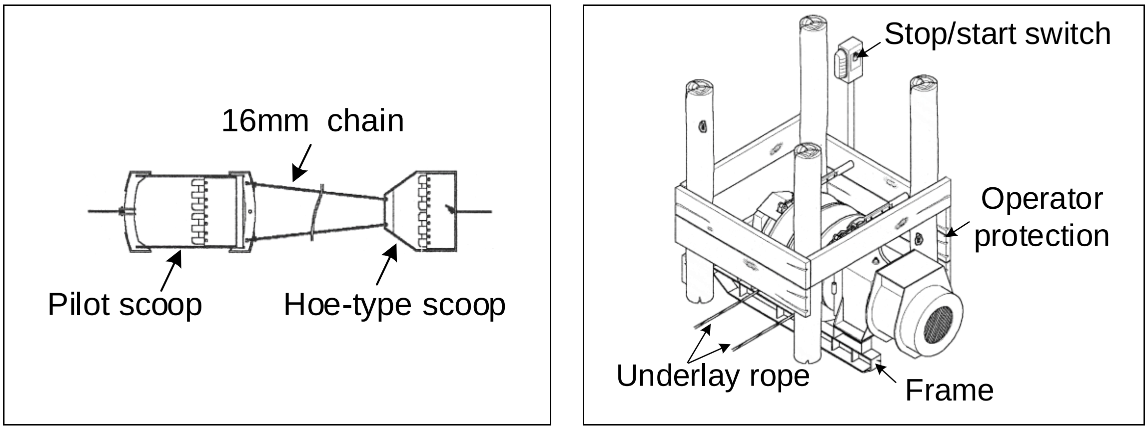


Figure 12: (A) Raise/winze scoop arrangement and (B) Typical full timber winch barricade setup

A scraper winch primarily consists of a mechanical winch powered by a squirrel cage induction motor [63]. The mechanical winch typically has two ropes/cables connected to a gully scoop with a driving mechanism. This mechanism consists of two drums with a clutch system that, when engaged, causes the planetary gears to turn the drum and wind the rope/cable. The pull rope drags the full scoop to the tipping point and the tail rope returns the empty scoop.

There are many types and sizes of scoop; however, the maximum width is governed by the width of the stope strike gully, which is typically 1.5 m. The most widely used type of scoop is a hoe-type scoop, which delivers the best overall performance and cleaning rates in the ore-extraction process [65].

The cleaning rate is determined by various factors such as: personnel, material sharing, delays caused by material handling, mechanical breakdowns, or repositioning of cleaning equipment [59]. More so, the number of trips per hour during the cleaning process is determined by the following [59]:

- Time required to fill a scoop as well as its travelling speed (m/s)

- The average travelling distance for each trip, which includes the reversal distance (m)
- Time required to unload material at the grizzly/ore pass
- The overall availability and efficiency of the scraper winch

Every factor that contributes to the cleaning rate affects the overall performance of the ore-extraction process, which further emphasises the importance of the optimisation thereof. Evidently, most operational costs are influenced by how efficiently these activities are carried out in the stope areas, see Figure 13 below.

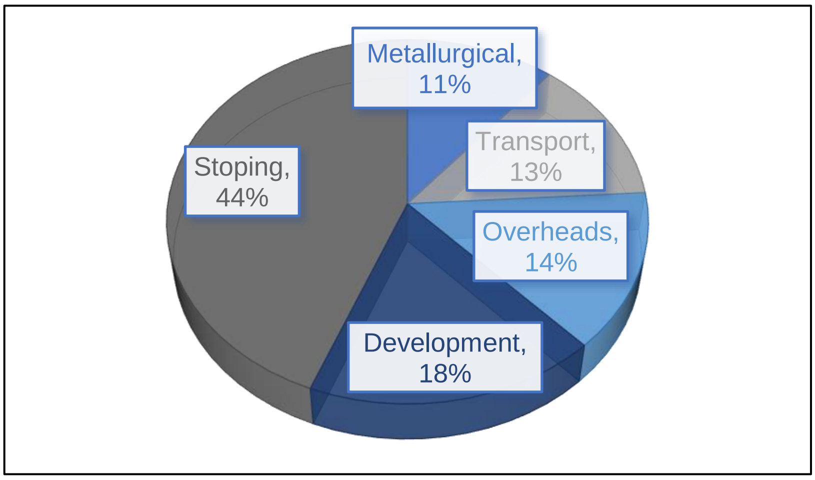


Figure 13: Distribution of activity-based costs for narrow reef mining (adapted from [66]**)**

From Figure 13 it is evident that stoping contributes to the bulk of the operational costs. Therefore, minimising these costs should be prioritised to achieve a maximum rate of face advance and increase productivity. Ultimately, it has become inescapable to optimise and improve the determining factors, especially the mechanical breakdowns and availability of scraper winches, to reduce the overall costs.

Research question 4: Can a novel failure prediction model be used to prioritise sub-component failure of scraper winches in the context of spare part allocation, which could result in smarter asset management and increased availability?

2.7 MODEL DEVELOPMENT

The use of mathematical models has been widely adopted across different disciplines to solve real-world problems [18]. Solving these problems requires an in-depth understanding of the underlying parameters to model a given data set accurately.

Mathematical modelling is classified into two categories, namely theory-based modelling and empirical modelling.

- ***Theory-based modelling***. Modelling is based primarily on established theories for component failures. This type of modelling is also known as a *physics-based* model or *white-box model* [18].
- ***Empirical modelling***. Modelling is based on failure data and does not require an understanding of the underlying mechanisms involved. These models are also known as a *data-dependent model* or *black-box model* [18].

Empirical modelling involves the following five steps [18]:

1. Data collection
2. Data analysis
3. Model selection
4. Parameter estimation
5. Model validation

Weibull model

Weibull models are data dependent; hence, they adopt an empirical model structure. A variety of Weibull models have been derived from the original two-parameter Weibull distribution, which is classified into seven different groups (Types I–VII) [18]. However, the main focus of this study was to use the standard two-parameter Weibull distribution as it has been used extensively to model failure times.

The two-parameter Weibull distribution function can be described by the following equation:

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}, t \geq 0 \tag{1}$$

where t is the failure time, and β and η are the shape and scale parameters, respectively. $F(t)$ thus defines the cumulative fraction of a group of parts that will fail by time t [67]. $\beta < 1$ indicates infant mortality, $\beta = 1$ indicates random failures, and $\beta > 1$ indicates wear-out failures [31].

[4]It is important to note that the Weibull analysis can only be applied if the data set can be described by the Weibull distribution. If the data follows a straight line on either the Weibull paper or the Weibull probability plot, approximations can be made by the two-parameter Weibull distribution [67].

Crow-AMSAA (NHPP)

Although the Crow-AMSAA model is also data dependent, it requires the historical events to be identical and statistically independent. Furthermore, this model is designed for reliability growth and the tracking thereof [20]. The Crow-AMSAA model assumes that the rate of occurrence of failure follows a power function of time and describes the cumulative NOF up to a certain time t, which follows a Poisson distribution. Plotting the cumulative NOF against the cumulative time on a log-log scale normally produces a straight line with slope β [68], [69]. The intensity function $\lambda(t)$ can be described by

$$\lambda(t) = \lambda\beta t^{\beta-1} \tag{2}$$

To determine the expected NOF from t_1 to t_2, the integral of equation (2) will give

$$E[N(\Delta t)] = \int_{t_1}^{t_2} \lambda(t)dt = \lambda t_2^{\beta} - \lambda t_1^{\beta} \tag{3}$$

where $\beta < 1$ indicates a slower failure rate, $\beta > 1$ indicates a faster failure rate, and $\beta \approx 1$ indicates no improvement or deterioration.

2.7.1 Data collection

[5]**Weibull distribution**

It is important to present the data in the correct format. Therefore, the data must firstly be grouped in increasing order of time to failure in either cumulative or non-cumulative form. Thereafter, it is possible to calculate the failure probabilities using the Bernard's approximation [29], [67], [70].

$$\tilde{F}_i = \frac{i-0.3}{n+0.4} \approx F(t) \tag{4}$$

where i is the observed value and n the sample size.

The next step is to prepare the data for the Weibull probability plot, which must be presented in a double logarithmic scale using the following equations [67]:

$$y = \ln\{\ln[1/(1-F(t))]\} \tag{5}$$

[4] Paragraph excerpted from Articles
[5] Section excerpted from Articles

$$x = \ln(t) \tag{6}$$

Table 1 represents the data preparation according to the above-mentioned criteria.

Table 1: Weibull probability plot data preparation requirements (adapted from Article I)

t	F(t)	$x = \ln(t)$	$y = \ln\{\ln[1/(1-F(t))]\}$
t_i	$F(t_i)$	x_i	y_i
⋮	⋮	⋮	⋮
t_n	$F(t_n)$	x_n	y_n

Finally, the data is represented graphically by the Weibull probability plot, which is the first visual indication of how well the Weibull distribution fits the data. As mentioned, this distribution is a two-parameter, a three-parameter or a mixed Weibull distribution, assuming the data can be described by the Weibull distribution.

Crow-AMSAA (NHPP)

The data collection and preparation requirements for the Crow-AMSAA (NHHP) model are a trivial exercise. The actual failure data is presented in either continuous or discrete formats, depending on the analysis requirements [20]. In this study, failure times are represented cumulatively in an increasing order; hence, the continuous format was adopted.

2.7.2 Parameter estimation

[6]Weibull distribution

Various methods can be used to estimate the parameters of the Weibull distribution. These methods have been studied extensively and include, but are not limited to, the graphical procedure and analytical procedures [71], [72], [73], [74]. Analytical procedures include methods such as the maximum likelihood estimation, method of moments, and the least squares method [71]. However, the graphical procedure is the most practical and easiest method. It mainly involves the linearisation of the unreliability function of the two-parameter Weibull distribution to produce a straight line in the form:

$$y = mx + c \tag{7}$$

where $y = \ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right)$, $m = \beta$, $x = \ln(t)$, and $c = -\beta\ln(\eta)$

Introducing the above equations into equation (8) gives

$$\ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right) = \beta\ln(t) - \beta\ln(\eta) \tag{8}$$

The shape parameter can now be calculated by determining the slope of the regression line, which is described by the following equation:

[6] Section excerpted from Articles

$$\beta = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sum(x-\bar{x})^2} \tag{9}$$

where $\bar{x}$ and $\bar{y}$ are the average values.

Finally, the scale parameter can be calculated from the intercept of the regression line

$$c = \bar{y} - \beta\bar{x} = -\beta\ln(\eta) \tag{10}$$

$$\eta = e^{\frac{\beta\bar{x}-\bar{y}}{\beta}} \tag{11}$$

[7]Crow-AMSAA (NHPP)

Similar to the Weibull models, the parameters of the Crow-AMSAA (NHPP) model must also be estimated. Most commonly, the maximum likelihood estimation is used to estimate the parameters. The parameter estimates are given by

$$\hat{\lambda} = \frac{\sum_{q=1}^{k} N_q}{\sum_{q=1}^{k}\left(T_q^{\hat{\beta}} - S_q^{\hat{\beta}}\right)} \tag{12}$$

$$\hat{\beta} = \frac{\sum_{q=1}^{k} N_q}{\hat{\lambda}\sum_{q=1}^{k}\left(T_q^{\hat{\beta}} lnT_q - S_q^{\hat{\beta}} lnS_q\right) - \sum_{q=1}^{k}\sum_{i=1}^{N_q} lnX_{iq}} \tag{13}$$

where k is the number of systems under analysis, q the observed system, N_q the NOF of the observed system, S_q the starting time of the observed system, T_q the end time of the observed system, and X_{iq} the age of the i^{th} occurrence of failure with $i = [1, \dots, N_q]$.

Generally, these equations cannot be solved for explicitly. Therefore, packages in SciPy, a Python-based ecosystem of open-source software for mathematics, science, and engineering, were used to achieve this.

2.7.3 Data set suitability

[8]Weibull distribution

It is crucial to test how well the data set fits the distribution. There are numerous families of GOF tests for the Weibull distribution. These tests include tests based on the Weibull probability plot, empirical distribution function, normalised spacings, and Laplace transform [75].

In the GOF tests of the Weibull distribution for component failure, tests based on the empirical distribution function will be considered to validate the assumption that the data does indeed follow the Weibull distribution. One of these tests is known as the Anderson–Darling GOF test, which is designed for small data samples [76].

[7] Section excerpted from Articles
[8] Section excerpted from Articles

The primary objective of the Anderson–Darling GOF test is to determine the observed significance level or probability value. The observed significance level is the smallest significance level at which the null hypothesis (H_0) can be rejected [77]. Therefore, a decision can be made to either reject or accept H_0.

Firstly, there is the Anderson–Darling (AD) statistic,

$$AD = \left[\sum_{i=1}^{n} \left(\frac{1-2i}{n}\left\{\ln\left(1-e^{-Z_i}\right) - Z_{n+1-i}\right\}\right) - n\right] \quad (14)$$

where $Z_i = \left(\frac{t_i}{\eta}\right)^{\beta}$,

let $k_i = \frac{1-2i}{n}\left\{\ln\left(1-e^{-Z_i}\right) - Z_{n+1-i}\right\}$ (15)

The above equations are used to iterate through each time step and finally present the Anderson–Darling value, which is described in Table 2.

Table 2: Anderson–Darling GOF test for the Weibull distribution (adapted from Article I)

i.	t	Z(i)	Z(n+1−i)	k	AD
1	t_i	Z_i	Z_{n+1-i}	k_i	$\sum_{i=1}^{n} k_i$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	
n	t_n	Z_n	Z_1	k_n	

After Table 2 has been completed, the Anderson–Darling GOF statistic for small samples needs to be adjusted,

$$AD^* = \left(1 + \frac{0.2}{\sqrt{n}}\right) AD \quad (16)$$

Thereafter, the observed significance level (OSL) parameter is calculated,

$$OSL = 1/\left\{1 + e^{-0.1+1.24\ln(AD^*)+4.48(AD^*)}\right\} \quad (17)$$

The following criteria are used as the decision rule based on the observed significance level value [77]:

reject H_0 if OSL $\leq \alpha$

do not reject H_0 if OSL $> \alpha$

If $\alpha = 0.05$ is selected, it implies that if the Weibull distribution assumption (H_0) is rejected, the error committed is less than 5% [76], [77].

[9]Crow-AMSAA (NHPP)

It is further crucial to test the compatibility of the Crow-AMSAA (NHPP) model and data by applying a statistical GOF test. Since the starting time for each system in this study is zero, the CVM GOF test will be considered. Furthermore, the CVM GOF test requires the failure

[9] Section excepted from Articles

data to be completed over a continuous interval $[0, T_q]$ with successive failure times $[0, X\_(1,q) < X\_(2,q) < \cdots < X\_(N\_q,q) \leq T\_q, (q = 1, \dots, k)]$.

Crow's step-by-step procedure is used as follows (adapted from Article III) [69]:

1. Specify if the data set is failure terminated ($X_{N_q,q} = T_q$) or time terminated ($X_{q,q} < T_q$)

$$\text{Let } M = \sum_{q=1}^{k} M_q \,, M_q = \begin{Bmatrix} N_q - 1 \text{ If failure terminated} \\ N_q \text{ If time terminated} \end{Bmatrix} \tag{18}$$

2. Divide each successive failure time by the corresponding end time T_q

$$Y_{iq} = \frac{X_{iq}}{T_q}, i = 1, \dots, M_q, (q = 1, \dots, k) \tag{19}$$

3. Calculate $\bar{\beta}$, the unbiased estimate of β_C

$$\bar{\beta} = \frac{M-1}{\sum_{q=1}^{k} \sum_{i=1}^{M_q} \ln\left(\frac{T_q}{X_{iq}}\right)} \tag{20}$$

4. Treat the $M\ Y_{iq}'s$ as one group and order them in descending format $[Z_1 < Z_2 < \cdots < Z_M]$
5. Calculate the CVM statistic C_M^2

$$C_M^2 = \frac{1}{12M} + \sum_{j=1}^{M} \left(Z_j^{\bar{\beta}} - \frac{2j-1}{2M}\right)^2 \tag{21}$$

6. Determine the critical value from the desired significance level and corresponding M value from Table 3

Table 3: Critical values for CVM GOF test (Adapted from [69] **and Article III)**

M	Significance level				
	0.20	0.15	0.10	0.05	0.01
2	0.138	0.149	0.162	0.175	0.186
3	0.121	0.135	0.154	0.184	0.230
4	0.121	0.134	0.155	0.191	0.280
5	0.121	0.137	0.160	0.199	0.300
6	0.123	0.139	0.162	0.204	0.310
7	0.124	0.140	0.165	0.208	0.320
8	0.124	0.141	0.165	0.210	0.320
9	0.125	0.142	0.167	0.212	0.320
10	0.125	0.142	0.167	0.212	0.320
11	0.126	0.143	0.169	0.214	0.320
12	0.126	0.144	0.169	0.214	0.320
13	0.126	0.144	0.169	0.214	0.330
14	0.126	0.144	0.169	0.214	0.330
15	0.126	0.144	0.169	0.215	0.330
16	0.127	0.145	0.171	0.216	0.330
17	0.127	0.145	0.171	0.217	0.330
18	0.127	0.146	0.171	0.217	0.330
19	0.127	0.146	0.171	0.217	0.330
20	0.128	0.146	0.172	0.217	0.330
30	0.128	0.146	0.172	0.218	0.330
60	0.128	0.147	0.173	0.220	0.330
100	0.129	0.147	0.173	0.220	0.340

7. If C_M^2 < critical value, then the hypothesis is accepted that the failure times for the k systems follow a NHPP with intensity function $\lambda(t) = \lambda\beta t^{\beta-1}$

2.7.4 Failure prediction

Overview

[10]Predicting the expected NOF or the next failure of a component at a given current age involves conditional failure probabilities [78]. Thus, if the goal is to predict the time to failure of a component from a specified current age, the probability of failure will disperse into a collection of values within the probability domain. This is also known as the percentile life, which is a critical property of the Weibull distribution and which can also be referred to as the B-life [79].

Extensive research has been conducted in the appended articles (Appendix B, C and D). Therefore, only a brief overview is given on how the failure prediction was applied. In summary, a failure prediction was made based on the current age of the equipment. From this, a band of most probable failures was produced containing an upper and lower limit [36], [80].

Upper limit

The B-life until failure is determined by using the original estimated Weibull parameters and a specified current survival age. The B-life value represents the corresponding reliability at a specific survival age, which can also represent the maximum reliability parameter for the specified percentile life. The B-life of the specific component is calculated using the conditional life equation [78],

$$\mathrm{Life_B} = \eta \left\{ \ln \left[\frac{1}{(1-\mathrm{P}) \exp\left(-\left(\frac{\mathrm{current_{age}}}{\eta} \right)^{\beta} \right)} \right] \right\}^{\frac{1}{\beta}} \tag{22}$$

where $\mathrm{P} = [0.10, \ldots, 0.99]$

[11]**Lower limit**

The lower limit B-life of the component is determined from the conditional reliability lower bound. The procedure for computing the conditional reliability lower bound is rather complex and involves various mathematical models and theorems. Huang proposed a procedure for computing the conditional reliability lower bound without estimating the shape (β) parameter

[10] Paragraph excerpted from Articles
[11] Section excerpted from Articles

of the Weibull distribution [81]. This procedure is used to determine the minimum conditional reliability starting with the following equation,

$$\widehat{R}_c(\beta_0) = \exp\left[-\frac{\chi^2_{90,2}\{T^{\beta_0} - (T - t_0)^{\beta_0}\}}{\sum t_i^{\beta_0}}\right] \quad (23)$$

where $\chi^2_{90,2}$ is the chi-squared statistic with 90% confidence level and two degrees of freedom, T represents a possible future failure time, t_0 the current survival age, and β_0 the observed shape parameter.

A mathematical relationship exists between $\widehat{R}_c$ and β_0 such that the function yields a minimum at some value of β_0 [81]. This value is solved for using Python and represents the minimum conditional reliability, which formulates new β and η parameters.

Once the new β parameter has been determined, a 100γ percent confidence lower bound on η can be calculated using the following equation [81],

$$\hat{\eta} = \left(\frac{\sum_{i=1}^{n} t_i^{\beta}}{\chi^2_{90,2}}\right)^{\frac{1}{\beta}} \quad (24)$$

It is then possible to determine the lower limit B-life of the component by plugging the new shape and scale parameters into the conditional life equation, refer to equation (20).

2.7.5 Model verification

To verify the integrity of the model developed in Python, it was benchmarked against constructed and published benchmark problems, see Table 4.

Table 4: Published and constructed benchmark problems

Parameter(s) verified	Reference
• Weibull β and η parameters estimation	Published results online [82]
• Anderson–Darling GOF – OSL	Published results online [76]
• Minimum conditional reliability R_{min} and β_{min}	Published results online [81]
• Crow-AMSAA (NHPP) β_c and λ parameters estimation • Variance-and covariance of β and λ $Var(\lambda), Var(\beta), Cov(\beta,\lambda)$ & $Cov(\beta,\lambda)$ • Expected number of failures $E[N(\Delta t)]$	Published results online [83]
• Cramér-von Mises goodness-of-test • CVM statistic - C^2	Published results online [84]
• Fisher Matrix confidence bounds • Cumulative and instantaneous failure intensity (FI) $[FI_{cum}]_U, [FI_{cum}]_L, [FI_{inst}]_U$ & $[FI_{inst}]_L$ • Cumulative and instantaneous MTBF $[MTBF_{cum}]_U, [MTBF_{cum}]_L, [MTBF_{inst}]_U, [MTBF_{inst}]_L$	Published results online [20]

The numerical methodology in this thesis was verified using published and constructed benchmark problems, refer to Table 4. The following Python packages were used in conjunction with custom algorithms to achieve the required results.

- Reliability – a Python library for reliability engineering [85]
- Numpy - open-source project aiming to enable numerical computing with Python
- SciPy - open-source Python library used for scientific computing and technical computing

A summary of the benchmark results for the most important parameters used in the numerical methodology is shown in Table 5.

Table 5: Numerical methodology benchmark results

Parameter	Published result	Python model result	% Error
β	1.93262	1.93267	<1%
η	73.5256	73.5260	<1%
OSL	0.34660	0.34660	0%
R_{min}	0.9951	0.9902	<1%
β_{min}	2.6200	2.6192	<1%
β_c	1.30090	1.30090	0%
λ	0.00520	0.00520	0%
C^2	0.03400	0.03400	0%
$Var(\beta)$	0.13018	0.13018	0%
$Var(\lambda)$	0.00013	0.00013	0%
$Cov(\beta,\lambda)$	-0.00406	-0.00406	0%
$Cov(\beta,\lambda)$	-0.00406	-0.00406	0%
$E[N(\Delta t)]$	8.81850	8.81850	0%
$[FI_{cum}]_U$	0.05039	0.05039	0%
$[FI_{cum}]_L$	0.02499	0.02499	0%
$[FI_{inst}]_U$	0.03579	0.03579	0%
$[FI_{inst}]_L$	0.01327	0.01327	0%
$[MTBF_{cum}]_U$	40.01927	40.01927	0%
$[MTBF_{cum}]_L$	19.84581	19.84581	0%
$[MTBF_{inst}]_U$	75.34193	75.34193	0%
$[MTBF_{inst}]_L$	27.94261	27.94261	0%

From Table 5, it is clear that the numerical methodology, written in Python, can accurately reproduce the results from the published problems.

2.8 CONCLUSION

Critical mine services such as dewatering systems, compressed air systems, and scraper winch systems are essential for successful and sustainable mining operations. It is thus imperative to prioritise reliability optimisation of these systems to ensure that overall system availability is maintained to provide safe and sustainable operations.

The reliability engineering environment and equipment maintenance are fundamentally rooted. Thus, proper maintenance strategies will yield equipment reliability improvements. Proactive maintenance is one method for optimising system reliability strategically. Evidently, this maintenance strategy requires some form of equipment failure prediction. From literature it was found that Weibull models and the Crow-AMSAA (NHPP) model are best suited for equipment failure prediction.

These models have been studied extensively in the past and have proven to be successful for reliability optimisation. The need for implementing these models on critical mining machinery was thus realised. However, most condition-based models require a lot of field data, which is generally not possible in the mining industry. Therefore, a simplified, yet comprehensive failure prediction model was thus developed from literature.

What makes the method *practical* as viewed against the existing literature?
The ability of this model to make accurate predictions with small data sets while maintaining an acceptable level of accuracy makes it practical and easy to implement under the current data constraints.

What precisely makes the method *new* as viewed against the literature?
Considering that various reliability tools have been studied extensively in their separate applications, the combination thereof on a single application, have been overlooked. In this study, this was achieved by combining these tools such that their individual characteristics could be leveraged to simplify a complex problem with limited data.

What makes the method *unique* against the literature?
This model comprises a unique combination of Weibull-related functions, the Crow-AMSAA (NHPP) model, and quantile analyses. By leveraging the strong characteristics of each individual method, the simplification of a complex problem was made possible

What is the importance of the use of conditional models?
Conditional models provide the ability to make future predictions on the condition that equipment has reached a certain survival age. Therefore, considering the current age of the equipment and its remaining life, the future reliability parameters can be determined

conditionally, which enables better approximations on how reliable equipment will be in the future.

Why is the concept of *quantile analysis* important?

Provided that failure patterns change over time, quantile analysis makes it possible to identify shifts in data distributions, which enables proactive parameter adjustment within the model to adapt according to changing failure patterns.

Because of the model's simplicity and compatibility, most equipment failure patterns can be modelled and predicted. This is exceptionally useful in industry since mining personnel or the engineer can immediately get a good estimate on how long equipment could possibly operate, thereby enhancing decision-making and possibly improving maintenance procedures.

3. PUBLICATIONS SUMMARY

3.1 PREAMBLE

In this chapter, the most important results from the appended articles and their novelties are discussed and highlighted. Also, prominence is given to the solution of the initial problem statement formulated in the first chapter and the research questions in the second chapter. Additionally, unique correlations are drawn from the results, which are also discussed. The articles can be found in Appendix B, Appendix C, and Appendix D.

3.2 ARTICLE I

Title: Failure prediction of mine de-watering pumps

It is extremely difficult to quantify coming failures, especially if the pump has reached a certain age of survival. The proposed method proved to be successful in predicting a single pump failure. To validate the method further, the analysis was conducted on four different pumps, located on four different levels on a deep-level mine, illustrated in Figure 14.

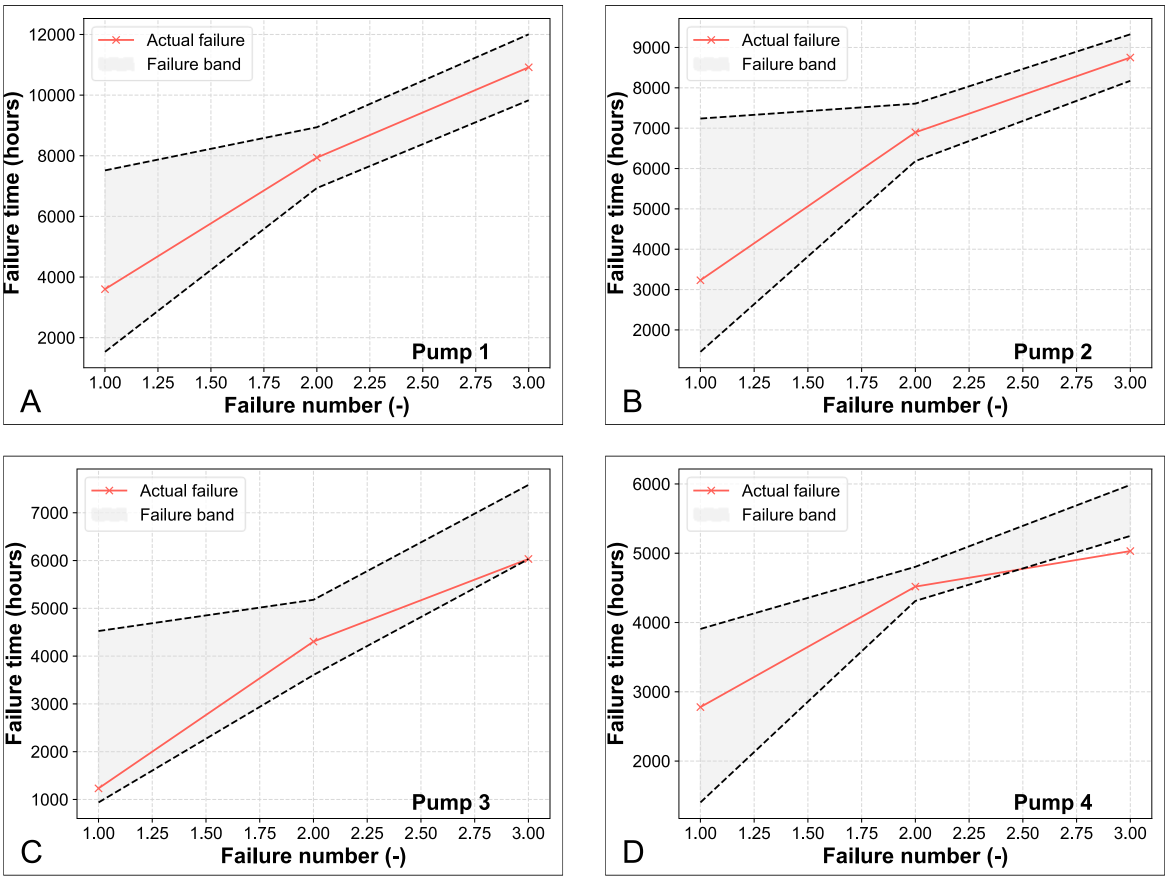


Figure 14: Dewatering pump failure prediction (adapted from Article I)

Following the results obtained from the failure prediction model, a highly unique correlation was found between the pump operating depth and its characteristic life, see Figure 15. This correlation may exist due to a variation in operating conditions underground. Thus, as the operating conditions get more extreme, the characteristic life of a dewatering pump decreases.

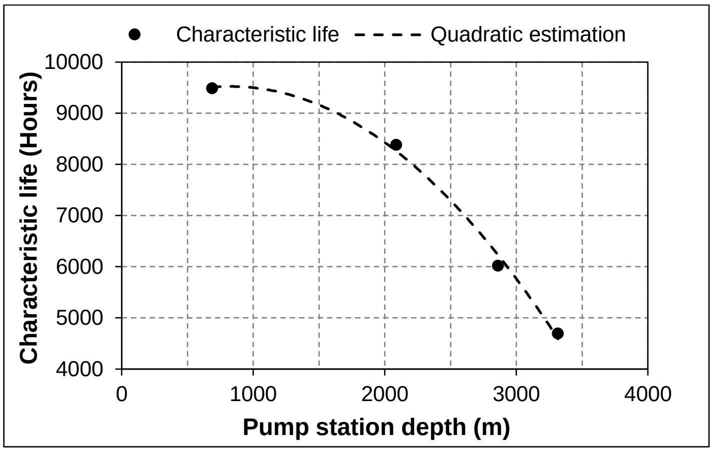


Figure 15: Dewatering pump characteristic life depreciation (adapted from Article I)

There is no correlation between the characteristic life and the required pumping head, which is a clear indication that other factors are involved. This strongly suggests that specific operating conditions and the operating depth can determine the service life of a dewatering pump regardless of the pumping head. Furthermore, this also indicates that the sequence of installation plays a significant role in the service life of these pumps. The pumps closer to surface will, therefore, have a higher characteristic life than those located further from surface.

Furthermore, exposure to dirty water is directly proportional to the operating depth on the deeper levels because the pumps are located near the settler ponds. These settler ponds filter out most suspended solids and impurities, resulting in cleaner water being pumped to surface, which becomes evident when looking at Figure 15.

Therefore, the application of the Weibull analysis and use of the original estimated parameters of a previously installed pump are constrained by similar operating and environmental conditions under which the newly installed pump will operate.

Following this, a range of most probable failure times can be generated according to the current age of survival of a specific pump with a 90% confidence lower bound on the minimum failure time. From this, the optimum replacement time can also be determined.

Answer to research question 2:

In Article I, a new failure prediction model was developed and applied to mine dewatering pumps. From this, the optimum replacement time can be determined in context of the LCC.

3.3 ARTICLE II

Title: Failure prediction of mine compressors

With convoluted compressor systems, countless variables are involved that can contribute to unexpected failures. The complexity of this problem makes statistical engineering indispensable. Several Weibull models were used to estimate the most probable failure times. These models were enhanced further using quartile deviation and a unique adjustment algorithm.

The final model outputs proved to be successful in predicting subsequent compressor failures. The method was applied to four different compressors, located at two different compressor houses, illustrated in Figure 16.

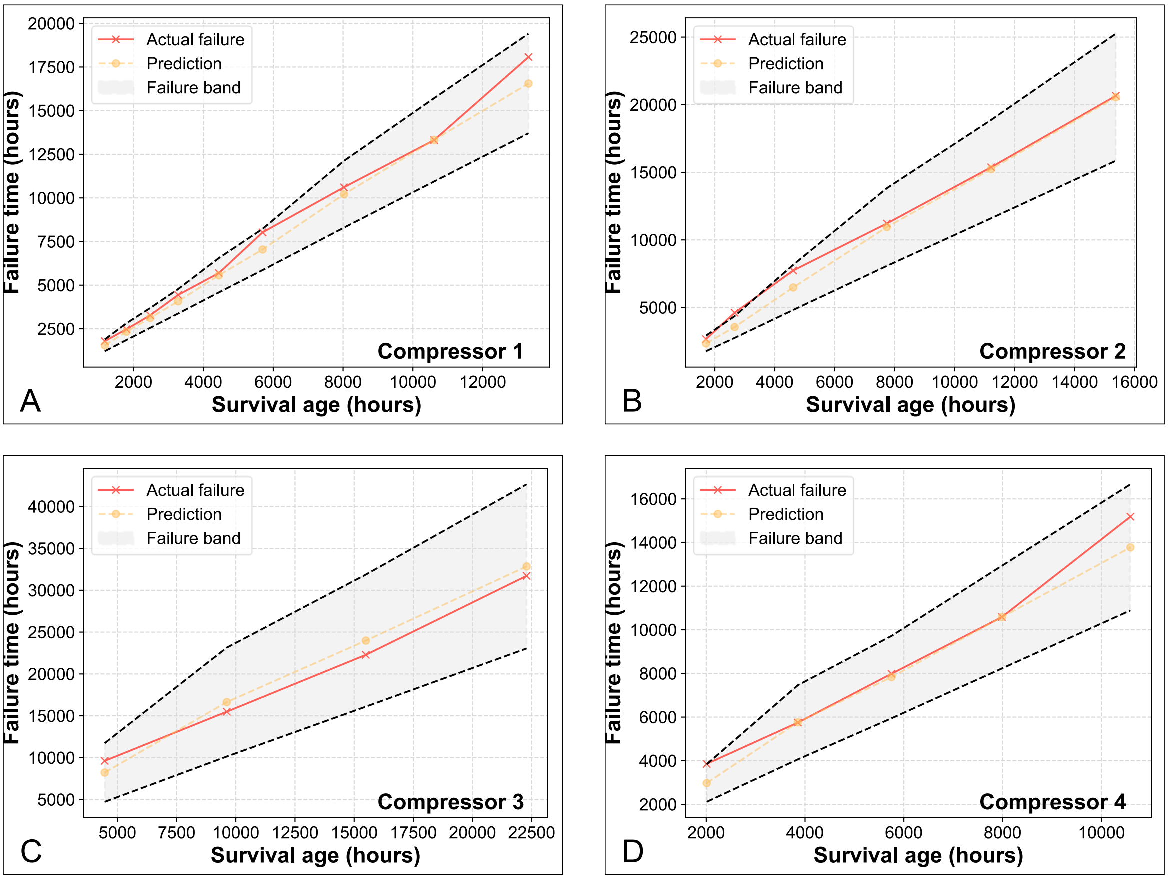


Figure 16: Compressor failure prediction (adapted from Article II)

From the model's additional results, a unique correlation was found between the number of start-ups and the characteristic life of the compressors. The compressors in this study are used as baseload compressors, which require them to run continuously. Depending on the control philosophy and demand requirements, these machines are switched off frequently and need to be started up again. The unique correlation is illustrated in Figure 17.

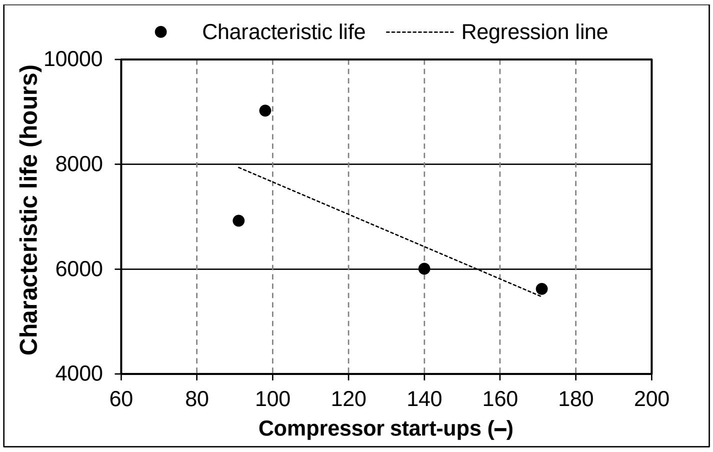


Figure 17: Compressor characteristic life depreciation (Adapted from Article II)

From Figure 17 it is evident that a negative correlation exists between the characteristic life of a compressor and the number of start-ups. It is further important to note that using more data points would probably yield more accurate results. However, this correlation was drawn from the model outputs, which again highlights the additional capabilities of the Weibull analysis.

Nevertheless, a possible cause of this correlation could be the deterioration of the large induction motors used to rotate an assembly of impellers mounted on a steel shaft. The size of a compressor's motor depends on the compressor's design specifications, which in this case, range from 1 MW to 8.5 MW. These induction motors rely on the interaction of magnetic fields to convert electric power into rotating power. During the motor starting time, magnetic fields and back electromotive force introduce transient conditions into the electric system. These transient events can affect the electric supply and other equipment connected to the system [86].

Ultimately, the methodology was validated on various compressors using the leave-one-out cross-validation (LOOCV) method. It was found that subsequent failures of the compressors were predicted successfully based on iterative training data sets of the proposed methodology. An average prediction accuracy of 92% was achieved across all compressors used in the study.

Answer to research question 3:

In Article II, the failure prediction model developed in Article I was modified to be more generic, whereafter it was applied to large mine centrifugal compressors. This model was used to predict the next component breakdown based on the current survival age of the compressor. Furthermore, this enables LLC optimisation, which is governed by the current failure pattern.

3.4 ARTICLE III

Title: Failure prediction of mine scraper winches

The ability of this model to make accurate predictions of mixed failure modes was leveraged as systems constraints to adjust parameters within the previously developed model. Furthermore, the Pareto principle was used to quantify sub-components that made up 20% of the system but caused 80% of the total breakdowns. This principle was extrapolated through all levels of information, which enabled better maintenance prioritisation, see Figure 21.

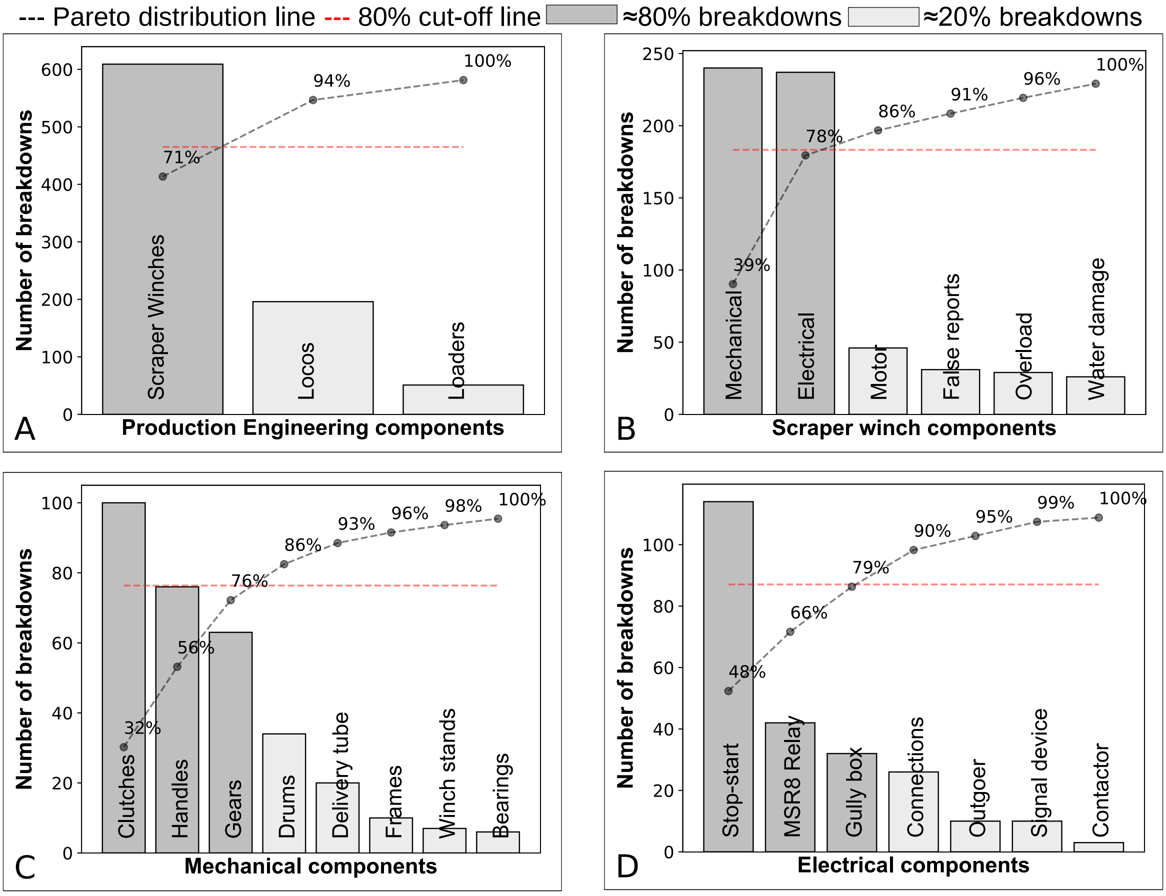


Figure 21: Pareto charts of production engineering (A), scraper winch components (B), mechanical components (C), and electric components (D) (Adapted from Article III)

In Figure 21, the darker grey columns represent the sub-components that caused 80% of the system failures but only made up 20% of the system components. Therefore, the failure prediction model was applied to these systems. The failure for each sub-component was predicted successfully, see the Figure 22 to Figure 24 below.

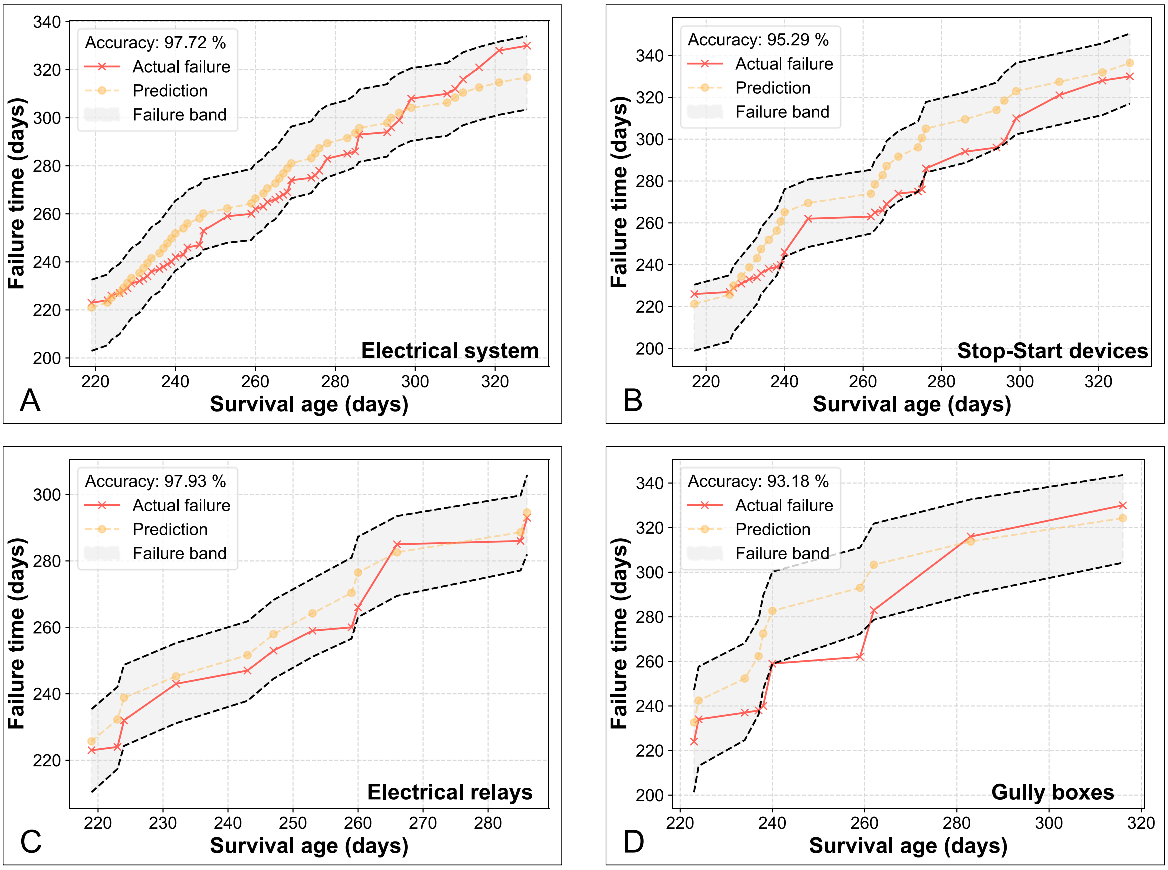
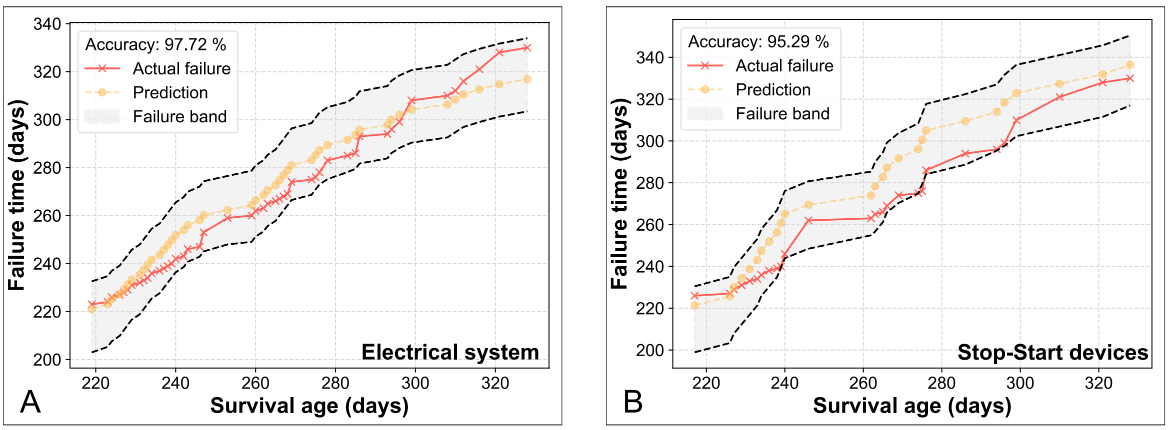


Figure 22: Failure prediction bands – mechanical system (Adapted from Article III)

The failure prediction model accurately predicted each subsequent failure with an accuracy of more than 90%. It is important to note that during the early failures, each sub-component displayed higher failure rates. However, it can be seen that the model readjusted based on the observed NOF and the substitution of newer data.

Due to the lack of current forecasting abilities, the increase in failures and changes in the failure pattern would go unnoticed. Therefore, the ability to identify changes in failure patterns provides critical change management information for maintenance planners.



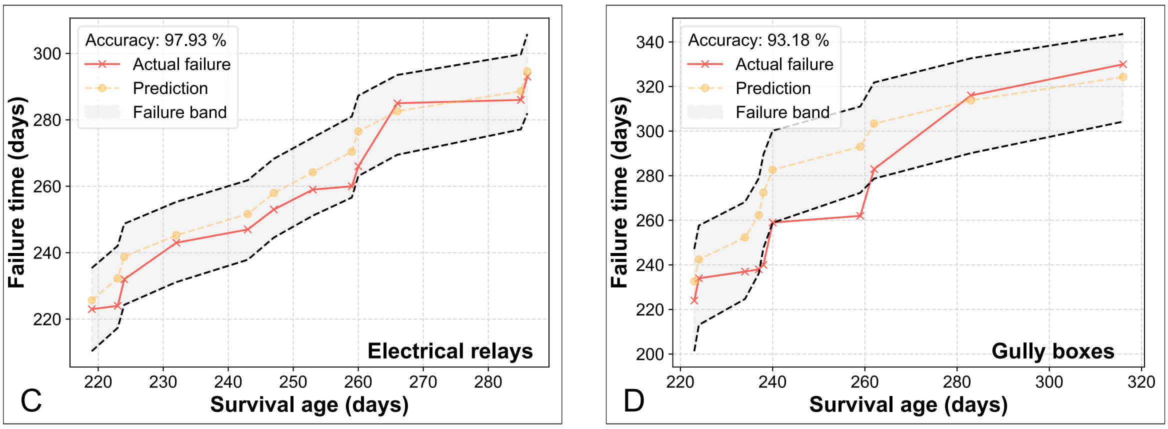


Figure 23: Cumulative failure prediction bands – Scraper winch electric system

From Figure 23(A) to (D), it is evident that the model predicted each subsequent failure accurately, where the x-axis and y-axis represent the survival age and failure times, respectively. Additionally, the expected NOF for each system was also determined and compared with the actual NOF that occurred, illustrated in Figure 24.

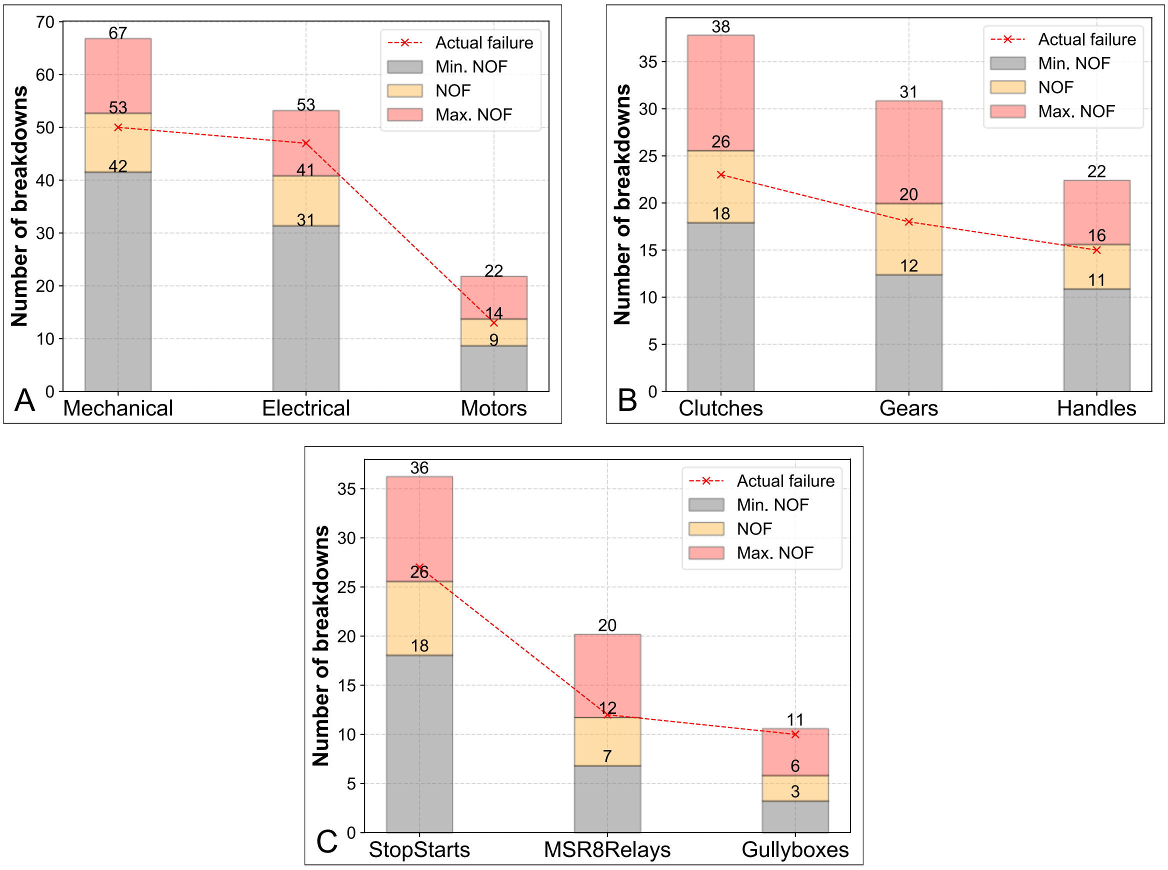


Figure 24: Scraper winch system expected NOF

The fact that the expected NOF can be predicted, given the specified operational time of these components, is extremely valuable for asset management. This is critical in a deep-level mining environment where the spares not only need to be ordered, but also be transported to various levels in anticipation of system failures.

It is further important to note that the Pareto principle pattern is revealed in each figure. This provides the ability to generate real-time Pareto charts that maintenance planners can use to allocate resources more accurately regarding asset procurement. Overall, the failure prediction model predicted both the cumulative failures and expected NOF accurately.

Research answer 4:

In Article III, the failure prediction model developed in Article I and Article II was integrated with the Crow-AMSAA (NHPP) model. In context of spare part allocation, the failure prediction model is able to generate dynamic Pareto charts based on current failure patterns. This enables smarter asset management and ultimately increased availability.

3.5 DISCUSSION

In this thesis, the importance of improved reliability was highlighted. Furthermore, to improve reliability, current maintenance strategies were evaluated and it was found that these strategies lack forecasting capabilities. From this, research was conducted on forecasting models which yielded the Weibull models and the Crow-AMSAA (NHPP) model being the most suitable solutions. These models have the ability to provide accurate failure analysis on a wide range of mechanical equipment. To achieve proper failure prediction, data acquisition is the primary constraint due to the empirical nature of these models.

Practical experience has shown that only high-level data can be obtained most of the time. This high-level data typically includes the date of equipment replacement or running hours. It can become quite challenging to process the data into usable data sets. For Article I, only running hours and pump replacement times were obtained. For Article II and Article III, maintenance records, exported from computerised maintenance management systems, were used. Consequently, the data processing phase could differ between different components. Fortunately, due to the flexibility of reliability models, an accurate failure analysis could still be conducted.

From literature it was found that it is challenging to predict component time to failure, which provided the opportunity to use research over the last 70 years to compare different methods and draw conclusions based on comparative studies. From this, Weibull models were regarded as the most widely used failure prediction models, especially the standard Weibull distribution function.

Therefore, a highly unique combination of the conditional Weibull distribution functions, the Crow-AMSAA model, and quantile analyses were used. Also, for the first time, a model developed by experts on the lower conditional reliability lower bound was used in conjunction with the standard conditional Weibull distribution. This enabled the first representation of a most probable failure range and constraint by quantile theory.

In summary, the model results are easy to interpret and can be used to optimise the maintenance schedules of any equipment under analysis. This enables the engineer or mining personnel to draw more accurate conclusions, which will ultimately enable better decision-making. This method was implemented successfully on mine dewatering pumps (Article I), compressors (Article II) and scraper winches (Article III).

Answer to research question 1:

Various reliability engineering tools were used to develop a new failure prediction model, which was successfully applied to critical mine machinery operating on a typical deep level mine. This model can be used to optimise existing maintenance strategies to produce a proactive framework.

4. CONCLUSION

4.1 PREAMBLE

This chapter gives a holistic summary and concluding remarks of this thesis. Furthermore, the novel contributions of each article are highlighted. Finally, the chapter concludes with recommendations for further research.

4.2 CONCLUSION

The importance of reliability has been highlighted multiple times in this thesis. Reliability is the fundamental backbone of optimum equipment utilisation and safe operation. In the mining industry, this is exactly what is required, thereby making it imperative to enhance equipment maintenance strategies and using the latest reliability tools. Currently, proactive maintenance strategies are not being used and are overlooked.

In the future, mechanisation will become a reality, which means that equipment will become more complex in design and installation, which could result in more unexpected equipment failures. If maintenance strategies do not evolve with the technology, imperfect planned or routine maintenance could possibly impede maximum equipment utilisation, which could require a significant amount of extra capital investment.

Maintenance is one of the primary cost contributors and consumes a significant proportion of the operational costs in the mining industry. Improving equipment reliability extends the longevity at the least cost, which can be achieved using a reliability-centred maintenance strategy. To achieve this, equipment failure patterns had to be studied extensively. Models included the Weibull models and the Crow-AMSAA (NHPP) model, which are the most widely used failure analysis models. Therefore, a new failure prediction model was developed from literature and applied to critical mine machinery.

In the first article, the model was applied to dewatering pumps operating under extreme conditions. The failures of previously installed dewatering pumps were used as input parameters for the model. Thereafter, the model outputs were used to predict the failures of newly installed dewatering pumps.

The methodology was validated on four pumps and it was found that the failures of new pumps were predicted successfully based on the Weibull analysis of previously failed pumps. It was further found that a quadratic relationship existed between the characteristic life of a dewatering pump and the operating depth underground. This is significant because all the factors affecting the service life of a dewatering pump are quantified regarding only the operating depth and the characteristic life.

In the second article, the failure prediction model was modified and enhanced further to be more generic, whereafter it was applied to large centrifugal mine compressors. The methodology was validated on various compressors using the LOOCV method. It was found that subsequent failures of the compressors were predicted successfully based on iterative training data sets of the proposed methodology. An average prediction accuracy of 92% was achieved across all compressors used in the study.

In the third article, the failure prediction model was adapted for multi-failure mode handling and reliability growth for repairable systems. The unique integration of the Crow-AMSAA (NHPP) model, therefore, enabled this functionality to model random failure patterns with human interaction successfully. From this, a cumulative failure prediction band was generated, governed by the observed NOF, which changed dynamically based on the current failure pattern. The results were validated using the LOOCV method, which yielded an overall prediction accuracy of 94% across all of the scraper winch components.

4.3 [12]FUTURE RESEARCH

4.3.1 Mine dewatering pumps

A quadratic relationship exists between the characteristic life of a dewatering pump and the pump station level or operating depth. This indicates that the service life of a dewatering pump depends significantly on the specific operating conditions and operating depth regardless of the pumping head.

Dewatering pumps are exposed to extreme temperatures and high humidity and are required to pump water from underground at heads between 500 m and 800 m. There is no correlation between the characteristic life and the required pumping head. This is a clear indication that other factors are involved – one of which is most likely the relationship between the characteristic life and the dirty water being supplied from the settler ponds.

This water can be corrosive and sometimes has a high content of suspended solids. This is especially the case on the deeper levels where pumping stations are located near the settler ponds. As the dirty mine service water is pumped to surface in a cascading configuration, the

[12] Section excerpted from Articles

quality might improve due to continuous settling of impurities and solids. However, further studies are needed to confirm this hypothesis.

4.3.2 Mine compressors

There is a negative correlation between the characteristic life and the number of compressor start-ups. These compressors require large induction motors to rotate an assembly of impellers mounted on a steel shaft. The size of a compressor's motor depends on the compressor's design specifications, but in this case, the size of the motors ranges from 1 MW to 8.5 MW.

These induction motors rely on the interaction of magnetic fields to convert electric power into rotating power. During the motor starting time, magnetic fields and back electromotive force introduce transient conditions into the electric system. Ultimately these transient events can affect the electric supply and other equipment connected to it. This may be a contributing factor to the depreciation in characteristic life, but further studies are required to confirm this hypothesis.

4.3.3 Mine scraper winches

The ability to predict sub-component failure of mine scraper winches was the main focus of this study. This provided the ability to optimise spare part allocation, which can result in smarter asset management, increased availability, and ultimately a more reliable system. However, the actual causes of failure can range from cable damage after blasting to abnormally high pull forces and have not been studied extensively.

Further research can be conducted regarding the root cause analysis of a scraper winch system and how these causes can be minimised by implementing preventive control measures. One example can be by introducing Industry 4.0 technologies, which will enable real-time monitoring of winch motor current and provide the ability to quantify the frequency of abnormal load situations. In combination with the current failure prediction model, proactive maintenance can be improved further by bridging the gap between condition monitoring and failure prediction.

4.3.4 Overall

With the mining industry migrating to better Industry 4.0 technologies, combining statistical methods, such as this failure prediction model, with condition monitoring can further improve the accuracy of failure predictions. Therefore, integrating existing condition monitoring systems with this failure prediction model is something to consider.

5. REFERENCE LIST

[1] H. Macmillan, “Plus ça change? Mining in South Africa in the last 30 years – an overview,” *Rev. Afr. Polit. Econ.*, vol. 44, no. 152, pp. 272–291, Apr. 2017.

[2] Mineral Council of South Africa, “Integrated annual review 2017,” 2018.

[3] C. Linnell, “A competitive analysis of the South African mining industry,” University of Pretoria, 2015.

[4] Mineral Council of South Africa, “Modernisation: Towards the mine of tomorrow,” 2019.

[5] V. Nick and P. Sihong, “Reliability analysis of underground mining equipment using genetic algorithms: A case study of two mine hoists,” *J. Qual. Maint. Eng.*, vol. 20, no. 1, pp. 32–50, Jan. 2014.

[6] E. Topal and S. Ramazan, “A new MIP model for mine equipment scheduling by minimizing maintenance cost,” *Eur. J. Oper. Res.*, vol. 207, no. 2, pp. 1065–1071, 2010.

[7] M. W. Lewis and L. Steinberg, “Maintenance of mobile mine equipment in the information age,” *J. Qual. Maint. Eng.*, vol. 7, no. 4, pp. 264–274, 2001.

[8] X. Zhou, L. Xi, and J. Lee, “Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation,” *Reliab. Eng. Syst. Saf.*, vol. 92, no. 4, pp. 530–534, 2007.

[9] Y. Chen, W. Gong, D. Xu, and R. Kang, “Imperfect maintenance policy considering positive and negative effects for deteriorating systems with variation of operating conditions,” vol. 15, no. 2, pp. 872–878, 2018.

[10] L. Bader, “The importance of preventive maintenance: A proper program finds problems early rather than waiting for disaster,” *ISE, vol 50, no. 1*, 2018.

[11] H. Pham and H. Wang, “Imperfect maintenance,” *Eur. J. Oper. Res.*, vol. 2217, no. 96, 1996.

[12] R. Moore, “Reliability- centered maintenance,” *Sel. Right Manuf. Improv. Tools*, pp. 221–245, 2007.

[13] H. P. Barringer and M. Kotlyar, “Reliability of critical turbo / compressor equipment,” in *Fifth International Conference on Process Plant Reliability*, 1996.

[14] P. Darling, *SME Mining Engineering Handbook*, 3rd ed. Elsevier, 2011.

[15] S. Cho, J. Shin, H. Jun, H. Hwang, C. Ha, and J. Hwang, "A study on estimating the next failure time of compressor equipment in an offshore plant," *Math. Probl. Eng.*, vol. 2016, 2016.

[16] R. B. Abernethy, *The New Weibull Handbook*, 5th ed. North Palm Beach, FL: Robert B. Abernethy, 2006.

[17] Z. Tang *et al.*, "Comparison of the Weibull and the Crow-AMSAA Model in prediction of early cable joint failures," *IEEE Trans. Power Deliv.*, vol. 30, no. 6, pp. 2410–2418, Dec. 2015.

[18] D. N. P. Murthy, M. Bulmer, and J. A. Eccleston, "Weibull model selection for reliability modelling," *Reliab. Eng. Syst. Saf.*, vol. 86, no. 3, pp. 257–267, 2004.

[19] J. T. Duane, "Learning curve approach to reliability monitoring," *IEEE Trans. Aerospace,* vol. 2, no. 2, pp. 563–566, Apr. 1964.

[20] ReliaSoft Corporation, "Reliability growth and repairable system analysis reference," *Reliawiki*. 2017.

[21] F. Tan, Z. Jiang, and T. Bai, "Reliability analysis of repairable systems using stochastic point processes," *J. Shanghai Jiaotong Univ.*, vol. 13, no. 3, p. 366, 2008.

[22] M. B. Muhammad, T. Raza, and M. A. Abd Majid, "Prediction of failures by using Crow/AMSAA model in Microsoft Excel.," *Proc. IEOM*. pp. 180–186, Jan-2016.

[23] P. Barringer, "Predict Failures: Crow-AMSAA 101 and Weibull 101," in *Proceedings of IMEC*, 2004, pp. 1–14.

[24] L. Y. Waghmode and A. D. Sahasrabudhe, "Product life cycle cost modelling - A suggested framework," *Proc. 1st ICETET*, pp. 745–748, 2008.

[25] H. P. Barringer, "Why you need practical reliability details to define life cycle costs For your products and competitors products," *Cycle*, pp. 1–8, 2003.

[26] "Reliability analysis using Weibull distribution applied to a booster pump used in oil drilling installations," *J. Tech. Univ. Sofia, Branch Plovdiv, Bulg. Fundam. Sci. Appl.*, vol. 22, no. October, pp. 31–37, 2016.

[27] H. P. Barringer, "Why You Need Practical Reliability Details To Define Life Cycle Costs For Your Products and Competitors Products !," *Cycle*, pp. 1–8, 2003.

[28] H. P. Barringer, "How to justify equipment improvements using life cycle cost and reliability principles," *Barring Assoc. Humble, TX*, pp. 1–12, 2001.

[29] D. Kececioglu, *Reliability Engineering Handbook*. PA: DEStech, 2002.

[30] H. Pham, *Recent advances in reliability and Quality Engineering*. World Scientific: Hackensack, NJ, 2001.

[31] P. A. Tobias and D. C. Trindade, *Applied Reliability*, 3rd ed. Boca Raton, FL: CRC Press, 2012.

[32] J. Van der Poel and C. C. Van Waveren, “Managing centrifugal pump reliability in the context of total cost of ownership,” *S. Afr. J. Ind. Eng.*, vol. 18, no. 2, pp. 57–70, 2007.

[33] P. Behera and B. Sahoo, “Leverage of multiple predictive maintenance technologies in root cause failure analysis of critical machineries,” *Int. Conf. Vib. Probl.*, 2015.

[34] M. N. Darghouth, A. Chelbi, and D. Ait-kadi, “Investigating reliability improvement of second-hand production equipment considering warranty and preventive maintenance strategies,” *Int. J. Prod. Res.*, vol. 55, no. 16, pp. 4643–4661, 2017.

[35] R. Rio, “Proactive asset management with IIoT and analytics,” *ARCwire Industry News*, 2015.

[36] J. A. Jacobs and M. J. Mathews, “Failure prediction of mine de-watering pumps,” *J. Fail. Anal. Prev.*, vol. 18, no. 4, pp. 927–938, 2018.

[37] C. Cilliers, “Cost savings on mine dewatering pumps by reducing preparation- and comeback loads,” M. Eng. Thesis, North-West University, Potchefstroom, 2013.

[38] J. Van Rensburg, A. Botha, and G. Bolt, “Energy efficiency via optimisation of water reticulation in deep mines,” *Ind. Commer. Use Energy*, pp. 124–132, 2011.

[39] J. C. Vosloo, “A New minimum cost model for water reticulation systems on deep mines,” North-West University (South Africa) Potchefstroom Campus, 2008.

[40] D. Stephenson, “Distribution of water in deep gold mines in South Africa,” *Int. J. Mine Water*, vol. 2, no. 2, pp. 21–30, 1983.

[41] L. H. Van Wyk, “Advances in mine dewatering pumps,” in *Int.Mine Water Assoc. Symp. Zambia*, 1993.

[42] G. Lane, K. Mohanarangam, and W. Yang, “Assessment of the flow pattern in a solvent extraction settler,” *9th Int. Conf. CFD Miner. Process Ind.*, no. December, pp. 1–6, 2012.

[43] J. De La Vergne and S. Mcintosh, *Hard Rock Miners Handbook*, vol. 4, no. 4. Stantec Consulting, 2000.

[44] J. Visser, “Protecting pump integrity in the mining sector,” *Mining Weekly*, 06-May-2014.

[45] B. H. P. and A. R. Budris, “Key considerations for pump Life cycle cost reduction,” *WaterWorld*, California, 2009.

[46] Hydraulic Institute, Europump, US Department of, and E. O. of I. Technologies, “Pump life cycle costs: A guide to LCC analysis for pumping systems,” .

[47] A. Romero, D. Millar, M. Carvalho, J. M. Maestre, and E. F. Camacho, “A comparison of the economic benefits of centralized and distributed model predictive control strategies for optimal and sub-optimal mine dewatering system designs,” *Appl. Therm. Eng.*, vol. 90, pp. 1172–1183, 2015.

[48] F. Mulubrhan, A. A. B. Mokhtar, and M. Muhammad, “Replacement analysis using probabilistic life cycle costing,” *ARPN J. Eng. Appl. Sci.*, vol. 11, no. 22, pp. 13042–13048, 2016.

[49] S. Graham, “Low life-cycle cost centrifugal pumps for utility applications,” *World Pumps*, vol. 2007, no. 484, pp. 30–33, 2007.

[50] A. R. Budris, “Reduce pump costs with predictive condition monitoring, fault Tolerant intelligent drives/controls,” *WaterWorld*, California, 2010.

[51] H. P. Barringer, “How To Justify Equipment Improvements Using Life Cycle Cost and Reliability Principles,” pp. 1–12, 2001.

[52] S. J. Fouché, “Improving efficiency of a mine compressed air system,” M. Eng. Thesis, North-West University, Potchefstroom, 2016.

[53] J. Vermeulen, “Simplified high-level investigation methodology for energy saving initiatives on deep-level mine compressed air systems,” PhD. Eng. Dissertation, North-West University, Potchefstroom, 2018.

[54] J. H. Marais, “An integrated approach to optimise energy consumption of mine compressed air systems,” PhD. Eng. Dissertation, North-West University, Potchefstroom, 2012.

[55] D. Nell, “Optimising production through improving the efficiency of mine compressed air networks with limited infrastructure,” M. Eng. Thesis, North-West University, Potchefstroom, 2017.

[56] K. Wygant, J. Bygrave, W. Bosen, and R. Pelton, “Tutorial on the application and design of integrally geared compressors,” in *in Asia Turbomachinery & Pump Symp., Singapore*, 2016.

[57] Siemens, “Adapting compressors to new challenges,” Erlangen, Germany, 2011.

[58] CAGI, “Elements of mechanical equipment life cycle cost analysis: Centrifugal air compressors,” Cleveland, 2012.

[59] S. Rupprecht, “Loading and hauling of broken rock in a narrow tabular orebody utilizing scraper winches,” in *SAIMM Underground Load and Haul, Rustenburg*, 2013.

[60] M. F. Handley, J. A. J. De Lange, F. Essrich, and J. A. Banning, “A review of the sequential grid mining method employed at Elandsrand Gold Mine,” *J. S. Afr. Inst. Min. Metall.*, vol. 100, no. 3. pp. 157–168.

[61] S. M. Rupprecht, “The potential of automatic scraper winches in underground narrow vein mining South African,” in *IMCET Proc. 26th*, 2019, pp. 603–611.

[62] N. C. Joughin, “Potential for the mechanization of stoping in gold mines,” *J. S. Afr. Inst. Min. Met.*, vol. 76, no. 6, pp. 285–300, Jan. 1976.

[63] J. F. Pritchard and C. F. Landy, “Scraper winch motors on South African gold mines-an investigation into their failure,” in *Proc. of IEEE AFRICON ’96*, 1996, vol. 1, pp. 435–440 vol.1.

[64] S. Schoombee, W. Hamer, and J. F. Van Rensburg, “Optimising gold ore transportation systems for electricity cost savings,” in *Proc. 2016 ICUE*, 2016, pp. 16–24.

[65] V. J. Solomon and P. van Niekerk, “Design of a stoping scraper scoop,” *J. S. Afr. Inst. Min. Met.*, vol. 79, no. 3, pp. 65–74, Jan. 1978.

[66] R. G. B. Pickering, “Presidential address: Has the South African narrow reef mining industry learnt how to change?,” *J. S. Afr. Inst. Min. Met.*, vol. 107, no. 9, pp. 557–565, Sep. 2007.

[67] R. B. Abernethy, J. E. Breneman, C. H. Medlin, and G. L. Reinman, *Weibull analysis handbook*. Defence Technical Information Center, Fort Belvoir, VA, 1983.

[68] W. T. Roberts and L. Mann, “Failure predictions in repairable multi-component systems,” *Int. J. Prod. Econ.*, vol. 29, no. 1, pp. 103–110, 1993.

[69] L. H. Crow, “Evaluating the reliability of repairable systems,” in *Proc. RAMS*, 1990, pp. 275–279.

[70] A. C. Márquez, *The Maintenance Management Framework: Models and Methods for Complex Systems Maintenance*. London: Springer-Verlag, 2007.

[71] F. N. Nwobi and C. A. Ugomma, “A comparison of methods for the estimation of Weibull distribution parameters,” *Metod. Zv. Adv. Methodol. Stat.*, vol. 11, no. 1, pp.

65–78, 2014.

[72] Z. Xu, “Comparing graphical method and a modified method to fit Weibull distribution,” *Comput. Sci.*, p. 53, 2012.

[73] K. S. R. Murthy and O. P. Rahi, “Estimation of Weibull parameters using graphical method for wind energy applications,” in *Proc. 18th NPSC*, 2014.

[74] M. Al-Fawzan, “Methods for estimating the parameters of the Weibull distribution,” *King Abdulaziz City Sci. Technol.*, vol. 8, no. May, pp. 1–11, 2000.

[75] M. Krit, “Goodness-of-fit tests in reliability : Weibull distribution and imperfect maintenance models,” *Univ. Grenoble*, 2014.

[76] J. L. Romeu, “Anderson-Darling: A goodness of fit test for small samples assumptions,” *Sel. Top. Assur. Relat. Technol.*, vol. Vol. 10, no. 5, pp. 1–6, 2003.

[77] J. Devore, *Probability and Statistics for Engineering and the Sciences*. Boston , MA: Brooks Cole, 2012.

[78] W. Nelson, J. I. McCool, and W. Q. Meeker, *Applied Life Data Analysis*. NY: John Wiley & Sons, 1982.

[79] K. M. Shuaib, P. G. Rasul, and P. A. Hesham, “Reliability and quantile analysis of the Weibull distribution,” *J. Stat.*, vol. 14, pp. 32–52, 2007.

[80] J. A. Jacobs, M. J. Mathews, and M. Kleingeld, “Failure prediction of mine compressors,” *J. Fail. Anal. Prev.*, vol. 19, no. 4, pp. 976–985, 2019.

[81] Z. Huang, “Conditional reliability lower bound for Weibull distribution without estimating shape parameter,” in *Proc. 1997 RAMS*, 1997, pp. 298–302.

[82] ReliaSoft Corporation, “Life Data Analysis Reference.” 2015.

[83] R. HotWire, “Predicting the number of failures for repairable systems,” *Reliability HotWire*, p. Issue 132, 2012.

[84] L. H. Crow and A. P. Basu, “Reliability growth estimation with missing data. II,” in *1988. Proceedings., Annual Reliability and Maintainability Symposium,* 1988, pp. 248–253.

[85] M. Reid, “Reliability – a Python library for reliability engineering (Version 0.5.1) [Computer software]. Zenodo. https://doi.org/10.5281/ZENODO.3938000.” 2020.

[86] S. McFadyen, “Motor starting - Introduction,” in *Motor starting and control primer: An Introduction to the Starting Techniques and Control of Electric Motors*, 2011.

APPENDIX A

App. A1: Co-Author Statement

I, **Marc John Mathews**, hereby provides consent that the articles listed below (**I to III**), may be used as part of Johan Jacobs's PhD (Eng.) thesis.

Signature: Date: 11/12/2020

I, **Hendrik Gideon Brand**, hereby provides consent that the article listed below (**III**), may be used as part of Johan Jacobs's PhD (Eng.) thesis.

Signature: Hendrik Brand Digitally signed by Hendrik Brand DN: cn=Hendrik Brand, o, ou, email=hgbrand@rems2.com, c=ZA Date: 2020.12.11 16:55:20 +02'00' Date: 11/12/2020

I, **Charl Cilliers**, hereby provides consent that the article listed below (**III**), may be used as part of Johan Jacobs's PhD (Eng.) thesis.

Signature: Date: 14/12/2020

I, **Kristy Nell**, hereby provides consent that the article listed below (**III**), may be used as part of Johan Jacobs's PhD (Eng.) thesis.

Signature: Date: 11/12/2020

I, **Jean Herman van Laar**, hereby provides consent that the article listed below (**III**), may be used as part of Johan Jacobs's PhD (Eng.) thesis.

Signature: Date: 11/12/2020

I, **Marius Kleingeld**, hereby provides consent that the articles listed below (**I to II**), may be used as part of Johan Jacobs's PhD (Eng.) thesis.

Signature: Date: 14/12/2020

ARTICLES

I. Jacobs, J.A., Mathews, M.J. & Kleingeld, M. Failure Prediction of Mine De-watering Pumps. J Fail. Anal. and Preven. 18, 927–938 (2018). Available online: https://doi.org/10.1007/s11668-018-0488-3

II. Jacobs, J.A., Mathews, M.J. & Kleingeld, M. Failure Prediction of Mine Compressors. J Fail. Anal. and Preven. 19, 976–985 (2019). Available online: https://doi.org/10.1007/s11668-019-00684-0

III. Jacobs, J.A., Brand, H.G., Cilliers, C., Campbell, K., Mathews, M.J. & van Laar, J.H. Failure Prediction of Mine Scraper Winches.

APPENDIX B

App. B1: Article I

J Fail. Anal. and Preven. (2018) 18:927–938
https://doi.org/10.1007/s11668-018-0488-3

CrossMark

TECHNICAL ARTICLE—PEER-REVIEWED

Failure Prediction of Mine De-watering Pumps

Johannes A. Jacobs · Marc J. Mathews · M. Kleingeld

Submitted: 25 April 2018 / Published online: 31 May 2018

Abstract The de-watering reticulation system of a deep level mine requires a network of pumps to pump water from underground to the surface. These de-watering pumps are exposed to extreme operating conditions, which can result in unacceptably short service lives. It is thus important for mining personnel to use the available tools to improve system operations and maintenance procedures. Current maintenance strategies involve reactive and preventive models, which can lead to failure creep. In order to implement proactive strategies, forecasting models are required. One of such models can be Weibull models, which has proven to be successful for many product failure mechanisms. The Weibull models have been used extensively in the reliability-engineering environment, but have not yet been implemented on a de-watering pump operating in extreme conditions on a deep level mine. A new practical method for predicting pump failure using various Weibull distribution functions was thus developed. The methodology was validated on four pumps, and it was found that the failures of new pumps were successfully predicted based on the Weibull analysis of previously failed pumps. It was also found that a quadratic relationship exists between the characteristic life of a de-watering pump and the operating depth underground. This is significant because all of the factors affecting the service life of a de-watering pump are quantified regarding only the operating depth and the characteristic life.

J. A. Jacobs (✉) · M. J. Mathews · M. Kleingeld
North-West University's Centre for Research and Continued Engineering Development (CRCED) in Pretoria, 77 Tijger Vallei Office Park, 13 Pony street, Silver Lakes, Pretoria, South Africa
e-mail: jjacobs@rems2.com

Keywords Pump failure prediction · Reliability engineering · Weibull analysis

Introduction

On a typical deep level mine, the de-watering reticulation system is one of the largest electrical energy consumers and can account for 25–50% of the mine's total energy usage [1]. The pumps in these systems are required to pump water from below the surface at pumping heads in excess of 800 m [2]. These pumps are thus exposed to extreme operating conditions which result in an unacceptably short service life [3]. The operating conditions can be defined as the environmental conditions, pumping head, corrosive water and sometimes high contents of suspended solids [3]. These demanding conditions may cause the pump to build up pressure as a result of suction or delivery valves not operating correctly [4].

Regarding the operating conditions, it is the relevant pump manufacturer's responsibility to mechanically optimise and improve the design of these pumps accordingly. This limits the mining personnel to only focus on reactive and preventive maintenance procedures in order to ensure minimum total cost of ownership [5, 6]. These strategies may result in failure creep and unplanned downtime due to random failures [7]. In order to produce a proactive framework, forecasting models can be integrated into existing maintenance strategies. It is thus important for these models to align well with random failure patterns [8, 9].

One of the primary methods used for pump failure prediction is to use real-time operational data. This is called condition monitoring and can be combined with preventative maintenance, asset management, equipment management and procurement applications to produce a positive return on investments [10]. The time to failure of some industrial machines can also be predicted using a technique called temporal data mining. This is a method that performs an analysis of temporal vibration data results which will produce the time until machine failure [11].

One method for strategically optimising the maintenance and operation of the pumps is to measure the reliability of the pumping system regarding Mean-Time-Between-Failures (MTBF) [12]. In a study involving a hydraulic system, it was found that the reliability is regarded as one of most efficient and important methods to study safe operation [13]. Also, a study that investigated the availability of a conveyor system showed that the improvement in reliability would yield a reduction in the number of failures [14]. It is evident that the reliability of a system is very important regarding the operational safety and number of failures of a component or system, in this case deep level mine de-watering pumps.

Models involving the reliability of a system are Weibull models, which, in this case, can be used to characterise the service life of a pump within its present operating state. A variety of Weibull models have been developed and studied extensively in the past [15]. These models can be seen as a collection of probabilistic and stochastic models derived from the Weibull distribution [15]. One such class of models is the standard Weibull model which has been proven to be successful for many product failure mechanisms as it can represent a wide variety of possible failure rate curve shapes [16].

The primary advantage of the Weibull models is the ability to provide reasonably accurate failure analysis and forecasts with extremely small data samples, even as little as two or three failures [17]. The Weibull plot is thus useful for maintenance planning, particularly reliability-centred maintenance [18]; it is, however, difficult to quantify a range of possible failure times, especially if a pump has reached a certain age of survival. Thus, if the engineering manager or mining personnel wants to know when the next failure will occur conditional distributions can represent such situations, in particular the conditional Weibull distribution [18].

This paper investigates the applicability of Weibull models and attempts to predict failure on mine de-watering pumps using the combination of the standard and conditional Weibull distributions in conjunction with quantile analysis. The final model can be integrated into existing maintenance strategies to produce a proactive framework.

Methodology

The prediction of component failure is difficult to quantify. Weibull models can, however, be used to provide a good estimate on probable failure times. The authors thus investigated the applicability of the Weibull models, for the first time, on a typical de-watering pump operating under extreme conditions on a deep level mine in South Africa.

In order to verify the applicability of the Weibull models, the de-watering pump failure intervals are required to satisfy the Weibull distribution criteria. Once the criteria are satisfied, it is possible to apply the Weibull analysis and use different models, associated with the Weibull distribution, to estimate and predict possible failure times. Successful prediction of failure will enable maintenance planners to produce a proactive framework.

There exists thus a need to develop a new method that will attempt to predict a probable failure range at median life relative to the current survival age of the de-watering pump that will enable integration of existing maintenance strategies to produce a proactive framework. The first step in this is to determine if the data set can be described by the Weibull distribution using the Weibull plot and a goodness-of-fit test. Thereafter, the median life upper- and lower limits, which will represent the probable failure range of the de-watering pump, will be determined. The results will then be validated using a previously installed de-watering pump and a newly installed de-watering pump. The Weibull analysis will be conducted on the previously installed de-watering pump and will be validated using the failure intervals of the newly installed de-watering pump. Figure 1 illustrates and describes the framework of the method.

Weibull Plot

Data set Suitability

The most important prerequisite for the Weibull analysis is to determine whether the data set can be described by a Weibull distribution. If the data can be graphically represented by a straight line on either Weibull paper or the Weibull probability plot, the data can be approximated by a 2-parameter Weibull distribution [19].

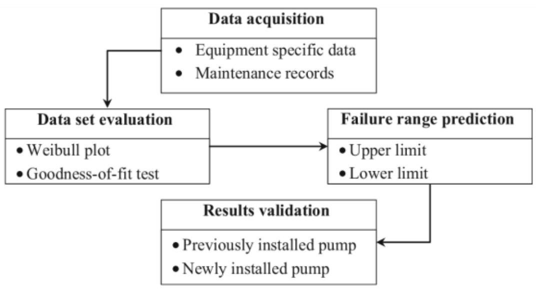


Fig. 1 De-watering pump failure prediction framework

Data Preparation

The first step is to group the data in increasing order of time to failure. Once the data are grouped correctly, it is possible to calculate the failure probabilities using the Bernard's approximation [19–21].

$$\tilde{F}_i = \frac{i - 0.3}{n + 0.4} \approx F(t) \quad \text{(Eq 1)}$$

where i is the observed value and n the total number of failures or sample size.

The next step is to prepare the data for the Weibull plot. The prepared data must be plotted in a double logarithmic scale, using the following equations [21],

$$y = \ln\{\ln[1/(1 - F(t))]\} \quad \text{(Eq 2)}$$

$$x = \ln(t) \quad \text{(Eq 3)}$$

Table 1 represents the data preparation according to the above-mentioned criteria.

After the data preparation is completed, it can be graphically represented by the Weibull probability plot. This will be the first visual indication on the nature of how the data are distributed. This distribution can either be the 2-parameter, 3-parameter or mixed Weibull distribution, for the purposes of assuming the data can be described by the Weibull distribution.

Parameter Estimation

As mentioned, for a 2-parameter Weibull distribution the data should follow a straight line. The straight line will then have an equal slope to the shape parameter (β) of the Weibull distribution, and its intersection ($y = 0$) will represent the scale parameter or characteristic life (η) [21]. There are many methods that can be used to estimate the parameters of the Weibull distribution [22] which include both the graphical procedure and analytical procedures among others. The latter include methods such as the maximum likelihood estimation, method of moments, and the least squares method [22]. If the data do follow a straight line on the Weibull probability paper, the most practical and easy method is the graphical procedure. The main objective will thus be to linearise the unreliability function of the 2-parameter Weibull distribution [22, 23], which is described by the following equation,

Table 1 Weibull plot data preparation requirements

t	$F(t)$	$x = \ln(t)$	$y = \ln\{\ln[1/(1 - F(t))]\}$
t_i	$F(t_i)$	x_i	y_i
$\vdots$	$\vdots$	$\vdots$	$\vdots$
t_n	$F(t_n)$	x_n	y_n

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad \text{(Eq 4)}$$

where t is the failure time, β and η the shape and scale parameters, respectively.

The unreliability function can be linearised so that the function represents a straight line in the form:

$$y = mx + c \quad \text{(Eq 5)}$$

where $y = \ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right)$, $m = \beta$, $x = \ln(t)$, and $c = -\beta\ln(\eta)$.

By introducing the above equations into Eq 5, there is

$$\ln\left(\ln\left(\frac{1}{1 - F(t)}\right)\right) = \beta\ln(t) - \beta\ln(\eta) \quad \text{(Eq 6)}$$

The shape parameter can now be calculated by determining the slope of the regression line which is described by the following equation

$$\beta = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sum(x - \bar{x})^2} \quad \text{(Eq 7)}$$

where $\bar{x}$ and $\bar{y}$ are the average values.

The scale parameter can be calculated from the intercept of the regression line,

$$c = \bar{y} - \beta\bar{x} = -\beta\ln(\eta) \quad \text{(Eq 8)}$$

$$\eta = e^{\frac{\beta\bar{x} - \bar{y}}{\beta}} \quad \text{(Eq 9)}$$

Once the two parameters are estimated, it is important to understand the characteristics of the Weibull distribution related to the specific component under analysis. The probability density function (PDF) and the cumulative distribution function (CDF) can be used to illustrate these characteristics. The shape parameter has the greatest effect on the distribution since the concavity of the distribution is directly proportional to the magnitude of this parameter [15]. Figure 2a and b illustrates the effect of the shape parameter on the PDF and CDF, respectively, keeping the scale parameter constant. $\beta < 1$ indicates infant mortality, $\beta = 1$ indicates random failures, and $\beta > 1$ indicates wear out failures [16].

The scale parameter has the same unit as the failure time of the de-watering pump, in this case hours, and represents the 63.2th percentile of the distribution. Figure 3a and b illustrates the effect of the scale parameter on the PDF and CDF, respectively, while keeping the shape parameter constant.

It is evident that a higher scale parameter will expand the shape of the distribution and a lower scale parameter will condense the distribution. Thus, in essence it can be discerned that a de-watering pump with a higher characteristic life and relatively low shape parameter will be more reliable and may thus represent a pump operating under relatively normal conditions.

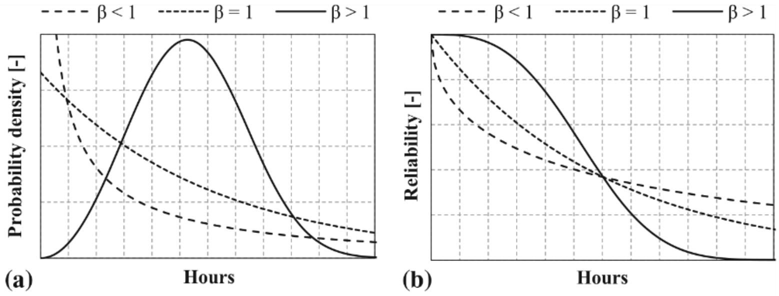


Fig. 2 Effect of the shape parameter on the PDF (**a**) and CDF (**b**), respectively

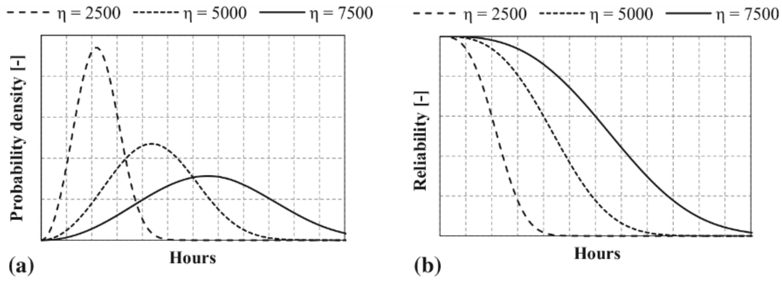


Fig. 3 Effect of the scale parameter on the PDF (**a**) and CDF (**b**), respectively

Goodness-of-Fit Test

There are numerous families of goodness-of-fit tests (GOF) for the Weibull distribution. These include tests based on the Weibull probability plot, on the empirical distribution function, on the normalised spacing's, and on the Laplace transform [24].

In the GOF tests of the Weibull distribution for de-watering pump failure, tests based on the empirical distribution function will be considered in order to validate the assumption that the data do indeed follow the Weibull distribution. One of these tests is known as the Anderson–Darling goodness-of-fit (AD GOF) test, and it is specialised for small data samples [25]. The primary objective of the AD GOF test is to determine the observed significance level (OSL) or probability value (*P* Value). The OSL is the smallest significance level at which the null hypothesis (H_0) can be rejected [26]. Hence, a decision can be made to either reject or accept H_0, which in this case is the assumption that the data follow the Weibull distribution.

Firstly, there is the Anderson–Darling statistic,

$$\mathrm{AD} = \left[\sum_{i=1}^{n}\left(\frac{1-2i}{n}\left\{\ln\left(1-e^{-Z_i}\right) - Z_{n+1-i}\right\}\right) - n\right] \qquad \text{(Eq 10)}$$

where $Z_i = \left(\frac{t_i}{\eta}\right)^{\beta}$,

$$\text{let } k_i = \frac{1-2i}{n}\left\{\ln\left(1-e^{-Z_i}\right) - Z_{n+1-i}\right\} \qquad \text{(Eq 11)}$$

Table 2 Anderson–Darling GOF test for the Weibull distribution

i	t	$Z(i)$	$Z(n+1-i)$	$k = \ln\{\ln[1/(1-F(t))]\}$	AD
1	t_i	Z_i	Z_{n+1-i}	k_i	$\sum_{i=1}^{n} k_i$
⋮	⋮	⋮	⋮	⋮	
n	t_n	Z_n	Z_1	k_n	

The above equations are used to iterate through each time step and finally present the AD value, which is described in Table 2.

After Table 2 is completed, the AD GOF statistic for small samples needs to be adjusted,

$$\mathrm{AD}^* = \left(1 + \frac{0.2}{\sqrt{n}}\right)\mathrm{AD} \qquad \text{(Eq 12)}$$

The OSL parameter can now be calculated,

$$\mathrm{OSL} = 1/\left\{1 + e^{-0.1+1.24\ln(\mathrm{AD}^*)+4.48(\mathrm{AD}^*)}\right\} \qquad \text{(Eq 13)}$$

The following criteria will be used as the decision rule, based on the OSL value [26]:

reject H_0 if $\mathrm{OSL} \le \alpha$

do not reject H_0 if $\mathrm{OSL} > \alpha$

$\alpha = 0.05$ was selected, which implies that if the Weibull distribution assumption (H_0) is rejected, the error committed is less than 5% [25, 26].

Failure Prediction

Predicting the coming number of failures or the next failure of a component at a given current age involves conditional failure probabilities [18]. Thus, if the goal is to predict the time to failure of a component from a specified current age, the probability of failure will disperse into a spread of values within the data set. This is also known as the percentile life, which is a very important property of the Weibull distribution and can also be referred to as the B-life [27]. There are many B-lives effectively used in manufacturing technology such as B-10, B-25, B-50, B-75 and B-90 lives.

Emphasis will be laid on the B-50 life, as this represents the median life of the component and entails the centroid of the conditional probability density function. The B-50 life also portrays the life at which the probability of failure and survival of the specific component is equal to 50%. The value and magnitude of median life is also dependent on the Weibull parameters and the current survival age and is hence given the name conditional median life. The requirement is thus to determine a range of possible failure times that will describe the B-50 life of the specific component. It is therefore evident that upper and lower limits will exist such that the next failure can be predicted within a range of possible failure times.

B-50 Life: Upper Limit

From the original estimated Weibull parameters and a specified current survival age, the median life until failure can be determined. This value will represent the age at which the component will be 50% reliable, which is also chosen as the maximum reliability parameter. The B-50 life of the specific component can be calculated using the conditional median life equation [18].

$$\text{Life}_{B50} = \eta\left\{\ln\left[\frac{1}{(1-P)\exp\left(-\left(\frac{\text{current}_{\text{age}}}{\eta}\right)^{\beta}\right)}\right]\right\}^{\frac{1}{\beta}} \qquad \text{(Eq 14)}$$

where $P = 0.5$.

B-50 Life: Lower Limit

The lower limit B-50 life of the component will be determined from the conditional reliability lower bound. The procedure for computing the conditional reliability lower bound is rather complex and involves various mathematical models and theorems. Zhaofeng Huang proposed a procedure for computing the conditional reliability lower bound without estimating the shape (β) parameter of the Weibull distribution [28]. This procedure will be used to determine the minimum conditional reliability starting with the following equation [28],

$$\widehat{R}_c(\beta_0) = exp\left[-\frac{\chi^2_{90,2}\left\{T^{\beta_0} - (T - t_0)^{\beta_0}\right\}}{\sum t_i^{\beta_0}}\right] \qquad \text{(Eq 15)}$$

where $\chi^2_{90,2}$ is the Chi-squared statistic with 90% confidence level and 2 degrees of freedom. T represents a possible future failure time, t_0 the current survival age and β_0 the observed shape parameter.

There exists a mathematical relationship between $\widehat{R}_c$ and β_0 such that the function yields a minimum at some value of β_0 [28]. The minimum value will represent the minimum conditional reliability, which will also comprise new β and η parameters. The process of determining the minimum conditional reliability is an iterative process, which can also be solved using the Newton–Raphson method [28]. Table 3 presents a more practical approach which will attain the same results, where $\beta_1 = 0.5$ and $\beta_n = 10$, thus

$$\beta_i = \beta_{i-1} + \frac{\beta_n - \beta_1}{n-1}(1 < i < n). \qquad \text{(Eq 16)}$$

Equation 16 will spread the values of β linearly between 0.5 and 10. This will produce a range of input values which will generate a range of output values from the conditional reliability function. The conditional reliability can then be plotted against the shape parameter, which will illustrate the location where the function is at a minimum, see Fig. 4.

Once the new β parameter is determined, a 100γ per cent confidence lower bound on η can be calculated using the following equation [28]

$$\widehat{\eta} = \left(\frac{\sum_{i=1}^{n} t_i^{\beta}}{\chi^2_{90,2}}\right)^{\frac{1}{\beta}} \qquad \text{(Eq 17)}$$

It is then possible to determine the lower limit B-50 life of the component by plugging the new shape and scale parameters into the conditional median life; refer to Eq 14.

Results

There are numerous applications of the Weibull analysis which ranges from the strength of steel to the height of

Table 3 Minimum conditional reliability calculation

i	β_0	$\sum t_i^{\beta_0}$	$\widehat{R}_c(\beta_0)$
1	β_i	$\sum t_i^{\beta_i}$	$\widehat{R}_c(\beta_i)$
⋮	⋮	⋮	⋮
n	β_n	$\sum t_n^{\beta_n}$	$\widehat{R}_c(\beta_n)$

adult males [17]. The Weibull analysis, however, has not yet been applied to a typical de-watering pump operating under extreme conditions in a deep level gold mine in South Africa. In this section, the newly developed methodology, described in the previous section, will be used to determine whether the Weibull analysis is indeed applicable on a typical de-watering pump and whether it is possible to predict pump failure therefrom.

This will be accomplished by implementing the Weibull analysis on a previously installed de-watering pump and predicting the failures of a newly installed pump. If the coming failures of the new de-watering pump could be predicted with the Weibull analysis of the previously installed pump, then the applicability of the Weibull analysis is satisfied.

This verification will also convey the fact that reliability-centred maintenance will be applicable and the current maintenance procedures can be optimised accordingly. This will ultimately increase the longevity of the individual de-watering pump and potentially avoid unnecessary repair and replacement costs. For simplification purposes, only one de-watering pump will be used to illustrate the methodology, but the discussion of the results will consist of the results from four individual de-watering pumps.

Data Collection and Preparation

The integrity and validity of the Weibull analysis is dependent on the quality of the data set. Performance data, recorded by the SCADA systems on the mine, and inspection and maintenance reports were used to generate the data set for each individual de-watering pump. Figure 5 describes and illustrates the data collection and processing process undertaken to generate the final data set.

Once the data were processed and used to generate the final data set, it was prepared for the Weibull analysis. The data were grouped in increasing order in terms of the time to failure and were transformed to generate the Weibull plot. Table 4 describes the data preparation for the de-watering pump.

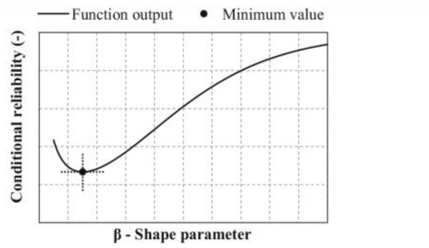


Fig. 4 Conditional reliability vs. shape parameter

From the data set described in Table 4 the Weibull plot could be generated. If the Weibull probability plot follows a straight line, a 2-parameter Weibull distribution can be assumed to describe the data set. Figure 6 illustrates the Weibull probability plot generated for the de-watering pump.

Parameter Estimation

From a visual perspective, it is evident that the data do follow a straight line on the Weibull probability plot. Thus, it was assumed that the data can be represented by the Weibull distribution and the parameters could be estimated using the graphical procedure. Table 5 describes the parameter estimation data requirements for the calculations.

The slope of the regression line is equal to the shape parameter of the distribution and was calculated using the data in Table 5 and Eq 7. The scale parameter was calculated from the intercept of the regression line, described by Eq 9. The results yielded the shape and scale parameters to be $\beta = 1.282$ and $\eta = 6022.800$, respectively. The characteristic curves of the Weibull distribution were then generated to obtain a better understanding of how the data set was distributed. Figure 7a and b illustrates these functions.

It is evident that the shape parameter of the de-watering pump is greater than unity, indicating that the failures are a result of it being in the wear out phase. It is also very close to unity, which can also imply that random failures may occur. The importance of these two functions is significant as any other reliability measure of interest can be derived or obtained therefrom.

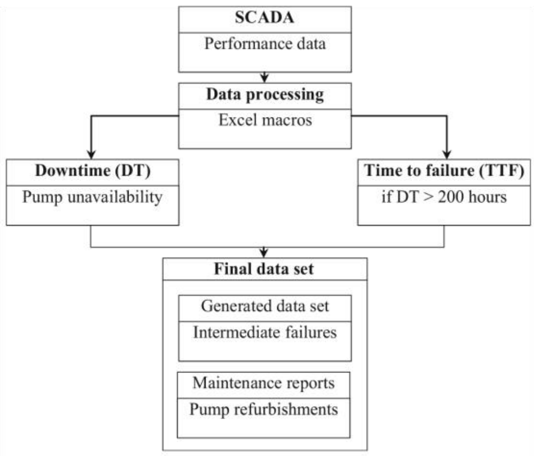


Fig. 5 De-watering pump time to failure data collection

Goodness-of-Fit Test

It is assumed that the data may be represented by the 2-parameter Weibull distribution, but it is very important to justify this assumption before moving on to predict the coming failures. As mentioned previously, the Anderson–Darling goodness-of-fit test will be done on the data set. The null hypothesis (H_0) is the assumption that the failure times of the de-watering pump can be represented by the 2-parameter Weibull distribution. Firstly, the data requirements must be established to determine the Anderson–Darling statistic. Table 6 describes the data set and the Anderson–Darling statistic.

The Anderson–Darling GOF test yielded the following results: AD = 0.240, AD^* = 0.268 and finally OSL = 0.631. It is evident that the OSL > α, as α = 0.05. Hence, the null hypothesis that the data can be represented by the 2-parameter Weibull distribution is accepted.

Table 4 De-watering pump data preparation

t (h)	$F(t)$ (–)	$x = \ln(t)$ (–)	$y = \ln\{\ln[1/(1 - F(t))]\}$ (–)
1849	0.206	7.522	– 1.467
5098	0.500	8.537	– 0.367
7921	0.794	8.977	0.458

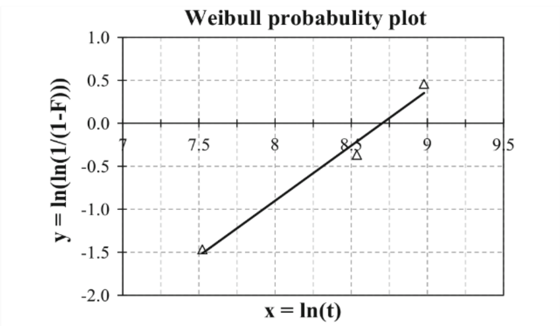


Fig. 6 Weibull probability plot for the de-watering pump

Table 5 Parameter estimation data requirements for the calculations

No.	$(x - \bar{x})(y - \bar{y})$ (–)	$(x - \bar{x})$ (–)
1	0.830	0.677
2	0.018	0.037
3	0.579	0.399

De-watering Pump Failure Prediction

As mentioned previously, the Weibull analysis was conducted on a previously installed pump after which the failure prediction was verified by the newly installed pump. The previously installed de-watering pump operated from March 2014–October 2015, in which it accumulated a total of 7921 h of service during this period. The de-watering pump was refurbished and the newly installed de-watering pump operated from October 2015–July 2017, in which it accumulated a total of 6133 h of service. Both of these de-watering pumps had intermediate failures during their operation, as determined using the process described and illustrated by Fig. 5. Table 7 describes the two data sets.

De-watering Pump B-50 Life: Upper Limit

Using the Weibull parameters of the previously installed de-watering pump, the upper limit or B-50 life of the newly installed de-watering pump was calculated for each intermediate time to failure. These intermediate failure times represent the current age of survival, as the de-watering pump was still operational after these failures, indicated by Table 8.

De-watering Pump B-50 Life: Lower Limit

In order to determine the lower conditional B-50 life of the de-watering pump, it was needed to first determine the minimum conditional reliability. This then produced new shape and scale parameters, after which the B-50 life could be determined. The minimum reliability calculation yielded the following results, described by Table 9.

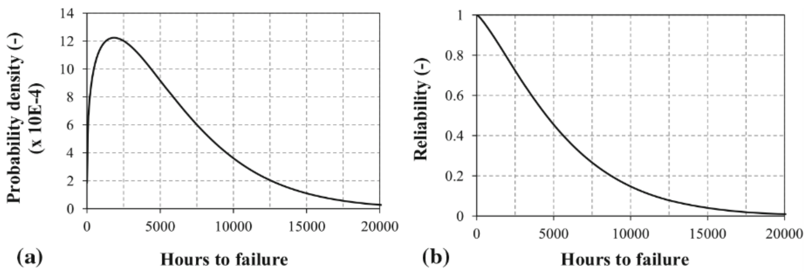


Fig. 7 PDF (**a**) and CDF (**b**) characteristic curves for a de-watering pump

The results from Table 9 can be graphically illustrated to clarify if the conditional reliability function has a minimum. This is illustrated by Fig. 8.

Once the minimum conditional reliability was determined, the corresponding shape parameter could be used to calculate the new scale parameter. Using Eq 14, the lower limit B-50 life can then be calculated. The minimum conditional reliability analysis yielded the following results, summarised in Table 10.

De-watering Pump B-50 Life: Failure Range

The resulting upper- and lower limit calculations now represent a range of possible B-50 life failure times. If the mining personnel or engineer wants to know when the next possible failure will occur, given that the pump has reached a specific current age of survival, the failure range can be specified. This will enable the mining personnel or engineer to make more informative decisions based on the prediction. The final results are described by Table 11 and illustrated by Fig. 10c.

As seen from Fig. 9, the broken lines represent the upper and lower limits and the red crosses represent the actual failures. It is evident that the actual failures occurred within the predicted range of failures gained from the Weibull analysis done on the previous installed pump. It must also be noted that the initial range of possible failures is quite broad, and this due to the fact that the probability of failure is random and the pump is probably in its burn-in phase.

Discussion of Results

As mentioned previously, it is extremely difficult to quantify the coming failures of a de-watering pump, especially if the pump has reached a certain current age of survival. Conditional Weibull distributions can be very helpful for such situations, but lack the ability to specify a typical range of probable coming failure times. However, by implementing quantile analysis in terms of percentile life and determining boundary conditions on these distributions, it is possible to generate a range of failure time estimates. The proposed method is both practical and easy to implement.

The proposed method proved to be successful in predicting a single pump failure. To validate the method further, it was conducted on four different pumps, located on four different levels on a deep level mine. Figure 10 illustrates the predicted coming failure ranges for each of these pumps, including the pump used in the method illustration.

Table 6 Anderson–Darling statistic calculation table

No.	t	$Z(i)$	$Z(n+1-i)$	$k = \ln\{\ln[1/(1-F(t))]\}$	AD
1	1849	0.220	1.421	1.014	0.240
2	5098	0.808	0.808	1.398	
3	7921	1.421	0.220	0.828	

Table 7 De-watering pumps intermediate failures and refurbishment time

No.	Previously installed pump (TTF)	Newly installed pump (TTF)
1	1849	1232
2	5098	4305
3	7921	6133

Table 8 Upper limit B-50 life of newly installed de-watering pump

No.	Current survival age (h)	B-50 life: upper limit (h)
1	0	4524.998
2	1232	5178.284
3	4305	7582.582

Table 9 Minimum conditional reliability data table

No.	β (−)	$\sum t^{\beta}$ (−)	$\widehat{R}_c(\beta)$ current age 1	$\widehat{R}_c(\beta)$ current age 2	$\widehat{R}_c(\beta)$ current age 3
0	0.500	203.400	0.218	0.434	0.615
1	0.975	11978.928	0.244	0.298	0.372
2	1.450	742138.488	0.289	0.267	0.230
3	1.925	47645578.730	0.349	0.278	0.151
4	2.400	3135002369	0.418	0.311	0.107
5	2.875	2.09854E+11	0.492	0.357	0.081
6	3.350	1.42226E+13	0.565	0.411	0.065
7	3.825	9.72921E+14	0.635	0.468	0.055
8	4.300	6.70352E+16	0.698	0.527	0.049
9	4.775	4.64534E+18	0.754	0.584	0.045
10	5.250	3.23407E+20	0.801	0.638	0.042
11	5.725	2.26011E+22	0.841	0.688	0.041
12	6.200	1.58441E+24	0.874	0.734	0.041
13	6.675	1.11358E+26	0.901	0.774	0.041
14	7.150	7.84329E+27	0.923	0.809	0.042
15	7.625	5.53391E+29	0.940	0.840	0.043
16	8.100	3.91009E+31	0.953	0.867	0.045
17	8.575	2.766E+33	0.964	0.889	0.046
18	9.050	1.95856E+35	0.972	0.908	0.048
19	9.525	1.38791E+37	0.978	0.924	0.051
20	10.000	9.84158E+38	0.983	0.937	0.053

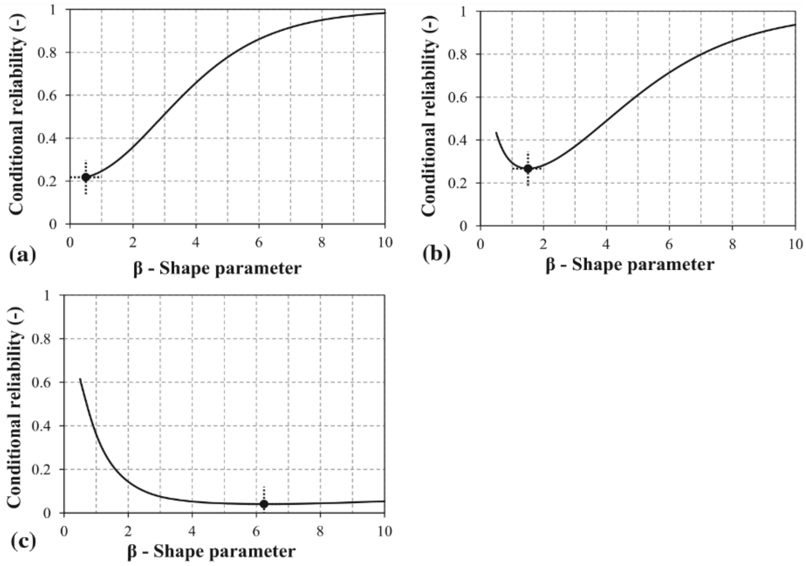


Fig. 8 Lower bound conditional reliability for each intermediate failure time

Table 10 Summary of the minimum conditional reliability analysis

No.	Current survival age	β $(-)$	$\widehat{R}_c(\beta)(-)$	$\hat{\eta}$ (h)	B-50 life: lower limit (h)
1	0	0.50	0.22	1950.795	937.266
2	1232	1.45	0.27	3901.212	3575.199
3	4305	6.20	0.04	6255.030	6023.862

Table 11 Summary of the minimum conditional reliability analysis

No.	Current survival age (h)	B-50 life: lower limit (h)	B-50 life: upper limit (h)	Actual failure (h)
1	0	937.266	4524.998	1232
2	1232	3575.199	5178.284	4305
3	4305	6023.862	7582.582	6133

As seen from Fig. 10a and b, only one actual failure has occurred, indicated by the red crosses. The black crosses indicate the predicted possible coming failure times. Figure 10d illustrates the actual failures of a de-watering pump located 3.5 km below surface. It is evident that the proposed method would have predicted the coming failures. It was only the last failure that fell short of the specified range. The reason for this was due to a level flood, where all of the pumps on the level had to be replaced.

It is also very interesting to note that the range size between the upper- and lower limit bands becomes more confined as the pump approaches its characteristic life. The reason is that this point represents the 63.2th percentile of

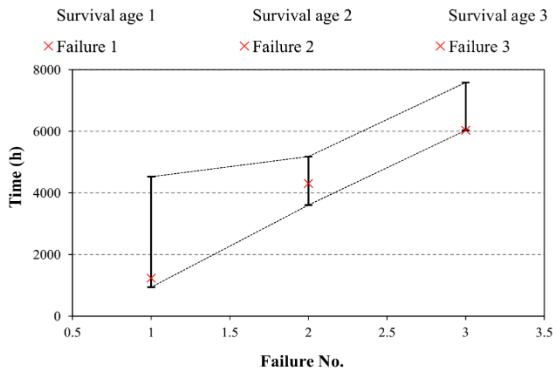


Fig. 9 De-watering pump failure prediction

the Weibull distribution. This is also due to the fact that there exists a mathematical relationship between the reliability of the pump and the characteristic life such that the function yields a minimum value.

A highly unique correlation between the operating depth and characteristic life exists as a result of the demanding conditions under which these de-watering pumps operate. Thus, as the operating conditions get more extreme, the characteristic life (scale parameter) of a de-watering pump decreases, as illustrated by Fig. 11. This implies that the Weibull distribution also has the ability to provide a possible indication of the operating condition of a typical de-watering pump.

As seen from Fig. 11, a quadratic relationship exists between the characteristic life of a de-watering pump and

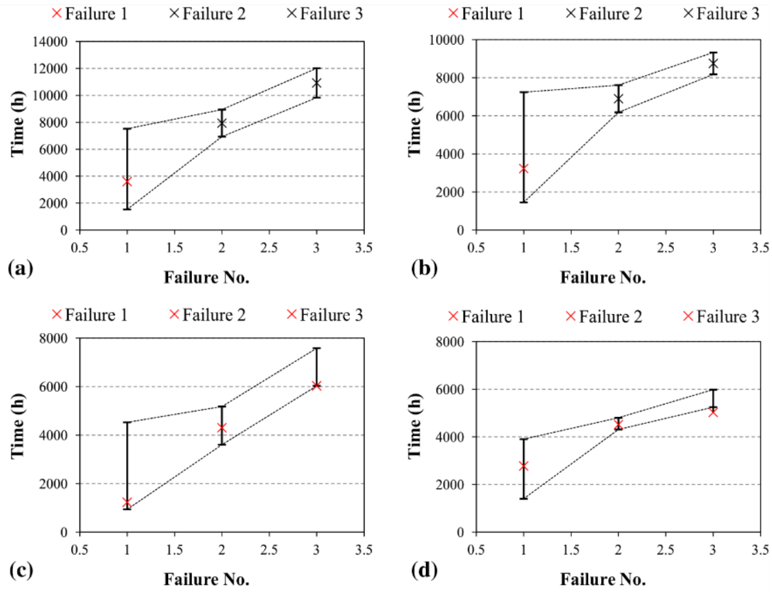


Fig. 10 De-watering pump failure prediction

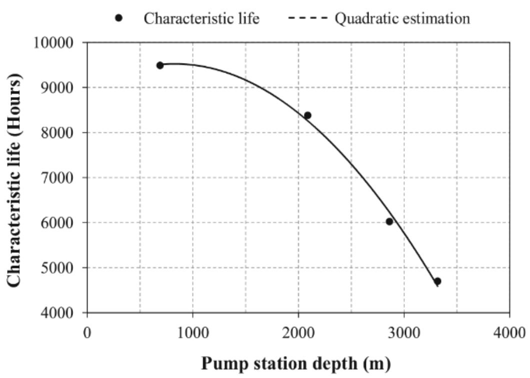


Fig. 11 De-watering pump characteristic life depreciation

the pump station level or operating depth. This indicates that the service life of a de-watering pump is very much dependent on the specific operating conditions and operating depth regardless of the pumping head. Hence, the implementation of the Weibull analysis on a previously installed pump is only applicable to a newly installed pump operating on the same level and under the same environmental conditions.

These de-watering pumps are all exposed to extreme temperatures and high humidity and are required to pump water from underground at heads between 500 and 700 m. There is no correlation between the characteristic life and the required pumping head, which is a clear indication that there are other factors involved. One of them is most likely the relationship between the dirty water being supplied from the settler ponds. This water can be corrosive and sometimes have a high content of suspended solids. This is especially the case on the deeper levels where the pumping stations are located near the settler ponds. As the dirty mine service water is pumped to surface in cascading configuration, the quality might improve due to continuous settling of impurities and solids. It is, however, needed for further studies to confirm this hypothesis.

The Weibull analysis, however, displayed very unique results in terms of the characteristic life and operating depth of a de-watering pump. As a result of the poor water quality with the presence of grit and small pieces of rock, the longevity of a typical de-watering pump will deteriorate. This is especially the case on the much deeper levels where the water quality is very poor. It was thus found that there exists a quadratic relationship between all of the factors affecting the de-watering pump's service life and the operating depth.

What do the results mean for the industry and what contribution will it have in the research field?

1. The methodology presented here can be used to predict failure on mine pumping systems operating under various underground conditions.
2. The methodology could be implemented on other similarly important aspects of mining such as ventilation, winders, drills, compressors. This could lead to cost savings and operational improvements.

3. The results show that the operating condition of the pump is extremely important to consider as it is directly related to pump failure (Fig. 11).
4. Currently, mines do not consider pump operational conditions, such as the water quality, to be one of the most important deciding factors when selecting the proper equipment. We have shown that parameters that are not considered are of the outmost importance in choosing the correct pump and determining pump failure.
5. The final model can be integrated into existing maintenance strategies to produce a proactive framework.

The Weibull analysis has proven to be applicable on a typical de-watering pump operating under extreme conditions on a deep level mine in South Africa. The newly proposed method yielded a range of possible failure times and was verified by two de-watering pumps. Ultimately, a range of coming failure times can thus be generated according to the current age of survival of a specific pump with a 90% confidence lower bound on the minimum failure time.

Conclusion

The failure rate of a de-watering pump has the potential to increase the life-cycle costs significantly. It is thus important to have all of the possible tools needed to reduce these costs. The Weibull analysis has been used numerous times on many different components to address this life-cycle issue. However, it has not been implemented on a de-watering pump operating in a deep level mine in South Africa. It is thus evident that there exists a need to investigate the implementation of the Weibull analysis on a de-watering pump in a deep level mine.

The data evaluation process yielded satisfying results, as all of the failure time data sets of the de-watering pumps complied with the Weibull distribution criteria. This also portrays the fact that there is only one failure mode present, which under further investigation is possible to quantify. The Weibull analysis was thus applied to several de-watering pumps, and the validation thereof was satisfied with historical data. Upper and lower limits on the B-50 life were considered and chosen as the range of possible failure times, which generated accurate predictions on life-cycle failures.

The proposed method thus validates the applicability of the Weibull analysis on a de-watering pump and predicts future failures. This is exceptionally useful in industry since the mining personnel or engineer can immediately get a good estimate on how long the pump could possibly operate, enhancing decision making and possibly improving maintenance procedures. It is therefore believed that using the Weibull analysis for pump failure prediction will ultimately increase the reliability of the de-watering system, opening doors to more energy saving initiatives.

Acknowledgments This work was supported by Enermanage (Pty) Ltd.

References

1. V. Tutterow, G. Hovstadius, A. McKane, Going with the flow: Life cycle costing for industrial pumping systems. *eScholarship*. University of California (2002). http://escholarship.org/uc/item/51m5d0x9.pdf
2. J.C. Vosloo, A New minimum cost model for water reticulation systems on deep mines, Thesis, North-West University, Potchefstroom Campus (2008). https://nwulib.nwu.ac.za/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=cat01185a&AN=nwu.b1710738&site=eds-live
3. L.H. van Wyk, Advances in mine dewatering pumps, in *International Mine Water Association & Zambia Consolidated Copper Mines Limited: The First African Symposium on Mine Drainage and Environment Protection from Mine Waste Water Disposal* (Chililabombwe, 1993), pp. 631–656
4. J. Visser, Protecting pump integrity in the mining sector. (2014). http://www.miningweekly.com/article/protecting-pump-integrityin-the-mining-sector-2014-05-06/rep_id:3650
5. H.J. Tolvanen, Life cycle energy cost savings and pump selection. World Pumps **2007**(490), 34–37 (2007)
6. A. Gambsky, Predictive maintenance saves money. Modern Casting **106**(10), 26–30 (2016)
7. L. Bader, The importance of preventive maintenance. https://www.abm.com/documents/articles/ISE-Bader-Article.pdf (2018)
8. M.N. Darghouth, A. Chelbi, D. Ait-kadi, Investigating reliability improvement of second-hand production equipment considering warranty and preventive maintenance strategies. Int. J. Prod. Res. **55**(16), 4643–4661 (2017). https://doi.org/10.1080/00207543.2016.1277277
9. R. Rio (2015) Proactive asset management with IIoT and analytics. *ARCwire Industry News*. https://www.arcweb.com/blog/proactive-asset-management-iiot-analytics
10. P. Mosher, Predicting failure—condition monitoring in action. World Pumps **484**, 24–28 (2007)
11. J. Nakamura, Predicting time-to-failure of industrial machines with temporal data mining (2007). Thesis. https://www.tacoma.uw.edu/sites/default/files/global/documents/institute_tech/jnakamura.pdf
12. J. van der Poel, C.C. van Waveren, Managing centrifugal pump reliability in the context of total cost of ownership. S. Afr. J. Ind. Eng. **18**(2), 57–70 (2007)
13. M.J. Rahimdel, M. Ataei, R. Khalokakaei, S.H. Hoseinie, Reliability-based maintenance scheduling of hydraulic system of rotary drilling machines. Int. J. Min. Sci. Technol. **23**(5), 771–775 (2013)
14. S. Furuly, J. Barabady, A. Barabadi, Availability analysis of the main conveyor in the Svea Coal Mine in Norway. Int. J. Min. Sci. Technol. **24**(5), 587–591 (2014)
15. D.N.P. Murthy, *Weibull models* (Wiley, Hoboken, 2004)
16. P.A. Tobias, D.C. Trindade, *Applied reliability*, 3rd edn. (CRC Press, Boca Raton, 2012)
17. R.B. Abernethy, *The new Weibull handbook*, 5th edn. (Robert B. Abernethy, North Palm Beach, 2006)

18. W. Nelson, J.I. McCool, W.Q. Meeker, *Applied life data analysis* (Wiley, New York, 1982)
19. R.B. Abernethy, J.E. Breneman, C.H. Medlin, G.L. Reinman, Weibull analysis handbook (1983). http://www.dtic.mil/dtic/tr/fulltext/u2/a143100.pdf. Accessed 9 December 2017
20. D. Kececioglu, *Reliability engineering handbook* (DEStech Publications, Lancastar Pennsylvania, 2002)
21. A.C. Márquez, *The maintenance management framework: Models and methods for complex systems maintenance* (Springer, London, 2007)
22. F.N. Nwobi, C.A. Ugomma, A comparison of methods for the estimation of Weibull distribution parameters. Metodol. Zvezki Adv. Methodol. Stat. **11**(1), 65–78 (2014)
23. ReliaSoft Corporation, Life data analysis reference (2015). http://www.synthesisplatform.net/references/Life_Data_Analysis_Reference.pdf
24. M. Krit, *Goodness-of-fit tests in reliability: Weibull distribution and imperfect maintenance models* (Université de Grenoble, Grenoble, 2014)
25. J.L. Romeu, Anderson-darling: a goodness of fit test for small samples assumptions. Sel. Top. Assur. Relat. Technol. **10**(5), 1–6 (2003)
26. J. Devore, *Probability and statistics for engineering and the sciences* (Brooks Cole, Boston, 2012)
27. K.M. Shuaib, P.G. Rasul, P.A. Hesham, Reliability and quantile analysis of the Weibull distribution. J. Stat. **14**, 32–52 (2007)
28. H. Zhaofeng, Conditional reliability lower bound for Weibull distribution without estimating shape parameter, in *1997 Proceedings of Annual Reliability and Maintainability Symposium* (1997), pp. 298–302

APPENDIX C

App. C1: Article II

J Fail. Anal. and Preven. (2019) 19:976–985
https://doi.org/10.1007/s11668-019-00684-0

TECHNICAL ARTICLE—PEER-REVIEWED

Failure Prediction of Mine Compressors

Johannes A. Jacobs · Marc J. Mathews · M. Kleingeld

Submitted: 9 June 2019 / Published online: 24 July 2019

Abstract A typical compressed air system on a deep-level mine requires a combination of compressors to supply sufficient energy to critical underground equipment for safe operation. These compressors are required to run continuously to maintain adequate system pressure. Hence, these systems account for approximately 20–40% of a mine's total energy consumption. It is of vital importance to minimize downtime and maximize availability. Models that involve reliability engineering can greatly improve decision-making to minimize unplanned failures. To achieve this, a unique failure prediction method was developed, based on previous work. The foundation of the previous method was based on a combination of the standard Weibull distribution, the conditional Weibull distribution and basic quantile analysis. It was applied to mine dewatering pumps and successfully predicted the coming failures with good accuracy. In this study, the model was improved and adapted for application on mine compressors. The methodology was validated on various compressors using the leave-one-out cross-validation method. It was found that subsequent failures of the compressors were successfully predicted based on iterative training data sets of the proposed methodology. An average prediction accuracy of 92.30% was achieved across all compressors used in the study.

Keywords Compressor failure forecasting · Reliability engineering · Weibull analysis · System safety

J. A. Jacobs (✉) · M. J. Mathews · M. Kleingeld
Centre for Research and Continued Engineering Development, North-West University, Pretoria, South Africa
e-mail: jjacobs@rems2.com

Introduction

On a typical deep-level mine, compressed air systems are imperative for proper operation of underground mining equipment. This network can either function as a standalone or ring feed system [1]. The former typically comprises of a single compressor house containing a combination of different compressors. A ring feed system is more complex and comprises of multiple compressor houses, each containing a combination of different compressors [1].

Regardless of the compressed air network configuration, it is imperative that these systems maintain a continuous supply of compressed air [2]. The underground compressed air pipe network is a convoluted system consisting of many sub-components. These components typically include rock drills, loading boxes, loaders, hoppers, refuge bays, etc. [3]. Refuge bays, which are a critical safety component, also require sufficient and continuous air supply to keep a positive pressure within the chamber, according to the Mine Health and Safety regulations [4].

As a result of the continuous operation to maintain adequate system pressure, these systems account for approximately 20–40% of a mine's total energy consumption [5–7]. However, the operating environment and system infrastructure differ from each system. Some of the working areas underground are estimated to be up to eight kilometers (5 miles) away from the surface compressed air connection [8].

It is the relevant compressor manufacturer's responsibility to improve and optimize the design of critical sub-components within the compressor. This limits the mining personnel and planners to only focus on conventional reactive and preventive maintenance. The preventive

Springer

maintenance is scheduled periodically by the planner's experience and historic failure data [9]. These strategies typically result in the system never being restored to a good-as-new condition, but rather to a continuously dilapidating operating condition. This exposes the system to creep failure and is also known as imperfect maintenance [10–12].

To achieve adequate system reliability, the utilization of predictive maintenance has proven to be effective and beneficial [13]. Predictive maintenance strategies primarily involve condition monitoring which includes vibration analysis, oil analysis, acoustic analysis, motor current signature analysis and infrared thermography [13]. In conjunction with forecasting models, current predictive maintenance strategies can be remodeled into a proactive framework. It is, however, required that these models align well with random failure patterns [14, 15].

A combination of condition-based models can be used to predict the next failure time. Consequently, these models require a lot of field data including the finite-state continuous-time Markov model, a linear regression method and their hybrid model [16]. These models can be improved further by using methods such as the Monte Carlo Markov Chain (MCMC) [16]. However, this may be very challenging when the data represent a high number of dimensions [17]. From practical experience, generally, only high-level data can be acquired in the mining industry. Hence, a more practical and simple approach regarding failure prediction modeling is required.

One such modeling technique involves reliability-based prediction models. Reliability involves a degree of uncertainty as the exact time of failures is unknown although failure probability exists [18]. Weibull models are typically used in the reliability environment. These models can be considered a collection of probabilistic and stochastic models derived from the Weibull distribution [19]. Various Weibull models have been developed and studied extensively in the past [19]. The most common one is the standard or two-parameter Weibull model. It has proven to be successful for many product failure mechanisms as it can represent a wide variety of possible failure rate curve shapes [20].

When attempting failure prediction, a unique combination of the standard Weibull models, conditional Weibull distributions and quantile analysis can be used [21]. From this, successful implementation of reliability-centered maintenance is possible [15]. From previous work, a unique failure prediction method was developed to predict the failure times of mine dewatering pumps operating on a deep-level gold mine [21]. In this study, the same method was used; however, it was improved and adapted for large centrifugal compressors.

The previous method required a full data set to determine the input parameters (Weibull parameters). These parameters were then used to predict all of the coming failures after a pump has been replaced. Compressors are very reliable machines, and consequently a total replacement is highly unlikely. It is thus required to predict subcomponent failure which may result in downtime, i.e., breakdowns. The model was adjusted to predict subsequent failures using the previous subsequent failures as the training data set. Ultimately, the final model outputs are displayed in a band of most probable failure times in cumulative form. This is especially useful for integration with existing maintenance strategies.

Methodology

Component time-to-failure (TTF) prediction can be difficult to quantify. Numerous statistical functions can be used to describe the type of distribution. However, within the spectrum of equipment life and reliability, Weibull models are commonly used. Hence, the applicability of a unique failure prediction technique is investigated, using a combination of the standard Weibull distribution, the conditional Weibull distribution and quantile analysis. This methodology was uniquely applied on large centrifugal mine compressors in a deep-level mine in South Africa.

The first step requires failure- and equipment-specific data. These data can either be obtained by a Supervisory Control and Data Acquisition (SCADA) system or from maintenance management software. The data processing phase may differ for each system, but the final data package should contain enough information to align accurately with actual component failures.

From the finalized data set, the TTF of the component can be presented as either cumulative or non-cumulative. The former represents the total operating time until failure, and the latter represents the incremental amount of operating time since the last failure. In both cases, the data set should satisfy the Weibull distribution criteria, which consist of a goodness-of-fit (GOF) test and the Weibull probability plot.

If the criteria are satisfied, failure ranges are determined using a unique combination of the conditional Weibull distribution and quantile analysis. This process is mathematically intensive, but the model outputs entail a unique collection of probable failure times, which is constrained by a certain percentile life. The results are then validated by either comparing the failures of a previously installed compressor to a newly installed compressor or by using the leave-one-out cross-validation (LOOCV) technique. Figure 1 illustrates the methodology framework.

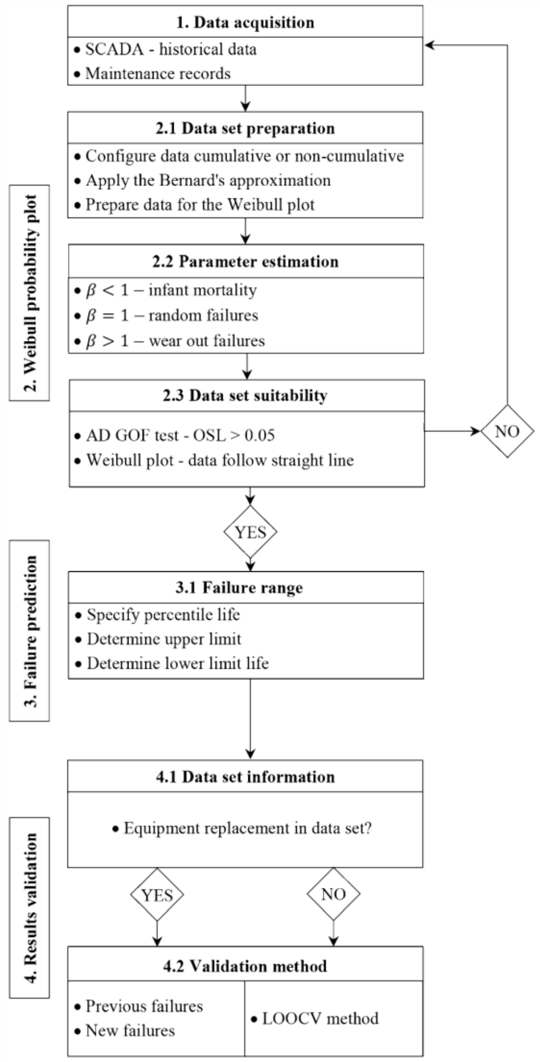


Fig. 1 Large centrifugal mine compressor failure prediction framework

Weibull Plot and Failure Prediction

The generic failure prediction method developed by the authors [21] for a two-parameter Weibull distribution is improved upon here. This method was specifically developed for failure data sets that adhere to the Weibull criteria and the Anderson–Darling goodness-of-fit (AD-GOF) test. The improved model is applied to a new and unique case study. The new model was enhanced and adapted in order to make more relevant/case specific predictions by using subsequent previous data points to make slight adjustments to the final output.

Upper Limit and Lower Limit Calculations

The conditional Weibull percentile Eq 1 can be used to calculate the specified percentile or B-Life (the lifetime at which a certain proportion of the population can be expected to have failed) [22]. This equation is used to calculate the upper and lower limits. To calculate the upper limit B-Life, the original calculated Weibull parameters from the training data set must be used. The training data set is the initial set of data which must consist of a minimum of three data points. These data can typically be obtained from maintenance records or equipment-specific reports. By using a training data set, the model is guaranteed to only use historical data points and not the current input to manipulate the parameters to produce a false output. This ensures that the predicted upper limit is classified as a non-repaint prediction value. More simply, the model will not change the outcome by re-painting the historical data.

$$\mathrm{Life_B} = \eta \left\{ \ln \left[\frac{1}{(1-P)\exp\left(-\left(\frac{\mathrm{current_{age}}}{\eta}\right)^{\beta}\right)} \right] \right\}^{\frac{1}{\beta}} \qquad \text{(Eq 1)}$$

with $P = [0.10 \ldots 0.90]$.

Here, η is the scale parameter from the training data set, β is the shape parameter from the training data set, and $\mathrm{current_{age}}$ refers to the current age of the compressor, i.e., the last data point of the training data set.

Calculating the lower limit is more complex and mathematically intensive, and the programming language Python was used to solve for the lower limit iteratively. The minimum reliability, $\hat{R}_c$, is firstly calculated using Eq 2 [23].

$$\hat{R}_c(\beta_0) = \exp\left[-\frac{\chi^2_{90,2}\left\{T^{\beta_0} - (T - t_0)^{\beta_0}\right\}}{\sum t_i^{\beta_0}}\right] \qquad \text{(Eq 2)}$$

where $\chi^2_{90,2}$ is the Chi-squared statistic with a 90% confidence level and 2 degrees of freedom. T represents the calculated upper limit, t_0 the current survival age (in days) and β_0 the observed shape parameter. The minimum reliability can be calculated numerically, as the function yields a minimum at some value of β_0 [23]. From this, a new β parameter can be determined at the minimum reliability. A

100γ percent confidence lower bound on η can be calculated using Eq 3 with the new β parameter [23].

$$\hat{\eta} = \left(\frac{\sum_{i=1}^{n} t_i^{\beta}}{\chi^2_{90,2}}\right)^{\frac{1}{\beta}} \quad \text{(Eq 3)}$$

From Eqs 2 and 3, a new η and β exists such that a lower limit B-Life can be solved for using Eq 1. See Fig. 2, which illustrates the upper and lower limit calculation framework.

Results

The Weibull analysis has been applied to numerous mechanical failure mechanisms. Depending on the requirements of component failure analysis, unique combinations of statistical models can be derived to achieve the adequate results. In this section, a unique combination of Weibull distributions was used in conjunction with quantile analysis to predict coming failures.

It is very important for the failure data to adhere to the Weibull criteria. Thus, verification measures were used to ensure that the Weibull analysis is indeed applicable on a large centrifugal compressor operating under unique conditions at a deep-level mine in South Africa.

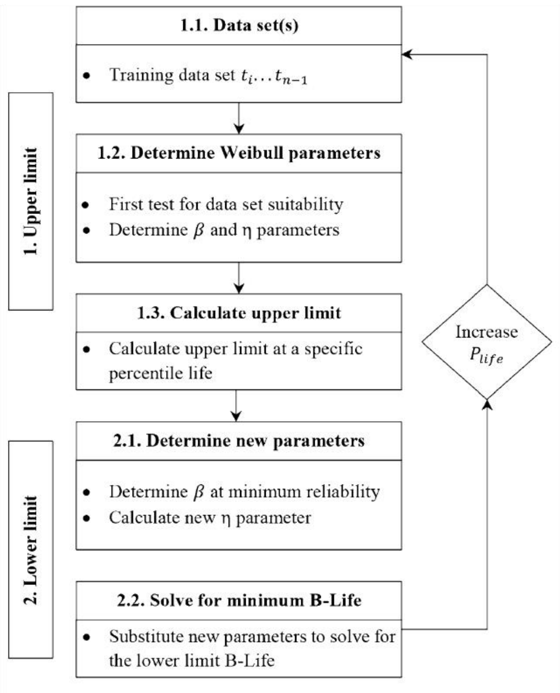


Fig. 2 Upper and lower limit calculation framework

These compressors are highly reliable and have been in operation for over 15 years. However, sub-component breakdowns can cause the compressor to shut down, which was the main focus of this analysis. Failure data were obtained for the subsequent sub-component failures and configured in cumulative form. This data set represented the model inputs, and the LOOCV technique was used for validation, as shown in Fig. 3.

For the first iteration, a minimum of three data points was chosen as the training data set. An upper and lower limit band was produced with most probable failure times. These failure times were then used to predict the fourth failure. This process was repeated until the last failure time, predicting each subsequent failure at a specified percentile life.

For simplification purposes, only one compressor was used to illustrate the methodology. Also, the methodology was illustrated using the maximum number of training data set points available. However, the methodology was applied iteratively to four additional compressors from the minimum amount of training data set points until the last failure point.

Data Acquisition

In the mining industry, maintenance management software is commonly used to plan scheduled maintenance, especially on expensive equipment. These software packages are used by maintenance planners to schedule periodic maintenance based on historical data and personal experience. Typically, work orders are assigned to the relevant mining personnel responsible for the specific area of work. The work orders, indicated in Table 1, are then classified according to the order type.

For this study, breakdown maintenance data were obtained for each compressor. The running hours were then processed to align with each breakdown date and configured to cumulative form, and the full data set is indicated in Table 2.

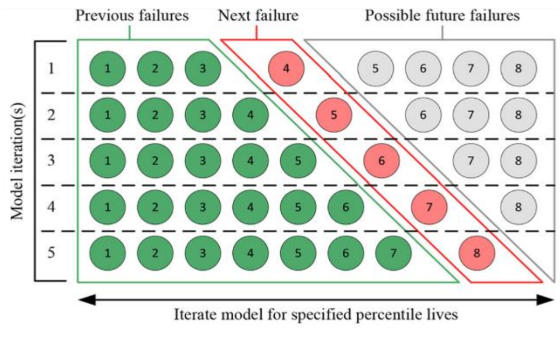


Fig. 3 Failure prediction model functional process framework

Table 1 Work orders for failure mode identification

Classification	Description
C1	Planned service order
C2	Scheduled service order
L1	Unplanned/planned maintenance
L2	Breakdown maintenance
L3	Scheduled maintenance—non-statutory
L4	Rotable order
L5	Capital/projects order
L6	Scheduled maintenance—statutory
L7	Consumable maintenance order
P1	Unplanned maintenance
P2	Planned routine maintenance
P3	Planned ad hoc maintenance
P4	Consumables

Table 2 Compressor failure data

Failure no. (–)	Cumulative running time (h)
1	613
2	1172.5
3	1792
4	2473.5
5	3273.5
6	4439.5
7	5693
8	8024.5
9	10,608.5
10	13,313
11	18,071

Data Set Preparation and Suitability

The failure data obtained from the maintenance management system are accurately logged and reliable. This is very important as the integrity of the final model outputs is highly dependent on the quality of the data set. The Weibull probability plot illustrates the first indication of the data distribution, see Fig. 4.

From Fig. 4, the training data set follows a straight line, which yields a reasonable assumption that the data can be described by the Weibull distribution. It is, however, important to verify the data set suitability for a two-parameter Weibull distribution. This can be achieved by applying an AD-GOF test to the data set, which requires the Weibull parameters to define the hypothesis. The graphical procedure was used to calculate the Weibull parameters by linearizing the unreliability function.

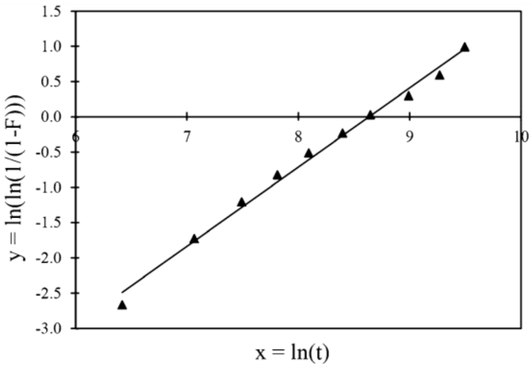


Fig. 4 Compressor Weibull probability plot

Table 3 AD-GOF test results

Parameter	Value
AD	0.113
AD*	0.120
OSL	0.899
H_0	Accept

The slope of the regression line is equal to the shape parameter. The scale parameter was calculated from the intercept of the regression line. The results yielded the shape and scale parameters to be $\beta = 1.12$ and $\eta = 5620.36$, respectively. Based on the assumption that the data set can be described by the Weibull distribution, the Weibull parameters can be used for the AD-GOF test procedure, refer to [21]:

1. Sort the original training data set in ascending order,
2. Establish the null hypothesis (H_0), which is the assumption of the Weibull distribution,
3. Calculate $Z(i) = \left(\frac{t_i}{\eta}\right)^{\beta}$ for each data point,
4. Let $k = \frac{1-2i}{n}\{\ln(1 - e^{-Z_i}) - Z_{n+1-i}\}$ for $i = 1\ldots n$,
5. Calculate the AD statistic and finally adjust it using $\mathrm{AD}^* = \left(1 + \frac{0.2}{\sqrt{n}}\right)\mathrm{AD}$,
6. Finally, calculate the OSL parameter,
7. If the OSL $> \alpha$, do not reject H_0, else reject H_0. Where $\alpha = 0.05$.

The AD-GOF test yielded the following results, indicated in Table 3.

From Table 3, it is evident that the null hypothesis was not rejected. Based on this result, the data set can be described by the Weibull distribution. This test was conducted on the full training data set. However, in the detailed model an exit loop exception was integrated into the code to ensure that with each iteration, the training data set adheres to all criteria.

Compressor Failure Prediction

Following the functional process framework, see Fig. 2, the methodology was applied on each iterative training data set after which the failure prediction was verified using the LOOCV technique. With each iteration, a certain percentile life was specified and an upper and lower limit was determined. Data for the compressor under analysis were obtained from October 2014–March 2017. The compressor had multiple breakdowns and during this period accumulated a total of 18,071 h of service.

Compressor B-Life: Upper and Lower Limits

Using the Weibull parameters of each subsequent training data set, the upper limit B-Life for the next probable failure was calculated. These subsequent upper limit failure times represent the most probable failure time to occur from the current age of survival. It also represents the maximum survival age at the specified B-Life.

The lower limit B-Life of the compressor is more complex to calculate. Hence, Python was used to solve for the lower limit B-Life iteratively. The process of calculating the final lower limit value is explained in Fig. 2. The upper and lower limit calculations yielded the following results, illustrated in Fig. 5.

From Fig. 5a and b, the x-axes and y-axes represent the survival age and the corresponding limit B-Life, respectively. The broken lines represent the actual failures, and the black broken lines represent the B-10, B-25, B-50, B-75 and B-90 percentile life boundaries. From Fig. 5a, the actual failures fall within the B-Life upper limit boundaries. From Fig. 5b, the lower limit boundaries fall short of the actual failures, which may be regarded as the conservative boundaries.

In this study, different percentile lives where used to calculate the final predicted value. Evidently, it was important to check if the variability in the data set was not excessive. The coefficient of quartile deviation ($Q \cdot D_w$) can be used to measure and compare the variability of two or more sets of lifetime data. For the upper and lower limit B-lives, the $Q \cdot D_w$ in both cases indicates relatively small variability between the data sets. The final predicted values were then calculated using an adjustment algorithm. To explain the functionality of this algorithm, a mock-up scenario will be used, as illustrated in Fig. 6.

From Fig. 6, the circles denote the failure times at a specific survival age and the black horizontal lines represent the upper and lower limits, respectively. At failure time number five, the model failed to predict the next failure accurately using a specified percentile life. The model will detect this and adjust the B-Life value accordingly, which will ensure successful failure prediction for the next probable failure times.

Compressor B-Life: Final Failure Range

From the self-adjusting failure prediction model, the final predicted failure values now represent a dynamic failure band with an upper and lower limit, see Fig. 6a. It is possible to meticulously select preferable B-Life boundaries to narrow down the final predicted range. However, this will eliminate the generic element of the model. Figure 6b illustrates the adjusted upper and lower limit boundaries for a more accurate prediction.

As shown in Fig. 7a and b, the x-axis and y-axis represent the survival age and B-Life of the compressor,

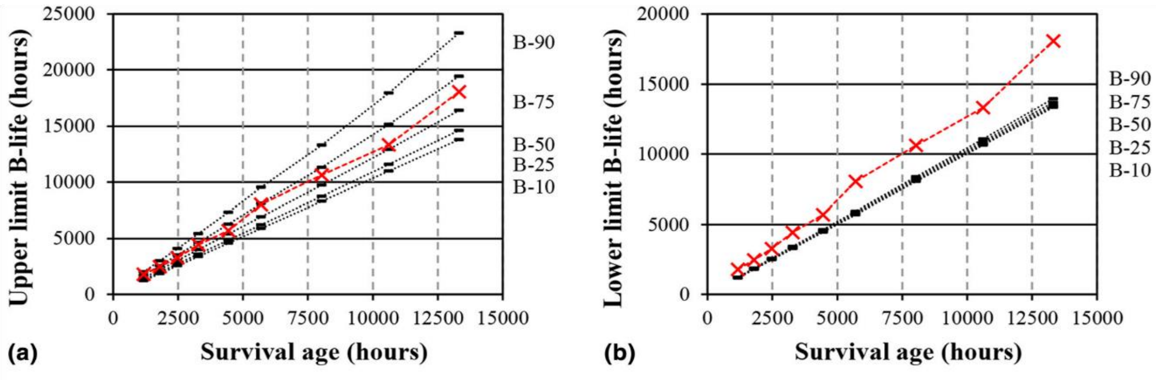


Fig. 5 Upper limit (**a**) and lower limit (**b**) failure prediction boundaries

respectively. The black broken lines represent both the upper and lower limits. The red crosses represent the actual failures and the yellow crosses the final predicted failures. It is evident that the actual failures fall within the predicted failure band from the failure prediction model. These values are conservative which conveys the fact that the failures would have been prevented.

The final model outputs are extremely useful for future maintenance planning. It is almost impossible to predict a random occurrence such as component failure. However, with this model it is possible to determine the most probable time at which the next failure might occur. This information can be used by the site maintenance planner or engineer, which will enable proactive response to critical equipment failure. Also, this model can be used as a line-of-sight information generator for top management, which will add value to asset management and procurement.

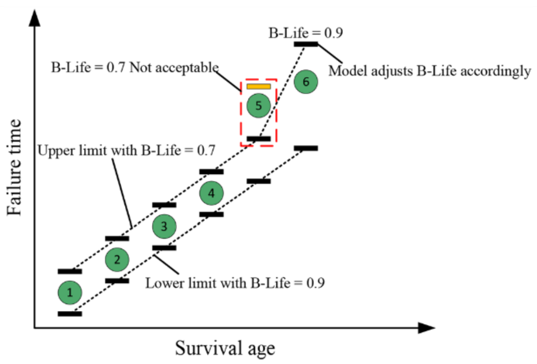


Fig. 6 Failure prediction model B-Life adjustment algorithm. *Not to scale—for illustration purposes only

Discussion of Results

It is very difficult to quantify and predict the coming failures of complex machinery such as large centrifugal compressors. There are countless variables within this system that can contribute to an unexpected failure. The complexity of this problem makes statistical engineering indispensable. As mentioned previously, a variety of Weibull models were used to estimate the most probable failure times. These models were further enhanced using quantile analysis, which produced a range of most probable failure times based on the specified data set's percentile life. This method is both practical and easy to implement, but in the same sentence produces powerful statistical information.

The final model outputs proved to be successful in predicting subsequent compressor failures. The method was applied to four different compressors, located at two different compressor houses. Figure 8 illustrates the predicted failures of four compressors.

Figure 8a represents the failure ranges for the compressor used in the methodology results section. The other figures illustrate the failure ranges of compressors located at a different compressor house. As seen from the above figures, the final model estimates are distributed according to the specified B-Life values. It yields simplicity for easy interpretation but accurately describes probable failure times.

The compressors used in this study are utilized as baseload compressors, which require them to run continually. Depending on the control philosophy and demand requirements, these machines are frequently switched off and need to be started up again. From some of the descriptive statistics obtained by the Weibull analysis, it was found that there is a negative correlation between the

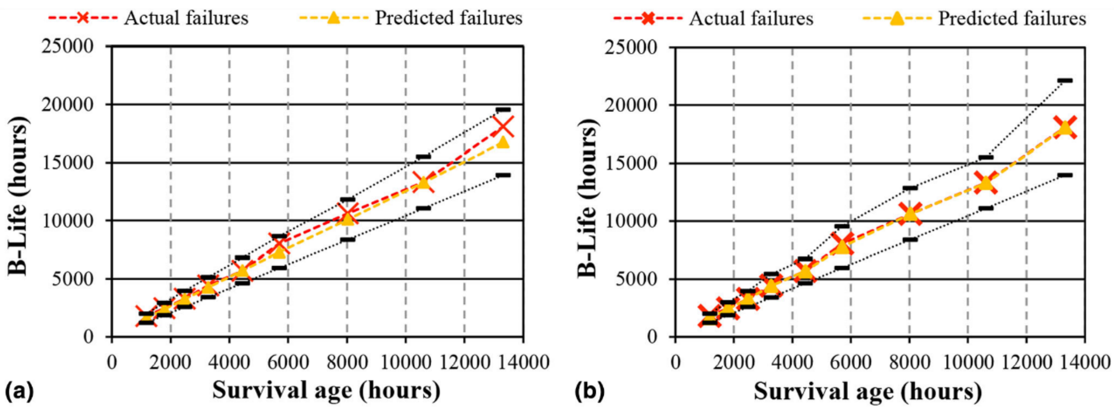


Fig. 7 Compressor failure prediction range

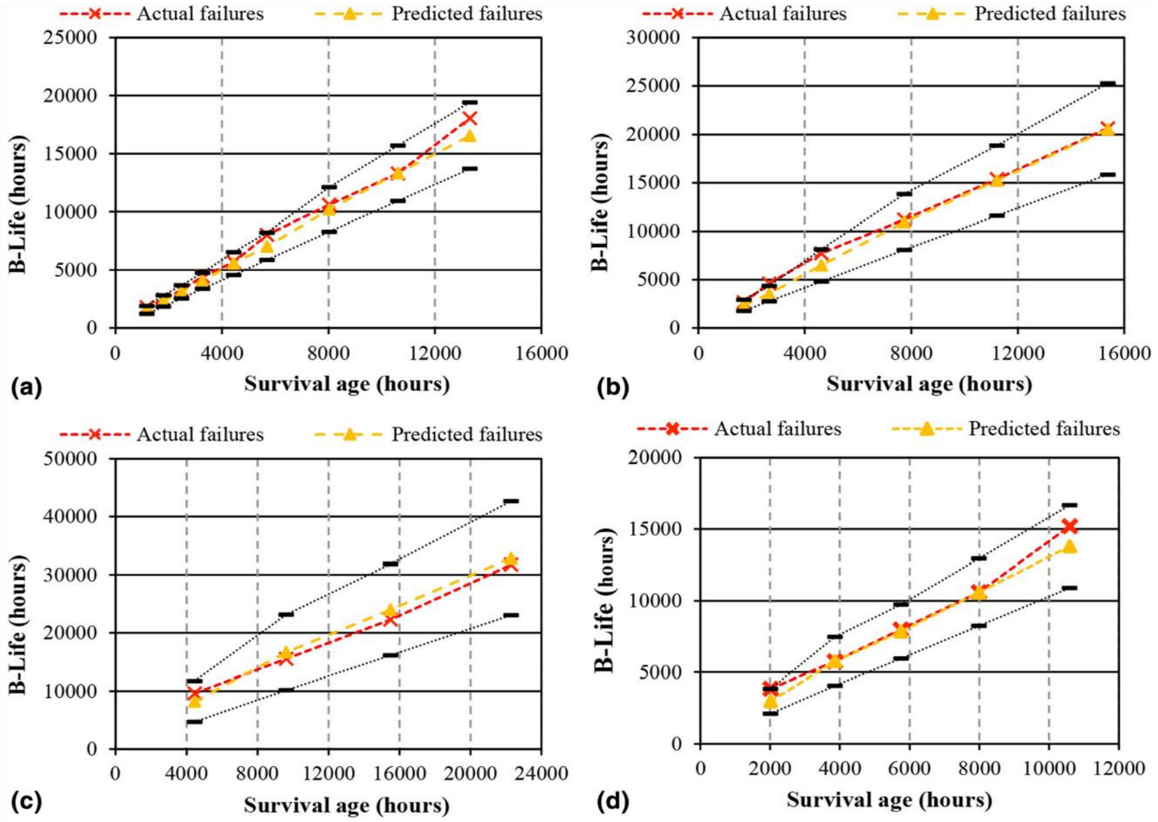


Fig. 8 Compressor failure prediction—model outputs

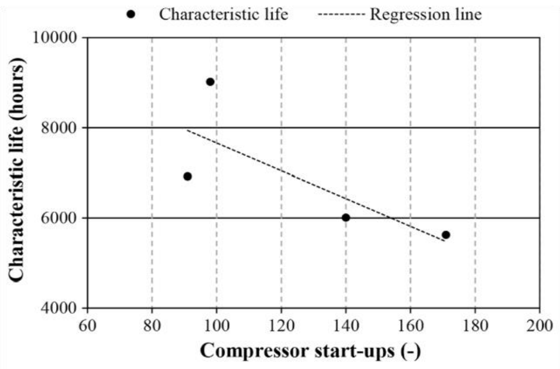


Fig. 9 Compressor characteristic life depreciation

characteristic life (scale parameter) and the number of compressor start-ups. This is illustrated in Fig. 9.

As shown in Fig. 9, there exists a negative correlation between the characteristic life and the number of compressor start-ups. It is important to note that the same operating duration was taken for all of the compressors and the number of start-ups during this time was used. From this, the data were normalized and a correlation was obtained.

These compressors require large induction motors to rotate an assembly of impellers mounted on a steel shaft. The size of the motor depends on the compressor's design specifications, but in this case, the size of the motors ranges from 1 to 8.5 MW.

These induction motors rely on the interaction of magnetic fields to convert electrical power into rotating power. During the motor starting time, magnetic fields and back electro-motive force (EMF) introduce transient conditions into the electrical system. Ultimately, these transient events can affect the electrical supply and other equipment connected to it [24]. This may be a contributing factor to the depreciation in characteristic life, but further studies are required to confirm this hypothesis. It is, however, very interesting that the Weibull analysis together with statistical correlations has the ability to guide the engineer in the direction of a better understanding.

Failure prediction model value added to the industry and contribution in the research field:

1. The methodology presented here is purposefully developed to be generic for any failure data set that adheres to the Weibull criteria.
2. The methodology can be used to predict failure of large centrifugal compressors operating on a deep-level mine.
3. As a result of the methodology being highly generic, it can be applied to various important aspects of mining. This includes ventilation systems, winders, rock drills, winches, etc. This can lead to better service delivery and operational improvements.
4. Currently, mines are focused on reactive and periodical maintenance strategies. This model can be integrated into the current maintenance structure, which will produce a proactive framework.
5. From a safety perspective, continuous system air pressure and supply are required for the underground refuge bays. This model will produce a proactive framework, which will enhance decision-making and prevent unplanned system failures to ensure refuge bay safety.
6. The effect of large compressor start-up procedures might be overlooked. A better optimized start-up procedure might improve the longevity of the compressors.

The Weibull distribution has successfully described the failure times of a typical large centrifugal compressor operating on a deep-level mine in South Africa. The proposed methodology yielded a range of most probable failure times after the compressor has reached a certain survival age. This method can further be integrated into a real-time continuous feedback platform using existing SCADA systems. Current real-time condition monitoring parameters can also be used in conjunction with this method to enhance proactive decision-making by the mining personnel.

Conclusion

Unexpected failures of a large centrifugal compressor can increase life-cycle costs significantly. Because of the complexity and size of the compressed air networks, a single compressor failure can cause a sudden system pressure reduction. If there is not the capacity for backup compressors, a sudden pressure reduction can cause the other compressors to operate close to their surge curves. Evidently, the entire system can be influenced by a single breakdown, especially refuge bays, which are a critical safety requirement for safe underground operations. It is thus imperative to continuously improve current control philosophies and maintenance strategies.

It was thus necessary to investigate forecasting methods to prevent such situations. One such method includes the Weibull analysis, which has been used extensively in the reliability engineering environment. However, it has not yet been implemented on large centrifugal compressors operating on a deep-level mine in South Africa.

A unique combination of the standard Weibull distribution, conditional Weibull distributions and quantile analysis was used to produce a highly generic prediction model. From the final results, it is clear that this methodology is applicable to large centrifugal compressors operating on a deep-level mine in South Africa.

The model outputs resulted in an average accuracy of 92.30% across all of the compressors used in this study. This is exceptionally useful in the mining industry, as the maintenance planners can integrate the model into existing maintenance structures with a quantifiable level of certainty. It is therefore believed that using this methodology for future failure, forecasting will enhance decision-making and increase system reliability.

Acknowledgments This work is sponsored by ETA Operations (Pty) Ltd.

References

1. S.J. Fouché, *Improving efficiency of a mine compressed air system* (2017). https://repository.nwu.ac.za/handle/10394/25343
2. A.G. Siemens, *Adapting compressors to new challenges* (2011). http://m.siemens.kz/assets/template/assets/resheniya/Adapting_compressors_to_new_challenges.pdf
3. J. Vermeulen, *Simplified high-level investigation methodology for energy saving initiatives on deep-level mine compressed air systems* (2018). https://repository.nwu.ac.za/handle/10394/30937
4. *Regulations relating to rescue, first aid, emergencypreparedness and response* (2014). http://www.gpwonline.co.za/Gazettes/Gazettes/38216_21-11_NationalRegulation.pdf
5. P. Maré, J.I.G. Bredenkamp, J.H. Marais, Evaluating compressed air operational improvements on a deep—level mine through simulations, in *2017 International Conference on the Industrial and Commercial Use of Energy (ICUE)* (2017)
6. H.J. van Staden, J.I.G. Bredenkamp, J.H. Marais, Improving sustainability of previously implemented energy savings strategies on mine compressed air systems, in *2017 International Conference on the Industrial and Commercial Use of Energy (ICUE)* (2017)
7. W. Booysen, *Reducing Energy Consumption on RSA Mines Through Optimised Compressor Control* (North-West University, Potchefstroom, 2010)
8. J.H. Marais, *An integrated approach to optimise energy consumption of mine compressed air systems* (2012). https://repository.nwu.ac.za/handle/10394/9519
9. X. Zhou, L. Xi, J. Lee, Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation. Reliab. Eng. Syst. Saf. **92**(4), 530–534 (2007)

10. L. Bader, *The importance of preventive maintenance* (2018). https://ie.binus.ac.id/2018/02/01/the-importance-of-preventive-maintenance/
11. Y. Chen, W. Gong, D. Xu, R. Kang, Imperfect maintenance policy considering positive and negative effects for deteriorating systems with variation of operating conditions. IEEE Trans. Autom. Sci. Eng. **15**(2), 872–878 (2018)
12. H. Pham, H. Wang, Imperfect maintenance. Eur. J. Oper. Res. **94**(3), 425–438 (1996). https://doi.org/10.1016/S0377-2217(96)00099-9
13. P. Behera, B. Sahoo, "Leverage of multiple predictive maintenance technologies in root cause failure analysis of critical machineries, in *International Conference on Vibration Problems*, 2015
14. M.N. Darghouth, A. Chelbi, D. Ait-kadi, Investigating reliability improvement of second-hand production equipment considering warranty and preventive maintenance strategies. Int. J. Prod. Res. **55**(16), 4643–4661 (2017)
15. R. Rio, Proactive asset management with IIoT and analytics. *ARCwire Industry News* (2015)
16. S. Cho, J.-H. Shin, H.-B. Jun, H.-J. Hwang, C. Ha, J. Hwang, A study on estimating the next failure time of compressor equipment in an offshore plant. Math. Probl. Eng. **2016**, 8705796 (2016). https://doi.org/10.1155/2016/8705796
17. H. Alan et al., *Marginal Likelihoods from Monte Carlo Markov Chains* (Cornell University, Ithaca, 2011)
18. H.P. Barringer, M. Kotlyar, Reliability of critical turbo/compressor equipment, in *Fifth International Conference on Process Plant Reliability*, 1996
19. DN Murthy Prabhakar, *Weibull models* (Wiley, Hoboken, 2004)
20. P.A. Tobias, D.C. Trindade, *Applied Reliability*, 3rd edn. (CRC Press, Boca Raton, 2012)
21. J.A. Jacobs, M.J. Mathews, Failure prediction of mine de-watering pumps. J. Fail. Anal. Prev. **18**(4), 927–938 (2018)
22. W. Nelson, J.I. McCool, W.Q. Meeker, *Applied Life Data Analysis* (Wiley, New York, 1982)
23. H. Zhaofeng, Conditional reliability lower bound for Weibull distribution without estimating shape parameter, in *Reliab. Maintainab. Symp. 1997 Proceedings, Annu.*, pp. 298–302, 1997
24. S. McFadyen, Motor starting—introduction, in *Motor Starting and Control Primer: An introduction to the Starting Techniques and Control of Electric Motors* (2011). https://myelectrical.com/notes/entryid/77/motor-starting-introduction

APPENDIX D

App. D1: Article III

Failure Prediction of Mine Scraper Winches

Johannes A Jacobs [a*], Hendrik G Brand [a], Charl Cilliers [b], Kristy Campbell [b],

Marc J Mathews [a], Jean H van Laar [b],

[a]Centre for Research and Continued Engineering Development, North-West University, Pretoria, South Africa
[b]ETA Operations (Pty) Ltd.

*Corresponding author: Email address: jjacobs@rems2.com

This work is sponsored by ETA Operations (Pty) Ltd.

ABSTRACT

The availability of ore transport systems on deep level mines is imperative in achieving production targets. System downtime can result in missed working shifts and production loss. A typical ore transport system consists of multi-level ore- and waste handling systems, and must operate in unison to ensure smooth flow of ore to the surface. A crucial component of these systems are scraper winches which operate in the stope areas under extreme environmental conditions. Therefore, it is well known that these scraper winches are subject to failure. Predicting these failures can enable the maintenance planner to determine optimum replacement time and apply smarter asset management. A failure prediction model was therefore developed using a unique combination of a previously developed model and the Crow-AMSAA (NHPP) model. The ability of the Crow-AMSAA (NHPP) model to make accurate predictions of mixed failure modes was leveraged as system constraints to adjust parameters within the previous model. Furthermore, the Pareto principle was extrapolated through all levels of information, which enabled better maintenance prioritisation. The final model successfully predicted the failures, with an average accuracy of 94% for each sub-component. Significantly, the model provided valuable information that can be used by a maintenance planner to enhance decision making and improve asset management.

Keywords:
Mine scraper winch failure, Reliability engineering, Failure analysis, Reliability growth

1. INTRODUCTION

Underground hard rock mines are used to access ore bodies that are too deep to reach with open pit mines [1]. These ore bodies are typically located at depths ranging from 500 m to 4 500 m below surface [2]. Hence, effective ore transport systems are imperative to achieve daily production targets [3].

In general, there are two methods of transportation in mines, namely vertical or near-vertical shafts, and through inclined shafts or openings [4]. Regardless of the method, the ore material moves through various material-handling systems on route to the hoisting shaft [5]. These are normally multi-level ore- and waste handling systems, that must operate in unison to ensure smooth flow of ore to the surface. Thus, increasing the likelihood of bottlenecks shifting along with different mining deployments due to the complexity and functionality of such a system [6].

In South Africa, mining operations predominantly employ conventional mining techniques to exploit the mineral reserves. Consequently, conventional stope cleaning methods are used and consists of using scraper winches as the cleaning method after blasting [7]. This method is cost-effective and highly practical, requiring low capital expenditure and maintenance costs [8].

However, it is well known that these scraper winches do not last longer than four to six months due to the extreme operating conditions. When subsequent unplanned failures occur and the underground ore storage cannot be controlled between acceptable limits, consecutively, up to three full working shifts can be lost [9], [10].

Typically, a large gold mine with multiple active shafts can have up to 1 000 scraper winches operating at any given time. Considering this, together with continuous unplanned winch replacements and production losses, substantial costs are involved to ensure production targets are met [10]. It is, thus, imperative to prioritise the reliability and availability of scraper winches in the ore-handling process.

Planning for future uncertainties should include an effective predictive and preventive maintenance program. Furthermore, prioritising this over a breakdown maintenance program can reduce the potential for personnel injury and increase equipment availability [11]. Additionally, various other factors influencing the reliability, availability, maintainability and cost (RAM-C) makes the selection of a suitable maintenance strategy inescapable.

Various methods exist for selecting the most suitable maintenance strategy. These include, but are not limited to: the analytic network process (ANP) method, analytic hierarchy process (AHP), fuzzy logic, and a technique for order preference by similarity to an ideal solution

(TOPSIS) [12], [13]. Additionally, these methods are fundamentally based on multi-criteria decision methods (MCDM), which are primarily driven by RAM-C. Furthermore, Yuqiang studied a component reallocation based maintenance policy for a used and repairable system based on the Weibull distribution [14].

Considering that all of these models involve reliability and availability further emphasises the importance thereof. In addition, the extreme operating conditions, data limitations and high failure rates of the equipment operating on a typical deep-level mine, can make the implementation thereof challenging. However, in previous work, a practical and generic failure prediction model was developed for mine de-watering pumps and compressors to overcome these constraints and challenges [15], [16].

Primarily, this model is based on a unique combination of Weibull models, conditional models and quantile analyses. Exclusively, each field has been studied extensively and are well known in the reliability engineering environment [17]–[20]. Although the developed model succeeded in producing accurate failure predictions, both case studies involved some degree of singularity. The model had to be adjusted or enhanced to remain applicable under various constraints.

In addition to this study, the Crow-Army Material System Analysis Activity (Crow-AMSAA) non-homogeneous Poisson process (NHPP) model was introduced, which mainly involves reliability growth plots and modelling repairable systems. The reliability growth plots are useful for mixed failure modes, compared to the Weibull plots that are useful for single failure modes [21]. To apply the Crow-AMSAA (NHPP) model successfully, however, requires the historical failure events to be identical, which typically involves human interaction [22].

Conventional stope cleaning requires that scraper winches be operated manually by an authorised winch operator. These scraper winches are subjected to high pull forces. Especially during stall situations where torque of up to 3.5 times higher than the nominal, can be developed [23]. Introducing human interaction and bad habits introduces a dynamic element to the equation, which adds to the difficulty of predicting failure throughout the entire life cycle.

It is, therefore, imperative to ensure optimum efficiency, availability, and safety of repairable systems through dynamical reliability assessment and failure prediction tools [24]. In this study, the observed expected number of failures (NOF) was used as an adjustment indicator to determine if the rate of occurrence of failure (ROCOF) is stable, increasing or decreasing. These correlations were, therefore, leveraged as system constraints to adjust parameters within the previous model.

Furthermore, in combination with the previous model's ability to adjust according to changes in failure patterns, enabled successful failure prediction of underground scraper winches. Ultimately, the final model can be integrated into existing maintenance strategies to produce a pro-active framework.

2. METHODOLOGY

When applying life data analysis, the component or equipment under analysis, when replaced, is typically assumed to be in an as-good-as-new condition. This is true when replacing the complete scraper winch system. However, a fully functional scraper winch system depends on multiple sub-components. Failure of these components generally result in a breakdown - after which the failed component is either replaced or repaired.

Consequently, the system cannot be considered as-good-as-new when only one component is replaced or repaired, which is typically the case. Thus, during the service life of such a system, it can have multiple lives as they fail, are repaired, and put back into service. The age of the system is effectively the same as it was prior to the replacement or repair. This is known as-bad-as-old and classified as a repairable system which introduces reliability growth [25].

The events that are observed follow a stochastic process, which is defined as a sequence of inter-dependent random events. These events are, therefore, dependent and not identically distributed. In other words, the quality of a new repair or replacement will determine the time-to-failure (TTF) and consequently might result in a different distribution entirely. The Crow-AMSAA (NHPP) model was therefore integrated to form part of the Reliability Growth Analysis (RGA) process [25].

This model can only be applied successfully if the data is reliable and accurate. Data can commonly be obtained from computerised maintenance management systems (CMMS) that typically provide detailed breakdown information which include: the call-out date, time-to-repair (TTR) and the cause of failure. This data may be site-specific and the format thereof will not always be the same. However, the data must be processed and populated cumulatively in TTF format.

With the data-set in the correct format, the Crow-AMSAA (NHPP) parameters can be estimated using the maximum likelihood estimation (MLE). Afterwards, the Cramér-von Mises (CVM) goodness-of-fit (GOF) test must be applied to the data-set with confidence bounds using the Fisher Matrix.

The rate of occurrence of failure (ROCOF), under the assumption that the data follows a power function of time, can then be determined using the NHPP model with 95% confidence. This value represents the primary system constraint as input to the previously developed model.

Finally, the failure prediction model produces the number of probable future failures and a detailed failure band with upper- and lower limits. The results must then be subjected to a validation method, in this case, the leave-one-out cross-validation (LOOCV) technique is used. The complete methodology framework is illustrated below in Figure 1.

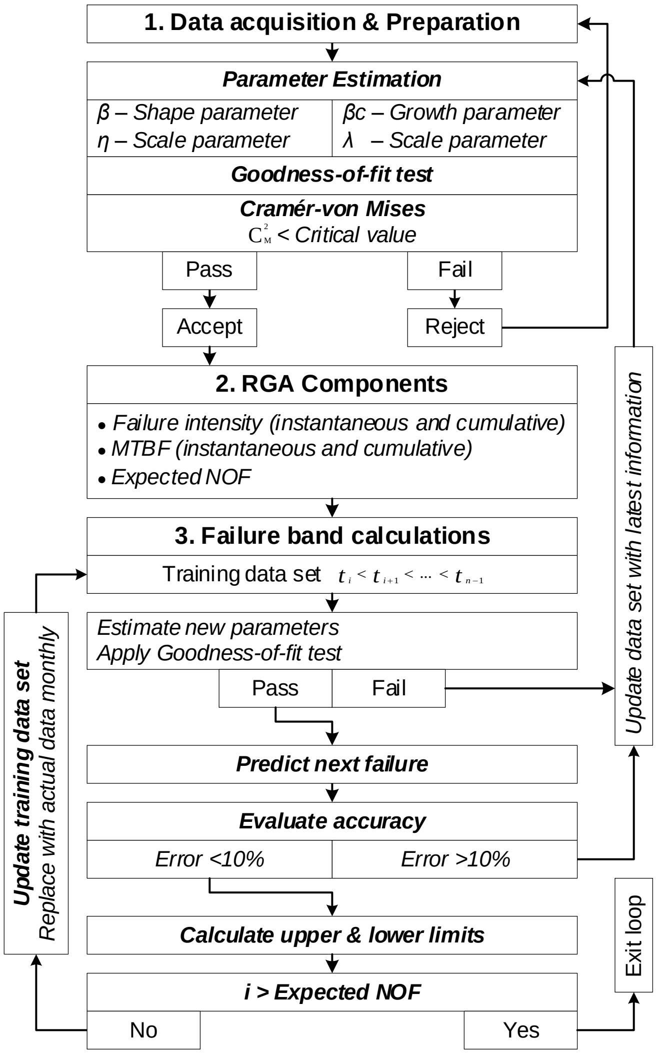


Figure 1: Failure prediction methodology framework

2.1. FAILURE PREDICTION MODEL

The failure prediction model developed, reported previously, for mine de-watering pumps [15] and compressors [16], is improved upon here. This model is primarily based on the standard Weibull distribution, conditional Weibull distribution and quantile analysis. The model was designed to adjust automatically, as more data becomes available and failure patterns change over time.

As mentioned in Section 1, the applicability of the Crow-AMSAA (NHPP) model on multi-failure mode systems was leveraged and used as system constraints to adjust parameters within the previously developed model. This enabled the model to make conditional TTF predictions based on the expected number of failures.

2.2. CROW-AMSAA (NHPP) MODEL PARAMETERS

To determine the number of failures (NOF) of a repairable system, the NHPP model is used. This model assumes that the ROCOF follows a power function over time. It describes the cumulative NOF up to time t, $N(t)$ which follows a Poisson distribution with parameter $\lambda(t)$. Furthermore, plotting the cumulative NOF against the cumulative time on a log-log scale normally produces a straight line with slope β_C [26], [27]. If k number of systems are present, the failure for each of those k systems is governed by the intensity function given by

$$\lambda(t) = \lambda\beta_C t^{\beta_C - 1} \quad (1)$$

From equation (1), the NHPP with intensity $\lambda(t)$ has the power law mean value function

$$E[N(t)] = \int_0^t \lambda(t)dt = \lambda t^{\beta_C}, \quad t > 0 \quad (2)$$

Therefore, the expected NOF between t_1 and t_2 is

$$E[N(\Delta t)] = \int_{t_1}^{t_2} \lambda(t)dt = \lambda t_2^{\beta_C} - \lambda t_1^{\beta_C} \quad (3)$$

The values of λ and β_C can be estimated based on data from the k systems. Suppose the q^{th} system is continuously observed from time S_q to T_q with $q = [1, \dots, k]$. Let N_q be the NOF observed during this time by the q^{th} system and X_{iq}, the age of the i^{th} occurrence of failure with $i = [1, \dots, N_q]$. Then the MLE of λ and β_C are values $\hat{\lambda}$ and $\hat{\beta}_C$ given by

$$\hat{\lambda} = \frac{\sum_{q=1}^{k} N_q}{\sum_{q=1}^{k}\left(T_q^{\hat{\beta}_C} - S_q^{\hat{\beta}_C}\right)} \quad (4)$$

$$\hat{\beta}_C = \frac{\sum_{q=1}^{k} N_q}{\hat{\lambda}\sum_{q=1}^{k}\left(T_q^{\hat{\beta}_C} lnT_q - S_q^{\hat{\beta}_C} lnS_q\right) - \sum_{q=1}^{k}\sum_{i=1}^{N_q} lnX_{iq}} \quad (5)$$

In general, these equations cannot be solved explicitly for $\hat{\lambda}$ and $\hat{\beta}_C$ and must be solved numerically. This was achieved by using packages in SciPy, a Python-based ecosystem of open-source software for mathematics, science, and engineering (Python).

After solving for $\hat{\lambda}$ and $\hat{\beta}_C$, a goodness-of-fit test must be applied to test the compatibility of the model. The CVM test is typically used when starting times for each system is 0 and failure data are complete over the continuous interval $[0, T_q]$, with successive failure times $[0, X_{1,q} < X_{2,q} < \cdots < X_{N_q,q} \le T_q, (q = 1, \dots, k)]$. The step-by-step procedure, described by Crow [27], can be used as follows:

1. Specify if data set is failure terminated ($X_{N_q,q} = T_q$) or time terminated ($X_{q,q} < T_q$)

$$Let\ M = \sum_{q=1}^{k} M_q\,,\ M_q = \begin{Bmatrix} N_q - 1 \text{ If failure terminated} \\ N_q \text{ If time terminated} \end{Bmatrix} \quad (6)$$

2. Divide each successive failure time by the corresponding end time T_q

$$Y_{iq} = \frac{X_{iq}}{T_q}, i = 1, \dots, M_q, (q = 1, \dots, k) \qquad 7$$

3. Calculate $\bar{\beta}_C$, the unbiased estimate of β_C

$$\bar{\beta}_C = \frac{M-1}{\sum_{q=1}^{k} \sum_{i=1}^{M_q} \ln\left(\frac{T_q}{X_{iq}}\right)} \qquad 8$$

4. Treat the $M\ Y_{iq}'s$ as one group and order them from smallest to largest $[Z_1 < Z_2 < \cdots < Z_M]$
5. Calculate the CVM statistic C_M^2

$$C_M^2 = \frac{1}{12M} + \sum_{j=1}^{M} \left(Z_j^{\bar{\beta}_C} - \frac{2j-1}{2M}\right)^2 \qquad 9$$

6. Determine the critical value from the desired significance level and corresponding M value from Table 1.

Table 1: Critical values for CVM goodness-of-fit test (Adapted from[27])

M	Significance level				
	0.20	0.15	0.10	0.05	0.01
2	0.138	0.149	0.162	0.175	0.186
3	0.121	0.135	0.154	0.184	0.230
4	0.121	0.134	0.155	0.191	0.280
5	0.121	0.137	0.160	0.199	0.300
6	0.123	0.139	0.162	0.204	0.310
7	0.124	0.140	0.165	0.208	0.320
8	0.124	0.141	0.165	0.210	0.320
9	0.125	0.142	0.167	0.212	0.320
10	0.125	0.142	0.167	0.212	0.320
11	0.126	0.143	0.169	0.214	0.320
12	0.126	0.144	0.169	0.214	0.320
13	0.126	0.144	0.169	0.214	0.330
14	0.126	0.144	0.169	0.214	0.330
15	0.126	0.144	0.169	0.215	0.330
16	0.127	0.145	0.171	0.216	0.330
17	0.127	0.145	0.171	0.217	0.330
18	0.127	0.146	0.171	0.217	0.330
19	0.127	0.146	0.171	0.217	0.330
20	0.128	0.146	0.172	0.217	0.330
30	0.128	0.146	0.172	0.218	0.330
60	0.128	0.147	0.173	0.220	0.330
100	0.129	0.147	0.173	0.220	0.340

7. If C_M^2 < critical value, then the hypothesis is accepted that the failure times for the k systems follow a NHPP with intensity function $\lambda(t) = \lambda\beta_C t^{\beta_C - 1}$

Once the CVM test is completed, the variance on the expected NOF can be calculated [25] using

$$Var\left(\widehat{N}(\Delta t)\right) = \left[\frac{\partial\widehat{N}(\Delta t)}{\partial\lambda}\right]^2 var(\hat{\lambda}) + \left[\frac{\partial\widehat{N}(\Delta t)}{\partial\beta_C}\right]^2 var(\hat{\beta}_C) + 2\left[\frac{\partial\widehat{N}(\Delta t)}{\partial\lambda}\right]\left[\frac{\partial\widehat{N}(\Delta t)}{\partial\beta_C}\right] cov(\hat{\lambda}, \hat{\beta}_C) \qquad 10$$

$$where\ \widehat{N}(\Delta t) = \hat{\lambda} t_2^{\widehat{\beta}_C} - \hat{\lambda} t_1^{\widehat{\beta}_C},\ \widehat{N}(\Delta t) > 0$$

From equation (10), the variance and covariance of the MLE's are required. To achieve this, the Fisher information matrix [25] can be used from the natural log-likelihood function

$$\Lambda = \sum_{q=1}^{k}\left[N_q(\ln(\lambda) + \ln(\beta_C)) - \lambda\left(T_q^{\beta_C} - S_q^{\beta_C}\right) + (\beta_C - 1)\sum_{i=1}^{N_q}\ln(x_{iq})\right] \qquad 11$$

where $\begin{bmatrix} -\frac{\partial^2\Lambda}{\partial\lambda^2} & -\frac{\partial^2\Lambda}{\partial\lambda\partial\beta_C} \\ -\frac{\partial^2\Lambda}{\partial\lambda\partial\beta_C} & -\frac{\partial^2\Lambda}{\partial\beta_C^2} \end{bmatrix} = \begin{bmatrix} Var(\hat{\lambda}) & Cov(\hat{\beta}_C,\hat{\lambda}) \\ Cov(\hat{\beta}_C,\hat{\lambda}) & Var(\hat{\beta}_C) \end{bmatrix}$

Finally, the two-sided approximate confidence bound can be calculated

$$\widehat{N}(\Delta t)_U = \widehat{N}(\Delta t) \times e^{\frac{z_{1-\frac{\alpha}{2}}\left(\sqrt{Var(\widehat{N}(\Delta t))}\right)}{\widehat{N}(\Delta t)}} \quad 12$$

$$\widehat{N}(\Delta t)_L = \widehat{N}(\Delta t) \times e^{\frac{z_{\frac{\alpha}{2}}\left(\sqrt{Var(\widehat{N}(\Delta t))}\right)}{\widehat{N}(\Delta t)}} \quad 13$$

where α is the confidence level and $z_{1-\frac{\alpha}{2}}$ the $1-\frac{\alpha}{2}$ percentile of a standard normal distribution.

2.3. FAILURE BAND CALCULATIONS

The failure band produced by the model can be described as a conditional TTF range of probable failures corresponding to the survival age of the equipment under analysis. This is fundamentally based on the conditional Weibull distribution with a specified percentile life (B-Life) and is comprehensively described in previous work [15], [16].

$$\mathrm{Life_B} = \eta\left\{\ln\left[\frac{1}{(1-\mathrm{P})\exp\left(-\left(\frac{\mathrm{current_{age}}}{\eta}\right)^{\beta}\right)}\right]\right\}^{\frac{1}{\beta}} \quad 14$$

where η and β are the Weibull scale-and shape parameters respectively, $\mathrm{current_{age}}$ the current age of the equipment, i.e. the last data point of the training data set, and $\mathrm{P} = [0.10 \ldots 0.90]$ the specified percentile lives.

Simply knowing the current age of the system and substituting this value into equation (14) is a trivial task. However, this requires a complete data set that needs to be updated after each failure, which is not always possible for scraper winch systems where the data is typically updated on a bi-weekly or monthly basis. This is where the previously developed model is modified. For each subsequent failure prediction, t_2 was solved for from equation (3) iteratively $(i = 0, \ldots, E[N(\Delta t)] - 1)$.

Let $E[N(\Delta t)]$ be the observed expected NOF ($E[N(\Delta t_0)]$) for each iteration:

$$(E[N(\Delta t_0)])_i = \frac{E[N(\Delta t_0)]_T}{E[N(\Delta t)]-i} \quad 15$$

where $E[N(\Delta t_0)]_T$ is the observed total expected NOF until the required time of operation.

Now, solving for t_2 from equation (3), for each iteration we have

$$(t_2)_i = \left[(t_1)_i^{(\beta_C)_i} + \frac{(E[N(\Delta t_0)])_i}{\lambda_i}\right]^{\frac{1}{(\beta_C)_i}} \quad 16$$

where new β_C and λ parameters are calculated as the data set is iteratively updated. A 90% confidence bound on the value of $(t_2)_i$ from equation (16) will yield upper-and lower values $(t_2)_i^U$ and $(t_2)_i^L$, respectively. These values, will be used as system constraints to determine the final upper-and lower limits.

It is now possible to calculate the minimum conditional reliability ($\widehat{R}_c$) to produce the lower limit failure band from the minimum β and η parameters [28]. For the training data set $(t_k, \ldots, t_n)$ where n is the size of the training data set:

$$\widehat{R}_c(\beta_0) = \exp\left[-\frac{\chi^2_{90,2}\{T^{\beta_0} - (T - t_{mission})^{\beta_0}\}}{\sum t_k^{\beta_0}}\right], k = 1, \ldots, n \quad 17$$

where $\chi^2_{90,2}$ is the chi-squared statistic with a 90% confidence level and 2 degrees of freedom, T the life requirement, $t_{mission}$ the mission time ($T - current_{age}$), and β_0 the observed shape parameter. Normalising equation (17) by $t_m = \max(t_1, t_2, \ldots, t_n)$ for each iteration:

$$\left[\widehat{R}_c(\beta_{min})\right]_i = \exp\left[-\frac{\chi^2_{90,2}\{(T/t_m)^{(\beta_{min})_i} - ((T - t_{mission})/t_m)^{(\beta_{min})_i}\}}{\sum (t_k/t_m)^{(\beta_{min})_i}}\right], k = 1, \ldots, n \quad 18$$

where $t_m = (t_2)_i$ and $T = (t_2)_i^L$

The minimum reliability cannot be solved explicitly, hence it was numerically solved using Python. From this, a new $(\beta_{min})_i$ parameter can be calculated. Finally, a $100\gamma\%$ confidence lower bound on η can be calculated $(\eta_{min})_i$ for each iteration

$$(\eta_{min})_i = \left(\frac{\sum_{k=1}^{n} t_k^{(\beta_{min})_i}}{\chi^2_{90,2}}\right)^{\frac{1}{(\beta_{min})_i}} \quad 19$$

The original and minimum β and η parameters can now be substituted into equation (14) to calculate the upper-and lower B-Lives respectively for each iteration, so finally:

$$(Life_B)_i^U = \eta_i \left\{\ln\left[\frac{1}{(1 - P_U)\exp\left(-\left(\frac{(t_2)_i}{\eta_i}\right)^{\beta_i}\right)}\right]\right\}^{\frac{1}{\beta_i}} \quad 20$$

and

$$(Life_B)_i^L = (\eta_{min})_i \left\{\ln\left[\frac{1}{(1 - P_L)\exp\left(-\left(\frac{(t_2)_i^L}{(\eta_{min})_i}\right)^{(\beta_{min})_i}\right)}\right]\right\}^{\frac{1}{(\beta_{min})_i}} \quad 21$$

3. RESULTS

A case study was selected that represents a typical ore-extraction system of a conventional deep-level mine, which mainly consists of scraper winches, locomotives, and loaders. Each system consists of multiple sub-components, that complicated the prioritisation of maintenance and repairs. The availability and efficient operation of these systems can additionally affect production targets. Therefore, it is imperative to properly prioritise and manage these systems to ensure minimum downtime. The methodology outlined in Figure 1, is applied in the subsequent sections.

3.1. DATA SET ACQUISITION & PREPARATION

Reliable maintenance and breakdown reports were obtained from the mine's CMMS. In this study, it was found that a smaller percentage of sub-components caused most of the breakdowns. The 80/20 principle (Pareto principle) was therefore used to improve decision making. This enabled the quantification of sub-components that make up 20% of the system, but caused 80% of the total breakdowns. Therefore, this principle was extrapolated through all levels of information. Figure 2 shows the breakdowns per system, starting at a high-level in (A) and focussing on individual components in (B), (C) and (D).

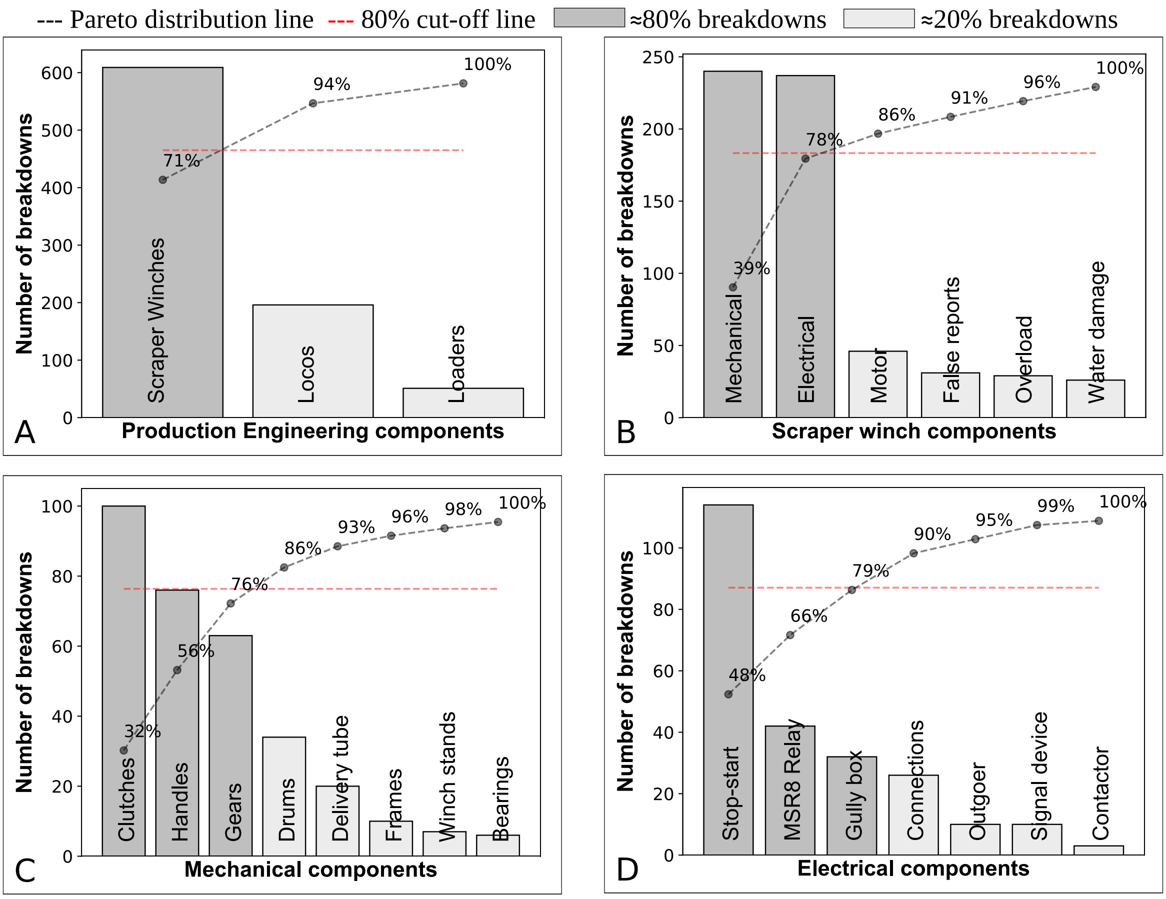


Figure 2: Pareto Charts of breakdowns per system from high-level (A) to individual components (B-D)

Figure 2 shows data collected over one year, where the bars and dotted lines represent the breakdowns and cumulative percentage of the failures, respectively. It was found that 20% of the sub-components of each respective system caused roughly 80% of the total breakdowns. Figure 2(A) shows that the amount of scraper winch breakdowns is significantly higher in comparison to that of the other Production Engineering systems.

Figure 2(B) shows that the failure of mechanical- and electrical systems are the primary causes for the number of breakdowns. Figures 2(C) and (D) show the detailed sub-components of the mechanical- and electrical systems, respectively. The breakdowns of these systems are driven by multi-failure modes, which are mostly governed by human intervention- and -error.

For simplification, only the electrical system with one sub-component was used to illustrate the methodology. However, the methodology was applied to all the systems and the results are included at the end of this section.

3.2. PARAMETER ESTIMATION

The NHPP model parameters were estimated using the MLE method. The data used, represents the actual failure times of various sub-components of scraper winches operating under extreme conditions. It was configured continuously in cumulative format over the interval $[0, T]$, where T is failure terminated. Table 2 shows the training data set, validation data set, estimated parameters, and CVM GOF test results for scraper winch breakdowns caused by electrical failure.

Table 2: Scraper winch electrical components data preparation results

Training data (days)						
1, 3, 5, 6, 7, 8, 9, 13, 15, 20, 21, 22, 24, 26, 27, 28, 29, 30, 33, 34, 35, 38, 40, 41, 43, 45, 49, 50, 53, 55, 56, 61, 62, 64, 65, 66, 69, 70, 71, 73, 76, 77, 78, 82, 84, 86, 94, 98, 100, 101, 103, 111, 112, 116, 119, 120, 121, 125, 128, 133, 135, 136, 140, 148, 150, 151, 152, 153, 154, 155, 156, 157, 167, 169, 170, 176, 181, 182, 184, 185, 188, 189, 191, 192, 194, 197, 198, 199, 203, 206, 209, 211, 217, 219						
Validation data (days)						
223, 224, 226, 227, 228, 229, 231, 232, 233, 234, 236, 237, 238, 239, 240, 242, 243, 246, 247, 253, 259, 260, 262, 263, 265, 266, 267, 268, 269, 274, 275, 276, 278, 283, 285, 286, 293, 294, 296, 299, 308, 310, 312, 316, 321, 328, 330						
Parameter Estimation & GOF test						
Data set	$\boldsymbol{M}$	$\boldsymbol{T_{end}}$	$\boldsymbol{\beta_C}$	$\boldsymbol{\lambda}$	$\boldsymbol{C_M^2}$	**Crit.**
Training	94	219	0.881	0.817	0.029	0.220
Complete	141	330	0.904	0.745	0.063	0.220

From Table 2 it is clear that the training- and complete data sets yielded successful results in the CVM GOF test as $C_M^2 < Critical\ value$. Regarding the NHPP parameters, $\beta < 1$ indicates a slower failure rate, $\beta > 1$, a faster failure rate and $\beta \approx 1$ no improvement or deterioration. Here, it can be observed that $\beta < 1$, indicating slower failure rate, which is related to increased reliability over time. However, this parameter increased over time from 0.881 to 0.904, approaching a value closer to 1, which indicates otherwise. This is a good indicator that repairs are only conducted after failures occur. This can be better visualised with reliability growth trends, which initiates the next step in the methodology framework.

3.3. RELIABILITY GROWTH ANALYSIS COMPONENTS

Typically, RGA is used to quantify and assess system parameters related to the reliability growth of the system under analysis. This is useful for observing reliability trends and the tracking thereof. These trends can either increase or decrease over time, depending on the changes made or the implementation of major fixes to the system.

This can be observed by analysing the failure intensity and mean time between failures (MTBF), with both indicating change in reliability over time. These trends are useful to visualise the improvement of reliability. Figure 3 illustrates these reliability growth trends.

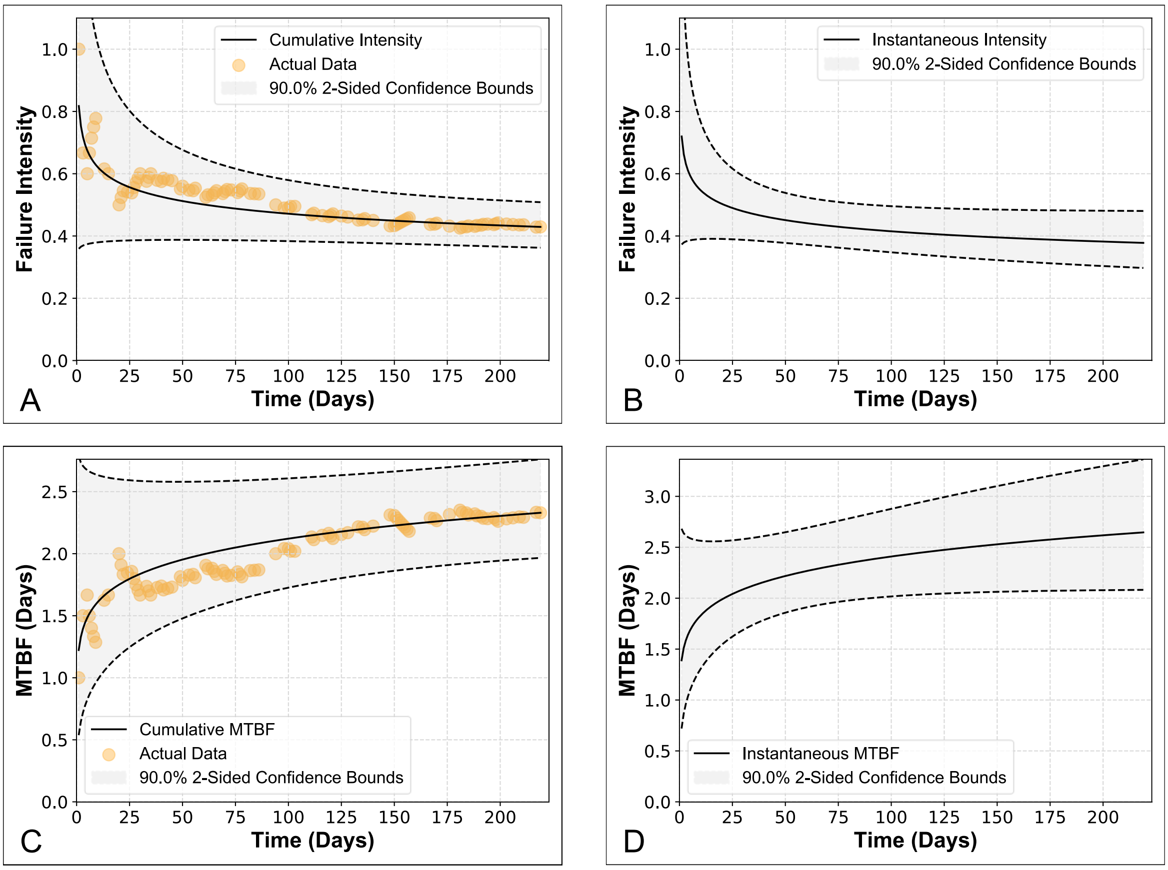


Figure 3: Reliability growth trends; Cumulative & Instantaneous failure intensity (A) and (B), Cumulative & Instantaneous MTBF (C) and (D)

As mentioned previously, the estimated parameter (β) is smaller than 1, which normally indicates an increase in reliability growth. This is reflected in Figure 3 by the failure intensity and MTBF trends. Figure 3(A) and (B) show that the failure intensity decreases over time. Figure 3(C) and (D) show an increase in MTBF over time. However, the failure intensity and the MTBF seems to stabilise as β approaches 1.

Hypothetically, if the training data set was the full data set at a certain point in time, this observation would have indicated that there are no system improvements. As a result, reliability growth is evident, and this system can be classified as a repairable system. After confirming that the data can be represented by the NHPP model, the expected NOF can be calculated with more confidence. Therefore, by specifying an arbitrary mission time and substituting for the parameters in equation (3), one can calculate the expected NOF.

Note that, all values were calculated in Python, which used more accurate values consisting of more than three decimal spaces.

$$E[N(\Delta t)] = (0.817_{\dots})(330^{0.880_{\dots}} - 219^{0.880_{\dots}})$$

$$E[N(\Delta t)] = 40.869_{\dots}$$

The variance of the NOF can now be calculated using equation (10):

$$Var(E[N(\Delta t)]) = (50.001_{\dots})^2(0.167_{\dots}) + (275.548_{\dots})^2(0.008_{\dots}) + 2(50.001_{\dots})(275.548_{\dots})(-0.036_{\dots})$$

$$Var(E[N(\Delta t)]) = 42.989_{\dots}$$

Finally, a 90% 2-sided confidence bound on $E[N(\Delta t)] = 40.869_{\dots}$ can be calculated using equations (12) and (13):

$$E[N(\Delta t)]_U = 40.869_{\dots} \times e^{\frac{1.645_{\dots}(\sqrt{42.989_{\dots}})}{40.869_{\dots}}} = 53.211_{\dots}$$

$$E[N(\Delta t)]_L = 40.869_{\dots} \times e^{\frac{-1.645_{\dots}(\sqrt{42.989_{\dots}})}{40.869_{\dots}}} = 31.390_{\dots}$$

Now that information is available regarding the expected NOF, governed by the NHPP, this value can be leveraged as a system constraint for the previously developed model. Subsequently, a failure band of most probable future failure times can be generated to reveal even more detail regarding failure patterns.

3.4. FAILURE PREDICTION BAND

The failure prediction band in this study describes the conditional TTF range of a scraper winch during its aging process. To achieve this, each subsequent failure is predicted based on the observed expected NOF, determined by the previous two calculated failures. Additionally, the upper- and lower limits are conditionally determined based on a specified percentile life.

This process is repeated iteratively over the time it requires to reach the originally calculated expected NOF. As mentioned, this method was applied on the electrical system to illustrate the methodology procedure. The results are shown in Figure 4.

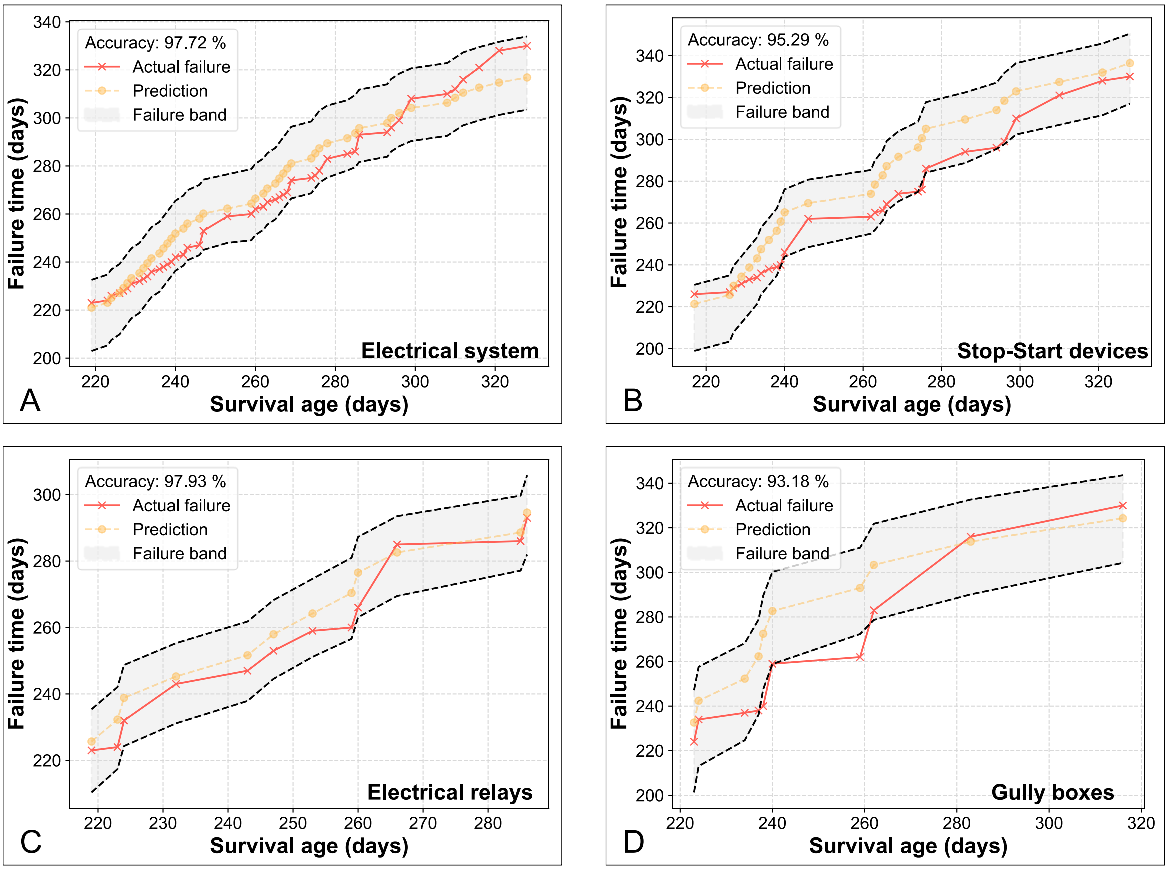


Figure 4: Cumulative failure prediction bands – Scraper winch electrical system

From Figure 4(A) to (D), it is evident that the model accurately predicted each subsequent failure, where the x-axis and y-axis represent the survival age and failure times, respectively. As depicted in Figure 4, during the early failures, each sub-component showed higher failure rates. However, the model dynamically adjusted accordingly, after the data set was updated after the first 30 days.

Knowing the root-cause for a sudden increase in failure rates would be ideal. However, due to the lack of forecasting capabilities of the current maintenance strategies, the change in failure patterns would go unnoticed. Therefore, the ability to quantify and visualise changes in failure patterns is invaluable. This information enables the maintenance planner to react pro-actively and to manage assets more effectively. This provides better line-of-sight (LOS), which enables smarter decision making and, ultimately, improves asset management and procurement.

4. DISCUSSION OF RESULTS

4.1. SCRAPER WINCH SYSTEM FAILURES

In the previous section, the failure prediction methodology framework was implemented. As mentioned, the availability and reliability of scraper winches is imperative to successful ore-extraction. A fully operational scraper winch system requires all its sub-components to be functional. Therefore, failure in any of these components may result in a breakdown and a possible missed shift.

Hence, the failure prediction model was applied to all the major components that contribute to 80% of the total breakdowns, selected based on the Pareto principle. For the mechanical system of a scraper winch, the resulting failure prediction bands for each component is shown in Figure 5.

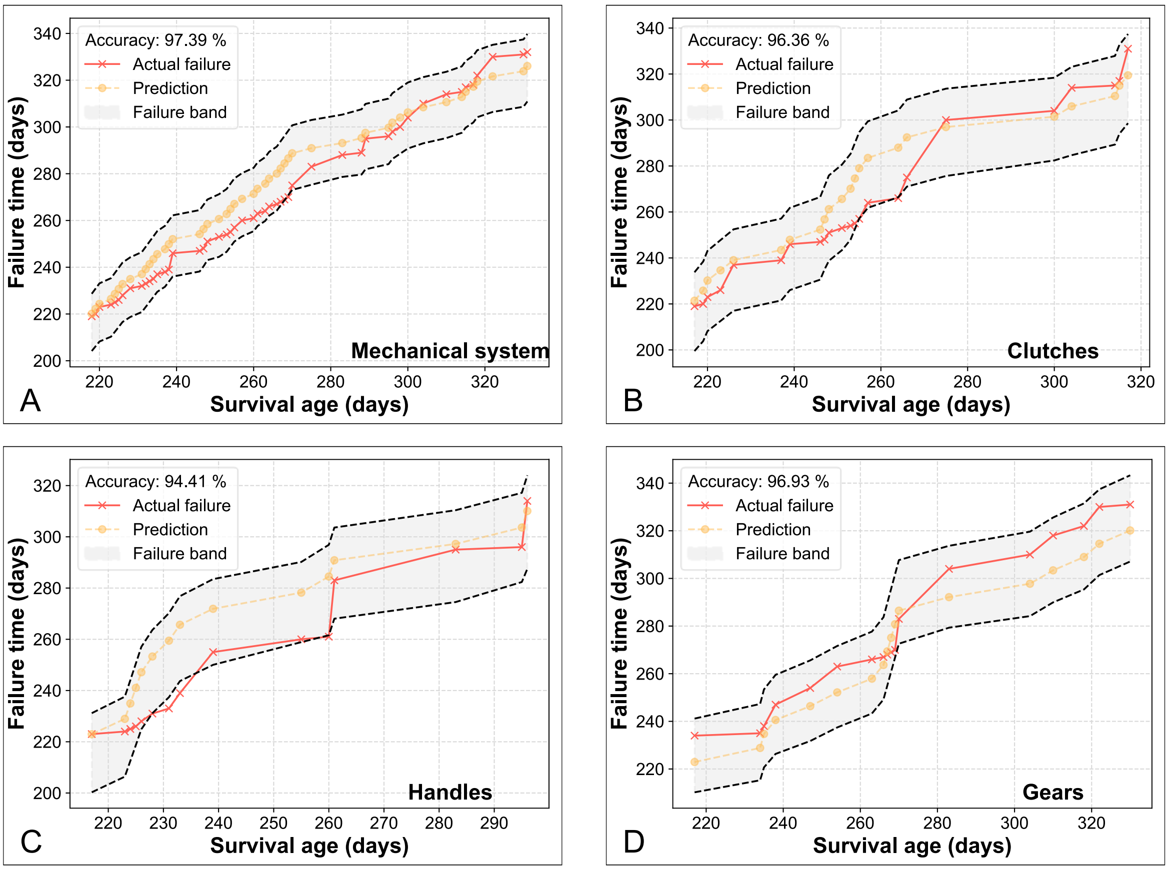


Figure 5: Cumulative failure prediction bands – Scraper winch mechanical system

Figure 5(A) to (D), show the failure prediction bands of the mechanical system components contributing to 80% of the breakdowns. The failure prediction model accurately predicted each subsequent failure with an accuracy of more than 90%.

Additionally, the expected NOF for each system was also determined and compared to the actual NOF that occurred. Considering that the expected NOF can be predicted, given the specified operational time of these components, is extremely valuable for asset management. This is critical in a deep-level mining environment where the spares not only need to be ordered, but transported to various levels in anticipation of system failures. These results are shown in Figure 6 below.

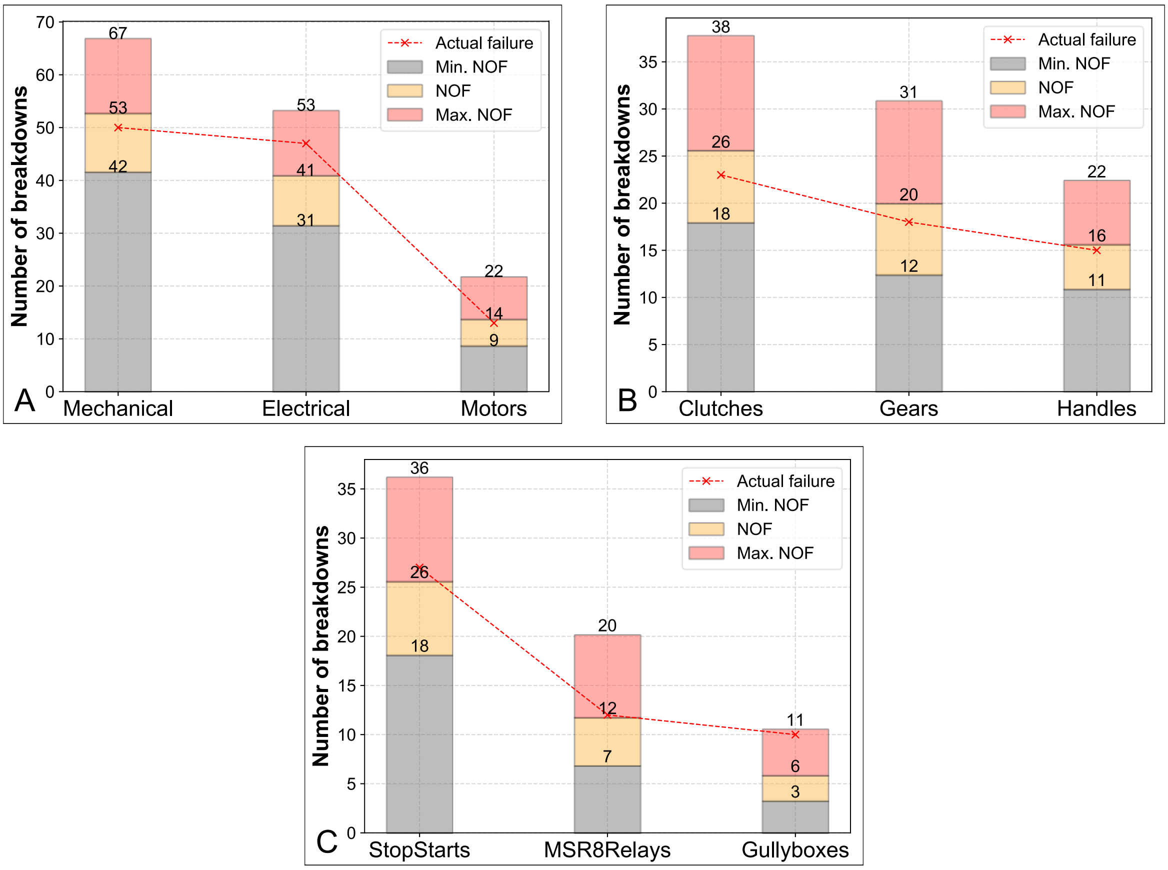


Figure 6: Scraper winch system expected number of failures

Figure 6(A) to (C) show the predicted number of failures compared to the actual failures of each system with a 90% 2-sided confidence bound (upper- and lower limits). It is also important to note that the Pareto principle pattern is revealed in each figure. This provides the ability to generate real-time Pareto charts that maintenance planners can use to allocate resources more accurately regarding asset procurement.

Overall, the failure prediction model accurately predicted both the cumulative failures and expected NOF.

4.2. INDUSTRY VALUE ADD AND CONTRIBUTION

Present maintenance strategies are primarily reactive. However, implementing reactive maintenance is not necessarily unsustainable, as some systems are better to repair as they fail. It is, however, important to optimise these strategies by introducing proper asset management based on accurate predictions. This enables a better understanding of the system and its failure patterns. Therefore, this study mainly focused on the ability to predict failure, where this information can be used in future studies to inform smarter decision making in the development of new maintenance strategies.

Failure prediction model value add to the industry and contribution in the research field:

1. The methodology presented in this article is purposefully developed to be practical and easy to implement on repairable systems.
2. The methodology can be used to predict failure of scraper winch systems and its sub-components.
3. The simplicity and generic capability of this methodology enables multi-system application in various aspects of mining. The implementation thereof can lead to better service delivery, minimum down time, and operational improvements.
4. The integration of this model into present maintenance strategies can produce a pro-acitve framework for asset management.
5. From a safety perspective, accidents associated with scraper winches pose a daily threat to the winch operators and the people working nearby. The ability of the model to predict the number of expected failures can be leveraged as a *hot-spot* identification tool. Meaning, that workplaces that has a greater potential for scraper winch failures can be identified which can be integrated into change risk management strategies as the workforce migrate to different workplaces. Furthermore, this will enable the prioritisation of weekly inspections based on the expected number of failures.
6. Pareto charts can be generated in real-time. Maintenance planners can use this information to optimise resource allocation regarding asset procurement.
7. The final failure prediction model can adapt for both single failure and multi-failure mode distributions.

5. CONCLUSION

The ore-extraction system of a deep-level mine depends on how effective ore transport systems are to achieve daily production targets. These are multi-level ore and waste handling systems and different methods are used to effectively transport ore from underground. It is therefore important to ensure that these systems are operational and available at any given time.

Conventional stope cleaning primarily uses scraper winches as the cleaning method. These scraper winches are exposed to extreme environmental conditions and pull forces. It is well known that these scraper winches do not last more than four to six months. This introduces the possibility of unplanned failures and if underground ore storage cannot be controlled between acceptable limits, up to three full working shifts can be lost.

Considering this, and the fact that a typical large gold mine can have up to a 1 000 scraper winches operating at any given time, substantial costs are involved to ensure that production targets are met. Therefore, prominence should be given to the reliability and availability of scraper winch systems, which forms an integral part in the ore-handling strategy.

It was therefore necessary to investigate failure prediction of scraper winches to prevent unplanned system downtime. In previous work, a generic failure prediction method was developed that addressed these issues on de-watering pumps and compressors. However, each of these systems presented different challenges and the method was enhanced accordingly.

In this study, the method was further modified by introducing the Crow-AMSAA (NHPP) model for multi-failure mode handling. This model is specifically designed with human interaction in mind. This is often the case with scraper winches where an authorised winch operator is required to operate the machine. The integration of this model provided the ability to determine the expected NOF. This value was used as a system constraint from which conditional upper- and lower limits were determined.

Ultimately, a cumulative failure prediction band was generated through an iterative process. The results were validated using the LOOCV method which yielded an overall prediction accuracy of 94%. Furthermore, the model successfully provided reliability growth information that can be used to identify changes in failure patterns. It is therefore evident that the implementation of this methodology for future failure prediction will provide valuable information for the maintenance planner. This information will ultimately enhance decision making and potentially increase system reliability.

6. REFERENCES

[1] M. Abzalov, Applied Mining Geology. Springer, Cham, 2016.

[2] M. S. D. Manzi, K. A. A. Hein, R. J. Durrheim, and N. King, “The Ventersdorp contact reef model in the kloof Gold Mine as derived from 3D seismics, geological mapping and exploration borehole datasets,” Int. J. Rock Mech. Min. Sci., vol. 66, pp. 97–113, 2014.

[3] J.N. de la Vergne, Hard Rock Miner’s Handbook, 5th ed. Edmonton, Alberta Canada: Stantec Consulting, 2008.

[4] L. D. Pareja, “Deep underground hard-rock mining - issues, strategies, and alternatives,” Queen’s University Kingston, Ontario, Canada, 2000.

[5] H. Hamrin, “Techniques in underground mining,” Encyclopaedia of Occupational Health & Safety. Jeanne Mager Stellman, Ph.D., Editor-in-Chief, 2011.

[6] K. Hindle and V. Limmer, “Understanding underground ore handling and shifting bottleneck identification using discrete-event simulation,” in Hoist and Haul 2010 - Proceedings of the International Conference on Hoisting and Haulage, 2010, pp. 267–276.

[7] S. Rupprecht, “Loading and hauling of broken rock in a narrow tabular orebody utilizing scraper winches,” in SAIMM Underground Load and Haul, Rustenburg, 2013.

[8] S. M. Rupprecht, “The potential of automatic scraper winches in underground narrow vein mining South African,” in IMCET Proc. 26th, 2019, pp. 603–611.

[9] S. Schoombee, W. Hamer, and J. F. Van Rensburg, “Optimising gold ore transportation systems for electricity cost savings,” in Proc. 2016 ICUE, 2016, pp. 16–24.

[10] J. F. Pritchard and C. F. Landy, “Scraper winch motors on South African gold mines-an investigation into their failure,” in Proc. of IEEE AFRICON ’96, 1996, vol. 1, pp. 435–440 vol.1

[11] P. Darling, SME Mining Engineering Handbook, 3rd ed. Elsevier, 2011.

[12] S. Ierace and S. Cavalieri, “Maintenance strategy selection: a comparison between fuzzy logic and analytic hierarchy process,” IFAC Proc. Vol., vol. 41, no. 3, pp. 228–233, 2008.

[13] E. Pourjavad, H. Shirouyehzad, and A. Shahin, “Selecting maintenance strategy in mining industry by analytic network process and TOPSIS,” Int. J. Ind. Syst. Eng., vol. 15, no. 2, pp. 171–192, 2013.

[14] Y. Fu, X. Zhu, and X. Ma, “Optimum component reallocation and system replacement maintenance for a used system with increasing minimal repair cost,” Reliab. Eng. Syst. Saf., vol. 204, p. 107137, 2020.

[15] J. A. Jacobs and M. J. Mathews, “Failure prediction of mine de-watering pumps,” J. Fail. Anal. Prev., vol. 18, no. 4, pp. 927–938, 2018.

[16] J. A. Jacobs, M. J. Mathews, and M. Kleingeld, “Failure prediction of mine compressors,” J. Fail. Anal. Prev., vol. 19, no. 4, pp. 976–985, 2019.

[17] D. N. P. Murthy, M. Bulmer, and J. A. Eccleston, “Weibull model selection for reliability modelling,” Reliab. Eng. Syst. Saf., vol. 86, no. 3, pp. 257–267, 2004.

[18] P. A. Tobias and D. C. Trindade, Applied Reliability, 3rd ed. Boca Raton, FL: CRC Press, 2012.

[19] W. Nelson, J. I. McCool, and W. Q. Meeker, Applied Life Data Analysis. NY: John Wiley & Sons, 1982.

[20] K. M. Shuaib, P. G. Rasul, and P. A. Hesham, “Reliability and quantile analysis of the Weibull distribution,” J. Stat., vol. 14, pp. 32–52, 2007.

[21] Z. Tang et al., “Comparison of the Weibull and the Crow-AMSAA Model in prediction of early cable joint failures,” IEEE Trans. Power Deliv., vol. 30, no. 6, pp. 2410–2418, Dec. 2015.

[22] M. B. Muhammad, T. Raza, and M. A. Abd Majid, “Prediction of failures by using Crow/AMSAA model in Microsoft Excel.,” Proc. IEOM. pp. 180–186, Jan-2016.

[23] D. JANICIJEVIC, “Scraper winch pull force investigation,” in Third International Platinum Conference - Platinum in Transformation, 2008, pp. 135–140.

[24] P. Yizhen, W. Yu, X. Jingsong, and Z. Yanyang, “Adaptive stochastic-filter-based failure prediction model for complex repairable systems under uncertainty conditions,” Reliab. Eng. Syst. Saf., vol. 204, p. 107190, 2020.

[25] ReliaSoft Corporation, “Reliability growth and repairable system analysis reference,” Reliawiki. 2017.

[26] W. T. Roberts and L. Mann, “Failure predictions in repairable multi-component systems,” Int. J. Prod. Econ., vol. 29, no. 1, pp. 103–110, 1993.

[27] L. H. Crow, “Evaluating the reliability of repairable systems,” in Proc. RAMS, 1990, pp. 275–279.

[28] Z. Huang, “Conditional reliability lower bound for Weibull distribution without estimating shape parameter,” in Proc. 1997 RAMS, 1997, pp. 298–302.