Methods for Availability Improvements of a Scaling Machine System

Andi Rahadiyan Wijaya
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Division of Operation and Maintenance Engineering
Luleå University of Technology
SE – 971 87
Sweden
To my family:
Ristya – Gita mantra of Devata
Krishna – Persona of Nirvana
Ziven – Given from Heaven
for allowing me

to be part of their life and love
Preface

The research work presented in this thesis has been carried out during the period 2009 to 2011 at the Division of Operation and Maintenance Engineering at Luleå University of Technology (LTU). The research program was sponsored by Swedish Research Council (SSF), Boliden Mineral AB and Jama Mining Machine AB within the project “Integrated maintenance for improved production and products” (InMaint).

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I wish to express my sincere gratitude to the Ministry of Education of Republic Indonesia for providing a scholarship which made it possible for me to pursue doctoral work at LTU.

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Andi Rahadiyan Wijaya
Abstract

Scaling is the process of cleaning loose material from the roof, face and wall of an underground mine room to make the room safe for the next operation. Due to the nature of the task, scaling incurs a high number of accidents. The use of a scaling machine to replace hand scaling has successfully reduced the number of accidents. However, due to the combination of a hostile environment (such as falling rock, dust, high humidity, etc.), the operation context (e.g. significant vibrations), and reliability and maintainability issues, the scaling machine is identified remains a major contributor to unplanned downtime.

The purpose of this research is to develop methods that can be used to identify availability related problems and improving the availability of the scaling machine system in a cost effective way. To this end, it examines the literature, case studies, and simulations studies and includes empirical data from field measurements, document studies, interviews, and observations. For the data analysis, theories and methodologies within reliability, availability and maintainability (RAM), ergonomics and optimisation have been combined with the best practices from the related industry.

A first result of this study is the development of a method for visualisation of the downtime. This method provides a visualisation of the downtime estimation and the precision and uncertainty of the estimation at a given confidence level, as along with factors influencing the failure. Second, it identifies components that significantly contribute to the downtime and the reason for that downtime (reliability and/or maintainability problems). Based on the failures analysis, it makes suggestions to improve the critical components. Third, it identifies and analyses performance shaping factors (PSFs) that can affect the reliability of scaling machine systems. Fourth, it proposes a methodology that can help the design team select which components of a system require improvement and to what level improvements should be made to optimise the availability of system in a cost effective way. Finally, it proposes a method for a robust-optimum multi-attribute age-based replacement policy. The proposed approach can be used to determine the interval time for preventive replacement that provides a robust and optimum solution for a multi-attribute age-based replacement policy.

These results are related to specific industrial challenges, and are expected to improve the availability of the scaling machine system in a cost effective way. The results have been verified through interaction with experienced practitioners from both the manufacturer and the user (i.e. mining company) of the scaling machine.

Keywords: Scaling machine, Reliability Availability Maintainability (RAM) analysis, Cost-optimisation, Availability improvement, Multi-attribute optimisation problem (MOP), Age-based replacement policy, Performance shaping factors (PSFs).
Abstract in Swedish (Sammanfattning)

Skrotningspecifikation innebär att löst material rensas bort från tak, front och väggar för att minimera rasrisken vid underjordsbrytning. Syftet med skrotning är att göra gruvrummet säkert för nästkommande arbeten. Skrotningsanordningar har identifierats som en av källorna till ett stort antal olyckor, vilket beror på de stora riskerna för nedfallande sten. Användandet av skrotare jämfört med manuell skrotningsanordning har också minskat antalet skrotningsrelaterade olyckor. På grund av kombinationen av en besvärlig miljö (till exempel fallande sten, damm, hög luftfuktighet etc.), drift faktorer (t.ex. betydande vibrationer), tillförlitlighet och underhållsmässighet är skrotningsmaskinen identifierad som en av de stora bidragsgivarna till oplanerade driftstopp.


De nya metoderna är verifierade och relaterade till specifika industriella utmaningar och förväntas förbättra förmågan hos användare och tillverkar, att förbättra tillgängligheten på ett kostnadseffektivt sätt.
List of appended papers

**Paper I**

**Paper II**

**Paper III**

**Paper IV**

**Paper V**
Distribution of work

In this section, the distribution of work is presented for all appended papers. The content of this section has been shared and accepted by all authors who have contributed to the papers.

**Paper I**: Andi Wijaya developed the initial idea in discussion with Prof. Jan Lundberg. The literature review, model development, data collection and analysis were done by Andi Wijaya. The results of data analysis were discussed with Prof. Jan Lundberg. The first version of manuscript was prepared by Andi Wijaya and improved with the suggestions and comment of Prof. Jan Lundberg. Prof. Uday Kumar provided input for improvement of the manuscript.

**Papers II and III**: Andi Wijaya developed the initial idea. The literature review, model development, data collection and analysis were done by Andi Wijaya. The results of data analysis were discussed with Prof. Jan Lundberg. The first version of manuscript was prepared by Andi Wijaya and improved with the suggestions and comments of Prof. Jan Lundberg and Prof. Uday Kumar.

**Paper IV**: Andi Wijaya developed the initial idea. The measurement set up, data collection and analysis were done by Andi Wijaya. The manuscript was written by Andi Wijaya. Prof. Jan Lundberg contributed to the discussions of the data analysis and provided suggestions and comments on the manuscript.

**Paper V**: Andi Wijaya and Prof. Jan Lundberg developed the initial idea. The measurement set up, data collection and analysis done by Andi Wijaya. The results of data analysis were discussed with Prof. Jan Lundberg. The first version of manuscript was prepared by Andi Wijaya and improved with suggestions and comments from Prof. Jan Lundberg.
### Abbreviation

<table>
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<tr>
<th>Abbreviation</th>
<th>Definition</th>
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<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
</tr>
<tr>
<td>AOF</td>
<td>Aggregate objective functions</td>
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<tr>
<td>APUC</td>
<td>Average production unit cost</td>
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<td>CER</td>
<td>Cost estimation ratio</td>
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<td>CM</td>
<td>Corrective maintenance</td>
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<tr>
<td>DFM</td>
<td>Design for maintainability</td>
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<td>DFR</td>
<td>Design for reliability</td>
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<td>GA</td>
<td>Genetic algorithm</td>
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<td>GSI</td>
<td>Geological strength index</td>
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<td>HGCZ</td>
<td>Health guidance caution zone</td>
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<td>MOP</td>
<td>Multi-objective optimisation problem</td>
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<tr>
<td>NPV</td>
<td>Net present value</td>
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<td>NSGA II</td>
<td>Non-dominated sorting genetic algorithm</td>
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<tr>
<td>PM</td>
<td>Preventive maintenance</td>
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<tr>
<td>PSFs</td>
<td>Performance shaping factors</td>
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<tr>
<td>SOP</td>
<td>Standard operating procedure</td>
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<tr>
<td>TBF</td>
<td>Time between failures</td>
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<td>TTF</td>
<td>Time to failure</td>
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<td>TTR</td>
<td>Time to repair</td>
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<tr>
<td>WBV</td>
<td>Whole-body vibration</td>
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</table>
Notation

$A(8)$ 8 hours equivalent of frequency-weighted root mean-square-acceleration value

$K_{xyz}$ kurtosis sum

$VDV$ vibration dose value

$VDV(8)$ 8 hours equivalent of vibration dose value

$a_{rms}$ root mean-square-acceleration

$a_{xyz}$ vector sum value of the root-mean-square acceleration

$a_{Dxyz}$ vector sum value of the acceleration dose

$cu$ currency units

$f^{trans}(t)$ transformed objective function

$f(t)$ objective function

$f_{opt}(t)$ objective function of the optimum multi-attribute age-based replacement policy

$f_{rob}(t)$ objective function of the robust multi-attribute age-based replacement policy

$g(t)$ inequality constraint

$h(t)$ equality constraint

$r_{RI}$ reliability improvement ratio

$t_{rob-opt}$ interval for replacement time of robust-optimum multi-attribute age-based replacement policy

$w$ scalar weight of objective function

$\alpha$ alpha significance level

$\delta$ positive tolerance of objective function

$\mu_x$ mean time to repair

$\mu_y$ mean time to failure
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"Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful?"

George E.P. Box and Norman R. Draper
(Empirical Model-Building and Response Surfaces, 1987)
1. Introduction

1.1. Background

Mining and agriculture are the primary or basic industries of early civilisation. Mining in its simplest form began with Paleolithic humans approximately 450,000 years ago (Hartman and Mutmansky, 2002). Today, mining is the cornerstone of industrial development throughout the world. Between 2005 and 2009, the big five mining companies (BHP Billiton, Rio Tinto, Anglo American, Vale and Xstrata) generated some 212 billion euros in operating profits, making mining one of the most profitable industries (Xerfi global, 2010). In Sweden, archaeological evidence indicates that copper was produced from the Falu mine early in the 8th century (Erickson and Qvarfort, 1996). The Kiruna iron ore mine was opened in 1898 and since then has become the largest and most modern underground iron ore mine in the world (Samskog et al., 2000). Today, about 100 exploration companies operate in Sweden (Newman, 2011). Mining industries contribute 9 percent of the Swedish gross domestic product and employ 0.5 percent of the total industrial labour force (Lithander, 2004).

Based on the excavation technique used, mining can be classified as either surface mining or underground mining. Surface mining is done by removing surface vegetation, dirt, and layers of bedrock to reach buried ore deposits. Underground mining consists of digging tunnels or shafts into the earth to reach buried ore deposits. Based on the type of access shaft used, underground mining can be classified as shaft mining, slope mining, and drift mining. Shaft mining requires vertical access shafts, slope mining uses diagonally sloping access shafts, and drift mining utilises horizontal access tunnels. A typical process cycle for drift mining is illustrated in Figure 1.1.

![Figure 1.1. A typical drift mining process cycle](image)

The process cycle starts with drilling, creating blasting holes by crushing the rock at the mine face. During the next process, charging, explosive agents are loaded into the blasting holes. This is followed by blasting, an action of breaking and displacing rock by means of explosives. After blasting, the broken rock is loaded into a haulage truck, which will take it to the crusher, by mucking and loading it. After the mining room is clean of broken rock, the next step is scaling. Scaling is the process of cleaning loose material from the roof, face, and walls to make the mining room safe for the next operation. The
processes after scaling are shotcreting and rock bolting. In shotcreting, fibre reinforced cement is sprayed into the mine roof, face, and walls to prevent smaller rocks from falling; rock bolting is a process of inserting a long steel bolt into the roof to support the roof, preventing and limiting the extent of roof falls.

As the above description of the process cycle for drift mining shows, scaling is an extremely important step in workplace safety. However, due to the nature of the task, scaling has a high number of accident occurrences. A study of accidents in underground mines between 1985 and 1994 found that one-third of the ground control injuries involved scaling (Grau and Posser, 1997). To decrease the number of accidents, the scaling activity has been mechanised by means of a scaling machine which consists of an impact hammer mounted on a pivoting arm which, in turn, is attached to a mobile chassis (see Figure 1.2).

![Scaling machine](Source: Jama mining machine AB, 2009)

The use of a scaling machine to replace hand scaling has improved work safety. Data from a Swedish mining company show that after the introduction of the scaling machine, the number of scaling-related accidents fell from about 10 a year to none or 1 a year (Quinteiro et al., 2001). Thus, the scaling machine is quickly becoming important to underground mining. However, due to a combination of a hostile environment (e.g. falling rocks, dust, high humidity, etc.), the operation context (e.g. significant vibrations), and reliability and maintainability issues, the scaling machine is a major contributor to unplanned downtime.

Today, mining industries are trying to balance scarce resources with an escalating demand for their products. In 1998, every inhabitant of the world needed at least 5 t of mining products per year; in 1900, each person required only 0.5 t per year (Martens and Rattmann, 2001). The demand is now greater than supply, and mining companies want to increase production. Mining projects considered infeasible only a decade ago are now seen as feasible, due to the escalating demand and the scarcity of resources. A good example is Aitik mining in the north of Sweden; in spite of the very low copper-to-ore content (about 0.25 percent) (Boliden Mineral AB, 2010), this mining project is now considered feasible. To make the operation financially viable, mining company has to adopt a strategy combining large-scale production with process efficiency (Atlas Copco, 2010).
1.2. Basic concepts and definitions

1.2.1. Dependability
Dependability is a collective term which describes availability and its influencing factors: reliability, maintainability, and maintenance supportability (EN 13306, 2001). The relation of these factors is illustrated in Figure 1.3.

1.2.2. System availability
System availability is defined as the ability of a system to be in a state to perform a required function under given conditions at a given instant of time or during a given time interval, assuming that the required external resources are provided (EN 13306, 2010). There are different classifications of availability and different ways to calculate it. A common classification is based on the span of time to which the availability refers and the types of downtimes used in the computation (for further discussion, see Kumar and Akersten, 2008; Stapelberg, 2009).

1.2.3. System reliability
System reliability is defined as the ability of a system to perform a required function under given conditions for a given time interval (EN 13306, 2010). In man–machine systems, system reliability depends on the reliability of the machine (machine reliability) as well as the reliability of the operator (human reliability).

Machine reliability is affected by the operating conditions and the inherent reliability of the machine itself. Inherent reliability is the maximum reliability which a machine can achieve, built into it during its design phase and manufacturing process. Operating
conditions refer to the environmental conditions under which the machine has to operate. A departure from the specified conditions increases the risk of degraded machine performance or even machine failure (Ghodrati, 2005).

Human reliability is defined as the ability of humans to accomplish a task successfully at any required stage in system operation within a stated minimum time limit (Dhillon, 2009). Lee, et al. (1988) report that depending upon the degree of human involvement in the system, 20 – 90 percent of system failures are related to human reliability. Factors influencing the man-machine interaction are defined as performance shaping factors (PSFs). PSFs are classified into three categories; external, internal, and task-specific (Pew and Mavor, 1998). External PSFs comprise those that originate outside the human and typically have negative impacts on performance (e.g. noise, vibration, temperature, etc.). Internal PSFs are specific to the individual (e.g. motivation, personality, cognitive styles, expertise, etc.). They are difficult to assess and often combine in ways that are hard to predict. Task-specific PSFs include task type, procedure, on-site training, task-related fatigue, interface quality, work processes, etc. A brief explanation of some of the PSFs related to the present study is provided below.

a. Whole-body vibration (WBV)

Whole-body vibration (WBV) occurs when a human is supported by a surface that is shaking, and the vibration affects body parts remote from the site of exposure (Mansfield, 2005). For example, in scaling when loose rocks are falling and hitting the boom and the body of a scaling machine, vibration is transmitted through the vehicle to the seat and footrest, the surfaces that support the operator. Consequently, the operator is subjected to vibration through the feet and buttocks, and if there is back support, through the back as well. The vibration is then transmitted through the operator’s body to the head which will move. WBV is capable of producing a wide variety of different effects, from the input information to the body (e.g. vision) to the output of information from the body (e.g. hand control). The effects caused by vibration in the body at any location are dependent on the vibration frequency, the direction of vibration, and the vibration magnitude as well as how it changes over time (Griffin, 1990).

b. Procedure

It is common knowledge that in the absence of standardised procedures, people tend to adopt different ways to accomplish a given task, depending on the task’s level of novelty. The resulting differences in work processes lead to variations in the work performance (e.g. quality of performed task, time to accomplish the task, number of errors, etc.). To prevent such variations in work performance, standardised work processes should be established (Hattemer-Apostel, 2001). A process document that describes in detail how an operator should perform a given operation is called a standard operating procedure (SOP). The objective of an SOP is to ensure that all workers perform tasks in the same way, a necessary condition of consistent output (De Treville et al., 2005). Studies show that the use of SOPs can improve the output consistency, efficiency, and learning rate (Levinthal and March, 1993; Edelson and Bennet, 1998). The concept of SOPs has changed (De Treville et al., 2005). Originally SOPs were developed by management, as it was believed workers were incapable of designing efficient processes. Today, SOPs are developed based on best practices; the
active involvement of workers in the development and refinement of SOPs is encouraged.

1.2.4. System maintainability

System maintainability is defined as the ability of a system under given conditions of use, to be retained in, or restored to, a state in which it can perform a required function, when maintenance is performed under given conditions and using stated procedures and resources (EN 13306, 2010). The objective of maintainability is to minimise maintenance time and labour hours considering design characteristics (e.g. accessibility, standardisation, modularisation, inter-changeability, etc.). Maintainability is primarily determined by the inherent maintainability of a machine and the operating condition.

1.2.5. Maintenance supportability

Maintenance supportability is defined as the ability of a maintenance organisation to have the right maintenance support at the necessary place to perform the required maintenance activity at a given instant of time or during a given time interval (EN 13306, 2010). Maintenance support could consist of spare parts, materials, personnel, support equipment, facilities, documentation, information, and information systems. To provide maintenance support that will effectively and efficiently support the applicable system throughout the life cycle, the functions and activities related to maintenance supportability should be addressed from an integrated overall system perspective (Candell and Söderholm, 2006).

1.2.6. Multi-objective optimisation problem

The multi-objective optimisation problem (MOP) is the process of simultaneously optimising two or more conflicting objectives subject to certain constraints. A generic MOP can be formulated as follows (Marler and Arora, 2004):

$$\min_{i \in \mathbb{R}} \{ f_1(t), f_2(t), \ldots, f_k(t) \} \quad (k \geq 2)$$

subject to

$$g_j(t) \leq 0; \quad j = 1, 2, \ldots, m$$

$$h_l(t) = 0; \quad l = 1, 2, \ldots, n$$

where $k$ is the number of objective functions, $g_j$ is the $j$-th inequality constraints, $h_l$ is the $l$-th equality constraints, $t$ is the vector of optimisation or decision variables. Various approaches for solving MOP have been proposed. The advantages and limitations of those approaches are pointed out in (Ehrgott and Gandibleux, 2000; Marler and Arora, 2004; Rangaiah, 2009). Brief descriptions of some of the methods used in the present study are provided below.

a. Waltz lexicographic method

The Waltz lexicographic method is a method for solving MOP when the objective functions have a different priority (i.e. one of the objective functions should be more prioritised than the others). In this method, objective functions are arranged in order of importance and then solved one at a time. After the first objective is optimised, the second objective is optimised subject to keeping the first objective within a certain percentage of its optimum. Then the third objective is optimised subject to keeping
the second objective within a certain percentage of its optimum. The optimisation process is continued until all objective functions are solved. The Waltz lexicographic method can be formulated as follows:

$$\min_{t \in T} f_i(t)$$  \hfill (2)

subject to

$$f_j(t) \leq f_j(t^*_{opt}) + \delta_j; \quad j = 1, 2, \ldots, i - 1, i > 1; i = 1, 2, \ldots, k.$$  

where $t$ is the vector of optimisation or decision variables, $k$ is the number of objective functions, $t^*_{opt}$ is a value of the decision variable corresponding to the optimal value of $j^{th}$ objective function, and $\delta_j$ is a positive tolerance for the $j^{th}$ objective function determined by the decision maker. For a detailed explanation see Waltz (1967).

b. Constructing a single aggregate objective function

Constructing a single aggregate objective function is a method for solving MOP by combining all of the objective functions into a single aggregate objective function (AOF). One requirement for this method is that the decision maker has to specify a priori scalar weights for each objective function. This method is formulated as follows:

$$\sum_{i=1}^{k} w_if_i(t)$$  \hfill (3)

where $k$ is the number of objective functions, $t$ is the vector of optimisation or decision variables, and $w$ is the scalar weight of objective function. The solution obtained depends on the weights specified which, in turn, are affected by the demands. Various methods for determining the weight of the objective function have been proposed (e.g. Gennert and Yuille, 1988; Rao and Roy, 1989; Lundberg, 2000; Saaty, 2003). In combining objective functions, one should consider their magnitude. When the objective functions have significantly different orders of magnitude, an incorrect solution point may occur. To avoid this problem, the objective functions should be normalised. A robust approach (Marler and Arora, 2005) to transforming objective functions is the upper-lower-bound approach (Koski, 1984), formulated as follows:

$$f^\text{trans}_i = \frac{f_i(t) - f_i^o}{f_i^\text{max} - f_i^o}$$  \hfill (4)

where $f_i^o = \min_{t \in T} f_i$ and $f_i^\text{max} = \max_{t \in T} f_i$. The value of $f^\text{trans}_i$, depending on the accuracy and the method with which $f_i^o$ and $f_i^\text{max}$ are determined, generally varies between 0 and 1.

c. Multi-objective genetic algorithm

The genetic algorithm (GA) is numerical search tool used to find the global maximum (or minimum) of a given objective function. The algorithm used in GA mimics the process of natural selection and genetics; thus, many biological terms are used to describe the algorithm. GA is best described by using it to solve a simple single-objective optimisation problem (SOP). Let $f(x, y)$ be a function of the decision variable of $x$ and $y$ as follows:
The objective of the optimisation is to find the minimum value of \( f(x, y) \) for a given constraint, namely, that the values of \( x \) and \( y \) are between 0 and 30. This optimisation problem can be formulated as an SOP as follows:

\[
\min f(x, y) = (x - 10)^2 + (y - 10)^2 - xy, \quad 0 \leq x \leq 30; \quad 0 \leq y \leq 30
\]

A visualisation of this SOP is provided in Figure 1.4.

![a. Surface plot](image1.png) ![b. Contour plot](image2.png)

**Figure 1.4. Visualisation of the single-objective function problem**

In solving the optimisation problem, the GA begins by randomly generating an initial population of candidate solutions. For example, let \( \mathbf{s}_1, \mathbf{s}_2, \mathbf{s}_3, \mathbf{s}_4, \mathbf{s}_5 \) be the initial population of candidate solutions (see Figure 1.4), where \( \mathbf{s}_1 \) is \((x: 10, y: 15)\), \( \mathbf{s}_2 \) is \((x: 20, y: 10)\), \( \mathbf{s}_3 \) is \((x: 25, y: 15)\), \( \mathbf{s}_4 \) is \((x: 10, y: 25)\), and \( \mathbf{s}_5 \) is \((x: 5, y: 5)\). The candidate solutions (i.e. individuals) are then represented as a string of numbers (i.e. sequences of binary digits 0 and 1) (see Figure 1.5).

![Figure 1.5. Illustration of candidate solution represented as a string of numbers](image3.png)

The next step is to select individuals from the population to be candidates for reproduction. In this selection, only the fittest populations will survive. Reproduction is performed by crossover and mutation procedures. In the crossover procedure, a new individual (i.e. child) is generated from a pair of individuals (i.e. parents) by combining the strings of parents. By letting \( \mathbf{s}_1 \) and \( \mathbf{s}_2 \) be parents, through the crossover procedure, two new individuals \( \mathbf{s}_6 \) and \( \mathbf{s}_7 \) are generated (see Figure 1.6), where \( \mathbf{s}_6 \) is \((x: 8, y: 10)\) and \( \mathbf{s}_7 \) is \((x: 22, y: 15)\). In the mutation procedure, a new individual is generated from the mutation of the string (changing from 0 to 1 and vice versa) of an individual parent. By letting \( \mathbf{s}_1 \) be an individual parent, through the mutation procedure, a new individual \( \mathbf{s}_8 \) is generated (see Figure 1.7), where \( \mathbf{s}_8 \) is \((x: 25, y: 11)\).
The set of new individuals (i.e. offspring population) is combined with the initial population (see Figure 1.8). A fitness evaluation is performed on all individuals in the combined population; the less fit are weeded out and the more fit are included in the next generation of the population. In Figure 1.8, the five fittest individuals in the combined population are $s_1, s_2, s_3, s_6$ and $s_7$; therefore, $s_4, s_5$ and $s_8$ are weeded out. Thus, the next generation of the population consists of $s_1, s_2, s_3, s_6$ and $s_7$. The process continues to improve the objective function until pre-specified stopping criteria are met.

By using a similar concept, the GA can be expanded into a multi-objective GA. The main difference is the selection phase. In the multi-objective case, the concept of dominance is directly or indirectly incorporated in this phase. Various algorithmic have been proposed by different researchers. This study adopts the non-dominated sorting genetic algorithm (NSGA-II) as it is one of the most efficient algorithms for multi-objective optimisation in a number of benchmark problems (Konak et al., 2006). The two key concepts in NSGA-II are a fast non-dominated sorting of the population for the sorting assignment and a crowding distance for the diversity mechanism. The flowchart of the NSGA-II is shown in Figure 1.9 and briefly described below.
First, a random population of size N is initialised. The initial population is then sorted based on non-domination into each front. All individuals not dominated by any other individuals are assigned front number 1. All individuals only dominated by individuals in front number 1 are assigned front number 2, and so on. Crowding distance is calculated for each individual within each front. The crowding distance is a measure of the Euclidian distance between each individual (how close an individual is to its neighbours). A less crowded region will result in better diversity in the population. Parents are selected by using the binary crowded tournament selection. In this selection, two individuals are selected at random to compete against each other, and the winner is returned to the tournament. An individual is selected as a winner if it has a better rank or if two individuals have the same rank; these individuals have a better crowding distance. New individuals are generated using crossover and mutation procedures to create an offspring population. The two populations (initial and offspring) are combined and compete with each other for inclusion in the next iteration. The best N solutions are selected to create a new population. Iterations are terminated when the maximum number of individuals in a generation is exceeded. For a detailed description, see Deb et al. (2002).

1.2.7. Robust design

Robust design is a philosophy popularised by Taguchi in the 1950s. The core concept is that uncertainty should be considered from the beginning, controlling the uncertainty that one can control and finding the best possible solution, one that is as insensitive as possible to the remaining uncertainty (Park, 1996). In the optimisation problem, a solution is considered robust if the output of the objective function for that solution contributes as little as possible to the perturbation of variation in the model variables and model parameters. Consider the following single optimisation problem:

$$\min_{x, p} f(x, p)$$

(5)

where $f$ is the objective function, $x$ is the model variable and $p$ is a vector of the model parameters. For constant model parameters, the output of the objective function is illustrated in Figure 1.10.
Figure 1.10 shows that with deterministic optimisation (with no variations), the optimum solution is $x_{\text{optimum}}$. This yields the lowest value of the objective function over the given range and would be the result of traditional optimisation. However, it is not robust. A slight deviation in the model variable ($\Delta x$) causes a much greater change in objective value than a similar change in $x_{\text{robust}}$. The worst case value is higher, and the overall performance change is also higher. The second solution ($x_{\text{robust}}$) is therefore more robust.

1.3. Motivation of the study

As mentioned above, mining industries are facing a problem of scarce resources in the midst of an escalating world demand for mining products. Therefore, mining companies must adopt strategies which combine large-scale production and efficiency if they are to make their operations financially viable. In the case of underground mining, large-scale production can be obtained by improving the utilization of mining rooms, but a consequence of this is increased operating hours of critical equipment. While the easiest way to handle this is to add more machines, this strategy will sacrifice process efficiency, as the cost per tonnes of mining products will increase. To satisfy both the high utilization of mining rooms and efficiency, a feasible strategy is to improve the availability of critical equipment.

The preliminary study reveals that this particular underground mine has a ratio of preventive maintenance (PM) to corrective maintenance (CM) of 23 percent which indicates the high occurrence of unplanned downtime. Furthermore, more than 20 percent of the unplanned downtime of mobile equipment is related to scaling machines. This high amount of unplanned downtime leads to monetary losses (direct and indirect) for the company. To minimize these losses, the availability of the scaling machine should be improved, and as the ultimate goal of the company is to maximize profit, this should be done in a cost effective way.

The present study focuses on the development of methods that can be used by the manufacturer and the user to identify availability related problems and improve the availability of the scaling machine system in a cost effective way. The collaborative research is jointly conducted by Luleå University of Technology, a mining company as a user of the scaling machine, and a manufacturing company as the machine’s developer.
2. Thesis approach

2.1. Statement of the problem

A downtime analysis can provide essential knowledge of a scaling machine’s unplanned downtime. Downtime analysis usually involves many people with various backgrounds (Wikoff, 2008). The present study, for example, involves a group of operators, maintenance personnel, a maintenance engineer, a product development team from the manufacturing company, and an academic. Given the group’s diversity, effective communication is a necessity. Visualisation methods (e.g. graphs) can help to eliminate the knowledge gap within the group. While the classic Pareto diagram is often used to present the downtime of equipment (Lin and Titmuss, 1995; Henessy et al., 2000; Kortelainen, 2003; Das, 2005), its use in maintenance engineering applications has some shortcomings. For example, where an outcome is the product of two factors, a Pareto diagram cannot visualise which one is dominant. The jack-knife diagram has been proposed as an alternative (Knight, 2001). Although it can overcome the shortcomings of Pareto diagram, it too has limitations. In the jack-knife diagram, the downtime is presented as a single value (point estimation) which in the past decade has been considered insufficient (Altman et al., 2000; Curran-Everett and Benos, 2004; Council of Science Editors, 2006). In analysing downtime, failure data is commonly estimated in a probabilistic model, and therefore, it is essential to consider the reliability of the estimation (Gardner and Altman, 2000). Two components may have the same downtime value, but at a given confidence level, their intervals may differ significantly. Thus, it is important when visualising failure data to show not only the point estimation, but also the interval estimation, so that the precision and the uncertainty of the estimation can be identified. It is important to provide a method for visualising downtime that can highlight the most significant downtime, identify the dominant factors influencing the downtime (i.e. reliability and/or maintainability problem), and provide the interval estimation for the downtime.

As noted in the introduction, the mining business is working on improving its efficiency. This means that improving the availability of the scaling machine system should consider both effectiveness (doing the right thing) and efficiency (doing the thing right). With respect to the former, two points should be considered. First which subsystem (i.e. components) of the scaling machine system contributes most to downtime? Second, what is the reason for downtime? Is it poor reliability, poor maintainability, or poor maintenance supportability? Different problems call for different strategies. When high downtime is due to the high failure frequency of components, the reliability of components should be improved (i.e. design for reliability). If the failure frequency of component(s) is low but there is a long time for repair, the maintainability of components should be improved (i.e. design for maintainability). When high downtime is related to the maintenance organisation (e.g. long waiting times for spare parts, administrative delays, unclear procedures, etc.), the ability of the maintenance organisation to support maintenance activities should be improved (e.g. integrated management system, outsourcing relationship management, etc.). Availability improvements should also be conducted in a cost effective way, as the ultimate goal for the company is profit. Ideally, availability improvements should require little/no cost, but in reality, this is difficult to
achieve. This has an impact on the selection (i.e. prioritising) of components that are needed to be improved their availability. The selection is no longer solely based on which components make a large contribution to the overall system availability. It may be more efficient to focus on improving two or three subsystems of a smaller contributor than on one subsystem of a larger contributor. The problem is becoming a bi-objective optimisation: the first objective is to maximise the availability of the system and the second is to minimise the cost of availability improvement. Thus, it is useful to develop a methodology that can help the engineering design team select which components should be improved and to what level the improvements can be done in a cost effective way.

A classical approach for the engineer seeking to improve the reliability of system is to simply improve the reliability of the machine. However, since the 1950s, the importance of the human aspect has been acknowledged (Dhillon, 1986). Except in the utopian dream of a fully automated mine, humans (i.e. operators) are always a central part of the mining system, not an optional extra (Simpson et al., 2009). As human reliability is affected by PSFs, attempts to improve the reliability of the scaling machine system should also consider these factors. So far there are only limited studies regarding PSFs in the mining machine (e.g. Schutte and Maldonado, 2003; Godwin et al., 2007; Lucas and Thabet, 2008; van Wyk and de Villiers, 2009), and these mainly focus on safety issues. Furthermore, no study has been performed on the PSFs of the scaling machine. PSFs can significantly degrade the performance of man-machine systems when they are not managed properly (Miller and Lawton, 2006). Thus, it is important to study the PSFs of the scaling machine.

One way to reduce the incidence of costly breakdowns and increase the availability of system is to implement PM (Gopalakrishnan et al., 1997). PM refers to proactive activities taken to avoid possible future problems. A common and popular PM policy is the age-based replacement policy (Wang, 2002). This policy consists of replacing an item by another when it reaches a certain age, $T$ (the replacement age) which is a constant, or when it fails, whichever occurs first (Barlow and Hunter, 1960). The main problem in is to determine the best timing for and frequency of replacement (Caivalcante et al., 2010). A common approach is to consider the minimum total cost (i.e. material cost, labour cost, downtime cost, etc.). However, minimising the cost is not the only goal. Maintenance activity is expected to support the production process with adequate levels of availability, reliability, and operability (Coetzee, 2004). In determining the replacement age, all these attributes should be taken into consideration and decisions should be based on a multi-attribute approach (Chareonsuk et al., 1997; Calvacante and de Almeida, 2007; Ferreira et al., 2009). Another important aspect is the model’s parameters. It is common to assume that the parameters for the model are known and deterministic. However, in practice, they must be estimated from historical data, which can be limited or entirely lacking (Leger and Cleroux, 1992). This uncertainty affects the output of the age-based replacement policy significantly (Mauer and Ott, 1995; Halim and Tang, 2009). From the above, it can be concluded that in determining the best time for replacement ($T$), the decision should be based on the multi-attribute approach, and the output of the model ($T$) should be less sensitive to the uncertainty of the model parameters (i.e. robust). A correspondingly appropriate methodology should be developed.
2.2. Research objectives
The objective of this research is to develop methods for a scaling machine system that can be used by the manufacturer and the user to identify availability related problems and required improvements.

2.3. Research questions
To fulfill the above objectives, the following research questions have been asked:

1. How can the downtime be visualised to highlight the most significant downtime, the dominant factors influencing the downtime (i.e. reliability and/or maintainability problem), and the interval estimation of the downtime?
2. What factors contribute to the downtime of a scaling machine system and how do they contribute?
3. How can we determine which components of the scaling machine need to be made more reliable and to what extent should reliability improvement be conducted to obtain optimum availability in a cost effective way?
4. How to determine the solution for preventive replacement interval of a component based on cost and reliability attributes and considering the optimality and robustness of the solution?

These research questions are answered by the five appended papers. Each paper makes its own contributions toward the research questions (see Table 2.1).

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2.4. Limitations of the study
Based on the available resources, the research objectives, and the industrial interests, the present study has the following limitations:

- The operating condition (e.g. working environment, level of application, work time, period of operation, etc.) can affect the reliability and maintainability of the system. In the present study, data are obtained from only one scaling machine operated in a single underground mining. Consequently, operating conditions should be taken into consideration before applying the study’s results, especially when the operating conditions are dissimilar.
- System availability is significantly affected by maintenance supportability (e.g. maintenance procedure, procurement of maintenance tools, spare parts and facilities, logistic administration, documentation, etc.). High system availability cannot be achieved if the maintenance supportability is poor. Based on input from the study’s participating industries, maintenance supportability is not the focus of the present...
study. Thus, throughout this thesis, maintenance supportability is assumed to be satisfactory.

- In analysing human reliability, all PSFs should be identified and analysed individually and in combination. A single PSF might affect the human reliability differently in the existence of other PSFs due to the combinatorial or interaction effect of PSFs. In the present study, however, only some PSFs were analysed.
- The cost of reliability improvements for components of a scaling machine is predicted by utilising generic model (the CER model). Ideally, a specific component calls for a specific model. However, a better model is not available for the scaling machine.
3. Research methods

3.1. Data collection and analysis

The present research is performed on a single underground mining in north of Sweden and failure data and vibration data are collected from a single scaling machine. The research objects, data collection and data analysis are described in the following section.

3.1.1. Research objects

The underground mine studied is one of the oldest operating mines in Sweden; it began operating in 1940. Cut and fill mining with hydraulic backfill is the predominant method (Krauland et al., 2001). Complex ore, containing copper, lead, zinc, gold, silver, and gold-copper are presently extracted at a depth of 900 – 1400 m below the ground. The geology of the mine is complex and irregular (Rådberg, et al., 1992). The host rocks are mainly sericitic, cordieritic, and chloritic quartzite which are considered strong rocks (Li, 2005). But in the immediate vicinity of the ore body, weak chloritic schist which varies in thickness from 0 to 3 metres is often observed. Depending on the chlorite content, this schist can be extremely weak (Board, et al., 1992). The geological strength index (GSI) varies between 50 – 80 and the uniaxial compressive strength of the intact host rock varies between 65 – 150 MPa. The variation is mainly due to the different grade of alteration, foliation, and chlorite content in the rock types. Combinations of varying rock mass conditions and high virgin stresses lead to different types of ground conditions in ramps and access drifts, including rock bursts, spalling, and squeezing conditions (Edelbro and Sandström, 2009).

The scaling machine investigated in the present research is a typical scaling machine used in underground mining in Sweden. The overall dimensions are 3 m height, 2.6 m width, and 14.6 m length, with an unloaded weight of 27 tonnes (see Figure 1.1). It has an articulated four-wheel drive chassis and retractable stabilizers. It is bi-directional in its operation. The driver sits in an isolated cabin which can be tilted up to 13°. The maximum effective reach of the boom is 9 m (3 m in front of the machine) and 8.5 m at a 45° approach angle. It can be operated in either diesel or electro-hydraulic modes by a 6-cylinder in-line turbocharged diesel engine with a displacement of 7146 cc (200 kW at 2300 rpm) or a 2 x 30 kW electric motor (400 – 1000 V). It is equipped with a hydraulic hammer (600 - 1150 J of impact factor (energy) with an impact rate of 10 – 25 Hz) and a water jet system for dust control. The electromechanical processes are controlled by a programmable logic controller (PLC) system with controller area network communication (Jama mining machine AB, 2009).

3.1.2. Failure data

The failure data used in the present research were collected over a period of two years. Main source of data are from the computerised maintenance management system; additional data are from the internal reports of maintenance personnel and the daily failure reports of hoses from the operators. Scaling is not a continuous process; thus, global time cannot be used to determine time between failures (TBF). Both diesel time and electric motor time are utilised as the scaling machine can be operated in both diesel and electro-hydraulic modes. For the hydraulic hammer, time to failure (TTF) is
determined from the record of stroke hours, as it gives a better representation of the operation hours of the hydraulic hammer. A flowchart for analysing failure data appears in Figure 3.1.

![Flowchart for analysing failure data](adapted from Walls and Bendell, 1986)

The failure data, TBFs/TTFs, and time to repairs (TTRs) are arranged in chronological order. If the cyclical patterns in the failure data are expected, the data are tested to determine whether they can be modelled as a time series (e.g. Ljung-Box test). If the data can be modelled as a time series, time series analysis (e.g. ARIMA) can be applied (Box et al., 2008). Otherwise, the failure data are tested for trends (e.g. Laplace trend test). A trend test looks for long term trends to determine whether the data set is identically distributed (Klefsjö and Kumar, 1992). If such a trend is observed, a non-stationary model (e.g. Non-homogeneous Poisson process (NHPP)) can be applied (Kumar et al., 1989; Coetzee, 1997). Otherwise, the failure data are tested for dependency (e.g. serial correlation test). A dependence test determines whether successive failures are dependent in data without a long term trend (Klefsjö and Kumar, 1992). If a dependency between successive failure data is observed, dependence may be built into a model. A possible models is the branching Poisson process (BPP) (Ascher and Feingold, 1984). If a dependency is not observed, then the failure data set is independent and identically distributed (i.i.d.) and the data set can be fitted to a standard distribution (e.g. Weibull, Log-normal, etc.) and tested for the fitness of the data (e.g. Goodness of fit test) to the standard distributions. In the present study, all statistical tests were conducted by Matlab software, and the alpha significance level ($\alpha$) used in all tests is 0.05.
3.1.3. Vibration data

In the present research, vibrations are measured with a tri-axial accelerometer (ICP 356A02, PCB Piezotronics) in conjunction with a 4-channel, 24-bit resolution data acquisition device (NI 9234, National Instrument). The accelerometer has a frequency sensitivity range of 0.5 – 6000 Hz. Vibration signals were recorded at the sampling frequency of 2500 Hz and were low pass-filtered at 1000 Hz to avoid aliasing. The analysis of vibration measurement data uses Matlab software.

3.2. Approach for solving MOP

In the present research, the appropriate approach for solving MOP is selected based on whether priority and a priori weights exist for objective functions. A priority exists if the objective functions are not considered equally important and can be ranked as “most important”, “next most important”, etc. (Waltz, 1967). An a priori weight exists when all objective functions are considered equally important but are not linear. One or more objective functions is more dominant. The degree of dominance is expressed in the relative values of the weights specified.

A flowchart for selecting the appropriate method appears in Figure 3.2. The first step is to check whether a priority for the objective function exists. If so, MOP is solved by utilizing the Waltz lexicographic method. If a priority does not exist, the next step is to check whether the objective functions have an a priori weight. If the answer is yes, then MOP is solved by constructing a single AOF. But if the answer is no, MOP is solved by using NSGA-II.

![Figure 3.2. Flowchart for selecting appropriate approach for solving MOP](image)

3.3. Method used in Paper I

Paper I proposes a method for visualising downtime. While it is based on the jack-knife diagram (Knights, 2001), it is intended to overcome its shortcomings. In the jack-knife diagram, downtime is presented as a single value (point estimation); in this method, downtime is presented as an interval estimation of the downtime. To do so, the paper assumes that the failure times have a Weibull distribution and the repair times have a lognormal distribution. By letting $\frac{\mu_e}{\mu_f}$ be the ratio of mean time to repair ($\mu_e$) and mean time to failure ($\mu_f$), the confidence interval of the estimated downtime for a given uptime can be solved by finding a confidence interval for $\frac{\mu_e}{\mu_f}$. The exact method is used, as it
provides a more accurate solution than the approximate method. The interval estimation of the downtime is then plotted on a log-log diagram as a function of the number of failures and the times to repair. The proposed method is then used to identify the availability related problem of a scaling machine. Analyses of the failures of the critical components and suggestions for improvement are based on observations, interviews, written reports from the operator, and a group discussion.

### 3.4. Method used in Paper II

Paper II proposes an approach for cost optimisation of reliability improvement. The proposed approach is a combination of the cost estimation ratio (CER) model (Forbes and Long, 2008) and NSGA II (Deb et al., 2002). The CER model is utilised to predict the cost of reliability improvement for each component of the scaling machine, and NSGA II is utilised to solve MOP. The CER model requires information on the average production unit cost (APUC) for each component. To maintain the confidentiality, the APUC data are encoded and expressed as a currency unit (cu), but the characteristics of the APUC data remain in the encoded APUC data. All data related to monetary value are also adjusted to the encoded APUC data and expressed as a currency unit (cu). The net present value (NPV) method is used to appraise the potential investments in reliability improvement.

### 3.5. Method used in Paper III

Paper III proposes a method for a robust-optimum multi-attribute age-based preventive replacement based on a combination of the multi-attribute age-based replacement policy and a robust design technique. A flowchart of the proposed method is shown in Figure 3.3.

![Flowchart for robust-optimum multi-attribute age-based replacement policy](image)

**Figure 3.3.** Flowchart for robust-optimum multi-attribute age-based replacement policy
The methodology begins with the formulation of the optimisation problem for the cost and reliability attributes. The classical cost model (Barlow and Hunter, 1960) is used for the former, while the reliability performance measure (Jiang and Ji, 2002) is used for the latter. The next step is the normalisation of the objective function for both optimisation problems to avoid an incorrect solution point, which might occur due to the different magnitudes of the objective functions. The two objective functions are combined into a single AOF of the optimum multi-attribute age-based replacement policy, \( f_{opt}(t) \), and an appropriate weight is assigned for each objective function. The selection of the weighting will significantly influence the final decision. The next step is to formulate an objective function for the robust multi-attribute age-based replacement policy, \( f_{rob}(t) \), by using the robust design approach. The priorities for \( f_{opt}(t) \) and \( f_{rob}(t) \) are assigned and a MOP with priority can be formulated for the two objective functions. The optimisation problem for the objective function with a higher priority is solved first. The acceptable tolerance \( \delta \) is assigned for the first objective function. Then the optimisation problem for the objective function with a lower priority is solved with respect to the acceptable tolerance assigned for the first objective function. At this point, the interval for the replacement time \( (t_{rob-opt}) \) of the robust-optimum multi-attribute replacement policy can be determined.

3.6. Method used in Paper IV

Paper IV analyses the WBV exposure of the scaling machine. Vibration measurements conducted in accordance with ISO 2361-1 (1997) are analysed in accordance with ISO 2361-1 (1997) and ISO 2361-5 (2004). A tri-axial accelerometer (ICP 356A02, PCB Piezotronics) is mounted in a circular rubber seat-pad and placed on the seat beneath the ischial tubersities of the driver (see Figure 3.4).

![Seat-pad equipped with tri-axial accelerometer](image)

**Figure 3.4. Measurement set up according to ISO 2361-1**

Vibration measurements are conducted for a single operator while performing scaling activity in three different mining rooms. The driver is a 51-year-old male, 180 cm tall and weighing 105 kg, with about 25 years of experience operating a scaling machine. The duration of vibration measurement for each mining room is 20 minutes. Frequency spectrum analyses are performed to analyse the characteristics of WBV exposure in relation to the response of the body of the seated person. To quantify the measured vibrations, the analysis uses the frequency weighted root-mean-square acceleration \( (a_{wrm}) \), the frequency weighted root-mean-square vector sum value \( (a_{xyz}) \), the 8 hr equivalent frequency-weighted root-mean-square acceleration value \( (A(8)) \), the vibration dose value \( (VDV) \), and the 8 hr equivalent vibration dose value \( (VDV(8)) \). The first three
methods ($a_{rms}$, $a_{xyz}$ and $A(8)$) are used to analyse the severity of the vibration exposure in general, while $VDV$ and $VDV(8)$ are used to analyse the severity of the exposure of vibration containing shocks.

3.7. Method used in Paper V

Paper V measures vibrations on the chassis of the scaling machine (see Figure 3.5). Ideally, the accelerometer should be placed on the boom; however, due to space restrictions and the risk that it would be damaged, in this study it is mounted on the chassis directly connected to the boom. The study uses a two-factor factorial design with replications in which three different drivers and three different mining rooms are crossed-fixed effects. Drivers are voluntary participants, and their experience operating a scaling machine varies from 3 – 25 years (mean = 15 years). Due to the production scheduling which is determined by the company to maximise the utilisation of the mining rooms, the study cannot perform equal replications for each combination. The duration of the measurement for each replication is one hour. The vector sum value of the root-mean-square acceleration ($a_{xyz}$), the vector sum value of the acceleration dose ($a_{Dxyz}$) and the kurtosis sum ($K_{xyz}$) are used to quantify the measured vibrations. The first method is used to quantify the global severity of the vibration, while the last two are used to quantify the severity of vibration signals containing shocks. An unbalanced two-way ANOVA is utilised for the statistical analysis, as this method can handle data with incomplete replications. The Tukey test is used post hoc. The alpha significance level ($\alpha$) used in the statistic tests is 0.05.

![Figure 3.5. Location of the accelerometer](image)
4. Summary of the appended papers

4.1. Paper I

**Purpose:** Paper I has two purposes. First, it develops a method for visualising downtime estimation, as well as the precision and uncertainty of the estimation at a given confidence level and factors influencing the failure leading to downtime. Second, it identifies the availability problem of a scaling machine using the proposed visualisation method and makes suggestions for improved availability.

**Findings:** Using the proposed visualisation method to analyse the downtime of scaling machine reveals the following: 1) by considering different scenarios (worst, most likely, and best), significant components can be ranked differently based on their downtime; 2) components with high downtimes are the central lubrication system (B), the hydraulic hammer (C), the boom (D), the seat (E), the hydraulic hoses (F), and the hydraulic cylinders (G); 3) the downtime of components B, C, D, F and G is caused by reliability problems, and the design for reliability (DFR) should be adopted to reduce downtime; the downtime of component E is due to maintainability problems, and the design for maintainability (DFM) should be adopted to reduce downtime. The paper analyses the failures of the scaling machine’s critical components and offers suggestions for improvement.

4.2. Paper II

**Purpose:** Paper II proposes an approach to optimising the cost of improving the scaling machine’s reliability.

**Findings:** The approach can be used to determine which components of the scaling machine need reliability improvement and to what extent they should be improved to obtain optimum availability in a cost effective way. The paper assumes that the CER model is valid for the scaling machine. Results of the NPV analysis indicate that improvements to obtain an availability of more than approximately 84.5 percent are not feasible. For a feasible investment, the maximum NPV obtained is approximately 210 currency units (cu) which corresponds to approximately 82 percent system availability and a total cost of investment of about 121 cu. The highest system availability obtained for a feasible investment is approximately 84.5 percent which corresponds to an NPV of about 3 cu and a total cost of investment of about 506 cu. Results from the study can be used to guide the design team when it is selecting which components need to be improved and to what extent.

4.3. Paper III

**Purpose:** Paper III proposes a method for determining the multi-attribute preventive replacement interval while considering the optimality and robustness of the solution.

**Findings:** Results from the two case studies show that the proposed method can be used to determine the solution for the multi-attribute preventive replacement interval while considering the optimality and robustness of the solution. In the case of the preventive replacement of hydraulic hammer, considering that two performance functions (cost and reliability) are equally important, the interval time for preventive replacement is $147 \leq t \leq$
209 h. In the case of the preventive replacement of the relays of the HVAC system, considering that the two performance functions are equally important, two interval times for preventive replacement are obtained. The first interval time is $9.5 \leq t \leq 9.9$ million switchings; the second is $12.4 \leq t \leq 13.6$ million switchings. The latter is considered superior to former, as it has a wider range, thereby providing more flexibility in scheduling.

4.4. Paper IV

Purpose: Paper 4 analyses the current condition of the external PSF (i.e. whole-body vibration) and determines how it might affect the performance of the operator.

Findings: The dominant frequency of the measured vibration peaks concurs with the resonance frequencies of the body of the seated person; in addition, the whole-body vibration degrades the ability of the driver to perform a manual task and causes discomfort. This combination may directly or indirectly contribute to the failure of the scaling machine system. The characteristic WBV exposure of the scaling machine is found to differ from any other mining equipment; the average magnitude of the measured vibrations is low but the vibrations contain multiple shocks with high amplitude. An assessment based on ISO 2631-1 indicates a high probability of adverse health effects; one based on ISO 2631-5 finds that the probability of adverse health effects on the spine is low to moderate. This supports the notion that the limits specified by ISO 2631-5 are too high.

4.5. Paper V

Purpose: The study seeks to determine best practice to prevent scaling machine failure. A work practice which results in lower vibration levels is considered better than practices yielding higher vibrations. As the geological condition of the mine may also affect vibrations, it is important to know the possibility of an interaction effect, whether a particular scaling style will result in lower vibration levels for all areas in the mine or in particular mining rooms. Therefore, the study examines the effect of the operator and the mining room, as well as their interaction.

Findings: The vibration analysis cannot determine differences among drivers. Therefore, the work practices of a driver have no significant effect on the measured vibrations. The measured vibration signal is affected by falling rocks. This is determined by the inherent characteristics of the mining room not the driver’s style.
5. Results and discussion

5.1. Results and discussion related to research question 1

RQ 1: *How can downtime be visualised to highlight the most significant downtime, the dominant factors influencing the downtime (i.e. reliability and/or maintainability problems) and the interval estimation of the downtime?*

The first research question is answered in Paper I; the findings are briefly discussed here.

To satisfy the first research question, the paper proposes a method for visualising downtime. Figure 5.1 illustrates the application of the proposed method to the downtime of a scaling machine. The downtime was calculated for the theoretical production hours of one year (i.e. 5300 hours). In interpreting the diagram, we read both axes (the time to repair and the number of failures) and the iso-downtime line (the constant downtime that appears as a straight line with a uniform negative gradient). The figure indicates that component E has a downtime of approximately 100 h, corresponding to approximately 6 failures and a time to repair of about 17 h. At a 90% confidence level, the downtime interval of component E is between 40 h and 220 h.

![Confidence log-log diagram of scaling machine corresponding to the theoretical production hours for a period of one year (i.e. 5300 hours)](image)

In the prioritisation of significant components based on their downtime, the proposed method can visualise their order based on the mean estimation (the most likely scenario), the upper limit estimation (the worst scenario) and the lower limit estimation (the best scenario). This kind of information is needed for activities where the decision should be based on all three scenarios (e.g. planning and budgeting maintenance activities). In some
cases, the maximum downtime is limited to a certain value; if this is the case, it is important to know the likelihood that the downtime of the components will exceed that limit. By using the proposed method, we can visualise which components will exceed the limit at a certain confidence level (e.g. 95%). In this method, the estimation of the downtime is presented as a function of time to repair and number of failures. This can highlight which factors (reliability and/or maintainability) contribute to downtime and which strategies (DFR and/or DFM) should be adopted to reduce it.

In the proposed visualisation approach, the failure times and the repair times are modelled with a Weibull distribution and a lognormal distribution. While these distributions are generally valid (Abernethy, 2000; Wiseman, 2001; Rausand and Hoyland, 2004; Schroeder and Gibson, 2005; Bovaird and Zagor, 2006), exceptions can occur. The proposed approach can be extended to cover the failure data with different distributions and to develop the appropriate interval estimation for the downtime.

5.2. Results and discussion related to research question 2

RQ 2: What factors contribute to the downtime of a scaling machine system and how do they contribute?

The second research question is answered by Papers I, IV and V. A brief discussion of the important findings is provided here.

The proposed method can determine the order of the components making a large contribution to overall system availability (see Figure 5.1). It does so by considering three different scenarios (most likely, worst and best). The order of significant components (from most significant to least significant) based on the mean estimation ($DT_M$) is the following: the hydraulic cylinders (G), the boom (D), the hydraulic hoses (F), the hydraulic hammer (C), the central lubrication system (B), the seat (E), the electronic system (M), the water system (I), the bearer (H), the hydraulic valves (N), the cabin (L), the chassis (K), the engine (A) and the transmission (J); the order based on the upper limit estimation ($DT_{UL}$) is D, G, C, E, F, B, N, K, I, M, H, L, J and A; the order based on the lower limit estimation ($DT_{LL}$) is D, G, F, C, B, M, I, E, H, K, N, J, L and A. Based on the upper limit and the lower estimation, the largest contributor is the boom; based on the mean estimation, the largest contributors are the hydraulic cylinders. Based on the upper limit estimation, the seat is among the top five components; using other estimations, it is not. These differences stem from the width and the skewing of the interval estimation of the differing downtimes of the components.

Results show six components have a high downtime ($DT_M \geq 100$ h) but for different reasons. The high downtimes of the central lubrication system, the hydraulic hammer, the boom, the hydraulic hoses and the hydraulic cylinders mainly result from reliability problems; the high downtime of the seat can be traced to maintainability. The DFR should be adopted to reduce the downtime of the former components, and the DFM should be adopted to reduce the downtime of the latter.

The study included failure analysis of the critical components. A group discussion led to suggestions for improvement; these were implemented where possible. A list of suggestions appears in Table 5.1, and brief descriptions of selected suggestions are provided in the following section.
Table 5.1. Suggestions for improvement

<table>
<thead>
<tr>
<th>No</th>
<th>Parts</th>
<th>Problem</th>
<th>Suggestion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Boom</td>
<td>Longitudinal weld cracks</td>
<td>Apply correct welding technique</td>
</tr>
<tr>
<td>2</td>
<td>Boom</td>
<td>Resonance problem</td>
<td>Reinforce the structure of the boom</td>
</tr>
<tr>
<td>3</td>
<td>Boom</td>
<td>High impact force from falling rocks</td>
<td>Use a triangular boom for allowing falling rocks to bounce off</td>
</tr>
<tr>
<td>4</td>
<td>Hammer</td>
<td>Resonance problem</td>
<td>Install a vibration-damping rubber pad in the hammer attachment</td>
</tr>
<tr>
<td>5</td>
<td>Hammer</td>
<td>Resonance problem</td>
<td>Replace the hammer with one having a lower working frequency range</td>
</tr>
<tr>
<td>6</td>
<td>Hoses</td>
<td>Failure of the neck of the nipple</td>
<td>Add protection for hoses by modifying the hammer fastener (see Fig. 5.5)</td>
</tr>
<tr>
<td>7</td>
<td>Hoses</td>
<td>Failure of the neck of the nipple</td>
<td>Provide a cover for the nipple (see Fig. 5.6)</td>
</tr>
<tr>
<td>8</td>
<td>Hoses</td>
<td>Failure of the neck of the nipple</td>
<td>Use strain relief in the nipple</td>
</tr>
<tr>
<td>9</td>
<td>Hoses</td>
<td>Failure of the neck of the nipple</td>
<td>Use a more robust nipple to provide better resistance against external and internal force</td>
</tr>
<tr>
<td>10</td>
<td>Hoses</td>
<td>Excessively vulnerable hoses</td>
<td>Optimise the length of the hoses</td>
</tr>
<tr>
<td>11</td>
<td>Hoses</td>
<td>Variation of hose length</td>
<td>Standardise hose length</td>
</tr>
<tr>
<td>12</td>
<td>Hoses</td>
<td>Excessively vulnerable hoses</td>
<td>Use non-lubricated bearings so that some hoses can be removed</td>
</tr>
<tr>
<td>13</td>
<td>Hoses</td>
<td>Crushing and abrasion</td>
<td>Use hose protector</td>
</tr>
<tr>
<td>14</td>
<td>Hoses</td>
<td>Crushing and abrasion</td>
<td>Use improved material in the hoses</td>
</tr>
<tr>
<td>15</td>
<td>Cylinder</td>
<td>Weld cracks on the cap end eye</td>
<td>Improve the design of the cap end eye</td>
</tr>
<tr>
<td>16</td>
<td>Seat</td>
<td>Long repair time</td>
<td>Use an integrated connector for cables and hoses</td>
</tr>
</tbody>
</table>

The main reason for the failure of the boom was weld crack (see Figure 5.2) in which a crack occurring in the root of the weld and running in the direction of the weld axis. These longitudinal cracks are caused by shrinkage stress in high constraint areas and by preheating or fast cooling problems (ASM International, 1997). A discussion with the product development team led to the discovery that an incorrect welding technique used by some of the welders had caused the cracks. The correct welding technique (i.e., welding towards areas of less constraint and preheating to even out the cooling rates when necessary) has now been implemented. Preliminary results indicate that the occurrence of cracks in weld areas has been reduced.

![Figure 5.2. Cracks in the weld areas](image-url)
The analysis of the natural frequencies of the boom revealed a resonance problem in the boom and hammer. The first natural frequency of the vertical boom is 25 Hz (Winza, 2010), which is close to the range of working frequencies of the hammer (8 – 16 Hz); see Figure 5.3. To tackle this resonance problem, one of three possible solutions can be implemented. The first is to replace the hammer with one that has a lower working frequency range. The second is to increase the damping ratio by inserting resilient material in the contact point of the boom and the hammer (e.g. installing a vibration-damping rubber pad in the hammer attachment). The third is to increase the natural frequency of the boom (e.g. reinforcing the structure of the boom in the critical area). The first solution has been implemented; the hammer (600 Joules) has been replaced by a bigger hammer (800 Joules) with a lower working frequency range (6.5 – 13 Hz); see Figure 5.3. Preliminary results indicate that the occurrence of failure of the boom has been reduced and the time to failure of the hammer has been improved.

![Figure 5.3. The amplification ratio of the vertical boom](image)

Analysis of the cylinders showed that the main reason for failure was a load suddenly applied to the cylinder. Understandably, during scaling, the cylinders may need to bear a load which sometimes exceeds the specifications, for example, when big rocks fall onto the boom. In the current design, the hydraulic system is equipped with an accumulator that can minimise the shock of a sudden load. However, when the load occurs too rapidly, the accumulator cannot handle it (it exceeds the accumulator response time). Therefore, the working loads of the cylinders should be determined and the specifications of the cylinder and accumulator upgraded accordingly.

The operators’ written reports show that 55% of the failures of the hydraulic hoses occur in the hydraulic hammer section. Discussions with the operators revealed that the most common failure mode is a broken nipple at the neck. There are two possible explanations. The failure may be due to excessive side force on the nipple when the side part of the hammer hits the wall of the mine room and the unprotected nipple is subjected to a bending force that propagates a crack on its neck (failure mode 1); see Figure 5.4.(a). Or it may occur when falling rock hits the hose, creating a sudden and excessive load which generates a combination of tensile and bending force onto the nipple (failure mode 2); see Figure 5.4.(b).
Figure 5.4. Broken nipple at the neck

To reduce the occurrence of failure due to the first failure mode, two design improvements are proposed. The first is to modify the dimension of the hammer fastener to provide a protection for the nipple (see Figure 5.5), so that when the side of the hammer hits the wall, the fastener frame, instead of the nipple, will bear the force. The second is to provide a cover for the nipple (see Figure 5.6) that can protect it from excessive side force. The cover has an opening for ease of maintenance, making it possible to replace the hoses without removing the cover.

Figure 5.5. Hammer fastener

Figure 5.6. Steel cover for the nipple of hydraulic hoses

To reduce the occurrence of failure due to the second failure mode, the following design improvement is proposed. The exposed hoses can be minimised by replacing part of the rubber hoses with a metal tube inside or under the boom. However, before implementing this design, a trade-off analysis should be conducted as it may improve the reliability of the hoses but reduce their maintainability.
Observation shows that the replacement of hoses is performed by operators on site. An operator may not have a spare hose on hand and must contact maintenance personnel in the workshop to have one delivered. Therefore, to reduce the waiting time, the company should determine the number of spare hoses that should be kept on the scaling machine. Observation also shows that the hoses are not the original equipment from the manufacturer; rather, they are manufactured in the workshop. There is no standardisation as to their length and variations occur; the problem is that when the hoses are too short, this puts additional strain on the nipple. Presently, the maintenance team is working to standardise the hoses. Another important aspect of the policy of having on site operators replace the hoses is work quality. The hydraulics system is designed to be maintained in a clean and dry environment as it is sensitive to dirt and water. Experience shows that 75 to 80 percent of all hydraulic machinery failures can be traced to contamination (Tocci, 2006). When replacement is performed on site, the risk that a contaminant will enter the hydraulic system increases, thereby increasing the risk for the failures. A cost-benefit analysis of the current policy should be carried out to determine whether hose replacement should be performed on site by the operator or in the workshop by maintenance personnel.

A discussion with maintenance personnel revealed that maintainability problems with the seat are caused by the number of cables and hoses that need to be disconnected and reconnected during the seat replacement. An integrated connector for cables and hoses would provide ease of maintenance and reduce the risk of making wrong connections. The manufacturing company is currently working on a design for such a connector.

Human factors (i.e. PSFs) can significantly contribute to the failure of the scaling machine system. The preliminary study (the problem inventory) identified a list of associated PSFs. The PSFs that require investigation are vibration, procedure, on-site training, interface quality, work processes and task-related fatigue. Based on available resource and industrial interest, this study focuses on two crucial PSFs: WBV and procedure.

Based on observation and interviews with the operators, we know that the exposure to WBV interferes with operator performance. To better understand the characteristics of WBV exposure caused by scaling machines, the study performed a WBV analysis. A detailed discussion is provided in Paper IV, but some important results related to research question 2 appear below.

Spectrum analysis of measured vibration signals indicates that the dominant frequencies of the vibration peaks in all three axes (horizontal, lateral and vertical) coincide with the frequency range where WBV can degrade the ability of the operator to perform manual tasks (e.g. controlling a joystick, pressing buttons, etc.). The dominant frequencies also coincide with the resonance frequencies of the seated person and the frequency range where this person is sensitive (see Figure 5.7). The combination of the degradation of operator performance and operator discomfort may directly and/or indirectly contribute to the failure of the scaling machine system. The characteristics of the WBV exposure caused by the scaling machine are different from the characteristics of the WBV exposure caused by other mining equipment (see Figure 5.8).
Figure 5.8 shows that for the scaling machine, the 8 hrs equivalent frequency-weighted root mean square acceleration value ($A(8)$) is considerably low but the 8 hrs equivalent vibration dose value ($VDV(8)$) is high. In the scaling machine, the average magnitude of the measured vibration signal is low, but the signal contains multiple shocks with high amplitude. This is due to the nature of the scaling activity (see Figure 5.9). A typical sequence of events in scaling consists of a period of hammering followed by a period of rock fall. In the hammering period, the operator detaches loose rocks from the rib and roof of the mine opening by oscillating the hydraulic hammer. The only source of vibration exposure in this period is the vibration propagated by the hydraulic hammer.
This vibration exposure is stationary and the magnitude depends on the impact factor of the hydraulic hammer which is typically low. In the rock falling period, the loose rocks are detached and may hit the arm and body of the scaling machine as they fall. This will propagate impulsive vibration to the cabin. The combination of these two periods of vibration creates a low average magnitude of WBV exposure, but the vibration contains multiple shocks with high amplitude. This type of exposure will cause the operator greater discomfort, because the human body is sensitive to changes in vibration signals.

![Figure 5.9. Characteristic of WBV exposure of scaling machine](image)

The maintenance of the suspension system also affects WBV exposure but is commonly neglected. After measuring, the study found that the ball joint on the piston rod of the horizontal suspension of the cabin was welded and could not move freely; this might reduce the effectiveness of the suspension system. In addition, the rubber mountings for the cabin have not been replaced since the scaling machine was first used, giving them an approximate age of 9,300 hours (6,500 electric motor hours and 2,800 diesel engine hours). Furthermore, the condition and effectiveness of the rubber mountings have never been inspected. As rubber mountings deteriorate with time and use, one might suspect that their effectiveness in attenuating vibration has diminished. When the horizontal suspension and the rubber mountings are in the good condition, a lower level of measured vibration is expected. After discussions with the maintenance engineer and maintenance personnel, the company decided to perform preventive replacement of the rubber mountings, with a replacement interval of 1,500 electric motor hours. The replacement interval will be adjusted when a better understanding of the wear rate of the particular rubber mountings has been gained.

In the study of the scaling machine’s WBV exposure, the vibration measurements were conducted only for a single driver and only in three different mining rooms within a single underground mine. The variability of the drivers (e.g. body mass, body posture, driving behaviour, etc.) as well as the variability of mining rooms (e.g. GSI, host rock mass, virgin stresses, etc.) may affect the results, and these factors should be considered before generalising the results. Despite its limitations, however, the present study provides a basis for understanding the WBV exposure caused by the scaling machine; no similar research has been performed.

The present study found that this particular underground mine has no standardised procedure on how to perform scaling activity. Different operators use different styles. To
determine which work practices constitute best practice and can therefore be used as a base to develop SOP, the study compared the measured vibrations of the scaling machine while the operators were working. While a detailed discussion is provided in Paper V, some important results related to research question 2 appear below.

A statistical analysis of the measured vibrations indicates that the operator and the interaction between the operator and mining rooms have no significant effect on the vector sum value of acceleration, the kurtosis sum value or the vector sum value of the acceleration dose. This result is inconsistent with the observation results which indicate a disparity in the operators’ driving behaviour. Each driver has a different style in hammering intensity, boom manoeuvring, hammering interval, etc. Therefore, it was expected that analysis of the vibration measurements would show differences. However, the variances in style do not significantly affect the vibration signals.

Despite the results of the vibration measurements, it cannot be concluded that there is no best practice for performing scaling. The measured vibration level is only one parameter that can be used as to determine best practice. Others include quality of work, time to complete the task, power consumption, etc. Furthermore, the current trend in the mining industry is towards lean mining (i.e. applying the lean concept in their production system) (Dunstan, et al., 2006; Klippel, et al., 2008; Wijaya, et al., 2009). In this particular mining company, for example, the lean concept has gradually been implemented over the past three years (Boliden Mineral AB, 2009). As standardisation is critical to the lean concept, data regarding the best practice for each mining activity, in this case scaling, are required. More study will determine which work practices can be considered best practice in scaling.

5.3. Results and discussion related to research question 3

RQ 3: *How can we determine which components of the scaling machine need to be made more reliable and to what extent should reliability improvement be conducted to obtain optimum availability in a cost effective way?*

The third research question is answered partially by Paper I and more so by Paper II.

Based on the downtime and considering different scenarios (worst, most likely and best), we can rank the significant components that make a large contribution to overall system availability (see Paper I). However this kind of information might not be sufficient for prioritising components that require improvements in their availability. It may be more efficient to focus on improving two or three subsystem of smaller contributors to a certain level of availability than one subsystem of a larger contributor. The problem can be formulated as a MOP, whereby the goals are to maximise the availability of the scaling machine and to minimise the total cost of investment in reliability improvement.

The MOP results show that the relation of the overall cost of reliability improvement and the availability of the system, as expected, follow the law of diminishing returns. This means that investment in reliability improvement will improve the availability of the system, but, at some point, the more the investment is increased, the less improvement there will be in the availability of the system. Thus, the decision maker has to make a decision as to the extent of the investment in reliability improvement. The relationship between reliability improvement and system availability appears in Figure 5.10.
Figure 5.10. Reliability improvement ratio of components correspond to Pareto-optimal solutions

(a) The hydraulic cylinders, the hydraulic hammer, the electronic system and the engine

(b) The hydraulic hoses, the central lubrication system, the cabin and the transmission

(c) The boom, the water system and the chassis
Figure 5.10 shows that up to a system availability of approximately 82 %, the increment of the reliability improvement ratio ($r_{RI}$) for all components tends to increase steeply. Up to this point, the reliability improvement of all components contributes significantly to the system’s availability improvement. After this point, the increment of the $r_{RI}$ of seven components (central lubrication system, cabin, transmission, water system, chassis, hydraulic hammer and engine) tends to be constant, while the increment of the $r_{RI}$ of four components (hydraulic cylinder, hydraulic hoses, boom and electronic system) continues to increase. For system availability above 82 %, the reliability improvement of the seven components does not significantly contribute to the availability improvement of the system, and/or the cost of the reliability improvement of the seven components is too high in comparison with the gains derived from availability improvement. The increment of the $r_{RI}$ of the four components continues to increase until the system availability reaches approximately 84 %, where the increment of the $r_{RI}$ of the hydraulic cylinders tends to be constant. At this point, improving the reliability of the hydraulic cylinders is not worthwhile; it is more beneficial to improve the reliability of three other components: hydraulic hoses, boom and electronic system.

As the MOP results do not provide a single solution, a number of possible investments with their corresponding availability should be considered by the decision maker. The choice of a solution depends on many factors, including cash flow availability, production demand, investment policy, time horizon, the possibility of new technology, etc., thereby making the decision-making process very complex. To deal with this complexity, a company should make prioritisation and consider the feasibility of the investment from a single perspective at a time. The first perspective to be considered is commonly financial (Northcott, 1992), as a company evaluates whether the investment will be profitable. This study evaluates investment by comparing the cost of the reliability improvement investment and the potential additional profit to be gained by decreasing the downtime as a result of the reliability improvement. The appraisal of investment is performed by using the net present value (NPV) method (see Figure 5.11).

![Figure 5.11. NPV of investment vs. availability of the system](image)

Figure 5.11 shows that for availability greater than approximately 84.5 % the NPV is negative, which indicates that an investment in availability greater than this percentage will not yield a profit. For availability below approximately 84.5 %, an investment will bring profit to the company; deciding which investment should be selected depends on other perspectives (cash flow, production demand, new technology, etc.). If the cash flow
for all possible investments is unconstrained and new technology is unlikely, the decision maker can choose between investing in the area with the highest NPV or with the greatest availability. If production demand is high and/or intangible profit (such as enhancement of the company’s reputation, customer satisfaction, etc.) is considered important, investments with a low NPV but high availability might be preferable to investments with a high NPV but low availability because the manager might think that high production and/or intangible profit should be achieved at any cost. In this scenario, the highest availability obtained is approximately 84.5%, which corresponds to an NPV of 3 \( cu \) and a total cost of investment of 506 \( cu \). In the scenario where tangible profit is superior to any other aspect, the decision maker may opt for the investment with the highest NPV. The highest NPV obtained is 210 \( cu \), which corresponds to an availability of approximately 82% and a total cost of investment of 121 \( cu \). In the case of the highest NPV, the component requiring the largest investment is the hydraulic cylinder; in the case of the highest availability, the component requiring the greatest investment is the boom. This difference is due to the relation between the overall cost of reliability improvement and system availability, which follows the law of diminishing returns. For the hydraulic cylinders, the point of diminishing returns is reached when the system availability approaches 84%. Thus, after this point, the cost for the reliability improvement of the hydraulic cylinders is too high when set against the gain to be derived from the improvement of the system availability; thus, improving the reliability of the boom is more worthwhile.

The results of the present study provide guidelines for the design team in selecting the components which need to be improved and in determining the extent to which the improvement should be achieved. The next step after optimising reliability improvement is to form a cross-functional team consisting of personnel representing engineering design, manufacturing, quality and reliability, and marketing. The team will conduct a feasibility analysis to determine whether the required reliability improvement (\( \tau_{RI} \)) of each component can be achieved for a given allowable investment allocation.

The above optimisation provides the optimum reliability improvement of the components for a single scaling machine considering the service life of the machine and the potential additional revenue as a result of reliability improvement. From the user point of view, however, there is another option, namely, the redundancy of the scaling machine. Thus instead of buying one scaling machine which is more reliable, the user can buy more machines with the current reliability. The NPV of this option is provided in Figure 5.12.
Figure 5.12 shows that providing one or two redundancies is considered a feasible investment, while providing three or more redundancies will not bring profit to the company. The maximum NPV is achieved by providing a single redundancy (562 cu). For a comparison of the option of working towards improving the reliability of the components of a single scaling machine (first option) and the option of providing a redundancy (second option), see Figures 5.11 and 5.12. The maximum NPV of the first option (210 cu) is much lower than the NPV of one redundancy but is higher than the NPV of two redundancies (179 cu). From a financial perspective, then, having a redundancy in one scaling machine is the most profitable scenario. However, as the decision for such an investment is multi-dimensional, other perspectives (cash flow, new technology, etc.) should be considered. Furthermore, having more machines will create a demand for additional resources (such as more service time, more inventory for spare parts, more overhead costs, etc.) which will have monetary consequences. In the current NPV analysis of the second option, these factors are not considered; results can be altered if these factors are included in the analysis. The scope of the present study, as well as the industrial interests (manufacturing and mining company), is focused on the improvement of the components of a single scaling machine (first option of investment). Thus, the second option was not comprehensively studied; it should, however, be considered in future research.

A limitation of the present study is that the cost of reliability improvement for the components is predicted by using a generic model. The CER model is based on the constructive cost model (Boehm, 1981) and is calibrated for various military projects with large variations in complexity, technology use, budget, size, etc. One might question the accuracy of this model when it is applied to a scaling machine, as some of the machine’s characteristics, including its complexity, technology and size, may differ from the characteristics of the projects upon which the model is based. Ideally, the assessment of a specific component calls for a specific model. As a better model for predicting the cost of reliability improvement for each component of the scaling machine is not yet available, a generic model has been used. From the engineering design team’s point of view, this approach is important as it provides a basis for approximating the investment required in the reliability improvement of the scaling machine. When a better model is available, its use will improve the accuracy of the present study. Despite the above limitation, the proposed approach has a generality that can be used by the engineering design team to determine which components of the machine need to be improved and to what extent the improvement should be achieved.

5.4. Results and discussion related to research question 4

RQ 4: How to determine the solution for preventive replacement interval of component based on cost and reliability attribute and considering the optimality and robustness of the solution?

The fourth research question is answered in Paper III. In order to determine the preventive replacement interval of a component based on cost and reliability attributes and considering the optimality and robustness of the solution, the paper proposes a methodology for a robust-optimum multi-attribute age-based preventive replacement. The
The proposed method is based on a combination of the multi-attribute age-based replacement policy and the robust design technique.

The approach is applied to two case studies. The first is the preventive replacement of the hydraulic hammer of the scaling machine and the second is the preventive replacement of the relays of an HVAC system. In the case of the hydraulic hammer, considering that the cost performance function is as important as the reliability performance function, the interval time for the preventive replacement is $147 \leq t \leq 209$ h. In the case of the HVAC relays, considering that the two performance functions are equally important, two interval times for preventive replacement are obtained. The first is $9.5 \leq t \leq 9.9$ million switchings and the second is $12.4 \leq t \leq 13.6$ million switchings. The latter is considered superior to the former, as it has a wider range, providing more flexibility for scheduling.

Attributes considered in the model are limited to cost and reliability. Other attributes, such as downtime, production loss, availability and spare part inventory costs, can be estimated indirectly by knowing the cost and reliability attributes (Chareonsuk et al., 1997). The importance of the attributes, however, varies from one company to another, depending on such factors as company philosophy, the type of production system, demand patterns, etc. A preliminary study should be conducted to identify which attributes apply to a particular company and therefore should be included in the model. The model presented herein may not be directly applicable to other companies, but the approach can be used to build suitable models.
6. Conclusions and further research

6.1. Conclusions

This thesis focuses on the development of methods that can be used by the manufacturer and user of scaling machines to identify problems in availability and to make the necessary improvements. More specifically, it offers the following.

- The study proposes a method for visualising the downtime of a system (i.e. scaling machine system). The proposed method provides a visualisation of the downtime estimation and the precision and the uncertainty of the estimation at a given confidence level, as well as the factors influencing failure. Such visualisation can be used for guidance in selecting an appropriate strategy (DFR and/or DFM) for reducing downtime.

- It identifies factors contributing to the downtime of the scaling machine system, including reliability, maintainability and performance shaping factors, and it proposes appropriate counter measures. It reaches the following conclusions:
  - Components with a high downtime (≥ 100 h) are the central lubrication system (B), hydraulic hammer (C), boom (D), seat (E), hydraulic hoses (F) and hydraulic cylinders (G). The downtime of component B, C, D, F and G is due to reliability problems, and DFR should be adopted to reduce their downtime; the downtime of component E is due to maintainability problems and DFM should be adopted to reduce its downtime.
  - The failure of the boom is mainly due to the cracks in weld areas that occur due to the use of an incorrect welding technique. Preliminary results indicate that the occurrence of cracks in weld areas is reduced after the correct welding technique has been applied.
  - There was a resonance problem in the boom and hydraulic hammer system. Replacing the hydraulic hammer with one having a lower working frequency range results in fewer failures on the boom and increases the time to failure of the hydraulic hammer.
  - There are two failure modes for broken nipples on hydraulic hoses. First, excessive side force on the nipple occurs when the side part of the hammer hits the wall of the mine room and the unprotected nipple is subjected to a bending force that propagates a crack on the neck of the nipple. Second, falling rock hitting the hose and propagating a sudden and excessive load generates a combination of tensile and bending forces acting on the nipple. Redesigning the hammer fastener and using strain relief are suggested as ways to overcome these two failure modes.
  - The failure of bearings in the hammer fastener is due to the lack of lubrication; the use of non-lubricated bearings is proposed.
  - An integrated connector for the cables and hoses of the seat is suggested as a way to improve the maintainability of the seat.
  - Analysis of external PSF (i.e. WBV) shows that the operators of scaling machines are exposed to WBV, and this interferes with their performance.
Analysis of task related PSF (i.e. procedure) shows that this particular mine has no standardised procedure for performing scaling activity. There is considerable disparity in the performance of scaling (hammering intensity, boom manoeuvring, hammering interval, etc.) among the operators. However, this disparity has no effect on the measured vibration levels.

- The study proposes a decision support method for availability improvement. This method can be used to determine which components of the system (in this case, a scaling machine) need to be improved with respect to reliability and how to obtain optimum availability in a cost effective way.
- Finally, it proposes a method for determining the preventive replacement interval of components based on cost and reliability attributes and considering the optimality and robustness of the solution. By using the proposed method, a company can determine an optimum and robust interval time for preventive replacement.

6.2. Further research

During this study, several interesting new research ideas came up. It was not possible to consider all of them in the present research. Hence, some are presented as suggestions for future study.

- The present study does not analyse maintenance supportability and it is assumed to be satisfactory. However, as maintenance supportability significantly affects system availability, an extension of the study to incorporate maintenance supportability is essential.
- Due to competition, the manufacturing company may need to reduce the price of its scaling machine. As a consequence, the reliability of its components will be downgraded. It is important to determine which components can be downgraded and to what extent this should be done to obtain maximum price reduction and maximum system availability. The approach proposed by the present study can be altered to resolve this problem.
- A generic model is used to estimate the cost of improving the reliability the scaling machine’s components. This can restrict the validity of the study. A dedicated model should be formulated to improve the present study.
- The study does not comprehensively consider availability improvement through redundancy (i.e. providing more scaling machines). A feasibility study of this kind of investment represents another research possibility.
- The model for age-based multi-attribute preventive maintenance is limited to cost and reliability attributes. To provide a more comprehensive view for decision makers, other attributes (availability, operability, etc.) should be incorporated into the model.
- PSFs are analysed individually. However, PSFs can affect human reliability interactively. Therefore, a more holistic and comprehensive study of the effect of PSFs on human reliability, especially the potential combined and interaction effect of PSFs, is called for.
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Appended papers
Paper I

Down time analysis of scaling machine

Wijaya, A.R., Lundberg, J. and Kumar, U.

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Downtime analysis of a scaling machine

Andi Rahadiyan Wijaya a,b*, Jan Lundberg a and Uday Kumar a

aDivision of Operation and Maintenance, Luleå University of Technology, Luleå, Sweden; bDepartment of Mechanical and Industrial Engineering, Gadjah Mada University, Yogyakarta, Indonesia

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Scaling machines are identified as one of the major contributors to unplanned downtime. In general, to gain a better understanding of downtime, an analysis of the downtime should be performed. Downtime analysis usually involves a group consisting of many people with various backgrounds. The use of a visualisation method can act as a bridge that eliminates the knowledge gap within the group. The present study has two purposes: firstly to develop a method for visualisation of downtime and secondly to analyse the downtime of a scaling machine utilising the proposed visualisation method. The proposed method provides a visualisation of the downtime estimation and the precision and the uncertainty of the estimation at a given confidence level, as well as the factors influencing the failure. An analysis of the failures of the critical components of the scaling machine has also been conducted and suggestions for improvement have been proposed.

Keywords: scaling machine; downtime analysis; confidence interval

Introduction

Scaling is the process of cleaning loose material from the roof, face and wall of the mine room in underground mining. The purpose of scaling is to make the mine room safe for the next operation and to prevent insecure material falling down. Due to the nature of the task, scaling has been identified as an operation with a high number of accident occurrences. A study of accidents in underground mines between 1985 and 1994 found that one-third of the ground control injuries involved scaling [1]. In order to decrease the number of scaling-related accidents, the scaling activity has been mechanised by means of a scaling machine. The scaling machine basically consists of an impact hammer mounted on a pivoting arm, which is in turn attached to a mobile chassis (see Figure 1).

The use of a scaling machine to replace hand scaling has successfully improved the work safety of the miner. Data from one of the mining companies in Sweden shows that, after the introduction of the scaling machine, the number of scaling-related accidents has been reduced from about 10 per year to none or 1 per year [2]. Thus, the scaling machine is becoming an important machine for underground mining. However, due to the combination of a hostile environment (such as dust,
high humidity, falling rock, etc.), the operation context, and reliability and maintainability issues, the scaling machine is identified as one of the major contributors to unplanned downtime. Historical data from the underground mine in Sweden that participated in the present study shows that more than 20% of the unplanned downtime of mobile equipment is related to scaling machines.

To gain a better understanding of the downtime of a scaling machine, an analysis of the downtime should be performed so that essential knowledge can be obtained, such as which component is dominant in contributing to the downtime, what type of problems (reliability and/or maintainability problems) contribute to the downtime of components, and which strategies (design for reliability and/or design for maintainability) should be adopted to reduce the downtime. Downtime analysis usually involves many people with various backgrounds. In the present study, for example, a group consisting of operators, maintenance personnel, a maintenance engineer, a product development team from the manufacturing company concerned and a representative of academia has been formed and has been engaged in analysing the downtime of the scaling machine. In this type of situation, success depends on the effectiveness of communication in the group. One way to improve the effectiveness of communication is to use a visualisation method, such as the use of graphs [3]. Such a method can act as a bridge that eliminates the barrier of the knowledge gap within the group. In maintenance engineering applications, the common way to present the downtime of equipment is to utilise the classic Pareto diagram [4–7]. However, the use of Pareto diagrams in maintenance engineering applications has some shortcomings [8]: i.e. (1) where an outcome is the product of two factors, a Pareto diagram based on one factor alone cannot determine which factor is dominant in contributing to the problems; (2) by focusing on any one factor to the exclusion of others, the Pareto diagram may fail to identify individual events having a high time consumption, or events that may consume relatively little average time, but have the ability to cause operational disturbances; (3) the Pareto diagram is not useful for trending comparisons across different time periods. To overcome these shortcomings, the jack-knife diagram has been proposed [8]. One shortcoming of this diagram is that the downtime is presented as a single value (point estimation). In the past decade, presenting data as a point estimation has been considered to be insufficient [9–11]. ‘Do not cross the river if you just know the average depth,’ runs a classic saying which emphasises the importance of providing the precision and the uncertainty of an estimation when presenting the estimation. In analysing downtime, failure data is commonly estimated in a probabilistic model, and therefore it is essential to consider the reliability of the estimation too [12]. Two components may have the same downtime value, but at a given confidence level their intervals may differ significantly. Therefore, it is important, when visualising failure data, to show
not only the point estimation, but also the interval estimation, so that the precision
and the uncertainty of the estimation can be identified.

The general purpose of the present study is to develop a method for visualisation
of downtime that can be helpful in analysing the downtime of a system by, for
example, highlighting the most significant downtime, identifying the dominant
factors influencing the downtime and providing the interval estimation for the
downtime. The specific purpose of the present study is to analyse the downtime of
a scaling machine utilising the proposed visualisation method.

**Interval estimation of the downtime**

In this study, interval estimation is carried out by using the assumption that the
failure times have a Weibull distribution and the repair times have a lognormal
distribution. It is well known that failure times are often modelled with a Weibull
distribution [13–15]. About 85–95% of all failure data are adequately described
with a Weibull distribution [16]. The reasons are that the Weibull distribution has
the ability to provide reasonably accurate failure analysis with a small sample size, that it
has no specific characteristic shape, and that, depending upon the values of the
parameters, it can adapt the shape of many distributions [13]. It is also known that
the lognormal distribution is widely used to model repair times [15,17,18]. About
85–95% of all repair times are adequately described by a lognormal distribution [16].
The skewness of the lognormal distribution, with a long tail to the right, provides
a fitting representation of the repair situation. In a typical repair situation, most
repairs are completed in a small time interval, but in some cases repairs can take a
much longer time.

The probability density function (pdf) of the Weibull distribution is given as

\[
g(y) = \frac{\beta}{\eta} \left(\frac{y}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{y}{\eta}\right)^\beta\right], \quad y > 0
\]  

(1)

where \( \beta > 0 \) is the shape parameter and \( \eta > 0 \) is the scale parameter of the
distribution. The expected value for the mean time between failures (MTBF) is
given by

\[
MTBF = \mu_y = \eta \Gamma\left(\frac{1}{\beta} + 1\right)
\]  

(2)

The probability density function of the lognormal distribution is given as

\[
f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2} \left(\frac{\ln(x) - \mu}{\sigma}\right)^2\right], \quad x > 0
\]  

(3)

where \( \mu \) and \( \sigma \) are the mean and standard deviation of the variable’s natural
logarithm. The expected value for the mean time to repair (MTTR) is given by

\[
MTTR = \mu_x = \exp\left(\mu + \frac{\sigma^2}{2}\right)
\]  

(4)
To determine the confidence interval of the downtime, let the MTTR and MTBF be given by

\[
\text{MTTR} = \frac{DT}{m}
\]

and

\[
\text{MTBF} = \frac{UT}{m}
\]

where \( DT \) is the downtime, \( UT \) is the uptime and \( m \) is the number of failures. For a given uptime, the downtime can be formulated as

\[
DT = \frac{\text{MTTR}}{\text{MTBF}} UT
\]

To determine the confidence interval of the downtime, it is assumed that the failure time distribution is a Weibull distribution and the repair time distribution is lognormal, and consequently the downtime can be estimated as

\[
DT = \frac{\mu_x}{\mu_y} UT
\]

The corresponding confidence interval of the estimated downtime can be solved by finding a confidence interval for \( \frac{\mu_x}{\mu_y} \). The confidence interval can be determined by using an approximate method or an exact method. In the approximate method, the confidence interval is determined by establishing the confidence intervals for \( \mu_x \) and \( \mu_y \) to obtain an 'at least' type confidence interval. In the exact method, the confidence interval for \( \frac{\mu_x}{\mu_y} \) is established simultaneously, which makes it more accurate than the approximate confidence interval. In the present study, the exact method [19] is adopted to determine the confidence interval of \( \frac{\mu_x}{\mu_y} \).

Let \( X_1, X_2, \ldots, X_m \) be a random sample of times to repair with the pdf as given in (3). It can be shown that [20]:

\[
U = \left( \frac{\prod_{i=1}^{m} X_i}{e^n} \right)^{1/m} = \frac{G}{e^n} \sim A \left( 0, \frac{\sigma^2}{m} \right)
\]

where \( G \) is the sample geometric mean of the time to repair.

Let \( Y_1, Y_2, \ldots, Y_m \) be a random sample of times to failure with the pdf as given in (1). It can be shown that [21]:

\[
V = 2^{\beta} \sum_{j=1}^{m} y_j^{\beta} \sim \chi^2 (2m)
\]

If \( U \) and \( V \) are independent, then the joint density of \((U, V)\) is given by [20]:

\[
f(u, v) = \frac{u^{m-1} e^{-u} 2^{m} e^{-\frac{v}{2m}}}{\Gamma(m) 2^{m} \sqrt{2\pi v}} \quad 0 < u < \infty, \ 0 < v < \infty
\]
By making the transformations \( W = U/V \) and \( Z = V \), the pdf of \( W \) is obtained as

\[
g(w) = c \int_0^\infty \exp \left[ -\frac{n}{2\sigma^2} \ln^2 z - \frac{1}{2} w^2 z \right] (wz)^{m-1} \, dwz
\]  

where

\[
c = \frac{\sqrt{m/s}}{\Gamma(m)2^m\sqrt{2\pi}}
\]  

Recalling that \( W = U/V \), the exact confidence interval for \( \mu_x/\mu_y \) can be determined by letting

\[
w = \frac{2\eta^{-\beta} \sum_{i=1}^m y_i^\beta}{G/\omega^m}
\]  

which can be reformulated as

\[
w = \exp \left( \mu + \frac{\xi}{s} \right) \cdot \frac{\Gamma \left( \frac{1}{\beta} + 1 \right) 2\eta^{-\beta} \sum_{i=1}^m y_i^\beta}{\exp \left( \frac{\xi}{s} \right) G}
\]  

By substituting (2) and (4) into (15), then

\[
w = \left( \frac{\mu_x}{\mu_y} \right) \cdot \left( \frac{\Gamma \left( \frac{1}{\beta} + 1 \right) 2\eta^{-\beta} \sum_{i=1}^m y_i^\beta}{\exp \left( \frac{\xi}{s} \right) G} \right)
\]  

If the 100\(p\)% confidence interval for \( w \) is given as \( P[a < w < b] = p \), then

\[
P \left[ a \cdot \frac{\exp \left( \frac{\xi}{s} \right) G}{\Gamma \left( \frac{1}{\beta} + 1 \right) 2\eta^{-\beta} \sum_{i=1}^m y_i^\beta} < \frac{\mu_x}{\mu_y} < b \cdot \frac{\exp \left( \frac{\xi}{s} \right) G}{\Gamma \left( \frac{1}{\beta} + 1 \right) 2\eta^{-\beta} \sum_{i=1}^m y_i^\beta} \right] = p
\]  

From the above equation, the 100\(p\)% confidence interval for \( DT \) is given as

\[
\left( a \cdot \frac{\exp \left( \frac{\xi}{s} \right) G}{\Gamma \left( \frac{1}{\beta} + 1 \right) 2\eta^{-\beta} \sum_{i=1}^m y_i^\beta} \right) \cdot UT < DT < \left( b \cdot \frac{\exp \left( \frac{\xi}{s} \right) G}{\Gamma \left( \frac{1}{\beta} + 1 \right) 2\eta^{-\beta} \sum_{i=1}^m y_i^\beta} \right) \cdot UT
\]  

where \( y \) is the time between failures, and \( a \) and \( b \) are the constants for the lower and upper limit, respectively.
To establish a 100\% confidence interval for DT, the value for a and b has to be determined, so that

$$P[a < w < b] = \int_a^b g(w)dw = p$$  \hspace{1cm} (19)

The choice for the level of the confidence interval is somewhat arbitrary, and in practice values of 90\%, 95\% and 99\% are often used [22]. In the present study, a 90\% confidence interval is used for the downtime throughout the study and the value for a and b is determined so that the following equations are satisfied:

$$\int_0^a g(w)dw = 0.05$$  \hspace{1cm} (20)

and

$$\int_0^b g(w)dw = 0.95$$  \hspace{1cm} (21)

**Jack-knife diagram with confidence interval**

The jack-knife diagram [8] is a graphical method for visualising downtime where the failure data is presented as a log–log graph (i.e. both the vertical axis and the horizontal axis of a plot are scaled logarithmically). The horizontal axis represents the time to repair (TTR) and the vertical axis represents the number of failures (m). The downtime is determined by multiplication of the time to repair and the number of failures. As the diagram presents the data in a log–log plot, a curve of a constant downtime can be presented as a straight line with a uniform negative gradient. In the present study, the jack-knife diagram is modified to include the interval estimation of the downtime. For the sake of convenience and to avoid confusion with the established use of the term in statistics (e.g. the jack-knife variance estimator), the modified jack-knife diagram shall be referred to as the confidence log–log diagram. To establish a confidence log–log diagram, three estimation points are to be determined. The first estimation point is the expected value (mean) of the downtime ($DT_M$), and the second and third estimation points are the upper limit and lower limit of the downtime ($DT_{UL}$ and $DT_{LL}$). These three estimations can be performed as follows:

$$DT_M = \left( \frac{\exp\left(\mu + \frac{s^2}{2}\right)}{\eta \Gamma\left(\frac{1}{\beta} + 1\right)} \right) \cdot UT$$  \hspace{1cm} (22)

$$DT_{LL} = \left( a \cdot \frac{\exp\left(\frac{s^2}{2}\right) G}{\Gamma\left(\frac{1}{\beta} + 1\right) 2\eta^{1-\beta} \sum_{i=1}^m y_i^\beta} \right) \cdot UT$$  \hspace{1cm} (23)
where

- $\sigma$ = the standard deviation of the lognormal distribution
- $G$ = the geometric mean of the lognormal distribution
- $\eta$ = the scale parameter of the Weibull distribution
- $\beta$ = the shape parameter of the Weibull distribution
- $y$ = the time between failures
- $a$ = the constant for the lower limit
- $b$ = the constant for the upper limit

After the three estimation points have been determined, the next step is to determine their coordinates in the diagram. For the $DT_M$, the abscissa (the time to repair) is the MTTR and the ordinate (the number of failures) is determined as

$$m_M = \frac{UT}{MTBF}$$

For the lower limit and upper limit of the downtime, the equation for determining the abscissa can be derived as follows. Let line $A$, $B$ and $C$ be the isodowntime lines of $DT_{LL}$, $DT_M$ and $DT_{UL}$ (see Figure 2). The points $DT_{LL}$, $DT_M$ and
DTUL lie on the line D, which is perpendicular to the three lines A, B and C. The relation of point DTM and DTUL can be formulated as:

\[
\log(m_{DTUL}) - \log(m_{DTM}) = \left( -\log(TTR_{DTUL}) + \log(DTUL) \right) - \left( -\log(MTTR) + \log(DTM) \right)
\]  

(26)

As the two lines are parallel and have a slope of -1, then

\[
\log(m_{DTUL}) - \log(m_{DTM}) = \left( \log(TTR_{DTUL}) - \log(MTTR) \right)
\]  

(27)

By substituting Equation (16) into Equation (15), Equation (15) can be reformulated as

\[
2(\log(TTR_{DTUL}) - \log(MTTR)) = \log(DTUL) - \log(DTM)
\]  

(28)

Therefore

\[
TTR_{DTUL} = 10^{\log(DTUL) - \log(MTTR)}
\]  

(29)

By using a similar procedure, the relation of point DTU and DTLL can also be formulated in the same way. Thus, the equation for determining the abscissa for the lower limit and upper limit of the downtime can be formulated as follows:

\[
TTR_L = 10^{\log(DTLL) - \log(DTM) + \log(MTTR)}
\]  

(30)

where

- TTR_L = the time to repair of the limit (upper or lower)
- DT_LL = the downtime of the limit (upper or lower)
- DT_M = the mean downtime.

The ordinates for the lower limit and upper limit of the downtime are determined as

\[
m_L = \frac{DT_L}{TTR_L}
\]  

(31)

The interval estimation is then established by connecting these three estimation points with a straight line, see Figure 3.

Failure data of scaling machine

The failure data used in this study was collected over a period of 2 years for a single scaling machine operated in an underground mine in Sweden. The overall dimensions of the scaling machine are 3 m in height, 2.6 m in width and 14.6 m in length, and its unloaded weight is 27 tonnes. It has an articulated four-wheel drive chassis and four retractable stabiliser legs. It is bi-directional in operation. The driver sits in an air suspension seat which has a lumbar support and is mounted in an isolated cabin which can be tilted up to 13°. The maximum effective reach of the
boom is 9 m (3 m in front of the machine) and the reach at a 45° approach angle is 8.5 m. It can be operated in both a diesel and an electro-hydraulic mode by a 6-cylinder in-line turbocharged diesel engine with a displacement of 7146 cc (200 kW at 2300 rpm) and a $2 \times 30$ kW electric motor (400–1000 V). It is equipped with a hydraulic hammer (with an impact factor of 600 J and an impact rate of 8–16 Hz).

The main source of the failure data is the computerised maintenance management system, and additional data has come from the internal reports of the maintenance personnel. The process of scaling is not a continuous process, and therefore global time cannot be used in determining the time between failures. Instead, both the diesel engine time and the electric motor time are utilised, as the scaling machine can be operated in both a diesel and an electro-hydraulic mode. For the hydraulic hammer, the time to failure is determined based on records of the stroke hours, as they give a better representation of the operation hours of the hydraulic hammer.

As the proposed method in the present study is based on the assumption that the repair time follows a lognormal distribution and the failure time follows a Weibull distribution, prior to the fitting of the collected data to the corresponding distribution, the data should be tested for the validity of the assumption of independent and identically distributed (i.i.d.) data. The Laplace trend test and an autocorrelation test were utilised for trend and serial correlation testing [23]. The parameters of the corresponding distribution are then determined by using the maximum likelihood estimation (MLE) method, and their fitness to the corresponding distribution is assessed by using the Kolmogorov–Smirnov test [24]. All the tests were conducted by using the Matlab software and the alpha significance level ($\alpha$) used in all the tests was 0.05. A summary of the failure data of the critical components of the scaling machine is given in Table 1.
Table 1. Summary of the failure data.

<table>
<thead>
<tr>
<th>Part</th>
<th>A No of failures</th>
<th>B Time to failure</th>
<th>C Weibull β</th>
<th>D Z</th>
<th>E MTBF</th>
<th>F Time to repair</th>
<th>G MTTR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor</td>
<td>5</td>
<td>2.95</td>
<td>1.19</td>
<td>8</td>
<td>1.52</td>
<td>1.09</td>
<td>0.54</td>
</tr>
<tr>
<td>Central lubrication system</td>
<td>21</td>
<td>2.90</td>
<td>1.23</td>
<td>37</td>
<td>1.60</td>
<td>1.23</td>
<td>0.48</td>
</tr>
<tr>
<td>Hyd. hammer</td>
<td>8</td>
<td>5</td>
<td>9</td>
<td>37</td>
<td>2.73</td>
<td>0.76</td>
<td>0.32</td>
</tr>
<tr>
<td>Boom</td>
<td>37</td>
<td>1.23</td>
<td>0.76</td>
<td>5</td>
<td>1.71</td>
<td>0.76</td>
<td>0.32</td>
</tr>
<tr>
<td>Seat</td>
<td>5</td>
<td>1.09</td>
<td>0.54</td>
<td>64</td>
<td>1.48</td>
<td>0.54</td>
<td>0.32</td>
</tr>
<tr>
<td>Hyd. hoses</td>
<td>64</td>
<td>74.50</td>
<td>0.65</td>
<td>46</td>
<td>97.71</td>
<td>0.65</td>
<td>0.32</td>
</tr>
<tr>
<td>Hyd. cylinders</td>
<td>46</td>
<td>72.10</td>
<td>0.71</td>
<td>88.36</td>
<td>97.71</td>
<td>0.71</td>
<td>0.32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Part</th>
<th>H No of failures</th>
<th>I Time to failure</th>
<th>J Weibull μ</th>
<th>K Z</th>
<th>L MTBF</th>
<th>M Time to repair</th>
<th>N MTTR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bearer</td>
<td>11</td>
<td>2.87</td>
<td>4.45</td>
<td>5.65</td>
<td>17.37</td>
<td>2.46</td>
<td>6.75</td>
</tr>
<tr>
<td>Water system</td>
<td>18</td>
<td>6.45</td>
<td>4.45</td>
<td>5.65</td>
<td>17.37</td>
<td>2.46</td>
<td>6.75</td>
</tr>
<tr>
<td>Transmission</td>
<td>5</td>
<td>0.92</td>
<td>0.54</td>
<td>0.92</td>
<td>0.53</td>
<td>0.53</td>
<td>0.63</td>
</tr>
<tr>
<td>Chassis</td>
<td>9</td>
<td>0.96</td>
<td>0.65</td>
<td>0.96</td>
<td>0.53</td>
<td>0.53</td>
<td>0.63</td>
</tr>
<tr>
<td>Cabin</td>
<td>9</td>
<td>0.65</td>
<td>0.71</td>
<td>0.65</td>
<td>0.53</td>
<td>0.53</td>
<td>0.63</td>
</tr>
<tr>
<td>Electronic system</td>
<td>6</td>
<td>0.92</td>
<td>0.92</td>
<td>0.92</td>
<td>0.53</td>
<td>0.53</td>
<td>0.63</td>
</tr>
<tr>
<td>Hyd. valve</td>
<td>25</td>
<td>2.88</td>
<td>0.71</td>
<td>2.88</td>
<td>0.53</td>
<td>0.53</td>
<td>0.63</td>
</tr>
</tbody>
</table>

Note: *MTBF, MTTR, μ, and σ are given in units of hours.
Confidence log–log diagram of scaling machine

To establish the confidence log–log diagram of a scaling machine, the first step is to determine the three estimation points of the downtime \((DT_M, DT_{LL},\text{ and } DT_{UL})\) for a given uptime. The value of the uptime used in the present study is the uptime that corresponds to the theoretical number of production hours in a year. During the time when this study was conducted, the theoretical number of daily working hours for the mine concerned was 16.5 hours per day, and operations stopped for 3 weeks per year for the summer holidays. Servicing machines is scheduled on a calendar basis and for the most utilised machines, preventive maintenance (PM) is scheduled every week. Since the scaling machine is one of the most utilised machines, when estimating the theoretical number of production hours, one should consider the duration of the time to service. The distribution fit test of the time to service shows that the time to service fits a lognormal distribution with \(\mu = 1.7\) h and \(\sigma = 0.8\) h, which gives a mean time to service of 7.1 h. Since PM is theoretically scheduled for every week, the theoretical service time for one year (with 49 working weeks in the year) is approximately 350 h. Thus, by considering the number of daily working hours, the number of working weeks in a year and the service time in a year, the theoretical number of production hours for a period of 1 year can be calculated as approximately 5300 h, and accordingly, the downtime will be calculated for a given uptime of 5300 h. The three estimation points of the downtime \((DT_M, DT_{LL},\text{ and } DT_{UL})\) are given in Table 2. The corresponding constants for the lower limit \((a)\) and the upper limit \((b)\) are determined by using equation (20) and (21). The value of \(a\) and \(b\) are solved numerically by using the MuPAD software. The second step is to determine the coordinates of the three estimation points of the downtime. For \(DT_M\), the abscissa is the MTTR value and the ordinate is determined from equation (25). For \(DT_{LL}\) and \(DT_{UL}\), the coordinates are determined by using equation (30) and (31). The coordinates of the three estimation points are presented in Table 2. The interval estimation of the downtime for each component is then established by connecting these three estimation points with a straight line. The confidence log–log diagram of the components of the scaling machine is shown in Figure 4.

In interpreting the diagram, we have to read both the corresponding axes (the time to repair and the number of failures) and the iso-downtime line (the constant downtime that appears as a straight line with a uniform negative gradient). For example, Figure 4 indicates that, for a given uptime of 5300 h, component E (the seat) has a downtime of approximately 100 h, corresponding to a number of failures of approximately 6 and a time to repair of approximately 17 h. Moreover, at a 90% confidence level, component E may have a downtime in the interval of approximately 40 h to 220 h. It can also be seen that the downtimes of component E (the seat) and M (the electronic system) are about the same (95 h and 100 h), but at a 90% confidence level, the ranges of the downtimes of the two components differ significantly. Component E has a downtime in the range of approximately 40 h to 220 h, while component M has a downtime in the range of approximately 50 h to 110 h. On the other hand, the downtimes of component I (the water system) and K (the chassis) differ significantly (85 h and 55 h), but at a confidence level of 95%, the two components have the same value of the downtime (115 h). Figure 4 also visualises the fact that the downtime of component G (the hydraulic cylinders) is higher than the downtime of component D (the boom), but, at a confidence level of 95%, the downtime of component D is higher than the downtime of component G.
In the prioritisation of significant components based on their downtime, Figure 4 visualises the fact that three different orders of rank can be created. The order of significant components based on the mean estimation (the high-likelihood scenario) is G, D, F, C, B, E, M, I, H, N, L, K, A and J, while the corresponding order based on the upper limit estimation (the worst scenario) is D, G, C, E, F, B, N, K, I, M, H, L, J and A, and the corresponding order based on the lower limit estimation (the best scenario) is H, I, J, K, L, M, N, G, E, A, N, F, B, D, M, C, H, I, K, J, L.
scenario) is D, G, F, C, B, M, I, E, H, K, N, J, L and A. This kind of information is needed especially for certain activities where the decision should be based on three scenarios (the optimistic, the most likely and the pessimistic scenarios), e.g. the planning and budgeting of maintenance activities. Furthermore, suppose that smoothness of operation (freedom from interruption) is taken into consideration in the prioritisation of significant components. For similar values of the downtime, a high frequency of interruption combined with interruptions of short duration is then less favourable than a low frequency of interruption combined with interruptions of long duration. This is because, every time the equipment resumes operation after a failure, it takes time for the equipment to reach normal performance, and, during this transition period, the productivity and the work quality of the equipment are lower than normal. It can then be seen in Figure 4, by comparing components E (the seat) and F (the hydraulic hoses), which in the worst scenario (the upper limit estimation) have about equal downtime (210 h), that a higher priority should be given to component F than to component E.

In some cases, the maximum downtime is limited to a certain value and, if so, it is important to know how likely it is that the downtime of the components will exceed that limit. Suppose that, due to the consequences of a failure, it is decided that the limit for the maximum downtime is 300 h and it is demanded that the maximum probability of error should be 5%. Then it can be seen in Figure 4 that component C (the hydraulic hammer), D (the boom) and G (the hydraulic cylinders) at a confidence level of 95% will exceed the limit.

Since in the confidence log–log diagram, the downtime is presented as a function of the time to repair and the number of failures, the diagram also highlights reliability and maintainability issues. It shows which components need to have their reliability and/or maintainability improved. Figure 4 shows six components with

![Figure 4. Confidence log–log diagram of scaling machine.](image-url)
a high downtime \( (DT_{\text{HM}} \geq 100 \text{ h}) \) for different reasons. The high downtimes of component B (the central lubrication system), C (the hydraulic hammer), D (the boom), F (the hydraulic hoses) and G (the hydraulic cylinders) are mainly due to reliability problems (a high value for the number of failures and a low value for the time to repair), while the high downtime of component E (the seat) is mainly due to maintainability problems (a low value for the number of failures and a high value for the time to repair). Thus, the strategy of design for reliability (DFR) should be adopted for reducing the downtime of component B, C, D, F and G, and the strategy of design for maintainability (DFM) should be adopted for reducing the downtime of component E.

**Failure analysis of critical components**

As mentioned in the introduction, a group consisting of representatives from a mining company as a user of the scaling machine, representatives from the manufacturing company which developed the scaling machine, and a representative of academia as a researcher in the present study has been formed and has been engaged in analysing the downtime of the scaling machine. A brief description of the representation from the mining company and the manufacturing company is provided in Table 3.

An analysis of the failures of the critical components has been conducted and suggestions for improvement have been proposed and implemented when possible. Concerning the failure of the boom, it was found that the main reason was cracks occurring in weld areas. Based on a discussion with the product development team of the manufacturing company, it was discovered that the cracks were due to an incorrect welding technique having been applied by some of the welders. A correct welding technique has now been included in the standard operating procedure by the manufacturing company. Preliminary results indicate that the occurrence of cracks in weld areas has been reduced since the correct welding technique has been applied. Based on an analysis of the natural frequencies of the boom, a resonance problem was noticed in the boom and hydraulic hammer system. The first natural frequency of the vertical boom (25 Hz) is close to the range of working frequencies of the hydraulic hammer (8–16 Hz). To tackle this resonance problem, three possible solutions can be implemented. The first involves shifting the working frequencies of the hydraulic hammer by replacing it with one that has a lower working frequency range. The second involves increasing the damping ratio, which can be achieved by inserting resilient material in the contact point of the boom and the hydraulic hammer (e.g. installing a vibration-damping rubber pad in the

<table>
<thead>
<tr>
<th>Position</th>
<th>No. of resources</th>
<th>Experience (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operators</td>
<td>4</td>
<td>11–31</td>
</tr>
<tr>
<td>Maintenance personnel</td>
<td>3</td>
<td>5–33</td>
</tr>
<tr>
<td>Maintenance engineer</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>Group leader</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>Product developers</td>
<td>3</td>
<td>10–15</td>
</tr>
</tbody>
</table>
hammer attachment). The third involves increasing the natural frequency of the boom, which can be achieved by reinforcing the structure of the boom in the critical area. A detailed discussion of the reinforcement can be found in [25]. The first solution has been implemented by changing the hydraulic hammer (600 J) with a bigger hammer (800 J) that has a lower working frequency range (6.5–13 Hz); and preliminary results indicate that the occurrence of failure of the boom has been reduced and the time to failure of the hydraulic hammer has been improved.

In the analysis of the failure of cylinders, it was detected that the main reason for the failure was the sudden load applied to the cylinder. It is understandable that, during the scaling activity, the cylinders may need to bear a load which exceeds the specification and which is propagated from the boom when big rocks fall onto the boom. In order to reduce the number of failures, an investigation to determine a possible working load for the cylinder should be performed, which may lead to an upgrading of the specification of the cylinder.

Concerning the failure of the hydraulic hoses, a perusal of the written reports of the operators has revealed that 55% of the failures occur in the hydraulic hammer section and the common failure mode is a broken nipple at the neck. There are two possible explanations as to what initiates the failure. Firstly, the failure may be due to an excessive side force on the nipple that occurs when the side part of the hammer hits the wall of the mine room and the unprotected nipple is subjected to a bending force that propagates a crack on the neck of the nipple. Secondly, the failure may be due to falling rock hitting the hose and propagating a sudden and excessive load which generates a combination of tensile and bending force acting on the nipple. To reduce the occurrence of failure due to the first phenomenon, the dimension of the hammer fastener has been modified to provide a protection for the nipple, so that, when the side part of the hammer hits the wall, the fastener frame instead of the nipple will bear the force. To reduce the occurrence of failure due to the second phenomenon, the use of strain relief is suggested. Based on observation, it has also been revealed that the replacement of hoses is performed by the operator on site. However, sometimes the operator does not have spare hoses at hand and needs to contact maintenance personnel in the workshop to have the spare hoses delivered. To reduce the waiting time involved in this connection, one needs to determine the required number of spare hoses to be available on the scaling machine, to achieve the required level of availability.

Based on a discussion with the maintenance personnel, it has been found that the maintainability problem concerning the seat is due to the number of cables and hoses that need to be disconnected and reconnected during the replacement of the seat. To tackle this issue, an integrated connector for cables and hoses is suggested, to provide ease of maintenance and to reduce the risk of making wrong connections. Currently, the manufacturing company is working on the design of an integrated connector for cables and hoses that will be implemented in a new seat.

Conclusions

In the present study, a method for the visualisation of downtime has been developed based on the jack-knife diagram. The method provides a visualisation of the downtime estimation and the precision and the uncertainty of the estimation at a given confidence level, as well as the factors influencing the failure. Such a
visualisation can be used for guidance in selecting an appropriate strategy (design for reliability and/or design for maintainability) for reducing the downtime.

Particular conclusions that can be drawn from the downtime analysis of the scaling machine are:

- By considering different scenarios (the worst, the high-likelihood and the best scenarios), three different orders of rank can be created for significant components based on their downtime.
- Components that have a high downtime ($\geq 100$ h) are the central lubrication system (B), hydraulic hammer (C), boom (D), seat (E), hydraulic hoses (F) and hydraulic cylinders (G).
- The downtime of component B, C, D, F and G is due to reliability problems, and therefore design for reliability should be adopted to reduce their downtime, while the downtime of component E is due to maintainability problems and design for maintainability should be adopted for reducing its downtime.
- The failure of the boom is mainly due to the cracks in weld areas that occur due to an incorrect welding technique. Preliminary results indicate that the occurrence of cracks in weld areas is reduced after the correct welding technique has been applied.
- It was indicated that there was a resonance problem in the boom and hydraulic hammer system. Replacing the hydraulic hammer with one that has a lower working frequency range results in fewer failures occurring on the boom and increases the time to failure of the hydraulic hammer.
- A redesign of the hammer fastener and the use of strain relief are suggested to reduce the failure of hydraulic hoses.
- An integrated connector for the cables and hoses of the seat is suggested to improve the maintainability of the seat.

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Wijaya, A.R., Lundberg, J. and Kumar, U.

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Andi R. Wijaya a,b, Jan Lundberg a and Uday Kumar a

a Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå, Sweden
b Department of Mechanical and Industrial Engineering, Gadjah Mada University, Yogyakarta, Indonesia

Abstract
Purpose – The scaling machine is considered as a bottleneck in underground mining. In improving the reliability of the scaling machine, one must, in a cost-effective way, select the components which need to be improved and determine the level to which the improvement should be performed. This paper aims to address this issue.

Design/methodology/approach – Cost estimation ratio (CER) model, non-dominated sorting genetic algorithm II (NSGA-II) and net present value (NPV) analysis have been used to build an approach to analyze cost optimization of reliability improvement for a scaling machine.

Finding – The study finds that the approach provides meaningful results that can be used as guidelines for the design team in selecting the components of the scaling machine which need to be improved and in determining the extent to which the improvement should be achieved.

Practical implications – Approach utilized in this paper can help and improve the decision-making related to reliability improvement of machine in determining which components of the machine need to be improved and to what extent the improvement should be achieved.

Originality/value – This paper present an approach for analyzing cost optimization of reliability improvement for a scaling machine. The approach is generic for application in different cases.

Keywords Scaling machine, Optimization, Reliability improvement, Genetic algorithm

Paper type Research paper

1. Introduction

In the underground mining, due to the combination of a hostile environment (such as dust, humidity, falling rock, etc.), the operation context, and reliability and maintainability issues, the scaling machine is identified as one of the major contributors to unplanned downtime.

Improving the availability of a system can be achieved by improving the reliability/design for reliability (DFR) or by improving the maintainability/design for maintainability (DFM). In a preliminary study (Wijaya et al., 2010), it was observed that most of the problems concerning the scaling machine are related to reliability issues, and therefore the present study will focus on DFR.

When improving the reliability of a system, two strategies can be implemented by the design team. The first is to improve the reliability of the components (subsystems) and the second is to provide redundancy. It is commonly acknowledged that in achieving a similar level of reliability improvement, the cost of the second strategy is less than the
cost of the first strategy (Mishra and Ljubojevic, 1973). However, in practice, providing redundancy is not always possible due to the restrictions of other design parameters. In the case of the scaling machine, providing redundancy is difficult to achieve, as providing redundancy for one component can violate the design restrictions of other components (e.g. adding extra hydraulic cylinders will mean an extra load for the boom to bear and the need for extra space in the boom). Thus, in this study, the option of redundancy is excluded from the reliability improvement.

In the improvement of component reliability, the cost of the improvement becomes a constraint as the improvement has to be accomplished in a limited budget. In this regard, one must select the components which need to be improved (i.e. perform reliability improvement allocation) in a cost-effective way. Based on a downtime analysis, the subsystems that make a large contribution to the overall system availability can be identified. However, it may be cheaper and more effective to focus on improving two or three subsystems which are smaller contributors to a certain level of reliability than to focus on one subsystem which is a larger contributor. Thus, to achieve the optimum availability of the system, reliability improvement should be optimized in a cost-effective way. The purpose of this paper is to analyze cost optimization of reliability improvement for a scaling machine.

2. Problem formulation

2.1. Scaling machine

The scaling machine used in this study is a typical scaling machine used in underground mining in Sweden (see Figure 1). The overall dimensions are 3 m in height, 2.6 m in width and 14.6 m in length, and the unloaded weight is 27 tonnes. It has an articulated four-wheel drive chassis and retractable stabilizers. It is bi-directional in operation. The driver sits in an isolated cabin which can be tilted up to 13°. The maximum effective reach of the boom is 9 m (3 m in front of the machine), and the reach at a 45° approach angle is 8.5 m. It can be operated in both a diesel and an electro-hydraulic mode by a 6-cylinder in-line turbocharged diesel engine with a displacement of 7,146 cc (200 kW at 2,300 rpm) and a 2 x 30 kW electric motor (400 – 1,000 V). It is equipped with a hydraulic hammer and a water jet system for dust control.

Figure 1. Scaling machine (Source: Jama Mining Machine AB)

2.1. Reliability block diagram (RBD) of a scaling machine

Prior to the optimization of the reliability improvement, it is important to construct a reliability block diagram (RBD) of the scaling machine system. The scaling machine is considered to be a system consisting of eleven major subsystems (components) which are connected as a series system. The RBD of a scaling machine is presented in Figure 2.
As the eleven subsystems are connected in series, the availability of the scaling machine is given as (Sherwin and Bossche, 1993)

\[ A_x = \frac{1}{1 + \sum_{i=1}^{11} \left( \frac{1 - A_i}{A_i} \right)} \]  

where \( A_i \) is the availability of subsystem \( i \).

2.3. Cost of reliability improvement

Since one of the important goals of reliability improvement is to achieve cost minimization, the relationship between investment and reliability improvement is always an important issue. The finance department and the manager need to know how much to invest in order to achieve a certain level of reliability (availability), and this is always a difficult question for the engineering designer or reliability engineer to answer. Due to the variability of different systems, building a generic model for the cost of reliability improvement is always a difficult task. However, some researchers have proposed mathematical models (Forbes et al., 2009; Rushdi and Alsulami, 2007; Saleh and Marais, 2006; Mettas, 2000).

In the present study, the cost estimation ratio (CER) model (Forbes and Long, 2008; Forbes et al., 2009) has been adopted to predict the cost of reliability improvement for each component of the scaling machine. The CER model was developed based on the constructive cost model (Boehm, 1981) and is calibrated for various military projects with large variation (e.g. in complexity, technology use, budget, size, etc.). One might question the accuracy of the CER model when it is applied to a scaling machine, as some of the machine’s characteristics (e.g. with regard to its complexity, the technology used, its size, etc.) may differ from the characteristics of the projects which the model is based on. Ideally, a specific component needs a specific model of the reliability improvement cost. However, to date a better model for predicting the cost of reliability improvement for each component of the scaling machine is not available. Thus a generic model of the cost of reliability improvement (the CER model) has been utilized in the present study. From the design team’s point of view, this approach is really important for providing a base for approximating the investment needed for reliability improvement of the scaling machine. When a better model of the cost of reliability improvement for specific components of the scaling machine has become available, it can be employed to improve the accuracy of the present study.

In the CER model, the required reliability investment \( I \) is formulated as

\[ I = \left[ \frac{r_{RI}}{0.3659} \right]^{2.119} \cdot APUC \]

where

\[ r_{RI} = \text{the ratio of reliability improvement} \]
APUC = the average production unit cost.

The reliability improvement ratio \( r_{RI} \) is defined as

\[
\frac{MTBF_I - MTBF_C}{MTBF_C}
\]

(3)

where

- \( MTBF_I \) = the mean time between failures after reliability improvement
- \( MTBF_C \) = the current mean time between failures.

The overall cost of reliability improvement \( IO \) for a system with \( n \) subsystems (components) can then be obtained by summing up all the investments to be made at the subsystem level \( I_i \), formulated as

\[
I_O = \sum_{i=1}^{n} I_i
\]

(4)

2.4. Reliability improvement optimization problem

An important aspect of this study is to determine which subsystem of the scaling machine is to be improved and to what extent the improvement should be made to optimize the availability in a cost-effective way. Thus the objective is to find the optimum availability of the scaling machine, in such a way as to minimize the total cost of investment for reliability improvement of the components of the scaling machine. The problem can be formulated as a multi-objective optimization problem as follows:

\[
\begin{align*}
\text{Max} & \quad A_S \\
\text{Min} & \quad I_O
\end{align*}
\]

(5)

subject to the constraints

- \( I_i \geq 0 \)
- \( A_i \leq 1 \)
- \( MTTF_i > 0 \)
- \( MTTR_i > 0 \)

In the formulation of this optimization problem, the following assumptions are made:

1. The system involves \( n \) independent sub-systems.
2. The system and its subsystems can be expressed in two states only: operated or failed.
3. The time to repair is independent of the reliability improvement.
4. The CER model is valid for predicting the cost of reliability improvement of scaling machine components.

It can be seen from equation (5) that the two objective functions conflict with each other (increasing \( A_S \) will increase \( I_O \)). Therefore, there is no single solution for this multi-objective optimization problem and the set of feasible solutions consists of non-dominated solutions and dominated solutions (see Figure 3). Non-dominated solutions (Pareto-optimal solutions) are a set of solutions which are superior to other solutions when all the objectives are considered, but inferior to other solutions with respect to one or more objectives (Mathur, 1991).
Various methods have been proposed by different researchers for solving the multi-objective optimization problem. In this study, the non-domination-based genetic algorithm (GA) for multi-objective optimization has been selected, as the GA works with a population of feasible solutions; therefore, it can be used in multi-objective optimization problems to capture a number of solutions simultaneously (Konak et al., 2006).

2.5. Multi-objective genetic algorithm

The GA is a numerical search tool whose aim is to find the global maximum (or minimum) of a given objective function. The GA begins by randomly generating an initial population of candidate solutions for the optimization problem. The candidate solutions (known as individuals) are represented as strings of numbers (generally sequences of the binary digits 0 and 1). The next step is the selection of individuals from the population to be candidates for reproduction. In this selection, only the fittest populations will survive. Reproduction is performed by a crossover and a mutation procedure (see Figure 4). In the crossover procedure, a new individual (known as a child) is generated from a pair of individuals (known as parents) by combining the strings of the parents. In the mutation procedure, a new individual is generated from a mutation of the string (changing from 0 to 1 and vice versa) of an individual parent.

A set of new individuals (known as the offspring population) is combined with the initial population. Fitness evaluation is performed on all the individuals in the combined population, and the less fit individuals are weeded out from the population, while the more fit individuals are included in the next generation of the population. The entire process described above can be termed as one generation and is continued to improve the objective function further until a pre-specified stopping criterion is met.

By using a similar concept, the GA can be expanded into a multi-objective GA. The main difference is in the selection phase, because, in the multi-objective case, the concept
Various algorithms have been proposed by different researchers. In this study, Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been adopted, as it is known as one of the most efficient algorithms for multi-objective optimization for a number of benchmark problems (Konak et al., 2006). The two key concepts in NSGA-II are a fast non-dominated sorting of the population for the sorting assignment and a crowding distance for the diversity mechanism. The flowchart of NSGA-II is shown in Figure 5 and briefly described below.

**Figure 5. Flowchart of NSGA-II**

First, a random population of size $N$ is initialized. The initial population is then sorted based on non-domination into each front. All the individuals not dominated by any other individuals are assigned front number 1. All the individuals only dominated by individuals in front number 1 are assigned front number 2, etc. The crowding distance is calculated for each individual within each front. The crowding distance is a measure of the Euclidian distance between each individual (how close an individual is to its neighbours). A less crowded region will result in better diversity in the population. Parents are selected by using a binary crowded tournament selection. In this selection, two individuals are selected at random to compete against each other and the winner is returned to the tournament. An individual is selected as a winner if it has a better rank or if the two individuals have the same rank, which provides a better crowding distance. New individuals are generated using a crossover and a mutation procedure to create an...
offspring population. The two populations (the initial and the offspring population) are combined, and the parents and offspring compete with each other for inclusion in the next iteration. The N best solutions are selected to create a new population. Iterations are terminated when the maximum number of generations is exceeded. Details of the algorithm of NSGA-II have been provided by Deb et al. (2002).

2.6. Failure data and the APUC

The failure data used in this study were collected over a period of 2 years for a single scaling machine operated in an underground mine in Sweden. The main source of the data is the computerized maintenance management system, and additional data have come from the internal reports of the maintenance personnel. The process of scaling is not a continuous process, and therefore global time cannot be used in determining the time between failures (tbf). Instead both the diesel engine time and the electric motor time are utilized, as the scaling machine can be operated in both a diesel and an electro-hydraulic mode. For the hydraulic hammer, the time to failure (ttf) is determined based on records of the stroke hours, as they give a better representation of the operation hours of the hammer. Prior to the reliability analysis, the data are tested for their independent and identically distributed (iid) characteristics. The reason is that the analysis of the reliability data is usually based on the assumption that the data are iid in the time domain. If this assumption is not valid, then classical statistical techniques for reliability analysis may not be appropriate and a non-stationary model such as the non-homogenous Poisson process (NHPP) can be applied (Ascher and Feingold, 1984; Kumar and Klefsjö, 1992). In the present study, the Laplace trend test and an autocorrelation test were utilized for trend and serial correlation testing. The tests were conducted using the Matlab software. The trend-free data were then analyzed as to how they fitted the distribution and the related parameters were analyzed for estimating the reliability. Different types of statistical distributions were examined and their parameters were estimated by using the EasyFit software. The Kolmogorov–Smirnov test was used for validation of the best fit to the distribution (Francois and Noyes, 2003).

The distribution and the parameters of the failure data of the components are shown in Table 1. The failure data for the hydraulic hammer were collected only for the final year of the two-year data collection period, since prior to that a different type of hammer had been used. Moreover, concerning the boom, the data for the first year were excluded from the analysis, since after that year a new boom (which had been manufactured using an improved welding technique) was used to replace the previous boom.

Due to the secrecy policy of the manufacturing company concerned, the APUC data have been encoded and are expressed as a currency unit (cu), but the characteristics of the APUC data still remain in the encoded APUC data. All the data related to monetary value have been adjusted to the encoded APUC data and are also expressed as a currency unit (cu). The APUC data for the components are shown in Table 1.
Table 1. Summary of failure data and APUC data

<table>
<thead>
<tr>
<th>Component</th>
<th>Time to failure</th>
<th>Time to repair</th>
<th>APUC (cu)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Distribution*</td>
<td>MTTF (hours)</td>
<td>Distribution*</td>
</tr>
<tr>
<td>Engine</td>
<td>W ($\beta$: 2.9 $\eta$: 560.4)</td>
<td>500.1</td>
<td>L ($\mu$: 0.9 $\sigma$: 0.5)</td>
</tr>
<tr>
<td>Central lubrication system</td>
<td>W ($\beta$: 1.2 $\eta$: 204.9)</td>
<td>193.2</td>
<td>G ($\alpha$: 2.2 $\beta$: 2.0)</td>
</tr>
<tr>
<td>Transmission</td>
<td>W ($\beta$: 1.0 $\eta$: 1130.4)</td>
<td>1108.7</td>
<td>L ($\mu$: 1.6 $\sigma$: 0.5)</td>
</tr>
<tr>
<td>Chassis</td>
<td>G ($\alpha$: 2.7 $\beta$: 213.5)</td>
<td>461.1</td>
<td>G ($\alpha$: 1.8 $\beta$: 3.0)</td>
</tr>
<tr>
<td>Cabin</td>
<td>W ($\beta$: 2.8 $\eta$: 408.9)</td>
<td>364.2</td>
<td>W ($\beta$: 1.4 $\eta$: 3.0)</td>
</tr>
<tr>
<td>Electronic system</td>
<td>W ($\beta$: 1.1 $\eta$: 168.2)</td>
<td>163.9</td>
<td>L ($\mu$: 0.9 $\sigma$: 0.5)</td>
</tr>
<tr>
<td>Hydraulic cylinders</td>
<td>W ($\beta$: 1.5 $\eta$: 97.7)</td>
<td>88.4</td>
<td>L ($\mu$: 1.7 $\sigma$: 0.6)</td>
</tr>
<tr>
<td>Hydraulic hoses</td>
<td>W ($\beta$: 1.1 $\eta$: 74.5)</td>
<td>72.1</td>
<td>L ($\mu$: 0.8 $\sigma$: 0.5)</td>
</tr>
<tr>
<td>Water system</td>
<td>W ($\beta$: 1.0 $\eta$: 165.7)</td>
<td>165.7</td>
<td>L ($\mu$: 0.8 $\sigma$: 0.6)</td>
</tr>
<tr>
<td>Boom</td>
<td>W ($\beta$: 1.5 $\eta$: 118.8)</td>
<td>107.0</td>
<td>L ($\mu$: 1.6 $\sigma$: 0.9)</td>
</tr>
<tr>
<td>Hydraulic hammer</td>
<td>W ($\beta$: 2.9 $\eta$: 219.4)</td>
<td>195.6</td>
<td>L ($\mu$: 1.5 $\sigma$: 0.7)</td>
</tr>
</tbody>
</table>

* W: Weibull distribution  G: Gamma distribution  L: Lognormal distribution

3. Results and discussion

The results of the optimization problem are represented as Pareto-optimal solution points (see Figure 6) and as the fraction of the reliability improvement ratio for each component, corresponding to the Pareto-optimal solution points (see Figure 7). For the purpose of clarity, the fraction of the reliability improvement ratio for each component (i.e. Figure 7) is plotted into three separate figures (see Figure 8a-c), and the trend line, in the form of a moving average of five points, is provided.

![Figure 6. Pareto frontier of availability and cost of investment](image-url)

Figure 6 shows that the relation of the overall cost of reliability improvement and the availability of the system, as expected, follows the law of diminishing returns. This means that the investment in the reliability improvement will improve the availability of the system, but, at some point, the more the investment is increased, the less the availability of the system is improved. Taking the example of an increment of the investment corresponding to 100 $cu$, increasing the investment from 100 $cu$ to 200 $cu$ will
give an improvement of the system availability by a factor of approx. 1.2%, while increasing the investment from 500 €\text{u} to 600 €\text{u} will only give an improvement of the system availability by a factor of less than 0.5%. Thus the decision maker has to take a decision as to what extent the investment in reliability improvement should be made.

Figure 7. Reliability improvement ratio for each component, corresponding to Pareto-optimal solutions
Figure 7 and 8a-c show that, up to a system availability of approximately 0.82, the increment of the reliability improvement ratio \( (r_{RI}) \) for all the components tends to increase steeply. These figures indicate that up to this point, the reliability improvement of all the components contributes significantly to the availability improvement of system. However, afterwards, the increment of the \( r_{RI} \) of seven components (the central lubrication system, cabin, transmission, water system, chassis, hydraulic hammer and...
engine) tends to be constant, while the increment of the $r_{RI}$ of four components (the hydraulic cylinder, hydraulic hoses, boom and electronic system) still increases. It is also indicated that, for system availability above 0.82, the reliability improvement of the seven components does not significantly contribute to the availability improvement of system and/or that the cost for the reliability improvement of the seven components is too high in comparison with the gain to be derived from the availability improvement. The increment of the $r_{RI}$ of the four components continues to increase until the system availability reaches approximately 0.84, where the increment of the $r_{RI}$ of the hydraulic cylinders tends to be constant. Moreover, it is indicated that, for system availability higher than 0.84, improving the reliability of the hydraulic cylinders is not worthwhile and that it is more beneficial to improve the reliability of three other components, namely the hydraulic hoses, boom and electronic system.

Figure 6 also shows that the optimization does not provide a single solution, and therefore a number of possible investments with their corresponding availability should be selected by the decision maker. The choice of a solution is dependent on many factors, such as the cash flow availability, the production demand, the investment policy, the time horizon, the possibility for new technology arriving, etc., which entails a complexity in the decision making process. To deal with this complexity, one should prioritize the perspectives to be adopted and consider the feasibility of the investment from a single perspective at a time. The first perspective to be considered is commonly the financial perspective (Northcott, 1992), which in short means evaluating whether the investment will bring profit to the company or not. In this study the investment is evaluated by comparing the cost of the reliability improvement investment and the potential additional profit to be gained from decreasing the downtime as a result of the reliability improvement.

The potential additional profit ($P_{pro}$) to be gained from the reliability improvement of the scaling machine can be estimated as

$$P_{pro} = om \cdot rev \cdot P_A$$

where
- $om$ = the operating margin
- $P_A$ = the potential additional production hours to be gained from the reliability improvement (hours)
- $rev$ = the revenue for the cycle concerned given as a monetary unit per unit of time (cu/hours)

The operating margin is a measurement of the proportion of the company's revenue which is left after all the operating costs and overheads have been paid. The operating margin is defined as the ratio of the operating profit to the revenue. The data for the operating margin are derived from the historical data of the company. The average value, for the past seven years, of the operating margin of the mining company which participated in the present study is 12.5%.

The potential additional production hours ($P_a$) to be gained from the reliability improvement of the scaling machine can be formulated as

$$P_a = (A_S - A_{SC}) \cdot P_s \cdot \eta$$

where
- $A_S$ = the availability of the system after the reliability improvement
- $A_{SC}$ = the availability of the system before the reliability improvement
$P_r = \text{the theoretical number of production hours (hours)}$

$\eta = \text{the utilization of the scaling machine (\%)}$

During the time when this study was conducted, the theoretical number of daily working hours for the mine concerned was 16.5 hours per day, and operations stopped for 3 weeks in a year for the summer holidays. Servicing machines is scheduled on a calendar basis and for the most utilized machines, preventive maintenance ($PM$) is scheduled every week. Since the scaling machine is one of the most utilized machines, when estimating the theoretical number of production hours, one should consider the duration of the time to service. The distribution fit test of the time to service shows that the time to service fits a lognormal distribution with $\mu = 1.7 \, h$ and $\sigma = 0.8 \, h$, which gives a mean time to service of 7.1 hours. Since $PM$ is theoretically scheduled for every week, the theoretical service time for one year (with 49 working weeks in the year) is 349 hours. Thus, by considering the number of daily working hours, the number of working weeks in a year and the service time in a year, the theoretical number of production hours for a period of one year can be calculated as 5,310 hours. The utilization of the scaling machine is not constant, as the major objective of underground mining is to maximize the utilization of the mine rooms under the constraint of the workforce and the mining machines. Furthermore, as the operations in underground mining consist of a series of activities which are dependent on each other, one succeeding activity cannot be executed before the preceding activity is terminated, and therefore a time of waiting may occur. Based on the recorded data, the average utilization of the scaling machine is estimated to be approx. 80%.

The revenue for the cycle of activities ($rev$) in this particular underground mine is determined as

$$rev = \frac{OV \cdot OS}{hF}$$

where

- $OV = \text{the ore value (cu/ton)}$
- $OS = \text{the average ore quantity of the cycle (ton)}$
- $hF = \text{the average time in the mine room per cycle (hours)}$

For the same reason as in the case of the $APUC$ data, the value for the revenue has been encoded in a similar way to the way in which the $APUC$ data was encoded. During the time when this study was conducted, the revenue for a cycle was 0.09 cu/hours.

In this study, the $NPV$ method has been utilized for investment appraisal. The reason is that the possible investments are varied in their scale (i.e. the total cost of the reliability improvement varies) and are also mutually exclusive (i.e. if one investment is made, the others must be rejected), and that, for this type of situation, the $NPV$ method should be used (Brigham and Daves, 2009). The basic idea of the $NPV$ method is to compare the present value of the future cash flows from the current investment with the cost of the investment. Thus the future cash flows from the investment are discounted back to their present value and compared to the initial cost of the investment. The $NPV$ is then determined by the difference between the present values of the inflows and outflows of the investment. It can be formulated as follows (Northcott, 1992):

$$NPV = -C_0 + \sum_{t=1}^{n} CF_t (1 + r)^{-t}$$

where

- $C_0 = \text{the initial cost of the investment}$
\[ CF_i = \text{the expected cash flow in year } i \]
\[ r = \text{the discount rate} \]
\[ n = \text{the project lifespan} \]

A positive value for the NPV indicates that the investment would add value (profit), and therefore the investment can be accepted, while a negative value for the NPV indicates that the investment would subtract value and that the investment should be rejected. A zero value for the NPV indicates that, from a financial perspective, the investment would neither add nor subtract value. In this case, the decision as to whether the investment should be accepted or not depends on the nature of the business. Concerning investments in reliability improvement, the effects of an unreliable system will not only be a tangible impact (production loss, time used for repair, the use of a number of spare-parts, etc.), but also an intangible impact (on worker morale, customer perception, as well as the subsequent effect on competitiveness, etc.). Therefore, some of the impacts of the unreliable system may be indirect and impossible to capture directly as financial losses (Madu, 2005). Thus it is quite common that investments with a zero value for the NPV are accepted.

In this study, the project life span is expressed in terms of service life. Service life here is defined as the length of time during which a machine is operated with a high degree of utilization. At the end of the service life, a new machine is purchased and the current machine will be assigned as a reserve machine. In the mine studied herein, there is no standard for the service life, but, based on previous experience, it is estimated that the service life of a scaling machine is approximately 12 years. The average value of the reference rate released by Sveriges Riksbank (Sweden’s central bank) for the period covering the past ten years has been adopted to represent the discount rate. During the time when this study was conducted, the average value was 2.5% (Sveriges Riksbank, 2011). The result of the NPV analysis is shown in Figure 9.

Figure 9 shows that, for an availability greater than approx. 84.5 % the NPV is negative, which indicates that an investment made to achieve an availability greater than approx. 84.5 % will not bring profit to the company (see the infeasible area). For an
availability below approx. 0.84.5 %, an investment will bring profit to the company (see the feasible area) and deciding which investment should be selected depends on other perspectives (e.g. cash flow availability, production demand, the possibility of new technology appearing, etc.). If one supposes that the cash flow for all the possible investments is not constrained and that the appearance of new technology is unlikely, then the decision maker can determine whether he/she will choose the investment in the feasible area which has the highest NPV or that with the highest availability. In the scenario where the production demand is high and/or intangible profit (such as enhancement of the company’s reputation, customer satisfaction, etc.) is considered to be an important aspect, investments with a low NPV but a high availability might be more preferable than investments with a high NPV but a low availability. This is because the manager might think that high production and/or intangible profit should be achieved at any cost. In this scenario, the highest availability obtained is approx. 84.5 %, which corresponds to an NPV of 3 cu and a total cost of investment of 506 cu. In the scenario where tangible profit is superior to any other aspect, the decision maker can select the investment that has the highest NPV. The highest NPV obtained is 210 cu, which corresponds to an availability of approx. 0.82 and a total cost of investment of 121 cu. The reliability improvement ratio ($r_{RI}$) and cost of investment ($I$) for each component and the system availability improvement ratio due to the reliability improvement of the component ($r_{AI}$), corresponding to the highest NPV and the highest availability in the feasible area, are shown in Table 2. The system availability improvement ratio due to the reliability improvement of a component ($r_{AI}$) is defined as the ratio of theoretical system availability obtained after the improvement of the corresponding component at a corresponding reliability improvement ratio and can be formulated as

$$ r_{AI} = \frac{A_{AI} - A_{SC}}{A_{SC}} $$

(10)

where

$A_{AI}$ = the system availability after the reliability improvement of component $i$

$A_{SC}$ = the system availability before the reliability improvement

<table>
<thead>
<tr>
<th>Component</th>
<th>Highest NPV</th>
<th>Highest availability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r_{RI}$ (%)</td>
<td>$I$ (cu)</td>
</tr>
<tr>
<td>Hydraulic cylinders</td>
<td>74</td>
<td>49.8 (1)</td>
</tr>
<tr>
<td>Boom</td>
<td>20</td>
<td>17.0 (2)</td>
</tr>
<tr>
<td>Hydraulic hammer</td>
<td>40</td>
<td>15.2 (3)</td>
</tr>
<tr>
<td>Hydraulic hoses</td>
<td>26</td>
<td>13.7 (4)</td>
</tr>
<tr>
<td>Chassis</td>
<td>10</td>
<td>6.1 (5)</td>
</tr>
<tr>
<td>Central lubrication system</td>
<td>40</td>
<td>6.1 (6)</td>
</tr>
<tr>
<td>Water system</td>
<td>41</td>
<td>4.7 (7)</td>
</tr>
<tr>
<td>Electronic system</td>
<td>7</td>
<td>3.9 (8)</td>
</tr>
<tr>
<td>Engine</td>
<td>11</td>
<td>2.7 (9)</td>
</tr>
<tr>
<td>Cabin</td>
<td>14</td>
<td>1.5 (10)</td>
</tr>
<tr>
<td>Transmission</td>
<td>3</td>
<td>0.6 (11)</td>
</tr>
</tbody>
</table>

* $r_{RI}$: Reliability improvement ratio  
  $I$: Cost of investment  
  $r_{AI}$: System availability improvement ratio due to reliability improvement of component
Table 2 shows that, in the case of the highest NPV, the component that needs the greatest allocation of investment is the hydraulic cylinder, while in the case of the highest availability, the component that needs the greatest allocation of investment is the boom. This difference is due to the relation between the overall cost of reliability improvement and the system availability, which follows the law of diminishing returns. For the hydraulic cylinders, the point of diminishing returns is reached when the system availability approaches 0.84 (see Figure 7 and 8). Thus, after this point, the cost for the reliability improvement of the hydraulic cylinders is too high in comparison with the gain to be derived from the improvement of the system availability, and improving the reliability of the boom is more worthwhile.

The results of this study can be used as guidelines for the design team in selecting the components which need to be improved and in determining the extent to which the improvement should be achieved. The next step after optimizing the reliability improvement is to form a cross-functional team consisting of personnel representing engineering design, manufacturing, quality and reliability, and marketing. The task of the cross-functional team is to conduct feasibility analysis to determine whether the demanded reliability improvement (rRI) of each component can be achieved for a given allowable investment allocation.

4. Conclusions
The conclusions derived from the present study are as follows:
- Based on the NPV analysis, an investment in reliability improvement to achieve a system availability of the scaling machine greater than approx. 84.5% is not feasible.
- For feasible reliability improvement investments,
  - the maximum NPV obtained is 210 cu, which corresponds to a system availability of approx. 82% and a total cost of investment of 121 cu,
  - the maximum system availability is approx. 84.5%, which corresponds to an NPV of 3 cu and a total cost of investment of 506 cu.
- In general, the approach utilized in this study can be used by the design team for determining which components of the machine need to be improved and to what extent the improvement should be achieved.

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References


Paper III

Robust-optimum multi-attribute age-based replacement policy

Wijaya, A.R., Lundberg, J. and Kumar, U.

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Robust-optimum multi-attribute age-based replacement policy

Andi R. Wijaya, Jan Lundberg and Uday Kumar

a Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå, Sweden
b Department of Mechanical and Industrial Engineering, Gadjah Mada University, Yogyakarta, Indonesia

Abstract
Purpose – A common model in the age-based replacement policy is based on the cost attribute and assumes that the model parameters are known. In practice, the model parameters are estimated from limited historical data, which brings uncertainty into the model. Moreover, minimizing the cost is not the only goal of the maintenance activity. From the decision maker’s point of view, the multi-attributes and the uncertainty of the age-based replacement policy are two important aspects to take into consideration in the decision making process. This paper aims to propose an approach for a robust-optimum multi-attribute age-based replacement policy.
Finding – The study finds that the proposed approach can determine the interval time for preventive replacement that provides a robust and optimum solution for a multi-attribute age-based replacement policy.
Design/methodology/approach – The proposed approach is based on a combination of the multi-attribute age-based replacement policy and robust design problem philosophy. A case study is provided for illustrating the application of the proposed method.
Practical implications – The proposed approach can be used by the decision maker in determining a robust-optimum interval time for preventive replacement of multi-attribute age-based replacement, a time interval which is not only optimum, but also robust.
Originality/value – This paper presents an approach that simultaneously considers the multi-attributes and the uncertainty in the age-based replacement policy which is till date is not available.
Keywords Age-based replacement policy, Multi-attributes, Robust design, Optimization
Paper type Research paper

Introduction
The age-based replacement policy is known as the most common maintenance policy (Wang, 2002). This policy consists of replacing an item when it reaches a certain time of life, \( t_{\text{opt}} \) (the optimum replacement time), or when it fails, whichever occurs first. A common approach in determining \( t_{\text{opt}} \) is to consider the minimum cost. However, minimizing the cost is not the only goal of the maintenance activity. The goal of the maintenance activity is to support the production process with adequate levels of availability, reliability and operability at an acceptable level (Coetzee, 1997). It emphasize that all the attributes are significant and in determining \( t_{\text{opt}} \), the decision should be based on the multi-attribute approach. Gopalaswamy et al (1993) argued that a preventive maintenance policy based on a single criterion (the cost-rate) is rather unreliable and forces the decision maker (DM) into a ‘corner’ by making him/her take decisions based on the cost-rate alone. Similar results were obtained by Azaiez (2002),
who identified that, in the eyes of the DM, cost is not the only parameter in selecting the appropriate replacement policy, but other parameters such as the quality of the output, labour productivity, and cash flow availability should also be considered. Furthermore, the problem becomes more complex when considering the fact that not all the aspects can be translated into monetary value. Failure will result not only in a tangible impact which can be directly captured as financial loss, but also in an intangible impact which cannot be directly captured as financial loss (Madu, 2005). Companies are realizing the importance of the intangible impacts (especially damage to the company’s reputation) and, in spite of the difficulties, they are attempting to include them in the costing scheme (Schiffauerova and Thomson, 2006). It can be concluded that DM prefer to take a broader view of the problem and to visualize all the important aspects simultaneously, rather than treat one aspect in isolation (Cavalcante and Almeida, 2007).

In the age-based replacement model, a common assumption is the parameters for the model are known and deterministic. However, in practice, they must be estimated from a limited historical data (Kobbacy, et al, 1997; van Noortwijk, 2000). This estimation will bring uncertainty in the model. Mauer and Ott (1995) demonstrate that uncertainty in the cost attribute can significantly change $t_{age}$. Halim and Tang (2009) construct a 90% confidence interval for $t_{opt}$ of relays and found that the spread of the confidence bound for $t_{opt}$ is large; the upper limit of $t_{age}$ is approximately four times the lower limit of $t_{opt}$.

In the field of engineering design, one approach dealing with uncertainty in models is to use the robust design technique which is a philosophy popularized by Taguchi in the fifties. A model solution is considered as robust if the output is less sensitive to the perturbation of variation in the model parameters. Thus the solution may not be the one that has the optimum output, but it is the one which has the lowest variance of the output.

The objective of this paper is to develop a method for determining a robust-optimum interval of preventive replacement, a solution which is not only optimum, but also robust.

**Overview of the proposed method**

In this study, a method for determining an interval of preventive replacement is proposed based on a combination of the multi-attribute age-based replacement policy and the robust design technique. A brief description of this method is presented in Figure 1. The proposed method begins with the formulation of the optimization problem for the cost attribute, $\gamma(t)$, and the reliability attribute, $\rho(t)$. The next step is the normalization of the objective functions by using the upper-lower-bound method. Normalization is performed to avoid an incorrect solution point due to different orders of magnitude. The objective functions are combined into a single aggregate objective function (AOF) of the optimum multi-attribute age-based replacement policy, $f_{opt}(t)$, and an appropriate weight is assigned. The next step is to formulate an objective function for the robust multi-attribute age-based replacement policy, $f_{rob}(t)$, by using the robust design approach. The problem is then formulated as a bi-objective optimization problem with the two objectives are the optimum multi-attribute age-based replacement, $f_{opt}(t)$, and the robust multi-attribute age-based replacement, $f_{rob}(t)$. The next step is to assign a priority for each objective so that a bi-objective optimization problem with priority can be formulated. The interval for the replacement time ($t_{rob-opt}$) of the robust-optimum multi-attribute replacement policy is determined by using the Waltz lexicographic approach. Firstly, the optimization problem for the objective function with a higher priority is solved. The acceptable tolerance ($\delta$) is
assigned for the first objective function. Secondly, the optimization problem for the objective function with a lower priority is solved with respect to the acceptable tolerance assigned. After $\delta$ is assigned for the second objective function, the interval for the replacement time ($t_{rob-opt}$) can be determined.

**Figure 1.** Flowchart of the robust-optimum multi-attribute age-based preventive replacement policy

**Description of the proposed method**

**Attributes of age-based replacement policy**

In preventive maintenance, the attributes to be considered are very large. The importance of the attributes depends on the company philosophy, the type of production system, the demand pattern, etc. All attributes are in fact related to each other and cannot be easily separated into independent attributes. In practice, two attributes that can give a brief representation of all the attributes are the cost and reliability attributes. The reason is that the other attributes, such as the downtime, production loss, availability and spare part inventory cost, can be estimated indirectly by knowing these two attributes. Therefore, in this study, the model is limited to these two attributes.

For the cost attribute, the classical cost model (Barlow and Hunter, 1960) is used. In this model, the objective is to minimize the rate of expected cost ($\chi(t)$), and the corresponding time ($t$) is the optimum replacement time. The model is formulated as:

$$
\min_{t \in T} \chi(t) = C_p \frac{R(t) + C_F [1 - R(t)]}{\int_0^T R(x) dx}
$$

where $R(t)$ is the reliability function, $C_R$ is the cost ratio, $C_P$ is the cost of preventive replacement and $C_F$ is the cost of failure replacement. For the reliability attribute, the
reliability performance measure (Jiang and Ji, 2002) is used. Reliability is a decreasing monotonic function which indicates that highest reliability is achieved when the time is zero \((t = 0)\). In preventive maintenance policy, it indicates that to reduce corrective maintenance, preventive maintenance should be done as early as possible. However, it will escalate the maintenance cost and reduce the time for the component to accomplish its mission. Ideally, preventive maintenance should be performed just before the component fails, thereby censoring as little useful service time of the component as possible. From this perspective, the objective of preventive maintenance policy is to minimize the corrective events but in the same time performing as little preventive maintenance as possible (i.e. timeliness measure). Accordingly, the reliability performance function can be formulated as (Jiang and Ji, 2002):

\[
\rho(t) = -\frac{\rho_1(t)}{\rho_2(t)}
\]  

(2)

where \(\rho_1(t)\) is a measure of corrective replacement rate and \(\rho_2(t)\) is a measure of preventive replacement rate. Measure of corrective replacement rate is defined as the ratio of number of preventive maintenance events and (expected) total number of corrective and preventive maintenance events. For the age replacement policy with a given replacement period \(T\), \(R(t)\) represent the fraction of preventive replacement and \(F(t)\), the cumulative distribution function, represent the fraction of corrective replacement

\[
\rho_1(t) = \frac{R(t)}{R(t) + F(t)} = R(t)
\]  

(3)

Measure of preventive replacement rate is determined by minimizing time between preventive replacement and failure occurrence in the long run. By utilizing mean square error (MSE), it can be formulated as:

\[
\rho_2(t) = \sigma^2 + (\mu - t)^2
\]  

(4)

where \(\mu\) and \(\sigma^2\) are the mean and variance of the life density. Combining eq. (3) and (4) into eq. (2), the reliability performance measure can be formulated as optimization problem as:

\[
\min_{t \in \mathbb{R}} \rho(t) = -\frac{R(t)}{\sigma^2 + (\mu - t)^2}
\]  

(5)

Small value of \(\rho(t)\) is preferred as the objective is to minimize corrective maintenance and in the same time to maximize the sufficient use of the lifetime.

Assuming that the inter-failure time follows a two-parameter Weibull distribution (Abernethy, 2000), eq. (1) and (5) are formulated as

\[
\min_{\ell \in \mathbb{R}} \chi(t) = C_e \left[ e^{-\left(\frac{t}{\tau}\right)^\beta} + C_s (1 - e^{-\left(\frac{t}{\tau}\right)^\beta}) \right]
\int_{0}^{\infty} 1 - e^{-\left(\frac{x}{\tau}\right)^\beta} dx
\]  

(6)
where $\eta$ and $\beta$ is the scale and the shape parameter of Weibull distribution.

Confidence interval of model parameters

In eq. (6) and (7), three model parameters ($C_R$, $\beta$ and $\eta$) need to be assigned. As these parameters are estimated from historical data, consequently, the model is exposed to the sampling risk. To address this risk, a statistical confidence interval (CI) is used. When the historical data for the cost ratio is sufficiently large, the $100(1-\alpha)\%$ CI for $C_R$ is approximated as (DeCoursey, 2003):

$$
\left[ \hat{C}_R - Z_{\alpha/2} \frac{s_{CS}}{\sqrt{n}}, \hat{C}_R + Z_{\alpha/2} \frac{s_{CS}}{\sqrt{n}} \right]
$$

(8)

where, $\hat{C}_R$, $\bar{C}_R$ and $\hat{C}_R$ are the lower limit, the upper limit and the average of $C_R$, $Z_{\alpha/2}$ is the $(1-\alpha/2)$ fractile of the standard normal variate, $s_{CS}$ is the standard deviation and $n$ is the sample size. However, in practice, such data is very limited and the value of the historical data may not relevant to the current situation due to a rapid change in business conditions. In this type of situation, the three-point estimation technique is commonly used (Project Management Institute, 2004). This technique is based on the judgment of experts who make three estimations of the cost ratio (the best-case ($C_{Rb}$), the most likely ($C_{Rm}$) and the worst-case ($C_{Rw}$) cost ratios). These estimations are then combined to yield the normal probability distribution. The average cost ratio and the standard deviation of the cost ratio are approximated as (Project Management Institute, 2004):

$$
\hat{C}_R = \left( C_{Rb} + 4C_{Rm} + C_{Rw} \right)/6
$$

(9)

$$
s_{CS} = \frac{C_{Rw} - C_{Rb}}{6}
$$

(10)

and the confidence interval for the cost ratio can be estimated as:

$$
\left[ \hat{C}_R - Z_{\alpha/2} s_{CS}, \hat{C}_R + Z_{\alpha/2} s_{CS} \right]
$$

(11)

For the Weibull parameters, the $100(1-\alpha)\%$ CI of $\beta$ and $\eta$ are approximated as (Abernethy, 2000):

$$
\left[ \hat{\beta}, \bar{\beta} \right] = \left[ \hat{\beta} \exp\left( -\frac{0.78 Z_{\alpha/2}}{\sqrt{n}} \right), \bar{\beta} \exp\left( \frac{0.78 Z_{\alpha/2}}{n} \right) \right]
$$

(12)

$$
\left[ \hat{\eta}, \bar{\eta} \right] = \left[ \hat{\eta} \exp\left( -\frac{1.05 Z_{\alpha/2}}{\beta \sqrt{n}} \right), \bar{\eta} \exp\left( \frac{1.05 Z_{\alpha/2}}{\beta \sqrt{n}} \right) \right]
$$

(13)

where, $\hat{\beta}$, $\bar{\beta}$ and $\hat{\beta}$ are the lower limit, the upper limit and the average of $\beta$, $\eta$, $\tilde{\eta}$ and $\tilde{\eta}$ are the lower limit, the upper limit and the average of $\eta$, $Z_{\alpha/2}$ is the $(1-\alpha/2)$ fractile of the standard normal variate, and $n$ is the sample size.

Multi-objective optimization

The generic multi-objective optimization problem (MOP) can be formulated as follows:
\[
\text{min } \{ f_i(x, p), f_j(x, p), \ldots, f_k(x, p) \} \quad (k \geq 2) \tag{14}
\]

subject to: \( g_j(x, p) \leq 0; \quad j = 1, 2, \ldots, m; \quad h_l(x, p) = 0; \quad l = 1, 2, \ldots, n \)

where \( k \) is the number of objective functions, \( m \) is the number of inequality constraints, \( n \) is the number of equality constraints, \( x \) is a vector of model variables and \( p \) is a vector of model parameters. A common approach to solve MOP is to use a priori articulation of preferences. In this approach, one specifies scalar weights for each objective functions and combines into a single aggregate objective function (AOF), which is formulated as:

\[
AOF = \sum_{i=1}^{k} w_i f_i(t) \tag{15}
\]

where \( w \) is the scalar weight of the objective function. The solution obtained depends on the weights specified. Incorrect solution point might occur if the objective functions have significantly different orders of magnitude. Therefore the objective functions should be normalized. Normalisation method which is considered to be the most robust is the upper-lower-bound (Marler and Arora, 2005). This method is formulated as follows:

\[
f_{i, \text{norm}} = \frac{f_i(t) - f_i^\text{\textsc{lo}}}{f_i^\text{\textsc{hi}} - f_i^\text{\textsc{lo}}} \tag{16}
\]

where \( f_i^\text{\textsc{lo}} = \min_{t \in T} f_i \) and \( f_i^\text{\textsc{hi}} = \max_{t \in T} f_i \). The value of \( f_{i, \text{norm}} \), depending on the method with which \( f_i^\text{\textsc{lo}} \) and \( f_i^\text{\textsc{hi}} \) are determined, generally varies between zero and one.

Using eq. (15) and (16), eq. (6) and (7) are combined into AOF as follows:

\[
\text{min } f_{\text{opt}}(t) = w_i \chi_{\text{norm}}(t) + w_j \rho_{\text{norm}}(t) \tag{17}
\]

The \( t_{\text{opt}} \) is found by evaluating \( f_{\text{opt}}(t) \) for range values of \( t \) and choosing the value that gives a minimum. However, as there are uncertainties in the model parameters, it will lead to uncertainty in the output \( f_{\text{opt}} \). From the DM’s point of view, this is a risky situation, as a small perturbation in the model parameters may change the output of the model \( f_{\text{opt}} \) and the time for optimum preventive replacement \( t_{\text{opt}} \), respectively. In order to obtain a robust solution for the output, the robust design technique is adopted in this study. By formulating the optimization problem of eq. (17) into a robust design principle, it can be stated that the preventive replacement is considered as robust if the aggregate objective function \( f_{\text{opt}} \) possesses as little sensitivity as possible to the perturbation of variation in the model parameters \( (\beta, \eta \text{ and } C_R) \) and the model variable \( (t) \).

**Robust design problem**

In the robust design problem (RDP), the performance function \( f \) is formulated as a function of the design variable \( (t) \), which is controllable, and the design parameters \( (p) \), which are uncontrollable, as follows:

\[
f = f(t; p) \tag{18}
\]

Assuming that the variation of \( p \) follows a normal distribution and letting \( p_0 \) be the nominal value of \( p \), the expected value of the variation in \( p \) \( (\mu_p) \) is presented as:

\[
\mu_p = E[p - p_0] = E[\Delta p] \tag{19}
\]

and the corresponding covariance matrix of \( \Delta p \) can be estimated as

\[
\text{P} = V[\Delta p] = E[(\Delta p - \mu_p)(\Delta p - \mu_p)^\text{T}] = E[\Delta p \Delta p^\text{T}] - \mu_p \mu_p^\text{T} \tag{20}
\]

Based on the theory of performance sensitivity distribution (Caro et al, 2005), the variation of the objective function \( (\Delta f) \) can be formulated as
\[ \Delta f = F \Delta p \]

where \( F \) is a Jacobian matrix of \( f \) with respect to \( p \) and is defined as

\[ F(t; p_0) = \left( \frac{\delta f}{\delta p} \right)_{p=p_0} \]

The expected value of \( \Delta f \) (\( \mu \)) can be represented as

\[ \mu_r = E[\Delta f] = F \mu_p \]

and the corresponding covariance matrix of \( \Delta f \) (\( \sigma \)) is estimated as

\[ \sigma = \sqrt{\text{Var}[\Delta f]} = E[(\Delta f - \mu_r)(\Delta f - \mu_r)^T] \]

Substituting eq. (21) and (23) into eq. (24) and using eq. (20), the above expression can be simplified as

\[ \sigma = FF' \]

In the light of RDP, the optimization problem depicted in eq. (17) is formulated into a RDP with a single performance function (\( f_{opt} \)) and three design parameters (\( C_R, \beta \) and \( \eta \)). For this type of problem, the matrix \( F \) is reduced to a 1 x 3 matrix and \( \sigma \) turns out to be a scalar (Al-Widyan and Angeles, 2005) which is formulated as

\[ \sigma = FF' \]

where \( \| \| \) is the Euclidean norm of vector \(
\). As the purpose is to render the objective function \( f \) as insensitive to variation \( \Delta p \) as possible, \( \sigma \) has to be minimizing. By using a trace inequality of positive-definite matrices and the fact that \( P \) is uncontrollable (Al-Widyan and Angeles, 2005), eq. (18) can be formulated as

\[ \min \ f_{rob} (t) = FF' \]

subject to: \( f(t; p_0) = f_o \).

The robust replacement time \( (t_{rob}) \) is determined by evaluating \( f_{rob}(t) \) for range values of \( t \) and choosing the value that gives a minimum.

### Robust-optimum replacement time

To obtain the robust-optimum replacement time, both optimization problems formulated in eq. (17) and (27) must be solved. If no priority is assigned, the objective functions can be combined into AOF. However, if one of the objective functions should be more prioritized than the other objective function, then it can be formulated as a bi-objective optimization with priority. A common way to solve this type of optimization problem is to use the Waltz lexicographic method (Marler and Arora, 2004). In this method, the objective functions are arranged in their order of importance and then solved one at a time. After the first criterion is optimized, the second criterion is optimzed, with the first criterion kept within a certain percentage of its optimum.

Suppose that the DM decides that the optimality of the solution (\( f_{opt} \)) is more important than the robustness of the solution (\( f_{rob} \)). Then, in the light of the Waltz lexicographic approach, the optimization is carried out with respect to the primary criterion (eq. (17)) and the \( t_{opt} \) is determined. Subsequently, the second optimization is solved for the secondary criterion (eq. (27)), with the primary criterion kept within a certain percentage of its optimum. It can be formulated as follows:

\[ \min \ f_{rob} (t) \]

subject to: \( f_{opt} (t_{opt}) \leq f_{opt} (t_{opt}) + \delta_{opt} \)
where $\delta_{opt}$ is the positive tolerance determined by the DM. The robust-optimum replacement time ($t_{rob-opt}$) is determined by evaluating $f_{rob}(t)$ for the range values of $t$ that satisfy the constraint ($f_{opt}(t) \leq f_{opt}(t_{opt}) + \delta_{opt}$) and by choosing the value that gives a minimum. In practice, the DM prefers an interval solution rather than a single solution, and he/she can accept a deviation from the minimum value of $f_{rob}$ by some tolerance ($\delta_{rob}$). The interval for $t_{rob-opt}$ can then be determined by evaluating the range value of $t$ that satisfies the constraints ($f_{opt}(t) \leq f_{opt}(t_{opt}) + \delta_{opt}$) and ($f_{rob}(t) \leq f_{rob}(t_{rob}) + \delta_{rob}$).

**Case studies**

To illustrate the application of the proposed method, two case studies are provided. In the first case study, the historical data is limited and the cost ratio is not high. In the second case study, we have a sufficient amount of historical data and the cost ratio is high.

**Case study 1: the hydraulic hammer of a scaling machine**

A downtime analysis of scaling machine shows that the hydraulic hammer is one of the main components that have a high amount of downtime (Wijaya et al, in press). To reduce the occurrence of the unplanned downtime, preventive replacement is adopted and the interval for preventive replacement of hydraulic hammer has to be determined.

The failure data was collected over a period of 1 year for a single scaling machine operated in an underground mine in Sweden. The time to failures of hydraulic hammer, in stroke hours, is presented in ascending order in Table 1. The cost data was collected over a period of 1 year for three scaling machines that used a similar type of hammer. The data is presented in ascending order in Table 2. With regard to the value of $C_R$, due to the secrecy policy of the company concerned, the data was encoded and expressed as a currency unit ($cu$), and therefore $C_R$ is given as 1 cu.

<table>
<thead>
<tr>
<th>No</th>
<th>Time to failure (stroke hours)</th>
<th>No</th>
<th>Time to failure (stroke hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>86</td>
<td>5</td>
<td>208</td>
</tr>
<tr>
<td>2</td>
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<tr>
<td>4</td>
<td>182</td>
<td>8</td>
<td>267</td>
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</table>

<table>
<thead>
<tr>
<th>No</th>
<th>Cost ratio ($C_R$)</th>
<th>No</th>
<th>Cost ratio ($C_R$)</th>
<th>No</th>
<th>Cost ratio ($C_R$)</th>
<th>No</th>
<th>Cost ratio ($C_R$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.00</td>
<td>9</td>
<td>1.62</td>
<td>17</td>
<td>2.88</td>
<td>25</td>
<td>4.21</td>
</tr>
<tr>
<td>2</td>
<td>1.00</td>
<td>10</td>
<td>2.12</td>
<td>18</td>
<td>2.97</td>
<td>26</td>
<td>4.37</td>
</tr>
<tr>
<td>3</td>
<td>1.14</td>
<td>11</td>
<td>2.41</td>
<td>19</td>
<td>2.97</td>
<td>27</td>
<td>4.43</td>
</tr>
<tr>
<td>4</td>
<td>1.28</td>
<td>12</td>
<td>2.41</td>
<td>20</td>
<td>3.14</td>
<td>28</td>
<td>5.25</td>
</tr>
<tr>
<td>5</td>
<td>1.28</td>
<td>13</td>
<td>2.41</td>
<td>21</td>
<td>3.39</td>
<td>29</td>
<td>5.64</td>
</tr>
<tr>
<td>6</td>
<td>1.42</td>
<td>14</td>
<td>2.41</td>
<td>22</td>
<td>3.53</td>
<td>30</td>
<td>6.12</td>
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<td>1.56</td>
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<td>2.41</td>
<td>23</td>
<td>3.62</td>
<td>31</td>
<td>6.65</td>
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<tr>
<td>8</td>
<td>1.56</td>
<td>16</td>
<td>2.41</td>
<td>24</td>
<td>4.09</td>
<td>32</td>
<td>8.96</td>
</tr>
</tbody>
</table>

The 90% CI of $C_R$ is determined by eq. (8), while for $\beta$ and $\eta$, eq. (12) and (13) are utilized. The 90% CI of the model parameters are shown in Table 3.
Table 3. The 90% confidence limits of the model parameters for hydraulic hammer

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Average</th>
<th>Lower limit</th>
<th>Upper limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beta ($\beta$)</td>
<td>$\hat{\beta} = 2.90$</td>
<td>$\beta = 1.84$</td>
<td>$\overline{\beta} = 4.56$</td>
</tr>
<tr>
<td>Eta ($\eta$)</td>
<td>$\hat{\eta} = 219.40$</td>
<td>$\eta = 171.85$</td>
<td>$\overline{\eta} = 280.10$</td>
</tr>
<tr>
<td>Cost ratio ($C_R$)</td>
<td>$\hat{C}_R = 3.15$</td>
<td>$C_R = 2.51$</td>
<td>$\overline{C}_R = 3.78$</td>
</tr>
</tbody>
</table>

Eq. (17) is utilized to formulate the optimization problem of the optimum preventive maintenance time. Prior to the formulation, each objective function needs to be normalized by utilizing eq. (16). The minimum value ($f^\text{min}$) and maximum value ($f^\text{max}$) of the objective function are determined for range values of $t > 0$ (as it is impossible to perform preventive maintenance when the equipment has not yet been utilized) and with respect to all the possible values of the model parameters at a 90% CI. Using this constraint, the minimum and maximum values for the reliability performance function are given as $f^\text{min} = -0.000377$ and $f^\text{max} = 0$, and those for the cost performance function are given as $f^\text{min} = 0.006865 \text{ cu/hr}$ and $f^\text{max} = 1.000424 \text{ cu/hr}$. Accordingly, the aggregate objective function is formulated as follows:

$$
\min_{t \in \mathbb{R}} f_{opt}(t) = w_1 \left( \frac{\chi(t) - 0.006865}{1.000424 - 0.006865} \right) + w_2 \left( \frac{\rho(t) + 0.000377}{0.000377} \right)
$$

(29)

Suppose that the DM considers that the cost performance function is equally important as the reliability performance function, then an equal weight to both objectives must be assigned (i.e. $w_1 = w_2 = 0.5$). The solutions for the selected model parameters (the lower, upper, and average values for all three model parameters) are shown in Table 4 and illustrated in Figure 2.

Table 4. Solutions for selected model parameters for hydraulic hammer

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>$\eta$</th>
<th>$C_R$</th>
<th>$t_{opt}$</th>
<th>$f_{opt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\beta}$</td>
<td>$\hat{\eta}$</td>
<td>$\hat{C}_R$</td>
<td>120</td>
<td>0.4112</td>
</tr>
<tr>
<td>$\overline{\beta}$</td>
<td>$\overline{\eta}$</td>
<td>$\overline{C}_R$</td>
<td>171</td>
<td>0.3662</td>
</tr>
<tr>
<td>$\overline{\beta}$</td>
<td>$\overline{\eta}$</td>
<td>$\overline{C}_R$</td>
<td>236</td>
<td>0.3130</td>
</tr>
</tbody>
</table>

Table 4 and Figure 2 show that the uncertainty in the model parameters ($\beta$, $\eta$ and $C_R$) has significantly influenced the optimum preventive maintenance time. The optimum replacement time ($t_{opt}$) in the case of the upper values for all three model parameters ($\overline{\beta}$, $\overline{\eta}$ and $\overline{C}_R$) is about twice the $t_{opt}$ in the case of $\hat{\beta}$, $\hat{\eta}$ and $\hat{C}_R$. Accordingly, it is necessary to find a robust preventive maintenance time.
A robust preventive maintenance time \( (t_{rob}) \) can be determined by solving the optimization problem expressed as eq. (27). The Matlab software is utilized to derive the solution and to solve the problem numerically. The derivation of the solution is shown in Appendix A, and the numerical solution, expressed as the sample standard deviation value \( (s) \) of \( f_{opt} \) at the average values of the three model parameters is shown in Figure 3.
Figure 3 shows that the value of $s$ is minimum when $t$ is close to zero. The value of $s$ is increasing dramatically in the time interval of $75 - 110h$ and then is decreasing in the time interval of $150 - 210h$ before it is increasing again. From the robustness point of view, preventive replacement should be performed as early as possible, which is practically not optimal, as the component will not have a sufficient usage time. Therefore both the robustness ($f_{rob}$) and the optimality ($f_{opt}$) of the solution should be considered.

To obtain the robust-optimum replacement time ($t_{rob-opt}$), the two objective functions ($f_{opt}$ and $f_{rob}$) are formulated as a bi-objective optimization problem with priority. Prior to the optimization process, the DM should assign the priority of both objective functions and determine the acceptable tolerance for each objective function. If one supposes that the DM gives greater priority to $f_{opt}$ than to $f_{rob}$, that he/she can accept a deviation of $f_{opt}$ by 10 percent of its optimal value ($\delta f_{opt} = 0.1 f_{opt}(t_{opt})$), and that a solution uncertainty ($\delta f_{rob}$) of $s \leq 5$ is acceptable, then eq. (28) is utilized. The process of the optimization problem is illustrated in Figure 4. In this figure, the acceptable tolerances for the objective function of the optimum preventive replacement ($\delta f_{opt}$) are presented as a percentage of $[f_{opt}(t) - f_{opt}(t_{opt})]/f_{opt}(t_{opt})$.

![Image](image_url)

Figure 4. Optimization process of robust-optimum preventive maintenance of the hydraulic hammer

As the acceptable tolerance for $f_{opt}$ is 10 percent of the optimal value ($f_{opt}(t_{opt})$), the optimization problem can be formulated as

$$\min_{t_{rob}} f_{rob}(t)$$

subject to: $f_{opt}(t) \leq f_{opt}(t_{opt}) + (0.1 \cdot f_{opt}(t_{opt}))$

Figure 4 shows that the corresponding values of $t$ that satisfy $f_{opt}(t_{opt}) + 0.1 f_{opt}(t_{opt})$ are 119 and 209 h, and therefore eq. (30) can be formulated as

$$\min_{t_{rob}} f_{rob}(t) \mid 119 \leq T \leq 209$$

(31)
which gives the solution \( t_{\text{rob-opt}} = 181 \, h \). As a solution uncertainty \( \delta_{t_{\text{rob}}} \) of \( s \leq 5 \) is acceptable, then the interval of \( t_{\text{rob-opt}} \) is given as \( 147 \leq t \leq 209 \, h \). The DM should select this interval for preventive replacement of the hydraulic hammer.

**Case study 2: the relays of a central heating, ventilating and air conditioning (HVAC) system**

Data on the failures of relays listed in a paper by Halim and Tang (2009) is adopted in this case study. The time to failure of the relays is presented in ascending order as a number of switch cycles (see Table 5). The three estimations of the cost ratio are 40, 60 and 90.

<table>
<thead>
<tr>
<th>Table 5. Relay failure times (in millions of switch cycles)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
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<td>3</td>
</tr>
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<td>4</td>
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<td>7</td>
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<td>8</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>10</td>
</tr>
</tbody>
</table>

The 90% confidence limits of the cost ratio can be determined by eq. (9), (10) and (11), while, for those of the Weibull parameters, eq. (12) and (13) are utilized. The 90% confidence limits of the model parameters are shown in Table 6.

<table>
<thead>
<tr>
<th>Table 6. The 90% confidence limits of the model parameters for relay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Beta</td>
</tr>
<tr>
<td>Eta</td>
</tr>
<tr>
<td>Cost ratio</td>
</tr>
</tbody>
</table>

Eq. (17) is utilized to formulate the optimization problem of the optimum preventive replacement time. Prior to the formulation, each objective function needs to be normalized by utilizing eq. (16) with respect to all the possible values of the model parameters at 90% confidence limits. The minimum and maximum values of the objective function are determined for a time increment (\( \Delta t \)) of 0.001 and range values of \( T > 0 \). By using this constraint, the aggregate objective function is formulated as follows:

\[
\min_{t_{\text{opt}}} \; f_{t_{\text{opt}}}(t) = w_1 \left( \frac{N(t) - 0.364}{1000 - 0.364} \right) + w_2 \left( \frac{\rho(t) + 0.0307}{-0.000000735 + 0.0307} \right)
\]

If one supposes that the decision maker decides that the cost performance function is equally important as the reliability performance function, the optimum replacement time \( t_{\text{opt}} \) can be determined by assigning an equal weight to both objectives (i.e. \( w_1 = w_2 = 0.5 \)). The solutions for the selected model parameters (the lower, upper, and average values for all three model parameters) are shown in Table 7 and illustrated in Figure 5a.
Table 7. Solutions for selected model parameters for relay

<table>
<thead>
<tr>
<th>β</th>
<th>η</th>
<th>C_R</th>
<th>t_\text{opt}</th>
<th>f_\text{opt}</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.2</td>
<td>9.379</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>0.2</td>
<td>0.1</td>
<td>11.754</td>
<td>0.50</td>
<td></td>
</tr>
<tr>
<td>0.3</td>
<td>0.1</td>
<td>14.011</td>
<td>0.40</td>
<td></td>
</tr>
</tbody>
</table>

It can be seen from Table 7 and Figure 5a that the uncertainty in the model parameters has a significant effect on the determination of the optimum replacement time. Thus it is necessary to find a robust replacement time. A robust replacement time (t_{rob}) can be determined by solving the optimization problem expressed as eq. (32). The derivation of the solution is shown in Appendix A, and the numerical solution, expressed as the sample standard deviation value (s) of f_{opt} at the average values of the three model parameters is shown in Figure 5b.

Figure 5. Solution of the objective function:
(a) optimum preventive replacement of the HVAC relay
(b) robust preventive replacement of the HVAC relay
Figure 5b shows that the global minimum is obtained when $t$ is zero. Within the interval of 5 – 20 million switch cycles, a local minimum and local maximum is observed. The value of $s$ is increasing dramatically in the interval of approx. 21 – 22 million switch cycles and then is decreasing till it approaches to the local minima at $t$ is approx. 16.5 million switch cycles. After this local minimum, the value of $s$ is increasing steadily. From the robustness point of view, preventive replacement should be performed as early as possible, which is practically not optimal, as the component will not have a sufficient usage time. Therefore both the robustness ($f_{rob}$) and the optimality ($f_{opt}$) of the solution should be considered. To obtain a robust-optimum replacement time ($t_{rob-opt}$), eq. (32) is utilized for solving the two objective functions. The process of optimization is illustrated in Figure 6.

![Figure 6. Optimization process of robust-optimum preventive replacement of the HVAC relay](image)

If one supposes that the decision maker decides that the acceptable tolerance for $f_{opt}$ is 10 percent of the optimal value ($\delta_{opt} = 0.10 \cdot f_{opt}(t_{opt})$), then the problem is formulated as

$$\min_{t \in T} f_{rob}(t)$$

subject to $f_{opt}(t) \leq f_{opt}(t_{opt}) + 0.10 \cdot f_{opt}(t_{opt})$

Figure 8 shows that the time interval that satisfies the required acceptable tolerance is 9.5 \leq T \leq 13.6, and therefore eq. (33) can be formulated as

$$\min_{t \in T} f_{rob}(t) \mid 9.5 \leq T \leq 13.6$$

which gives the solution $t_{rob-opt} = 13.6$ million switch cycles.

If one supposes that the decision maker thinks that a solution uncertainty ($\delta f_{rob}$) of $s \leq 3$ is acceptable, then the interval of $t_{rob-opt}$ is satisfied by two intervals, 9.5 \leq t \leq 9.9 and 12.04 \leq t \leq 13.40 million switch cycles. The second interval is more preferable, as it is wider and provides a lower value for both $f_{opt}$ and $f_{rob}$.

Thus it can be concluded in this case study on relays that the decision maker can select an interval time of 9.5 \leq t \leq 9.9 or 12.4 \leq t \leq 13.6 million switch cycles for preventive
replacement, as both intervals give a robust and optimum solution. Moreover, the second alternative is superior to the first alternative, as it has a wider range, providing more flexibility for scheduling.

Discussion of the case studies
In the case of hydraulic hammer, the global minimum of the robust solution is at \( t = 0 \) h which is not applicable. But the local minimum of robust solution (i.e. \( t = 180 \) h) is close to the global minimum of the optimum solution at the average values of the three model parameters (i.e. \( t = 171 \) h). Therefore, the interval solution based on the two objectives is quite similar to the interval solution based on a single objective as the interval solutions for objectives are overlapping and close to each other. Considering the both objectives, the interval solution is narrowing down. For this type of condition, the order of importance of the objective functions will not significantly effect on the obtained solution from the Waltz lexicographic method.

In the case of HVAC relays, the global minimum of robust solution is also not applicable (i.e. \( t = 0 \) million switch cycles), and the global minimum of the optimum solution is close to the local maximum of the robust solution. Therefore, the solution for each objective function is different and depending on the solution uncertainty for both objectives (\( \delta_{\text{opt}} \) and \( \delta_{\text{rob}} \)), there is a possibility that solution interval which satisfies the two objectives cannot be obtained. For example, if the decision maker decides the acceptable tolerance for \( f_{\text{opt}} \) is \( \delta_{\text{opt}} \leq 5 \% \) and the solution uncertainty (\( \delta_{\text{rob}} \)) of \( s \leq 2 \) is acceptable, then there will be no solution interval which can satisfy the two objectives and the obtained solution will satisfy a single objective only. In this type of condition, the order of importance of the objective functions has an effect on the obtained solution from the Waltz lexicographic method.

Conclusions
In the present study, a method for a robust-optimum multi-attribute age-based replacement policy is proposed. The proposed method can be used by decision makers to determine the interval time for preventive replacement that provides a robust and optimum solution.

References
Coetzee, J.L., 1997, Maintenance, Maintenance Publishers, Hatfield, SouthAfrica
Appendix A

1. Hydraulic hammer of scaling machine

The objective function for the preventive replacement is formulated as

\[ f_{opt}(t) = w_1 \left( \frac{\chi(t) - 0.006865}{1.000424 - 0.006865} \right) + w_2 \left( \frac{\rho(t) + 0.000377}{0.000377} \right) \]  \hspace{1cm} (A1)

where

\[ \chi(t) = \left[ \begin{array}{c} e^{\frac{\eta}{\beta}} \frac{1}{\Gamma(1+\frac{1}{\beta})} \\
1 - e^{\frac{\eta}{\beta}} \end{array} \right] dx \] ; \hspace{1cm} \rho(t) = e^{\frac{\eta}{\beta}} \left( \eta \Gamma \left[ \frac{2}{\beta} + 1 \right] - \eta^2 \Gamma^2 \left[ \frac{1}{\beta} + 1 \right] \right)

(A2)

In the light of the robust design problem, the scalar performance function, the design parameters vector and the scalar design variables are, respectively,

\[ f = f_{opt}, \hspace{0.5cm} p = \left[ \begin{array}{c} \eta \\
\beta \\
C_s \end{array} \right], \hspace{0.5cm} t = t \]  \hspace{1cm} (A3)

To minimize the variance \( \sigma_{f_{opt}} \), the norm of the gradient vector of \( f_{opt} \) with respect to \( \eta, \beta \) and \( C_s \) must be minimized, and, based on eq. (A1), it can be written as

\[ \frac{\Delta f}{\Delta \eta} = F \left[ \frac{\Delta \eta}{\eta} \right], \hspace{0.5cm} \frac{\Delta f}{\Delta \beta} = F \left[ \frac{\Delta \beta}{\beta} \right] \]  \hspace{1cm} (A4)

\[ \sigma^2 = FF^T = \sigma_{A^2}^2 + \sigma_{B^2}^2 + \sigma_{C^2}^2 \]

\[ \sigma_A \text{ is given as } \frac{w_1(\sigma_i - \sigma_i) + w_2(\sigma_i + \sigma_i)}{w_1w_{11} + w_2w_{14}}, \] and \( \sigma_C \) is given as

\[ -\beta \left[ \frac{w_1(\sigma_i - \sigma_i - \sigma_i - \sigma_i + \sigma_i + \sigma_i)}{w_1w_{11} + w_2w_{14}} \right], \] where

\[ k_2 = \frac{2k_2}{\eta^2} \left( \eta \Gamma \left[ \frac{2}{\beta} + 1 \right] - \eta^2 \Gamma^2 \left[ \frac{1}{\beta} + 1 \right] \right) \]

\[ k_4 = \frac{k_4}{\eta^3} e^{\frac{\eta}{\beta}} \Gamma \left[ \frac{1}{\beta} + 1 \right] \]

\[ k_6 = \frac{k_6}{\eta^4} e^{\frac{\eta}{\beta}} \Gamma \left[ \frac{1}{\beta} + 2 \right] \]

\[ k_8 = \frac{k_8}{\eta^5} e^{\frac{\eta}{\beta}} \Gamma \left[ \frac{1}{\beta} + 3 \right] \]

\[ k_1 = \frac{k_1}{\eta^6} e^{\frac{\eta}{\beta}} \Gamma \left[ \frac{1}{\beta} + 4 \right] \]

\[ k_9 = \frac{k_9}{\eta^7} e^{\frac{\eta}{\beta}} \Gamma \left[ \frac{1}{\beta} + 5 \right] \]

\[ k_{10} = \frac{k_{10}}{\eta^8} e^{\frac{\eta}{\beta}} \Gamma \left[ \frac{1}{\beta} + 6 \right] \]
\[
\sigma_i = \frac{k_i \left( e^{\left( \frac{t}{\eta} \right)^\beta} - C_k \left( e^{\left( \frac{t}{\eta} \right)^\beta} - 1 \right) \right) E \left( 1 - \delta \right) \left( \frac{t}{\eta} \right)^\beta \log \left( \frac{t}{\eta} \right) - \beta \log \left( \frac{t}{\eta} \right) }{k_i \beta^2 \eta R \left( \frac{t}{\eta} \right)^\beta}
\]

\[
\sigma_k = \frac{k_k \left( \eta \Gamma \left( \frac{2}{\beta} + 1 \right) - \eta \Gamma^2 \left( \frac{1}{\beta} + 1 \right) \right) \left( 1 - \eta \Gamma \left( \frac{1}{\beta} + 1 \right) \right)^{-\beta}}{k_k \beta^2 \eta \Gamma \left( \frac{1}{\beta} + 1 \right)}
\]

\[
\sigma_\alpha = \frac{k_\alpha C_\alpha e^{\left( \frac{t}{\eta} \right)^\beta} - 1}{k_\alpha}
\]

\[
\Gamma(z) = \int_0^z e^{-t} dt \quad \Gamma(z, x) = \int_0^z e^{-t} dt \quad E(x) = \int_x^\infty e^{-t} dt \quad \psi(x) = \frac{d\Gamma(x)}{dx} \quad \Gamma(x)
\]

\[
F(n, d, z) = \sum_{i=1}^{C_{n, k}} \frac{z^i}{k!} \cdot C_{n, k} = \prod_{j=1}^{(v_j + k)} \frac{\Gamma(v_j + k)}{\Gamma(v_j)}
\]

The sample standard deviation value \((s)\) of the AOF can be determined as

\[
s = \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2}
\]
2. Relays of an HVAC system

The objective function for the preventive replacement is formulated as

$$f_{opt}(t) = w_1 \left( \frac{\chi(t) - 0.364}{1000 - 0.364} \right) + w_2 \left( \frac{\rho(t) + 0.0307}{-0.000000735 + 0.0307} \right)$$

(A6)

Using the same approach as that in the case study on the hydraulic hammer, the norm of \( F \) can be derived and a similar result is obtained, eq. (A5), but with different constants.

The constants for the case of relays in an HVAC system are given as follows:

\[ k_1 = 72057594037927936 \quad k_3 = 2211638513648209 \quad k_5 = 2199023255552 \]

\[ k_4 = 2198222811086979 \quad k_3 = 138260508560274272 \quad k_6 = 1382274071030130625 \]
Paper IV

Whole-body vibration exposure from a scaling machine

Wijaya, A.R. and Lundberg, J.

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Whole-body vibration-exposure due to a scaling machine

Andi R. Wijaya\textsuperscript{a,b} and Jan Lundberg\textsuperscript{a}

\textsuperscript{a} Division of Operation and Maintenance Engineering, Luleå University of Technology, SE – 971 87 Luleå, Sweden

\textsuperscript{b} Department of Mechanical and Industrial Engineering, Gadjah Mada University, Yogyakarta 55281, Indonesia

Abstract: A field study was conducted to investigate the WBV-exposure of the scaling machine driver while performing scaling activity. The vibration was measured in accordance with the ISO 2631-1 standard and an assessment was carried out using the ISO 2631-1 and ISO 2631-5 standards. The results show that the dominant frequencies of the measured vibration peaks concur with the resonance frequencies of the body of the seated person and the frequency range where WBV can degrade the ability of the driver to perform manual tasks and is perceived by the driver to cause discomfort. An assessment based on ISO 2631-1 indicates a high probability of adverse health effects, while an assessment based on ISO 2631-5 shows the probability of adverse health effects on the spine to be low to moderate. This finding supports the notion that the limits specified in ISO 2631-5 are too high.

Keywords: scaling activity, whole-body vibration, vibration-exposure, ISO 2631-1, ISO 2631-5

1. INTRODUCTION

In the cycle of activities being carried out in underground mining, scaling is a crucial activity for making the workplace safe. Scaling is an operation where loose rock is removed from the sidewalls (rib) and hanging walls (roof) of the mine opening after blasting. Traditionally, scaling has been performed using hand scaling, as a result of which this activity has been known to have a high number of accident occurrences. A study of accidents in underground mines between 1985 and 1994 found that one third of the ground control injuries involved scaling [1]. To reduce the number of scaling-related accidents, the scaling machine has been introduced to replace hand scaling. The scaling machine basically consists of an impact hammer mounted on a pivoting arm, which is in turn attached to a mobile chassis. The use of a scaling machine to replace hand scaling has successfully reduced the number of scaling-related accidents from about 10 per year to none or one per year [2]. However, as is common in the case of heavy equipment operation, the use of a scaling machine exposes the drivers to whole-body vibration (WBV).

A number of studies on drivers have suggested a strong relation between exposure to WBV and the degradation of task performance. Exposure to WBV results in a decrement in the reaction time and steering ability of drivers [3,4]. It also contributes to a decline in visual acuity [5] and manual control [6]. Furthermore, prolonged exposure to WBV causes muscular and mental fatigue [5], which contributes to a declining task performance. Thus, in relation to the operation of heavy equipment such as a scaling machine, it can be concluded that exposure to WBV causes a degradation of the ability of
drivers to operate heavy equipment satisfactorily, which can lead to machine failure. In addition, a number of studies have suggested that continuous exposure to WBV could be either directly or indirectly connected to many health problems, including nervous, circulatory, digestive and reproductive system problems, as well as noise-induced hearing loss, and degenerative changes in the spine [7, 8, 9].

Despite the problems related to WBV-exposure, research concerning WBV experienced by underground mining equipment operators is limited, and only a few studies have been performed, mostly on load haul dump (LHD) vehicles [10, 11, 12, 13]. To date there has been no research performed on the WBV-exposure caused by the scaling machine.

The operation of the scaling machine consists of two work phases: travelling and scaling. In the travelling phase, the main source of vibration is the terrain conditions. Thus the level of WBV-exposure in the travelling phase can roughly be estimated from previous studies concerning WBV-exposure levels in the travelling phase of other heavy equipment used in underground mining (e.g. load haul dump vehicles). In the scaling phase, the source of vibration is the impact hammer striking the rock and falling rock hitting the arm and body of the machine. Thus it is not possible to estimate the level of WBV-exposure in the scaling phase based on studies of other heavy equipment.

The objective of the present study has been to evaluate whole-body vibration-exposure experienced by the driver of a scaling machine while performing scaling activity. The evaluation has been performed according to the ISO 2631-1 and ISO 2631-5 standards [14, 15].

2. METHODS
2.1. Scaling Machine and Subject
The scaling machine used in this study is a typical scaling machine used in underground mining in Sweden (see Figure 1).

![Figure 1. Scaling machine](Courtesy: Jama mining machine AB)

The overall dimensions are 3 m in height, 2.6 m in width and 14.6 m in length, and the unloaded weight is 27 metric tons. It has an articulated four-wheel drive chassis and four retractable stabilizer legs. It is bi-directional in operation. The driver sits in an air suspension seat which has a lumbar support and is mounted in an isolated cabin which can be tilted up to 13°. The maximum effective reach of the boom is 9 m (3 m in front of the machine) and the reach at a 45° approach angle is 8.5 m. It can be operated in both a diesel and an electro-hydraulic mode by a 6-cylinder in-line turbocharged diesel engine with a displacement of 7,146 cc (200 kW at 2,300 rpm) and a 2 x 30 kW electric motor (400 – 1,000 V). It is equipped with a hydraulic hammer (with an impact factor of 600 – 1,150 J and an impact rate of 10 – 25 Hz). Only one driver participated in this study. The
2.2. Measurement of Whole-Body Vibration

Vibration measurements were performed in three different mine rooms in an underground mine in Sweden. The duration of the vibration measurement for each mine room was 20 minutes. The vibration measurements were conducted in accordance with ISO 2361-1. A tri-axial accelerometer (ICP 356A02, PCB Piezotronics) was utilized in conjunction with a 4-channel, 24-bit resolution data acquisition device (NI 9234, National Instruments), to measure vibrations in three translational axes (a horizontal = x-axis, a lateral = y-axis and a vertical = z-axis). The accelerometer was mounted in a circular rubber seat-pad and placed on the seat beneath the ischial tuberosities of the driver (see Figure 2). This accelerometer had a frequency sensitivity range of 0.5 – 6,000 Hz. The vibration signals were recorded at a sampling frequency of 2,500 Hz and were low-pass filtered at 1,000 Hz to avoid aliasing.

Figure 2. Illustration of measurement set-up

2.3. Analysis of Whole-Body Vibration-Exposure

The International Organization for Standardization (ISO) has released two standards concerning WBV-exposure, ISO 2631-1 and ISO 2631-5. ISO 2631-1 is a primary standard which provides guidance on the quantification of WBV-exposure in relation to human health and comfort, vibration perception and motion sickness. ISO 2631-5, on the other hand, is an additional standard that provides guidance for quantifying health risks specifically affecting the lumbar spine and the vertebral endplates due to WBV-exposure containing transient shocks. In the scaling phase, the driver is exposed to vibration which contains multiple high-shock components and which is propagated by the impact hammer and by rock striking the arm and body of the scaling machine. Thus the analysis of WBV-exposure should be performed in accordance with both standards. All the analyses performed in this study have been carried out with the Matlab software.

2.3.1 Analysis of WBV-exposure in accordance with ISO 2631-1
ISO 2631-1 suggests that WBV-exposure should be presented as a frequency-weighted root-mean-square acceleration \( a_{\text{awrms}} \), in ms\(^{-2}\), which is formulated as:

\[
a_{\text{awrms}} = \sqrt[3]{\frac{1}{T} \int_0^T a_\omega^2(t) \, dt}
\]  

(1)

where \( a_\omega(t) \) is the instantaneous frequency-weighted acceleration and \( T \) is the duration of the measurement. The value of \( a_{\text{awrms}} \) is calculated for each axis (x, y and z) using the appropriate weighting factors \( W_d \) for the x-axis and y-axis, \( W_k \) for the z-axis. The assessment of the WBV-exposure shall be made with respect to the highest \( a_{\text{awrms}} \) in any axis. In the case where the vibration in two or more axes is comparable, the frequency-weighted root-mean-square vector sum is used to estimate the health risk. The frequency-weighted root-mean-square vector sum value \( a_{\text{xyz}} \), in ms\(^{-2}\), is calculated as:

\[
a_{\text{xyz}} = \sqrt{k_x^2 a_x^2 + k_y^2 a_y^2 + k_z^2 a_z^2}
\]  

(2)

where \( a_x, a_y, \) and \( a_z \) are the \( a_{\text{awrms}} \) in the x-axis, y-axis, and z-axis, respectively and \( k_x, k_y, \) and \( k_z \) are scaling factors in the x-axis, y-axis, and z-axis, respectively. The scaling factors in respect of the assessment of adverse health effects are given as \( k_x = k_y = 1.4 \) and \( k_z = 1.0 \). ISO 2631 also suggests determination of the crest factor \( (CF) \), which is the modulus of ratio between the maximum instantaneous peak value of the frequency-weighted acceleration and the frequency-weighted root-mean-square acceleration. \( CF \) is formulated as follows:

\[
CF = \frac{\max[a_\omega(t)]}{a_{\text{awrms}}}
\]  

(3)

If the crest factor exceeds 9, an additional analysis (to determine the vibration dose value) should also be performed and reported. The vibration dose value \( (VDV) \), in ms\(^{-1.75}\), is calculated as:

\[
VDV = \sqrt[4]{\frac{1}{T} \int_0^T a_\omega^4(t) \, dt}
\]  

(4)

The value of \( VDV \) is calculated for each axis (x, y and z) and the assessment of the WBV-exposure shall be made with respect to the highest \( VDV \) in any axis. In the case where the vibration in two or more axes is comparable, the \( VDV \) sum value \( (VDV_{xyz}) \), in ms\(^{-1.75}\), is calculated as:

\[
VDV_{xyz} = \sqrt{k_x^4 VDV_x^4 + k_y^4 VDV_y^4 + k_z^4 VDV_z^4}
\]  

(5)

In the assessment of adverse health effects due to WBV-exposure, ISO 2631-1 suggests the use of health guidance caution zone (HGCZ) limits. The corresponding lower and upper limits of the 8-hour-equivalent frequency-weighted root-mean-square (r.m.s.) acceleration value \( (A(8)) \) are 0.45 and 0.90 ms\(^{-2}\), respectively. When the \( A(8) \) is lower than the lower limit, this indicates a low probability of adverse health effects, but when the \( A(8) \) is within the lower and upper limits, this indicates a moderate probability of adverse health effects, and when the \( A(8) \) is higher than the upper limit, this indicates a high probability of adverse health effects. For the 8-hour-equivalent \( VDV \) (\( VDV(8) \)), the corresponding lower and upper limits are 8.5 and 17 ms\(^{-1.75}\), respectively. Similarly to the HGCZ limits of the \( A(8) \), a value of \( VDV(8) \) within the limits indicates a moderate
probability of adverse health effects and values of $VDV(8)$ which are lower and higher than the limits indicate a low and high probability of adverse health effects, respectively.

The $A(8)$ and $VDV(8)$ values for the case where the vibration in two or more axes is comparable can be estimated by using the following equations:

$$VDV(8) = VDV \frac{\left(8\right)}{T}$$  \hspace{1cm} (7)

$$A(8) = a \left(\frac{T_d}{8}\right)^\frac{1}{2}$$  \hspace{1cm} (8)

where $T$ is the duration of the measurement and $T_d$ is the daily exposure time. The daily exposure time is determined as follows: from the 8 hrs of scheduled working time, 1.5 hrs are excluded to compensate for time for meal breaks and travel time to and from the mine room, which gives an available time for the scaling phase of 6.5 hrs. Historical data show that the utilization of the scaling machine is approximately 0.80. Thus the daily exposure time can be estimated to be 5.2 hrs.

### 2.3.2 Analysis of WBV-exposure in accordance with ISO 2631-5

The analysis of WBV-exposure in this standard involves estimation of the acceleration dose in the spine. The acceleration dose ($D_k$), in ms$^2$, is calculated as

$$D_k = \left[ \sum A_{ik}^6 \right]^{\frac{1}{6}}$$  \hspace{1cm} (9)

where $A_{ik}$ is the $i^{th}$ peak of the spinal response acceleration, $a_{ik}(t)$, in the $k$-direction ($k = x, y, z$). The spinal response acceleration, $a_{ik}(t)$, is determined from the instantaneous vibration acceleration measured at the seat-pad by using the appropriate biomechanical model of the spinal response, as described in ISO 2631-5. The equivalent spinal static compressive stress ($S_e$), in MPa, during the measurement period is calculated from the total $D_k$ of each axis by using the following equation:

$$S_e = \left[ \left(0.015 \cdot D_{ix}\right)^6 + \left(0.035 \cdot D_{iy}\right)^6 + \left(0.032 \cdot D_{iz}\right)^6 \right]^{\frac{1}{6}}$$  \hspace{1cm} (10)

The estimated daily equivalent spinal static compressive stress ($S_{ed}$), in MPa, can be calculated as

$$S_{ed} = S \left(\frac{T_d}{T}\right)^{\frac{1}{6}}$$  \hspace{1cm} (11)

where $T$ is the duration of the measurement and $T_d$ is the daily exposure duration. A risk factor ($R$) is determined for the assessment of the adverse health effects related to the human response acceleration dose. It is defined as follows:

$$R = \left[ \sum_{i=1}^{n} \left( \frac{S_{ed} \cdot N^2}{S_u - c} \right) \right]^{\frac{1}{6}}$$  \hspace{1cm} (12)

where $N$ is the number of exposure days per year, $i$ is the year counter, $n$ is the number of years of exposure, $S_u$ is the ultimate strength of the lumbar spine for a person of an age of
\[(b + i)\text{ years}, \text{ } b\text{ is the age at which the exposure starts, and } c \text{ is a constant representing the static stress due to the gravitational force. The value of } c \text{ for the driving posture (which is applied in the present study) is given as 0.25 MPa. The value of } S_{ui}, \text{ in MPa, can be derived as:}

\[S_{ui} = 6.75 - 0.066(b + i)\]  \hspace{1cm} (13)

The \( R \) value is unique to the driver, as it depends on the age at which the driver was first exposed to vibration and on the lifetime exposure, which will vary among the drivers. The \( R \) value is calculated for the particular driver participating in the study, for the particular underground mine concerned. The characteristics of the participating driver are as follows: age at first exposure \((b) = 26\text{ years, yearly exposure } (N) = 196\text{ days and total years of exposure } (n) = 25\text{ years.}

In the assessment of the adverse health effects due to WBV-exposure, ISO 2631-5 suggests the following HGCZ limits: \( R < 0.8 \) indicates a low probability of adverse health effects on the spine, while \( 0.8 < R < 1.2 \) indicates a moderate probability of adverse health effects on the spine, and \( R > 1.2 \) indicates a high probability of adverse health effects on the spine. Similarly, \( S_{ed} < 0.5 \text{ MPa indicates a low probability of adverse health effects on the spine, while } 0.5 < S_{ed} < 0.8 \text{ indicates a moderate probability of adverse health effects on the spine, and } S_{ed} > 0.8 \text{ indicates a high probability of adverse health effects on the spine.}

3. RESULTS AND DISCUSSION

3.1. Frequency Analysis

A frequency analysis of the un-weighted WBV measured for the three axes (the horizontal, the lateral and the vertical axis) is shown in Figure 3, 4 and 5. As the frequency spectrums of the measured signals of the three mine rooms are similar, only the frequency spectrums obtained from the measured signals of mine room 2 are plotted here.

![Figure 3. Frequency spectrum of unweighted measured vibration signal for x-axis](image-url)
Figure 3 shows that, for the horizontal axis, the primary peak occurs in the range of 1 to 2 Hz, the secondary peak occurs around 6 Hz, the tertiary peak occurs around 11 Hz and the quaternary peaks occur in the range of 30 to 40 Hz. Figure 4 shows that, for the lateral axis, the primary peak occurs in the range of 1 to 4 Hz and the secondary peak occurs around 11 Hz. In addition, Figure 5 shows that, for the vertical axis, the primary peak occurs in the range of 1 to 7 Hz, the secondary peak occurs around 11 Hz and the tertiary peak occurs around 22 Hz.
This indicates that the dominant frequencies of the vibration peaks in all three axes coincide with the frequency range where WBV can degrade the ability of the driver to perform manual tasks. Laboratory studies have revealed that disruption of manual task performance (e.g. controlling a joystick, pressing buttons, etc.) occurs in the frequency range between 2 and 10 Hz for the vertical axis, with the greatest decrements occurring in the range of 4 to 5 Hz, while, for the horizontal and lateral axes, such disruption typically occurs below 3 Hz [16].

From the health risk and driver discomfort point of view, the dominant frequencies of the vibration peaks also coincide with the resonance frequencies of the seated person and the frequency range where the seated person is sensitive. Biodynamic studies have shown that, for a seated person, resonance of the body occurs at about 4 – 8 Hz for the vertical axis and at about 1 – 2 Hz for the horizontal and the lateral axis [17]. One can suspect that resonance of the body or its parts due to WBV causes adverse health effects, primarily with chronic exposure [18]. Concerning WBV discomfort, several studies show that, in the case of horizontal vibration, the frequency range of 2 – 3 Hz is perceived to cause the greatest discomfort for seated persons [5]; and that the use of a seat back shifts the frequency range to 4 – 6 Hz [19]. In the case of lateral vibrations, on the other hand, the peaks of discomfort occur in the frequency range of 1 – 2 Hz [20, 21]. In addition, in the case of vertical vibration, the peaks of discomfort occur in the frequency range of 3 – 6 Hz [5].

Thus it can be concluded that the dominant frequencies of the vibration peaks of measured signals concur with the resonance frequencies of the body of seated persons, and occur in the frequency range where WBV can degrade the ability of the driver to perform manual tasks and is perceived by the driver to cause discomfort.

3.2. ISO 2631-1 Analysis

The results of the WBV-exposure analysis based on ISO 2631-1 are summarized in Table 1 and 2.

<table>
<thead>
<tr>
<th>Mine room</th>
<th>Acceleration (m/s²)</th>
<th>Health risk assessment</th>
<th>Crest factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a₀</td>
<td>a₁</td>
<td>a₂</td>
</tr>
<tr>
<td>1</td>
<td>0.22</td>
<td>0.19</td>
<td>0.27</td>
</tr>
<tr>
<td>2</td>
<td>0.43</td>
<td>0.44</td>
<td>0.40</td>
</tr>
<tr>
<td>3</td>
<td>0.17</td>
<td>0.24</td>
<td>0.28</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mine room</th>
<th>Vibration dose value (m/s¹.⁷⁵)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>VDVₓ</td>
</tr>
<tr>
<td>1</td>
<td>13.68</td>
</tr>
<tr>
<td>2</td>
<td>18.95</td>
</tr>
<tr>
<td>3</td>
<td>9.48</td>
</tr>
</tbody>
</table>

It can be seen from Table 1 and 2 that, in general, the frequency-weighted root-mean-square accelerations and vibration dose values in mine room 2 are higher than those in mine room 1 and 3. This discrepancy is due to the differences in the host rock characteristics (e.g. structure, stability, hardness, etc.) between the mine rooms. The
geological strength index (GSI) of the underground mine studied varies between 50 – 80 and the uniaxial compressive strength of the intact host rock varies between 65 – 150 MPa [22]. When the rock structure is loose, the occurrence of falling rock hitting the boom of the scaling machine is more frequent than when the rock structure is solid. The rock characteristics also affect the size and impact of the falling rock, which, in turn, will also affect the magnitude of the shock-induced vibration.

It can also be seen from Table 1 and 2 that, for mine room 1 and 3, the frequency-weighted root-mean-square acceleration ($a_{\text{rms}}$) and vibration dose value ($VDV$) of the z-axis are higher than the $a_{\text{rms}}$ and $VDV$ of the x- and the y-axis. For mine room 2, on the other hand, the $a_{\text{rms}}$ and $VDV$ of the y-axis are higher than the $a_{\text{rms}}$ and $VDV$ of the other two axes. However, the $a_{\text{rms}}$ and $VDV$ of the three axes are comparable, which indicates that there is no dominant axis in the measured vibration signal. Thus the analysis should be performed based on the vector sum of the three axes.

Table 1 and 2 also show that, for each mine room, the crest factor value is above 9 for at least one axis. This indicates that the character of the vibration measured is non-stationary (containing shocks).

Concerning the assessment of the adverse health effects due to WBV, Table 1 and 2 reveal that the assessment based on $A(8)$ gives different results in comparison with the assessment based on $VDV(8)$. The results of the assessment based on $A(8)$ indicate a low to moderate probability of adverse health effects, while the results of the assessment based on $VDV(8)$ indicate a high probability of adverse health effects. This discrepancy is understandable, as the crest factor of the measured vibration signals are high, which indicates that the measured signals contain multiple shocks. In this regard, the assessment based on $A(8)$, which is not sensitive to the shocks contained in the vibration signal, will underestimate the severity of the WBV-exposure. Moreover, the assessment based on $VDV(8)$, which is more sensitive to the shocks contained in the vibration signal, will provide a better assessment of the severity of the WBV [14]. Furthermore, based on a study of the relation between the alternative WBV-exposure analyses and the occurrence of low back pain (LBP) among professional drivers, Bovenski [23] concludes that $VDV$ analysis provides a better prediction for the occurrence of LBP than analysis based on root-mean-square acceleration ($a_{\text{rms}}$). Thus the assessment should be based on $VDV(8)$.

The results of the VDV analysis indicate that the driver of the scaling machine is exposed to potentially harmful levels of WBV. This finding supports the notion that mine workers operating such machines are exposed to a high level of WBV [24]. Several studies have reported that underground mine workers who operate mobile equipment have a higher prevalence of low back injury and neck injury when compared to underground mine workers who do not operate mobile equipment; and that a high level of WBV-exposure is likely to contribute to this high prevalence [11].

3.2.1. Comparison of the WBV-exposure caused by the scaling machine and that caused by other mining equipment
To gain a better understanding of the characteristics of the WBV-exposure caused by the scaling machine, the results are compared to those for the WBV-exposure caused by other mining equipment (used both in underground and open pit mining). The comparison is shown in Figure 6.
Figure 6. WBV-exposure caused by mining equipment

It can be seen from Figure 6 that the characteristics of the WBV-exposure caused by the scaling machine are different in comparison with the characteristics of the WBV-exposure caused by other mining equipment. The average magnitude of the measured vibration signal is low, as can be seen from the value of \( A(8) \), which is very low. However, the signal contains multiple shocks with a high amplitude, which makes the value of VDV(8) high. This characteristic difference is due to the nature of the scaling activity. During the scaling activity, the scaling machine is in a static position and is stabilized by four supporting legs. A typical sequence of events in the scaling activity consists of a period of hammering and a rock falling period. In the hammering period, the operator detaches loose rocks from the rib and roof of the mine opening by oscillating the hydraulic hammer. The only source of vibration-exposure in this period is the vibration propagated from the hydraulic hammer. The character of this vibration-exposure is stationary and the magnitude depends on the impact factor of the hydraulic hammer. The root-mean-square acceleration \( (a_{rms}) \) of the WBV-exposure in this period is typically low (see Figure 7). In the rock falling period, the loose rocks are detached and may hit the arm and body of the scaling machine when they fall down. This will propagate impulsive vibration to the cabin. The combination of these two periods creates a low average magnitude of WBV-exposure, but the vibration contains multiple shocks with a high amplitude.
3.2.2. Reduction of WBV-exposure

Commonly, to reduce WBV-exposure, two strategies are applied. The first strategy is to apply administrative control and the second is to apply engineering control. When practising administrative control, one can adopt a policy involving regular rest periods and work rotation, for example, to reduce the duration of the WBV-exposure. When practising engineering control, reducing the vibration at its source and altering the path of its transmission from the source to the receiver are the two common methods. In the case of the scaling machine, reducing the vibration at its source is an unfeasible method, as the main source is the occurrence of falling rock. Altering the path of transmission can be achieved by properly and correctly inserting the suspension system (the floating cabin, seat suspension, etc.). Some important aspects should be considered in this strategy. The first aspect is the damping properties, as they will govern the amplification and attenuation region of the suspension system. It is quite common that the natural frequency of the seat system coincides with the natural frequency of the body of the seated person [5] and, as a result, that resonance occurs in the frequency where the seated person is more sensitive. The second aspect is the direction of the suspension system. In a study of the effect of seat design on vibration comfort, Wijaya et al. [27] found that the use of a sliding seat provides better attenuation of vibration containing transient vibration than the use of a fixed seat. The third aspect is the interaction of the seat design with other design aspects and the driver’s awareness of the importance of adopting a good sitting posture. It is quite common that a good seat design becomes ineffective because of improper use. An example of this problem is the use of the back rest, which is designed to prevent the driver from adopting a slumped posture (with the spine severely bent forward), as sitting in a slumped posture increases the force on the lumbar spine. A rule of thumb is that the more the back rest is reclined, the less is the stress in the lumbar spine [28]. However, a reclining back rest may reduce the sightline of the driver. Thus other details, such as the windscreen and the tilting cabin function, should be designed to provide an optimized sightline for the driver while keeping him or her seated in an appropriate posture. The

![Figure 7. Measured vibration signal for a typical sequence of events in the scaling activity](image-url)
design of the arm rest should also be taken into consideration, as one of the purposes of the arm rest is to provide additional support for the body weight and decrease the low back load. In a scaling machine, the manoeuvring is performed using a joystick and control buttons that are located on the arm rest. The dimensions of the arm rest should be designed to accommodate the anthropometric characteristics of the driver. Inappropriate dimensions may result in awkward forearm postures and a lack of proper support [28].

Another important aspect which will affect the WBV-exposure and which is quite commonly neglected is the maintenance of the suspension system. In the present study, it was revealed, after the measurement, that the ball joint on the piston rod of the horizontal suspension of the cabin was welded and could not move freely, which might reduce the effectiveness of the suspension system. Moreover, the rubber mountings for the cabin have never been replaced since the scaling machine was first used, which gives them an approximate age of 9,300 hours (6,500 electric motor hours and 2,800 diesel engine hours). Furthermore, the condition and the effectiveness of the rubber mountings have never been inspected. As the rubber mountings deteriorate with time and use, one can suspect that their effectiveness in attenuating vibration has been diminished. Based on a discussion with the maintenance engineer and maintenance personnel, it has been decided that they will perform a preventive replacement of the rubber mountings with a replacement interval of 1,500 electric motor hours. The replacement interval will be adjusted later on, when a better understanding of the wear rate of the particular rubber mountings has been gained.

3.3. ISO 2631-5 Analysis

The results of the WBV-exposure analysis based on ISO 2631-5 are summarized in Table 3.

<table>
<thead>
<tr>
<th>Mine room</th>
<th>Equivalent static compressive stress</th>
<th>Health risk assessment</th>
<th>Risk factor</th>
<th>Health risk assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_d$</td>
<td>$S_{ed}$</td>
<td>Low</td>
<td>0.42</td>
</tr>
<tr>
<td>1</td>
<td>0.23</td>
<td>0.37</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.34</td>
<td>0.53</td>
<td>Moderate</td>
<td>0.60</td>
</tr>
<tr>
<td>3</td>
<td>0.21</td>
<td>0.33</td>
<td>Low</td>
<td>0.37</td>
</tr>
</tbody>
</table>

The health risk assessment (see Table 3) shows that, based on the estimated daily equivalent spinal static compressive stress ($S_{ed}$), the probability of adverse health effects on the spine due to WBV-exposure caused by the scaling machine is low to moderate. Moreover, based on the risk factors ($R$), the probability is low. These results are contradicted by the health risk assessment based on VDV, which indicates a high probability of adverse health effects. The high crest factor value indicates that the measured vibration signals contain a great number of shocks with a high magnitude. Logically, the lumbar spine and the vertebral endplates are vulnerable to this type of WBV-exposure, and the health risk assessment based on spinal response (ISO 2631-5) should be able to show this. This contradictory result is consistent with the findings of previous studies. Results from studies on WBV-exposure analysis performed on LHD vehicles [13, 25], locomotives [29, 30] and forklifts [31] indicate that the assessment
based on $S_{ed}$ and $R$ gives a lower prediction of the health risk when compared to the assessment based on VDV.

In a study of the WBV-exposure caused by LHD vehicles, Smets et al. [25] argued in favour of two possible explanations for this inconsistency. The first is that the WBV-exposure caused by LHD vehicles is due to a prolonged dose of WBV at an $a_{rms}$ that exceeds the caution zone proposed by ISO 2631-1, and is less likely to be due to WBV resulting from the multiple shocks contained within the measured signal. The second explanation is simply that the limits specified in ISO 2631-5 are too high. In the present study, it has been found that the WBV-exposure caused by the scaling machine can be explained as exposure to the multiple shocks contained in the measured vibration signal, rather than as prolonged exposure to WBV at an $a_{rms}$ that exceeds the caution zone proposed by ISO 2631-1, as can be seen from Figure 9 and 10. Thus the first possible explanation is not applicable to the case of the scaling machine. Based on the results of the health risk assessment of LHD vehicles and the scaling machine, which are similar (i.e. a high probability of adverse health effects based on ISO 2631-1 and a low to moderate probability of adverse health effects based on ISO 2631-5), regardless of the fact that the characteristics of their WBV-exposure are different, there is evidence confirming that the second explanation is more acceptable. In fact the ISO 2631-5 standard itself points out that the assessment of adverse health effects due to WBV-exposure in ISO 2631-5 has not yet been epidemiologically validated and that the risk limits defined by the $S_{ed}$ and $R$ factors may need to be adjusted when more experience of their use has been gained and is compared with existing experience of the adverse effects of long-term exposure [15]. The findings of the present study, together with the findings of previous studies [13, 25, 29, 30, 31] provide strong evidence that can be used as a basis for adjusting the limits to appropriate values.

### 3.4. Limitation

One limitation of the present study is that the vibration measurements were conducted only for a single driver. The variability of the drivers (e.g. their varying body mass, body posture, driving behaviour, etc.) may affect the results and must be considered. Results from field and laboratory studies [32, 33, 34] show a negative relationship between the body mass index (BMI) and vibration-exposure. In this study, the participating driver had a BMI of 32. Thus it can be expected that a higher value of vibration-exposure will be measured ($a_{rms}$ and $VDV$) on a driver who has a lower value of BMI than the driver who participated in this study. Due to their different body posture characteristics, different drivers may adopt different driving postures to obtain their optimum sightline. This will have an effect on the variety of the pelvic motion and the resonance frequency of the seated human body [35, 36, 37], which will give differences in the vibration-exposure measured. To study the influence of the driver on the vibration measured on the scaling machine, a video camera was installed to record the scaling technique of different drivers. The preliminary results of the video recording analysis indicate a disparity in the driving behaviour of the different drivers. In performing the scaling task, each driver has a different style (e.g. different hammering intensity, boom manoeuvring, hammering interval, etc.), which may affect the vibration-exposure measured on the seated person. So far the underground mine studied has not drawn up a standard operating procedure...
stating how to perform the scaling task and drivers are allowed to adopt their own style in performing the task.

Despite its limitation, this study provides a basis for understanding the vibration-exposure caused by the scaling machine, which is a result which no similar research has achieved to date.

4. CONCLUSIONS
The conclusions derived from the present study are as follows:
1. The dominant frequencies of the measured vibration peaks of the scaling machine concur with the resonance frequencies of the body of the seated person and the frequency range where WBV can degrade the ability of the driver to perform manual tasks and is perceived by the driver to cause discomfort.
2. The character of the WBV-exposure caused by the scaling machine is different from the character of that caused by other mining equipment. The average magnitude of the measured vibration is low, but it contains multiple shocks with high amplitude.
3. The assessment of adverse health effects based on ISO 2631-1 indicates that the driver of the scaling machine is exposed to potentially harmful levels of WBV.
4. Administrative control (involving regular rest periods and a work rotation policy, for example) and engineering control (e.g. through appropriate seat design) can be adopted to reduce WBV-exposure. Inspection and maintenance of the suspension system should be performed to ensure its effectiveness.
5. Contradictory results are obtained when the assessment of adverse health effects is based on ISO 2631-5, which is a finding that supports the notion that the limits specified in ISO 2631-5 are too high.

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Paper V

Effect of operator, mining rooms and their interaction on the measured vibration level of a scaling machine

Wijaya, A.R. and Lundberg, J.

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The effect of the operator, the mine room and their interaction on the measured vibration level of a scaling machine

Andi R. Wijaya\textsuperscript{a,b} and Jan Lundberg\textsuperscript{a}

\textsuperscript{a}Division of Operation and Maintenance Engineering, Luleå University of Technology, SE – 971 87 Luleå, Sweden
\textsuperscript{b}Department of Mechanical and Industrial Engineering, Gadjah Mada University, Yogyakarta 55281, Indonesia

Abstract: The objective of the present study is to find out the effect of the operator, the mine room and their interaction on the vibration measured on a scaling machine. Vibration measurements were conducted for three different mine rooms and three different drivers. The vector sum value of the root-mean-square acceleration, the vector sum value of the acceleration dose and the kurtosis sum were utilized to quantify the measured vibration. The unbalanced two-way ANOVA and the Kramer-Tukey test were utilized for the statistical analysis. The results show that the operating styles of the drivers in performing scaling activity and their interaction with the mine rooms have no significant effect on the vector sum value of the acceleration, the vector sum value of the acceleration dose and the kurtosis sum value. The mine rooms have a significant effect on the kurtosis sum value and the vector sum value of the acceleration dose, but not on the vector sum value of the acceleration.

Keywords: scaling activity, driver, mine room, vibration measurement

Introduction

In the cycle of activities carried out in underground mining, scaling is a crucial activity for making the workplace safe. Scaling is an operation where loose rock is removed from the sidewalls (rib) and hanging walls (roof) of the mine opening after blasting. This activity is known to have a high number of accident occurrences, due to the nature of the task (Grau and Posser, 1997). The use of the scaling machine to replace hand scaling has successfully reduced the number of scaling-related accidents from about 10 per year to none or 1 per year (Quinteiro et al., 2001). Thus the scaling machine is becoming an important machine for underground mining. However, due to the combination of the hostile environment of the mine room and reliability-related issues, the scaling machine is identified as one of the major contributors to unplanned downtime. Data from one of the underground mines in Sweden have shown that more than 20% of the unplanned downtime of mobile equipment is related to scaling machines.

Considering the scaling machine system as a man–machine system, the reliability of the system is not only dependent on the reliability of the machine, but also on the reliability of the operator. Research on system reliability has shown that, depending upon the degree of human involvement in a system, 20% - 90% of the system failures are related to the operator (Lee et al., 1988). In this regard, attempts to improve the reliability of the system should also consider factors influencing the interaction between man and the machine, i.e. performance-shaping factors (PSFs). PSFs can be classified into three categories, namely external, internal and
task-specific PSFs (Pew and Mavor, 1998). External PSFs comprise those PSFs which originate outside the human and typically have negative impacts on human performance (e.g. vibration, noise, temperature, etc.). A previous study on whole-body vibration (WBV) exposure caused by a scaling machine (Wijaya and Lundberg, in press) has shown that the dominant frequencies of measured vibration peaks concur with the resonance frequencies of the body of the seated person and the frequency range where WBV can degrade the ability of the driver to perform manual tasks and is perceived by the driver to cause discomfort. It is suspected that these combinations can significantly influence the reliability of the system (i.e. the occurrences of failures). Internal PSFs are those PSFs which are specific to the individual (e.g. intelligence, personality, cognitive styles, etc.), which are difficult to assess and often combine in ways that are hard to predict. Task-specific PSFs include procedures, on-site training, task complexity, etc. Extent studies on the effects of operator and work practices on task performance have been performed, mainly related to high-risk tasks (e.g. nuclear power control, air traffic control, etc.). However, the number of studies related to mining machinery is limited. Patnayak et al. (2008) performed a study on an electric shovel used for oil sands mining, and reported that different operators adopted different styles in performing their task, which had a significant effect on the performance of the shovel (i.e. on the hoist power consumption and productivity). However, the impact of the different practices on eventual shovel maintenance and reliability is not known. Hall and McAree (2005), in a study on an excavator, found that, when comparing two digging styles adopted by operators, namely altus and brevis digging, the former style resulted in lower loading of the machine. To date, no study has been performed on the effects of operator and work practices on the task performance of a scaling machine.

A preliminary study was performed in one of the underground mines in northern Sweden. Based on the observations made in this preliminary study, it was established that in the mine concerned there was no standardized procedure for how to perform scaling activity. Different operators adopted different styles in performing scaling activity, which can affect the work performance, e.g. the quality of the work and the time required to accomplish the task, and can directly/indirectly affect the reliability of the scaling machine system. One way to diminish the variation of work practices is to establish a standardized procedure (i.e. a standard operating procedure). The objective of a standard operating procedure (SOP) is to ensure that all the workers are performing tasks in the same way (De Treville et al., 2005). Several studies show that the use of SOPs can improve the output consistency, efficiency and learning rate of a given process (Edelson and Bennet, 1998; Levinthal and March, 1993; Suzuki, 1993).

The concept of SOPs can be said to have originated in the era of Taylorism, but the development process of SOPs has changed drastically (De Treville et al., 2005) since then. In the era of Taylorism, SOPs were developed merely by management, as it was believed that the workers were incapable of designing efficient processes. Today, however, the active involvement of workers in the development and refinement of SOPs is encouraged and SOPs are commonly developed based on the best practices. Therefore, in the case of scaling activity, it is important to know which operating style in performing the task can be
considered as the best practice. Two aspects are considered in determining the best practice, first aspect is related to the task (i.e. how the operator accomplish the task) and second aspect is related to the machine (i.e. how the operator handle the machine). Comparison of work practices can be performed by subjective and objective measurement. In general, the objective measurement is considered to be more superior to the subjective measurement. In case of scaling activity, work practices can be measured objectively in term of time to accomplish the task, the power consumption, number of rework, mechanical load on the machine, number of machine failure, etc. In the present study, comparison of the work practices is performed in term of the mechanical load on the scaling machine by means of vibration measurement. The work practice which gives a lower measured vibration is considered to be better than other work practices that give a higher measured vibration. Furthermore, the performance of scaling activity is also affected by the geological conditions of the mine room. The geological conditions (such as the geological structure, rock mass, groundwater, etc.) can affect the rock stability of the mine room, which accordingly will also affect the performance of the scaling activity. In the underground mine concerned, the geological conditions in the different mine rooms vary significantly (Edelbro and Sandström, 2009). Therefore, in the comparison of the different work practices (i.e. scaling styles), the mine room should be taken into consideration, especially to determine the possibility of an interaction effect, i.e. whether a particular scaling style will give a lower vibration level for all the mine rooms or only for a particular mine room. The objective of the present study is to find out the effect of the operator, the mine room and their interaction on the vibration measured on the scaling machine.

Method

The present study was performed in a single underground mine located in Sweden. During the time when this study was performed, complex ore containing copper, lead, zinc, gold and silver and a gold-copper ore were extracted at a depth of 900 – 1,400 m below the ground surface. The predominant mining method applied in the mine is cut and fill mining with hydraulic backfill (Krauland et al., 2001). The host rock mass mainly comprises sericite-, cordierite- and chlorite-quartzite. The geological strength index (GSI) varies between 50 and 80 and the uniaxial compressive strength of the intact host rock varies between 65 and 150 MPa. The variation is mainly due to the different grades of alteration and foliation, and the chlorite content in the rock types (Edelbro and Sandström, 2009).

The scaling machine used in this study is a typical scaling machine used in underground mining in Sweden (see Figure 1). The overall dimensions are 3 m in height, 2.6 m in width and 14.6 m in length, and its unloaded weight is 27 tons. It has an articulated four-wheel drive chassis and four retractable stabilizer legs. It is bi-directional in operation. The driver sits in an air suspension seat which has a lumbar support and is mounted in an isolated cabin which can be tilted up to 13°. The maximum effective reach of the boom is 9 m (3 m in front of the machine), while the maximum reach at a 45° approach angle is 8.5 m. The scaling machine can be operated in both a diesel and an electro-hydraulic mode by a 6-cylinder in-line turbocharged diesel engine with a displacement of 7,146 cc (200 kW at 2,300 rpm) and a 2 x
30 kW electric motor. It is equipped with a hydraulic hammer (with an impact factor of 600 – 1,150 J and an impact rate of 10 – 25 Hz).

The experiment used in this study has a two-factor factorial design with replications (Montgomery, 2001) in which the driver and the mine room were crossed-fixed effects. Mine room in this study is defined as an opening space that immediately attach to the mine face (the exposed area of a mineral bed from which mineral is being extracted) and connecting to the mine ramp (a secondary or tertiary inclined opening, driven to connect levels, usually driven in a downward direction, and used for haulage). Measurements were conducted in three different mine rooms for three different drivers, which gave nine possible combinations. Due to the production scheduling, which is determined by the company with the aim of maximizing the utilization of the mine rooms, an equal replication for each combination could not be performed. The drivers participated voluntarily and their experience of operating a scaling machine varied from 3 – 25 years (the mean = 15 years). The three mine rooms were selected simply because, during the period when the present study was performed, excavation was taking place in these particular mine rooms. A study of the geological properties of each mine room was not performed.

A tri-axial accelerometer (ICP 356A02, PCB Piezotronics) was utilized in conjunction with a 4-channel, 24-bit resolution data acquisition device (NI 9234, National Instruments) to measure vibrations in three translational axes (the horizontal axis = z-axis, the lateral axis = y-axis, and the vertical axis = z-axis). Ideally, the accelerometer should be placed on the boom, but, due to the space restriction and the risk of the accelerometer being damaged, it was mounted on the part of the chassis that was directly connected to the boom (see Figure 2). The accelerometer had a frequency sensitivity range of 0.5 – 6,000 Hz. The vibration signals were recorded at a sampling frequency of 2,500 Hz and were low-pass filtered at 1,000 Hz to avoid aliasing. The duration of the vibration measurement for each replication was 1 hour. The vibration analyses were carried out with the Matlab software.
The measured vibration signals were analyzed in time domains. Three analysis methods were adopted. The first analysis method was the root-mean-square acceleration method, which is a standard method for quantifying the global severity of a vibration (Lalanne, 2009a). This method is basically used to express the overall energy of a particular random vibration event by means of calculating the mean value of the absolute value of the signal. The root-mean-square acceleration ($a_{rms}$), in m/s$^2$, is formulated as:

$$ a_{rms} = \sqrt{\frac{1}{T} \int_0^T a^2(t) dt} $$  \hspace{1cm} (1) $$

where $a(t)$ is the instantaneous acceleration and $T$ is the duration of the measurement. In assessing multi-axis vibration measurement, individual measurements made in orthogonal axes should be combined. For the root-mean-square acceleration, the orthogonal axes are combined into the vector sum value of the acceleration by using the root sum of the squares. The vector sum value of the acceleration ($a_{xyz}$), in m/s$^2$, is calculated as:

$$ a_{xyz} = \sqrt{a_x^2 + a_y^2 + a_z^2} $$  \hspace{1cm} (2) $$

where $a_x$, $a_y$, and $a_z$ are the root-mean-square acceleration in the x-axis, y-axis, and z-axis, respectively. The root-mean-square acceleration method has a limitation in quantifying the severity of a vibration signal containing shocks, in that the algorithm is relatively insensitive to occasional shocks. In the present study, the vibration induced by scaling activity is characterized by a random signal containing shocks which occur due to falling rock hitting the machine. Therefore two additional methods, namely acceleration dose calculation and the kurtosis method, which are sensitive to occasional shocks, were also utilized.

The second analysis method used was acceleration dose calculation, which is a type of counting method. Counting methods were initially developed for the study of aeronautical structures (Lalanne, 2009b), and are now commonly used for the study of fatigue damage in structures. The basic principle of acceleration dose calculation involves counting the occurrences of acceleration peaks in the measured vibration signal and summing up all the acceleration peaks. A peak is defined here as the maximum absolute value of the response acceleration between two consecutive zero crossings. The acceleration dose ($a_D$), in m/s$^2$, is formulated as:

$$ a_D = \left[ \sum_i a_{pi}^4 \right]^{1/4} $$  \hspace{1cm} (3) $$

where $a_{pi}$ is the $i$th peak of the acceleration. The fourth power term in the acceleration dose calculation is used to take into account the differences in the peaks’ magnitude (i.e. the differences between high peaks and low peaks). Peaks of a considerably lower magnitude than the highest peak will not significantly contribute to the acceleration dose value. For multi-axis vibration measurement, individual measurements made in orthogonal axes are combined into the vector sum value of the acceleration dose by using the root sum of the quad. The vector sum value of the acceleration dose ($a_{Dxyz}$), in m/s$^2$, is calculated as:

$$ a_{Dxyz} = \left[ a_{Dx}^4 + a_{Dy}^4 + a_{Dz}^4 \right]^{1/4} $$  \hspace{1cm} (4) $$

where $a_{Dx}$, $a_{Dy}$, and $a_{Dz}$ are the acceleration doses in the x-, y-, and z-axis, respectively.
The third analysis method applied was the kurtosis method. Kurtosis is a statistical parameter used to measure the size of the tails of distribution. In the analysis of vibration signals, kurtosis is used for measurement of the peakedness of a signal. When there are more peaks in a signal, the kurtosis value becomes larger (Said and Sharaf-Eldeen, 2011). The kurtosis method is commonly used for machine diagnosis, since the vibration signal from an undamaged machine is not impulsive, while that from a damaged machine contains shocks. The kurtosis value \((K)\) is formulated as:

\[
K = \frac{1}{T} \int_0^T (a(t) - \bar{a})^4 dt \left( \frac{1}{T} \int_0^T a^2(t) dt \right)^{-\frac{3}{2}}
\]

where \(a(t)\) is the instantaneous acceleration and \(T\) is the duration of the measurement. The vibration induced by scaling activity is characterized by a multi-axis excitation where the magnitude of the vibration in the three axes is comparable. Therefore, when examining the severity of the vibration, the analysis should consider all the three axes simultaneously, rather than analyze them individually. In this process, the kurtosis values of individual measurements made in orthogonal axes are combined into the kurtosis sum. The kurtosis sum \((K_{xyz})\) here is calculated as the scalar sum of the kurtosis value and is formulated as:

\[
K_{xyz} = K_x + K_y + K_z
\]

where \(K_x\), \(K_y\), and \(K_z\) are the kurtosis values in the \(x\)-axis, \(y\)-axis, and \(z\)-axis, respectively.

For the statistical analysis, due to the inequality of the numbers of replications, the unbalanced two-way ANOVA using the General Linear Model procedure was utilized (Rutherford, 2001). The null hypotheses tested are as follows: \(H_0\) – the driver has no effect on the measured vibration (i.e. \(a_{xyz}\), \(a_{Dxyz}\) and \(K_{xyz}\)); \(H_0\) – the mine room has no effect on the measured vibration; and \(H_0\) – there is no interaction between the driver and the mine room which affects the measured vibration. Tukey-Kramer multiple comparison tests were used for the post hoc test (Montgomery, 2001). The alpha significance level \((\alpha)\) used in all the statistical tests is 0.05. The statistical analyses were performed using the Minitab software.

**Results and discussion**

The results for the measured vibrations for the three different mine rooms and the three different drivers are presented in Table 1. The results are presented as mean and standard deviations of the vector sum value of the acceleration, the kurtosis sum and the vector sum value of the acceleration dose. The results of a statistical analysis of these measurement results are given as \(p\) values in Table 2. (The \(p\) value signifies the probability that a test statistic is significantly different from the null hypothesis.)
Table 1 Mean and standard deviations of the vector sum value of the acceleration ($a_{xyz}$), the kurtosis sum ($K_{xyz}$) and the vector sum value of the acceleration dose ($a_{Dxyz}$)

<table>
<thead>
<tr>
<th>Driver</th>
<th>Mine room</th>
<th>No. of measurements</th>
<th>$a_{xyz}$ (ms$^{-2}$)</th>
<th>Mean</th>
<th>SD</th>
<th>$a_{Dxyz}$ (ms$^{-2}$)</th>
<th>Mean</th>
<th>SD</th>
<th>$K_{xyz}$</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>3</td>
<td>0.89</td>
<td>0.25</td>
<td></td>
<td>61.26</td>
<td>18.03</td>
<td></td>
<td>350.19</td>
<td>177.26</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>3</td>
<td>1.03</td>
<td>0.25</td>
<td></td>
<td>76.83</td>
<td>10.05</td>
<td></td>
<td>256.28</td>
<td>82.57</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>5</td>
<td>0.91</td>
<td>0.06</td>
<td></td>
<td>64.55</td>
<td>13.83</td>
<td></td>
<td>99.39</td>
<td>31.69</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>8</td>
<td>0.89</td>
<td>0.16</td>
<td></td>
<td>60.56</td>
<td>9.32</td>
<td></td>
<td>301.33</td>
<td>258.10</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>4</td>
<td>0.90</td>
<td>0.15</td>
<td></td>
<td>63.30</td>
<td>15.87</td>
<td></td>
<td>126.81</td>
<td>91.12</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>5</td>
<td>0.89</td>
<td>0.07</td>
<td></td>
<td>51.95</td>
<td>7.87</td>
<td></td>
<td>77.66</td>
<td>35.00</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>A</td>
<td>4</td>
<td>0.85</td>
<td>0.24</td>
<td></td>
<td>53.60</td>
<td>8.11</td>
<td></td>
<td>172.40</td>
<td>69.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>3</td>
<td>0.86</td>
<td>0.10</td>
<td></td>
<td>72.11</td>
<td>10.97</td>
<td></td>
<td>252.44</td>
<td>61.18</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>5</td>
<td>1.05</td>
<td>0.08</td>
<td></td>
<td>66.65</td>
<td>8.48</td>
<td></td>
<td>76.10</td>
<td>36.90</td>
<td></td>
</tr>
</tbody>
</table>

Table 2 Results of a two-way ANOVA test for the vector sum value of the acceleration ($a_{xyz}$), the kurtosis sum ($K_{xyz}$) and the vector sum value of the acceleration dose ($a_{Dxyz}$)

<table>
<thead>
<tr>
<th>Source of variation</th>
<th>$p$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$a_{xyz}$</td>
</tr>
<tr>
<td>Driver</td>
<td>0.66</td>
</tr>
<tr>
<td>Mine room</td>
<td>0.46</td>
</tr>
<tr>
<td>Driver × mine room</td>
<td>0.31</td>
</tr>
</tbody>
</table>

*Statistically significant at $\alpha = 0.05$

Table 2 shows that the operator has no significant effect on the vector sum value of the acceleration, the kurtosis sum value and the vector sum value of the acceleration dose. This result is unexpected, as it is inconsistent with the results of the preliminary study. In the preliminary study, observations were performed by means of videotape analysis, for which purpose a video camera was installed to record the scaling technique of different drivers. The results indicate that a disparity in the driving behaviour of the drivers exists. Each driver has a different operating style (involving, for example, a different hammering intensity, boom manoeuvring, hammering interval, etc.) in performing the scaling task. Therefore, it was expected that an analysis of the vibration measurement would confirm the results of the preliminary study. However, the vibration measurement shows that the different scaling styles of the drivers do not significantly affect the measured vibration signal and the vibration analysis is not able to highlight the differences among the drivers. The measured vibration signal (see Figure 3) is dominated by the occurrence of shocks which occur due to falling rock hitting the machine. The occurrence of falling rock is beyond the control of the driver and is determined by the inherent characteristics of the mine room, rather than the operating style of the driver in performing scaling activity.
Table 2 also shows that the mine room has no significant effect on the vector sum value of the acceleration, but it does have a significant effect on the kurtosis sum value and the vector sum value of the acceleration dose. To know which particular mine room differs from the other mine rooms, Tukey-Kramer multiple comparison tests were conducted and the results are shown in Table 3.

Table 3 Results of Tukey-Kramer multiple comparison tests for the kurtosis sum ($K_{xyz}$) and the vector sum value of the acceleration dose ($a_{Dxyz}$)

<table>
<thead>
<tr>
<th>Pair comparison of mine rooms</th>
<th>$a_{Dxyz}$ Mean differences</th>
<th>$a_{Dxyz}$ p value</th>
<th>$K_{xyz}$ Mean differences</th>
<th>$K_{xyz}$ p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – 2</td>
<td>-12.3</td>
<td>0.04*</td>
<td>62.8</td>
<td>0.55</td>
</tr>
<tr>
<td>1 – 3</td>
<td>-2.6</td>
<td>0.82</td>
<td>190.3</td>
<td>0.01*</td>
</tr>
<tr>
<td>2 – 3</td>
<td>9.7</td>
<td>0.11</td>
<td>127.5</td>
<td>0.08</td>
</tr>
</tbody>
</table>

* Statistically significant at $\alpha = 0.05$

Table 3 indicates a discrepancy between the two analysis methods ($a_{Dxyz}$ and $K_{xyz}$). Based on $a_{Dxyz}$, mine room 1 and 2 are significantly different, while, based on $a_{Dxyz}$, the difference is not significant. On the other hand, the difference between mine room 1 and 3 is not significant based on $a_{Dxyz}$, while, based on $K_{xyz}$, the difference is significant. To gain a better understanding of this discrepancy, the two analysis methods were tested for a series of artificial signals. The artificial signals consisted of a pure sinusoidal signal and a shock signal (i.e. to represent the occurrence of falling rock), with the number of shocks in the composed signal varying from 1 to 10 (see Figure 4). The acceleration dose and the kurtosis value of the composed signals are presented in Figure 5.
Figure 5 shows that, as the number of shocks in the signal increases, the increase in the acceleration dose value is monotonic, while the increase in the kurtosis value is not monotonic. When the number of shocks in the signal is more than 6, the kurtosis value decreases. The reason for this non-monotonic behaviour is related to the formulation of kurtosis. Kurtosis is basically determined by two factors, the average of the fourth power of the deviations from the mean as the numerator and the fourth power of the standard deviation as the denominator. When the number of shocks in the signal increases, the value of the numerator and the denominator increases. However, at some point (in this example when the number of shocks is more than 6), the denominator increases faster than the numerator. Consequently, the kurtosis value decreases. From this illustration, it can be concluded that the kurtosis method is suitable for analyzing signals containing infrequent shocks, but is not suitable for analyzing signals containing frequent shocks (as in the case of the present study).

Table 3 indicates that, based on the Tukey-Kramer test, the vector sum value of the acceleration dose of the vibration measured in mine room 1 is significantly lower than that of the vibration measured in mine room 2. One possible explanation of this difference is that the variability of the inherent rock mass properties of the mine rooms affects the rock stability of the rooms. In the present study, however, a measurement of the rock properties of each mine...
room was not performed, and therefore a precise explanation of the difference between mine room 1 and 2 cannot be provided. However, in general, the geology of the mine concerned is complex and irregular (Rådberg et al., 1992). The host rocks are mainly composed of sericitic, cordieritic and chloritic quartzite, which is considered as a strong rock (Li, 2005). However, in the immediate vicinity of the orebody, weak chloritic schist which varies in thickness between 0 and 3 metres is often observed. The strength of this schist, depending on the chlorite content, can be extremely low (Board et al., 1992). The ore and host rocks have a foliated metamorphic texture (i.e. a schistose texture) and were affected by tectonically induced shear movements which resulted in a very irregular geological structure in the mine concerned (Rådberg et al., 1992). Furthermore, the rock stability of the mine room is also affected by the mining activity (i.e. blasting), which has induced stresses on the rock around the perimeter of the opening. The combination of these two factors (the inherent rock mass properties and the blast damage to the rock) has resulted in a variability of the rock stability between the mine rooms, and maybe even within the mine rooms.

As has been mentioned in the introduction, the initial motive of the present study was to find the best practice that could be used as a base for developing an SOP. The results of the present study, however, indicate that the style of the operator in performing the scaling task has no significant effect on the measured vibration level. However, it cannot be concluded that a best practice for performing scaling activity does not exist. The measured vibration level is only one of the possible parameters that can be used as a basis for determining the best practice in performing scaling activity. Other parameters such as the quality of the work, the time required to accomplish the task, the power consumption, etc. should also be taken into consideration. Furthermore, the current trend in the mining industry is lean mining (i.e. applying the lean concept in the production system) (Jon et al., 2000; Dunstan et al., 2006; Klippel et al., 2008; Wijaya et al., 2009). In the mining company concerned, for example, the lean concept has been gradually implemented during the past three years (Boliden Mineral AB, 2009). As standardization is one of the critical foundations in the lean concept, data regarding the best practice for each mining activity (e.g. scaling activity) are required. Therefore, further research is needed to determine which work practice shall be considered as the best practice for performing scaling activity.

Conclusions

The conclusions derived from the present study are as follows:
1. The operators and their interaction with the mine rooms have no significant effect on the vector sum value of the acceleration, the vector sum value of the acceleration dose and the kurtosis sum value.
2. The mine rooms have a significant effect on the kurtosis sum value and the vector sum value of the acceleration dose, but not on the vector sum value of the acceleration.
3. For analyzing signals containing frequent shocks, acceleration dose analysis provides more consistent results than kurtosis analysis.
Acknowledgments

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