Reliability and Operating Environment Based Spare Parts Planning

Behzad Ghodrati

Luleå University of Technology
Division of Operation and Maintenance Engineering

Reliability and Operating Environment Based Spare Parts Planning

Behzad Ghodrati
Division of Operation and Maintenance Engineering
Luleå University of Technology
Abstract

The required spare parts planning for a system/machine is an integral part of the product support strategy. The number of required spare parts can be effectively estimated on the basis of the product reliability characteristics. The reliability characteristics of an existing machine/system are influenced not only by the operating time, but also by factors such as the environmental parameters (e.g. dust, humidity, temperature, moisture, etc.), which can degrade or improve the reliability. In the product life cycle, for determining the accurate spare parts needs and for minimizing the machine life cycle cost, consideration of these factors are useful.

Identification of the effects of operating environment factors (as covariates) on the reliability may facilitate more accurate prediction and calculation of the required spare parts for a system under given operating conditions. The Proportional Hazard Model (PHM) method is used for estimation of the hazard (failure) rate of components under the effect of covariates.

The existing method for calculating the number of spare parts on the basis of the reliability characteristics, without consideration of covariates, is modified and improved to arrive at the optimum spare parts requirement.

In this research, an approach has been developed to forecast and estimate accurately the spare parts requirements considering operating environment and to create rational part ordering strategies. Subsequently, two models (exponential and Weibull reliability based) considering environmental factors are developed to forecast and estimate the required number of spare parts within a specific period of the product life cycle. This study only discusses non-repairable components (changeable/service parts), which must be replaced upon failure.

To test the models, the data collection and classification was carried out from two mining companies in Iran and Sweden and then the case studies concerning spare parts planning based on the reliability characteristics of parts, with/without considering the operating environment were done. The results show clearly the differences between the consumption patterns for spare parts with and without taking into account the effects of covariates (operating environment) in the estimation.

The final discussion treats a risk analysis of not considering the system’s working conditions through a non-standard (new) event tree approach in which the organizational states and decisions were included and taken into consideration in the risk analysis. In other words, we used the undesired states instead of barriers in combination with events and consequent changes as a safety function in event tree analysis. The results of this analysis confirm the conclusion of this research that the system’s operating environment should be considered when estimating the required spare parts.

Keywords: Product support; Spare parts planning, Reliability, Proportional hazard model, Operating environment, Risk analysis, non-repairable components, Renewal process
Acknowledgments

The present research work has been carried out during the years 2001-2005, at the Division of Operation and Maintenance Engineering, Luleå University of Technology, Sweden, under the supervision of Professor Uday Kumar, Head of the Division. The research program was sponsored mainly by Luleå University of Technology and received partial financial support from the Euro project, and these contributions are thankfully acknowledged.

I would like to express my gratitude to my supervisor, Professor Uday Kumar, not only for providing me with all the necessary facilities, guidance, and continuous support during the research, but also for accepting me as a PhD student, and arranging a scholarship and solving my financial problem.

I also wish to express my sincere thanks to Professor Per Anders Akersten for his unspiring help and useful comments in improving my work and scientific writings.

I am particularly grateful to all the colleagues at my Division, Javad Barabadi, Arne Nissen, Farid Monsefi and especially to Aditya Parida for his sincere fellowship and support. And I am also thankful to Eva Setterqvist and Monica Björnfot for their unsparing kindness and aid.

I wish to express my gratitude to my family, my wife, Saeideh, who suffered hardships but encouraged me to “go on”, and my son, Shayan, who also understood me.

I am also indebted to my parents, especially my mother, who blessed me, and my brothers for their support, kindness, and encouragement.

I would like to thank all my Iranian friends at Luleå University of Technology, Javad Barabadi, Parviz Pourghahramani, Abbas Keramati, Mohammad-Reza Akhavan and others.

I would like to express my gratitude to my wife and my parents by dedicating this thesis to them.

Behzad Ghodrati

Luleå, December 2005
List of appended papers


- Ghodrati, B., Kumar, U. and Kumar, D. (2003), “Product support logistics based on product design characteristics and operating environment”, in the proceeding of 38th Annual International Logistics Conference and Exhibition (SOLE-2003), 12-14 August, Huntsville, Alabama, USA

Additional papers, not included


- Ghodrati, B., Kumar, U. and Kumar, D. (2003), “Product support (Spare parts procurement) strategy based on reliability characteristics and geographical location”, in the proceeding of *International Conference on Industrial Logistics*, 16-19 June, Vaasa, Finland
Contents

Abstract ........................................................................................................................ iii
Acknowledgments ........................................................................................................... v
List of appended papers ............................................................................................... vii
Additional papers, not included ................................................................................... vii
Contents ........................................................................................................................ ix
Notation and some definitions .................................................................................. xi
PART I – THEOREtical FOUNDATION ................................................................ 1
  1 Introduction and background ........................................................................ 1
     1.1 Problem definition and discussion .................................................... 2
     1.4 Research proposition and objective ............................................. 6
     1.5 Research question ........................................................................... 6
     1.6 Focus and delimitation ................................................................. 7
     1.7 Outline of the thesis ....................................................................... 7
  2 Research design ................................................................................................. 9
     2.1 Dimensions of research ................................................................. 9
        2.1.1 The use of research ................................................................ 9
        2.1.2 The purpose of research studies ......................................... 9
        2.1.3 Research approach ............................................................... 11
        2.1.4 Research strategy ................................................................. 13
        2.1.5 Data collection techniques used ....................................... 14
        2.1.6 Data analysis ...................................................................... 15
     2.2 Research quality ............................................................................... 16
        2.2.1 Reliability ............................................................................ 16
        2.2.2 Validity ............................................................................... 17
     2.3 Steps of the research process ......................................................... 17
  3 Theoretical framework – Basic concepts related to the research ............. 21
     3.1 Product support ............................................................................. 21
        3.1.1 Factors influencing the product’s dependability ................. 24
        3.1.2 Application type of the product ......................................... 25
        3.1.3 Geographical locations of the product ............................. 26
     3.2 Product support logistics ................................................................ 27
        3.2.1 Spare parts management ................................................... 27
        3.2.2 Spare parts inventory ......................................................... 28
     3.3 Reliability issues ............................................................................. 33
        3.3.1 Reliability characteristics (measures) ................................ 35
        3.3.2 Reliability prediction methods .......................................... 36
        3.3.3 Reliability models ............................................................... 39
        3.3.4 Operating-environment-based reliability analysis ............ 40
           3.3.4.1 Proportional hazard model (PHM) .................. 41
     3.4 Risk assessment and analysis ......................................................... 45
        3.4.1 Performance measurement ................................................ 45
        3.4.2 Risk definition ..................................................................... 46
        3.4.3 Risk analysis process ........................................................ 48
           3.4.3.1 Fault tree analysis .................................................... 48
           3.4.3.2 Event tree analysis ................................................... 50
PART II – EMPIRICAL WORK AND FINDINGS ........................................... 53
  4 Research project and process ...................................................................... 53
     4.1 Analysis design - Spare parts estimation (forecasting) ................... 54
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1.1 Product reliability characteristics and operating environment based spare parts estimation</td>
<td>55</td>
</tr>
<tr>
<td>4.1.2.1 Poisson process model for forecasting the required spare parts</td>
<td>57</td>
</tr>
<tr>
<td>4.1.2.2 Renewal process model for forecasting the required spare parts</td>
<td>58</td>
</tr>
<tr>
<td>4.2 Spare parts classification</td>
<td>61</td>
</tr>
<tr>
<td>4.3 Study and analysis of the exponential and the Weibull models in spare parts estimation</td>
<td>61</td>
</tr>
<tr>
<td>5 Validity and reliability of model</td>
<td>67</td>
</tr>
<tr>
<td>5.1 Case study design</td>
<td>67</td>
</tr>
<tr>
<td>5.2 Data collection and classification</td>
<td>68</td>
</tr>
<tr>
<td>5.3 Case study analysis</td>
<td>72</td>
</tr>
<tr>
<td>5.4 Discussion</td>
<td>74</td>
</tr>
<tr>
<td>6 Research results and discussion</td>
<td>77</td>
</tr>
<tr>
<td>7 Summary of appended papers</td>
<td>79</td>
</tr>
<tr>
<td>7.1 First paper</td>
<td>79</td>
</tr>
<tr>
<td>7.2 Second paper</td>
<td>80</td>
</tr>
<tr>
<td>7.3 Third paper</td>
<td>81</td>
</tr>
<tr>
<td>7.4 Fourth paper</td>
<td>82</td>
</tr>
<tr>
<td>7.5 Fifth paper</td>
<td>83</td>
</tr>
<tr>
<td>PART III – CONCLUSIONS</td>
<td>85</td>
</tr>
<tr>
<td>8 Concluding remarks</td>
<td>85</td>
</tr>
<tr>
<td>8.1 Research contribution</td>
<td>86</td>
</tr>
<tr>
<td>8.2 Self criticism</td>
<td>87</td>
</tr>
<tr>
<td>8.3 Suggestions for future research</td>
<td>88</td>
</tr>
<tr>
<td>References</td>
<td>89</td>
</tr>
<tr>
<td>Appendix</td>
<td>97</td>
</tr>
</tbody>
</table>
**Notation and some definitions**

*EOQ*: Economic order quantity

*σ*: Standard deviation

*Φ_{t-p}*: t-distribution value

*Φ_p^{-1}*: Inverse normal function

*t*: System/machine operation time

*β*: Shape parameter

*η*: Scale parameter

*λ(t)*: Failure rate

*R(t)*: Reliability function

*F(t)*: Failure function

*f(t)*: Probability density function

*MTBF*: Mean time between failure

*MTTF*: Mean time to failure

*MTTR*: Men time to repair

*MTTS*: Mean time to support

*h(t)*: Hazard function

*A(t)*: Cumulative failure (hazard) rate

*P(t)*: Probability function

*N*_: Total number of required spare parts

*M(t)*: Renewal function

*Φ*: Average time to failure

*ζ*: Coefficient of variation of the time to failure

*E[N(t)]*: Expected value of number of failure

*z*: Covariate parameter

*α*: Regression coefficient

*L*: Lead time

*d*: Average demand

**Reliability function**

The reliability of an item is the ability of the item to perform the required function for a specified period of time (or mission time) under given operating conditions (International Electrotechnical Vocabulary [IEV] 191-12-01). The reliability function,
Reliability and Operating Environment Based Spare Parts Planning

$R(t)$, is defined as the probability that the system will not fail during the stated period of time, $t$, under stated operating conditions.

$$R(t) = P\text{ (the system does not fail during }[0, t]) = 1 - F(t)$$

Reliability is a decreasing function with time $t$ i.e. for $t_1 < t_2$, $R(t_1) > R(t_2)$, and it is usually assumed that $R(0) = 1$.

In the above equation, $F(t)$ is a failure function and is a basic (logistic) reliability measure. It is defined as the probability that an item will fail before or at the moment of operating time $t$. Here time $t$ is used in a generic sense and it can have units such as hours, number of cycles, etc.

$$F(t) = P\text{ (failure will occur before or at the time } t) = P\text{ (TTF} \leq t)$$

where $f(t)$ is the probability density function of the time-to-failure random variable (TTF) [In the case of an absolutely continuous distribution function].

**Mean time to failure (MTTF)**

MTTF represents the expectation of the time to failure (International Electrotechnical Vocabulary [IEV] 191-12-07). It is used as a measure of reliability for non-repairable items. Mathematically, MTTF can be defined as:

$$MTTF = \int_0^\infty f(t)dt = \int_0^\infty R(t)dt$$

**Mean operating time between failures (MTBF)**

MTBF represents the expectation of the operating time between failures (International Electrotechnical Vocabulary [IEV] 191-12-09). MTBF is extremely difficult to predict for fairly reliable items. However, it can be estimated if the appropriate failure data are available. In fact, it is very rarely predicted with an acceptable accuracy.

**Mean time to repair (MTTR)**

MTTR represents the expectation of the time to restoration (International Electrotechnical Vocabulary [IEV] 191-13-08).

**Mean time to support (MTTS)**

MTTS can be defined as a term that represents the expectation of the time to support and is a measure of the system’s supportability characteristics.

**Failure rate**

The failure rate is the limit, if it exists, of the quotient of the conditional probability that the instant of a failure of a non-repaired item falls within a given time interval $(t, t + \Delta t)$ and the duration of this time interval, $\Delta t$, when $\Delta t$ tends to zero, given that the item has not failed up to the beginning of the time interval.

The instantaneous failure rate (also called the hazard rate in the same sense in this thesis) is expressed by the formula:
where $F(t)$ and $f(t)$ are respectively the distribution function and the probability density of the failure instant, and where $R(t)$ is the reliability function (International Electrotechnical Vocabulary [IEV] 191-12-02).

The term is applicable to non-repairable items and to repairable items before the first failure, but also has meaning for a repairable item after it has failed and been repaired (Blanks, 1998). Meanwhile, the failure rate for a stated period in the life of an item is the ratio of the total number of failures in a sample to the cumulative observed time for that sample. However, usually and also in this thesis, these two terms (hazard rate and failure rate) are used in the same sense.

**Covariates**

All those factors which may have an influence on the reliability characteristics of a system are called covariates. Covariates are also called explanatory variables. Examples of covariates are the operating environment (dust, temperature and humidity, etc.), the skill of operators, etc.

**Strata**

The strata of a data set are obtained by grouping the data on the basis of discrete values of a single or combinations of a set of covariates. For example, a particular covariate may be assigned two discrete values to represent low and high (or bad and good) operating characteristic parameter values associated with the failure of an item. This covariate can be used to form two strata of the failure.

**Renewal process**

The failure process for which the times between successive failures are independent and identically distributed with an arbitrary distribution is called a renewal process.
PART I – THEORETICAL FOUNDATION

1 Introduction and background

Generally, due to a lack of technology and other compelling factors (like economic limitations, environmental conditions, etc.), in the design phase, it is impossible to design a product that will fulfill its expected function completely during its entire life cycle. Therefore, the need for support is becoming vital to enhance system effectiveness and minimize unplanned stoppages. Product support, also commonly referred as after sales service, consists of the different forms of assistance and support that manufacturers offer customers to help them gain the maximum value from products. For instance, typical technical forms of support include installation, maintenance and repair services, and the availability of spare parts. This assistance can be provided in different forms and in different stages of the product life cycle. Product support falls into two broad categories, namely support to the customer and support to the product. The research presented in this thesis is focused on support to the product, which is greatly influenced by the product reliability characteristics. The product reliability characteristics (see e.g. Blanchard and Febrycky, 1998; Markeset and Kumar, 2001) are important for us to understand. Specifically, it is important to ascertain:

- how the product reliability characteristics influence the product support and
- how to evaluate support requirements (e.g. spare parts), using what are called dependability characteristics.

The operating environment parameters for the product also influence the product’s dependability characteristics. Consequently, these factors influence the dimensioning of product support and its evaluation and forecasting to achieve efficiency and cost-effectiveness. For existing systems and machines, incorporating environmental parameters in reliability analysis is a powerful tool for forecasting the services, repairs and spare parts required due to the effect of environmental factors.

In fact, reliability is a function of time/load and the operating environment of a product, which comprises factors such as the surrounding environment (e.g. temperature, humidity and dust), condition-indicating parameters (e.g. vibration and pressure), and human aspects (e.g. the skill of the operators). The variables related to these factors are referred to as covariates. Spare parts constitute one of the product support issues that can be divided into two types, namely repairable and non-repairable. Actually, for many types of spare parts, subassemblies and modules, replacing them upon failure is more economical than repairing them. For example, bearings, gears, electronic modules, gaskets, seals, filters, light bulbs, hoses, and valves are parts which are mostly replaced rather than repaired. These parts are referred to as service parts or non-repairable parts. In the present research we deal with non-repairable parts.

Spare parts management and logistics is an aspect of product support management which influences the product life cycle cost. The availability of spare parts upon
Reliability and Operating Environment Based Spare Parts Planning

demand decreases the product down-time and increases the utilization of the system/machine and consequently the profitability of the project. If the optimum number of spare parts is stored in the inventory, this minimizes the product life cycle cost as a goal function, and the optimum number is calculated taking different factors into account, such as the part criticality, the part purchasing cost, the distance between the manufacturer and user, and the lead time. The principle objective of any inventory management system is to achieve an adequate service level with the minimum risk and the minimum inventory investment. Since investments in spare parts can be substantial, management is interested in decreasing stock levels whilst maximizing the service performance of a spare part management system. To assess the result of improvement actions, performance indicators (such as the fill rate and service rate) are needed. For example, sometimes the duration of unavailability of parts is a major factor of concern. Then the waiting time for parts is a more relevant performance indicator.

Performance measurement for risk concerning spare parts (unavailability, incorrect, obsolesce, etc), represents a problem in its own right. Usually risk items in spare parts are not issued, but their presence in the stock is justified. In this control category, the most important factor in performance measurement is the risk of shortage. The target level of inventory, reorder point, and order quantity are calculated on the basis of the significance of each category for preventing shortages.

1.1 Problem definition and discussion

As a result of some limitations in the design phase, such as the state of the art of the technology used, economic limitations, environmental conditions, etc., systems/machines are not able to meet users’ requirements fully in terms of system performance and effectiveness. This is often due to poorly designed reliability and maintainability characteristics combined with a poor maintenance and product support strategy, which often lead to unplanned and unforeseen stoppages (Markeset and Kumar, 2003a). Therefore, the need for support to compensate for this weakness is vital.

When studying the concept of “product support”, there are a few questions whose answers clarify the subject, namely:

- What is product support? And why is it required and important?
- Which factors influence product support and how?
- How can we consider and integrate these factors in product design and product support to minimize the product’s life cycle cost (LCC)?

The concept of product support/after sales service includes the different forms of assistance that manufacturers/suppliers offer customers to help them gain the maximum profit from a product (Markeset, 2003). Typical forms of support include installation, training the operators/users of the product, maintenance and repair services (generally termed service), documentation, the availability of spare parts, upgrades (enhanced functionality), customer consulting, and warranty schemes (Goffin, 2000). In fact, product support entails all the activities necessary “to ensure that a product is available for trouble-free use to consumers over its useful life span” (Loomba, 1996).
In addition, product support is important for manufacturers as well, because:

- It is essential for achieving customer satisfaction and good long-term relationships (Armistead and Clark, 1992; Athaide et al., 1996).
- It can provide a competitive advantage (Armistead and Clark, 1992; Goffin, 1994). As product differentiation becomes harder in many markets, companies are increasingly regarding customer support as a potential source of competitive advantage (Loomba, 1996).
- It plays a role in increasing the success rate of new products (Cooper and Kleinschmidt, 1993).
- It can be a major source of revenue (Berg and Loeb, 1990; Goffin, 1998; Hull and Cox, 1994). Over the working lifetime of a product, the support revenues from a customer may be far higher than the initial product revenue. However, this often receives too little management attention (Knecht et al., 1993).

Product support needs to be fully evaluated during new product development (NPD), as good product design can make customer support more efficient and cost-effective (Armistead and Clark, 1992).

An important aspect of user/customer satisfaction is reducing the down-time and repair costs of the system/machine. To achieve this, product maintainability issues are playing an important role and should be considered seriously both in the product design and the support management phases (Blanchard et al., 1995). The most economic approach is to optimize the product maintainability and supportability during the design. A modular approach to product design can reduce repair costs (Hedge and Kubat, 1989), as can good diagnostics (Armistead and Clark, 1992). This approach can be used similarly in designing product support and in optimizing it. The nature and reliability of the equipment obviously have a large influence on the key elements of product support. Customers expect reliable products and a quick response in the event of failure.

Meanwhile, the spare part, as an item of product support, is important. The logistics of spare parts and inventory levels for them are different depending on the spare part in question, and ordinary approaches used for stock control in manufacturing situations do not apply to spare parts (Fortuin and Martin, 1999). In the area of parts logistics, supplying spare parts can be a highly profitable business. With the expansion of high-technology equipment in industries worldwide, the need for spare parts to maximize the utilization of this equipment is paramount. Spare parts forecasting and management improve productivity by reducing idle machine time and increasing resource utilization (Orsburn, 1991). It is obvious that spare parts provisioning and inventory control are complex (Bartmann and Beckmann, 1992; Langford, 1995; Petrovic & Pavlovic, 1986), because of the trade-offs necessary concerning the part availability of slow and fast moving parts (Fortuin and Martin, 1999). The effectiveness of spare parts management is based on factors which require improvements in data acquisition and methods of forecasting the spare parts requirements, analyzing the data on the demand for such parts, and developing proper stocking and ordering criteria for these parts.

The data are obtained with part identification and usage information. Usually parts can be classified as unique or common (concerning the application of the parts), and
Reliability and Operating Environment Based Spare Parts Planning

critical or non-critical to the operation or machine. From this classification the process of data collection can begin (Sheikh et al., 2000).

In the past, when many products had high failure rates, the most important aspect of support was fast and reliable repair (Lele and Karmarkar, 1983). New technologies have now typically led to more reliable products. A key aspect of support is the management of the field support organization – including the engineers who install and maintain equipment, the in-situ spare parts inventory, etc. If decisions about product support requirements are taken at the design stage, then this will affect the product reliability and consequently how often products require maintenance and repair (Lele, 1987; Markeset and Kumar, 2003a).

The early evaluation of all the aspects of product support at the design stage has been termed “design for supportability” (Goffin, 2000). To achieve this, it has been recognized that engineers with experience of environmental factors influencing the technical characteristics of the product and customer support should be involved in the development stage. Initially, the customer support requirements may not be recognized as important, but then poor product design will mean higher repair costs and can lead to dissatisfied customers. To avoid that, companies should consider reliability and repair times at the design stage and typically set quantitative goals for product reliability (mean-time-between-failures, MTBF) and ease-of-repair (mean-time-to-repair, MTTR).

The reliability of a system can be defined as “the ability of a system/machine to perform or operate a required function without failure under given conditions for a given time interval” (International Electrotechnical Vocabulary [IEV] 191-02-06). It is a function of time that gets influence by the environment in which the system is operating. The modern concept of reliability is a quantitative measure that can be specified and analyzed. Reliability is now a parameter of design that can be traded off against other parameters such as cost and performance. The necessity of expressing reliability as a quantitative measure arises due to the ever-growing complexity of systems, the competitiveness in the market and the scarcity of resources (Kumar, 1996).

It is essential to evaluate all the aspects of support at the design stage, i.e. installation times, fault diagnosis times, field access times, repair times/costs, spare part needs, etc.; but for existing systems, some of these aspects, such as the repair time and spare parts needs, can be evaluated in the operation phase to optimize the product life cycle cost. For evaluating these issues, the analysis of field data helps the designer and engineer to modify the design and/or product support strategy for improvement of the system reliability and for calculation of the required spare parts. Sound spare parts management improves productivity by reducing the idle machine time and increasing the resource utilization (Orsburn, 1991). It is obvious that spare provisioning is a complex problem and requires an accurate analysis of all the conditions and factors that affect the selection of appropriate spare provisioning models.

In the literature there exist a large number of papers in the general area of spare provisioning, especially in spare parts logistics (Chelbi and Ait-Kadi, 2001; Kennedy et al., 2002; Langford, 1995; Orsburn, 1991). Most of these researches deal with repairable systems and spares inventory management (Aronis et al., 2004; Sarker and Haque, 2000; Smith and Schaefer, 1985). These researches mostly provide a queuing
theory approach to determining the spare parts stock at hand to ensure a specified availability of the system (Graves, 1985; Berg and Posner, 1990; Dhakar, Schmidt and Miller, 1994; Huiskonen, 2001). These models have been further extended to incorporate the inventory management aspect of maintenance (Gross et al., 1985; Hall and Clark, 1987; Ito and Nakagawa, 1995; Sherbrooke, 1992; Kumar et al., 2000a).

On the other hand, quantitative techniques based on reliability theory have been used for developing methods to forecast the failure rates of the required items to be purchased and/or stocked (Jardine, 1998; Gnedenko et al., 1969; Kales, 1998; Lewis, 1996; Lipson and Sheth, 1973; Wååk and Alfredsson, 2001; Xie et al., 2000). This failure rate has been used to determine more accurate demand rates.

In the specific area of spare parts management of non-repairable (mechanical) systems, which often fail with time-dependent failure rates (ageing), there are some renewal theory based prediction models available for forecasting the needs for spares in a planning horizon (Gnedenko et al., 1969; Kumar et al., 2000b).

Finally, as a result we can say that most of the research works in the spare parts domain have been carried out in inventory management. Guaranteeing the availability of systems/machines requires that spare parts should always be available on demand. However, estimation and calculation of the required number of spare parts for storage to ensure their availability when required, with respect to techno-economical issues (reliability, maintainability, life cycle cost, etc.), have rarely been considered and studied (notable exceptions being, for example, Sheikh et al., 2000; Tomasek, 1970).

Most of the research and articles on reliability consider the operation time as the only variable for estimating the reliability. However, covariates are usually not considered in reliability models (parametric reliability methods such as exponential and Weibull reliability models; see for example O’Connor, 1991; Hoyland and Rausand, 1994). None of the surveyed literature that has contained required spare parts calculations based on the reliability characteristics of the product has considered the operating environment as a factor influencing reliability (Jardine, 1998; Lewis, 1996). Not considering covariates may give rise to errors in the estimation of the reliability characteristics of a system and may lead to wrong conclusions concerning product support and spare parts forecasting. Therefore, the estimations are not accurate enough, because the reliability characteristics of a product are a function of the operation time and operating environment.

In mining industry, the major part of down-time can be due to shortage or waiting for spare parts which, in turn is mainly due to wrong estimation of spare parts consumption. Mining companies often follow the recommendation of manufacturers regarding spare parts consumption, which is only based on the operating time of machine. Often manufacturers do not take into account the effect of operating environment on the reliability of the system/components which have in general negative effect on the life-length of the components and spare parts. Therefore, as mentioned earlier, it is very important to assess the effect of operation environment on the life-length of components and thereby getting the better estimate spare parts consumption. If the effect of operating environment is known, then it will facilitate better and optimal spare parts planning.
It is, therefore, desirable to estimate the magnitude of the effects of covariates so that the reliability characteristics of a system can be interpreted in a better way. Kumar (1996) has studied some of the methods that can be used for reliability analysis of a system whose lifetime is influenced by covariates. However, most of the reliability methods that are used for spare parts forecasting and calculation (as mentioned earlier) do not take into consideration the effect of covariates, which leads to a lack of appropriate forecasting and inventory management.

1.4 Research proposition and objective
The reliability characteristics of equipment influence the product support dimensioning, e.g. the estimation of the required number of spare parts. However, the product reliability is affected by factors other than the product operating time. These factors are referred to as covariates and include, for instance, the product’s operating environment conditions (e.g. dust, temperature, humidity, etc.) and human aspects (e.g. the skill of the operators). The identification and quantification of the effects of the product operating conditions may help in forecasting, calculating, and managing the quantity of required spare parts with respect to minimizing the product life cycle cost.

The main objective of the present study is to develop an approach and decision model for the integration of the product reliability characteristics with considering of the product operating environment in the optimal estimation of product support (required spare parts). This research is concerned broadly with development of improved tools and techniques that enable the effective analysis and planning of spare parts.

The sub-objectives of this research work are:

- The study and analysis of the effect of the operating environment (covariates) on the product reliability characteristics (reliability prediction), and consequently on the quantity of required spare parts.
- The analysis of the risk of shortages in the spare parts inventory due to not considering the product operating environment and its consequences.
- The study of the classification of spare parts to optimize the spare parts logistics.

1.5 Research question
The proposition is transformed into a research question and an overall research objective. The main research question is:

“How do we integrate the product reliability characteristics and the product’s operating environment conditions in a decision model to forecast the required spare parts (as an issue of product support) to minimize the product life cycle cost (comprises operation, downtime and support costs)?”

There are some related questions that are also needed to be answered. These questions are listed as follows:
• What is the effect of environmental factors (covariates) on the product reliability?
• Do covariates affect the product support requirements (e.g. spare parts estimation)?
• Will the spare parts estimation based on the incorporated operating environment information give a better value of the goal function (e.g. lower life cycle cost) in practice?

1.6 Focus and delimitation
This research is governed by some limitations, which are:

• The product support focus is on the estimation of the number of spare parts.
• Only non-repairable components / parts in repairable systems are studied. In other words one component systems or systems with special attention to one component are studied.
• Only the operation and maintenance phases are dealt with in the study (i.e. the design and manufacturing phases were not considered).
• Only single echelon (one level) system with focus only one location of manufacturer/supplier are considered and studied.
• Only two mining (both surface and underground) working environment have been considered in the present research. The other industrial operating environments were not dealt in this study.

1.7 Outline of the thesis
The thesis consists of three parts, which comprise eight chapters and five appended papers. The present chapter (Chapter 1) contains an introductory discussion on product support and product reliability issues, the research proposition and question, and the overall objective. The thesis is devoted to finding answers to research questions that are concerned with analyzing the impact of covariates on required spare parts forecasting. This chapter starts with a background to product support and product reliability characteristics and ends with the research objective and question.

Chapter 2 describes the methodology that has been used in this research. It explains the different phases of research, which include the research purpose, the research approach, the research strategy, data collection, data analysis and evaluating the research quality. There is a discussion of some basic concepts with respect to research methodology in this context and then of the methods chosen. The research process, however, requires a sequence of steps, which are also discussed in this chapter.

Chapter 3 presents the theoretical framework (as well as including a literature survey) related to the subject. The issue of product support and its importance are discussed. The chapter also deals with the factors influencing product support and the
Reliability and Operating Environment Based Spare Parts Planning

conventional inventory management methods for spare parts as an issue of relevance to product support, with respect to LCC minimization.

A description of the factors and issues related to product reliability characteristics also comes in this chapter. After a short description of the common and applicable reliability models, this chapter discusses the product operating environment influencing the product reliability and failure rate. The integration of these factors in the product reliability calculations is also discussed.

And finally the issues of risk assessment and risk analysis are discussed as a management tool for making decisions. Two risk analysis methods named event tree and fault tree analysis are discussed briefly in Chapter 3 as well.

Chapter 4 from Part II, “Research project and process”, is the core of the thesis, and deals with calculations and forecasting of the required spare parts based on the reliability characteristics of the product (system) and the operating environment factors on the specific time horizon, which is the contribution of the thesis. In this chapter two models based on the homogenous Poisson process and renewal theory are introduced for determining the required number of spare parts. Spare parts classification is also discussed for finding the criticality of parts and consequently the confidence level of spare parts availability in a fixed working period.

At the end of this chapter two methods of spare parts estimation is studied and analyzed. The results of this analysis come in the conclusions.

In Chapter 5 the validity and reliability of improved models are tested by performing some case studies on loaders and LHD machines in Iran and Sweden. This chapter comprises the process of data collection, data analysis and discussion of the results drawn from the case studies.

A summary of the appended papers comes in Chapter 7, with the important points of each paper highlighted.

Concluding remarks, the research contribution and recommendations for future research are discussed in Part III - Chapter 8.
2 Research design

2.1 Dimensions of research

Six dimensions of research are discussed in this section, namely how research is used, the purpose of research studies, the research approach, the research strategy, the technique for data collection and data analysis techniques.

2.1.1 The use of research

There are two types of research, basic research and applied research. This is, of course, not a rigid classification. Some research is performed to advance general knowledge, whereas other research is carried out to solve specific problems.

Those who seek an understanding of the fundamental nature of a subject/topic are engaged in basic research (also called academic research or pure research). Applied research, by contrast, primarily aims at applying and tailoring knowledge to address a specific practical issue. Those engaged in applied research want to answer a policy question or solve a pressing problem.

Basic research advances fundamental knowledge about the problem in question. It focuses on refuting or supporting theories. The questions asked by basic researchers seem impractical (Neuman, 2003). Nevertheless, a new idea or fundamental knowledge is not generated only by basic research. Applied research can build new knowledge as well.

Applied research conducts a study to address a specific concern or to offer solutions to a problem. Applied research usually means a quick, small-scale study that provides practical results that people can use in the short term (Neuman, 2003). The results of applied research may be available only to a small number of decision makers or practitioners, who decide whether or how to put the research results into practice and who may or may not use the results wisely.

Considering the essence of the present research, it is to be classified in the applied research group. This is motivated by the fact that it uses fundamental and other related experimental knowledge and provides practical solutions and results for spare parts estimation and inventory management performed to avoid a shortage when a part is required. The mining industry, in general, faces with down time of machines which the shortage of required spare parts is one of the reasons for it. This research provides an approach in practice to prevent the lack of spare parts when are needed.

2.1.2 The purpose of research studies

The purpose of research may be classified into three groups based on what the research is trying to accomplish: exploring a new topic, describing a phenomenon, or explaining why something occurs (Babbie, 1998). Studies may have multiple purposes (e.g. both to explore and to describe), but one purpose is usually dominant.
Exploration: If the researcher has explored a new topic or issue in order to learn about it and if the issue was new or no other researchers had written about it, this is called exploratory research. The researcher’s goal is to formulate a more precise question that future research can answer. Exploratory research rarely yields definitive answers (Neuman, 2003). It addresses the “what” question.

Description: Descriptive research presents a picture of the specific details of a subject or situation. Descriptive research focuses on “how” and “who” questions. Descriptive researchers use most data-gathering techniques, such as surveys, field research, content analysis and historical comparative research.

Explanation: The desire to know “why”, to explain, is the purpose of explanatory research. It builds on exploratory and descriptive research and proceeds to identify the reason why something occurs. Going beyond focusing on a topic or providing a picture of it, explanatory research looks for causes and reasons (Neuman, 2003). Table 1 represents briefly a specification of these three groups of research.

<table>
<thead>
<tr>
<th>Goals of Research</th>
<th>Exploratory</th>
<th>Descriptive</th>
<th>Explanatory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Become familiar with the basic facts, setting and concerns</td>
<td>Provide a detailed, highly accurate picture</td>
<td>Test a theory’s predictions or principles</td>
<td></td>
</tr>
<tr>
<td>Create a general mental picture of condition</td>
<td>Locate new data that contradict past data</td>
<td>Elaborate and enrich a theory’s explanation</td>
<td></td>
</tr>
<tr>
<td>Formulate and focus questions for future research</td>
<td>Create a set of categories or classify types</td>
<td>Extend a theory to new issues or topics</td>
<td></td>
</tr>
<tr>
<td>Generate new ideas, conjectures or hypotheses</td>
<td>Clarify a sequence of steps or stages</td>
<td>Support or refute an explanation or prediction</td>
<td></td>
</tr>
<tr>
<td>Determine the feasibility of conducting research</td>
<td>Document a causal process or mechanism</td>
<td>Link issues of topics with general principles</td>
<td></td>
</tr>
<tr>
<td>Develop techniques for measuring and locating future data</td>
<td>Report on the background or context of a situation</td>
<td>Determine which of several explanations is best</td>
<td></td>
</tr>
</tbody>
</table>

The present study tries to answer the following questions: which factors influence the product/system reliability characteristics and consequently the number of failures, how they exert this influence and what the results are. It can therefore be concluded that this research is to be grouped in the exploratory (introducing operating environment in spare parts planning) and descriptive (defining the effect of operating environment on the failure rate and spare parts estimation) classes. In fact, we can classify the present research as a prescriptive research category as well, which indicates how can make and take decision about the required spare parts for preventing the system down-time. This study attempts to find out the risk of ignoring the product operating environment for the product availability as well. Product availability can be improved through minimization of down-time by increasing the availability of required spare parts and decreasing the repair time (mean time to repair).
2.1.3 Research approach

The research approach, in fact, involves building and testing theory from two directions, namely the deductive and the inductive (Neuman, 2003). In practice, most researchers are flexible and use both approaches at various points in a study (Figure 1).

**Deductive:** In a deductive approach, the researcher begins with an abstract, logical relationship among concepts, and then moves toward concrete empirical evidence. The theory suggests the evidence that the researcher should gather. After the researcher has gathered and analyzed the data, he/she learns that the findings do or do not support the theory.

**Inductive:** In an inductive approach, the research starts with detailed world-scale observations and moves toward more abstract generalizations and ideas. In the beginning, the researcher may only have a topic and a few vague concepts. By more observation, he/she refines the concepts, develops empirical generalizations, and identifies preliminary relationships. This method builds the theory from the ground up.

There is a third approach, which is a combination of the deductive and inductive approaches, named “Abduction”. In the abduction approach, “the researcher can start with a deductive approach and make an empirical collection of data based on a theoretical framework, and then continue with the inductive approach to develop theories based on the previously collected empirical data. During the research process an understanding of the phenomenon is developed and the theory is adjusted with respect to the new empirical findings” (Alvesson & Sköldberg, 1994 cited by Holmgren, 2003).

According to the essence of abduction research, the present study coincides with this type of research, because it starts with a literature review in order to identify the need for further investigation of product reliability characteristics related to support (deductive approach). Some models were adapted from the literature for analyzing the collected data. Then a model was made and improved based on findings. The model
Reliability and Operating Environment Based Spare Parts Planning

was then applied in an inductive approach by studying the empirically obtained data. Thereafter the validity of the model was proved and conclusions were drawn based on the experience gained from empirical case studies.

Qualitative and quantitative research
From another point of view, research can be performed through a quantitative or qualitative approach. Each category uses several specific research techniques (e.g. surveys, interviews, and historical analysis), and yet there is much overlap between the types of data and the styles of research. Most qualitative researchers examine qualitative data and vice versa.

Although both styles of research share basic principles of science, the two approaches differ in significant ways (Table 2). Each has its own strengths, limitations and topics or issues.

Table 2. Quantitative style versus qualitative style (Source: Neuman, 2003)

<table>
<thead>
<tr>
<th>Quantitative Style</th>
<th>Qualitative Style</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure objective facts</td>
<td>Construct social reality, cultural meaning</td>
</tr>
<tr>
<td>Focus on variables</td>
<td>Focus on interactive processes, events</td>
</tr>
<tr>
<td>Reliability is key</td>
<td>Authenticity is key</td>
</tr>
<tr>
<td>Value-free</td>
<td>Values are present and explicit</td>
</tr>
<tr>
<td>Independent of context</td>
<td>Situationally constrained</td>
</tr>
<tr>
<td>Many cases, subjects</td>
<td>Few cases, subjects</td>
</tr>
<tr>
<td>Statistical analysis</td>
<td>Thematic analysis</td>
</tr>
<tr>
<td>Research is detached</td>
<td>Research is involved</td>
</tr>
</tbody>
</table>

Table 3 represents the results of a comparison between qualitative and quantitative research. The comparison was performed for different stages of research, from the initiating stage (determining the purpose of the research) until the end step (outcomes).

The key features common to all quantitative methods can be seen when they are contrasted with qualitative methods. For example, most quantitative data techniques are data condensers. They condense data in order to see the big picture. Qualitative methods, by contrast, are best understood as data enhancers. When data are enhanced, it is possible to see key aspects of cases more clearly (Neuman, 2003).

The methods applied in the present research can be classified as quantitative methods, because the data used were mostly statistical data collected from databases, reports and interviews. Moreover, the outcomes were used to recommend a final decision to implement.
Table 3. Comparison between qualitative and quantitative research in different stages of research (Source: Mercator Research Group, 2004)

<table>
<thead>
<tr>
<th>Objective/purpose</th>
<th>Qualitative Research</th>
<th>Quantitative Research</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>To gain an understanding of underlying reasons and motivations. To provide insights into the setting of a problem, generating ideas and/or hypotheses for later qualitative research. To uncover prevalent trends in thought and opinion.</td>
<td>To quantify data and generalize results from a sample to the population of interest. To measure the incidence of various views and opinions in a chosen sample. Sometimes followed by qualitative research, which is used to explore some findings further.</td>
</tr>
<tr>
<td>Sample</td>
<td>Usually a small number of non-representative cases. Respondents selected to fulfill a given quota.</td>
<td>Usually a large number of cases representing the population of interest. Randomly selected respondents.</td>
</tr>
<tr>
<td>Data collection</td>
<td>Unstructured or semi-structured techniques, e.g. individual depth interviews or group discussions.</td>
<td>Structured techniques such as field data, reports and interviews.</td>
</tr>
<tr>
<td>Data analysis</td>
<td>Non-statistical.</td>
<td>Statistical; data are usually in the form of tabulations, etc. Development and computer experimentation</td>
</tr>
<tr>
<td>Outcome</td>
<td>Exploratory and/or investigative. Findings are not conclusive and cannot be used to make generalizations about the population of interest. Develop an initial understanding and sound base for further decision making.</td>
<td>Used to recommend a final course of action. Findings are conclusive and usually descriptive in nature</td>
</tr>
</tbody>
</table>

2.1.4 Research strategy

The selection of a research strategy mostly depends on which kind of information the researcher is looking for due to the purpose of the study and the research questions (Yin, 1994). Yin (1994) presents five different research strategies to apply when collecting and analyzing empirical evidence, as listed in Table 4.

Table 4. Criteria for selecting an appropriate research strategy for different forms of research questions (Source: Yin, 1994)

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Form of research question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment</td>
<td>How, why</td>
</tr>
<tr>
<td>Survey</td>
<td>Who, what, where, how many, how much</td>
</tr>
<tr>
<td>Archival analysis</td>
<td>Who, what, where, how many, how much</td>
</tr>
<tr>
<td>History</td>
<td>How, why</td>
</tr>
<tr>
<td>Case study</td>
<td>How, why</td>
</tr>
</tbody>
</table>

Archival analysis and history strategies refer to the past conditions of the case under study. The remaining strategies (experiments, surveys and case studies) usually refer to the present situation, as explained below:

**Experiments**: Experimental research uses the logic and principles found in natural science research. Experiments can be conducted in laboratories or in real life. They usually involve a relatively small number of cases and address a well-focused question. Experiments are most effective for explanatory research.
Surveys: Survey techniques are often used in descriptive or explanatory research. In survey research, the researcher asks many people numerous questions in a short time period, and then summarizes the answers to questions in percentages, tables, or graphs. Surveys give the researcher a picture of what the present situation is for the topics studied.

Case studies: In case study research the researcher examines, in depth, many features of a few cases over a period of time. In fact, the researcher measures precisely a common set of features of many cases, usually expressed in numbers. The data are usually more detailed, varied and extensive. Case studies use the logic of analytic instead of enumerative induction (Neuman, 2003). The researcher carefully selects one or a few key cases to illustrate an issue and study it (or them) analytically in detail.

With reference to the different forms of research strategy presented above and considering the goal, approach and the questions of the present research, this study can be classified into both the experimental and the case study research strategy groups. We have used scientific logic and principles (e.g. reliability analysis methods) and have applied them in the real life of a system/machine to find out some further features. We have also examined the findings of present research study in a few cases and confirmed those findings.

2.1.5 Data collection techniques used
Every researcher collects data using one or more techniques. The techniques may be grouped into two categories (Neuman, 2003): quantitative, collecting data in the form of numbers, and qualitative, collecting data in the form of words or pictures. The quantitative techniques which were used in this research will be discussed. Yin (1994) presents six main sources of collecting data, which are listed in the Table 5.

Archival records (existing statistics), documentation, direct observation (in the collection of information about covariates) and interview were the quantitative data collection methods used in this research. In existing statistics the researcher locates a source of previously collected information, often in the form of company reports or previously conducted surveys used as a data collection method. Then the researcher reorganizes or combines the information in new ways to address a research question.

In this study we collected our required data from the reports of maintenance, repair and inventory crew and operators of machines. These data consist mostly of the mean time to failure and the ordering and holding cost of components. The operating environment influencing factors were studied and defined through direct observation, interview and the study of reports and documents (see Chapters 5.1 and 5.2).

Sometimes the existing quantitative information consists of stored surveys or other data that the researcher re-examines using various statistical procedures.


### Table 5. Different data collection methodologies and their comparative strengths and weaknesses (Source: Yin, 1994)

<table>
<thead>
<tr>
<th>Source of Evidence</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
</table>
| Documentation      | • Stable – can be reviewed repeatedly  
                   • Unobtrusive – not created as a result of the case study  
                   • Exact – contains exact names, references, and details of an event  
                   • Broad coverage – long span of time, many events, and many settings  | • Retrievability – may be low  
                   • Biased selectivity, if collection is incomplete  
                   • Reporting bias – reflects (unknown) bias of author  
                   • Access – may be deliberately blocked |
| Archival Records   | • Same as above for documentation  
                   • Precise and quantitative | • Same as above for documentation  
                   • Accessibility – may be poor for privacy reasons |
| Interviews         | • Targeted – focus directly on case study topic  
                   • Insightful – provide perceived causal inference | • Bias due to poorly constructed questions  
                   • Response bias  
                   • Inaccuracies due to poor recall  
                   • Reflexivity – interviews give what interviewer wants to hear |
| Direct Observations| • Reality – cover events in real time  
                   • Contextual – cover context of event | • Time-consuming  
                   • Selectivity – unless broad coverage  
                   • Reflexivity – events may proceed differently because they are being observed  
                   • Cost – hours needed by human observers |
| Participant-Observations | • Same as above for direct observations  
                   • Insightful into interpersonal behaviors and motives | • Same as above for direct observations  
                   • Bias due to investigator’s manipulation of events |
| Physical Artifacts  | • Insightful into cultural features  
                   • Insightful into technical operations | • Selectivity  
                   • Availability |

#### 2.1.6 Data analysis

According to Yin (1994), it is significant that every research and investigation should have a general analytic and logical strategy to help and guide the decisions regarding what will be analyzed and why? “Data analysis consists of examining, categorizing, tabulating, or otherwise recombining the evidence to address the initial propositions of a study” (Yin, 1994).

The analytical method is used in the present research to find out the number of required spare parts based on the system/machine reliability characteristics (mean time to failure of parts) and the operating environment factors which the system is subjected to. Inventory management has also been carried out to find out how many parts should be stored in the inventory and the time to renew it.

For the purpose of preliminary investigations into the statistical nature of breakdowns of studied parts, data were classified according to their chronological order and
reordering was avoided to study the nature of trends present in the data sets. After testing the IID assumption, the relevant reliability analysis method was chosen. For the study of the influence of the operating environment, the proportional hazard model (PHM), which is a regression analysis based method, was implemented. Then for the purpose of validity, the model was tested for proportionality assumption. Finally, the number of breaks and failures in a planning horizon was calculated and based on that the number of spare parts was estimated.

2.2 Research quality

2.2.1 Reliability
Reliability means dependability or consistency. The reliability of quantitative research means that the numerical results produced by an indicator do not vary because of characteristics of the measurement process or the measurement instrument itself. Neuman (2003) stated that there are three type of reliability:

**Stability reliability** is reliability across time. It addresses the question: “Does the measure deliver the same answer when applied in a different time period?” The researcher can examine an indicator’s degree of stability reliability by using the test-retest method, with which one retests or re-administers the indicator to the same case. If what one is measuring is stable and the indicator has stability reliability, then one will obtain the same results each time.

**Representative reliability** is reliability across groups of cases. It addresses the question: “Does the indicator deliver the same answer when applied to different cases?” An indicator has high representative reliability if it yields the same result for a construct (model) when applied to different cases.

**Equivalence reliability** applies when the researcher uses multiple indicators; i.e. when multiple specific measures are used in the operationalization of a construct. Equivalence reliability addresses the question: “Does the measure yield consistent results across different indicators?” If several different indicators measure the same construct, then a reliable measure gives the same result with all the indicators.

According to Yaremko et al. (1986), reliability is a general term indicating consistency of measurements derived from repeated estimations of the same subject under the same condition. Meanwhile, Yin (1994) states that reliability indicates that the sequences and operations of a research, such as the data collection procedure, can be repeated by another researcher with the same results. With high reliability, it is possible for another researcher to achieve the same results on condition that the same methodology is used. For this reason, it is important to describe the data collection method in one’s research, which was already performed in this research (see Chapter 5.2).

Yin (1994) recommends that, in order to achieve reliability, a case study protocol and case study database should be constructed. In the present study a similar process has been implemented. We have defined which type of data has been required and how it has been obtained, and in addition the source of data (reports) is available for recollection and reanalysis. Consequently, it can be claimed that an acceptable level of reliability has been achieved in this research.
2.2.2 Validity

According to Neuman (2003) validity is an overused term meaning truthful. It refers to the bridge between a construct and the data. There are several general types of validity (Neuman, 2003):

**Internal validity:** This means that there are no errors internal to the design of the research project. The term is used primarily in experimental research to talk about possible errors of results that may arise despite attempts to institute control. High internal validity means that there are few such errors. Internal validity is only of concern for explanatory research and case studies, where the causal relationships between variables are studied (Yin, 1994).

**External validity** is used primarily in experimental research. It is the ability to generalize findings from specific settings and small groups (cases) to a broad range of settings and number of cases. It addresses the question: “If something happens in a laboratory or among the particular group of subjects (e.g. cases), can the findings be generalized to the ‘real’ (non-laboratory) world or to the general public?”

**Statistical validity:** This validity means that the correct statistical procedure has been chosen and its assumptions are fully met. Different statistical tests or procedures are appropriate for different conditions, which is discussed in textbooks that describe statistical procedures.

<table>
<thead>
<tr>
<th>Reliability (Dependent measure)</th>
<th>Validity (True measure)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stability – over time</td>
<td>Internal – design of the research project</td>
</tr>
<tr>
<td>Representative – across sub-groups</td>
<td>External – generalization of findings</td>
</tr>
<tr>
<td>Equivalence – across indicators</td>
<td>Statistical – correct statistical process used</td>
</tr>
</tbody>
</table>

With regard to the validity of the present research, the findings can be used in any cases, which indicate the generality of the results and output of the study. The statistical analyses and procedures which have been used were tested for accuracy and confidence (e.g. proportionality and standard error). Therefore, regarding these criteria, the validity of the study is confirmed.

Figure 2 depicts a summary of the research method selected and performed in this thesis.

2.3 Steps of the research process

The research process requires a sequence of steps. Various approaches suggest somewhat different steps, but most seem to follow the eight steps classified in the four phases of the Improvement Cycle (Deming, 1993), which comprises Plan, Do, Study and Act. According to this classification, the present research has gone through the process shown in Figure 3.
The process begins with the researcher selecting a topic (a general area of study or issue). A topic is usually too broad for conducting research. This is why the next step is crucial. The researcher narrows the topic down into specific research questions that should be addressed in the study.

In the present study the topic was narrowed down into the following question: “How do we integrate the product reliability characteristics, the geographical location of the product use, and the product’s operating environment conditions in a decision model to forecast the required spare parts (as an issue of product support) and minimize the total product support cost (inventory and spare parts delivery cost)?”

When learning more about a topic and narrowing the focus, the researcher usually reviews past research or the literature on a topic or question. The researcher also develops a possible answer or hypothesis.

After specifying a research question, the researcher proceeds further with a detailed literature survey, a study of the background of the topic, and the acquisition of feedback. Then the researcher plans how to carry out the specific study. The fourth step involves making a decision about the many practical details of conducting the research. Now the researcher is ready to gather the data or evidence.
Once the researcher has collected the data, the next step is to manipulate or analyze the data to see any patterns that may emerge. The patterns help the researcher to give meaning to or interpret the data. Finally, the researcher informs others by writing a report that describes the background to the study, how he/she conducted it and what was discovered.

The theory, which is revised and renewed constantly, supports all the steps continuously. It helps research to be on the right track and improves the accuracy and the robustness of the study.
3 Theoretical framework – Basic concepts related to the research

3.1 Product support

A product is the output of a manufacturer/producer and can be used as a consumer good or for the production of other products. It can be classified according to (Markeset, 2003):

(a) Product characteristics, into two groups: consumer products and industrial products, and

(b) Ownership, into two groups: functional products and conventional products. In the case of the functional products on the contrary to conventional products category, the user does not buy a machine/system but the function that it delivers (Markeset and Kumar, 2005). To avoid the complexities of maintenance management, many customers/users prefer to purchase only the required function and not the machines or systems providing it. In this case the responsibility for the maintenance and product support lies with the organization delivering the required function.

In the present research, the industrial product was studied mostly from the conventional point of view and to a certain extent from the functional point of view.

Usually, due to technological, economical, and environmental constraints in the design phase, machines/systems are often unable to fulfill customers’ needs completely in terms of system performance during their entire life cycle. This is often due to poorly designed technical characteristics of the system and a poor product support strategy (in the case of new product). Then to compensate for this shortcoming for existing products, the need for support is becoming important to enhance system efficiency and prevent unplanned stoppages (Figure 4).

\[
\begin{align*}
\text{State of the art of technology} & \quad \text{Constraints in design phase} & \quad \text{Unplanned Stoppage} \\
\text{Economy} & \quad \text{Poorly designed reliability} & \\
\text{Environmental conditions} & & \\
\end{align*}
\]

\[
\begin{align*}
\text{Lack of logistics} & \quad \text{Constraints in product support and logistics} & \\
\text{Geographical distribution} & \quad \text{Poor product support strategy} & \\
\end{align*}
\]

**Figure 4. Typical reasons for unplanned stoppage creation**
However, industrial systems need support throughout their lifetimes. The dimensioning of product support (spare parts and a service delivery system/strategy) will be greatly influenced by the product design characteristics. The relationship between the application type (the type of use and application environment), the product design and the product support is illustrated in Figure 5 (Markeset and Kumar, 2003b). The broken lines indicate a technological pull, whereas the continuous lines indicate a technological push.

![Figure 5. The relationship between product design characteristics, application type and product support (Source: Markeset and Kumar, 2003b)](image)

In order that industrial systems may be able to perform their expected function, some of the typical technical forms of support needed include installation, maintenance, repair services, and provision of spare parts. Such forms of support are supplied by original equipment manufacturers (OEM)/suppliers, and are characterized as product support. Product support includes all the activities that ensure that a product is available for trouble-free operations over its useful life span (Loomba, 1996).

Maintenance is, in general, a process that is activated and can be defined as the combination of all the technical and associated administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required function (International Electrotechnical Vocabulary [IEV] 191-07-01).

Maintenance objectives can be summarized under four headings: ensuring the system function (availability, efficiency and product quality); ensuring the system life (asset management); ensuring safety; and ensuring human well-being (Dekker, 1996). For production equipment, ensuring the system function should be the prime maintenance objective. Here, maintenance has to provide the right (but not the maximum) reliability, availability, efficiency and capability (i.e. producing at the right quality) of production systems, in accordance with the need for these characteristics.

Consideration of maintenance should start in the design phase of systems. However, the maintenance concept or strategy describes what events (e.g. failure, passing of time) trigger what type of maintenance (inspection, repair, replacement), and it can be determined both after the design phase and in the operations phase (Dekker, 1996). In general, maintenance management attempts to optimize the maintenance tasks, and
minimizing the repair time is an issue of maintenance optimization that comprises the availability of spare parts when required.

The product support and maintenance needs of systems are mainly decided during the design and manufacturing phase (see e.g. Blanchard, 2001; Blanchard and Fabrycky, 1998; Goffin, 2000; Markeset and Kumar, 2001; Smith and Knezevic, 1996; Dekker, 1996).

Product support, in fact, is a form of assistance that manufacturers/suppliers offer to users/customers to help them gain the maximum value (profit) from the manufactured products. It is reasonable to assume that users/customers will, in most instances, tend to prefer products that are intuitively usable and/or well supported, as there will be fewer problems associated with the use of such products. Such support may be described as falling into one of the two broad categories, namely support to customers and support to products (Markeset and Kumar, 2003a; Mathieu, 2001), of which the second is the target of this research.

Product support is important in the modern industrial world. Today, managements are paying more attention to product support, because products support:

- plays a key role for many products in achieving customer satisfaction,
- can be a considerable source of revenue and profit, and
- can provide a competitive advantage in marketing.

Leading companies achieve a competitive advantage with product support. For example, some companies focus on design for supportability (e.g. Kodak), and some believe that the capability to upgrade is very important and, to reduce costs, these companies focus on the field upgradeability of products (e.g. Hewlett-Packard) (Goffin, 2000). In brief, product support is an essential part of business.

Anyway, it can be asserted that the importance of product support is that it increases customer satisfaction, so that customers become interested in purchasing the product again and again.

The factors that influence product support can be placed into two broad categories:

- engineering aspects
- business management and organizational aspects

This research focuses on the product dependability characteristics and application type factors, which belong to the category of engineering aspects, and the geographical locations of the product, which belong to the category of business and organizational aspects.

Figure 6 shows some key items of the engineering and business management categories.
Dependability is the collective term used to describe the availability performance and its influencing factors: reliability performance, maintainability performance and maintenance support performance. Dependability is used only for general description in non-quantitative terms (International Electrotechnical Vocabulary [IEV] 191-02-03). The reliability, availability, and maintainability of the product are important and have an immense influence on product support. Products usually require maintenance and the installation of spare parts, which are performed at regular times to ensure product reliability. The effective performance of systems is critical to the success of all organizations, and reliability and availability measures are one of the most common sets of measures used in evaluating the performance of such equipment (Cassady et al., 2004). When reliability and availability performance are inadequate, engineers need to prioritize their improvement efforts. These efforts could comprise actions that reduce the occurrence of system failure and improve the execution of system maintenance. Improvement of the speed of equipment repair is an effective and beneficial approach which is implemented with adequate product support and availability of spare parts.

There are some measures (e.g. the reliability importance measure and the availability importance measure) that can provide an index for use to give guidelines in developing an availability improvement strategy (Barlow and Proschan, 1975; Xie, 1989; Cassady et al., 2004). The availability importance measure, for instance, denotes the marginal, relative improvement in availability resulting from decreasing the failure rate or increasing the repair rate of components.

In addition, high reliability does not mean that the product will be maintenance-free, since materials degrade over time, and many technical characteristics are dependent
on the same mechanisms causing the need for maintenance (e.g. friction clutches, brakes, etc.) (Markeset and Kumar, 2003b).

To produce reliable products, to respond quickly to service demands, and to avoid user/customer dissatisfaction by reducing the system down-time (less repair time) and repair costs, companies should consider the reliability characteristics at the design and product support dimensioning stages. Additionally, as mentioned before, high reliability does not mean that we do not need to perform service or maintenance, but that service or maintenance is needed to a lesser degree. The highly reliable product or the design-out-maintenance approach often proves too costly or impossible due to the state of the art of the technology. Therefore, one often ends up with design for easy, cost-effective and efficient maintenance and support. When defining reliability, failure is defined as the termination of the ability of an item to perform a required function (International Electrotechnical Vocabulary [IEV] 191-04-01). After failure the item has a fault. Failure is an event, as distinguished from a fault, which is a state.

Normal products most often require maintenance and service to be performed at regular intervals to ensure product reliability and availability. In order to deliver the product/equipment or the required function, the manufacturer has to design the product, manufacture it and provide the required support (e.g. spare parts) to meet the expected performance demand. Support is needed to compensate for product unreliability, loss of performance quality and effectiveness, and a lack of usability (Markeset and Kumar, 2003a).

3.1.2 Application type of the product

The application type of the product refers to the situation of the operator, the work conditions and the environmental factors. The environmental conditions in which the equipment is to be operated, the road conditions, maintenance facilities, maintenance crew training, operator training, etc., often have a considerable influence on the product reliability characteristics (Kumar and Kumar, 1992; Kumar et al., 1992) and consequently on the product support (this topic will be discussed in detail in Chapter 3.3). Thus the operating environment should be considered seriously when dimensioning the product support and drawing up the service delivery performance strategies, since it will have an impact on the operational and maintenance costs and service quality. Generally, the recommended maintenance program for systems and components is based on their age without any consideration of the operating environment. This, in turn, leads to many unexpected system and component failures. This creates poor system performance and a higher Life Cycle Cost (LCC) due to unplanned repairs and/or restoration, as well as support.

The application type of the product comprises for instance the working environment, user/customer/operator characteristics, operating place, working time length and etc.

The application type of the product should be taken into consideration in the design phase of a new product and the support dimensioning phase of an existing product, to provide a support plan for achieving the optimum conditions. In other words, the users’ environments must be analyzed before deciding the service and maintenance concept for industrial systems/products. Furthermore, the users and the operating environment can also influence the degree of support needed to achieve the expected
performance level (Markeset, Kumar, 2003b). Then service, repair and other issues of product support should be designed considering the system’s operating environment parameters. For example, we cannot offer the same support to unique systems which are working in different geographical locations such as Argentina and Russia.

3.1.3 Geographical locations of the product
This factor is important in the delivery of support and service for products. If the manufacturer is located close to the user, it may take a shorter time to get hold of spare parts and assistance, while if the user is far away from the manufacturer, the service delivery system becomes very critical. The distance of the user from the manufacturer, distributor/supplier can bring an additional influence on spare parts management. To optimize the product support, this issue also needs to be considered in the design phase of the product and product support by the manufacturer, supplier, and customer. Finally, in product support, a prompt response to the customers’ requests plays a key role in customer satisfaction. Therefore, with respect to these points (fast response, repair and spare parts), the geographical distribution of customers is becoming a critical factor in decision-making concerning service delivery strategies, spare parts logistics and inventory management. In spare parts logistics, for instance, the geographical distribution of the customers (the product working places) has an influence on the lead time, and consequently the quantity of stored parts.

In addition, there has to be a trade-off between the product’s dependability and the geographical locations of the product (Figure 7). In this context, to arrive at optimal product dependability characteristics for various geographical locations, the LCC analysis is a useful and powerful tool in correct decision-making. In other words, when considering and analyzing the life cycle cost of a new product, one can find out which rate (percentage) of reliability and availability should be designed for a product in relation to the product’s geographical location, in order to optimize the LCC. If the life cycle cost for one alternative is higher compared to the other one in the same conditions, the lowest life cycle cost alternative in the normal situation is naturally preferred.

![Figure 7. Trade-off between product dependability and geographical location of product (adapted from Markeset & Kumar, 2003b)](image-url)
3.2 Product support logistics

Optimal spares provisioning is a prerequisite for all types of maintenance tasks, such as inspections, preventive maintenance, and repairs. With the exception of preventive activities, spare parts for maintenance tasks are usually required at random intervals. Thus, the fast and secure coordination of the demand for spare parts with the supply of spare parts at the required time is an important factor for the punctual execution of the maintenance process. Missing materials are one of the most frequently cited reasons for delay in completion of maintenance tasks. As spare parts for machinery are often of a very high quality, this problem cannot be solved simply by an increased warehouse stock.

Through the optimization of product support logistics, material stocks of spare parts can be optimized to support maximum availability with minimum stocks.

The aim of product support logistics is to minimize the product support costs, including costs for ordering, holding, transportation, product down-time, etc. Therefore, since the present research deals with spare parts issues in product support, in the field of logistics we discuss spare parts inventory management and the ordering process for required spare parts.

The conditions for planning the logistics of spare parts differ from those for planning the logistics of other materials in several ways:

- The service requirements are higher, as the effects of stock-outs may be financially remarkable.
- The demand for parts may be extremely sporadic and difficult to forecast.
- The prices of individual parts may be very high. These conditions lead to the necessity to streamline the logistic system of spare parts. This streamlined process saves time and money. Therefore, spare parts management is naturally an important area of inventory research (Huiskonen, 2001).

3.2.1 Spare parts management

The spare parts program of a plant is an essential part of the overall spare parts management, because it ensures that there will always be an adequate supply of spare parts at hand when they are needed and that the plant will never experience costly delays in repairs while awaiting spare parts. However, maintaining this inventory can also result in significant additional costs for plant/product operation if it is not optimized.

An effective spare parts management program has several broad objectives:

- To ensure that the spare parts inventory contains at least one of every part which is likely to be needed to carry out repairs of an important system/component whose failure would result in an unacceptable impact on plant safety or production;
- To ensure that the “at-hand” replenishment of spare parts for each important component is sufficient to prevent any unacceptable losses in plant or safety system availability which would follow the occurrence of more than one failure during a typical inventory replenishment cycle;
- To maintain the necessary inventory at the optimum cost.
Historically, inventories have contained several different classes of spare parts, each of which tends to have its own individual analytical requirements when decisions are made about whether to stock, and how many to stock, which affect the considered service level of spare parts:

- Expensive spare components or large assemblies for important systems/components, e.g. hydraulic pumps in LHDs (loading, hauling and dumping machines), etc.;
- Medium-grade piece parts and complete assemblies for important systems, e.g. pumps, valves, controls, and breakers;
- Smaller (cheap) generic parts needed to maintain and repair important systems/components, e.g. bolts, fasteners, gaskets, cables, and connectors.

After the classification of spare parts has been carried out, the next task is to optimize the actual number of spares which are purchased for the on-site inventory.

Actually the spare parts classification scheme can provide a focusing mechanism which can be used in the management of the overall plant spare parts inventory.

### 3.2.2 Spare parts inventory

Inventory control of spare parts plays an increasingly important role in modern operations management. The trade-off is clear: on one hand a large number of spare parts ties up a large amount of capital, while on the other hand too little inventory may result in poor customer service or extremely costly emergency actions (Aronis et al., 2004).

A general approach which can be used to determine an appropriate inventory and its replenishment for the existing and equipment in use is shown in Figure 8.

Following a decision that a particular part should be kept in the inventory, the next question to be answered is how many parts the inventory should contain. Part replenishment is determined on the basis of the expected usage rate of the part and the economic risk associated with allowing a depleted inventory to occur during the part replenishment cycle which would otherwise follow the removal of parts from stock.

Factors which influence the usage rate and replenishment include:

- the part failure rate and usage rate per component,
- the number of similar components.

This provides the annual usage rate. However, to control handling charges and to exploit the substantial discounts offered by some vendors for multiple purchases, many smaller parts have “economic ordering quantities”. Both of these factors are considered during the determination of replenishment, in which the analyst calculates the probability of incurring additional failures during the re-order and inventory replenishment cycle.
The probability that a spare will not be available when needed will be a function of the number normally held in the inventory (part replenishment), the number of similar components and their reliability, the operating environment (part usage rates) and the time taken to restock parts after they have been removed from the inventory (replenishment cycle).

When the dependability analysis has shown a component to be a candidate for inclusion in the spare part inventory because it has a high importance measure, the benefit from maintaining spares can be calculated by varying the associated mean
down-time and measuring its effect on the system’s equivalent forced outage rate (EFOR).

When the part usage rate is calculated from the number of similar components and their failure rates and compared to the length of the part replacement cycle, it is possible to calculate the probability that a needed part will not be available.

This information can be used to modify the unavailability for the affected components in the dependability model, and a series of sensitivity studies can be performed to determine the optimum sparing level, i.e. the minimum number of parts to be stored on-site, which would provide adequate assurance that a critical component would not be unavailable due to the lack of a needed spare part.

The principle objective of any inventory management system, as mentioned earlier, is to achieve an adequate service level with a minimum inventory investment and minimum administrative costs which can be achieved for instance directly by save on ordering cost by ordering more that what is needed. This will cause to blocked capital in inventory. To solve that, the economic order quantity (EOQ) (Figure 9) which originates from Harris (1913) and Wilson (1934) made it popular, can be used and is the lot size that minimizes the total inventory cost, concerning both holding and ordering with respect to elimination of shortages, and can be calculated as (Krajewski and Ritzman, 2005):

$$EOQ = \sqrt{\frac{2DS}{H}}$$  \hspace{1cm} (3.1)

where:  
D = the annual demand (units/year)\[equals N_T \text{ in one year}\]  
S = the cost of ordering or setting up one lot ($/lot)  
H = the cost of holding one unit in the inventory for a year (often calculated as a proportion of the item’s value)

![Figure 9. Economic Order Quantity](Source: Krajewski and Ritzman, 2005)

There are two popular systems in inventory management:

- Periodic review system (P system) and
- Continuous review system (Q system)
Inventory management – P system

The periodic review (P) system (fixed interval reorder or periodic reorder system) is an inventory control system in which the inventory position is reviewed periodically (the time between orders (TBO) is fixed) and a new order is placed at the end of each review.

In this model we are required to define two basic parameters: the time between reviews (P), and the target inventory (target cycle service in our case) level (ILt). In other words, in this model of inventory management, we want to calculate and know: (a) the time between the reviews of the inventory and the ordering of a new lot size of required items (spare parts etc.), and (b) the target level of the required items in the inventory to try to keep the availability of parts in the inventory necessary to eliminate shortages.

Inventory management – Q system

The continuous review (Q) system, sometimes called a reorder point (ROP) system or fixed order quantity system, is another inventory control system. In this system, the inventory position (IP) measures the item’s ability to satisfy future demand. When the inventory position reaches a predetermined minimum level, called the reorder point (R), a fixed quantity (Q) of the item is ordered. When the demand is certain, the reorder point (R) equals the demand during the lead time, but when the demand is uncertain, then the safety stock should be added to average demand during lead time (see for example Krajewski and Ritzman, 2005 for more information).
3.3 Reliability issues

The reliability of a system is a function of time and the environment in which the
system is operating. When defining reliability, we can say that the reliability of a
system is the probability that it will perform or operate the required functions without
failure under a given condition for an intended operating period. Lower reliability
means increased unplanned stoppages and consequently unscheduled repairs and
decreased availability. Although more stand-by units may increase the system
availability, they do not decrease the incidence of system failures (Kumar and
Granholm, 1988).

The study of product reliability requires a framework that incorporates many
interrelated technical, operational, commercial and management issues. Some of the
important issues in each of these areas are as follows (Blischke and Murthy, 2000):

**Technical issues:**
- Understanding deterioration and failure (material science)
- The effect of design on product reliability (reliability engineering)
- The effect of manufacturing on product reliability (quality variations and
control)
- Testing to obtain data for estimating part and component reliability (design of
experiments)
- The estimation and prediction of reliability (statistical data analysis)

**Operational issues:**
- Operational strategies for low-reliability/unreliable systems
- Effective maintenance (maintenance management)

**Commercial issues:**
- Cost and pricing issues (reliability economics)
- Marketing implications (warranties, service contracts)

**Management issues:**
- The impact of reliability decisions on business (business management)
- The risk to individuals and society resulting from product unreliability (risk
theory)
- The effective management of risks from a business point of view (risk
management)

Figure 10 shows some of the important issues and the disciplines involved in product
reliability analysis.

For product reliability management, a life cycle approach is necessary. The
manufacturer must make decisions with regard to various reliability issues during the
product life cycle. The reliability of a product has a significant impact on operation
and maintenance requirements. A product with low reliability has a smaller
acquisition cost, but the operating and maintenance costs can be high. On the other
hand, a more reliable product will cost more, but have smaller operating and
maintenance costs.
This means that the reliability of the product is a very important factor in choosing between different options. One approach to deciding on the strategies for acquisition, operation and maintenance is the life cycle cost (LCC) analysis approach.

Figure 11 presents a comparison between design out maintenance (DOM) and design for maintenance (DFM), showing important parameters from the points of view of product reliability characteristics and product support.

The LCC is the total cost of owning, operating, maintaining, and finally discarding the product. The maintenance costs, as a part of the product support costs, are influenced by the product reliability and the maintenance strategies used (for corrective and preventive maintenance). Finally, we can say that the product performance is influenced by the following two sets of factors:
Theoretical Framework – Reliability Issues

- **Factors prior to the sale and use of the product:** These are primarily technical and engineering factors related to the design, development and manufacturing of the product. The manufacturer has reasonable control over these factors and in some cases (for example defense acquisitions) the customer may have a significant influence (Blischke and Murthy, 2000).

- **Factors during use:** These relate to the environment and the mode of usage. The latter includes factors such as the duty cycle, intensity of usage, operating environment factors, etc. The performance of a product ordinarily degrades as the environment becomes harsher and/or the usage intensity increases. These factors are, to a significant degree, under the control of the customer (user) in the case of conventional products, and the manufacturer has very little (and often no) control over them. However, in the case of functional products, these factors are under the control of the manufacturer as a user.

### 3.3.1 Reliability characteristics (measures)

The reliability characteristics or measures used to specify reliability must reflect the operational requirements of the item. Manufacturers and customers use reliability measures to quantify the effectiveness of a system. The use of any particular reliability measure depends on what is expected of the system and what we are trying to measure. Several life cycle decisions are made using reliability measures as one of the important design parameters.

In a broader sense, reliability metrics can be classified as (Kumar et al., 2000b):

(a) Basic reliability measures, which are used to predict the system’s ability to operate without maintenance and logistics support. Reliability measures like the reliability function and the failure function fall under this category.

(b) Mission reliability measures, which are used to predict the system’s ability to complete the mission. These measures consider only those failures that cause mission failure. Reliability measures such as the mission reliability, maintenance-free operating period (MFOP), failure-free operating period (FFOP), and hazard function fall under this category.

(c) Operational reliability measures, which are used to predict the performance of the system when operated in a planned environment, including the combined effect of design, quality, environment, maintenance, support policy, etc.; measures such as the Mean Time Between Failure (MTBF), Mean Time Between Overhaul (MTBO), Maintenance Free Operating Period (MFOP), Mean Time Between Critical Failure (MTBCF), Mean Time Between Unscheduled Removal (MTBUR) and Mean Time To Failure (MTTF) fall under this category.

(d) The contractual reliability measure, which is used to define measures for and evaluate the manufacturer’s program. Contractual reliability is calculated by considering the design and manufacturing characteristics. Basically it is the inherent reliability characteristic. Measures such as the Mean Time To Failure (MTTF), Mean Time Between Failure (MTBF) and Failure Rate fall under this category.
The selection of a specific measure to quantify the reliability requirements should include mission and logistic reliability along with maintenance and support measures. Currently, many manufacturers specify reliability by using the mean time between failure, mean time to failure and failure rate.

3.3.2 Reliability prediction methods
Reliability plays an important role in many aspects of a product life cycle. For example, accurate reliability estimates are required before a design is released to the production facility and before the product is finally released for distribution to customers (Luxhoj and Shyur, 1997). Furthermore, reliability estimation is critical in determining the optimal maintenance, inspection, spare parts estimation and replacement schedules. In other words, accurate estimation and prediction of the hazards of mechanical systems are critical to maintenance (particularly predictive maintenance) activities (Sun et al., 2004). This has led many manufacturers to conduct real-life testing on components and products to estimate their reliabilities accurately.

Failure prediction of mechanical systems can be conducted in two ways: fault diagnosis from condition monitoring signals and statistical analysis of historical failure data. Most existing statistical models require historical operational data and mature statistical techniques to be effective.

Testing systems/components in normal operating conditions requires an extensive amount of time and a large number of tools in order to obtain accurate measures of reliabilities. Accelerated life testing is an approach that is used to obtain reliability and failure rate estimates of systems/components in a much shorter time.

The statistical method is another approach for predicting product reliability under special circumstances (e.g. prediction at later stages or update predictions of item while some data are available, reliability prediction of existing item). When the failure time data involve complex distributions that are largely unknown, or when the number of observations is small, making it difficult to fit a failure time distribution accurately and to avoid making assumptions that would be difficult to test, non-parametric statistics-based models are used. A widely used non-parametric method is “multiple regressions”. It is assumed that the covariates (external factors influencing reliability, e.g. operating environmental factors, applied stresses, etc.) are independent variables of the regression model used to predict the time to failure of the individual component. The proportional hazards model (PHM) is a non-parametric approach developed by Cox (1972), in which a baseline hazard function is modified multiplicatively by covariates. PHM, represented by \( h(t) = h_0(t)\psi(z, \alpha) \), indicates that the hazard of a system will change when its covariates change, i.e. covariates are explanatory variables and hazard is the response variable in PHM.

The advantage of this approach is that it is essentially distribution-free, and no additional assumptions are necessary about the failure times. The model is quite flexible. For example, if one assumes a particular form for the baseline hazard function \( h_0(t) \), a fully parametric proportional hazards model is obtained. For instance, Jardine et al. (1999) use a Weibull hazard function for \( h_0(t) \) in their PHM.
model. A distribution-free model can be obtained if no specific form is assumed for \( \lambda_0(t) \).

The proportional covariate model (PCM) is another model for prediction of the failure and reliability of mechanical systems/components. The PCM model, however, presents that in practice response covariates are often monitored and recorded to determine the deterioration of a system. In this situation, covariates (condition monitoring data) are response variables and the hazard becomes the explanatory variable (Sun et al., 2004). PHM is not perfectly suitable for modelling this scenario, as the statisticians Moore and McCabe (2003) have demonstrated that the regression results will be different if the explanatory variable and response variables are interchanged.

According to Sun et al. (2004), PCM is different from PHM in the following aspects:

1. PCM predicts the hazard of a system using the covariates caused by the deterioration of a system and is therefore more suitable for situations where symptoms of a system are monitored. On the other hand, PHM predicts the hazard of a system using covariates that affect the hazard of a system and is more suitable for situations where environmental conditions are monitored. These environmental conditions will cause the failure rate of a system to change.

2. In PHM, a baseline hazard rate, \( h_0(t) \), is used to describe the relationship between covariates and hazard, whereas in PCM, a baseline covariate function, \( C(t) \), is employed to describe the relationship between the covariates and the hazard. The baseline hazard rate \( h_0(t) \) is the hazard rate without any influence from covariates. The baseline covariate function \( C(t) \) represents the rate of change of covariates when the hazard changes.

The PCM model is quite a new and immature method which was not tested completely yet and has some unclear points 1. This is the reason why it did not apply in the present research and instead the well-known PHM method was used to predict the failure rate of components.

Another method for modelling failures at the component level is the stress-strength model. If \( X \) represents the strength of a part which is subjected to a stress, \( Y \), there are two alternatives in reliability estimation (see Blischke and Murthy, 2000 for more information):

**Deterministic stress and random strength:** In this case the reliability (\( R \)) is given by:

\[
R = P\{X > Y\} \\
R = 1 - F_X(Y)
\]

where \( F_X(Y) \) is the distribution function.

**Random stress and strength:** In this case we define \( Z = X - Y \) and the reliability is given by:

\[
R = P\{Z > 0\} = 1 - F_Z(0)
\]
For example, if the stress and strength are exponentially distributed, then:

\[ R = \frac{\lambda_y}{\lambda_x + \lambda_y} \]  

(3.4)

Since the product is employed under conditions that are unknown and perhaps new, and many items are intended for a use different from typical and tested applications, it is common to modify predicted values by the application of environmental and other influencing factors. The aim is to account for different conditions, such as temperature, humidity, voltage stress and so on. The adjustment is accomplished by multiplication of the predicted failure rate by appropriate constants. Generally this method of prediction is particularly useful for items where failure is a result of breakage, rupture, etc. (Blischke and Murthy, 2000).

The “Part Stress Analysis” and the “Parts Count” methods are another two methods of reliability prediction. These methods vary in the degree of information needed to apply them. The Part Stress Analysis method requires a greater amount of detailed information and is applicable during the later design phase, when actual products/components are being designed (MIL-HDBK-217F). The Parts Count method requires less information, generally part quantities, the quality level, and the application environment. This method is applicable during the early design phase and during proposal formulation. In general, the Parts Count Method will usually result in a more conservative estimate (i.e. higher failure rate) of the system reliability than the Parts Stress Method (MIL-HDBK-217F).

In fact, the Part Stress Analysis method is a refinement of the Parts Count method in that it involves the same basic steps (Intellect, 2003). In the former method the system must be defined and a reliability model developed. The Parts Count method is based on the principle that the reliability of any component depends upon the baseline failure rates and the environments in which the item is to be used. Basic assumptions of the method are that the baseline failure rates are constant with time, and part failures are independent of each other. The part failure rates are calculated by multiplying the baseline failure rates by an appropriate environmental factor.

Comparison of different methods has led to the “stress analysis” method being used as a standard approach that is more applicable in the reliability prediction of electronic modules, where the failure rates are constant.

Therefore, to summarize our discussion on different reliability prediction methods, the “Proportional Hazard Model” is applicable in a variety of different cases, especially for the prediction of the reliability and failure rate of mechanical parts. As mentioned before, it is essentially distribution-free, no additional assumption is necessary about the failure times, and it is quite flexible. In addition, it uses covariates that affect the hazard of a system and is more suitable for situations where environmental conditions are monitored (as in our case). These environmental conditions will cause the failure rate of a system to change.

With respect to these points and considering the sources of the data used in this research, which mostly are field data taken from reports and interviews (see Chapter 5.2 for details), we found that the “Proportional Hazard Model” is more suitable for studying the reliability and predicting the failure rate of components and consequently
for predicting the average number of required spare parts, with taking into consideration the influencing factors of the operating environment (making a distribution assumption at the end). Furthermore, as mentioned earlier, PHM predicts the hazard of a system with considering the covariates that affect the hazard of a system and is appropriate for situations (environmental conditions) at hand.

3.3.3 Reliability models

The exponential and Weibull reliability models are generally the most common models used for the reliability analysis of systems. The main assumption in the exponential model is that the times between failures are exponentially distributed or, expressed simply the failure (hazard) rate is independent of time.

For example, the failure of electronic components that have a constant failure rate follows this model. However, there are several other mechanical parts which do not conform to the exponential model (i.e. do not have a constant failure rate), and fail due to ageing with time. Ageing or wear-out mechanisms such as corrosion, oxidation and wear are time-dependent processes. They result in increasing failure rates for the parts, characterized by the Weibull model with shape parameter $\beta > 1$.

The Weibull reliability model is a most versatile model for characterizing the life of machine parts (mechanical systems). The failure density function of the two-parameter Weibull distribution is defined as:

$$f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta - 1} \exp\left[-\left(\frac{t}{\eta}\right)^\beta\right] t \geq 0, \eta > 0, \beta > 0 \quad (3.5)$$

And the reliability function is given by:

$$R(t) = \int_{t}^{\infty} f(x) dx = \exp \left[-\left(\frac{t}{\eta}\right)^\beta\right] \quad \text{(3.6)}$$

$$\lambda(t) = \left(\frac{\beta}{\eta}\right)\left(\frac{t}{\eta}\right)^{\beta - 1} \quad \text{(3.7)}$$

where:

$t > 0, \quad \beta > 0, \quad \eta > 0$

The parameter $\eta$ is the “characteristic life” parameter. It has the same units as $t$ and the parameter $\beta$ is a “shape” parameter and is a non-dimensional quantity. The great versatility of the Weibull distribution stems from the possibility of adjusting it to fit the many cases where the hazard rate either increases or decreases, because this distribution has no fixed characteristic shape.

$\beta = 1$ represents the constant failure rate and the reliability model is converted to:

$$R(t) = \exp(-\lambda t), t \geq 0 \quad (3.8)$$

with the failure rate:

$$\lambda(t) = \frac{1}{\eta} = \frac{1}{MTBF} \quad (MTTF \text{ for non-repairable components)}$$
This model represents the exponential reliability model. In the model \( R(t) \) is the reliability of the system, \( \lambda \) is the constant failure rate \( =1/MTTF \), and \( t \) is the period of operation. The exponential distribution is the most widely used and well-established statistical distribution, and it explains the general failure distribution of a system during its normal operating life period, when the failure occurs at random. The most important factor for the applicability of this model is that the hazard rate must be constant and the age should have no effect on the failure rate of the system.

\[ \beta > 1 \] representing an increasing failure rate. In the Weibull model, the \( \beta \) and \( \eta \) parameters can be determined by plotting \( \ln(\ln(1/R(t_i))) \) against \( \ln(t_i) \), and the slope and intercept of the best fitted straight line to this data are the value of \( \beta \) and \( \eta \) respectively.

\[ R(t) = \frac{i - 0.3}{n + 0.4} \] is the median rank formula and its advantages is that it is relatively easy to put confidence limits on the line, and that censored data can be dealt with (Leitch, 1995).

### 3.3.4 Operating-environment-based reliability analysis

Only the parametric reliability methods with a specific assumption about the lifetime distribution (e.g. an exponential or a Weibull distribution) were very popular at the beginning of reliability analysis of systems (Davis, 1952; O’Connor, 1991; Høyland and Rausand, 1994). Restrictions on the fulfillment of assumptions of distribution fitting led to the development of non-parametric reliability models based on the method suggested by Kaplan & Meier (1958) and Nelson (1969). The advantages of non-parametric models are that no specific distributional form needs to be assumed concerning the failure data and that censored data can be considered easily (Kumar, 1996). These models can be used for modeling the effect of other factors than time (e.g. operating environment and the system/machine situation), as covariates, on the reliability of the system. A major contribution to the concept of non-parametric regression methods for modeling the effects of covariates was made by the method named the Proportional Hazard Model (PHM) and suggested by Cox (1972). The literature survey carried out for this thesis indicates that a relatively small number of industrial applications of these methods (especially in spare parts forecasting) have been performed and reported in international journals (e.g. Newby, 1988; Bendell et al., 1991; Kumar and Klefsjö, 1994b; Kumar, 1996; Jardine et al., 2001).

Meanwhile, during the present research, it was found that most of the previous research on the reliability analysis of systems considers the operation time as the only variable for estimating the reliability of a system. However, as mentioned earlier and is known there are other factors than time that influence the reliability characteristics of a system in its operation life cycle. These factors may include, for instance, the operating environment (e.g. temperature, pressure, humidity, or dust), the operating history of the machine (e.g. overhauls, effects of repair or types of maintenance) or the type of design or material, which are referred to as risk factors or covariates. These factors generally affect the failure behavior of a system, but are usually ignored in the reliability analysis. Thus, the operating environment as an additional factor influencing the system reliability characteristics is better to be considered seriously when reliability and hazard rate analysis is performed. Then reliability can be defined on the basis of the intended function, the product operating life (time), and the
environment of use (which includes exterior influence factors such as dust, temperature, etc., and the operators’ skills and competence).

One method for analyzing the effects of covariates on the hazard rate (reliability) is to use regression models, which generally can be broadly classified into two groups, parametric and non-parametric regression models, on the basis of the approaches used (Lawless, 1982; 1983). In parametric models, the lifetime of a system is assumed to have a specific distribution that depends on covariates, one example of such a model being the “Weibull regression model” (Smith, 1991). In non-parametric models, however, the general approach is to decompose the hazard rate into two parts. The “proportional hazard model” (Cox, 1972), as said before, is an example of a non-parametric model, which initially developed to assess the effects of environmental covariates on the hazard (covariates are explanatory variables and the hazard is the response variable in PHM) and has been used in the present research for calculating the system’s failure rates. The proportional hazard model (PHM) was initially applied in medical analysis (Cox and Oakes, 1984) and thereafter started to apply and use in engineering reliability analysis (Jardine et al., 2001; Kumar and Westberg, 1996; Ansell and Phillips, 1997).

3.3.4.1 Proportional hazard model (PHM)

A valuable statistical procedure to estimate the risk of equipment failing when it is subjected to its operating environment and conditions is the proportional hazards model (PHM). The PHM model is based on the assumption that the hazard function for an item/component of equipment is a product of the baseline hazard function of that item and an exponential term incorporating the effect of a number of explanatory variables or covariates. The generalized form of the proportional hazards model (PHM) that is most commonly used is written as (Cox, 1972):

\[
h(x, z) = h_0(x) \exp(z \alpha)
\]

(3.9)

where \( h(x, z) \) is the hazard function, \( z \alpha = \sum z_i \alpha_i \), and \( \alpha \) (column vector) is the unknown parameter of the model or regression coefficient of the corresponding \( n \) covariates \( (z) \) (row vector consisting of the covariate parameters) indicating the degree of influence which each covariate has on the hazard function; and \( h_0(x) \) is the baseline hazard rate.

The PHM an ingenious distribution free approach to the analysis of data, first suggested by Cox (1972) (Lawless, 1982). If one assume a particular form for \( h_0(t) \), a fully parametric proportional hazard model is obtained. The most important such model is the Weibull model, for which \( h_0(t) = (\beta / \eta)(t/\eta)^{\beta-1} \); this is also includes the exponential model as the special case \( \beta = 1 \).

An advantage of the method is that it is essentially distribution free: certain properties of the procedure do not depend upon the underlying lifetime distribution or, in other words, on \( h_0(t) \). This is actually true only when there is no censoring, but with many types of censoring the dependence on \( h_0(t) \) is small (Lawless, 1982). If the data come from a specific proportional hazard model such as the Weibull model, there will be
some loss of efficiency in using the distribution free approach rather than the one based on the correct parametric model. In certain situations, however, this loss of efficiency is only slight (Lawless, 1982).

In this model it is assumed that, in the real life of a system, the hazard (failure) rate is influenced by the time during which and the covariates under which it operates. In other words, the hazard rate of a system is the product of the baseline hazard rate \( \lambda_0(t) \), dependent on time only, and another positive functional term, basically independent of time. This term incorporates the effects of a number of covariates, such as temperature, pressure, and others. The effects of covariates may be to increase or to decrease the hazard rate. For example, in the case of bad operating conditions, poor and incomplete maintenance or incorrect spare parts, the observed hazard rate is greater than the baseline hazard rate. However, in the case of good operating conditions, or improved and reliable components of a system, the observed hazard rate will be smaller than the baseline hazard rate (Kumar and Klefsjö, 1994b). The basic concept of this model is shown in Figure 12.

The baseline hazard (failure) rate is assumed to be identical to the total hazard rate when the covariates have no influence on the failure pattern.

Therefore, the observed hazard rate of a system with respect to the exponential form of function, which includes the effects of covariates, may be given as (Kumar and Klefsjö, 1994b; Jardine et al., 2001):

\[
\lambda(t, z) = \lambda_0(t) \exp(z \alpha) = \lambda_0(t) \exp(\sum_{j=1}^{n} \alpha_j z_j) \quad (3.10)
\]

where \( z_j, j = 1, 2, \ldots, n \) are the covariates associated with the system and \( \alpha_j, j = 1, 2, \ldots, n \) are the unknown parameters of the model, defining the effects of each one of the \( n \) covariates.

The multiplicative factor, \( \exp(z \alpha) \), may be termed the relative risk of failure due to the presence of the covariate \( z \). The reliability functions are given by:

\[
R(t) = [R_0(t)]^{\exp(\sum_{j=1}^{n} \alpha_j z_j)} \quad (3.11)
\]
where

\[ R_0(t) = \exp\left[-\int_0^t \lambda_0(x)dx\right] = \exp[-\Lambda_0(t)] \quad (3.12) \]

and \( R_0(t) \) is the baseline reliability function dependent only on time, and \( \Lambda_0(t) \) is the cumulative baseline hazard rate.

1 The following Figure (Figure 13) represents a schematic illustration of the effect of incorporating external and internal influencing factors on the hazard rate of a system/component.

**Figure 13. The factors influencing the system/components hazard rate**

In PHM, the hazard rate is a function of the baseline hazard rate and a positive function which incorporates the effect of covariates and can be written as:

\[ h(t, z) = h_0(t)\psi(z(t)) \]

However, in PCM the hazard rate is a function of the baseline covariates, which are a the function of hazard rate itself, or in other words:

\[ h(t, z) = h_0(t)\psi\left(f(h(t, z))\right) \]

where:

\[ z_i(t) = f(h(t, z)) \]

\[ h(t, z) = h_0(t)\psi\left(f(h(t, z))\right) \]

As is seen, the hazard function \([h(t, z)]\) appears on both sides of the equation, which is strange and makes this model unclear and not easy to implement.
3.4 Risk assessment and analysis

The issues of risk assessment and hazard evaluation in facilities subject to high-risk accidents have reached a status of top priority and cannot be disregarded on any ground. Plant managers nowadays are forced to employ increasingly onerous risk assessment and reduction activities, while still relying on limited budgets and scarcity of resources.

Therefore, the techno-economical optimization of prevention/protection activities becomes a priority. A number of process hazards and risk analysis methods are available to perform safety studies. They are thoroughly described in textbooks and other literature (e.g. CCPS Guidelines for Chemical Process Quantitative Risk Analysis, 2000; Henley and Kumamoto, 1992). Of course, it should be noted that currently no commonly agreed upon standard risk assessment procedure exists. In fact, the actual procedure utilized will be the result of the integration of distinct tools and techniques as required by site-specific factors, and the decisional and judgmental contribution of the analyst or plant manager is always required. Although a qualitative hazard evaluation and risk assessment may still be sufficient in several applications, a detailed quantitative analysis is required if any kind of economic justification or optimization of risk-reducing measures must be pursued, when the physical consequences of accidents must be evaluated, and when relevant losses are possible.

When faced with a risk reduction task, technicians must properly balance preventive and protective approaches. In this case, apart from design modifications and the improvement of operational procedures, the role of maintenance and product support should not be underestimated in pursuing a risk reduction strategy. In fact, while it is largely agreed that correct management of maintenance and product support is critical to preserving the operability, availability and competitiveness of production systems (Duffuaa et al., 1999; Campbell, 1995), it is also undeniable that plants’ or components’ reliability has a direct impact on the risk level of the entire system (Smith, 1991; Lees, 1996). It follows that there is a very strict link between the risk level and maintenance and support activities, since a correct product support policy including maintenance may effectively contribute to risk reduction as much as other structural choices or other operational and managerial activities.

In fact, for maintainable systems, the availability and reliability of single components or the entire system may be strongly influenced by the adopted maintenance and support policies. These policies positively affect the probability of occurrence of accidents, the magnitude of accidents or the capability of loss minimization.

Therefore, using this perspective, quantitative risk assessment techniques become strategic levers for safety management and risk reduction, especially when accidents (e.g. due to a shortage of spare parts) with relevant consequences are involved.

3.4.1 Performance measurement

Since investments in spare parts as an issue of product support can be substantial, management is interested in decreasing stock levels whilst maximizing the service performance of a spare part management system. To assess the result of improvement actions, performance indicators (such as the fill rate and service rate) are needed. For
Reliability and Operating Environment Based Spare Parts Planning

example, sometimes the duration of the unavailability of parts is a major factor of concern. Then the waiting time for parts is a more relevant performance indicator.

Performance measurement for risk concerning spare parts (unavailability, incorrect, obsolesce, etc), represents a problem in its own right. Usually risk items in spare parts are not defined and issued, but their presence in the stock is justified. In this control category, the most important factor in performance measurement is the risk of unavailability. In general, this risk can be expressed simply as (Fortuin and Martin, 1999):

\[
RISK_i = \text{Probability} (D_i > S_i) \times C_i
\]

where:
- \( RISK_i \) = expected financial loss due to risk item \( i \) being out of stock
- \( D_i \) = demand for item \( i \) during its entire (or remaining) life cycle
- \( S_i \) = initial number of items of type \( i \) in the stock
- \( C_i \) = financial consequences if an out-of-stock situation for item \( i \) occurs

In the following we will discuss in greater detail the concept of risk analysis and the risk of unavailability of spare parts when required.

3.4.2 Risk definition

Kaplan and Garrick (1981) have discussed a number of alternative definitions of risk. These include:

- Risk is a combination of uncertainty and damage.
- Risk is the ratio of hazards to safeguards.
- Risk is a triplet combination of events, probability and consequences.

The term probabilistic risk analysis refers to the process of estimating the risk of an activity based on the probability of events whose occurrence can lead to undesired consequences.

The term hazard expresses the potential for producing an undesired consequence without regard to how likely such a consequence is. Thus, one of the hazards of the spare parts inventory is the shortage of a spare part when it is required, which could produce a number of different undesired consequences. The term risk usually expresses not only the potential for an undesired consequence, but also how probable it is that such a consequence will occur.

Probabilistic risk analysis (PRA) attempts to estimate the frequency of accidents and the magnitude of these consequences by different methods, such as fault tree and event tree methods.

In fact, maintenance plays a pivotal role in managing risks at an industry site and it is important that the right risk assessment tools should be applied to capture and evaluate the hazards at hand to allow a functional risk based approach (Rasche and Wooley, 2000).

Risk management, which often refers to a safety management system (SMS) and making decisions based on risk, is a complex issue with many aspects. What is risk
and what are the key drivers? These are the basic questions, which must be cleared up at the beginning.

In the spare parts management context, event probabilities ($P_e$) such as equipment or component failure rates, the availability of spare parts, etc., can either be estimated using subjective expert opinion or calculated using objective historical data from maintenance and inventory information systems or suitable databases. The consequences ($C$) that will arise out of those failures or shortages are established through consequence analysis.

Unplanned stoppages or unnecessary down-time will always result in a temporary upset to the operations flow and output. The cumulative unavailability of the machine (in the case of spare parts shortages) and beneficiation process and the added cost can quickly affect the financial performance of the system.

Risk management is an iterative process, as shown in Figure 14.

![Figure 14. Risk management](image)

Successful risk management depends on a clearly defined scope for the risk assessment, comprehensive and detailed hazard mapping and a thorough understanding of possible consequences.

There are several tools and techniques available to the managers and engineers that can help to estimate the level of risk better. These techniques may be either ‘subjective – qualitative’ or ‘objective – quantitative’, as shown in Figure 15. Both types of techniques have been used effectively in establishing risk-based safety and maintenance strategies in many industries (Rasche and Wooley, 2000).
Quantitative methods are probably ideal for maintenance applications where some data are available and decisions on the system safety and criticality are to be made. Even very basic reliability analysis of maintenance data can be used effectively in determining the optimum maintenance intervention, replacement intervals or monitoring strategy.

Fault Tree and Event Tree analysis (FTA/ETA), which can be classified as quantitative methods as well, are tried and tested system safety tools originating from the defense, nuclear and aviation industries. While ETA draws the growth of an event and yields quantified risk estimates of all the event paths, FTA is implemented specifically through the combination of ‘and’ & ‘or’ gates and event probabilities. In the following these methods will be presented in greater detail.

### 3.4.3 Risk analysis process

As mentioned earlier briefly, risk analysis can be performed in different steps, as follows:

1. Define the potential event sequences and potential incidents.
2. Evaluate the incident outcomes (consequences).
3. Estimate the potential incident frequencies. Fault tree or generic databases may be used for initial event sequences. Event trees may be used to account for mitigation and post-release events.
4. Estimate the incident impacts on health and safety, the environment and property (e.g. economy).
5. Estimate the risk. This is achieved by combining the potential consequence for each event with the event frequency, and adding up all the consequences.

### 3.4.3.1 Fault tree analysis

Fault tree analysis (FTA) is a technique which can be used to predict the expected probability of failure/hazard of a system in the absence of actual experience of failure.
This absence may be due to the fact that there is very little operating experience, or the fact that the system failure/hazard rate is so low that no failures have been observed. The technique is applicable when the system is made up of many parts and the failure/hazard rate of the parts is known.

The fault tree analysis always starts with the definition of the undesired event whose possible causes, probability and conditions of occurrence are to be determined. The probability of failure can be the probability of failure on demand (such as the probability that a car will fail to start when the starter switch is turned). In our case the event will be “system down-time” and is shown in the top box as a top event.

The fault tree technique has been evolving for the past four decades and is probably the most widely used method for the quantitative prediction of system failure. However, it becomes exceedingly difficult to apply in very complicated problems.

Figure 16 shows an example of the form of a fault tree, and represents a part of a case study that has been carried out during this research. As is seen, the system/machine down-time and consequently the state of no production have been considered as the top event. The down-time can be due to either a lack of raw material, some failure in the system or the unavailability of power for the machine. The failure of the system was considered for analysis in this case.

![Fault Tree Analysis](image-url)
3.4.3.2 Event tree analysis

An event tree is a graphical logic model that identifies and quantifies possible outcomes following an initiating event. The event tree provides systematic coverage of the time sequence of event propagation.

The event tree structure is the same as that used in decision tree analysis (Brown et al., 1974). Each event following the initiating event is conditional on the occurrence of its precursor event. Outcomes of each precursor event are most often binary (success or failure, yes or no), but can also include multiple outcomes (e.g. 100%, 40% or 0%).

Event trees have found widespread applications in risk analysis. Two distinct applications can be identified. The pre-incident application examines the systems in place that would prevent incident that can develop into accidents. The event tree analysis of such a system is often sufficient for the purposes of estimating the safety of the system. The post-incident application is used to identify incident outcomes. Event tree analysis can be sufficient for this application.

Pre-incident event trees can be used to evaluate the effectiveness of a multi-element proactive system. A post-incident event tree can be used to identify and evaluate quantitatively the various incident outcomes that might arise from a single initiating (hazardous) event.

Fault trees are often used to model the branching from a node of an event tree. Moreover, the top event of a fault tree may be the initiating event of an event tree. Note the difference in meaning of the term initiating event between the applications of fault tree and event tree analysis. A fault tree may have many basic (initiating) events that lead to the single top event, but an event tree will have only one initiating event that leads to many possible outcomes. The sequence is shown in the logic diagram below (Figure 17).

![Logic diagram for event tree analysis](image)

The following Figure (Figure 18) shows a part of the constructed event tree that was implemented for studying and assessing the risk of not considering the system operating environment when estimating the required number of spare parts in the defined planning horizon. Both event tree and fault tree analysis in the present
research have been used in a modified and non-standard way which the organizational states and decisions as well as events and consequents changes are introduced and taken into account in the analysis. It has been discussed in detail in the appended paper.

Figure 18. Event tree analysis (a part of a case study as an example)
PART II – EMPIRICAL WORK AND FINDINGS

4 Research project and process

The quality and cost-effectiveness of a system/product, which are basically related to dependability concerns, are essential attributes that a system/product must possess in order to survive in today’s competitive environment. Therefore, the need for support has become vital for the enhancement of system effectiveness and for the prevention of unplanned stoppages.

The availability of a system is its ability to be in the state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided. This ability depends on the combined aspects of reliability performance, maintainability performance and maintenance support performance (International Electrotechnical Vocabulary [IEV] 191-02-05). Consequently, the value of the operational availability, $A_o$, of a system or product is determined by the following formula:

$$A_o = \frac{MTTF}{MTTF + MTTR + MTTS}$$  \hspace{1cm} (4.1)

where $MTTF$, $MTTR$ and $MTTS$ represent the mean time to failure, mean time to repair and mean time to support, and are measures of the system’s reliability, maintainability and supportability characteristics, respectively. In reality, it is the operational availability which is generally used as a performance measure for a given product or system.

Supportability, as a characteristic influencing availability, can be defined as the ability of a system to support the mission objectives. Supportability is also heavily influenced by logistics considerations, such as spare parts, personnel, strategic resources, test equipment and tools (Smith and Knezevic, 1996).

It is generally accepted that the availability and location of spare parts have a great impact on the supportability of a product/system (Markeset and Kumar, 2005). Accurate prediction of the required spares level will save a considerable amount of money.

According to Green (1993), excessive sparing is not cost-effective in that there are more spares than can be used. Conversely, when enough spares are not available, the equipment down-time can jeopardize the mission, and totally an inordinate amount of time and money is spent preparing these parts when the spare parts preparation process is implemented in a complicated way.

For essential capital investment equipment such as manufacturing plant, mining equipment, or an airplane, inappropriate spares provisioning or a lack of spares is now being recognized as an extremely important factor in determining the supportability of a system (Smith and Knezevic, 1996).
The availability/utility of machines and industrial systems can be improved by on-time support and maintenance. Support based on system/component reliability is a techno-economical way to achieve the optimum operation. Providing the required spare parts is an important issue in this context. Therefore, the required spare parts should be available in stock in the event of repair and replacement of the failed or worn components to minimize the system down-time and maximize the machine utilization. Sound spare parts management improves productivity by reducing idle machine time and increasing resource utilization. It is obvious that spares provisioning is a complex problem and requires an accurate analysis of all the conditions and factors that affect the selection of appropriate spare provisioning models.

It is necessary then that the required number of spare parts should be forecasted properly and kept prepared, while taking economic factors into consideration, so that faulty components can be replaced in the minimum time possible when required. Estimation of the required spare parts can be accomplished through different approaches, one of which is a realistic and well-founded method based on the system’s reliability characteristics and taking into consideration the operating environment.

### 4.1 Analysis design - Spare parts estimation (forecasting)

In the literature there exist large numbers of papers and monographs in the general area of spare provisioning, especially in spare parts logistics (Chelbi and Ait-Kadi, 2001; Kennedy et al., 2002; Langford, 1995; Orsburn, 1991). Generally, most of these papers deal with repairable systems and spares inventory management (Aronis et al., 2004; Sarker and Haque, 2000; Smith and Schaefer, 1985). They mostly provide a queuing theory approach to determine the spare parts stock at hand to ensure a specified availability of the system (Graves, 1985; Huiskonen, 2001). These models have been extended further to incorporate the inventory management aspect of maintenance (Gross et al., 1985; Hall and Clark, 1987; Ito and Nakagawa, 1995; Sherbrooke, 1992; Kumar et al., 2000a).

The following common features have been discussed in the existing literature:

- Mostly repairable systems have been dealt with.
- Queuing theory has been used, with the demand rate $\lambda$ and the repair rate $\mu$. There is a problem with this, since the failure rate is based on the operational time to failure, while the demand rate (used in inventory models) and repair rate (used in availability models) are based on the calendar time. This distinction has not been very clearly dealt with in the papers.
- These queuing theory based models primarily deal with constant failure rates and constant repair rates (exponential time to failure and time to repair), although this assumption is restrictive, particularly for mechanical parts. Mechanical parts often fail due to aging with time. The aging or wear-out mechanisms, such as creep, fatigue, corrosion, oxidation, diffusion, and wear, are all time-dependent processes.
On the other hand, quantitative techniques based on reliability theory have been used for estimating the failure rates of the required items to be purchased and/or stocked (Jardine, 1998; Gnedenko et al., 1969; Kales, 1998; Lewis, 1996; Lipson and Sheth, 1973; Wååk and Alfredsson, 2001; Xie et al., 2000). This failure rate has been used to determine more accurate demand rates.

As a result we can say that most of the research work in the spare parts domain has been carried out in inventory management. Guaranteeing the availability of systems/machines, as mentioned earlier, assumes that spare parts are always available on demand. Estimation and calculation, however, of the required number of spare parts for storage to ensure their availability when required, with respect to techno-economic issues (reliability, maintainability, life cycle cost, etc.), have rarely been considered and studied (notable exceptions being, for example, Sheikh et al., 2000; Tomasek, 1970).

None of the surveyed literature dealing with required spare parts calculations based on the reliability characteristics of a product has considered the operating environment as a factor influencing reliability (e.g. Jardine, 1998; Lewis, 1996). Therefore, the estimations are not accurate enough, because in the real life situation, as mentioned earlier, it has been proved that there are several factors other than time that have an influence on the reliability characteristics of parts/systems. By taking these factors (covariates) into account in our calculation, we can assume the term $\exp(az)$ in the hazard rate function $[h(t, z)]$ to be proportionate to the actual working conditions, as a constant coefficient. Then:

$$R(t) = \left[ \exp \left( - \int \lambda_0(x) dx \right) \right]^{\sum_{j=1}^{n} \zeta_j} = [\exp(-\Lambda_0(t))]^{\sum_{j=1}^{n} \zeta_j}$$ (4.2)

Therefore, it appears reasonable to take operating environment issues into account when studying and analyzing systems’ reliability, according to the estimate and forecast of the required spare parts, which has been almost neglected up till now.

### 4.1.1 Product reliability characteristics and operating environment based spare parts estimation

The environmental conditions in which equipment is to be operated, such as the temperature, humidity, dust, etc. often have considerable influence on the product reliability characteristics (Kumar and Kumar, 1992; Blischke and Murthy, 2000; Kumar et al., 1992). Thus, an operating environment and its factors, represented by covariates, should be seriously considered when dimensioning product support and drawing up service delivery performance strategies, as this one factor will likely have a significant impact upon the operational/maintenance cost and service quality.

Some important examples of operating environment factors (covariates) are:

- Working environment:
  - Climatic conditions such as the temperature and humidity in which a system will be working.
  - Physical environment factors such as dust, smoke, fumes, corrosive agents, and the like.
- User characteristics: such as operator skill, education, culture, and language.
- Operating place or location: this factor refers to workplace settings such as outdoor (free) or closed (surrounded) spaces, the branch of industry that will be using the product and/or other characteristics of the area (such as mines) where a product will be used.
- Level of application: the system may be intended to have a major/main purpose, a minor or auxiliary purpose, or even a standby purpose in an operational setup.
- Work time and period of operation: planning may call for a product to be in continuous or part-time operation.

An operating environment can also influence the degree of support needed to achieve an expected performance level (Markeset and Kumar, 2003b).

The covariates influence the system’s (including the components’) hazard (failure) rate, so that the observed hazard rate may be either greater or smaller than the baseline hazard rate (Figure 11). Meanwhile, for better estimation of the reliability characteristics, the use of regression models is suggested because of the possibility of including the covariates.

The proportional hazard model (PHM) was introduced by Cox (1972), and it is a regression type model. The PHM is a complement to the set of tools used in reliability analysis and provides some particularly advantageous features (Kumar and Klefsjö, 1994b; Jardine et al., 2001). This model is classified as a multiplicative and mostly non-parametric regression model which considers covariates and which assumes that the hazard rate of a system/component is a product of the baseline hazard rate $\lambda_0(t)$, dependent on time only, and a positive functional term, $\psi(z, \alpha)$, basically independent of time, incorporating the effects of a number of covariates such as temperature, pressure and changes in design. Thus:

$$\lambda(t) = \lambda(t, z) = \lambda_0(t)\psi(z, \alpha)$$

where $z$ is a row vector consisting of the covariates, and $\alpha$ is a column vector consisting of the regression parameters.

Two popular mathematical models that are used in spare parts provisioning are based on renewal theory and the homogeneous Poisson process as a special case of a renewal process. The homogeneous Poisson process can be used whenever the failure rate is constant (meaning that each failure mode and other factors which influence the demand should follow the exponential distribution). Whenever the failure rate is not constant, we use renewal theory to forecast demands for spares. It is important to note that the above statement is valid only for non-repairable spares (components).

In addition, with regard to a system that comprises several different non-repairable components, when the system fails due to the failure of any of the components, for retaining the system in, the failed item is replaced with a new one. In other words, the minimal repair is carried out for the system, and the failure rate of the system after the replacement of the failed components is the same as that just before the failure. Therefore, in this category of system, failure occurs according to a non-stationary Poisson process (Blischke and Murthy, 1994). The failure rate associated with the
failure distribution function is a reliability measure which is used in this case for calculating the average required number of spare parts for a defined time horizon. However, for each non-repairable item/component in a system, failures and hence replacements over time occur according to a renewal process, since each failed item is replaced by a new one (Blischke and Murthy, 1994). In other words, the time to failure (or time between replacements) is used as a reliability measure in this context for estimating the number of required spare parts (Figure 19).

**Figure 19.** Comparison between the failure rate of a single component and that of a system

### 4.1.2.1 Poisson process model for forecasting the required spare parts

With the assumption of replacing the parts/components upon failure, homogeneous Poisson process models can be used when the time to failure follows an exponential distribution with a constant mean value; i.e. when the failure rate is constant. A constant failure rate could mean that the number of occurrences per time unit does not vary over time, but instead normally means that the conditional probability of failure per time unit is constant. Consequently, items with an age-related failure mechanism cannot be modeled using the Poisson process. However, the Poisson process can be used to model higher indenture spares such as Line Repairable Units (LRU) in the steady state.

In LRU with a large number of components which can be modeled using an independent renewal process, theorems by Palm (1938) and Drenick (1960) state that in the steady state the time between removals at the LRU level follows an exponential distribution; i.e. the demand follows a Poisson process.

The exponential reliability model is a simple and applicable model to use, especially when the effects of covariates are considered in the study of non-repairable elements/systems. Therefore, in this case the total number of spare parts available, with the assumption of an exponentially distributed lifetime for them, can be calculated through the use of the following equation (see Billinton and Allan, 1983; and Kumar et al., 2000b for background information):
Reliability and Operating Environment Based Spare Parts Planning

\[ 1 - P(t) = \exp(-\lambda t) \times \sum_{x=0}^{\infty} \frac{(\lambda t)^x}{x!} \quad (4.4) \]

where:
- \( P(t) \) = Probability of a shortage of spare parts (1- \( P(t) \) = Confidence level of spare part availability or service level)
- \( \lambda \) = Failure rate of an objective part (with regard to the effect of covariates)
- \( t \) = Operation time of system
- \( N \) = Total number of spare parts available in period \( t \)

This equation is based on a Poisson distribution that represents the probability of an isolated event which occurs a specified number of times in a given interval of time, and, as mentioned before, one requirement of the Poisson distribution is that the hazard rate should be constant. In such circumstances the hazard rate is generally termed the failure rate.

If \( q \) represents the number of the same part in use at the same time, then \( q \) is entered into the equation in the form of multiplication by \( \lambda t q \). In this way the calculated \( N \) will represent the total required number of spare parts for the whole system.

The confidence level of spare parts availability can be defined based on certain criteria, some of which are discussed as an example in Chapter 4.2.

4.1.2.2 Renewal process model for forecasting the required spare parts

Renewal theory was originally used to analyze the replacement of equipment upon failure, to find the distribution of the number of replacements and the mean number of replacements (Kumar et al. 2000b). It is the most appropriate tool for predicting the demand for consumable items.

Generally in the analytical world, function evaluation is much faster and optimization is feasible. The classes of analytical models that we identify and like to compare are those based on general renewal processes. The reason is that component (non-repairable parts) failure processes are naturally described by renewal processes.

The theory of renewal processes is well developed and matures (Gnedenko et al., 1969; Ross, 1997; Rigdon and Basu, 2000). A (an ordinary) renewal process is characterized by one entity, the distribution for the time between renewals, denoted by \( F(t) \). If \( N(t) \) represents the number of renewals (in our case the number of failures) that occur by time \( t \), and if one assumes that the time-to-failure random variables \( X_i, i \geq 1 \) are independent and have a common distribution \( F(t) \), then the probability distribution of the number of failures is given by:

\[ P[N(t) = n] = F^n(t) - F^{n+1}(t) \quad (4.5) \]

where \( F^n(t) \) is the \( n \)-fold convolution of \( F(t) \) and is given by:

\[ F^n(t) = \int_{0}^{t} F^{n-1}(t-x)dF(x) \quad (4.6) \]


\( F^n(t) \) denotes the probability that the \( n^{th} \) failure will occur by time \( t \). The expected number of failures, \( M(t) \), during a length of \( t \) is given by:

\[
M(t) = \sum_{n=1}^{\infty} F^n(t)
\]

The above equation is known as the \textit{Renewal Function}, and it gives the number of renewals during \((0, t]\) and can be also written as (Blischke and Murthy, 1994):

\[
M(t) = F(t) + \int_{0}^{t} M(t-x)f(x)dx
\]

For instance, for an exponential time to failure distribution:

\[
F(t) = 1 - \exp(-\lambda t)
\]

Moreover, as it is known that the Weibull reliability model is an appropriate model for characterizing the life of machine parts (mechanical systems), then by substituting the Weibull cumulative distribution function for the time to failure, we have:

\[
F(t) = 1 - \exp\left[-\left(t / \eta \right)^{\beta}\right]
\]

Consider replacements of a part having an average time to failure denoted by \( \overline{T} \) and a standard deviation of time to failures denoted by \( \sigma(T) \) (so that \( \zeta = \sigma(T) / \overline{T} \) denotes the coefficient of variation of the time to failures), and if the operation time \( t \) of the system or machine in which this part is installed is quite long and several replacements need to be made during this period, then the average number of failures \( E[N(t)] = M(t) \) will stabilize to the asymptotic value of the \textit{renewal function} as (Gnedenko et al., 1969):

\[
N_e = M(t) = E[N(t)] = \frac{t}{\overline{T}} + \frac{\zeta^2 - 1}{2}
\]

And the corresponding \textit{failure intensity} or \textit{renewal rate function} is given by:

\[
m(t) = \frac{dM(t)}{dt} = \frac{dE[N(t)]}{dt} = \frac{1}{\overline{T}}
\]

The standard deviation of the number of failures in time \( t \) is:

\[
\sigma[N(t)] = \sqrt{\frac{t}{\overline{T}}}
\]

If time \( t \) in the above equations representing a planning horizon is large, then \( N(t) \) is approximately normally distributed (based on a central limit theorem) with mean = \( \overline{N(t)} \). Then the approximated\(^2\) number of spares \( N_t \) needed during this period with a probability of shortage = \( 1-p \) is given by:

\[
N_t = \frac{t}{\overline{T}} + \frac{\zeta^2 - 1}{2} + \zeta \sqrt{\frac{t}{\overline{T}}} \Phi^{-1}(p)
\]

where \( \Phi^{-1}(p) \) is the inverse normal distribution function and is available in probability textbooks. Assuming the Weibull reliability model to be a most versatile
model for characterizing the life of mechanical parts, and integrating the effect of covariates with regard to the proportional hazard model, we have:

\[
\lambda(t) = \frac{\beta_0 t^{\beta-1}}{\eta_0} \exp\left(\sum_{j=1}^{n} \alpha_j z_j\right)
\]

(4.15)

\[
\lambda(t) = \frac{\beta_0 t^{\beta-1}}{\eta_0} \exp\left(-\sum_{j=1}^{n} \alpha_j z_j\right)
\]

(4.16)

\[
\lambda(t) = \left[\frac{\beta_0 t^{\beta-1}}{\eta_0} \exp\left(-\sum_{j=1}^{n} \alpha_j z_j\right)\right]^{\frac{1}{\beta}}
\]

(4.17)

This equation indicates the Weibull distribution with the shape parameter and scale parameter as:

\[
\begin{cases}
\beta = \beta_0 \\
\eta = \eta_0 \left[\exp\left(\sum_{j=1}^{n} \alpha_j z_j\right)\right]^{\frac{1}{\beta}}
\end{cases}
\]

(4.18)

The reliability model obtained by assuming that \(\beta_0\) = baseline shape parameter and \(\eta_0\) = baseline scale parameter can be defined as:

\[
F(t) = 1 - R(t) = 1 - \exp\left(-\left(\frac{t}{\eta}\right)^\beta\right) = 1 - \exp\left(-\frac{t}{\eta_0} \left[\exp\left(\sum_{j=1}^{n} \alpha_j z_j\right)\right]^{\frac{1}{\beta}}\right)
\]

(4.19)

Thus, it can be concluded that the influencing covariates change the scale parameter only and the shape parameter remains almost unchanged.

\(\beta_0\) and \(\eta_0\) are the initial (baseline) shape and scale parameters respectively in the Weibull distribution. The coefficient of variation of the time to failures can be calculated based on the shape and scale parameter as below:

\[
\zeta = \frac{\sigma(T)}{\bar{T}}
\]

(4.20)

where:

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

(4.21)

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

(4.22)
4.2 Spare parts classification

There are other important factors, such as the geographical location of the machine/system, the cost, and the criticality of the part, which influence decision-making concerning how much to order and when to order. Therefore, spare parts need to be evaluated in terms of these factors as well.

The operating location, for instance, can be seen from the point of view of the geographical location or the distance between the user (product) and the manufacturer/supplier. This factor has an influence on the lead time for service and spare parts delivery, as a short distance to the product’s working place involves shorter lead time and prompts replies in product support. However, if the product user is located far away from the manufacturer, the lead time for spare part/service delivery becomes long and very critical. This factor can be classified as near, moderate or far (i.e. the distance between the working place and the manufacturer/supplier).

Equipment criticality is defined as the importance of equipment for sustaining production in a safe and efficient way, and is a function of the use of the equipment, rather than of the equipment itself. It is possible to distinguish between different types of spare parts demand, i.e. critical and non-critical demand, with critical demand originating from failures of parts installed in vital equipment, and non-critical demand from parts installed in essential and auxiliary equipment (see Dekker et al., 1998 for detail).

The criticality is based on the cost of not completing the process, the assigned equipment function or the mission. The criticality can also be classified as low, moderate, and/or high, for example. Highly critical parts are those which are absolutely essential for mission success, and moderately critical parts are such that, if they are out of stock at the time of demand, they will have only a slight to moderate effect on mission success, whereas parts of low criticality are not absolutely essential for mission success. For instance, if one part with low criticality is not available on demand, we can either find it on the market or use another alternative part as a substitute.

Reserving stock for critical components/items generally increases the service level for critical demand and decreases the service level for non-critical demand (Dekker et al., 1998).

Figure 20 presents a hypothetical example of spare parts classification (a schematic illustration). This factor (the category of spare parts) might be taken into account when we define the confidence level of spare parts’ availability.

4.3 Study and analysis of the exponential and the Weibull models in spare parts estimation

There are some advantages and disadvantages of implementing the exponential and/or the Weibull renewal processes in spare parts estimation. For instance, the exponential model is simple and easy to implement concerning both the required data collection
and analysis. Nevertheless, the approximated Weibull renewal processes model is more appropriate for calculating the total number of available spare parts accurately.

Below come the results of a comparison between the two methods which are based on the implemented calculation process. The calculation process was carried out based on the different values of the baseline mean time to failure ($MTTF_0$), the shape parameter ($\beta$), and the effect of covariates ($Co.Eff. = \exp(\sum a_jz_j)$ as an assumed fix coefficient). In the implemented calculation process we used both the exact exponential model and the approximated Weibull renewal model methods for estimating the average required number of spare parts in a specified planning horizon.

- In both the exact exponential and the approximated Weibull models, the number of required spare parts decreases as the baseline mean time to failure increases. The ratio of the number of spare parts estimated through the exponential method to that estimated through the Weibull method is approximately two to one (on average). In addition, the slope of the lines is sharp before 3000 hrs and afterwards it subsides. We can therefore conclude that for the working period before 3000 hrs it is more beneficial to use the Weibull model, which is more accurate (a big difference in the number of required spare parts compared to the exponential model). For the period after 3000 hrs the exponential model, which is easy to use and implement, can replace the Weibull model. From another point of view, for the component costing less it might be more economical to use the exponential model than the accurate but costly (more time-consuming) Weibull model. [Figure 21 shows the average number of required spare parts based on different values of the baseline mean time to failure. The beta value ($\beta = 3.5$), the coefficient of covariates ($Co.Eff. = 1.5$) and the system operation time ($t = 5600$ hrs) were assumed to be constant].
The exponential model is influenced more by covariates in comparison with the Weibull renewal model. We found that this is only due to the fact that the covariates affect directly (in the multiplication form) the failure rate in the exponential model, whereas in the Weibull model, the covariates affect only the scale parameter as a part of factors in the failure rate [Figure 22 where $\beta=3$, $MTTF_o=3000$ (hrs) and $r=5600$ (hrs) were assumed to be constant]. When the effect of covariates is equal to one, there is no environmental/external influence on the number of failures and consequently on the number of required spare parts. A value of the effect of covariates less than one indicates a worse situation for the system operating condition, whereas a value of the effect of covariates greater than one represents a good/improved working environment.

The multi-comparison of the effects of covariates and the $\beta$ value (Figure 23) shows that the covariates have less influence on the average required number of spares for components with a high $\beta$. This event confirms our previous
Reliability and Operating Environment Based Spare Parts Planning

statement, which indicates that the exponential model acquires more effect than the Weibull model with covariates.

![Multi-Comparison between Weibull & exponential methods](image)

**Figure 23.** The multi-analysis of the effects of covariates and the $\beta$ value on the average number of required spare parts

- With an increasing $\beta$ value, the average number of required spare parts decreases. This is more predictable, because an increasing beta means that the component failure rate increases, whereas the system failure intensity is not affected in the same way. Therefore, for $\beta \leq 1.5$ the exponential model is more suitable in the context of application and analysis costs [in Figure 24 Co.Eff. $= 1.5$, $MTTF_\beta = 3000$ (hrs) and $t = 5600$ (hrs) were assumed to be constant].

![Comparison between Weibull & exponential methods](image)

**Figure 24.** The plot for the average number of required spare parts against the $\beta$

2 The difficulty in obtaining $M(t)$ [the mean number of the renewal function] from equation 4.12 is that it appears on both sides of the equation. If equation 4.12 can be approximated so that $M(t)$ appears only on the left hand side of the equation and the right hand side contains only known or prescribed functions, then we have an approximate solution that may be obtained either analytically or computationally.
There are different approximations that have been suggested by different researchers and research centers (Spearman, 1989; Smeitink and Dekker, 1990; Blischke and Murthy, 1994; Cui and Xie, 2003; NTNU, 2005). The approximation method which is used in the present research to find out the number of failures and consequently the average number of required spare parts was compared with a couple of these suggested methods (for t=5600 hrs). The results (as presented in Table 7 as a sample) were very close to each other, which state the acceptability of our results.

Table 7. The mean number of the renewal function in the case of the Weibull distribution with different values of the shape parameter and different approximation methods

<table>
<thead>
<tr>
<th>Approximated Renewal</th>
<th>$M_{\text{Gnedenko}}$</th>
<th>$M_{\text{Spearman}}$</th>
<th>$M_{\text{Murthy}}$</th>
<th>$M_{\text{NTNU}}$</th>
<th>$M_{\text{Dekker}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta=1$</td>
<td>2.800014</td>
<td>2.80003</td>
<td>2.8000</td>
<td>2.799192</td>
<td>2.8026</td>
</tr>
<tr>
<td>$\beta=3$</td>
<td>2.375542</td>
<td>2.37554</td>
<td>2.3678</td>
<td>2.401217</td>
<td>2.3641</td>
</tr>
<tr>
<td>$\beta=5$</td>
<td>2.271713</td>
<td>2.37171</td>
<td>2.3037</td>
<td>2.261201</td>
<td>2.2447</td>
</tr>
</tbody>
</table>

* The approximation method suggested by Gnedenko has been used in this research work.

As is seen in Figure 25, the curve of the probability density function moves to the right hand side with an increasing the $\beta$ value. This means that the probability of failure at the beginning of operation is high when the $\beta$ value is less in comparison with a high $\beta$ value. In other words, with an increasing $\beta$ value, the time to the first failure increases as well, which is considered in this study for non-repairable modules. This is an important and substantial issue in warranty cost evaluation, which has been considered and studied in a research project for a leading mobile phone company. However, with regard to the useful life of equipment, if the equipment’s life tends to be infinite, the system/component with a high $\beta$ value will need more spares. If the manufacturer offers a longer warranty period just by increasing the $\beta$ value of components, then this may result in the customer being dissatisfied after the warranty period due to an increased number of failures. Therefore, there is an important trade-off between the $\beta$ value and the life length of equipment and the warranty cost.

Figure 25. The probability of density function based on different values of $\beta$
5 Validity and reliability of model

5.1 Case study design

Sometimes industrial companies are faced with machine down-time due to a shortage of required spare parts, and this is because of the manufacturer’s/supplier’s recommendation for the average number of required spare parts to be kept in stock. In most cases the manufacturer is not aware of the prevailing environmental factors when estimating the average number of required spare parts. Consequently, to avoid down-time caused by the unavailability of spare parts (more common in the mining industry in particular), it is suggested that companies should take the operating environment factors into consideration when estimating the spare parts need.

The reliability of the models provided (for estimating the required number of spare parts with respect to the system operating environment) is an important issue that can guarantee the validity of the models. This was verified in the mining industry, which is a huge and complex industry that is faced with machine down-time and consequently loss of production and financial losses, by estimating of the number of different spare parts for a hydraulic system on mine loaders and LHD machines (Figure 26) in two big iron ore mines:

1. Open pit iron ore mine in Iran
2. Underground iron ore mine (Kiruna) in Sweden

Life today would be difficult without such basics as water and electricity. In industry the same could be said with regard to hydraulic power. Hydraulic loaders are a part of the machine-fleet used in mines for loading, hauling, and piling up ore and gangue. The hydraulic systems of these loaders, which include different repairable and non-repairable parts, play a key role in the operation of the machines. In connection with this, our case studies mostly concern spare parts for hydraulic systems, such as hydraulic seals, hydraulic jacks, hydraulic brake pumps, and some other parts, e.g. the wheel roll bearings of loaders (Figure 27 and Figure 28).
As was mentioned before, we selected non-repairable parts for study and analysis. The selection and definition of covariates are very important in reliability analysis with covariates, because any statistical inference is based on the way in which they are formulated. This process should be based on the failure mechanism of the system under study. In the studied cases, the formulation of covariates (influencing factors except time) was carried out based on observation, and the experience of operators and maintenance crew.

The covariates which were mostly considered in the study and analysis are:

- Operator skill: this covariate refers to the operator’s experience in operating the system/machine.
- Maintenance crew skill: this factor affects the quality of service, repair and maintenance and the condition of the system after service.
- Hydraulic oil quality: this is used to denote the quality of hydraulic oil in the brake system at work.
- Climatic conditions: these conditions, e.g. temperature, humidity etc., influence component/system failure (e.g. the effect of the temperature on the viscosity of the hydraulic oil and the elasticity of rubber components in the pump, such as gaskets).
- Physical environment (e.g. the existence of dust, chemical materials, etc.): this factor presents that the system is exposed to corrosive conditions.
- Overload: this is considered when the overload in the loader/LHD bucket creates an extra force (more than the allowed limit) on the system and consequently on the components.

5.2 Data collection and classification

Appropriate data collection is one of the most important steps in reliability analysis. A data collection system must be designed to facilitate correct and effective reliability analysis.

Data on reliability characteristics can be obtained by two methods, either directly from the field or from sample testing in laboratories, and the required analyzed data in this research were obtained from the field (two iron ore mines). Data collection in the field is expensive and time-consuming work. Nevertheless, data acquired from the field are most representative of the system reliability and maintainability characteristics, and all possible efforts should be made to collect data from the field.
As soon as the project for this thesis was conceptualized as an investigation of the required number of spare parts based on the reliability characteristics of industrial systems/machines, some mining companies\(^4\) were contacted for their support and help in the retrieval of field failure data for use in this study.

The failure data collected in the Choghart iron ore mine (in Iran) were not collected with the intention of using them in reliability studies. However, the LKAB Kiruna mine (in Sweden) had a system of failure data collection which could be used after just a little processing for reliability analysis. To start with, the operation and maintenance cards for a fleet of loader machines in Choghart iron ore mine were collected for eight years from 1995 (in LKAB we obtained the required data directly from the Department of Maintenance databases). The data collection was carried out during three and half years. The purpose was to examine the content of these cards for possible use for reliability studies. It was not an easy task to go through the cards and sort out the required information.

However, most of the information needed, such as the time between failures of machines and the time to failure of non-repairable components, was drawn out. For the purpose of preliminary investigations into the statistical nature of the breakdowns of these machines and their major subsystems and components, several interviews were held with machine operators, maintenance crew and management.

Finally the collected data, which were in the form of the working time and down-time of systems/machines, were subjected to a process of refining which involved sorting, analyzing, and finding out the censored and uncensored data. Then the mean time to failure of the items was calculated and classified as shown in Tables 8 and 9. The data were classified in their chronological order and reordering was avoided to study the presence of a trend, if any, in the field failure data.

From the above-mentioned sources, the times to successive failures of the subsystems and components, e.g. the brake hydraulic pump, hydraulic seal and systems, and brake pads, were calculated.

Table 8 and 9 are based on the data sets from LKAB (Kiruna Mine) in Sweden and Choghart iron ore mine in Iran, respectively. These data sets have been used in this research work to indicate the subject (see Appendix A for a sample of raw data from the iron ore mine in Iran). In fact, the collected data have been sorted and refined in the form of the mean time to failure, which is presented in the following tables.

The formulation of covariates (influencing factors except time) was carried out based on observation, service and repair cards and reports, and the experience of operators and maintenance crew. In this research, as mentioned earlier, we mostly deal with covariates such as:

\(^4\) Mining operations and their environment were found to be an interesting and relevant field of industry that could be used for collecting data for application in the present research. In fact, the working environment of mining machinery and mining operations is completely suited to the purpose of this research.
Table 8. The mean time to failure (hours) of the hydraulic jack mounted on the LHD machines in Kiruna Mine

<table>
<thead>
<tr>
<th>Ser. No.</th>
<th>MTTF</th>
<th>Ser. No.</th>
<th>MTTF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2536</td>
<td>11</td>
<td>2964</td>
</tr>
<tr>
<td>2</td>
<td>1200</td>
<td>12</td>
<td>272</td>
</tr>
<tr>
<td>3</td>
<td>3060</td>
<td>13</td>
<td>1196</td>
</tr>
<tr>
<td>4</td>
<td>3652</td>
<td>14</td>
<td>3920</td>
</tr>
<tr>
<td>5</td>
<td>2564</td>
<td>15</td>
<td>2312</td>
</tr>
<tr>
<td>6</td>
<td>644</td>
<td>16</td>
<td>3696</td>
</tr>
<tr>
<td>7</td>
<td>1380</td>
<td>17</td>
<td>3108</td>
</tr>
<tr>
<td>8</td>
<td>2776</td>
<td>18</td>
<td>1216</td>
</tr>
<tr>
<td>9</td>
<td>1004</td>
<td>19</td>
<td>2368</td>
</tr>
<tr>
<td>10</td>
<td>916</td>
<td>20</td>
<td>2640</td>
</tr>
</tbody>
</table>

Table 9. The mean time to failure (hours) of different non-repairable components from the Iranian iron ore mine which were used in the research work

<table>
<thead>
<tr>
<th>Ser. No.</th>
<th>Roll-bearing</th>
<th>Hydraulic brake pump</th>
<th>Hydraulic seal</th>
<th>Brake pad</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9720</td>
<td>6020</td>
<td>1505</td>
<td>1353</td>
</tr>
<tr>
<td>2</td>
<td>7940</td>
<td>5348</td>
<td>1337</td>
<td>1321</td>
</tr>
<tr>
<td>3</td>
<td>3890</td>
<td>6508</td>
<td>1627</td>
<td>1251</td>
</tr>
<tr>
<td>4</td>
<td>4990</td>
<td>7704</td>
<td>1926</td>
<td>1621</td>
</tr>
<tr>
<td>5</td>
<td>5350</td>
<td>7032</td>
<td>1758</td>
<td>1319</td>
</tr>
<tr>
<td>6</td>
<td>4080</td>
<td>5676</td>
<td>1419</td>
<td>1442</td>
</tr>
<tr>
<td>7</td>
<td>5260</td>
<td>10680</td>
<td>1572</td>
<td>1673</td>
</tr>
<tr>
<td>8</td>
<td>5640</td>
<td>5716</td>
<td>1429</td>
<td>1180</td>
</tr>
<tr>
<td>9</td>
<td>3300</td>
<td>6280</td>
<td>1570</td>
<td>1345</td>
</tr>
<tr>
<td>10</td>
<td>4030</td>
<td>5288</td>
<td>1322</td>
<td>1301</td>
</tr>
<tr>
<td>11</td>
<td>9180</td>
<td>6708</td>
<td>1677</td>
<td>1189</td>
</tr>
<tr>
<td>12</td>
<td>5280</td>
<td>7798</td>
<td>1947</td>
<td>1533</td>
</tr>
<tr>
<td>13</td>
<td>8990</td>
<td>9980</td>
<td>1497</td>
<td>1860</td>
</tr>
<tr>
<td>14</td>
<td>3830</td>
<td>5836</td>
<td>1459</td>
<td>1225</td>
</tr>
<tr>
<td>15</td>
<td>5610</td>
<td>1423</td>
<td>1976</td>
<td>1976</td>
</tr>
<tr>
<td>16</td>
<td>8530</td>
<td>1633</td>
<td>1399</td>
<td>1399</td>
</tr>
<tr>
<td>17</td>
<td>9490</td>
<td>1361</td>
<td>1870</td>
<td>1870</td>
</tr>
<tr>
<td>18</td>
<td>4330</td>
<td>1607</td>
<td>1242</td>
<td>1242</td>
</tr>
<tr>
<td>19</td>
<td>2080</td>
<td>1529</td>
<td>1723</td>
<td>1723</td>
</tr>
<tr>
<td>20</td>
<td>2590</td>
<td>1577</td>
<td>1279</td>
<td>1279</td>
</tr>
<tr>
<td>21</td>
<td>5100</td>
<td>1849</td>
<td>1923</td>
<td>1923</td>
</tr>
<tr>
<td>22</td>
<td>9980</td>
<td>1767</td>
<td>1504</td>
<td>1504</td>
</tr>
<tr>
<td>23</td>
<td>8820</td>
<td>1496</td>
<td>1710</td>
<td>1710</td>
</tr>
<tr>
<td>24</td>
<td>5850</td>
<td>1419</td>
<td>1692</td>
<td>1692</td>
</tr>
<tr>
<td>25</td>
<td>7510</td>
<td>1975</td>
<td>1883</td>
<td>1883</td>
</tr>
</tbody>
</table>

- the working environment, comprising the climatic conditions (e.g. the temperature and humidity) and the physical environment (e.g. the presence of dust and chemical water), and
- the user characteristics (e.g. the machine operator’s skill)

The operating environment factors were taken out with direct observation and interviews with people on the site. The final data for application in calculating the
hazard rate were obtained in the form of the mean time to failure of items and the list of influencing operating environmental factors and their existing situations.

In the next step, we codified them with numeric values, -1 for a bad situation like the presence of water (moisture) and dust, and +1 for a good and desirable condition like the absence of overload and the presence of a skilled operator.

The following table (Table 10), for example, contains the data sets used for demonstrating the concept. The column entitled “lifetime” exhibits times to failure of a particular type of brake pump mounted on a mine loader. A cell in the censored column with a zero value indicates that the loader was stopped due to some other reason than the pump, but that the pump was serviced, bringing its failure rate to that of a pump that is as good as new. And a cell with the value 1 indicates pump failure and the replacement of the pump with a new pump.

Table 10. Field data and codified values of influencing covariates collected from iron ore mine - Iran

<table>
<thead>
<tr>
<th>Ser. No.</th>
<th>Life time (Hours)</th>
<th>Censored</th>
<th>HOQ</th>
<th>SCSK</th>
<th>PHENV</th>
<th>CLCON</th>
<th>OPSK</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6020</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>2</td>
<td>5348</td>
<td>0</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>6508</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>7704</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>7032</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>5676</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>7</td>
<td>10680</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>5716</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>9</td>
<td>6280</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>10</td>
<td>5288</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>6708</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>7788</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>9000</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>5836</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table explanation

1. Covariates: the following abbreviations are used for denoting the covariates:
   - **HOQ**: Hydraulic Oil Quality
   - **SCSK**: Service and maintenance Crew Skill
   - **PHENV**: Physical Environment
   - **CLCON**: Climatic Condition
   - **OPSK**: loader’s Operator Skill

2. To explain the various figures in Table 2, we will consider row 1.
   For instance, column 2 indicates that the loader failure takes place after working 6020 hours due to a brake pump failure, as indicated by 1 in the censored column 3 (also indicating replacement by a new pump). Considering column 4, with an HOQ of +1, this indicates that the hydraulic oil used was standard oil recommended by the manufacturer. In column 5, +1 indicates that the service crew were skilled; in column 6, +1 indicates that the physical environment was good and acceptable (e.g., the existence of less dust); in column 7, -1 indicates that the climatic condition was not good (e.g., high temperature); and finally in column 8, -1 indicates that the loader operator was not expert enough in his job.
5.3 Case study analysis

For the purpose of this study, the available information about the operating conditions of the system(s) was determined and codified by a numeric value. As pointed out earlier, the selection and definition of operating environment factors are very important in reliability analysis with covariates, because any statistical inference is based on the way in which they were formulated. In this research work the information on the operating environment was uniformly formulated based on two alternatives, good/desired (+1) and bad/undesired (-1) conditions. This process should be based on the failure mechanism of the system under study.

After defining and formulizing the influencing covariates, we started with the assumption that a replaced system/component had the same $\lambda_0(t)$ (with $\lambda_0(t)$ being the baseline failure rate) when the failed part was deemed to be a non-repairable item.

The regression vector $\alpha$ in the PHM model may be estimated without making any assumption about the functional form of the baseline hazard rate, by maximizing likelihood functions which are obtained by considering the contribution to the hazard rate by the observed and censored times to failures. In the case of censored times to failure, their contribution to the likelihood function is considered only up to the time just before a censored time.

Let $t_1 < t_2 < \ldots < t_k, k < n$ be the uncensored times to failure of $n$ items, and let there be $n - k$ censored failure times. Let $F(t_i)$ be the risk set of the items which were functioning and non-censored, just prior to the observed failure at time $t_i$. If the number of tied failures, denoted by $d_i$, at each failure point is small compared to the number of items, $m$, in the risk set at time $t_i$, the likelihood function for the vector $\alpha$ is given by (Kalbfleisch and Prentice, 1980):

$$L(\alpha) = \prod_{i=1}^{k} \frac{\exp(S_i \alpha)}{\sum_{m \in \mathcal{F}(t_i)} \exp(z_m \alpha)}$$

(5.1)

where $S_i$ is the sum of the covariates observed at the failure time $t_i$ and $L(\alpha)$ is the conditional probability that the failure occurred at the time $t_i$. The above likelihood function is an approximation of the marginal or the partial likelihood function for the regression vector $\alpha$ in the case of a small number of tied failures (Kumar and Klefsjö, 1994).

The value of $\alpha$ that maximizes the above equation may be obtained by using numerical methods. The estimated value is then tested for its significance, so that it can be verified whether the particular covariate has any effect on the failure behavior of the system.

For modeling covariates in the proportional hazard regression (Cox, 1972) analysis, we used the SYSTAT software with the input of the mean time to failure of parts/components and the influencing covariates. SYSTAT finds the significant covariates through the iterative step-down process based on the maximum likelihood as mentioned above. In the “step-down procedure” all the covariates were first considered together. Then, the covariates found to have no significant value (based on
the corresponding p-value) were eliminated in the subsequent calculations. The next iteration was carried out with the remaining covariates. The corresponding estimates of \( \alpha \) (the regression coefficient) were finally obtained for the remaining significant covariates.

The estimates of \( \alpha \) were tested for their significance on the basis of t-statistics (the ratio of the estimated \( \alpha \) to the standard error of the estimates) and/or the p-value (obtained from the table for the unit normal distribution). One minus the p-value for a covariate gave a measure of importance when we were considering whether to retain any particular covariate in the model. Table 11 represents an example of the estimation process of covariates.

To satisfy the proportionality assumption of the hazard rates, the plots of the logarithm of the estimated cumulative hazard rates against time should be simply shifted by an additive constant \( \hat{\alpha} \), the estimate of the regression parameter \( \alpha \) of the covariate, which is taken as strata. Therefore, the plot should be almost parallel and separated properly matching to the different values of \( \hat{\alpha} \), if the proportionality assumption is correct (Kumar and Klefşjö, 1994a). For example, Figure 29 gives this graph for the covariate OPSK (loader operator’s skill).

**Figure 29.** An example (for the OPSK covariate) of a graphical test for the proportionality assumption of the hazard rates

In addition, the data were tested for the IID (independent identical distribution) assumption for the reliability model (Figure 30 illustrates a flow chart of dealing with field data which was used in this research). For this purpose, it could be checked by plotting the cumulative time to failures (TTFs) versus the cumulative failure number, as shown, for instance, in Figure 31. If the plotted points lie on a straight line, this implies that there is no trend in the failure data. Then the assumption of an identical distribution of the TTFs under consideration is not contradicted.

On the other hand, regarding the non-reparability of parts (the research subject), we are allowed to conclude data are independent. A test for serial correlation is also performed by plotting the \( i^{th} \) TTF against the \((i-1)^{th}\) TTF, \( i=1,2,3,\ldots,n \), as shown in Figure 32, for example, which indicates that no general correlation among the TTFs was present. Thus, we can conclude that the independence assumption in our model is confirmed.
Table 11. Estimation of covariates (the estimates of α and standard error (S.E.) were obtained by maximizing the likelihood function)

<table>
<thead>
<tr>
<th>Step number 0</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables included:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HOQ</td>
<td>-2.021</td>
<td>0.043</td>
</tr>
<tr>
<td>SCSK</td>
<td>-1.99</td>
<td>0.046</td>
</tr>
<tr>
<td>PHENV</td>
<td>-1.094</td>
<td>0.274</td>
</tr>
<tr>
<td>CLCON</td>
<td>-0.992</td>
<td>0.321</td>
</tr>
<tr>
<td>OPSK</td>
<td>-1.779</td>
<td>0.075</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step number 1</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables included:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HOQ</td>
<td>-1.985</td>
<td>0.047</td>
</tr>
<tr>
<td>SCSK</td>
<td>-1.868</td>
<td>0.062</td>
</tr>
<tr>
<td>PHENV</td>
<td>-0.862</td>
<td>0.388</td>
</tr>
<tr>
<td>OPSK</td>
<td>-1.829</td>
<td>0.067</td>
</tr>
<tr>
<td>Variables excluded:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLCON</td>
<td>-1.027</td>
<td>0.304</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step number 2</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables included:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HOQ</td>
<td>-1.892</td>
<td>0.058</td>
</tr>
<tr>
<td>SCSK</td>
<td>-1.754</td>
<td>0.079</td>
</tr>
<tr>
<td>OPSK</td>
<td>-1.726</td>
<td>0.084</td>
</tr>
<tr>
<td>Variables excluded:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLCON</td>
<td>-0.745</td>
<td>0.456</td>
</tr>
<tr>
<td>PHENV</td>
<td>-0.889</td>
<td>0.374</td>
</tr>
</tbody>
</table>

Final Model Summary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOQ</td>
<td>-1.253</td>
<td>0.662</td>
<td>-1.892</td>
<td>0.058</td>
</tr>
<tr>
<td>SCSK</td>
<td>-0.827</td>
<td>0.471</td>
<td>-1.754</td>
<td>0.079</td>
</tr>
<tr>
<td>OPSK</td>
<td>-0.895</td>
<td>0.518</td>
<td>-1.726</td>
<td>0.084</td>
</tr>
</tbody>
</table>

95.0 % Confidence Intervals

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOQ</td>
<td>-1.253</td>
<td>-2.551</td>
<td>0.045</td>
</tr>
<tr>
<td>SCSK</td>
<td>-0.827</td>
<td>-1.751</td>
<td>0.097</td>
</tr>
<tr>
<td>OPSK</td>
<td>-0.895</td>
<td>-1.910</td>
<td>0.121</td>
</tr>
</tbody>
</table>

5.4 Discussion

When building a model based on renewal theory and non-constant failure rates, the parameters that we need to estimate increase considerably. Especially when the effect of operating environment factors comes under consideration in the estimation, there are several different items and parameters that should be considered.
An important point to make is that in some cases it is questionable (in fact in many cases incorrect) to spend money and effort on trying to reduce the model error by going from an exponential model (based on the homogeneous Poisson process) to a more accurate demand process description. Usually the model error/uncertainty resulting from the Poisson approximation in a general condition is small in relation to other sources of uncertainty (Kumar et al., 1989; Wååk and Alfredsson, 2001).

The results of case studies show that, among the factors influencing the spares estimation, the effect of covariates (operating environment factors) is significant at a 90% confidence level (Paper 3). The baseline mean time to failure takes second place with regard to significance for consideration. It is therefore seriously recommended to take the influencing factors of the operating environment into consideration when analyzing the reliability characteristics of components/systems and when estimating the required number of spare parts, in order to make the final result as accurate and realistic as possible.
The results of the comparison indicate that the exponential model is influenced more by the effects of covariates.

Concerning the subject of the application of the exponential and the Weibull reliability models for estimating the required number of spare parts, as mentioned earlier (Chapter 4.1.2), from the customer/user point of view, in the case of the single component the Weibull renewal model is more applicable and accurate. However, the exponential model is more suitable when a system (involving multi-components) is under study to determine the required number of spare parts.
6 Research results and discussion

In today’s highly dynamic and constantly changing industrial environment, issues relating to product support are becoming increasingly important. However, the extent of the attention given to these issues varies considerably depending on the perspectives of the interested persons or professions. These are likely to vary from design engineers at the conceptual stages of product development to manufacturers and users in the later stages. Additionally, the make-up of a particular product support package varies according to the type of system/mission and application, and the stages of the machine/system life.

A lack of timely support or incomplete support is likely to cause unexpected downtime, which in turn will lead to losses for which one is unable to compensate. Falling within the definition of product support items are spare parts. The lack of a critical spare part can cause an untimely stoppage of a machine/system. The forecasting of product support and spare parts requirements based on the reliability and maintainability (R&M) characteristics of systems/components, together with the system’s operating environment(s), is one of the most effective strategies for prevention of unplanned stoppages.

The operating environment of a system/machine has a considerable influence on the performance of the system and its technical characteristics, such as its reliability and maintainability. Forecasting the required support/spare parts based on the technical characteristics and the system’s operating environment is an optimal way to prevent unplanned disruptions or stoppages. This part replacement strategy can be critical for the manufacturer/supplier when developing a product support package as a way to help ensure user satisfaction. For the end-user this strategy can be equally useful in those instances where the manufacturer’s/supplier’s support has stopped or has never been used.

Two models (based on the exponential and the Weibull renewal reliability models) are provided in the present research to determine the number of required spare parts, with respect to the effect of the external factors, except time, on the reliability characteristics of components, through the proportional hazard model. The models are verified with an estimation of the number of spare brake pads, hydraulic brake pumps, roll bearings of front wheels and hydraulic seals used in mine loaders, and the number of spare hydraulic jacks used on LHD machines, as non-repairable components. The reliability of these non-repairable parts and their operational impact are assessed both when considering environmental factors and when ignoring them.

The difference between the results obtained when determining the required spare parts considering the influence of the operating environment and those obtained when determining the required spare parts without considering the influence of the operating environment demonstrates that for the optimization of the product support logistics, it is necessary to take into account the environmental factors. When including these important parameters, we can better optimize any spare part inventory level, ordering value, and time between orders, which will also help to minimize the product life cycle cost.
When comparing the spare parts estimations based on the exponential and the Weibull renewal models, we found that:

- When building a model based on renewal theory and non-constant failure rates, the parameters that we need to estimate increase considerably, especially when the effect of operating environment factors comes under consideration in the estimation.

- In some cases it is questionable (in fact in many cases incorrect) to spend money and effort on trying to reduce the model error by going from an exponential model to a more accurate demand process description. Usually the model error/uncertainty resulting from implementing the exponential model in a general condition for a multi-component system is small in relation to other sources of uncertainty. The “more accurate” model (e.g. the Weibull renewal model) requires more input data (which is seldom available or is costly to achieve) and is less applicable to real-world situations.

- Based on various $MTTFo$, there is quite a big difference between the results of the two methods. In the case where $\beta < 2$ and the coefficient of the effect of covariates is equal to or smaller than 1, the difference between the output results of the two methods is small and sometimes negligible. In these cases then the Weibull renewal method can be replaced with the simple exponential method, which is probably more economical to implement.

- In the Weibull renewal model with an increasing $\beta$ value, the number of required spare parts decreases. However, with regard to the useful life of equipment, if the equipment’s life tends to be infinite, the system/component with a high $\beta$ value will need more spares. This is an important point for the manufacturer when estimating the warranty cost of products.

The risk associated with ignoring the operating environment factors when estimating the required spare parts is remarkable. The implemented risk analysis indicates that ignoring this factor might cause irretrievable losses in terms of production and ultimately in financial terms. The risk analysis was carried out through two risk analysis methods, namely event tree and fault tree analysis. The implemented event tree analysis was not a standard form of event tree analysis, but rather a special form where a safety function was defined as an undesired situation (state) as well, instead of a state similar to a barrier in the standard form of event tree analysis.

Sometimes the studied companies (LKAB and Choghart Iron Ore Mine) had been faced with down-time for their LHDs and loaders due to a lack of availability of required spare parts. This was because the manufacturer/supplier had recommended an incorrect number of required spare parts to be kept in stock. In most cases the manufacturer is not aware of the environmental factors or has not considered these issues in the estimation of the number of required spare parts. In the Choghart Iron Ore Mine in Iran, after locating the risk of a shortage of spare parts due to ignoring the operating environment, the spare parts estimation, logistics and inventory management systems were modified based on the presented spare parts estimation methods, and the risk of a shortage was reduced remarkably.
Summary of appended papers

This thesis includes an extended summary and the following five papers appended in full. The followed approaches, the results and the conclusions of the appended papers are summarized in this chapter.

5. Ghodrati, B., Kumar, U. and Kumar, D. (2003), “Product support logistics based on product design characteristics and the operating environment”, in the proceedings of *38th Annual International Logistics Conference and Exhibition (SOLE-2003)*, 12-14 August, Huntsville, Alabama, USA

7.1 First paper

The first paper focus more on the engineering aspects of required spare parts forecasting to guarantee the availability of systems/machines assuming that spare parts should always be available always on demand.

Most of the research carried out in the field of required spare parts calculations based on the reliability characteristics of products has not considered the operating environment as a factor influencing the reliability characteristics, and, therefore, the estimations have not been accurate enough. In contrast to previous research, these papers focus on the influence of the working environment and the operator skill on the product reliability characteristics with a view to optimizing product support (spare parts provisioning).

Emphasis here is on product design characteristics such as the reliability and the product hazard rate, and how to calculate the spare part requirements based on those influencing factors.

The exponential reliability model is a simple and applicable model, and probably the best model to use when the effects of covariates are considered in the study of non-repairable elements/systems. Therefore, in this paper a model was improved and the
average number of required spare parts was calculated with the assumption of an exponentially distributed life time for the spare parts.

To validate the model, the hydraulic brake pump is the item that was studied to analyze the effect of the operating environment on the mean time to failure and consequently to forecast the spare part needs.

When the predicted numbers of failures in both conditions (with and without covariates) are compared, we find a substantial difference.

The difference in the results when determining the required spare parts, considering and not considering the influence of the operating environment, demonstrates that for the optimization of product support logistics, it is necessary to take into account environmental factors. When including these important parameters, we can better optimize any spare part inventory level, ordering value, and time between orders, which will also help to minimize the product life cycle cost.

7.2 Second paper

Generally, most of the work and research in the spare parts domain has been carried out in inventory management. Attempts have always been made to secure the availability of systems/machines by keeping spares in stock. However, the estimation and calculation of the required number of spare parts for storage to guarantee their availability when required, with respect to techno-economical issues (reliability, maintainability, life cycle cost, etc.), have rarely been considered and studied.

In required spare parts calculations based on the reliability characteristics of products, the operating environment conditions have not been considered. It seems that the estimations are not supported confidently, as we know that the reliability characteristics of a product are a function of the operation time and the operating environmental factors.

Therefore, when estimating and forecasting the required spare parts accurately, it appears reasonable to take operating environment issues into account, which has been done in this paper. This is motivated by the fact that, for large quantities of items, even a very small error in forecasting the demand for spares can make a huge difference in the support cost.

Usually the manufacturer/supplier provides the information on the required number of spares for each component of the system for a stated period of time (initial provisioning). However, demand prediction for spare parts and maintenance requirements constitute the weakest aspect of stock management today in all industries.

The paper demonstrates that, while assuming the Weibull reliability model as a most versatile model for characterizing the life of machine (mechanical) parts and integrating the effect of covariates, the influencing covariates change the scale parameter only and the shape parameter remains unchanged.
For verification of the improved model presented in this paper for forecasting the average required number of spare parts, a case study was conducted on the hydraulic jack mounted on the LHD machines in Kiruna iron ore mine in Sweden. For modeling the influencing covariates we used the proportional hazards regression model.

It is found that the operating environment of a system/machine has considerable influence on the system’s performance and technical characteristics, such as its reliability and maintainability. Forecasting the required support/spare parts based on the technical characteristics and the system-operating environment is an optimal way to prevent unplanned disruptions or stoppages.

### 7.3 Third paper

Every industrial-mechanical system needs support during its life period in order to be available and perform the defined function. There are different forms of product support, one of which is the delivery of the required spare parts. Therefore, the required spare parts should be available in stock in the event of repair and replacement of the failed or worn components to minimize the system down-time and maximize the machine utilization.

Estimation of the required spare parts can be accomplished through different approaches, one of which is a realistic and well-founded method based on the system’s reliability characteristics and taking into consideration the operating environment.

Two popular mathematical methods that are used in spare parts provisioning are based on the Weibull and exponential renewal models. The exponential model can be used whenever the failure rate is constant (meaning that each failure mode and other factors which influence the demand should follow the exponential distribution). Whenever the failure rate is not constant, the Weibull model can be used to forecast demands for spares. This statement is valid only for non-repairable spares that are not repaired.

In this paper an attempt has been made to study and analyze the problem (estimation of the required non-repairable spare parts), to estimate the differences between the two methods (a constant versus a non-constant failure rate) and to calculate the percentage of error.

When building a model based on renewal theory and non-constant failure rates, the parameters that we need to estimate increase considerably. Especially when the effect of operating environment factors comes under consideration in estimation, there are several different items and parameters that should be considered.

A comparison between the Weibull and the exponential methods for calculating the average number of required spare parts indicates that, based on various $MTTF_o$, the number of spare parts obtained when implementing the exponential method is almost twice the number obtained with the Weibull method. With an increasing $\beta$ value, the average number of required spare parts decreases and for $\beta \leq 1.5$ the exponential model is more suitable in the context of application and analysis costs. The results of the

81
study indicate that the exponential model is influenced more by the effects of covariates.

Finally, the study demonstrates that, from the customer/user point of view, in the case of the single component the Weibull renewal model is more applicable and accurate. However, the exponential model is more suitable when a system (multi-components) is under study to determine the required number of spare parts.

A sensitivity analysis was carried out as well to find out which factors have a significant impact on the estimation of spare parts. This study shows that, among the factors influencing the spares estimation, the effect of covariates (operating environment factors) is significant at a 90% confidence level. The baseline mean time to failure takes second place with regard to significance for consideration. It is therefore seriously recommended to take the influencing factors of the operating environment into consideration when analyzing the reliability characteristics of components/systems and when estimating the required number of spare parts, in order to make the final result as accurate and realistic as possible.

### 7.4 Fourth paper

This paper, after a brief discussion of the concepts product support, product operating environment, spare parts requirements, spare parts logistics and inventory management, deals with the concept of risk analysis related to spare parts shortage.

The term hazard expresses the potential for producing an undesired consequence without regard to how likely such a consequence is. Therefore, one of the hazards of the spare parts inventory is the shortage of a spare part when it is required, which could produce a number of different undesired consequences.

The term quantitative risk analysis refers to the process of estimating the risk of an activity based on the probability of events whose occurrence can lead to undesired consequences. Consequently, the term risk usually expresses not only the potential for an undesired consequence, but also how probable it is that such a consequence will occur.

There are several tools and techniques available to managers and engineers that can help to estimate the level of risk better. Fault Tree and Event Tree Analysis (FTA/ETA), which are considered as semi-quantitative methods, are used in this paper for analyzing the risk of unavailability of spare parts when required.

Fault Tree Analysis (FTA), which is classified as a deductive method, is concerned with the identification and analysis of conditions and factors which cause or contribute to the occurrence of a defined undesirable event, usually one which significantly affects system performance, economy, safety or other required characteristics. FTA is often applied to the safety analysis of systems.

An event tree is a graphical logic model that identifies and quantifies possible outcomes following an initiating event. The event tree provides systematic coverage of the time sequence of the event propagation.
In this paper we have attempted to analyze the risk of ignoring the effects of operating environment factors on the output of a process in the form of the system’s/machine’s down-time and loss of production. For this risk analysis we carried out mainly event tree analysis, but also applied fault tree analysis as a complementary method. Both event tree and fault tree analysis were performed in a modified and non-standard way which the organizational states and decisions, as well as the events and consequent changes, were introduced and taken into account in the analysis.

In fact, as mentioned above, the implemented event tree is not a standard form of event tree analysis. This is a special form where a safety function is defined as an undesired situation (state) as well, instead of a state similar to a barrier in the standard form of event tree analysis.

The studied cases are the hydraulic pump and brake system of the fleet of loaders in the iron ore mine in Iran.

Through the case study it was found that the high-probability outputs (machine down-time and loss of production) mostly belong to the situation in which the operating environment has been ignored. Therefore, it is important and recommended to take this factor into consideration when estimating the average number of required spare parts and managing the spare parts inventory.

7.5 Fifth paper

The focus of this paper is more on the management and logistics aspects of product support and spare parts estimation. It was pointed out that management is considering and paying more attention to product support, because it:

- plays a key role for many products in achieving customer satisfaction,
- can be a considerable source of revenue and profit,
- can provide a competitive advantage in marketing.

In this paper, after a short explanation of product classification based on two groups, namely conventional and functional products, product support issues were classified into two categories: support to the customer (STC), which is based on client characteristics and support for the product (STP), which is mainly based on the product characteristics.

Product support strategy is discussed in this paper as well. In the section on this topic, products are classified into four groups, and a different support strategy for each group of products is analyzed, classified and presented.

Moreover, a brief comparison of product life cycle costs between products with high and low reliability is made in this paper.

In the case study on hydraulic seals presented in this paper, it is seen that the two covariates, high dust level and poor operator skill, cause an increase in the failure rate, while, on the other hand, the covariate “oil type” causes a reduction in the failure rate.
In the logistics and inventory management section we evaluated and classified the spare parts in terms of lead-time and criticality of parts. Lead-time is an important factor in inventory management and has an influence on when spare parts should be ordered and how many should be ordered to minimize the inventory cost and maximize the availability of parts when required. In addition, the criticality of parts is another important factor in decision making about the quantity of parts in the warehouse.

Based on these two factors (lead-time and criticality), the spare parts were classified into 9 categories and then the confidence level of the spare parts availability was obtained for each category.

Finally, the economic order quantity with respect to the annual demand rate and the reorder point in the continuous review (Q) system for inventory management were calculated.
PART III – CONCLUSIONS

8 Concluding remarks

Due to some constraints in the product design phase, products cannot fulfill their function completely. Therefore, product support is becoming an important issue in the product life cycle. This issue concerns the different forms of support that manufacturers offer to customers to help them compensate for the technical defects of products originating in the design phase. Spare parts are included in product support and their availability when required is very important. Reliability-centered spare part forecasting is a useful and applicable method that can help us to predict, procure and store in order to secure the availability of a system/machine.

Spare part needs are dependent on not only the product characteristics, such as reliability and maintainability, but also the customer’s skills and capabilities, and the environment in which the product is working. Consequently, for realizing the prediction of spare parts needs, the product’s operating environment parameters should be taken into account when calculating the product’s reliability characteristics (failure rate).

The remarkable influence of considering and/or ignoring the operating environment factors on the forecasting and estimation of required spare parts is validated by the result of case studies and risk analysis as well. The results of risk analysis demonstrate a considerable risk associated with ignoring these working environment factors, which might cause irretrievable loses. Therefore, product support specifications should be based on the design specifications and the conditions faced by the customer.

From an economic point of view, the current level of spares kept in stock should be matched with the cost. In other words, one should balance the number of spares, the ordering cost, the purchase cost, and the holding cost to optimize the stock level. Different factors influence this procedure, such as the geographical location of the user, the criticality of the part, the cost of the part, etc.

The following are some of the conclusions drawn from the present research:

- The system’s operating environment has a considerable influence on the system’s reliability characteristics (e.g. failure rate) and consequently on the spare parts need.
- To calculate the reliability of the system in operation accurately, the operating environment factors should be taken into account. These factors may cause the hazard (failure) rate to increase or decrease, and may therefore influence the forecasted number of spare parts.
- A reliable prediction of the spare parts consumption can be made if the operating environment is considered together with the reliability characteristics of the system.
- Based on the result from risk analysis, there is a considerable risk associated with ignoring the operating environment factors when estimating the required spare parts for the next planning horizon.
In the studied cases, from the customer/user point of view, in the case of the single component when the shape parameter (Beta) is fixed, the Weibull renewal model is more applicable and accurate. However, the exponential model is more suitable when a system (multi-components) is under study to determine the required number of spare parts.

A comparison between the Weibull renewal and the exponential methods for calculating the average number of required spare parts indicates that, based on various $MTTF_o$, there is quite a big difference between the results of the two methods.

In the Weibull renewal model for calculating the number of spare parts, the influencing covariates change the scale parameter only and the shape parameter remains almost unchanged (i.e. is not affected significantly).

The calculated results in the comparison between the Weibull renewal and the exponential models indicate that the exponential model is influenced more by the effects of covariates.

The number of failures and consequently the number of required spare parts decrease as the shape parameter ($\beta$) of the components increases. This affects the warranty cost of a system, where the warranty cost can be reduced by improving the $\beta$ value for the components.

There is a trade-off between the $\beta$ value and the life length of equipment and the warranty cost, which should be optimized in the design and manufacturing phase.

Spare parts inventory management (logistics) is an issue of considerable importance that has a direct influence on the product’s LCC. Therefore, after determining the required number of spare parts, the inventory management should be optimized on the basis of the cost of the spare part, the ordering cost, the holding cost, and the cost of the unavailability of the part.

8.1 Research contribution

Considering the importance of the availability of spare parts for reducing and preventing the down-time of a system, which imposes a considerable loss on organizations, the present research tries to introduce a practical and realistic method for the determination and storage of the required number of spare parts. Most of the research on required spare parts calculations based on the reliability characteristics of products has not considered the operating environment as a factor influencing the reliability characteristics, and, therefore, such estimations are not accurate enough. In contrast, the present research focuses on the influence of the operating environment and human factors (e.g. the operators’ skill) on the product reliability characteristics for optimizing the product support (spare parts provisioning).

For this purpose, two models (based on the Poisson process and Weibull renewal theory) were developed which consider the significant factors influencing the prediction of spare parts (Papers I and II). The system operating environment is one of the most important factors that up to now have rarely been considered in research concerning required spare parts, and especially in research on the forecasting of spare part needs for systems. In other words, required spare parts forecasting based on the reliability characteristics of products with considering the working environment is the main contribution of the research presented in the present thesis.
The application conditions for the exponential and the Weibull renewal models constitute another contribution of this research. The study demonstrates that, from the customer/user point of view, in the case of the single component the Weibull renewal model is more applicable and accurate. However, the exponential model is more suitable when a system (multi-components) is under study to determine the required number of spare parts.

An additional contribution of this research work is its investigation of the risk of a shortage of spare parts that is associated with ignoring the real working conditions of a system. This is proved by case studies in Iran (covering the hydraulic brake pump, hydraulic seal, brake pad and roll bearings of loader front wheels). In one of the biggest mining companies in Iran, after locating the risk of a shortage of spare parts, the spare parts logistics and inventory management systems were modified based on the presented spare parts estimation methods, and the risk of a shortage was reduced remarkably.

In the present research, a risk analysis of not considering the system’s working conditions in spare parts planning was performed through a new and non-standard event tree and fault tree analysis. We introduced and implemented an event tree analysis in which the states of organization and managerial decisions were included and taken into consideration in the risk analysis. In other words, we used undesired states instead of barriers in combination with events and consequent changes as a safety function in event tree analysis.

The difference in the results concerning the determination of the required spare parts, considering and not considering the influence of the operating environment, demonstrates that for optimization of product support logistics it is necessary to take into account the environmental factors. When including these important parameters, we can better optimize any spare part inventory level, ordering value, and time between orders, which will also help to minimize the product life cycle cost.

### 8.2 Self criticism

In this research:

- The focus is on components and subsystems. Multi-component systems have not been considered and analyzed.

- Only non-repairable components were analyzed and studied. The research has not dealt with repairable components and sub-systems.

- There are some assumptions associated with the research and the application of the findings, such as the identical distribution of failure data for the purpose of simplification, which in some cases are not appropriate and relevant to real-life situations.

- Working environment situations and factors were the only external covariates that were considered. Other factors such as the system operating history, previous repairs and internal covariates were not considered in this research.
8.3 Suggestions for future research

The reliability characteristics of products are usually used for dimensioning product support with regard to engineering aspects. However, a subjective estimate of the effect of covariates is considered for the reliability improvement of a system. The effect of a covariate can be integrated in the dimensioning of product support for effective logistic management. Future work should be directed more towards obtaining the optimum product support and the average number of spare parts required to prevent stoppages. Some suggestions for future research are as follows:

- Investigations analyzing certain covariates to find out the optimal conditions for the cost-effective operation of a system.

- Development of a simple and applicable model for required spare parts prediction for a system with respect to covariates as a guideline for engineers at the operation site.

- Investigation of the integration of covariates (the product’s operating environment factors) in planning the product design for optimizing the product support needs.

- Investigation of the influence of the product operating environment on the maintenance and support strategy.

- Development of a reliability model which will integrate the covariates directly in the estimation and calculation of the required available spare parts.
References


Bartmann, D. and Beckmann, M.J. (1992), “*Inventory Control: Models and Methods*”, Berlin: Springer Verlag


Blanks, H.S. (1998), “*Reliability in Procurement and Use*”, West Sussex: John Wiley and Sons Ltd.


Reliability and Operating Environment Based Spare Parts Planning


Appendix

A sample of raw data collected from iron ore mine in Iran for hydraulic seal launched on the hydraulic jack in mining loader machine.

Table AP1. Start and stop working time (hrs) of loader in the iron ore mine in Iran

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>38610</td>
<td>39499</td>
<td>13</td>
<td>51356</td>
<td>51449</td>
<td>25</td>
<td>64427</td>
<td>66034</td>
</tr>
<tr>
<td>2</td>
<td>39505</td>
<td>41010</td>
<td>14</td>
<td>51512</td>
<td>52939</td>
<td>26</td>
<td>66039</td>
<td>68068</td>
</tr>
<tr>
<td>3</td>
<td>41021</td>
<td>42958</td>
<td>15</td>
<td>52943</td>
<td>53465</td>
<td>27</td>
<td>68078</td>
<td>68808</td>
</tr>
<tr>
<td>4</td>
<td>42965</td>
<td>43290</td>
<td>16</td>
<td>53470</td>
<td>54447</td>
<td>28</td>
<td>68826</td>
<td>69676</td>
</tr>
<tr>
<td>5</td>
<td>43305</td>
<td>45207</td>
<td>17</td>
<td>54452</td>
<td>55599</td>
<td>29</td>
<td>69688</td>
<td>70085</td>
</tr>
<tr>
<td>6</td>
<td>45212</td>
<td>47138</td>
<td>18</td>
<td>55604</td>
<td>56087</td>
<td>30</td>
<td>70093</td>
<td>72342</td>
</tr>
<tr>
<td>7</td>
<td>47142</td>
<td>49000</td>
<td>19</td>
<td>56098</td>
<td>57112</td>
<td>31</td>
<td>72350</td>
<td>74317</td>
</tr>
<tr>
<td>8</td>
<td>48905</td>
<td>49067</td>
<td>20</td>
<td>57117</td>
<td>58676</td>
<td>32</td>
<td>74323</td>
<td>75348</td>
</tr>
<tr>
<td>9</td>
<td>49075</td>
<td>49326</td>
<td>21</td>
<td>58681</td>
<td>60504</td>
<td>33</td>
<td>75365</td>
<td>76536</td>
</tr>
<tr>
<td>10</td>
<td>49335</td>
<td>49741</td>
<td>22</td>
<td>60510</td>
<td>61506</td>
<td>34</td>
<td>76545</td>
<td>78464</td>
</tr>
<tr>
<td>11</td>
<td>49746</td>
<td>50718</td>
<td>23</td>
<td>61519</td>
<td>62556</td>
<td>35</td>
<td>78469</td>
<td>80744</td>
</tr>
<tr>
<td>12</td>
<td>50722</td>
<td>51351</td>
<td>24</td>
<td>62561</td>
<td>64422</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appended papers
Paper I

Operating environment-based spare parts forecasting and logistics: a case study

Operating environment-based spare parts forecasting and logistics: a case study

BEHZAD GHODRATI* and UDAY KUMAR

Division of Operation and Maintenance Engineering, Luleå University of Technology, SE 971 85 Luleå, Sweden

In today’s highly dynamic and constantly changing industrial environment, issues relating to product support are becoming increasingly important. However, the extent of attention given to these issues varies considerably depending on the perspective of the interested person or profession. These are likely to vary from design engineers at the conceptual stages of product development to manufacturers and users in the latter stages. Additionally, the make up a particular product support package varies according to type of system/mission, application and stages of machine/system life. The lack of timely or incomplete support is likely to cause unexpected downtimes, which in turn will lead to losses for which one is unable to compensate. Falling within the definition of product support items are spare parts. The lack of a critical spare part can cause untimely stoppage of machine/system. Forecasting of product support and spare parts requirements based on reliability and maintainability (R&M) characteristics of system/components together with system operating environment(s) is one of the most effective strategies for prevention of unplanned stoppages. In this paper the effects of environmental factors on hydraulic brake pump used in mine loaders are presented and analysed. The reliability of this non-repairable part and its operational impact are assessed for both when the environmental factors are considered and when they are ignored. From the study, it is found that the forecasting for brake pump inventory is more accurate when environmental factors are included in the calculations. These results demonstrate the value of the inclusion of environmental factors data in the product support logistics’ optimisation process.

Keywords: Product support; Reliability; Operating environment; Spare parts; Logistics

1. Introduction and background

Often the industrial systems need support throughout their lifetimes. To perform their expected function, some typical technical forms of support include installation, maintenance, repair services and support of spare parts. Such forms of support are extended by original equipment manufacturer (OEM)/suppliers, and characterised as product support. Product support includes all activities that ensure that a product is available for trouble-free operations over its useful lifespan (Loomba 1998).

Product support, in fact, is a form of assistance that manufacturers/suppliers offer to users/customers to help them gain maximum value (profit) from the manufactured products.
It is reasonable to assume that users/customers will, in most instances, tend to prefer products that are intuitively usable and/or well supported as there will be fewer problems associated with use. Such support may be described as falling into one of two broad categories, namely: support to customer and support to product (Mathieu 2001, Markeset and Kumar 2003a).

Maintenance and spare parts support are two basic and critical issues of support to a product. The unpredictability of the end-user’s technological competence and other compelling factors (economy, environmental situations, etc.) make it impractical during the design phase to engineer a product that will fulfil its function without the need of service during operation. So, the need for support has become vital for the enhancement of system effectiveness and for the prevention of unplanned stoppage.

Sound spare parts management improves productivity by reducing idle machine time and increasing resource utilisation. It is obvious that spares provisioning is a complex problem and requires an accurate analysis of all conditions and factors that affect the selection of appropriate spare provisioning models.

In the literature, there exist large numbers of papers in the general area of spare provisioning, especially in spare parts logistics (Orsburn 1991, Langford 1995, Chelbi and Ait-Kadi 2001, Kennedy et al. 2002). Most of these papers deal with repairable systems and spares inventory management (Smith and Schaefer 1985, Aronis et al. 1999, Sarker and Haque 2000). They mostly provide a queuing theory approach to determine the spare parts stock in hand to ensure a specified availability of the system (Graves 1985, Huiskonen 2001). These models have been extended further to incorporate the inventory management aspect of maintenance (Gross et al. 1985, Hall and Clark 1987, Sherbrooke 1992, Ito and Nakagawa 1995, Kumar et al. 2000).

On the other hand, quantitative techniques based on reliability theory have been used for developing the failure rates of the required items to be purchased and/or stocked (Gnedenko et al. 1969, Lipson and Sheth 1973, Lewis 1996, Jardine 1998, Kales 1998, Xie et al. 2000, Wååk and Alfredsson 2001). This failure rate was used to determine more accurate demand rates.

In the specific area of spare parts management of non-repairable systems (mechanical), which often fail with time-dependent failure rates (ageing), there are some renewal theory-based prediction models available for forecasting the needs of spares in a planning horizon (Gnedenko et al. 1969, Kumar et al. 2000).

Finally, as a result we can say that most of the work and research in the spare parts domain has been done in inventory management; to guarantee the availability of systems/machines, assuming that spare parts are available always on demand. Estimation and calculation, however, of required number of spare parts for storage to ensure their availability when required, with respect to techno-economical issues (reliability, maintainability, life cycle cost, etc.), have rarely been considered and studied [notable exceptions are Sheikh et al. (2000) and Tomasek (1970)].

None of the surveyed literature in the required spare parts calculations based on the reliability characteristic of a product has considered the operating environment as an influencing factor on reliability (Jardine 1998, Lewis 1996). Therefore, the estimations are not accurate enough, because the reliability characteristic of a product is a function of operation time and operating environment.

2. Operating environment

Environmental conditions in which equipment is to be operated such as temperature, humidity, dust, etc. often have considerable influence on product reliability characteristics (Kumar and Kumar 1992, Kumar et al. 1992, Blischke and Murthy 2000). Thus, an operating
environment should be seriously considered when dimensioning product support and service delivery performance strategies, as this one factor will probably have a significant impact upon operational/maintenance cost and service quality.

Some of the important examples of operating environment are:

1. **Working environment:**
   a. climatic conditions such as temperature and humidity in which a system will be working;
   b. physical environment factors of dust, smoke, fumes, corrosive agents, and the like.

2. **User characteristics:** such as operator skill, education, culture and language.

3. **Operating place or location:** this factor refers to workplace settings such as outside (free) or closed (surrounded) spaces, the industry that will use a product and/or other area characteristics (such as mines) where a product will be used.

4. **Level of application:** the system may be intended to have a major/main purpose, a minor or auxiliary purpose and even a standby purpose in an operational set-up.

5. **Work time and period of operation:** planning may call for a product to be in continuous or part-time operation.

An operating environment can also influence the degree of support needed to achieve an expected performance level (Markeset and Kumar 2003b).

This paper focuses on the influence of first and second factors (the working environment and operator skill) on the product reliability characteristics for optimising product support (spare parts provisioning). Emphasis here is on product design characteristics such as reliability and product hazard rate, and how to calculate required spare part requirements based on those influencing factors. Product hazard rate is, for the purpose of this article, defined as the rate at which a product will experience some form of failure during usual operation [for a more detailed definition see Kumar and Klefsjö (1994) and Kumar et al. (1992)].

### 3. Reliability characteristics of products

Reliability of a system is a function of the time of operation and the environment under which the system is operating. Lower reliability means a greater probability that there will be an unexpected number of failures leading to unscheduled repairs and a consequent decrease in system availability in its service life. As noted earlier, there are many factors that can influence the reliability characteristics of a system, and the reliability level of product has an influence on the product support. If we intend to achieve a failure-free operation throughout the life of the system, we have to design system/components with a mean time to failure (MTTF) greater than the operating life of the system/components. This situation is referred to as “design out failures”, and is also called design out maintenance (DOM). Life cycle costing (LCC) analysis can be used during a decision-making process concerning the level of reliability of a system and/or components of a system. However, the DOM approach often proves too costly or impossible due to state-of-the-art technology, therefore one often ends up with a design for maintenance (DFM) approach.

Our literature survey shows that most research and articles on reliability consider operating time as the only variable when estimating reliability of a system (Billinton and Allan 1983, Al-Bahi 1993, Barlow and Proschan 1996, Blanks 1998, Kumar et al. 2000, Sheikh et al. 2000). Usually overlooked are other factors that may influence reliability characteristics of a system during its working lifetime. For example, if a system is used in different climatic conditions then the reliability characteristics will not be the same in these different situations. Kinds of variables
that can account for differences include, for instance, working environment (e.g. temperature, pressure, humidity, dust, or voltage stress) and operating history of a machine (e.g. overhauls, effects of repair, or type of maintenance). These factors can easily affect the failure rate (behaviour) of a system yet are ignored in most reliability analyses. In the proportional hazard model (PHM) (Cox 1972), the hazard (failure) rate of a system is the product of baseline hazard rate $\lambda_0(t)$, dependent on time only, and one another positive functional term (that is basically independent of time), which incorporates the effects of covariates such as temperature and pressure.

The baseline hazard rate is assumed to be identical and equal to the hazard rate when the covariates have no influence on the failure pattern. The covariates can influence the hazard rate so that the observed hazard rate is either greater (e.g. in the case of poor maintenance or incorrect spare parts) or smaller (e.g. a new improved component of a system or reliable components) when compared with the baseline hazard rate (see figure 1).

![Effects of Covariates](image)

Figure 1. Effects of risk factors (covariates) on hazard rate of system.

Hence, the actual hazard rate (failure rate) in PHM with respect to exponential form of time-independent function, incorporating the effects of covariates, can be defined as:

$$\lambda(t,z) = \lambda_0(t) \exp(z\alpha) = \lambda_0(t) \exp\left(\sum_{j=1}^{n} \alpha_j z_j\right)$$  \hspace{1cm} (1)

where $z_j$, $j = 1, 2, \ldots, n$, are the covariates associated with the system and $\alpha_j$, $j = 1, 2, \ldots, n$, are the unknown parameters of the model, defining the effects of each one of the $n$ covariates.

### 4. Required spare parts calculation

For several types of industrial parts and subassemblies, replacement of an entire unit upon failure of a part is more economical than repair. Bearings, gears, gaskets, seals, filters, hoses and valves are some of the kinds of parts that are normally replaced rather than repaired.

The hydraulic brake pump can also be classified as belonging to this group, because usually its repair cost is high (includes part and work costs) and the repaired pump is not as good as new and creates problems in the loader work process (for instance, leakage of brake oil). Due to mining industry interest and the criticalities of the part, we selected it for the case study.
It is known that the Weibull reliability model is an appropriate model for characterising the life of machine parts (mechanical systems). The exponential reliability model, however, is a simple, applicable and probably the best model to use when the effects of covariates are considered in the study of non-repairable elements/systems. Meanwhile, the percentage of error in the calculation of MTTF when assuming an exponential model instead of the Weibull model (for $1 < \beta < 2$) is small (about 5%, and it is negligible in comparison with error in data collection, which is usually about 10–15%) (see, e.g. Kumar 1989). In addition, most practical applications within the field of logistic support assume constant failure rates or, rather, constant demand rates (Sherbrooke 1986, Wååk and Alfredsson 2001). So, in this case the number of required spare parts with the assumption of exponentially distributed lifetime for them can be calculated through the use of the following equation [see Billinton and Allan (1983) and Kumar et al. (2000) for background information]:

$$1 - P(t) = \exp(-\lambda t) \times \sum_{X=0}^{N} \frac{(\lambda t)^X}{X!}$$

where $P$ is the probability of shortage of spare parts ($1 - P =$ confidence level of spare part availability), $\lambda$ is the failure rate of an object part (with regard to effect of covariates), $t$ is the operation time of the system and $N$ is the total number of required spare parts in period $t$.

If there are $q$ numbers of the same part in use at the same time then $q$ is entered into the equation in the form of multiplying by $\lambda tq$. This way the calculated $N$ will represent the total required number of spare parts for the whole system.

5. Case study

Hydraulic loaders are part of a machine-fleet used in open pit and/or quarry mines for loading, hauling and piling up of ore and gangue. The brake system is one of the critical subsystems of the loaders that include many non-repairable components. The hydraulic brake pump is one of the items that was studied for analysing the effect of the operating environment on MTTF and consequently forecasting the spare part needs. Some minor parts of the pump (such as the gasket and seal), however, could be replaced in order to restore the failed pump to functional mode; but in most cases, for economical reasons (time and repair work costs), the pump is replaced completely with a new one upon failure. Figure 2 shows the parts of the hydraulic brake pump that was mounted on the loader.

Owing to the importance of the hydraulic brake pump for the safe operation of the loader, failure time data were obtained from an iron ore mine in Iran and analysed to identify important factors that influence the performance of the pump. In this case (iron ore mine), there was a fleet of 10 loaders. Usually two to three of them had problems in the brake system. One of these problems was hydraulic brake pump failure resulting in downtime because the spare pump was not in stock (the manufacturer recommended the number of spares in stock). After accurate study on the shortage of spares, it was identified that the numbers of estimated and stocked spare pumps were incorrect.

The spare parts inventory has been managed based on manufacturer/supplier recommendation, which was mostly based on historical data, experience and system characteristics. The effects of environmental influencing factors (covariates) on the system failure rate were not considered.

For the purpose of this study, the available information about the operating conditions of the pump was determined and codified by a numeric value wherever required. Selection and definition of covariates are very important in the reliability analysis with covariates because
any statistical inference is based on the way they were formulated. This process should be based on the failure mechanism of the system (hydraulic brake pump in our case) under study. In this case, the formulation of covariates (influencing factors except time) was carried out based on observation and the experience of operators and maintenance crew, which are as follows:

1. Operator skill: this covariate refers to the operator’s experience in driving, loading and hauling, and also brake usage frequencies. It is denoted by \( OPSK \) and is assigned \(-1\) for unskilled operator and \(+1\) for expert operator.

2. Maintenance crew skill: this factor affects the quality of service, repair and maintenance and the condition of pump after service, and is denoted by \( SCSK \). This covariate, like operator skill, is assigned \(-1\) for unprofessional crew and \(+1\) for expert crew.

3. Hydraulic oil quality: the indicator \( "HOQ" \), which is used to denote the quality of hydraulic oil in the brake system at work, is assigned \(-1\) for non-standard and non-manufacturer/supplier-recommended brake oil and \(+1\) for standard and manufacturer-recommended hydraulic brake oil.

4. Climatic conditions: these conditions, such as temperature, humidity, etc. influence pump failure (e.g. the effect of the temperature on the viscosity of hydraulic oil and elasticity of rubber components in the pump, such as gaskets). For this covariate, the indicator \( "CLCON" \) is used to denote the condition and it is assigned the value \(-1\) when the climatic condition is bad (high temperature and humidity) and \(+1\) for better (optimum) conditions.

5. Physical environment (such as existence of dust, chemical materials, etc): this factor presents that pump is exposed to corrosive conditions when the brake oil consists of pollution and dust. Indicator \( "PHENV" \) denotes this covariate. The value is \(-1\) when dust and pollution is present and \(+1\) when either less or no pollution is present.

In this study, we started with the assumption that a replaced pump had the same \( \lambda_0(t) \) [with \( \lambda_0(t) \) being the baseline failure rate] when the failed pump was deemed to be a non-repairable item. For modelling covariates in the regression analysis, we used a “step down procedure” where all the covariates were first considered together. Then, covariates found to have no significant value were eliminated in the subsequent calculations. The corresponding estimates of \( \alpha \) (regression coefficient) were obtained using the software SYSTAT. The estimates of \( \alpha \) were tested for their significance on the basis of \( t \)-statistics (the ratio of the estimated \( \alpha \) to
the standard error of the estimates) and/or \( p \)-value (obtained from the table of unit normal distribution). One minus the \( p \)-value for a covariate gave a measure of importance when we considered whether to retain any particular covariate in the model. The estimates of \( \alpha \) for the five covariates are listed in “step number 0” in table 1. With the step down procedure we found that the effects of three covariates (\( HOQ \), \( SCSK \) and \( OPSK \)) were significant at the 10% \( p \)-value; these are listed in the subsequent steps in table 1.

The PHM analysis showed that the hazard rate of the hydraulic brake pump is best modelled by:

\[
\lambda(t, z) = \lambda_0(t) \times \exp(-1.253HOQ - 0.827SCSK - 0.895OPSK). \tag{3}
\]

As noted earlier, with this approach the pump is classified (assumed) as a non-repairable item (the pump is treated as having had no repair or repaired as good as new; in practice a pump is discarded after failure). Therefore, the failure data were assumed to be independent and identically distributed (IID). For discussion on IID see Kumar (1989).

To satisfy the proportionality assumption of the hazard rates, the plots of the logarithm of the estimated cumulative hazard rates against time should simply be shifted by an additive constant \( \alpha \), the estimate of the regression parameter \( \alpha \) of the covariate, which is taken as strata.

---

**Table 1. Estimation of covariates (the estimates of \( \alpha \) and standard error (SE) were obtained by maximising the likelihood function).**

<table>
<thead>
<tr>
<th>Step number 0</th>
<th>Variables included</th>
</tr>
</thead>
<tbody>
<tr>
<td>( HOQ )</td>
<td>-2.021 0.043</td>
</tr>
<tr>
<td>( SCSK )</td>
<td>-1.99 0.046</td>
</tr>
<tr>
<td>( PHENV )</td>
<td>-1.094 0.274</td>
</tr>
<tr>
<td>( CLCON )</td>
<td>-0.992 0.321</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step number 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables included:</td>
</tr>
<tr>
<td>( HOQ )</td>
</tr>
<tr>
<td>( SCSK )</td>
</tr>
<tr>
<td>( PHENV )</td>
</tr>
<tr>
<td>( OPSK )</td>
</tr>
<tr>
<td>Variables included:</td>
</tr>
<tr>
<td>( CLCON )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step number 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables excluded:</td>
</tr>
<tr>
<td>( HOQ )</td>
</tr>
<tr>
<td>( SCSK )</td>
</tr>
<tr>
<td>( OPSK )</td>
</tr>
<tr>
<td>Variables excluded:</td>
</tr>
<tr>
<td>( CLCON )</td>
</tr>
<tr>
<td>( PHENV )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Final model summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>( HOQ )</td>
</tr>
<tr>
<td>( SCSK )</td>
</tr>
<tr>
<td>( OPSK )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>95.0% confidence intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>( HOQ )</td>
</tr>
<tr>
<td>( SCSK )</td>
</tr>
<tr>
<td>( OPSK )</td>
</tr>
</tbody>
</table>
Therefore, the plot should be almost parallel and separated, matching the different values of \( \alpha \), if the proportionality assumption is correct (Kumar and Klefsjö 1994). For example, figure 3 depicts this graph for covariate \( \text{OPSK} \).

![Survival Plot](image)

**Figure 3.** An example (\( \text{OPSK} \) covariate) of graphical test for proportionality assumption of the hazard rates.

Then, when using the assumptions of the exponential reliability model for this item, the mean time to failure is 12,000 (manufacturer recommendation) hours and:

\[
\lambda_0(t) = \frac{1}{\text{MTTF}} = \frac{1}{12,000} = 8.33 \times 10^{-5}.
\]

This failure rate is constant with this approach.

The loaders use standard and manufacturer-recommended hydraulic oil (the corresponding covariate is +1); however, the maintenance and service crew, and also the loader operators, are not expert enough in their job (the corresponding covariates are assigned by −1). So in this condition:

\[
\lambda(t, z) = 8.33 \times 10^{-5} \times \exp(-1.253 \times (+1) - 0.827 \times (-1) - 0.895 \times (-1)) = 1.33 \times 10^{-4}.
\]

The expected number of failures in 1 year (two working shifts per day) when \( 1/\lambda(t, z) = 7510 \) hours is considered to be the MTTF of the pump with a 95% confidence of availability equal to:

\[
0.95 = \exp(-1.33e - 4 \times 5400 \times 10) \times \sum_{X=0}^{N} \frac{(1.33e - 4 \times 5400 \times 10)^X}{X!} (6)
\]

\( N \approx 12 \text{(unit/year)} \).

If, for comparison, we calculate the required number of spare parts without considering covariates (the effect of the operating environment’s condition), we have:

\[
0.95 = \exp(-8.33e - 5 \times 5400 \times 10) \times \sum_{X=0}^{N} \frac{(8.33e - 5 \times 5400 \times 10)^X}{X!} (7)
\]

\( N_s \approx 8 \text{(unit/year)} \).

When the predicted numbers of failures in both conditions (with and without covariates) are compared, we find a substantial difference. As the covariate factors are critical in real-life...
working conditions, their use makes for better optimisation of the management of systems. Machine life will be improved and possible downtime due to lack of spare parts will be minimised.

Further, as mentioned earlier, sometimes the company is faced with downtime of loaders due to a shortage in availability of required spare parts, and this is because of the manufacturer/supplier’s recommendation that a fewer number of required spare parts be kept in stock (eight units). In most cases the manufacturer is not aware of the environmental factors and as such has not considered these issues in the estimation of the number of required spare parts (as in this case). So, to avoid downtime regarding the unavailability of spare parts (more common in an improving country, such as the country studied), it was suggested that the mine company should take the operating environment factors into consideration while estimating the spare parts need. The company has increased the stock level of the hydraulic brake pump up to 10 and, after 1.5 years, they have less downtime and greater efficiency compared with their previous condition. There are still, however, some problems due to shortage of parts, which need economy improvements to be solved.

6. Conclusion

The operating environment of system/machine has considerable influence in system performance and its technical characteristics such as reliability and maintainability. Forecasting required support/spare parts based on technical characteristics and the system-operating environment is an optimal way to prevent unplanned disruptions or stoppages. This part replacement strategy can be critical for the manufacturer/supplier when developing a product support package as a way to help ensure user satisfaction. For the end-user this strategy can be equally useful in those instances where manufacturer/supplier support has stopped or never been used.

The difference in the results of determining the required spare parts, considering and not considering the influence of the operating environment, demonstrates that for optimisation of product support logistics it is necessary to take into account environmental factors. When including these important parameters, we can better optimise any spare part inventory level, ordering value and time between orders, which will also help to minimise product life cycle cost.

References


Mathieu, V., Product services: from a service supporting the product to a service supporting the client. *Industrial Marketing*, 2003, **24**(3), 311–319.


Appendix

Table A1 contains the data sets used for demonstrating the concept. The column with lifetime exhibits times to failure of a particular type of brake pump. A cell in the censored column with zero value indicates that the loader was stopped due to some reason other than the pump, but the pump was serviced bringing its failure rate to as good as new condition; and a cell with value unity indicates pump failure and its replacement with a new pump.

Table A1. Field data used for analysing and demonstrating the concept.

<table>
<thead>
<tr>
<th>Ser. No.</th>
<th>Lifetime (hour)</th>
<th>Censored</th>
<th>HOQ</th>
<th>SCSK</th>
<th>PHENV</th>
<th>CLCON</th>
<th>OPSK</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6,020</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>−1</td>
</tr>
<tr>
<td>2</td>
<td>5,348</td>
<td>0</td>
<td>−1</td>
<td>1</td>
<td>−1</td>
<td>−1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>6,508</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>7,704</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>7,032</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>5,676</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>−1</td>
</tr>
<tr>
<td>7</td>
<td>10,680</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>5,716</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>−1</td>
<td>−1</td>
</tr>
<tr>
<td>9</td>
<td>6,280</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
<td>−1</td>
</tr>
<tr>
<td>10</td>
<td>5,288</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>6,708</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>7,788</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>−1</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>9,000</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>5,836</td>
<td>1</td>
<td>−1</td>
<td>−1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Explanation of the table

The following abbreviations are used for denoting the covariates: HOQ, hydraulic oil quality; SCSK, service and maintenance crew skill; PHENV, physical environment; CLCON, climatic condition; and OPSK, loader’s operator skill.

To explain the various figures in table A1, we shall consider row 1. For instance, column 2 indicates that the loader failure takes place after working 6,020 hours due to brake pump failure as indicated by 1 in the censored column 3 (also indicating replacement by a new pump). Considering column 4 with HOQ, +1 indicates the hydraulic oil used was standard oil recommended by the manufacturer, column 5, +1 indicates service crew were skilled, column 6, +1 indicates physical environment was good and acceptable (such as less dust), in column 7, −1 indicates climatic condition was not good (e.g. high temperature) and, finally, column 8, −1 indicates that the loader operator was not expert enough in his job.
Paper II

Reliability and operating environment-based spare parts estimation approach

APPLICATIONS AND CASE STUDIES

Reliability and operating environment-based spare parts estimation approach

A case study in Kiruna Mine, Sweden

Behzad Ghodrati and Uday Kumar

Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå, Sweden

Abstract

Purpose – With continuous technological development in the twenty-first century, the industry and industrial systems have become complex and making their availability more critical. In this context, the product support and its related issues such as spare parts play an important role. Lack of timely or incomplete support, such as the lack of spare parts when required, is likely to cause unexpected downtimes, which in turn often lead to incompensatable losses. Therefore the importance of predicting the correct support to keep the system functionally available needs to be emphasized. Required number of spare parts could be obtained based on technical and life parameters. This paper seeks to examine the system reliability and operating environment, which are the two parameters to be considered in this article.

Design/methodology/approach – A model is provided in this paper to determine the number of required spare parts with respect to the effect of the external factors, except time, on the reliability characteristics of components through the proportional hazard model. The model is verified with estimation of the number of spare hydraulic jacks, used on a load-haul-dump (LHD) machine, as non-repairable components. The reliability of this non-repairable part and its operational impact are assessed, while considering environmental factors and ignoring them.

Findings – The results indicate that the operating environment of system/machine has considerable influence on system performance. Forecasting the required support/spare parts based on technical characteristics and the system-operating environment is an optimal way to prevent unplanned stoppages.

Practical implications – The environmental conditions in which the equipment is to be operated, such as temperature, humidity, dust, road conditions, maintenance facilities, maintenance crew training, operators’ skill, etc., often have considerable influence directly on the system/machine or component reliability and indirectly on the product supportability characteristics. Spare parts, are classified as a product support item whose availability is important when planned or unplanned maintenance is to be carried out. Forecasting the required number of spare parts, based on technical characteristics and operating environmental conditions of a system, is one of the best ways to optimize unplanned stoppages.

Originality/value – Previously, the state of the specific technology and other factors have demonstrated the need for support in enhancing system effectiveness and preventing unexpected downtime. This paper sets the required number of spare parts necessary to fulfill this need.

Keywords – Spare parts, Operations management, Distribution and inventory management, Systems and control theory, Sweden

Paper type – Case study
Introduction

Generally, the industrial products need support throughout their lifetime. Some typical forms of support needed to perform their expected function includes installation, maintenance, repair services, availability of spare parts, and documentation to user guiding and training. Such supports extended by original equipment manufacturer (OEM) and/or suppliers, entails all activities “to ensure that a product is available for trouble-free use to consumers over its useful life span” (Loomba, 1998).

Product support can briefly be defined as any form of assistance that manufacturers/suppliers offer to users/customers to help them gain maximum value (profit) from the manufactured products and it is important in the recent industrial world scenario. Meanwhile, the management considers and pays more attention to product support, because it:

1. plays a key role for many products in achieving customer satisfaction;
2. can be a considerable source of revenue and profit; and
3. can provide a competitive advantage in marketing.

Maintenance and subsequently spare parts support are two basic and critical issues of product support. Usually, due to state of the art of technology and other compelling factors, such as economy, environmental situations, end-user technological competence, etc., in the design phase, it is impossible to design a product that will fulfill its total functions. So the need for support has become vital to enhance system effectiveness and prevent unexpected downtime. In this paper we will consider and discuss the required number of spare parts to enhance the availability of system/machine by minimization of the equipment downtime for repair and service.

In a previous paper (Ghodrati and Kumar, 2004) we assumed constant failure rate for non-repairable components and provided an exponential time to failure distribution based model. But in this paper, considering the best fit distribution for time to failure of mechanical components as Weibull distribution we have attempted to provide a new model that coincides with the real situations and actual requirements.

Spare parts estimation – background

With the advancement of high technology equipment in industries worldwide the need for spare parts to optimize the utilization of equipment is becoming paramount. Sound spare parts management improves productivity by reducing idle machine time and increasing resource utilization. It is obvious that spares provisioning is a complex problem and requires an accurate analysis of all conditions and factors that affect the selection of appropriate spares provisioning models.

In the literature, there are a large number of papers in the general area of spare provisioning, especially in spare parts logistics (Chelbi and Ait-Kadi, 2001; Kennedy et al., 2002; Langford, 1995; Orsburn, 1991). Most of these papers deal with the repairable systems and spares inventory management (Aronis et al., 1999; Sarker and Haque, 2000; Smith and Schaefer, 1985). They mostly provide a queuing theory approach to determine the spare parts stock on hand to ensure a specified availability of the system (Graves, 1985; Huiskonen, 2001).

These models have been further extended to incorporate the inventory management aspect of maintenance (Gross et al., 1985; Hall and Clark, 1987; Ito and Nakagawa, 1995; Sherbrooke, 1992; Kumar et al., 2000).
The following common features have been presented in the literature:

1. They mostly deal with repairable system.

2. They have used queuing theory with demand rate λ and repair rate μ. There is a catch in this, since the failure rate is based on operational time to failure, where the demand rate (used in inventory models) and repair rate (used in availability models) are based on calendar time. This distinction was not very clearly dealt with in the papers.

3. These queuing theory based models primarily deal with constant failure rates, and constant repair rates (exponential time to failure and time to repair), whereas this assumption is restrictive, particularly for mechanical parts. Mechanical parts often fail due to aging with time. The aging or wear out mechanisms such as creep, fatigue, corrosion, oxidation, diffusion, and wear are all time dependent processes.

In addition, quantitative techniques based on reliability theory have been used for developing the failure rates of the required parts to be purchased and/or stocked (Jardine, 1998; Gnedenko et al., 1969; Kales, 1988; Lewis, 1996; Lipson and Sheth, 1973; Wååk and Alfredsson, 2001; Xie et al., 2000). This failure rate was used to determine more accurate demand rates.

In the specific area of spare parts management of non-repairable components (mechanical), which often fail with time dependent failure rates (ageing), there are some renewal theory based prediction models available for forecasting the needs of spares in a planning horizon (Gnedenko et al., 1969; Kumar et al., 2000).

Generally, most of the work and research in the spare parts domain have been done in the inventory management. It has always been attempted to secure the availability of systems/machines with existence of spares in stock. Estimation and calculation, however, of required number of spare parts for storage to guarantee its availability when required, with respect to techno-economical issues (reliability, maintainability, life cycle cost, etc.), has rarely been considered and studied. Fewer researches have been relatively accomplished in this area (for example the notable exceptions are Sheikh et al., 2000; Tomasek, 1970). In the surveyed literature about the required spare parts calculations based on reliability characteristics of product, the operating environment conditions have not been considered (see for example Jardine, 1998; Lewis, 1996). It seems that the estimations are not supported confidently, as we know that the reliability characteristics of a product is a function of operation time and operating environmental factors.

Therefore, it appears reasonable to take operating environment issues into account when studying and analyzing the systems’ reliability, according to the estimate and forecast of the required spare parts, which has been neglected up till now.

**Reliability characteristics of equipment**

Generally, system reliability characteristics and factors such as mean time to failure (MTTF) and mean time to repair (MTTR) for both the component and the whole system are required for reliability analysis and spare parts forecasting. System operating environmental factors such as dust, temperature, humidity, pollution, vibration, operators’ skill, etc. (known as covariates) are required as well in this context. The covariates influence system’s (includes components) hazard (failure) rate so that the observed hazard rate is either greater or smaller than the baseline hazard rate.
Thus, for better estimation of the reliability characteristics, the use of regression models is suggested because of the possibility of including the covariates.

The proportional hazard model (PHM) was introduced by Cox (1972), which is a regression type model. The PHM is a complement to the set of tools use in reliability analysis and provides some particular advantageous features (Kumar and Klefsjö, 1994). This model is classified as multiplicative and non-parametric regression model considering covariates that assumes the hazard rate of a system/component is a product of baseline hazard rate \( l_0(t) \), dependent on time only and a positive functional term \( \phi(z, \alpha) \), basically independent of time, incorporating the effects of a number of covariates such as temperature, pressure and changes in design. Thus:

\[
\lambda(t) = \lambda(t, z) = l_0(t)\phi(z, \alpha),
\]

where \( z \) is a row vector consisting of the covariates, and \( \alpha \) is a column vector consisting of the regression parameters.

**Mathematical model for required spare parts forecasting**

Spare parts forecasting and inventory management is one of the most challenging problems in the whole integrated logistic support process. On one hand the operators want replacement parts to be in stock when required but on the other hand they cannot afford to have capital tied up in inventory. The cost of spares for an operator of a fleet of trucks, or loaders over the life of the system far exceeds the cost of the original system (truck or loader), but it depends on how the fleet is operated, maintained and supported (Kumar et al., 2000).

For large quantities of items, even a very small error in forecasting the demand for spares can make a huge deference in the support cost.

Usually, the manufacturer/supplier provides the information on the required number of spares of each component of the system for a stated period of time (initial provisioning). However, as mentioned by Pironet (1998), demand prediction for spare parts as well as maintenance requirements is the weakest aspect of stock management today, in all armed forces and industries alike.

Two popular mathematical models that are used in spare parts provisioning are based on Poisson process and renewal theory. The Poisson process can be used whenever the failure rate (equal to the demand rate and/or hazard rate for the non-repairable equipments) is constant. This means that each failure mode and other factors, which influence the demand, should follow the exponential distribution (this model was discussed in Ghodrati and Kumar, 2004). Whenever the failure rate is not constant we use renewal theory to forecast demands for spares, which is discussed in this paper.

**Renewal process models for forecasting spares**

Let \( N(t) \) denote the number of renewals (in our case the number of demands) that occur by time \( t \). Assuming that the time between renewal random variables \( X_i, i \geq 1 \), is independent and have common distribution \( F(t) \), then the probability distribution of number of renewals is given by:

\[
P[N(t) = n] = F^n(t) - F^{n+1}(t),
\]
where \( F^n(t) \) is the \( n \)-fold convolution of \( F(t) \) and given by:

\[
F^n(t) = \int_0^t F^{n-1}(t-x) dF(x),
\]

\( F^n(t) \) denotes the probability that the \( n \)th renewal occurs by time \( t \). The expected number of renewals, \( M(t) \), during a length of \( t \) is given by:

\[
M(t) = \sum_{n=1}^{\infty} F^n(t).
\]

The above equation is known as the Renewal Function.

The renewal rate function \( m(t) = dM(t)/dt \) gives the expected number of renewals per unit time.

By substituting the Weibull cumulative distribution function for time to failure, \( F(t) = 1 - R(t) \), as:

\[
F(t) = 1 - \exp[-(t/\eta)^b].
\]

These functions can be evaluated for the Weibull model.

Considering replacements of a part having an average time to failure as \( \bar{T} \) and standard deviation of time to failures as \( \sigma(T) \) (coefficient of variation of time to failures, \( V = \sigma(T)/\bar{T} \)). If the operation time \( t \) of the system or machine on which this part is installed is quite long and several replacements need to be made during this period, then the average number of failures \( E[N(t)] = M(t) \) will stabilize to the asymptotic value of the renewal function as (Gnedenko et al., 1969):

\[
N(t) = M(t) = E[N(t)] = \frac{t}{\bar{T}} + \frac{V^2 - 1}{2} = \text{Average number of failures in time } t
\]

And the failure intensity or renewal rate function is given by:

\[
m(t) = \frac{dM(t)}{dt} = \frac{dE[N(t)]}{dt} = \frac{1}{\bar{T}}.
\]

The standard deviation of number of failures in time \( t \) is:

\[
\sigma[N(t)] = V \sqrt{\frac{t}{\bar{T}}}
\]

If time \( t \) in above equations representing a planning horizon is large, then \( N(t) \) is normally distributed (based on central limit theorem) with mean = \( \bar{N}(t) \) and the number of spares \( N_t \) needed during this period with a probability of shortage = \( 1 - p \) is given by (Sheikh et al., 2000):

\[
N_t = \frac{t}{\bar{T}} + \frac{V^2 - 1}{2} + V \sqrt{\frac{t}{\bar{T}}} \Phi^{-1}(p),
\]
where $F^{-1}(p)$ is the inverse normal function and is available in probability textbooks. While assuming the Weibull reliability model as a most versatile model for characterizing the life of machine (mechanical) parts and integrating the effect of covariates with regard to proportional hazard model, we have:

$$
\lambda(t) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta-1} \exp \left( \sum_{j=1}^{n} \alpha_j z_j \right)
$$

Assuming:

$$
c = \exp \left( \sum_{j=1}^{n} \alpha_j z_j \right)
$$

$$
\lambda(t) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta-1} \times c = \frac{\beta}{\eta} \left( c^{1/\eta} \frac{t}{\eta} \right)^{\beta-1}
$$

Assuming:

$$
k = c^{1/\eta}
$$

$$
\lambda(t) = \frac{\beta}{\eta} \left( kt \right)^{\beta-1}
$$

The reliability model with assuming the $\eta_0 =$ baseline scale parameter, can be defined as:

$$
F(t) = 1 - R(t) = 1 - \exp \left( - \frac{\beta}{\eta_0} \left( \frac{kt}{\eta_0} \right)^{\beta-1} \right) = 1 - \exp \left( - \frac{1}{k} \left( \frac{kt}{\eta_0} \right)^{\beta} \right)
$$

$$
F(t) = 1 - \exp \left( - \frac{kt}{k^{1/\beta} \eta_0} \right)^{\beta}
$$

This equation indicates the Weibull distribution with the scale parameter $\eta = \eta_0 k^{1/\beta} c^{-1}$ and with substitute of $k = c^{1/\eta}$, we have $\eta = \eta_0 c^{1/\beta}$. Thus, it can be concluded that the influencing covariates change the scale parameter only and the shape parameter remains unchanged. So:

$$\begin{cases}
\beta = \beta_0 \\
\eta = \eta_0 c^{-1/\beta}
\end{cases}
$$

The coefficient of variation of time to failures ($V = \sigma(T)/\bar{T}$) can be calculated based on the shape and scale parameters as follows:

$$
\bar{T} = \eta \Gamma \left( 1 + \frac{1}{\beta} \right),
$$

$$
\sigma(T) = \eta \sqrt{\Gamma \left( 1 + \frac{2}{\beta} \right) - \Gamma^2 \left( 1 + \frac{1}{\beta} \right)}.
$$
Model verification – case study
The dominating machine for loading rock in the Kiruna underground iron ore mine in Sweden is the load-haul-dump (LHD) machine, which is used to pick up ore or waste rock from the mining points and for dumping it into trucks or ore passes. An investigation of a fleet of LHD machines deployed at this mine shows that the hydraulic systems are most critical sub-systems. The lifting cylinder (jack) (Figure 1) is a part of hydraulic system, which has been considered and studied in this paper.

The operation and maintenance cards for a fleet of LHD machines were collected and required information such as time to failure was obtained from the cards (see appendix for list of data). For the purpose of preliminary investigations into the statistical nature of breakdowns of lifting jack, data were classified in their chronological order and the reordering was avoided to study the nature of trends presents in the data sets. Three T2500 (25 tone bucket) model machines that are working in the same condition with the same age were studied. With non-repairable assumption for hydraulic jacks some minor parts of it (such as gasket or seal), however, could be replaced in order to restore the failed jack in functional mode. The time to failures (TTFs) of the hydraulic jacks are given in the Appendix.

The plot of cumulative number of failures of the hydraulic jacks against cumulative time to successive failures explores the presence of trends in the TTFs (convexity of the curve, Figure 2) (see for detail Kumar and Klefsjö, 1989). A test for serial correlation is also done by plotting the ith TTF against the (i − 1)th TTF, i = 1, 2, 3, …, n, as shown in Figure 3, which indicates that no correlation in general among the TTFs was present.

Thus, we can conclude that the collected data are independent (serial correlation test based) and not identically distributed (trend test based).

For the purpose of this study, the available information about the operating conditions of the hydraulic jack was determined and codified by a numeric value wherever required.

Selection and definition of covariates are very important in the reliability analysis with covariates because any statistical inference is based on the way they were formulated. This process should be based on the failure mechanism of the system/components (hydraulic jack in our case) under study. In this case the formulation of covariates (influencing factors except time) were carried out based on observation and the experience of operators and maintenance crew, and are as follows:

![Figure 1. Hydraulic jack](image_url)
(1) **Human factors.** In mining industry, 25-35 percent of the machine breakdowns are attributed to human related causes (Kumar, 1990). Therefore it will not be an exaggeration to define and discuss the human factor as a critical covariate. This covariate can be considered as:

- **Operator skill:** this covariate refers to the operator’s experience in driving, loading and hauling. It is denoted by OPSK and is assigned $-1$ for unskilled and $+1$ for an expert operator.

- **Maintenance crew skill:** this factor affects the quality of service, repair and maintenance and the condition of jacks after service, and denoted by MCSK. This covariate like operator skill is assigned $-1$ for unprofessional and $+1$ for an expert crew.

(2) **Machine (LHD) factors.** This item indicates the parameters which belongs to machine and operating system and in this case for instance includes:
Hydraulic oil quality: the indicator “HOILQ” which is used to denote the quality of hydraulic oil in the system at work is assigned $-1$ for non-standard and non-manufacturer/supplier recommended oil and $+1$ for standard and manufacturer recommended hydraulic oil.

Hydraulic system temperature: this factor has influence on the viscosity of hydraulic oil and elasticity of rubber components in jack (such as seals and gaskets). For this covariate, the indicator “STEMP” is used to denote the condition and it is assigned the value $-1$ when the temperature is higher than $55-60^\circ C$ and $+1$ for better (optimum) condition (less than $50^\circ C$).

Environmental factors. This parameter indicates the effect of operating environmental factors such as existence of dust, chemical materials, etc. on the jack. This covariate is present the jack is exposed to corrosive conditions when the pollution and dust exist in the hydraulic oil and operating environment. Indicator “ENDUS” denotes this covariate. The value $-1$ signifies presence of dust and pollution and vice versa for $+1$.

We assumed that a replaced jack had the same baseline failure rate $\lambda_0(t)$ when the failed jack was considered to be a non-repairable item. For modeling covariates we use the proportional hazards regression (Cox, 1972), which is a hybrid model – partly nonparametric, which allows for an arbitrary survivor function like the Kaplan-Meier estimator, and partly parametric, in which covariates are assumed to induce proportional shifts of the arbitrary hazard function. The Kaplan-Meier (product limit) estimator is equivalent to the Cox model without covariates. When comparing the parameter estimates of a Cox model with those of a fully parametric model such as the Weibull, it is important to note that the coefficients are expected to have opposite signs and will differ by a scale factor.

In the Cox regression analysis, when there is little theoretical reason to prefer one model specification over another, stepwise methods of covariate selection can be useful. The software SYSTAT, which is used for estimation of regression coefficients, uses a “step down procedure” where all the covariates are first considered together in the model. In SYSTAT, because the forward selection (step up procedure) cannot be used with the Cox model unless at least one covariate is forced into the model. For this reason we used backward elimination (step down procedure) with all stepwise procedures as it is less likely to miss potentially valuable predictors.

Thus, covariates found to have no significant value were eliminated in the subsequent calculations. The corresponding estimates of $\alpha$ (regression coefficient) were obtained and were tested for their significance on the basis of $t$-statistics (the ratio of the estimated $\alpha$ to the standard error of the estimates) and/or $p$-value (obtained from the table of unit normal distribution). One minus the $p$-value for a covariate gave a measure of importance when we considered whether to retain any particular covariate in the model. The estimates of $\alpha$ for the five covariates are listed in step number 0 in Table I. By following the step down procedure we found that the effects of three covariates (ENDUS, OPSK and STEMP) were significant at the 10 percent $p$-value.

So, the best hazard rate model based on the PHM analysis can be defined as:

$$A(t, z) = A_0(t) \times \exp(-1.201\text{OPSK} - 1.425\text{ENDUS} - 0.748\text{STEMP}).$$
### Table I.
Estimation of covariates (the estimates of $\alpha$ and standard error (S.E.) were obtained by maximizing the likelihood function)

#### Step number 0 (first step)

<table>
<thead>
<tr>
<th>Variables included</th>
<th>t-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCSK</td>
<td>-0.041</td>
<td>0.968</td>
</tr>
<tr>
<td>OPSK</td>
<td>-0.707</td>
<td>0.480</td>
</tr>
<tr>
<td>ENDUS</td>
<td>-0.737</td>
<td>0.461</td>
</tr>
<tr>
<td>HOILQ</td>
<td>-1.604</td>
<td>0.109</td>
</tr>
<tr>
<td>STEMP</td>
<td>-1.761</td>
<td>0.078</td>
</tr>
</tbody>
</table>

#### Step number 1

<table>
<thead>
<tr>
<th>Variables included</th>
<th>t-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPSK</td>
<td>-1.770</td>
<td>0.077</td>
</tr>
<tr>
<td>ENDUS</td>
<td>-2.151</td>
<td>0.031</td>
</tr>
<tr>
<td>HOILQ</td>
<td>-1.344</td>
<td>0.179</td>
</tr>
<tr>
<td>STEMP</td>
<td>-1.741</td>
<td>0.082</td>
</tr>
<tr>
<td>Variables excluded:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MCSK</td>
<td>-1.409</td>
<td>0.159</td>
</tr>
</tbody>
</table>

#### Step number 2

<table>
<thead>
<tr>
<th>Variables included</th>
<th>t-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPSK</td>
<td>-2.668</td>
<td>0.008</td>
</tr>
<tr>
<td>ENDUS</td>
<td>-2.689</td>
<td>0.007</td>
</tr>
<tr>
<td>STEMP</td>
<td>-1.684</td>
<td>0.092</td>
</tr>
<tr>
<td>Variables excluded:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MCSK</td>
<td>-0.916</td>
<td>0.360</td>
</tr>
<tr>
<td>HOILQ</td>
<td>-1.461</td>
<td>0.144</td>
</tr>
</tbody>
</table>

#### Final Model Summary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPSK</td>
<td>-1.201</td>
<td>0.450</td>
<td>-2.668</td>
<td>0.008</td>
</tr>
<tr>
<td>ENDUS</td>
<td>-1.425</td>
<td>0.530</td>
<td>-2.689</td>
<td>0.007</td>
</tr>
<tr>
<td>STEMP</td>
<td>-0.748</td>
<td>0.444</td>
<td>-1.684</td>
<td>0.092</td>
</tr>
</tbody>
</table>

#### 95.0% Confidence Intervals

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPSK</td>
<td>-1.201</td>
<td>-2.084</td>
<td>-0.319</td>
</tr>
<tr>
<td>ENDUS</td>
<td>-1.425</td>
<td>-2.463</td>
<td>-0.386</td>
</tr>
<tr>
<td>STEMP</td>
<td>-0.748</td>
<td>-1.620</td>
<td>0.123</td>
</tr>
</tbody>
</table>
Goodness-of-fit tests

The constant ratio of any two hazard rates with respect to time is the basic assumption of the proportional hazard model. This can be indicated as:

$$\frac{\lambda(t, z_1)}{\lambda(t, z_2)} = \frac{\lambda_0 \exp(z_1 \alpha)}{\lambda_0 \exp(z_2 \alpha)} = \exp(\alpha(z_1 - z_2)),$$

where $z_1$ and $z_2$ are any two different levels of a covariate assumed to be associated with the system. To satisfy the proportionality assumption of the hazard rates (whether the PHM fits a given data set), the plot of logarithm of the estimated cumulative hazard rates against time should simply be shifted by an additional constant $\alpha$, the estimate of the regression parameter $\alpha$ of the covariate is taken as strata (Kalbfleisch and Prentice, 1980).

For instance, Figure 4 represents the result of this test for the covariate OPSK as a strata.

As it is seen in Figure 4, the plots are approximately parallel and separated appropriately corresponding to the different values of the regression parameter $\alpha$. It implies that the proportionality assumption is correct.

Based on the results from trend test, the time to failure cannot be exponentially distributed and on the other hand it follows the power law process with shape parameter $\beta_0 = 3$ and scale parameter $\eta_0 = 4,500$ hour (manufacturer recommendation).

With this assumption the hazard rate is equal to:

$$\lambda(t) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta - 1} \exp\left( \sum_{j=1}^{n} \alpha_j z_j \right) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta - 1} \times \exp(-1.201\text{OPS}K - 1.425\text{EN}DUS - 0.748\text{STEM}P).$$

In this study, the LHD operators were not expert enough. This is because the operators are not driving the LHD directly by sitting in it; rather the LHD is remote controlled far away from the operational location. Therefore, the operator is not in the working place and does not feel the realities. Some times the hydraulic pressure is more than the

![Survival Plot](image)

Log-rank test, stratification on OPSK strata range 1 to 2

Method: TARONE-WARE

Chi-Sq statistic: 12.887 with 1 df

Significance level (p value): 0.000

Figure 4. A graphical test for goodness-of-fit of the PHM
allowed range, which causes rise in hydraulic oil temperature. This in turn causes the deterioration of jack’s component and finally leads to failure of jack. So, the corresponding covariates are assigned by \(-1\) for both operator’s skill and the hydraulic system temperature (OPSK and STEMP). Dust is the most significant factor as an environmental covariate, which the jacks have protection, in various ways, against it. For instance there is a filter, which refines the hydraulic oil of the system from dust and other physical particles. So, due to dust protection, the corresponding covariate for ENDUS is assigned by \(+1\). While considering these concepts, we have:

\[
c = \exp \left( \sum_{j=1}^{n} a_j z_j \right) = \exp(-1.201 \times (-1) - 1.425 \times (+1) - 0.748 \times (-1)) = 1.69,
\]

\[
\left\{ \begin{array}{l}
\beta = \beta_0 = 3 \\
\eta = \eta_0 e^{-1/\beta} = 4500 \times 1.69^{-1/3} = 3.779 \text{ (hr)}
\end{array} \right.
\]

\[
T = \eta \Gamma \left( 1 + \frac{1}{\beta} \right) = 3.779 \times \Gamma \left( 1 + \frac{1}{3} \right) \approx 3.374 \text{ (hr)}
\]

\[
\sigma(T) = \eta \sqrt{\Gamma \left( 1 + \frac{2}{\beta} \right) - \Gamma^2 \left( 1 + \frac{1}{\beta} \right)} = 3.779 \times \sqrt{\Gamma \left( 1 + \frac{2}{3} \right) - \Gamma^2 \left( 1 + \frac{1}{3} \right)} \approx 1.227 \text{ (hr)}.
\]

\[
V = \frac{\sigma(T)}{T} = \frac{1.227}{3.374} = 0.364.
\]

The expected number of required spare jacks in one year (two working shifts per day) when \(T = 3.374\) hours is considered to be the real mean time to failure of the jack with a 95 percent confidence of availability is equal to:

\[
N_t = \frac{t}{\overline{T}} + \frac{V^2 - 1}{2} + V \sqrt{\frac{T}{\overline{T}} \Phi^{-1}(p)} = \frac{5.600}{3.374} + \frac{0.364^2 - 1}{2} + 0.364 \sqrt{\frac{5.600}{3.374} \times 1.645} \approx 2 \text{ (piece/year)}.
\]

If we ignore the effect of covariates on the jack hazard rate, then the required number of spare jacks will be calculated as:

\[
\overline{T}_0 = \eta_0 \Gamma \left( 1 + \frac{1}{\beta} \right) = 4.500 \times \Gamma \left( 1 + \frac{1}{3} \right) \approx 4.020.
\]
This difference in required spare parts might not seem to be important and significant, but in one year it is 4 jacks for a fleet of 12 LHD (existent number of LHD-T2500 in Kiruna mine) and is considerable in the sense of spare parts forecasting and inventory management.

**Conclusions**

Some times the LKAB Company faces downtime of LHDs due to shortage in availability of required spare parts. This is because of the manufacturer/supplier’s recommended less number of required spare parts to be kept in stock. In most cases the manufacturer is not aware of the environmental factors or has not considered these issues in the estimation of the number of required spare parts (like in this case). So, to avoid downtime regarding the unavailability of spare parts, it is suggested that the mine company should take the operating environmental factors into consideration while estimating the spare parts need. The operating environment of system/machine has considerable influence in system performance and its technical characteristics such as reliability and maintainability. Forecasting required support/spare parts based on technical characteristics and the system-operating environment is an optimal way to prevent unplanned disruptions or stoppages.

**References**


\[
\begin{align*}
\sigma(T_0) &= \mathbf{\eta_0}\sqrt{\Gamma\left(1+\frac{2}{\beta}\right) - \Gamma^2\left(1+\frac{1}{\beta}\right)} = 4.500 \times \\
&\sqrt{\Gamma\left(1+\frac{2}{3}\right) - \Gamma^2\left(1+\frac{1}{3}\right)} = 1.448 \\
V &= \frac{\sigma(T_0)}{T_0} = \frac{1.448}{4.020} = 0.364 \\
N_0 &= \frac{t}{T_0} + \frac{V^2 - 1}{2} + V\sqrt{\frac{t}{T_0} - \Phi^{-1}(\rho)} = \frac{5.600}{4.020} + 0.364^2 - 1 - \frac{1}{2} + 0.364\sqrt{\frac{5.600}{4.020}} \times 1.645 \\
&= 1.65 \text{ (piece/year)}.
\end{align*}
\]

Spare parts estimation


Appendix
Table AI contains the data sets used for demonstrating the concept. The column with TTFs exhibits time to failure of a particular type of hydraulic jack.

<table>
<thead>
<tr>
<th>#</th>
<th>TTFs</th>
<th>MCSK</th>
<th>OPSK</th>
<th>ENDUS</th>
<th>HOILQ</th>
<th>STEMP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2536</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>2</td>
<td>1200</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>3</td>
<td>3060</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>3652</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>2564</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>644</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>7</td>
<td>1380</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>8</td>
<td>2776</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>9</td>
<td>1004</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>10</td>
<td>916</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>11</td>
<td>2964</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>272</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>13</td>
<td>1196</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>14</td>
<td>3920</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>2312</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>16</td>
<td>3696</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>17</td>
<td>3108</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>1216</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>19</td>
<td>2368</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>2640</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
</tbody>
</table>

The following abbreviations are used for denoting the covariates:

- **MCSK**: Maintenance and service crew skill
- **OPS_K**: Operator’s Operator Skill
- **HOILQ**: Hydraulic Oil Quality
- **ENDUS**: Environmental factors and dust (specially)
- **STEMP**: System temperature (Hydraulic system)

Table AI. Field data used for analyzing and demonstrating the concept.
Table explanation: if we consider row 1, for instance column 2 indicates that the hydraulic jack failure takes place after working 2536 hours. Considering column 3 with MCSK, $+1$ indicates that the maintenance and service crew were skilled, column 4, $+1$ indicates that the LHD operators were expert enough in their job, column 5, $-1$ indicates physical environment was not good and acceptable (such as existence of dust), in column 6, $+1$ indicates the hydraulic oil used was standard oil recommended by manufacturer, and finally column 7, $-1$ indicates system’s temperature condition was not good (for example high temperature).
Paper III

Weibull and exponential renewal models in spare parts estimation: A comparison

Accepted for publication in the International Journal of Performability Engineering
Weibull and exponential renewal models in spare parts estimation: A comparison

Behzad Ghodrati*

Division of Operation and Maintenance Engineering
Luleå University of Technology, Luleå
SE-971 87 Luleå, Sweden

Abstract
Providing the required spare parts is an important issue of product support, which is important for system/machine utility improvement. Required spare parts estimation can be performed through different approaches, one of the realistic and well-founded spare parts estimation method is based on the system’s reliability characteristics and taking into consideration the operating environment. To forecast the required number of spare parts in the future for existed machine, in some cases, the assumption of a constant failure rate does not differ much from the assumption of a non-constant failure rate, and can be made with an acceptable error. In this paper we study and compare two renewal models namely exponential and Weibull models used in estimation of spare parts for non-repairable components. We also estimate the differences between the two models and calculate the percentage of error. Furthermore, a sensitivity analysis was carried out as well, based on the results of a case study, which had been conducted on the hydraulic system of LHD machines in Kiruna Mine in Sweden to find out which factor has a significant impact on the estimation of the number of required spare parts.

Key words: Spare parts estimation, Mechanical system, Non-repairable components, Proportional hazard model, Renewal models

1. Introduction

Every industrial-mechanical system needs support during its life period in order to be available and perform the defined function. There are different forms of product support, one of which is the delivery of the required spare parts. In other words, important parts of the support system are spare part stocks and the control of the inventory. Generally, inspection and repair constitute an important issue for industrial systems in keeping the utilization at the appropriate level. This can be achieved by replacing worn-out and failed components with new ones.

Therefore, the required spare parts should be available in stock in the event of repair and replacement of the failed or worn components to minimize the system downtime and maximize the machine utilization. Consequently, it is necessary that the required number of spare parts should be forecasted properly and kept prepared, while taking economic factors into consideration, so that faulty components can be replaced in the minimum time possible when required. Estimation of the required spare parts can be accomplished through different approaches, one of which is a realistic and well-founded method based on the system’s reliability characteristics and taking into consideration the operating environment [1, 2]. Manufacturers and customers use reliability measures to quantify the effectiveness of the system. In the reliability analysis the failure rate can be considered either constant or non-constant. For instance, the failure rate of electronic modules and components is constant and time-independent. In contrast, the failure rate of most mechanical parts and systems is non-constant (increasing or decreasing) and working-time-dependent [3]. Much of the research within the field of reliability concerns non-constant failure rates; i.e. the distribution for the time between failures is assumed not to be an exponential distribution.

In some cases, for forecasting and estimating the required number of spare parts in the future based on the reliability characteristic of machines, the assumption of a constant failure rate does not differ much from the assumption of a non-constant rate, and can be made with an acceptable error. In addition, the present authors believe that non-Poisson approaches could be justified for reliability and maintenance analyses that tend to be on the component level, but not for logistic support analyses and spares optimization.

In this paper an attempt has been made to study and analyze the problem (estimation of the required number of non-repairable spare parts), to estimate the differences between the two methods based on reliability characteristics (Weibull model versus exponential model) and to calculate the percentage of error. The application condition of each model is studied as well, that presents in the case of single component alone and/or a component in a system which model is applicable. Totally the advantages and disadvantages of both models are discussed. Moreover, a sensitivity analysis was carried out based on the result of a case study in the Kiruna iron ore mine in Sweden to find out which factor has a significant impact on the estimation.

In the real life of a system, the hazard rate is influenced by the time during which and the operating environment factors (covariates) under which the system operates. In other words, the hazard rate of a system is the product of the baseline hazard rate \( h_0(t) \), dependent on time only, and another positive functional term basically independent of time. This term incorporates the effects of a number of covariates, such as temperature, pressure, and others. The effects of covariates may be to increase or to decrease the hazard rate. For example, in the case of bad operating conditions, poor and incomplete maintenance, or incorrect spare parts, the observed hazard rate is greater than the baseline hazard rate. However, in the case of good operating
conditions, or improved and reliable components of a system, the observed hazard rate will be smaller than the baseline hazard rate [4].

One method for analyzing the effects of the covariates on the reliability (and also the hazard rate) is to use regression models, which generally can be broadly classified into two groups, parametric and non-parametric regression models, on the basis of the approaches used [5]. The “proportional hazard model” [6] is an example of a non-parametric model whose general approach is to decompose the hazard rate into two parts. The generalized form of the proportional hazards model (PHM) that is most commonly used is written as [6]:

$$ h(t, z) = h_0(t)e^{(z\alpha)} $$  \tag{1}$$

where \( z\alpha = \sum_{i=1}^{n} z_i \alpha_i \), \( \alpha \) is the regression coefficient of the corresponding \( n \) covariates (\( z \)), and \( h_0(t) \) is the baseline hazard rate.

The baseline hazard rate is assumed to be equal to the total hazard rate when the covariates have no influence on the failure pattern.

Therefore, the observed hazard rate of a system with respect to the exponential form of function, which includes the effects of covariates, may be given as [4]:

$$ \lambda(t, z) = \lambda_0(t)e^{(z\alpha)} = \lambda_0(t)e^{\sum_{j=1}^{n} \alpha_j z_j} $$ \tag{2}$$

where \( z_j, j = 1, 2, \ldots, n \) are the covariates associated with the system and \( \alpha_j, j = 1, 2, \ldots, n \) are the unknown parameters of the model, defining the effects of each one of the \( n \) covariates.

2. Expected number of failures

Consider an item which upon failure is subjected to replacement; i.e. the hazard rate after repair is same as the hazard rate at the beginning. If \( N(t) \) is the total number of failures by time \( t \), then \( M(t) = E[N(t)] \) is the expected number of failures by time \( t \). It can be shown under this assumption:

$$ E[N(t)] = M(t) = \int_0^t h(x)dx $$ \tag{3}$$

For an exponential time to failure distribution with considering the effect of covariates (influencing factors except time), the expected number of failures is equal to:

$$ E[N(t)] = \int_0^t \lambda(x)e^{\sum_{j=1}^{n} \alpha_j z_j}dx = \lambda x e^{\sum_{j=1}^{n} \alpha_j z_j} $$ \tag{4}$$

And for the Weibull distribution by integrating the effect of covariates, the expected number of failures will be equal to:

$$ E[N(t)] = \int_0^t \left( \frac{x}{\eta} \right)^{\beta-1} e^{-(x/\eta)^{\beta}} \sum_{j=1}^{n} \alpha_j z_j dx = \left( \frac{t}{\eta} \right)^{\beta} e^{\sum_{j=1}^{n} \alpha_j z_j} = \left( \frac{t}{\eta} \right)^{\beta} e^{\sum_{j=1}^{n} \alpha_j z_j} $$ \tag{5}$$

3. Required spare parts estimation

Spare parts forecasting and inventory management constitute one of the most challenging problems in the whole process of integrated logistic support. On the one hand, the operators want replacement parts to be in stock when required, but on the other hand, they cannot fulfill this wish because capital would then be bound up in the inventory. Any money spent on spares means less money available to pay for fuel, wages, and a new system or to gain interest. In addition, every stocked spare incurs on-going costs in the form of storage costs, handling charges and possibly deterioration costs through a limited shelf life or obsolescence. On the other hand, a lack of spare parts availability might cause uncompensated loss through system downtime and non-production.

The cost of maintenance and spares for an operator of a fleet of trucks or loaders over the life of the system usually exceeds the cost of the original system (truck or loader), depending on how the fleet is operated, maintained and supported [7]. For large quantities of items, even a very small error in forecasting the demand for spares can make a huge difference in the support cost.

Usually the manufacturer/supplier provides information on the required number of spares for each component of the system for a stated period of time (initial provisioning). Unfortunately, as mentioned by Pironet [8], demand prediction for spare parts and maintenance constitutes the weakest aspect of stock management today in all armed forces and industries alike.

Any successful model used for stock management should be able to predict the demand as accurately as possible. The demand due to failure can be modeled either using a renewal theory (when the time to failure is non-exponential) or using a Poisson process as a special case of the renewal process (if the time to failure is exponentially distributed).
4. **Mathematical models for demand prediction**

Two popular mathematical methods that are used in spare parts provisioning are based on the Weibull and exponential renewal models. When we are talking about a system that comprises several different non-repairable components, in the case of the failure of system due to the failure of any components, just for retaining in the system, the failed item is replaced with a new one. In other word, for system minimal repair is done where the failure rate of the system after replacement of the failed components is the same as that just before failure. So, in this category for the considered system failure occur according to a non-stationary Poisson process [9]. The failure rate associated with the failure distribution function is a reliability measure which is used in this case for calculating the average required number of spare parts for a defined time horizon. But, for each non-repairable item/component in a system, failures and hence replacements over the time occur according to a renewal process, since each failed item is replaced by a new one [9]. In other word, the time to failure (or time between replacements) is used as a reliability measure in this context for estimating the number of required spare parts (Fig. 1).

![Fig. 1: Comparison between the failure rate of single component and system](image)

In addition, the exponential model can be used whenever the failure rate is constant (meaning that each failure mode and other factors which influence the demand should follow the exponential distribution). Whenever the failure rate is not constant, we have used (in this research) the Weibull model to forecast demands for spares. It is important to note that the above statement is valid only for non-repairable spares (components) that are not repaired.

### 4.1 Exponential model for forecasting the required spare parts

A constant failure rate could mean that the number of occurrences per unit time does not vary over time and the conditional probability of failure per unit time is constant. The homogeneous Poisson process can be used to model higher indenture spares such as Line Repairable Units (LRU) in the steady state when the failure rate is constant.

In LRU with a large number of components which can be modeled using an independent renewal process, theorems by Palm [10] and Drenick [11] state that in the steady state the time between replacements at the LRU level follows an exponential distribution; i.e. the demand follows a homogeneous Poisson process.

The exponential reliability model is a simple and applicable model to use, especially when the effects of covariates are considered in the study of non-repairable elements/systems. Therefore, in this case the average number of required spare parts, with the assumption of an exponentially distributed lifetime for them, can be calculated through the use of the following equation [1]:

\[
1 - P(t) = \exp(-\lambda t) \sum_{\lambda = 0}^{\infty} \frac{\lambda^\lambda}{\lambda!}
\]

where:
- \( P = \text{Probability of a shortage of spare parts} \) 
- \( \lambda = \text{Failure rate of an objective part (with regard to the effect of covariates)} \) 
- \( t = \text{Operation time of system} \) 
- \( N = \text{Total average number of required spare parts in period} \)

If \( q \) represents the numbers of the same part in use at the same time, then \( q \) is entered into the equation in the form of multiplication by \( \lambda q \). In this way the calculated \( N \) will represent the total required number of spare parts for the whole system.

### 4.2 Weibull renewal model for forecasting the required spare parts

Renewal process was originally used to analyze the replacement of equipment upon failure, to find the distribution of the number of replacements and the mean number of replacements [12]. It is the most appropriate tool for predicting the demands for consumable items.
Generally in the analytical world, function evaluation is much faster and optimization is feasible. The classes of analytical models that we identify and like to compare are those based on general renewal processes. The reason is that component (non-repairable parts) failure processes are naturally described by renewal processes. The theory of renewal processes is well developed and matures [13, 14, and 15]. A (an ordinary) renewal process is characterized by one entity, the distribution for the time between renewals, denoted by \( F(t) \).

If \( N(t) \) represents the number of renewals (in our case the number of failures) that occur by time \( t \), and if one assumes that the time to failure random variables \( X_i, i \geq 1 \) are independent and have an identical distribution \( F(t) \), then:

\[
F^n(t) = \int_0^{F^{-1}(t-x)} dF(x) 
\]

(7)

\( F^n(t) \) denotes the probability that the \( n \)th failure will occur by time \( t \). The expected number of failures, \( M(t) \), during a length of \( t \) is given by:

\[
M(t) = \sum_{n=1}^{\infty} F^n(t)
\]

(8)

The above equation is known as the **Renewal Function** and it gives the expected number of renewals during \((0, t]\). Consider replacements of a part having a mean time to failure denoted by \( \bar{T} \) and a standard deviation of time to failures denoted by \( \sigma(T) \) (so \( \zeta = \sigma(T) / \bar{T} \) denotes the coefficient of variation of the time to failures), and if the operation time \( t \) of the system or machine in which this part is installed is quite long and several replacements need to be made during this period, then the average number of failures \( E[N(t)] = M(t) \) will stabilize to the asymptotic value of the renewal function as [13]:

\[
N_i = M(t) = E[N(t)] = \frac{t}{\bar{T}} \cdot \frac{\zeta^2 - 1}{2}
\]

(9)

The standard deviation of the number of failures in time \( t \) is:

\[
\sigma[N(t)] = \zeta \sqrt{\frac{t}{\bar{T}}}
\]

(10)

If time \( t \) in the above equations representing a planning horizon is large, then \( N(t) \) is normally distributed (based on a central limit theorem) with mean \( = N(t) \). Then the number of spares \( N \) needed during this period with a probability of shortage \( = p \) is given by [3]:

\[
N_i = \frac{t}{\bar{T}} + \frac{\zeta^2 - 1}{2} + \zeta \sqrt{\frac{t}{\bar{T}}} \Phi^{-1}(p)
\]

(11)

where \( \Phi^{-1}(p) \) is the inverse normal function and is available in probability textbooks. Assuming the Weibull reliability model to be a most versatile model for characterizing the life of mechanical parts, and integrating the effect of covariates with regard to the proportional hazard model (see [2] for details), we have:

\[
\beta = \beta_0 \quad \eta = \eta_0 \left[ \exp \left( \sum a_i z_i \right) \right]^{-1/\rho}
\]

(12)

where \( \beta_0 \) and \( \eta_0 \) are the initial (baseline) shape and scale parameters respectively in the Weibull distribution.

5. **Comparison between the Weibull and exponential renewal models based spare parts estimation**

There are some advantages and disadvantages of implementing the Weibull and/or the exponential models in spare parts estimation. For instance, the exponential model (as a homogeneous Poisson process model) is simple and easy to implement concerning both the required data collection and analysis. Nevertheless, the approximated Weibull renewal model is more appropriate for calculating the total number of available spare parts accurately. Here come bellow the results of a comparison between two methods, which is concluded from the implemented calculation process. Calculation process was carried out based on the different values of baseline mean time to failure (MTTF_0), the shape parameter (\( \beta \)), and the effect of covariates (Co.Eff. = exp(\( \sum a_i z_i \)) as an assumed fix coefficient). In the implemented calculation process we used both the exact exponential and the approximated Weibull models for estimating the required average number of spare parts in a specified planning horizon.
As can be seen in Fig. 2, in both the exact exponential and the approximated Weibull models, the number of required spare parts decreases as the baseline mean time to failure increases. The ratio of the number of spare parts estimated through the exponential method to that estimated through the Weibull method is approximately two to one (in average). In addition, the slope of the lines is sharp before 3000 hrs and afterwards it subsides. We can therefore conclude that for the working period before 3000 hrs it is more beneficial to use the Weibull model, which is more accurate (big difference in the number of required spare parts compare to exponential model). For the period after 3000 hrs the exponential model which is easy to use and implement can replace the Weibull model. From another point of view, for the component costing less it might be more economical to use the exponential model than the accurate but costly (more time-consuming) Weibull model.

**Comparison between Weibull & exponential methods**

(Beta=3.5 & Co.Eff.=1.5)

<table>
<thead>
<tr>
<th>Beta</th>
<th>Weibull</th>
<th>Exponential</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>3.4</td>
<td>6.4</td>
</tr>
<tr>
<td>1.3</td>
<td>6.6</td>
<td>10.7</td>
</tr>
<tr>
<td>1.7</td>
<td>11.6</td>
<td>17.1</td>
</tr>
<tr>
<td>2.3</td>
<td>17.6</td>
<td>23.6</td>
</tr>
<tr>
<td>3.4</td>
<td>26.4</td>
<td>32.4</td>
</tr>
</tbody>
</table>

Fig. 2: The plot for the average number of required spare parts against the baseline mean time to failure for the Weibull and exponential methods (Beta value ($\beta = 3.5)$, the coefficient of covariates (Co.Eff. = 1.5) and system operation time ($t = 5600$ hrs) are assumed constant)

The graph for the required average number of spare parts based on the $\beta$ values (Fig. 3) indicates that with an increasing $\beta$ value, the number of required spare parts decreases. This is more predictable, because an increasing beta means that the component failure rate increases, whereas the system failure intensity is not affected in the same way. As it is seen (Fig. 4) the curve of the probability density function curve moves to right hand side with increasing the $\beta$ value. It means that the probability of failure at the beginning of operation is high when the $\beta$ value is less in compare to high $\beta$ value. In other word, with increasing the $\beta$ value, the time to the first failure is increasing as well, which is considered in this study for non-repairable modules. The plotted line is, however, still saw-tooth-shaped, with slightly sharper teeth. This is an important and considerable issue in the warranty cost evaluation, but for the useful life of equipment, however, if its life tends to be infinite the system/component with high $\beta$ value will need more spares for a fixed life length.

**Comparison Between Weibull & Exponential methods**

(MTTFo=3000 hrs & Co.Eff.=1.5)

<table>
<thead>
<tr>
<th>Beta</th>
<th>Average number of required spare parts (Nt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4,8</td>
<td>6.7</td>
</tr>
<tr>
<td>2,9</td>
<td>6.7</td>
</tr>
<tr>
<td>2,3</td>
<td>6.7</td>
</tr>
<tr>
<td>2,1</td>
<td>6.7</td>
</tr>
<tr>
<td>1,9</td>
<td>6.7</td>
</tr>
</tbody>
</table>

Fig. 3: The plot for the average number of required spare parts against the $\beta$ value for the approximated Weibull and exponential methods

This is an important and considerable issue in the warranty cost evaluation which has been considered and studied as a research project for a leading mobile phone company. But for the useful life of equipment, however, if its life tends to be infinite the system/component with high $\beta$ value will need more spares. If the manufacturer offers longer warranty period just by increasing the $\beta$ value of components, then on the side the customer may get dissatisfaction after warranty period due to
the increased number of failure. Then there is an important trade-off between $\beta$ value and the life length of equipment and the warranty cost.

![PDF plot for different values of Beta](image)

**Fig. 4:** The probability of density function based on different value of $\beta$

Therefore, based on the result of the analysis, it can be claimed that for $\beta \leq 1.5$ the exponential model is more suitable in the context of application and analysis costs.

In addition, as is seen in Fig. 5, with increasing $\beta$ the difference between the exponential and the approximated Weibull models will decrease when the baseline mean time to failure ($MTTF_0$) decreases.

![Comparison between Weibull & exponential methods](image)

**Fig. 5:** The plot for the average number of required spare parts against the $\beta$ value for the approximated Weibull and the exact exponential methods based on different $MTTF_0$ values ($Co.Eff. = 1.5$ and $r = 5600$ (hrs) are assumed constant)

In Fig. 6, the required average number of spare parts is plotted against the effect of covariates $\left[ \exp \sum_{j=1}^{n} \alpha_j z_j \right]$, showing that the exponential model is influenced more with covariates in compare to Weibull renewal model.

We found that this is due to only that the covariates affect directly (in the multiplication form) the failure rate in the exponential model, whereas in the Weibull model, the covariates affect only the scale parameter as a part of factors in the failure rate. The effect of covariates equal one means there is no environmental/external influence on the number of failure and consequently on the number of required spare parts.

The value of the effect of covariates less than one indicates the worse situation of system operating condition whereas the value of the effect of covariates more than one represents the good/improved working environment.

The multi-comparison of the effects of covariates and $\beta$ value (Fig. 7) presents that the covariates have less influence on the average required number of spares for components with high $\beta$. This event confirms our previous statement which indicates that the exponential model gets more effect than Weibull model by covariates.
Comparison between Weibull & exponential methods
(Beta=3 & MTTFo=3000 hrs)

Fig. 6: The plot for the average number of required spare parts against the effect factor of covariates for the Weibull and the exponential methods ($\beta=3$, $MTTF_o=3000$ (hrs) and $t=5600$ (hrs) are assumed constant)

Multi-Comparison between Weibull & exponential methods
(MTTFo=2000 hrs)

Fig. 7: The multi-analysis of the effects of covariates and $\beta$ value on the average number of required spare parts ($MTTF_o=2000$ (hrs) and $t=5600$ (hrs) are assumed constant)

6. Sensitivity analysis of the evaluation factors

A sensitivity analysis was carried out as well, based on the results of a case study (see the appendix for a sample of the data set used), which had been conducted on the hydraulic system of LHDs in Kiruna Mine in Sweden to find out which factor has a significant impact on the estimation (calculation of the number of required spare parts). For this purpose we applied the factorial design statistical method and Analysis of Variance (ANOVA) for the number of required spare parts, considering the three main factors (effects) – $MTTF_o$, $\beta$, and the effect of covariates – and their double interactions. The ANOVA table (Table 1) partitions the variability in the number of required spare parts (No of Req Spare Parts) into separate pieces for each of the effects. It then tests the statistical significance of each effect by comparing the mean square against an estimate of the experimental error.

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>d.f.</th>
<th>Mean Square</th>
<th>F-Ratio</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: MTTFo</td>
<td>19.7192</td>
<td>1</td>
<td>19.7192</td>
<td>35.10</td>
<td>0.1065</td>
</tr>
<tr>
<td>B: Eff. Cov.</td>
<td>43.8048</td>
<td>1</td>
<td>43.8048</td>
<td>77.97</td>
<td>0.0718</td>
</tr>
<tr>
<td>C: Beta</td>
<td>10.4882</td>
<td>1</td>
<td>10.4882</td>
<td>18.67</td>
<td>0.1448</td>
</tr>
<tr>
<td>AB</td>
<td>11.8098</td>
<td>1</td>
<td>11.8098</td>
<td>21.02</td>
<td>0.1367</td>
</tr>
<tr>
<td>AC</td>
<td>1.7672</td>
<td>1</td>
<td>1.7672</td>
<td>3.15</td>
<td>0.3268</td>
</tr>
<tr>
<td>BC</td>
<td>3.8088</td>
<td>1</td>
<td>3.8088</td>
<td>6.78</td>
<td>0.2334</td>
</tr>
<tr>
<td>Total error</td>
<td>0.5618</td>
<td>1</td>
<td>0.5618</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>91.9598</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R-squared = 99.3891%
In this case, one effect (the effect of covariates) has P-values less than 0.1, indicating that they are significantly different from zero at the 90.0% confidence level (the null hypothesis is contradicted). The R-Squared statistic indicates that the model as fitted explains 99.3891% of the variability in the number of required spare parts. Fig. 8 plots the estimated effects in decreasing order of importance at 90.0% confidence intervals for the estimates.

Generally, the effect of $\beta$ is reflected in some way in the effect of $MTTF_\alpha$. Therefore, the re-analysis of the influencing factors after eliminating the factor $\beta$ shows that the factor effect of covariates ($Eff.Cov.$) is still significant. This can be concluded from the normal probability plot for the number of required spare parts (Fig. 9), which shows that the plot of $Eff.Cov.$ is located out of the normal probability line.

Fig. 8: Pareto chart for the number of required spare parts – the effect of covariates is significant at a 90% confidence interval

Fig. 9: Normal probability plot for the number of required spare parts

7. Discussion and conclusion

The mathematical models based on the exponential and Weibull renewal methods are two popular models used in spare parts provisioning. The exponential model can be used whenever the failure rate is constant (meaning that each failure mode and other factors which influence the demand should follow the exponential distribution). Whenever the failure rate is not constant, the Weibull model can be used to forecast demands for spares. This statement is valid only for non-repairable spares that are not repaired.

When building a model based on renewal theory and non-constant failure rates, the parameters that we need to estimate increase considerably. Especially when the effect of operating environment factors comes under consideration in estimation, there are several different items and parameters that should be considered.

An important point to make is that in some cases it is questionable (in fact in many cases incorrect) to spend money and effort on trying to reduce the model error by going from an exponential model to a more accurate demand process description. Usually the model error/uncertainty resulting from the implementing exponential model in a general condition for a multi components system is small in relation to other sources of uncertainty [7, 16]. The “more accurate” model requires more input data (which is seldom available or is costly to achieve) and is less applicable to real-world situations (for example, due to the lack of accuracy in superposition).

This study shows that, among the factors influencing the spares estimation, the effect of covariates (operating environment factors) is significant at a 90% confidence level. The baseline mean time to failure takes second place with regard to significance for consideration. It is therefore seriously recommended to take the operating environment influencing factors
into consideration when analyzing the reliability characteristics of components/systems and when estimating the required
number of spare parts, in order to make the final result as accurate and realistic as possible.
A comparison between the Weibull renewal and the exponential methods for calculating the number of required spare parts
indicates that, based on various $\text{MTTF}$, there is quite a big difference between the results of the two methods. The number of
spare parts obtained when implementing the exponential method is almost twice the number obtained with the Weibull
method for different values of baseline mean time to failure. For the two cases where $\beta < 2$ and the coefficient of the effect of
covariates is equal to or smaller than 1, the difference between the output results of the two methods is small and sometimes
negligible. In these cases then the Weibull renewal method can be replaced with the simple exponential method, which is
probably more economical to implement. Consequently, the nature of the work, the price of spares (economy), and the
criticality of the availability of spare parts influence the decision as to which method is more suitable to use.
In the Weibull renewal model with an increasing $\beta$ value, the number of required spare parts decreases. Finally, the study
demonstrates that, from the customer/user point of view, in the case of the single component the Weibull renewal model is
more applicable and accurate. However, the exponential model is more suitable when a system (multi-components) is under
study to determine the required number of spare parts.

Acknowledgement
The author is thankful to anonymous referees for their useful comments to improve the manuscript. The author is also
grateful to Professor Per-Anders Akersten and Professor Uday Kumar for their valuable help and comments to improve the
content of the paper.

References
44 no. 2, pp. 177-188, 1994.
1972.
58, 1938.
York, 1969.
Biographical Sketch:

Behzad Ghodrati did his Master of Technology from the Faculty of Engineering of Tehran University- Iran, and at the moment doing his PhD in the Division of Operation and Maintenance Engineering, Luleå University of Technology- Sweden.

His research interest includes Reliability management, product support engineering and spare parts estimation based on system/component reliability characteristics and also system operating environment and

Appendix

The following table (Table 2) shows a sample of the data set used in the sensitivity analysis of evaluation factors ($MTTF_o$, effect of covariates and beta). The values –1 and +1 in the table indicates the worse/undesired (less $MTTF_o$) and good/desired (high Beta) values or conditions, respectively, in the working environment.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>12</td>
</tr>
<tr>
<td>2</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
Paper IV

Spare parts estimation and conducted risk assessment – Case study in Choghart iron ore mine

Submitted for publication
Spare Parts Estimation and Risk Assessment Conducted at Choghart Iron Ore Mine – A Case study

Behzad Ghodrati†

Div. of Operation and Maintenance Engineering
Luleå University of Technology, Luleå, 97753- Sweden

Abstract
Spare parts needs – as an issue in the field of product support – are dependent on the characteristics of the product in question, e.g. its reliability and maintainability, and the characteristics of the environment in which the product is going to be used (e.g. the temperature, humidity, and the user/operator’s skills and capabilities), which constitute covariates. The covariates have a significant influence on the system reliability characteristics and consequently on the number of required spare parts. Ignoring this factor might cause irretrievable losses in terms of production and ultimately in terms of economy. This was proved by the event tree risk analysis method used in a modified and non-standard form in the present research. It has been found that the percentage of risk associated with not considering the system operating environment in spare parts estimation is high compared to the percentage of risk involved when this is taken into account.

1. Introduction – Product support
Most industrial products and systems wear and deteriorate with use. In general, due to economical and technological considerations, it is almost impossible to design a machine/system that is maintenance-free. In fact, maintenance requirements come into consideration mainly due to the lack of proper designed reliability and tasks performance quality. Therefore, the role of maintenance and product support can be perceived as the process that compensates for deficiencies in design, with regard to the reliability of the product and the quality of the output generated by the product (Markeset and Kumar, 2003).

The product support and maintenance needs of systems to a large extent are decided during the design and manufacturing phase (see e.g. Blanchard, 2001; Blanchard and Fabrycky, 1998; Goffin, 2000; Markeset and Kumar, 2001; Smith and Knezevic, 1996).

Furthermore, the strategies adopted by owners/users concerning systems operation and maintenance also considerably affect maintenance and product support needs. Hence, we can assert that product design and product support (e.g. required spare parts) both affect the service and support performance, and therefore the product support strategy for customers must be defined in terms of these two dimensions (for more information see Cohen and Lee, 1990).

The service delivery performance in the operational phase can be enhanced through better provision of spare parts and improvement of the technical support system. However, to ensure the desired product performance at a reasonable cost, we have to design and develop maintenance and product support concepts right from the design phase. The existing literature appears to have paid little attention to the influence of product design characteristics, influenced by the product operating

† Corresponding author’s e-mail: Behzad.Ghodrati@ltu.se
environment, in the dimensioning of product support, especially in the field of spare parts planning.

Therefore, spare parts needs (as an issue in the field of product support) are dependent on the engineering characteristics of the product in question, e.g. its reliability and maintainability, the operators’ skills and capabilities and the environment in which the product is going to be used. Therefore, product support specifications should be based on the design specifications and the conditions faced by the customer. The risk associated with the ignoring of the system operating environmental factors is remarkable and play an important role in the cost of operation (Ghodrati and Kumar, 2005a).

2. Operating environment

The operating environment should be seriously considered when dimensioning product support and service delivery performance strategies. Generally, the recommended maintenance program for systems and components is based on their age and condition without any consideration of the operating environment. This, in turn, leads to many unexpected system and component failures. This creates poor system performance and a higher Life Cycle Cost (LCC) due to unplanned repairs and/or restoration, as well as support. The environmental conditions in which the equipment is working, such as the temperature, humidity, dust, the maintenance crew’s and operator’s skill, the operation profile, etc., often have a considerable influence on the product reliability characteristics and thereby on the maintenance need and product support requirement (Kumar and Kumar, 1992; Kumar et al., 1992). Furthermore, the “Distance” in many ways (not only in geographical terms, but also in terms of infrastructure, culture, etc.) of the user from the manufacturer and distributor/supplier can exert an additional influence on spare parts management.

3. Spare parts

Industrial systems and technical installations may fail and therefore repair is needed to restore them to working condition. These systems and installations are also subject to planned maintenance. In most cases, maintenance and repair require pieces of equipment to replace defective parts. The common name for these parts is spare parts. They may be subdivided into:

1. Repairable parts, also called recoverable items and recyclable parts. If a repairable item has failed and a shutdown of the system is unavoidable, the user has to accept at least the time required to repair the item before the system is up again. In this situation the user only has to wait for the time that it takes to repair the item.

2. Non-repairable parts, also called disposables, throwaway parts or consumables, which are considered and studied in the present research. In other words, we limit ourselves to non-repairable spare parts in the normal phase. If such a part fails, it is removed and replaced by a new item.

Apparently, the control and management of spare parts constitute a complex matter. Common statistical models for inventory control lose their applicability, because the demand process is different from that assumed due to the machine characteristics, operating situation and unpredictable events during operation. An essential element in many models is forecasting demand, which requires some historical demand figures, which are unavailable or invalid for new and/or less consumption parts. Moreover, the shorter life cycles of products and better product quality further reduce the possibility of collecting historical demand figures. Unfortunately, the pragmatic approaches of spare parts inventory management and
control are not validated in any way, and then controllability and objectivity are hard to guarantee (Fortuin and Martin, 1999). The product reliability characteristics and operating environment based spare parts forecasting method (Ghodrati and Kumar, 2005a and 2005b), as a systematic approach, may improve this undesirable situation. The key questions in any logistic management are the following:

- Which items are needed as spare parts?
- Which items do we put in stock?
- When do we (re)order?, and
- How many items do we (re)order?

Therefore, the main objective of this research study was to estimate the required number of spare parts and the associated risks (i.e. risk of shortage of spare parts due to not considering the operating environment leading to financial losses).

4. **The context of spare parts logistics**

As mentioned earlier, spare parts are required in the maintenance process of systems. Regarded from the point of view of a spare parts supplier or systems manufacturer, we can make a distinction between two types of industrial products that require spare parts:

1. **Conventional products**: These are the products and systems sold to customers and installed at the customer's site for the purpose of providing products or services. These systems are under the users' control, and are exemplified by machines in production departments, transport vehicles, TVs, computers and private cars. Mostly there is a Technical Service Department within the client location/organization performing maintenance and controlling an inventory of spare parts.

   In some cases a Technical Service Department of the firm that sold the system, i.e. the original equipment manufacturer (OEM), carries out the maintenance of these systems under separate contracts and conditions.

2. **Functional products**: In the functional products category, the user does not buy a machine/system but the function that it delivers (Markeset and Kumar, 2003a). To avoid the complexities of maintenance management, many customers/users prefer to purchase only the required function and not the machines or systems providing it. In this case the responsibility for the maintenance and product support lies with the organization delivering the required function.

   The diversity of the characteristics of spare parts management situations that have to be taken into account is usually quite large. Therefore, we need to categorize the entire assortment of spare parts. This can be conveniently accomplished according to the characteristics of an individual aspect, after which specialized control methods can be developed for each category (e.g. defining the criticality and the risk of shortage).

   The following are examples of criteria that can be used for categorization:

- Demand intensity
- Purchasing lead-time
- Delivery time
- Planning horizon
- Essentiality, vitality, criticality of a part
- Price of a spare part
- Costs of stock keeping
- (Re-)ordering costs
In fact, in any given situation, not all the criteria are necessarily relevant and usable. Therefore, as mentioned previously, it is wise to classify the spare parts into groups, to establish appropriate levels of control over each category. Based on the source of supply and cost, the spare parts can be classified (in our case as well) into three groups of items, A, B and C, as follows:

**A:** Parts which can be procured overseas only and whose unit cost is very high (such as hydraulic pumps).

**B:** Parts which can be procured overseas only and whose unit cost is not high (e.g. seals).

**C:** Parts that are available locally (e.g. brake pads).

### 4.1. Estimation of the required number of spare parts

The environmental conditions in which the equipment is to be operated, such as the temperature, humidity, dust, etc., often have a considerable influence on the product reliability characteristics (Kumar and Kumar, 1992; Blischke and Murthy, 2000; Kumar et al., 1992). In fact, the reliability characteristics (e.g. the failure (hazard) rate) of a system are a function of the time of operation and the environment in which the system is operating.

The failure (hazard) rate of a system/component is the product of the baseline hazard rate \( \lambda_0(t) \), dependent on time only, and one other positive functional term (that is basically independent of time) which incorporates the effects of operating environment factors (covariates), e.g. the temperature, pressure and operator’s skill.

The baseline hazard rate is assumed to be identical and equal to the hazard rate when the covariates have no influence on the failure pattern.

Therefore, the actual hazard rate (failure rate) in the Proportional Hazard Model (PHM) (Cox, 1972) with respect to the exponential form of the time-independent function, which incorporates the effects of covariates, can be defined as follows:

\[
\lambda(t,z) = \lambda_0(t) \exp(z \alpha) = \lambda_0(t) \exp \left( \sum_{j=1}^{n} \alpha_j z_j \right)
\]

where \( z_j, j = 1, 2, \ldots, n \) are the covariates associated with the system and \( \alpha_j, j = 1, 2, \ldots, n \) are the unknown parameters of the model, defining the effects of each one of the \( n \) covariates.

### 4.2. Spare parts inventory management

The logistics of spare parts is very important and difficult, since the demand is hard to predict, the consequences of a stock-out may be disastrous, and the prices of parts are high. If the parts are under stocked, then the defective systems/machines cannot be serviced, resulting in lost production and consequently customer dissatisfaction.

On the other hand, if the parts are overstocked, the holding costs are high. Situations where some parts have a very high inventory level and some are in shortage could be quite common. In such a service system, an efficient inventory management system is essential.

The requirements for planning the logistics of spare parts differ from those of other materials in several ways: the service requirements are higher as the effects of stock-outs may be financially remarkable, the demand for parts may be extremely sporadic and difficult to forecast, and the prices of individual parts may be very high. These characteristics set pressures for streamlining the logistic system of spare parts, and with high requirements for material flow, it is natural that spare parts management should be an important area of inventory research in the phases of design of technological systems and product support systems.
The principle objective of any inventory management system is to achieve an adequate service level with minimum inventory investment and administrative costs. The optimum spare parts management strategy must describe what level of service is to be offered and whether the customers are segmented and prioritized in terms of service, and it must ensure the availability of parts and the quality of service at reasonable costs as a main concern in maintenance.

In general terms, when designing a spare parts logistics system, the following factors at least usually have to be considered: the product-specific characteristics (e.g., the reliability characteristics), the location of customers and their special requirements, and the system/machine operating environment.

There are some operational characteristics of maintenance spare parts that can be used for estimation of the spare parts need and control of the inventory. The most relevant control characteristics are: criticality, demand and value (Huiskonen, 2001). The criticality of an item is probably the first aspect that is defined by the spare part logistics practitioners. The criticality of a part is related to the consequences of the failure of a part for the process in question in the event of a replacement not being readily available.

The impact of a shortage of a critical part may be a multiple of its commercial value. One practical approach is to relate the criticality to the time in which the failure has to be corrected. With respect to criticality, parts are either highly critical, medium-critical or non-critical (Huiskonen, 2001). High criticality means operationally that the need for the parts in the event of failure is immediate, and parts of medium criticality allow some lead-time to correct the failure.

From the logistics control point of view, it is most essential to know how much time there is to react to the demand need, i.e., whether the need is immediate or whether there is some time to operate.

The predictability of demand is related to the failure mode and process of a part, the intensity of operation and the possibilities of estimating the failure pattern and rates by statistical means. From a control point of view, it is useful to divide the parts in terms of predictability into at least two categories: parts with random failures (e.g., electronic parts) and parts with a predictable wearing pattern (e.g., mechanical parts), and the present research deals with the second category. The value of a part is a common control characteristic.

5. Risk analysis

5.1. Performance measurement
Since investments in spare parts can be substantial, management is interested in decreasing stock levels whilst maximizing the service performance of a spare part management system. To assess the result of improvement actions, performance indicators (such as the fill rate and service rate) are needed. For example, sometimes the duration of the unavailability of parts is a major factor of concern, and then the waiting time for parts is a more relevant performance indicator.

Performance measurement for risk represents a problem in its own right. Usually risk items are not issued, but their presence in stock is justified. In this control category, the most important factor in performance measurement is the risk of unavailability. In general, this risk can be expressed as (Fortuin and Martin, 1999):

\[
RISK_i = \text{Probability (}D_i > S_i\text{)} \times C_i
\]

where:
\[ RISK_i = \text{expected financial loss due to risk item } i \text{ being out of stock} \]
\[ D_i = \text{demand for item } i \text{ during its entire (or remaining) life cycle} \]
\[ S_i = \text{initial number of items of type } i \text{ in stock} \]
\[ C_i = \text{financial consequences if an out-of-stock situation occurs for item } i \]

In the following we will discuss in greater detail the concept of risk analysis and the risk of unavailability of spare parts when required.

### 5.2 Risk definition:

Kaplan and Garrick (1981) have discussed a number of alternative definitions of risk, including the following:

- Risk is a combination of uncertainty and damage.
- Risk is the ratio of hazards to safeguards.
- Risk is a triplet combination of an event, its probability and its consequences.

The term quantitative risk analysis refers to the process of estimating the risk of an activity based on the probability of events whose occurrence can lead to undesired consequences.

The term hazard expresses the potential for producing an undesired consequence without regard to how likely such a consequence is. Therefore, one of the hazards of the spare parts inventory is the shortage of a spare part when it is required, which could produce a number of different undesired consequences. The term risk usually expresses not only the potential for an undesired consequence, but also how probable it is that such a consequence will occur.

Quantitative risk analysis attempts to estimate the frequency of accidents and the magnitude of their consequences by different methods, such as the fault tree and the event tree methods.

In fact, maintenance plays a pivotal role in managing risks at an industrial site, and it is important that the right risk assessment tools should be applied to capture and evaluate the hazards at hand to allow a functional risk-based approach (Rasche et al., 2000). Unplanned stoppages or unnecessary downtime will always result in a temporary upset to the operations flow and output. The cumulative unavailability of the machine (in the case of a spare parts shortage) and the beneficiation process and the added cost incurred can quickly affect the financial performance of a system.

### 6. Risk management

Risk management is an iterative process, as shown in Figure 1. The successful risk management depends on a clearly defined scope for the risk assessment, comprehensive and detailed hazard mapping and a thorough understanding of the possible consequences.

There are several tools and techniques available to the managers and engineers that can help to estimate the level of risk better. These may be either ‘subjective – qualitative’ or ‘objective – quantitative’, as shown in Figure 2. Both categories of techniques have been used effectively in establishing risk-based safety and maintenance strategies in many industries (Rasche et al., 2000).

Quantitative methods are probably ideal for maintenance applications where some data is available and decisions on system safety and criticality are to be made. Even very basic reliability analysis of maintenance data can be used effectively in determining the optimum maintenance intervention, replacement intervals or monitoring strategy.
Fault Tree Analysis and Event Tree Analysis (FTA/ ETA), which are considered as semi-quantitative methods, are tried and tested system safety tools originating from the defense, nuclear and aviation industries.

![Risk Management Process Diagram](image)

**Figure 1. Risk management process**

While ETA draws the growth of an event and yields quantified risk estimates of all event paths, FTA is concerned with the identification and analysis of conditions and factors which cause or contribute to the occurrence of a defined undesirable event, usually one which significantly affects system performance, economy, safety or other required characteristics. FTA is often applied to the safety analysis of systems (IEC 1025, 1990). In the following these methods will be presented in greater detail.

![Risk Analysis Options](image)

**Figure 2. Risk Analysis Options [Source: Rasche and Wooley, 2000]**
6.1 Risk analysis process:
As mentioned earlier briefly, the risk analysis can be accomplished through different steps as follows:

1. Define the potential event sequences and potential incidents.
2. Evaluate the incident outcomes (consequences).
3. Estimate the potential incident frequencies. Fault tree or generic databases may be used for initial event sequences. Event trees may be used to account for mitigation and post-release events.
4. Estimate the incident impacts on the health and safety, the environment and property (e.g. economy).
5. Estimate the risk. This is achieved by combining the potential consequence for each event with the event frequency, and determining the total risk by summing over all consequences.

7.1 Fault tree analysis
Fault Tree Analysis (FTA) is classified as a deductive method which determines how a given system state can occur.

FTA is a technique that can be used to predict the expected probability of the failure/hazardous outcome of a system in the absence of actual experience of failure (Rasmussen, 1981). This lack of experience may be due to the fact that there is very little operating experience, or the fact that the system failure/hazard rate is so low that no failures have been observed. The technique is applicable when the system is made up of many parts and the failure/hazard rate of the parts is known.

The fault tree analysis always starts with the definition of the undesired event whose possible causes, probability and conditions of occurrence are to be determined. The probability of failure can be a probability of failure on demand (such as the probability that a car will fail to start when the starter switch is turned). In our case the event will be “system downtime” and is shown in the top box as a top event.

The fault tree technique has been evolving for the past four decades and is probably the most widely used method for the quantitative prediction of system failure. However, it is becoming exceedingly difficult to apply in very complicated problems.

7.2 Event tree analysis
An event tree is a graphical logic model that identifies and quantifies possible outcomes following an initiating event. The event tree provides systematic coverage of the time sequence of the event propagation.

The event tree structure is the same as that used in decision tree analysis (Brown et al., 1974). Each event following the initiating event is conditional on the occurrence of its precursor event. The outcomes of each precursor event are most often binary (success or failure, yes or no), but can also include multiple outcomes (e.g. 100%, 40% or 0%).

Event trees have found widespread applications in risk analysis. Two distinct applications can be identified. The pre-incident application examines the systems in place that would prevent incident that can develop into accidents. The event tree analysis of such a system is often sufficient for the purposes of estimating the safety of the system. The post-incident application is used to identify incident outcomes. Event tree analysis can be adequate for this application.

Pre-incident event trees can be used to evaluate the effectiveness of a multi-element proactive system. A post-incident event tree can be used to identify and
evaluate quantitatively the various incident outcomes that might arise from a single initiating (hazardous) event.

Fault trees are often used to describe causes of an event in an event tree. Moreover, the top event of a fault tree may be the initiating event of an event tree. Note the difference in the meaning of the term initiating event between the applications of fault tree and event tree analysis. A fault tree may have many basic events that lead to the single top event, but an event tree will have only one initiating event that leads to many possible outcomes. The sequence is shown in the logic diagram below (Figure 3).

**Figure 3. Logic diagram for event tree analysis**

8. Case study

As mentioned earlier, operation stoppages in the case of system/machine downtime are mostly due to the lack/unavailability of required spare parts. Wrong estimation of the required number of spares in the specific time horizon is one of the reasons for these events. The system/machine operating environment is an important factor which affects the function of machines.

This factor also influences the maintenance and support plan of a system, and ignoring this factor is one of the most significant reasons for inaccurate forecasting of the required number of spare parts.

In the present research we have attempted to analyze the risk of ignoring the effects of operating environment factors on the output of a process in the form of the system/machine downtime and loss of production. For this risk analysis we carried out mainly event tree analysis, but also applied fault tree analysis as a complementary method. Both event tree and fault tree analysis have been used in an especial and non-standard way which the organizational states and decisions as well as events and consequents changes are introduced and taken into account in the analysis.

The studied cases concern the hydraulic pump of brake system of the fleet of loaders in the Choghart Iron Ore Mine in Iran.

8.1 Construction of event tree

The construction of an event tree is sequential, and like fault tree analysis, is performed from the left to the right (in the usual event tree convention). The construction begins with the initiating event, and the temporal sequences of occurrence of all the relevant safety functions or events are entered. Each branch of the event tree represents a separate outcome (event sequence – as shown in Figure 4).

The initiating event (Step 1) is usually a failure/undesired event corresponding to a release of failure/hazard. The initiating event in our case is “ignoring the product
operating environment”, and the frequency of this incident was estimated from the historical records.

The safety function and organizational states (Step 2) are actions or barrier that can interrupt the sequence from an initiating event to a failure/hazardous outcome (in other words, safety functions/organizational states and decisions are different state descriptions and are components of a chain of explanations). Safety functions can be of different types, most of which can be characterized as having outcomes of either success or failure with regard to demand. In our case this step comprises:

a) Inadequate product support planning (organizational state)
b) Inadequate/poor spare parts estimation (organizational decision)
c) Shortage of spare parts when required (event)
d) Excessive system/machine downtime (consequent event)
e) Loss of production in the case of system downtime (consequent event)
f) Economic loss in the case of loss of production (consequent event)

As it is observed and also mentioned earlier, this is not a standard form of event tree analysis. This is an special form that safety function is defined as an undesired situation (state) as well, instead of state similar to barrier in the standard form of event tree analysis.

The event tree (Step 3) graphically displays the chronological progression of an incident. As mentioned before, the event tree starts with the initiating event and is constructed from the left to the right.

Each heading in the event tree corresponds to state/event/condition (Step 5) of some outcomes taking place if the preceding event has occurred. Therefore, the probability associated with each branch is conditional and defers from one state to other (e.g. based on long/short term decision and criticality of spare parts). As discussed earlier, these may be based on reliability data, historical records, and experiences, or may be derived from fault tree modeling. The source of conditional probability data in our case is historical records (e.g. daily reports from the operators, the maintenance crew at the workshop and the inventory system), interview with managements of maintenance and spare parts inventory departments and experiences, which is shown upon the branches in figure 4.

The frequency of each outcome is determined by multiplying the initiating event frequency with the conditional probabilities along each path leading to that outcome. The quantitative evaluation (Step 6) of the event tree requires conditional probabilities at every node/branch.

The output of event tree analysis can be either qualitative or quantitative. The qualitative output shows the number of outcomes that result in the success versus the number of outcomes resulting in the failure of the protective system in a pre-incident application. The qualitative outcome from a post-incident analysis is the number of more hazardous outcomes versus the number of less hazardous ones. The quantitative output is the frequency of each event outcome.

The event tree shown in Figure 4 was developed on the bases of the existing situations and experiences of the involved people (e.g. maintenance and inventory managements) who were aware of the related consequences of events. There are 15 output branches that cover the most possible combinations of branches and cases. The upper branches represent the success (yes) connected to poor situations such as the existence of poor product support planning and/or loss of production (output), and the lower branches represent the corresponding failure (no), indicating a strong need for
accurate spare parts estimation, for instance. The complete event tree analysis (Figure 4) includes the estimation of all the output branches’ frequencies. As is seen from the estimated frequencies, the sequences listed below serially have a high probability of loss (classified into two consequences groups: CRASH and HARD) related to ignoring the product operating environment factors in the dimensioning of product support and system function. These high probability outputs mostly belong to the situation in which the operating environment has been ignored. Therefore, it is important and recommended to take this factor into consideration when estimating and managing the spare parts inventory.

\[
\begin{align*}
\text{CRASH :} & \\
ABCDEF &= 71.9712 \\
ABC\overline{DEF} &= 47.9808 \\
\overline{ABCDEF} &= 55.9776 \\
\overline{ABC\overline{DE}F} &= 55.9776
\end{align*}
\]

\[
\begin{align*}
\text{HARD :} & \\
\overline{ABCDEF} &= 30.8448 \\
\overline{ABCD\overline{E}F} &= 17.9928 \\
\overline{ABCD\overline{E}F} &= 7.7112 \\
\overline{ABCD\overline{E}F} &= 5.1408
\end{align*}
\]

---

**Event Tree**

*Ignoring Operating Environment in spare parts estimation*

---

**Figure 4.** Event tree analysis for the risk of ignoring the product operating-environment factor in spare parts planning
8.2 Fault tree analysis

A simple fault tree analysis was also carried out as a complementary method to event tree analysis in this research, to ascertain the influence of not considering the system’s working environment on the system downtime, which causes a need for repair, maintenance and consequently spare parts. As can be observed in the fault tree chart (Figure 5), the probability of system stoppage is influenced and controlled by the operating environmental factors. This fault tree (Figure 5) is in order to show the effect of operating environment on spare parts requirements and so is not complete (no exact probability corresponding to gates are calculated). In addition, this figure because of using only OR gates, then is not considered system level.

Figure 5. Partial fault tree analysis
Conclusions

The need for spare parts (as an item of product support) is dependent on product characteristics such as reliability and maintainability, the customer’s skills and capabilities, and the environment in which the product is working.

Therefore, product support specifications should be based on the design specifications and the conditions faced by the customer. The remarkable influence of considering and/or ignoring the operating environment factors on the forecasting and estimation of the required spare parts is validated by the result of risk analysis.

Previous researches (Ghodrati and Kumar 2005a; Ghodrati and Kumar 2005b) have clearly shown that the operating environment has a significant influence on the planning of product support and spare parts requirements, through product reliability characteristics. In the present research we have performed a risk analysis of not considering the system working conditions in spare parts planning through a new and non-standard event tree and fault tree analysis. We introduced and implemented an event tree analysis in which the states of organization and managerial decisions took place in risk analysis. In other word, we used the undesired states instead of barriers in combination with events and consequent changes as a safety function in event tree analysis.

Based on the results from the event tree analysis, there is a considerable risk associated with ignoring these working environment factors, which might causes irretrievable losses. The result of assessment confirms the conclusions of those previous researches.

References


Paper V

**Product support logistics based on product design characteristics and operating environment**

*In: proceeding of 38th Annual International Logistics Conference and Exhibition (SOLE-2003), 12-14 August, Huntsville, Alabama, USA*
Product support logistics based on product design characteristics and operating environment

Behzad Ghodrati *, Uday Kumar †
Division of Operation and Maintenance Engineering
Luleå University of Technology
SE 971 85 Luleå - SWEDEN
Tel.: +46 (920) 491456 *, +46 (920) 491826 † - Fax: +46 (920) 491935
E-mail: Behzad.Ghodrati@ce.luth.se *, Uday.Kumar@ce.luth.se †
Dhananjay Kumar ‡
Nokia Research Center, Nokia House, Summit Avenue
Farnborough, Hampshire, GU14 ONG, UK
Dhananjay.Kumar@nokia.com ‡

Abstract

To improve the reliability, maintainability, and supportability (RMS) of a product, it is necessary to understand the factors influencing the product performance. This factors can be user environment, human (operator) aspects like training, and technical characteristics of the product. The environmental conditions in which the equipment is to be operated, such as temperature, humidity, dust, road conditions, maintenance facilities, maintenance crew training, operator training, etc, often have considerable influence directly on the product reliability and indirectly on the product supportability characteristics. Thus operating environment should be considered seriously while dimensioning product support and service delivery performance strategies since it will have an impact on operational and maintenance cost and service quality to provide product support plan in an optimal condition.

Spare parts are classified, as a product support items whose availability is important when planned or unplanned maintenance is to be carried out. Forecasting the required support/spare parts based on technical characteristics and operating environmental conditions of a system, is the one of the best ways for optimizing unplanned stoppages. This paper discusses about product support (required spare part) logistics based on product design characteristics and operating environment both for conventional and functional products

1. Introduction

A product is an object that is made by manufacturer/producer for consumption or for production of other products. Generally, it can be classified according to product
characteristics into two groups: Consumer products and Industrial products. Consumer products are made for consumption such as personal computer, TV, car, etc. Industrial products are those, which are being used for production goods or for producing other products either for consumer or industry. Industrial product’s customer may be a more professional customer and may set up special product criteria, specification, requirements, etc (Kumar and Kumar, 2003). Mining equipment, car assembling machine, crusher, and etc are the examples of this type of product.

On the other hand, product can be classified based on ownership as well. According to this, a product can be classified into two groups: Functional products and Conventional products. In functional products category, the user does not buys a machine/system but the function it delivers (Markeset and Kumar, 2002a). To avoid the complexities of maintenance management, many customers/users prefer to purchase only the required function and not the machines or systems so that the responsibility of maintenance and product support lies with organization delivering the required function.

The conventional product is that; the customer buys and uses the product and accepts the responsibility of maintenance, and the service provider delivers product support and services according to the requirements and agreement.

Every product, and especially the industrial product need support in their working during the lifetime. Typical forms of support include installation, maintenance, repair services, availability of spare parts, warranty schemes, and documentation to user guiding and training. In fact product (or customer) support entails all activities “to ensure that a product is available for trouble-free use to consumers over its useful life span” (Loomba, 1998).

Product support can briefly be defined as any form of assistance that manufacturers/suppliers offer to users/customers to help them gain maximum value (profit) from the manufactured products, and it is important in the recent industrial world scenario. Meanwhile, the management considers and pays more attention to product support, because it:

- Plays a key role for many products in achieving customer satisfaction.
- Can be a considerable source of revenue and profit.
• Can provide a competitive advantage in marketing.

On the other hand, it is undeniable that the environmental conditions in which the equipment is to be operated, such as temperature, humidity, dust, etc. often have considerable influence on the product reliability characteristics (Kumar and Kumar, 1992; Kumar et al., 1992). Thus operating environment should be considered seriously while dimensioning product support and service delivery performance strategies since it will have an impact on operational and maintenance cost and service quality. In general, since new products are often employed under conditions that are also new and many items are intended for uses different from typical applications, it is common in many applications to modify predicted values by application of environmental and other factors. The intent is to account for different conditions, such as temperature, humidity, dust, voltage stress, etc.

2. Product support

Product support which sometimes known as customer support and/or after-sale support, is the name given to the different forms of assistance and aid that manufacturers offer customers to help them gain maximum value (profit) from the product. This assistance can be provided in different forms and stages of product life cycle. With this concept, product support falls into two board categories, namely support to customer and support to product (Figure 1)(Markeset and Kumar, 2002a, Mathieu, 2001). Support to customer is based on client characteristics such as culture, their educational level, geographical location, social/political environment, organization’s vision, goal and strategy. This type of support addresses the general quality of interactions between a seller and a customer (Parasuraman, 1998), and includes, extra documentation, consultancy, training, and etc. Support to product, which is based on product characteristics, includes support from the initial phase of product generation to phase of product in use. These are in the form of installation, maintenance, up gradation, and improvement in the reliability and maintainability with respect to product operating environmental characteristics such as
dust, humidity, temperature, employees/human, level of competence, and etc. In other word, we can compare the support to product as hardware side, and support to customer as software side of product support.

Maintenance and spare parts support are two basic and critical issues of support to product, because often due to lack of technology and other compelling factors (like economy, environmental situations, etc), in the design phase it is impossible to design a product that will fulfill its function. So the need for support is becoming vital to enhance system effectiveness and prevent unexpected failure (Figure 2).

Figure 1. Classification of product support
Product technical characteristics such as product reliability and maintainability are more useful factors in defining and obtaining the required maintenance and especially spare parts needs. Meanwhile, it can be used in decision making between design for and design out maintenance, in design phase.

![Diagram showing typical restrictions that cause unexpected failure](image)

**Figure 2. Typical restrictions that cause unexpected failure**

In other words, while considering maintenance in design, either we can try to design out maintenance or try to optimize the design with respect to maintenance issues, and decision can be made for each alternative relating to different factors such as: application type, geographical distribution, cultural, socio-political situation, operational environment, and etc of the product/system.

Furthermore, the state of the art of technology is important in decision-making. Lack of available technology might not allow the desired elimination of maintenance, or it might be too costly.
3. Product support strategy

The manufacturers due to some factors and restrictions, mentioned earlier, attempt to optimize maintenance needs during product development & manufacturing phases, and the spare parts are becoming an important issue in this scenario. How many spare parts are required? When and how much should be ordered? And so on, are some questions that should be answered in product support management phase and discussion. Spare parts forecasting differs for repairable and non-reparable systems, and in this paper we are discussing just about non-repairable parts. Non-repairable spare parts need can be studied in two categories as:

a. For new product
b. For existing product

And each of the above categories can be further subdivided into two sub-categories as:

i. Conventional product
ii. Functional product

In the class ai (new and conventional product), the customer is owner of system, and owner normally performs operation and maintenance processes. The manufacturer attempt to optimize the reliability of system and its components based on product LCC,
competitive market, customer competence and needs. In this case, support generates
revenue for manufacturer, but cost for customer. So, manufacturer profits from selling the
system/machine and deliver support services to product. Meanwhile the manufacturer
wants maximum profit at lowest cost, then focus on optimum reliability, since by
improving reliability, not only the cost of product is increased, but also revenue from
product support will be decreased. Then the manufacturer should focus on trade-offs
between product price (market competitive), performance (customer needs) and costs.

In the category aii (new and functional products), the manufacturer is responsible for
delivering total functional performance instead of just delivering and supporting a
physical product performing a function. The physical function needs to be designed for
maximum performance effectiveness and efficiency at minimum LCC (Markeset and
Kumar, 2003). This means that the operational and maintenance costs needs to be as low
as possible.

Product weaknesses causing the need for services to support product, must be designed
out, if possible. If not, the product needs are to be designed for cost effective reliability,
and thereafter for easy maintenance and support at lowest cost.

Services and maintenance, which are directed at enhancing product exploitation, need to
be minimized by incorporating them into the training of operation and maintenance
personnel, or designed out through improved product reliability, improved
documentation, etc. The manufacturer will not make any profit in maintenance and
support. In this scenario, the manufacturer would like to optimize product reliability
based on geographical location of operating of system (distance between manufacturer
and operation place), customer competence, political and geopolitical situation of
customer, and infrastructure facility and utilization in operation place. Then the required
spare parts can be obtained and managed to procure.

Customer is responsible for anything (operation, maintenance, upgrade, etc), as
mentioned earlier for bi (existing and conventional products). Then he/she can calculate
and procures required spare parts based on product condition and its technical parameters.

In bii (existing and functional products), the manufacturer is delivering performance with
an existing product, and has less possibility to influence performance through product
design. Since the manufacturer owns the product/machine, and hence has to live with the weaknesses, there will be no profit from conventional services to support the product or customer. In other words, improved profit is coming from improved operational, maintenance and product support strategies. Reliability is influenced by how the product is used, by the operation environment, load, etc. Improving the preventive maintenance strategy and product support strategy (availability of spare parts in situ when required) also can influence system/machine availability. Consequently, training of operation, maintenance, and support personnel will be important to ensure effective and efficient function performance (Markeset and Kumar, 2003).

4. Product reliability characteristics

Reliability of a system is a function of time and the environment, under which the system is operating. Reliability of a system is the probability that it will perform or operate the required functions without failure under a given condition for an intended operating period. Lower reliability means increased unscheduled repairs and decrease availability. More stand-by units may increase the system availability but do not decrease the incidence of system failures (Kumar and Granholm, 1988).

Life Cycle Cost (LCC) analysis can be used to compare and making decision between design alternatives. If the life cycle cost of one alternative is higher compared to the other one, then the lowest life cycle cost alternative is naturally preferred (figure 4).

If the reliability of a system is too low, maintainability issues such as accessibility to spare parts that need to be maintained, serviceability and interchangeability of parts and systems, use of modular design have to be considered (Blanchard et al., 1995, Kumar, 2001).

4.1 Operating environment based reliability analysis

Our literature survey shows that most of the researches and articles on reliability considers the failure time as the only variable for estimating reliability of a system. The reliability models, which also uses only time as an influencing factor, may not be suitable
for the reliability analysis, because there are other factors that may influence the reliability characteristics of a system during its working lifetime (Kumar, 1993). For example if a system is used in different geographical or climatic conditions, then its reliability characteristics will not be equal in different condition. These variables may, for instance, include working environment (e.g. temperature, pressure, humidity, dust, or voltage stress), operating history of a machine (e.g. overhauls, effects of repair or type of maintenance) or the type of design or material, which are referred to as risk factor or covariates.

Figure 4. Comparison between high and low reliable products

For an item under consideration, with failure density function \( f(t) \) and reliability function \( R(t) \), the failure nature can be modeled by the hazard rate \( \lambda(t) \) given by the relation:

\[
\lambda(t) = \frac{f(t)}{R(t)},
\]

where \( \lambda(t) \, dt \) is approximately the conditional probability of failure in the
time interval \((t, t+dt)\) given survive to time “\(t\)”. As mentioned earlier, the hazard rate of a system, in general, is influenced not only by the time, but also by the covariates under which it operates. The hazard rate of a system is the product of baseline hazard rate \(\lambda_0(t)\), dependent on time only, and one another positive functional term, basically independent of time, which incorporates the effects of a number of covariates. The baseline hazard rate is assumed to be identical and equal to the total hazard rate when the covariates have no influence on the failure pattern. The covariates may influence the hazard rate so that the observed hazard rate is either greater (e.g. in the case of poor maintenance or incorrect spare parts) or smaller (e.g. a new improved component of a system or reliable components) compared to the baseline hazard rate. The basic concept of this model is shown in figure 5 (Kumar and Klefsjö, 1994).

So, the actual hazard rate (failure rate) with respect to exponential form of time independent function, which incorporating the effects of covariates can be defined as (Kumar and Klefsjö, 1994):

\[
\hat{\lambda}(t,z) = \lambda_0(t) \exp\{\sum_{j=1}^{n} \alpha_j z_j\} \tag{1}
\]

where \(z_j, j = 1, 2, ..., n\), are the covariates associated with the system and \(\alpha_j\).
$j = 1, 2, ..., n,$ are the unknown parameters of the model, defining the effects of each one of the $n$ covariates. The above model is commonly known as proportional hazards model (PHM) (see for details Kumar and Klefsjö, 1994)

5. Required spare parts calculation

For several types of spare parts, subassemblies and modules, replacing them, upon failure is more economical than repairing them. Bearings, gears, electronic modules, computer parts, gaskets, seals, filters, light bulbs, hoses, and valves are some of such parts, which are mostly replaced rather than repaired. In real-life situation as mentioned earlier, there are several factors except time that has influence on reliability characteristics of parts/system. To account for these covariates into calculation we can assume the term $\exp(\alpha z)$ in the hazard rate function $\lambda(t, z)$ proportionate to actual working condition, as a constant coefficient. Then:

$$R(t) = \exp(\sum_{j=1}^{n} \alpha_j z_j) \times \exp\left[-\int_{0}^{t} \lambda_0(x)dx\right] = \exp(\sum_{j=1}^{n} \alpha_j z_j) \times \exp[-\Lambda_0(t)] \quad (2)$$

where $\Lambda_0(t)$ is the cumulative baseline hazard rate.

The above exponential reliability model is generally a simple, applicable, and probably the best model while the effects of covariates are coming into calculation. If specially, the under study items are non-repairable (as mentioned before). In case of non-repairable items, the number of required spare parts can be calculated by (adapted from Billinton and Allan, 1983):

$$P(t) = \exp(-\dot{\lambda}t) \times \sum_{x=0}^{\infty} \frac{(\dot{\lambda}t)^x}{x!} \quad (3)$$

where:

$P = \text{Confidence level of spare parts’ availability [1- p (shortage)]}$
\[ \lambda = \text{Failure rate of objective part (with regarding to effect of covariates)} \]
\[ t = \text{operation time of system} \]
\[ N = \text{Total number of required spare parts in period “} t \text{"} \]

If there is \( q \) number of same part that are in use at the moment; then \( q \) is entering in equation in form of multiplying by \( \lambda q \). So the calculated \( N \) will represent the total required number of spare parts for whole system.

6. Case study

Life today would be difficult without such basics as water and electricity. In industry the same could be said with regard to hydraulic power. The hydraulic loaders are used commonly in the open pit mines for loading, hauling, and piling up of ore and gangue. The hydraulic bucket lifting system of these loaders, which includes different repairable and non-repairable parts, plays a key role in the operation of machine. The hydraulic seal, which is used in hydraulic jacks, is one of non-repairable parts that were studied for analyzing of the effect of operating environment on mean time to failure and consequently forecasting of spare part needs. The figure 6 shows a number of seals that was mounted on hydraulic lifting jack.

![Figure 6. Hydraulic jack and seals](image)
For studying of operating environment influence on failure rate of these seals, we analyzed the failure time data, which has been obtained from an Iron ore mine in Iran. We identified the important environmental factors influencing the performance of the seals, and codified them by numeric value. With respect to importance of selection and formulating of covariates in statistical inference, the covariates are formulated as follows in this case study:

1. **Roughness of jack rod:** The indicator “RNR” is used to denote the hydraulic jack rod condition regarding to rod surface finishing and smoothness, which is assigned the value \(-1\) for rough, and \(1\) for smooth surface.

2. **Type of hydraulic oil:** the indicator “OILTYPE” is used to denote the type of hydraulic oil is assigned \(1\) for the standard/manufacturer recommended type and \(-1\) for other types.

3. **Dust:** this factor is denoted by the indicator “DUST”, and is assigned \(1\) for insignificant (less and soft material such as clay…) and \(-1\) for significant (excessive and hard material like sand, quartz…) dust.

4. **Pollution (oil, gasoline, chemical water…):** this parameter appears as a corrosion that accelerated the failure, and denoted with indicator “POLUTION”, which is assigned value \(-1\) for pollution existence and \(1\) for non existence.

5. **Temperature:** the temperature of parts and operation environment influences the abrasion and failure rate of the seals. The indicator “TEMP” is used to denote this covariate, and is assigned the value \(-1\) for temperature above \(+35\) °C or below \(-15\) °C, and \(1\) for temperature between \(-15\) to \(+35\) °C.

6. **Operator’s skill:** this factor has much influence on failure rate of seals, and appears in the form of the hydraulic jack’s interior oil pressure (excessive oil pressure at the time of lifting more than allowed load). The indicator “OPSKILL” is used to denote this factor and assigned the value \(1\) for skilled and \(-1\) for inexpert operator.

For checking the IID (independent identical distribution) assumption for data (inherent assumption of the exponential reliability model, eqn no. 2), cumulative time to failures
(TTFs) Vs cumulative failure number is plotted in Figure 7. The plotted points form a straight line. It implies that there is no trend in the failure data. Then the assumption of identical distribution for the TTFs under consideration is not contradicted. On the other hand, regarding to non-reparability of part we allow concluding data as independent.

![Plot showing no trend in TTFs of hydraulic seals](image)

**Figure 7. Showing no trend in the TTFs of hydraulic seals**

Same baseline hazard rate $[\lambda_0(t)]$ for seals after failure and replacement have been assumed.

The SYSTAT software was used for estimating the correspond value of $\alpha$, and were tested for their significance on the basis of $p$-value. In the other word, $1-p$ for a covariate indicates the importance of its considerations in the model. The following table shows the estimates of $\alpha$ for the six covariates ($t$-ratio in table 1 indicates the $t$-test statistic for each covariate, uses for determining $p$-value).

The results show that the effects of three covariates (DUST, OPSKILL, OILTYPE) are significant at 10% $p$-value.

The best model for hazard rate of seal according to the result of the PHM analysis is:

$$\lambda(t,z) = \lambda_0(t) \times \exp(-0.783 \text{DUST} - 0.777 \text{OPSKILL} + 0.397 \text{OILTYPE})$$

(4)

To satisfy the proportionality assumption of the hazard rates, the plots of the logarithm of the estimated cumulative hazard rates against time should be simply shifted by an
Table 1. Estimation of covariates

<table>
<thead>
<tr>
<th>Step number 0</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
<th>Variables included:</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-2.678</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>TEMP</td>
<td>0.056</td>
<td>0.953</td>
<td></td>
</tr>
<tr>
<td>RNR</td>
<td>-1.240</td>
<td>0.215</td>
<td></td>
</tr>
<tr>
<td>OILTYPE</td>
<td>1.104</td>
<td>0.270</td>
<td></td>
</tr>
<tr>
<td>POLUTION</td>
<td>1.432</td>
<td>0.152</td>
<td></td>
</tr>
<tr>
<td>OPSKILL</td>
<td>-2.586</td>
<td>0.010</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step number 1</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
<th>Variables included:</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-2.698</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>RNR</td>
<td>-1.240</td>
<td>0.215</td>
<td></td>
</tr>
<tr>
<td>OILTYPE</td>
<td>1.205</td>
<td>0.228</td>
<td></td>
</tr>
<tr>
<td>POLUTION</td>
<td>1.531</td>
<td>0.126</td>
<td></td>
</tr>
<tr>
<td>OPSKILL</td>
<td>-2.728</td>
<td>0.006</td>
<td></td>
</tr>
</tbody>
</table>

| Variables excluded: |
| TEMP         | 0.056   | 0.955|

<table>
<thead>
<tr>
<th>Step number 2</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
<th>Variables included:</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-2.760</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>OILTYPE</td>
<td>1.212</td>
<td>0.226</td>
<td></td>
</tr>
</tbody>
</table>

| Variables excluded: |
| TEMP         | -0.480  | 0.631|
| OILTYPE      | 1.104   | 0.270|

<table>
<thead>
<tr>
<th>Step number 3</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
<th>Variables included:</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-2.820</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>OILTYPE</td>
<td>1.438</td>
<td>0.150</td>
<td></td>
</tr>
</tbody>
</table>

| Variables excluded: |
| TEMP         | -0.480  | 0.631|
| OILTYPE      | 1.104   | 0.270|

<table>
<thead>
<tr>
<th>Step number 4</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
<th>Variables included:</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-2.630</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>OPSKILL</td>
<td>-2.672</td>
<td>0.008</td>
<td></td>
</tr>
</tbody>
</table>

| Variables excluded: |
| TEMP         | -0.732  | 0.464|
| OILTYPE      | 1.705   | 0.088|
| POLUTION     | 0.195   | 0.845|
| RNR          | -1.394  | 0.163|

<table>
<thead>
<tr>
<th>Step number 5</th>
<th>t-ratio</th>
<th>&quot;p&quot;</th>
<th>Variables included:</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-2.831</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>OPSKILL</td>
<td>-2.802</td>
<td>0.005</td>
<td></td>
</tr>
</tbody>
</table>

| Variables excluded: |
| TEMP         | -0.732  | 0.464|
| OILTYPE      | 1.705   | 0.088|
| POLUTION     | 0.195   | 0.845|
| RNR          | -1.394  | 0.163|

Final Model Summary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-0.783</td>
<td>0.277</td>
<td>-2.831</td>
<td>0.005</td>
</tr>
<tr>
<td>OPSKILL</td>
<td>-0.777</td>
<td>0.277</td>
<td>-2.802</td>
<td>0.005</td>
</tr>
<tr>
<td>OILTYPE</td>
<td>0.397</td>
<td>0.238</td>
<td>1.705</td>
<td>0.088</td>
</tr>
</tbody>
</table>

95.0 % Confidence Intervals

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUST</td>
<td>-0.783</td>
<td>-1.325</td>
<td>-0.241</td>
</tr>
<tr>
<td>OPSKILL</td>
<td>-0.777</td>
<td>-1.320</td>
<td>-0.233</td>
</tr>
<tr>
<td>OILTYPE</td>
<td>0.397</td>
<td>0.069</td>
<td>0.862</td>
</tr>
</tbody>
</table>

additive constant α, the estimate of the regression parameter α of the covariate which is taken as strata (Kalbfleisch and Prentice, 1980). Therefore, the plots should be approximately parallel and separated appropriately corresponding to the different values of the regression parameter α, if the proportionality assumption is correct as is seen for example in figure 8 (Kumar and Klefsjö, 1994).
Figure 8. An example (DUST covariate) of graphical test for proportionality assumption of the hazard rates

With assuming 3000 hour as a mean time to failure for this part (seal), and applying the exponential reliability model as a common model in analyzing of system characteristics, the constant baseline hazard rate is given by

\[ \lambda_0(t) = \frac{1}{MTTF} = \frac{1}{3000} \approx 3.33e^{-4} \]  \hspace{1cm} (5)

In this case study, the loader operators are almost expert, and hydraulic oil is standard and adapted to manufacturer recommendations. Dust in this mine due to the nature of rocks, is excessive. So according to this condition:

\[ \lambda(t,z) = 3.33e^{-4} \times \exp(-0.783 \times (-1) - 0.777 \times 1 + 0.397 \times 1) = 4.98e^{-4} \]  \hspace{1cm} (6)

The predictable number of required seal in one working year (two working shift per day) with respect to 2007 hours as a mean time to failure of seals with 90% confidence of accessibility when it is required, is equal to:
In the ideal circumstance, where no covariate existing, the required number of seals is equal to:

\[
0.90 = \exp(-4.98e - 4 \times 5450 \times 2) \times \sum_{X=0}^{N} \frac{(4.98e - 4 \times 5450 \times 2)^X}{X!} \quad (7)
\]

\[ N \approx 8 \text{ (units/Y/loader)} \]

In comparison the number of required seals in both conditions, with or without considering the operating environmental factors’ affect, the significance of these factors and their role in actual life of parts is appeared. We can also conclude for optimizing of system organization with respect to real life factors, operating environmental parameters should be taken into account in process management of system/machine.

7. Inventory management requirements

Lead-time is one of important factors in the inventory management. This factor has influence on when and how many/much should order to minimize inventory cost and maximize the availability of parts when is required. On the other hand the criticality of parts is also another important factor in decision making about its quantity in warehouse. Then we can evaluate and classify the spare parts in term of lead-time (which represents indirectly geographical location of system) and criticality (Table 2).

The number of stars for each item indicates the importance of the item to consider and pay more attention for its availability when required. Since the studied loader’s model in our case study is Volvo, many dealers in different parts of world are offering this part to sale. With considering a dealer in Sweden, due to the distance between operating location (Iran) and dealer, and also the criticality of part, it can be classified in the $S_{LM}$ category.
Table 2. Classification of spare parts (adapted from Sheikh et al., 2000)

<table>
<thead>
<tr>
<th>Criticality</th>
<th>Lead-time</th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>S_LE</td>
<td>S_ML</td>
<td>S_MM</td>
<td>S_SHM</td>
</tr>
<tr>
<td>Moderate</td>
<td>S_ML</td>
<td>S_MM</td>
<td>S_MHI</td>
<td></td>
</tr>
<tr>
<td>Long</td>
<td>S_LL</td>
<td>S_SL</td>
<td>S_SLH</td>
<td></td>
</tr>
</tbody>
</table>

Another option is that the user decide to purchase from local dealers, then it can be classified in the S_SM* category.

With assumption the cost of one seal equal 500 SEK, the cost of ordering one lot equal 300 SEK, and the annual holding cost equal 15% of the part cost, the economic order quantity with respect to annual demand rate (8) is (Krajewski and Ritzman, 1999):

\[
EOQ = \sqrt{\frac{2DS}{H}} = \sqrt{\frac{2 \times 8 \times 300}{75}} \approx 8 \text{ (Units/loader)} \quad (9)
\]

This is the quantity which with that the total inventory cost will be minimum. For the “continuous review (Q) system” as inventory position controlling and management, we need to calculate the “reorder point”. The “reorder point” is equal to the sum of average demand during lead-time and safety stock. The safety stock is calculated based on the confidence level of cycle service and the number of standard deviations from mean. If average lead-time in this case is 45 days, and assume 90% confidence level of cycle service, then:

\[
\sigma_{(\text{leadtime})} = \sqrt{\frac{t}{T}} = \sqrt{\frac{5450}{2007}} \approx 1.65 \text{ (Units/loader)} \quad (10)
\]

\[
\text{Reorder point}= d \times L + \sigma_d \times \sqrt{L \Phi_{(\sigma \mid 1)}} = 0.667 \times 1.5 + 51.375 \times 1.5^{1/2} \times 1.645 \approx 2 \text{ (U. /L.)} \quad (11)
\]

It means whenever the inventory position reaches 2 units/loader (1 unit/loader, is safety stock), we should order 8 units/loader.
8. Conclusion

In the beginning, one attempts to make a product as reliable as possible, with less maintenance needs and cheap, But this approach is not feasible mainly due to technological limitations. Then the design for maintenance alternative becomes mooted, and this option demand that the reliability and maintainability characteristics with supportability issues like required spare parts of the product should be taken in account. Using the reliability techniques can optimize the forecasting and calculating for required spare parts during the product life.

The reliability analysis of the hydraulic seal failure time data shows that the environment in which the machine/system is used, plays a critical role in reliability and consequently availability characteristics of machine, and some times cause more spare parts requirements. These covariates cause the hazard rate increase. Then the formulation and selection of a covariate is very important in the sense that the statistical inferences are based on the covariates considered. However, we can optimize it with modifying some effective parameters, such as user/operator training, and use of high performance material such as low friction composite or abrasion resistant polyurethane which enhance the performance characteristics of the seal and leading to a longer seal life.

References


About the authors

**BEHZAD GHODRATI**  
Behzad Ghodrati obtained his B.Sc. and M.Sc. in Mining Engineering from Technical Faculty – Tehran University, Iran in 1989 and 1993 respectively. Then he joined to Sahand University of Technology, Tabriz, Iran in 1994 as a lecturer and was actively involved in teaching and research in the field of Mining Machinery, Mining Economy and Management. He joined the postgraduate program of Luleå University of Technology, Sweden in September 2000. At the present, he is doing his Ph.D. in the field of product support management, and the temporary title of his research is: **INTEGRATION OF PRODUCT DESIGN CHARACTERISTICS IN DIMENSIONING OF PRODUCT SUPPORT FOR EFFECTIVE SUPPLY CHAIN MANAGEMENT.**  
E-mail: Behzad.Ghodrati@ce.luth.se

**Uday Kumar, PhD**  
Professor of Mechanical Engineering (Operation and maintenance Eng.)  
Dr. Kumar obtained his B. Tech from BHU, India during the year 1979. After working for 6 years in Indian mining industries, he joined the postgraduate program of Luleå University of Technology, Sweden in 1986 and obtained a PhD degree in field of Reliability and Maintenance during 1990. He worked as a Senior Lecturer and Associate Professor and was actively involved in teaching, research and consultancy in the field of reliability and maintenance at Luleå University. In 1997, he was appointed as a Professor of Mechanical Engineering (Maintenance) at Stavanger University College, Stavanger, Norway. Since July 2000, he has taken up a position as a Professor of Mechanical Engineering at Luleå University of Technology, Luleå. He is also member of the editorial boards and reviewer for many international journals. He has published more than 80 Papers in International Journals and Conference proceedings mainly in the field of reliability and maintenance. His research interests are Product support, Equipment management, Equipment maintenance, Reliability and maintainability analysis, Life Cycle Costing, Risk analysis, System analysis, etc.  
e-mail: uday.kumar@ce.luth.se

**Dhanajay Kumar, PhD**  
Dhananjay Kumar graduated in Mechanical Engineering in 1987 from India. He worked for a utility company from 1987-1990 in India. In 1996, he obtained a PhD in Reliability Engineering from Lulea University of Technology, Sweden. He worked for a utility company from 1996-1999. Presently, he is working as a senior research engineer for Nokia since 1999 in the area of Reliability Engineering.  
E-mail: dhanajay.kumar@nokia.com