On reliability and maintenance modelling of ageing equipment in electric power systems

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Abstract

Maintenance optimisation is essential to achieve cost-efficiency, availability and reliability of supply in electric power systems. The process of maintenance optimisation requires information about the costs of preventive and corrective maintenance, as well as the costs of failures borne by both electricity suppliers and customers. To calculate expected costs, information is needed about equipment reliability characteristics and the way in which maintenance affects equipment reliability. The aim of this PhD work has been to develop equipment reliability models taking the effect of maintenance into account.

The research has focussed on the interrelated areas of condition estimation, reliability modelling and maintenance modelling, which have been investigated in a number of case studies. In the area of condition estimation two methods to quantitatively estimate the condition of disconnector contacts have been developed, which utilise results from infrared thermography inspections and contact resistance measurements. The accuracy of these methods were investigated in two case studies. Reliability models have been developed and implemented for SF6 circuit-breakers, disconnector contacts and XLPE cables in three separate case studies. These models were formulated using both empirical and physical modelling approaches. To improve confidence in such models a Bayesian statistical method incorporating information from the equipment design process was also developed. This method was illustrated in a case study of SF6 circuit-breaker operating rods. Methods for quantifying the effect of maintenance on equipment condition and reliability have been investigated in case studies on disconnector contacts and SF6 circuit-breakers. The input required by these methods are condition measurements and historical failure and maintenance data, respectively.

This research has demonstrated that the effect of maintenance on power system equipment may be quantified using available data. However, realising the full potential of these methods requires the gathering and utilisation of failure and maintenance data as well as condition measurements to be improved.
Preface

This thesis was written as part of the Ph.D. project ‘Reliability modelling of power system equipment with special reference to ageing and maintenance’ at the KTH School of Electrical Engineering, Division of Electromagnetic Engineering at the Royal Institute of Technology.

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List of papers


Contents

Abstract iii
Preface v
List of papers vii

1 Introduction 3
  1.1 Background ............................................. 3
  1.2 Definitions ............................................. 6
  1.3 Main Results ........................................... 7
  1.4 Thesis Outline .......................................... 9

2 Condition Estimation 11
  2.1 Introduction ........................................... 11
  2.2 Condition Modelling ................................... 12
  2.3 Condition Estimation Error ............................ 15
  2.4 Conclusions ............................................ 19

3 Reliability Modelling 21
  3.1 Introduction ........................................... 21
  3.2 Empirical Modelling Approach ........................ 24
  3.3 Physical Modelling Approach .......................... 33
  3.4 Conclusions ............................................ 39

4 Maintenance Modelling 41
  4.1 Introduction ........................................... 41
  4.2 Condition Improvement .................................. 41
  4.3 Reliability Improvement ................................. 43
  4.4 Conclusions ............................................ 48

5 Closure 49
  5.1 Conclusions ............................................ 49
  5.2 Future Work ............................................ 50

References 51
To my growing family
Chapter 1

Introduction

This chapter provides a general background to the thesis as well as necessary definitions, problem formulation, thesis contribution and outline.

1.1 Background

The purpose of electric power transmission and distribution systems is to transmit electric power from the generator to the consumer. Transmission systems normally transfer the bulk of the power by high-voltage links between main load centres, whereas the purpose of distribution systems is to distribute power to the consumers through lower voltage networks. Transmission and distribution systems are made up of various types of equipment; overhead lines and underground cables connect substations that comprise several equipment types, such as circuit-breakers, disconnectors and transformers. In order to ensure system reliability the equipment needs to be maintained. The aim of equipment maintenance is to extend the mean time to failure for the equipment and, by extension, for the power system as a whole. In general, these maintenance activities may be divided into Corrective Maintenance (CM) and Preventive Maintenance (PM).

Historically, PM of electric power system equipment has been carried out with fixed time intervals, so called time-based maintenance. However, the electric power industry has during the 1990s undergone a process of re-regulation, which resulted in a shift in the utilities' view of maintenance. PM has gradually become an instrument of competition, focusing on cost-effectiveness. Consequently, in order to reduce costs many companies have started to shift maintenance strategies from time-based preventing strategies to more sophisticated strategies such as Reliability Centred Maintenance (RCM). At the KTH School of Electrical Engineering at KTH a method called Reliability Centred Asset Management (RCAM) has been developed. RCAM is a method which takes the idea of RCM one step further by
deducing cost-efficient maintenance plans in which the benefit of equipment maintenance is related to the system reliability and total cost [1].

In general, the purpose of quantitatively modelling the effect of maintenance is to assist in decision making by using known facts more effectively, by increasing the proportion of factual knowledge, and by reducing the reliance on subjective judgment [2]. In RCAM this is achieved by introducing equipment reliability models, which quantify the effect of maintenance, into the maintenance optimisation procedure.

The work carried out within this Ph.D. project is part of the Reliability Centred Asset Management programme at the Division of Electromagnetic Engineering at the KTH School of Electrical Engineering [3].

1.1.1 Condition Estimation

Condition estimation is commonly applied to many different types of equipment in power systems and is used to estimate the current condition of the equipment. The estimations may be based on measurements of some physical quantity related to one or more failure mechanisms or on the results from visual inspections. In this thesis thermography is investigated as an example of a method to assess equipment condition. Thermography measures and images the infrared radiation from an object in some specified spectral band and is routinely carried out in substations in most power systems [4]. There are several case studies [5],[6],[7] and guidelines [4],[8],[9] on the use of thermography on electric equipment. A few studies have been carried out with the aim to improve the use of thermography by better interpretation of the images [10] and improving the ability to save and compare results [11]. These guidelines and studies, with the exception of [8], focus on the benefits of thermography, making only general assumptions about accuracy.

Other methods of estimating equipment condition include e.g., optical inspections, resistance measurements, ultrasonic testing, vibration analysis, partial discharge (PD) measurements, dielectric loss measurements ($\tan \delta$) and oil analysis [4],[12].

1.1.2 Reliability Modelling

Reliability modelling methods for power system equipment can generally be divided into empirical and physical approaches.

Previous empirical models of equipment reliability include a detailed study on distribution system capacitor reliability using failure data [13]. In [14] two different methods were proposed to model the reliability of power system equipment using failure data. The proposed methods were applied to reliability modelling of reactors. Results from case studies on reliability models for medium voltage cable joints
and bushings using failure data were presented in [15]. In a study of on-load tap changers two methods were used to make optimistic and pessimistic estimations of failure rates [16]. Both methods took the effect of censored lifetime observations into account. The above case studies have all been applied to equipment that are natural to consider as non-repairable, i.e. they are replaced when a failure occurs.

Physical reliability models include a model for XLPE cables where the annual failure rate was based on accelerated water tree ageing [17]. In [18] and [19] the insulation degradation of XLPE cables was investigated. Other publications on the ageing of cable insulation include a literature study on ageing phenomena and modelling of electric insulation materials [20]. Ageing models for cable insulation based on PD detection were introduced in [21]. In [22] the main factors contributing to the ageing process were discussed.

Few case studies have been focussed on modelling equipment reliability when the equipment may be considered repairable. [23] proposed to model the reliability of overhead lines as repairable systems. Circuit-breakers are another example of equipment that are typically not replaced the first time they fail and are often viewed as repairable systems comprising several different parts [24]. Reliability models for circuit-breakers have been applied in the form of Markov models [25]. No white box reliability model implemented for circuit-breakers has been found in the literature.

1.1.3 Maintenance Modelling

Few publications in the international literature treat the subject of quantifying the effect of maintenance on equipment reliability. [26] introduced a Markov model for probabilistic evaluation of the effect of maintenance equipment on reliability. In [27] the Markov model was applied to air-blast circuit breakers. Similar models were applied in [28] where a model to describe the impact of PM on circuit-breakers and protection systems for substation reliability was proposed. [29] presented results from a Markov model to quantify the effect of transformer maintenance. These models are all black box models and does link the effect of a specific maintenance task to the equipment reliability.

A white box modelling approach was proposed in [1] and [29] where an application study on the effect of preventive maintenance for XLPE cables was presented. The studied maintenance action involved the injection of silicon into the insulation of the cable to prevent water tree growth. In [30] a method for evaluating the effect of wood pole replacement was proposed. The method simulated the change in line strength due to pole strength decay and pole replacement as a function of time, taking into account statistical uncertainties in pole strength and loads.
1.1.4 Aim

The aim of this Ph.D. project is to develop methods for equipment reliability modelling taking into account the effect of ageing and maintenance. To achieve this overall aim this work has essentially focussed on condition estimation, reliability modelling and maintenance modelling.

1.1.5 Problem Formulation

By being able to accurately estimate equipment condition, model its reliability and the effect of maintenance on reliability, the process of maintenance planning may be shifted away from the reliance of subjective judgement and increasing the proportion of factual knowledge in the decision making process. This is necessary in order to produce cost-effective maintenance strategies for electric power systems and is therefore an important step in the RCAM process.

The problem of establishing how maintenance affects reliability is complex since each type of apparatus has its particular characteristics and failure modes. Continuous equipment development makes comparison between equipment with different years of manufacturing difficult. This problem is aggravated by the fact that many different makes and models of equipment are installed in the networks hence limiting equipment population sizes. High reliability equipment and failure data with low levels of detail and varying quality coupled with high costs of life tests make the use of traditional methods of reliability modelling challenging for power system equipment [31].

1.2 Definitions

The definitions used in this thesis are adopted from [32], [33], [34] and [35].

- **System**: a collection of two or more parts, interconnected to perform one or more functions.
- **Equipment**: a functional unit, comprising one or more sub-components, with a well defined function in a system.
- **Sub-component**: a sub-system comprising two or more parts that are all replaced at sub-component replacement.
- **Part**: an item which is not subject to disassembly and is therefore discarded the first time it fails.
- **Non-repairable system**: a system which is discarded after the first time that it ceases to perform satisfactorily.
1.3. MAIN RESULTS

- **Repairable system**: a system which, after failing to perform at least one of its required functions, can be restored to performing all of its required functions by any method other than replacement of the entire system.

- **Model**: a simplified mathematical description of a system, equipment, sub-component, part *etc.*, to assist calculations and predictions.

- **Condition**: a quantitative measure of a physical property resisting an applied stress.

- **Reliability**: The ability of an item to perform a required function, under given circumstances and operational conditions and for a stated period of time.

- **Maintenance**: the combination of all technical, administrative and managerial actions during the life cycle of a piece of equipment intended to retain it in, or restore it to, a state in which it can perform the required function.

- **Preventive maintenance**: maintenance carried out with the intention to reduce the probability of failure or degradation of a part.

- **Corrective maintenance**: maintenance carried out after a failure has been recognised with the intention to restore the part to a state in which it can perform its required function.

- **Black box reliability model**: a modelling approach in which an equipment failure is not linked to sub-component or part failures.

- **White box reliability model**: a modelling approach in which an equipment failure is modelled in terms of failures of sub-components or parts.

1.2.1 Power System Hierarchy

The electric power system is a typical example of a multi-level structure where there are several modules at each level. In Figure 1.1 the power system structure is shown as a four level structure. Note that the diagram in Figure 1.1 is not a physical representation but rather a logical relationship between components that indicates the link between system performance and equipment performance. This hierarchy will be used throughout this thesis.

1.3 Main Results

The work presented in this thesis is focused on practical methods for modelling the reliability of electric power system equipment, including the effect of maintenance. The presented methods use existing data to the greatest possible extent.

The main contributions in this thesis are summarised below.
• Presentation of the results from a study on high voltage circuit breaker failures in the Swedish and Finnish transmission systems, illustrating the possibility of modelling the reliability of power system equipment using available failure and maintenance data.

• Development of a method to model the effect of maintenance to power system equipment using real data by modelling the equipment as a series system comprising only the most critical parts.

• Implementation of a method to model the reliability of power system equipment parts by making use of information from the design process as well as failure statistics and maintenance records. By employing Bayesian statistical methods, a reliability model based on information from the design process and right-censored failure data can be developed before any actual failures have occurred.

• Development of a quantitative method to establish the contact condition of disconnectors using thermography. This includes the investigation and quantification of error sources when using thermography in the field, as well as the proposed Monte Carlo simulation method used to estimate the accuracy of thermography measurements.

• Development of a method for estimating the contact hazard rate for aged disconnector contacts using thermography. The proposed method may be used as a base when making maintenance decisions for disconnectors that cannot be measured by thermography due to low load.

• Presentation of a quantitative model on the effect of maintenance to disconnector contact condition.
• Demonstration of an example of a reliability model for aged XLPE cables based on knowledge of the ageing process and system characteristics.

1.3.1 Author’s Contributions

In Paper I Prof. Roland Eriksson formulated the model. Assoc. Prof. Lina Bertling collected and analysed the cable failure data and the author performed the calculations. In Paper II the author formulated the implementation for the Bayesian method together with Assoc. Prof. Lina Bertling. The author performed all data analysis and calculations. In Paper III the disconnector contact thermal model was developed by author together with Prof. Roland Eriksson. The thermography measurements were carried out by Roger Eriksson at Vattenfall Service and Göran Ohlsson at STRI together with the author. The author performed all data analysis and calculations. The Monte Carlo simulation algorithm was developed by the author together with Prof. Roland Eriksson. In Paper IV the author developed the method for estimating disconnector contact hazard rates. The author performed all calculations. In Paper V the author is responsible for developing the model describing the effect of maintenance on equipment reliability. The author also collected and analysed the failure data. In Paper VI the author is responsible for developing the model describing the effect of maintenance on equipment reliability. The author collected and analysed the failure data. The author is also responsible for the development of the maintenance task prioritisation algorithms. In Paper VII the measurements were carried out by Jesper Carlsson at STRI together with Roger Eriksson from Vattenfall Service and the author. The author is responsible for data analysis and formulating the regression models as well as improving the Monte Carlo simulations.

1.4 Thesis Outline

This thesis constitutes a summary of the results found in the appended papers, providing a general background and introducing relevant theory.

In Chapter 2 different methods of estimating equipment condition is introduced including results from two case studies. Chapter 3 presents different approaches and methods of modelling the reliability of power system equipment along with results from four case studies. Chapter 4 presents approaches and methods for modelling the effect of maintenance on power system equipment condition and reliability. It also presents results from two case studies. Chapter 5 presents a summary of the presented work and the conclusions drawn as well as proposing some ideas regarding future work.
Chapter 2

Condition Estimation

This chapter provides a brief background and introduction to methods useful for modelling part condition based on condition measurements. Two modelling approaches are illustrated in two case studies.

2.1 Introduction

The purpose of condition measurements of power system equipment is to estimate its current condition. The ultimate use of condition estimation is to determine the equipments' need for maintenance leading to Condition Based Maintenance (CBM). The most common CBM method is the trending of measurements, setting limits on the measurements and then basing any maintenance decision on comparing a specified measurement with its limit [36]. Note that condition measuring is different from condition monitoring in the sense that it is carried out with regular intervals rather than being applied continuously [37]. CBM in electric power systems is applied in order to estimate the need for PM actions and thus reducing the total maintenance costs by carrying the correct PM task at the right time.

Figure 2.1 illustrates the process for modelling the condition of a part. The process constitutes the combination of a measurement and a model to estimate the part condition. This condition estimate may then be passed on and used in a reliability model to predict future behaviour of the part.

It is often practically impossible to directly measure the physical quantity describing a parts' condition. In such situations it may be more practical to use measurements of other quantities with some known relationship to the sought quantity. The following sections elaborate on different approaches to estimate part condition.
2.2 Condition Modelling

If the relationship between the part condition and the measurement is not known or is too complex to model physically one option is to use empirical models. Empirical models are based on observations only and do not include any explicit information of part failure mechanisms or operating conditions. Models like these include statistical models such as linear regression models:

$$Y = X\beta + \varepsilon$$  \hspace{1cm} (2.1)

where $X$ is a matrix of the explanatory variables, i.e. the measured quantities, $Y$ is a vector of the response variables i.e., the condition and $\beta$ is a vector of the regression parameters. The error term vector, $\varepsilon$, represents all unpredicted or unexplained variations in the response and is assumed to be independent of $X$. These errors are here assumed to be random with a normal distribution with zero mean and constant variance $\sigma^2$. In case there is only one explanatory variable and two parameters, the expression (2.1) may be reduced to an equivalent formulation that shows the simple linear regression as a model of conditional expectation:

$$E(y|x) = \alpha + \beta x$$  \hspace{1cm} (2.2)

For a fitted model the parameters $\alpha$ and $\beta$ correspond to the intercept and slope of the fitted line respectively. In order to determine how likely an estimate is, confidence intervals or prediction intervals are used. Confidence intervals estimate a quantity that cannot be observed for the population (e.g. its mean), whereas the prediction interval predicts the distribution of individual points.

Case Study: Estimating Disconnector Contact Condition Using Resistance Measurements

As described in Paper III thermography for estimating disconnector condition is only useful if the disconnector contacts are subjected to a sufficiently high load at the time of measuring. Since this relationship of temperature rise and load exists it is important to be able to compare the condition of contacts measured at different
loads. This may be done by calculating the temperature rise at nominal load [9]:

\[ \Delta T_n = \Delta T_{\text{meas}} \left( \frac{I_n}{I_{\text{load}}} \right)^a \]  \hspace{1cm} (2.3)

where \( I_n \) [A] is the disconnectors rated load current and \( I_{\text{load}} \) [A] is the load current at the time of measuring, \( a \) is an object-specific constant and \( \Delta T_{\text{meas}} \) [K] is the measured temperature rise. There are many disconnectors that are normally lightly loaded or normally open. In these cases thermography is not an alternative and contact resistance measurements may be an option. A drawback of contact resistance measurements is that the equipment has to be taken offline.

*Paper VII* summarises the results from an investigation into the accuracy of condition estimation of electric contacts via thermography measurements in the field. In *Paper VII* two aged horizontal centre break disconnecter poles were loaded up to their nominal load in stages and the contact temperature rises were measured using thermocouples attached to the contacts. Before and after the temperature rise tests the contact resistance was measured using 100A DC. The measurements were carried out in two sets. After the first set of measurements the contacts were subjected to maintenance and the measurements were repeated. The investigated disconnecter type comprises two rotating and one main contact per phase rendering 12 measurements.

The investigation in *Paper VII* resulted in a linear regression model for estimating the contact condition using resistance measurements. The model was based both on measurements of contact resistance and on temperature rise measurements at nominal load. The model is a linear regression model (see equation 2.2) estimating the expected temperature given the resistance measurements:

\[ E(\Delta T_n|R) = 17.3 + 0.4R \]  \hspace{1cm} (2.4)

where \( R \) [\( \mu \Omega \)] is the measured contact resistance. Figure 2.2 shows the model including 95\% prediction intervals as well as the resistance measurements. In the figure a B indicates that the measurement was made before maintenance and an A indicates that the measurement was made after maintenance.

The accuracy of the model in (2.4) is compared to Monte Carlo simulations of the accuracy of thermography based condition estimations in Figure 2.3 presented in the following case study.
Figure 2.2. Linear regression model describing the relationship between contact resistance and temperature rise at nominal load, including 95% prediction intervals.
2.3 Condition Estimation Error

When estimating equipment condition from single measurements it is important to also estimate the errors present. In general, the total error for condition estimation, \( \varepsilon_{\text{condition}} \), is the sum of the measurement error, \( \varepsilon_{\text{measure}} \), and the model error, \( \varepsilon_{\text{model}} \), such that:

\[
\varepsilon_{\text{condition}} = \varepsilon_{\text{measure}} + \varepsilon_{\text{model}}
\]  

(2.5)

Case Study: Simulating Thermography Measurement Accuracy

*Paper III* presents a method to estimate the thermography measurement error using Monte Carlo simulation, when estimating the condition of disconnector contacts. In a recent study, reported in *Paper VII*, this method was subsequently improved and the error distributions were estimated with greater accuracy. The report summarises the results from an investigation of condition assessment accuracy for disconnector contacts via thermography measurements in the field. In *Paper VII* two aged horizontal centre break disconnectors were mounted outdoors and loaded up to their nominal load in stages. The contact temperature rises were measured by infrared thermography. Using thermocouples attached to the contacts the accuracy of the thermography in field-like conditions could be estimated.

In general, the error, \( \varepsilon_{\Delta T} \), when estimating a contact's temperature rise at nominal load by using equation (2.3) is:

\[
\varepsilon_{\Delta T} = \varepsilon_{\text{thermo}} + \varepsilon_{\text{calc}}
\]  

(2.6)

where \( \varepsilon_{\text{calc}} \) is the error introduced due to the uncertain value of the exponent \( a \) in equation (2.3) and \( \varepsilon_{\text{thermo}} \) is the thermography measurement error. In *Paper VII* the thermography measurement error is defined as the deviation of the thermography rise measurement from the reference temperature rise as measured by the thermocouples. The thermography measurement error is defined as:

\[
\varepsilon_{\text{thermo}} = \varepsilon_{\varepsilon} + \varepsilon_{\text{rand}} + \varepsilon_{\text{hid}}
\]  

(2.7)

where \( \varepsilon_{\varepsilon} \) is the influence of the uncertain object emissivity and \( \varepsilon_{\text{rand}} \) is due to random variations (e.g., variations in the object temperature, atmosphere radiation and reflected radiation). The fact that the contacts are sometimes hidden under protective caps and may not be visible to the naked eye (and hence not accessible for direct thermography) gives rise to the error \( \varepsilon_{\text{hid}} \). Statistical distributions for the errors \( \varepsilon_{\text{thermo}} \) and \( \varepsilon_{\text{calc}} \) were estimated and reported in *Paper VII*.

The Monte Carlo method proposed in *Paper VII* simulates the confidence bounds for estimated temperature rise at nominal load, \( \Delta T_n \), given a measurement made at lower load. The Monte Carlo simulation was carried out by applying the following steps \( N \) times for each measurement:

\[
\varepsilon_{\Delta T} = \varepsilon_{\text{thermo}} + \varepsilon_{\text{calc}}
\]  

(2.6)
1. Obtain a temperature rise measurement $\Delta T_{\text{meas}}$ made at load $I_{\text{load}}$.

2. Sample a thermography measurement error from the distribution estimated in Paper VII and add error to $\Delta T_{\text{meas}}$.

3. Sample an exponent $a$ from the distribution estimated in Paper VII.

4. Calculate $\Delta T_n$ using equation (2.3).

5. GOTO step 2 (repeat $N$ times).

6. Use the 95% percentiles for the resulting distribution of $\Delta T_n$ as confidence bounds.

7. GOTO step 1 (for every measurement $\Delta T_{\text{meas}}$).

Figure 2.3 shows some results from Paper VII. The figure shows (from the left) simulated confidence bounds for $\Delta T_n$ for thermography measurements made at $I = 1000\,\text{A}$, $I = 2000\,\text{A}$ and $I = I_n = 3150\,\text{A}$, respectively. Furthermore, $\Delta T_n$ was also estimated using resistance measurements and the linear regression model presented in equation (2.4). Finally, (farthest to the right) the figure shows the reference temperature rise as measured by the thermocouples at $I = I_n = 3150\,\text{A}$.

In Paper III the probability of finding a disconnector contact to be failed or degraded in spite of it being new, was simulated using Monte Carlo simulations. Figure 2.4 shows the simulation results of the probability of maintaining a healthy contact given the steady state load at the time of measuring. In the figure the white bars indicates the probability of finding the contact to be degraded and the black bars indicates the probability of discovering a failure, given that the contact is healthy. In the figure $\Delta T_n$ is the measured temperature rise converted using equation (2.3), $\Delta T_{\text{max}}$ is the maximum allowed contact temperature rise and $\Delta T_{\text{true}}$ is the true contact temperature rise at nominal load.
2.3. CONDITION ESTIMATION ERROR

![Diagram](image)

**Figure 2.3.** Estimations of $\Delta T_n$ using both thermography and contact resistance measurements, including 95% confidence intervals.
Figure 2.4. Monte Carlo simulated probability of maintaining a healthy connector contact (white bars = contact found degraded, black bars = contact found to be failed).
2.4 Conclusions

The results from the case studies presented in this chapter demonstrates that it is possible to estimate part condition based on condition measurements provided that it is practically feasible to measure the physical quantity. Moreover, by modelling the accuracy of condition measurements it is possible to calculate the probability of making an erroneous maintenance decision based on such a measurement.
Chapter 3

Reliability Modelling

This chapter presents a theoretical background to the reliability modelling techniques used in the appended papers. It also presents results from four case studies carried out within the Ph.D. project.

3.1 Introduction

The purpose of modelling the reliability of aged power system components is to predict future failure behaviour. The reasons for modelling reliability of aged power system equipment are different depending on the application. For the electric utility the reason is often maintenance planning. However, for the manufacturer of power system equipment it may be to comply with business standards or for warranty reasons.

3.1.1 Reliability Measures

It is assumed that the time at which a part fails is a random variable and across a population of identical parts, the dispersion in the time to failure can be represented by a probability distribution function (PDF). The time to failure is the time elapsing from when the part is put into operation until it fails for the first time, i.e. the time to failure is equal to the part lifetime\(^1\). Part lifetimes are assumed to be statistically independent and are represented by the random variable \(X\), where \(x\) is an observation of \(X\) with the starting point set to \(x = 0\). Furthermore, any maintenance action is assumed to take negligible time.

There are four primary measures of reliability. These measures are equivalent and

\(^1\)Note that the measure of lifetime, as used in this thesis may differ from calendar time (e.g. number of operations or cycles).
knowledge of any of the four measures implies knowledge of all of them by known relationships [38],[39],[35].

**Probability Density Function**

The PDF, \( f(x) \), indicates where in time a failure is more or less likely to occur, thus giving:

\[
\int_0^\infty f(x) \, dx = 1
\]  

(3.1)

The probability that the lifetime \( X \) is between the times of special interest, \( a \) and \( b \) (where \( 0 < a < b \)), is then defined as:

\[
P(a \leq X \leq b) = \int_a^b f(x) \, dx
\]  

(3.2)

**Cumulative Distribution Function**

The cumulative distribution function (CDF), is defined as:

\[
F(x) = P(X \leq x) = \int_0^x f(u) \, du \text{, for } x > 0
\]  

(3.3)

The CDF is the probability that the part fails within the interval \((0, x]\).

**Reliability Function**

The reliability function, or survivor function as it is sometimes called, is defined as:

\[
R(x) = P(X > x) = \int_x^\infty f(u) \, du \text{, for } x > 0
\]  

(3.4)

This is the probability that the part does not fail in the interval \((0, x]\).

**Hazard Function**

The hazard function, or hazard rate, is a measure of the probability that a part, still working at age \( x \), is about to fail.

The hazard function is the limit of the probability that a part fails (for the first and only time) in a small interval, given survival of the beginning of the interval. The hazard function for a part can be written:

\[
h(x) = \lim_{\Delta x \to 0} \frac{P(x < X \leq x + \Delta x | x \leq X)}{\Delta x}
\]  

\[
= \frac{F(x + \Delta x) - F(x)}{\Delta x} \cdot \frac{1}{R(x)} = \frac{f(x)}{R(x)}
\]  

(3.5)
where $x > 0$ is the age of a part measured in appropriate units. The algebraic form of equation (3.5) indicates that the hazard function is the rate at which a surviving part fails [38]. The equation also implies that when $\Delta x$ is small:

$$P(x < X \leq x + \Delta x | X > x) = h(x) \cdot \Delta x$$

(3.6)

For a series system comprising $n$ parts, assuming that only one failure mode is present at anyone part at any time, the hazard function for the time to failure of the system at calendar time $t$ is:

$$h(t) = \sum_{i=1}^{n} h_i(x)$$

(3.7)

where $h_i(x_i)$ is the hazard rate of part $i$, $1 \leq i \leq n$, in the series system. Since the system can fail due to $n$ causes, the system fails at time $T$ given by:

$$T = \min_{i} \{X_1, X_2, ..., X_i\}$$

(3.8)

This model is often referred to as the Competing Failure Mode model.

Other Measures: Failure Intensity

When modelling the reliability of repairable systems, which is often the case for power system equipment, other measures of reliability are necessary such as the failure intensity.

Let $N(t)$ be the number of failures on the equipment in the interval $(0, t)$, where $t$ is measured in calendar time. The intensity function for the counting process $N(t)$ is given by:

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(N[t + \Delta t] - N(t) = 1)}{\Delta t}$$

(3.9)

The failure intensity has the simple interpretation that $\lambda(t) \cdot \Delta t$ is approximately the probability that a failure, not necessarily the first, occurs in $(t, t + \Delta t]$. The intensity $\lambda(t)$ is the statistical mean of the intensity process at time $t$ and applies primarily to reliability prediction during the equipment design phase. During that phase no information is available on failures or maintenance [40]. To be able to model the behaviour of a specific piece of equipment whilst in service, the model must include the equipment history. Such a model is defined by the conditional intensity process $\lambda(t|H^t)$ of the counting process $N(t)$. Let $H^t$ be the complete history of the equipment up to, but not including, time $t$. This history incorporates all available information on events not fixed by time $t$, such as maintenance activity and failures of the equipment up to time $t$. This information will consist of at least two elements: the time elapsed since the last PM or Corrective Maintenance (CM) for all parts and the part hazard [40]. Thus, given that the equipment has a specific history $H_t$ at time $t = 0$ (i.e. the moment just before but not including
the probability of at least one failure occurring in \([t, t + \Delta t]\) is approximately \(\lambda(t|H^t) \cdot \Delta t\). The conditional failure intensity process is defined as:

\[
\lambda(t|H^t) = \lim_{\Delta t \to 0} \frac{P(N[(t - 0) + \Delta t] - N(t - 0) = 1|H^t)}{\Delta t}
\]  

(3.10)

The conditional intensity process is completely determined by the different part ages, \(x_i\), and the parts' inherent hazard rates through the relation [40]:

\[
\lambda(t|H^t) = \sum_{i=1}^{n} h_i(x_i)
\]  

(3.11)

where \(1 \leq i \leq n\). The conditional intensity process for a part may be interpreted as a sequence of truncated hazard functions updated by each CM [40], which is essentially the equipment hazard function from failure \(N(t)\) to failure \(N(t) + 1\) [41].

### 3.1.2 Censored Data

Censoring is common in reliability data analysis and occurs when it is not possible to observe the time of failure for a part. Three ways in which reliability data can be censored are presented below [39], [42]:

1. Right-censored data; part \(i\) has not failed at time \(x_i\), giving \(X > x_i\). Such data is very often the result of inspections in which no fault has been discovered. This information can nevertheless be very important for establishing the reliability of the equipment population in question.

2. Left-censored data; part \(i\) has failed before time \(x_i\), giving \(X \leq x_i\). This situation may occur when a component breaks down before its first inspection.

3. Interval-censored data; part \(i\) has failed between times \(x_{i-1}\) and \(x_i\), giving \(x_{i-1} < X \leq x_i\). This type of censoring occurs when a unit is found to have failed between two inspections.

The censoring options listed above are denoted Type I censoring. Type I censoring refers to censoring that occurs as a function of time.

### 3.2 Empirical Modelling Approach

In the empirical approach to reliability modelling, all information on stress and condition for a part comes from the PDF, \(f(x)\), on the time to failure, \(X\). No explicit modelling of the stress and conditions is carried out and no detailed knowledge about equipment failure mechanisms and operating conditions is required [39].

There are a number of methods that may be used to model reliability and each
method carries advantages and disadvantages. The most straightforward and perhaps the most common way to model equipment reliability is to fit failure data to a known statistical distribution. This method is simple to use but requires access to a considerable amount of failure data. Furthermore, it is assumed that the equipment is a non-repairable system. However, this method may be applied to a repairable system by assuming that the system is in a conceptual state of As Bad As Old (ABAO) after every failure has been repaired [43].

3.2.1 Distribution Parameter Estimation

The most widely used parametric technique in reliability modelling is the maximum likelihood method (MLM) [38]. This technique selects the parameter estimates to be those values that are most likely to have produced the observed data.

For \( n \) observations \( x_1, x_2, \ldots, x_n \) of the discrete random variable \( X \) the likelihood is proportional to the product of the probabilities of the individual values:

\[
\prod_{i=1}^{n} P(X = x_i)
\]

The likelihood of a single observation \( x \) is the probability that that observation actually occurred i.e. \( P(X = x) \). If, in a reliability analysis, all times of failure are known, the definition of the likelihood function is [44]:

\[
L(x, \theta) = \prod_{i=1}^{n} f(x_i | \theta)
\]  

(3.12)

where \( x = x_1, x_2, \ldots, x_n \) are independent observations of the random variable \( X \), given that the PDF \( f(x_i | \theta) \) is known, \( \theta = \theta_1, \theta_2, \ldots, \theta_m \) where \( \theta \) represents an unknown parameter. In this case the estimated distribution parameters are those maximising (3.12).

However, if the component times of failure are not known the likelihood contributions have to be established separately for each censoring type [42]. For right censored failure times the contribution to the total likelihood is:

\[
L_i(\theta) = \int_{x_i}^{\infty} f(x)dx = F(\infty) - F(x_i) = 1 - F(x_i)
\]  

(3.13)

when the failure time for the \( i^{th} \) failure is somewhere in the interval \( (x_i, \infty) \). In the case of left-censored data the likelihood contribution is:

\[
L_i(\theta) = \int_0^{x_i} f(x)dx = F(x_i) - F(0) = F(x_i)
\]  

(3.14)
If a component’s failure time is somewhere between \( x_{i-1} \) and \( x_i \), i.e. interval-censored, the likelihood contribution is:

\[
L_i(\theta) = \int_{x_{i-1}}^{x_i} f(x) \, dx = F(x_i) - F(x_{i-1})
\]

(3.15)

Following (3.12) the total likelihood can be written as the joint probability of the data, assuming \( n \) independent observations:

\[
L(\theta) = \prod_{i=1}^{n} L_i(\theta)
\]

\[
= \prod_{i=1}^{m+1} [F(x_i)]^{l_i} [F(x_{i-1}) - F(x_{i+1})]^{d_i} [1 - F(x_i)]^{r_i} [f(x_i)]^{b_i}
\]

(3.16)

where \( l_i, d_i, r_i, b_i \) is the number of left-censored, interval-censored, right-censored and exact observations at time \( x_i \) respectively. Consequently, \( n = \sum_{j=1}^{m+1} (b_j + l_j + d_j + r_j) \).

**Case Study: Estimating Distribution Parameters For SF\(_6\) Circuit-Breaker Parts**

A study presented in Paper V estimated the parameters for the statistical distributions of the time to failure for the most critical parts in a specific type of SF\(_6\) circuit-breaker (CB).

In this study failure data and maintenance records were collected for all SF\(_6\) and minimum oil CBs from the Finnish transmission system during the period 1994-2006, and from the Swedish transmission system during the period 1999-2006. The voltage levels in the Finnish transmission system are 110, 220 and 400kV, and 220 and 400kV in the Swedish transmission system. The total population of SF\(_6\) and minimum oil CBs is 1546 and the total operating history is 16384 years. The CB population data, failure data and maintenance records derive from the asset management and SCADA systems of the Swedish and Finnish transmission system operators (TSO).

A detailed analysis of the failed parts and the operating frequencies of the CBs led the study to focus on one specific type of SF\(_6\) CB from a specific Original Equipment Manufacturer (OEM). This type of CB had known problems with the operating mechanism for CBs with high operating frequencies and a new more reliable design of operating mechanism had been released. The analysis in Paper V focusses only on the older operating mechanism design as well as CBs with an operating mechanism \( \geq 50 \) operations/year (where an operation is defined as an open-close cycle).
3.2. EMPIRICAL MODELLING APPROACH

<table>
<thead>
<tr>
<th>Table 3.1. Estimated Weibull parameters for the critical CB parts</th>
</tr>
</thead>
<tbody>
<tr>
<td>CB part</td>
</tr>
<tr>
<td>Close-operation lock</td>
</tr>
<tr>
<td>Open-operation lock</td>
</tr>
<tr>
<td>Remaining</td>
</tr>
</tbody>
</table>

Following previous experience [43] it was assumed that the times to failure were Weibull distributed. This assumption was tested in Paper V. Consequently, the PDF for the time to failure for part $i$ is [45]:

$$f_i(x_i) = \frac{\beta_i}{\eta_i} \left( \frac{x_i}{\eta_i} \right)^{\beta_i-1} \exp \left[ -\left( \frac{x_i}{\eta_i} \right)^{\beta_i} \right], \text{ for } x_i \geq 0$$ (3.17)

where $\beta > 0$ and $\eta > 0$ are the Weibull shape and scale parameters and $x_i$ is the age of part $i$ measured in the number of accumulated operations. The part hazard rate is then [45]:

$$h_i(x_i) = \frac{\beta_i}{\eta_i} \left( \frac{x_i}{\eta_i} \right)^{\beta_i-1}, \text{ for } x_i \geq 0$$ (3.18)

The Weibull parameters were estimated by the MLM using the Statistics Toolbox in Matlab [46]. The result from this estimation is found in Table 3.1, where the scale parameter is in the number of accumulated operations. Figure 3.1 shows the part hazard rates, calculated using (3.18), for a shunt reactor CB of the investigated make and model in the Swedish transmission system with an operating frequency of 346 operations/year.
Figure 3.1. Reliability model for the critical parts of a circuit-breaker with an operating frequency of 346 operations/year.
3.2. EMPIRICAL MODELLING APPROACH

3.2.2 Bayesian Reliability Modelling

A common problem encountered when modelling the reliability of power system components is the lack of failure data. This problem can be alleviated by the use of Bayesian statistical methods. Bayesian methods allow the combination of any previous knowledge about the process with sample data, such as failure statistics or maintenance records, and is illustrated in Figure 3.2. In Figure 3.2, let \( x = x_1, x_2, \ldots, x_n \) be observations of \( X \) and denote this data set \( DATA \). The prior information may come from experiences from the process of designing the equipment. Such experience often includes the results from different types of destructive tests.

Bayes' Theorem

Bayes' theorem was first formulated by reverend Thomas Bayes and was presented posthumously in 1763 [47]. Bayes’ theorem provides a mechanism for combining prior information with sample data to make inferences on model parameters [39], [42].

Let \( B_1, B_2, \ldots B_n \) be mutually exclusive and exhaustive events contained in a sample space \( S \), such that:

\[
P\left( \bigcup_{i=1}^{n} B_i \right) = 1
\]

\[
B_i \cap B_j = \emptyset \text{ for } i \neq j
\]
30  CHAPTER 3. RELIABILITY MODELLING

\[ P(B_i) > 0 \text{ for each } i \]

and let \( A \) be an event such that \( P(A) > 0 \). Then for each \( k \):

\[ P(B_k|A) = \frac{P(A|B_k)P(B_k)}{\sum_{i=0}^{\infty} P(A|B_i)P(B_i)} \quad (3.19) \]

The basic concept of the Bayesian point of view is that, in the continuous case, \( \theta \) is interpreted as a realisation of the random variable \( \Theta \) with some density \( f(\theta) \). This density represents the prior belief about the value of \( \Theta \), before any observations have been made. \( f(\theta) \) is called the prior density of \( \Theta \). The conditional distribution of \( \Theta \), given \( X = x \), is then:

\[ f(\theta|x) = \frac{f(x, \theta)}{f(x)} \quad (3.20) \]

where \( f(x, \theta) \) is the joint distribution of \( X \) and \( \Theta \) and is given by:

\[ f(x, \theta) = f(x|\theta) \cdot f(\theta) \quad (3.21) \]

In (3.20) the marginal distribution of \( X \), \( f(x) \) is:

\[ f(x) = \int_0^{\infty} f(x|\theta) \cdot f(\theta) \quad (3.22) \]

In (3.20), the denominator, as described in (3.22), is only used as a normalising constant due to the fact that when a value for \( X \) has been observed (3.22) is constant [39]. Hence, \( f(\theta|x) \) is always proportional to \( f(x|\theta) \cdot f(\theta) \), which can be written as:

\[ f(\theta|x) \propto f(x|\theta) \cdot f(\theta) \quad (3.23) \]

Furthermore, Bayesian statistical methods make predictions of future events possible, such as failure of a component from a specified population. Future events can be predicted by using the Bayesian posterior predictive distribution [42].

If \( X_0 \) represents a random variable for a new observation, the posterior predictive PDF of \( X_0 \) is then [39]:

\[ f(x_0|x) = \int_0^{\infty} f(x_0|\theta) \cdot f(\theta|x) \quad (3.24) \]

When applying Bayesian statistical methods for reliability data analysis the integration operation for calculating the normalising constant in (3.22) plays a critical role. This integral is rarely possible to evaluate using analytical methods, except in simple cases [48]. A way to overcome this difficulty is to use numerical techniques such as Monte Carlo simulation.
3.2. EMPIRICAL MODELLING APPROACH

Case Study: SF₆ Circuit-Breaker Operating Rod

In Paper II a Bayesian statistical method was applied to combine the information from the design process with failure statistics and maintenance records. The method was applied to an SF₆ circuit breaker operating rod by using Markov Chain Monte Carlo (MCMC) to calculate the integral found in equation (3.22). The method provides a means of updating the reliability model as new information becomes available. This updating information may be failure statistics or maintenance records (e.g., collected annually).

Within the RCAM research conducted at the KTH School of Electrical Engineering, other work has been carried out within the field of Bayesian statistics and reliability modelling of power system equipment. In [49] a study on the use of expert knowledge as prior information for lifetime modelling of stator windings of hydro power generators was presented. In [50], a study subsequent to Paper II, the same method was implemented using a simple rejection sampling method producing comparable results.

By using prior information from the design process found in [51] and updating it with the information gained from failure statistics and maintenance records presented in [31] the posterior distribution was produced. Figure 3.3 shows the prior, updating and the posterior predictive information used in Paper II, where the relative age is simply $A = \frac{\text{accumulated age}}{\text{design limit}}$. The curve based on the updating information is fitted to the failure and maintenance data from [31]. To predict future operating rod failures the Bayesian posterior predictive distribution was simulated by using equation (3.24).

In conclusion, the investigation carried out in Paper II shows that it is possible to model part reliability by adding information from the design process as well as maintenance records and by using Bayesian statistical methods.
Figure 3.3. The prior, updating and posterior predictive distributions of the operating rod relative lifetime expressed as relative age, $A$. 
3.3 Physical Modelling Approach

Unlike the empirical approach, the physical approach models the condition and stress explicitly [39]. This approach requires detailed knowledge about component failure mechanisms and actual operating conditions.

3.3.1 Stress vs. Condition Modelling

In stress-condition analyses (often referred to as Load-Strength), both the stress, $L$, and condition, $S$, are assumed to be independent random variables. The stress may be applied voltage, mechanical stress or temperature and the condition refers to any resisting physical property. A failure occurs when the stress exceeds the condition.

Deterministic Stress and Random Condition

The static reliability of a part, subjected to a stress application, is represented by the probability that the condition exceeds the stress:

$$R = P(S > L)$$

(3.25)

In cases where $S$ is deterministic and $L$ is a random variable with distribution function $F(l)$ the reliability is:

$$R = 1 - F(s)$$

(3.26)

Random Stress and Condition

In a stress-condition analysis where both the stress, $L$, and the condition, $S$, are random the reliability may be described by [52]:

$$R = P(S > L) = \int_{-\infty}^{\infty} f(l) \left( \int_{-\infty}^{s} f(s) ds \right) dl$$

(3.27)

$$= \int_{-\infty}^{\infty} f(s) \left( \int_{-\infty}^{s} f(l) dl \right) ds$$

(3.28)

where $f(l)$ and $f(s)$ are the PDFs for the stress and condition respectively. Furthermore, by defining the random variable $Y = S - L$ with the PDF [44]:

$$f(Y) = \int_{-\infty}^{\infty} f(l) f(y + l) dl$$

(3.29)

and then substituting (3.29) into (3.4) the part reliability can be written as [52]:

$$R = P(Y > 0)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(l) f(y + l) dl dy$$

(3.30)
For multiple stress applications the reliability can be expressed as [52]:

\[ R = \int_{-\infty}^{\infty} f(s) \left( \int_{0}^{s} f(l)dl \right)^n ds \]  

(3.31)

If the \( n \) stress applications are statistically independent, the total reliability is given by:

\[ R = (1 - p^n) \]  

(3.32)

where \( p \) is the probability of failure per stress application.

Since stresses often vary with time and part condition decreases as it deteriorates due to different failure mechanisms, both the part condition and the applied stress may be considered to be functions of time. The lifetime \( X \) of a part is then represented by the shortest time until \( S(x) < L(x) \) [39]. This may be expressed as:

\[ X = \min\{x; S(x) < L(x)\} \]

**Normally Distributed Stress and Condition**

A common assumption is that both stress, \( L \), condition, \( S \), are normally distributed so that \( L \sim N(\mu_L, \sigma_L) \) and \( S \sim N(\mu_S, \sigma_S) \), giving the CDFs:

\[ F(l) = \Phi \left( \frac{l - \mu_L}{\sigma_L} \right) \]  

(3.33)

and

\[ F(s) = \Phi \left( \frac{s - \mu_S}{\sigma_S} \right) \]  

(3.34)

Setting \( Y = S - L \), makes \( \mu_Y = \mu_S - \mu_L \) and \( \sigma_Y = \sqrt{\sigma_S^2 + \sigma_L^2} \), which gives:

\[ R = P(Y > 0) = \Phi \left( \frac{\mu_S - \mu_L}{\sqrt{\sigma_S^2 + \sigma_L^2}} \right) \]  

(3.35)

It is, however, often assumed that as the part ages the stress remains independent of part age whereas the condition decreases with increasing age. The condition is then modelled with a decreasing mean and an increasing or decreasing variance such that [38]:

\[ R(x) = P(S(t) > L) = \int_{-\infty}^{\infty} \Phi \left( \frac{l - \mu_L}{\sigma_L} \right) \left( 1 - \Phi \left( \frac{l - \mu_S(x)}{\sigma_S(x)} \right) \right) \]  

(3.36)

where \( \mu_L \) and \( \sigma_L \) are the constant parameters of the Normal stress distribution, \( \mu_S(x) \) and \( \sigma_S(x) \) are the age-dependent parameters of the stress. The evolution of the parameters with age may be assigned any plausible form.
3.3. PHYSICAL MODELLING APPROACH

Case Study: Modelling Aged XLPE Cable Reliability

This subsection presents an example of a reliability model of aged XLPE cables based on stress-condition modelling using experimental measurements of the insulation strength. The model is based on the fact that failure of electrical insulation occurs when the voltage stresses (random) are higher than the insulation strength (random). Consequently, the stress in this case is overvoltages causing breakdown of the electrical insulation and the condition is the electrical breakdown strength of the insulation.

In the analysis carried out in Paper I the final failure process in water tree degraded cables is assumed to start as a result of an overvoltage. The overvoltage is assumed to initiate an electrical tree which immediately or a short time thereafter leads to insulation breakdown. Both the breakdown of the electrical insulation and the overvoltages are described by statistical distributions.

In Paper I an example of a reliability model was produced for a single open-loop of a typical 11kV urban area cable distribution system. The cable length was 10km and the overvoltages were assumed to be normally distributed with a mean value of \( \mu_o = 1.73 \) p.u. and a standard deviation of \( \sigma_o = 0.5 \) p.u. These assumptions were based on practical experiences from cable distribution networks. The breakdown voltage of the insulation was assumed to be normally distributed and to degrade as a function of time. The assumptions regarding the mean value, \( \mu_{bd} \), and the standard deviation, \( \sigma_{bd} \), were made from several studies of insulation breakdown voltage in relation to water tree length. Furthermore, it was assumed that one overvoltage initiated one breakdown site and that there were no simultaneous failures. The failure rate was calculated from the reliability obtained by using the complement to equation (3.35).

The assumed values of the breakdown voltage are presented in Figure 3.4a. In Figure 3.4b the results produced by the reliability model was compared to the actual failure rate experienced in aged XLPE cables in service.

In conclusion, by using assumptions based on the ageing process and the distribution system behaviour it is possible to find overvoltage and insulation characteristics that can be fitted to agree with failure statistics for water tree ageing in XLPE cables.
Figure 3.4. a) Variations of standard deviation and mean value of the breakdown voltage with time and b) comparisons of failure rates.
3.3. PHYSICAL MODELLING APPROACH

Case Study: Estimating Hazard Rate for Disconnector Contacts Using Thermography

This subsection presents an illustration example of a reliability model of aged disconnector contacts based on stress-condition modelling using field measurements of contact temperature rises. The proposed method was presented in Paper IV. The method assumes that contact ages depend on time but does not require any estimation of functions for mean and variance for the condition since these values are estimated from condition measurements. In this illustration the limit for the stress is the maximum temperature rise, \( \Delta T_{\text{max}} \), which is a deterministic value set by the International Electrotechnical Commission (IEC) Standards [53]. A contact failure is defined as the moment when \( \Delta T_n > \Delta T_{\text{max}} \), where \( \Delta T_n \) is the temperature rise at nominal load [54]. The stress-condition model is based on the fact that a contact failure occurs when the temperature rise (random) at nominal load exceeds the limit \( \Delta T_{\text{max}} \) (deterministic).

Since the thermography measurements of the disconnector contacts are not normally saved unless there is some indication of a failure or degradation the method is illustrated using an artificial test case. The test case population comprises 100 horizontal break disconnectors of different ages. Every disconnector comprises six rotating terminal contacts that are measured via thermography once a year; the three centre main contacts are not included in the example. In this illustration it is assumed that all measurements are of acceptable quality, resulting in 600 measurement points. If a temperature rise above \( \Delta T_{\text{max}} \) is discovered the contact is considered to be failed. The maintenance action for this failure mode is to replace the entire contact leaving it in an As Good As New (AGAN) state. It is assumed that the collection of the measurement data starts at an arbitrary point in time with an existing aged contact population.

Figure 3.5 shows the contact hazard rate for one of the test cases presented in Paper IV, estimated with the proposed method as well as the MLM. For comparison the empirical hazard is also included. The differences in the results from the proposed method and the MLM has to do with the fact that the MLM treated the contact age at the time of measuring as the time of failure. The proposed method, on the other hand, considered the probability of failure given the contact age.
Figure 3.5. Estimated disconnector hazard rates using thermography measurements using artificial test data.
3.4 Conclusions

The results from the case studies presented in this chapter suggests that equipment reliability models can be created by using information on how power system characteristics affect the stress on the equipment and the relationship between the ageing process and equipment condition. It has also been shown that by saving all condition measurements of sufficient quality it is possible to estimate hazard rates for those parts that cannot be measured directly.

The results from the presented case studies also demonstrated that existing failure statistics and maintenance records may constitute the basis for equipment reliability models. This type of modelling requires substantial amounts of detailed failure information which is often difficult to obtain in practice. By implementing Bayesian statistical methods in equipment reliability modelling the problem of limited failure statistics may be partly alleviated. It has been shown that these methods can be used to incorporate reliability information from the equipment design process, thereby increasing the confidence in a given reliability model.
Chapter 4

Maintenance Modelling

This chapter presents a theoretical background to the techniques used in the appended papers to model the effect of maintenance on power system equipment. It also presents results from two case studies carried out within the Ph.D. project.

4.1 Introduction

In this thesis the aim of modelling maintenance is to quantify the effect of a specific PM action on the equipment reliability. If the equipment is considered to be a repairable system, a white box reliability model is necessary in order to link the effect of a specific maintenance action to the equipment reliability.

4.2 Condition Improvement

Condition estimations lend themselves readily to assessing the effect of maintenance by estimating the part condition before and after maintenance. The expected effect of maintenance may then be predicted using statistical models, such as the linear regression model in equation (2.1). Strictly speaking, these models will not, by themselves, reveal anything about the effect the maintenance has on equipment reliability but rather the effect it has on the equipment condition. However, since an improvement of condition also improves the reliability it is possible to use the condition estimations as input data in reliability models, thus enabling modelling the effect on the equipment reliability.

Case Study: Estimating the Effect of Maintenance for Disconnector Contacts

The report Paper VII summarises the results from an investigation into the accuracy of condition assessment of electric contacts via thermography measurements
in the field.

In Paper VII two aged horizontal centre break disconnectors were loaded up to
their nominal load in three stages and the contact temperature rises were measured
both using thermography and thermocouples attached to the contacts. The disconnect-
ector comprises two rotating and one main contact per phase.

The measurements were carried out in two sets. After the first set of measure-
ments the contacts were subjected to minor or major maintenance and the measure-
ments were repeated. Minor maintenance involves minor activities such as inspecting
and operating the disconnecter. The operating of an aged disconnecter will, in most
cases, reduce contact resistance by removal of the contact surface film. Major
maintenance includes both cleaning and lubricating of the contact surfaces. Major
maintenance is performed on the main contacts at every maintenance opportunity
whereas only minor maintenance will be performed for the rotating contacts un-
less a failure have been indicated by thermography inspection. Major maintenance
for the rotating contacts are much more complicated than minor maintenance and
requires the disconnecter to be disassembled. The maintenance activities in this
study were carried out by the same contractors that normally maintain this type
of equipment.

The investigation in Paper VII resulted in a linear regression model describing
the effect of maintenance on disconnecter contact condition. The effect of mainte-
nance was illustrated by $y = \Delta T^B_n - \Delta T^A_n$ where $\Delta T^B_n$ is the temperature rise at
nominal load before maintenance and $\Delta T^A_n$ is the temperature rise at nominal load
after maintenance. The regression model describing the reduction of the contact
temperature rise due to maintenance is:

$$
E(y|M, \Delta T^B_n) = -17.8 + 3.5M + \Delta T^B_n
$$

(4.1)

where $M$ is a parameter indicating whether major or minor maintenance was car-
ried out [0 or 1], where 1 means major and 0 means minor maintenance. Figure 4.1
shows the effect of carrying out major maintenance on the disconnecter contacts as
a linear regression model. In the figure the dashed lines are 95% prediction intervals
and the dash-dot line indicates extrapolation beyond the observed effects. In order
to avoid unreasonable predictions one should be careful to use linear regression
models to extrapolate beyond the observed effects.

The regression model presented here is only valid for the investigated contacts
since the statistical sample was small.
4.3 Reliability Improvement

Unlike the modelling of condition improvement presented in section 4.2 the reliability improvement models also include the expected future behaviour of the equipment.

In this work power system equipment is modelled as repairable systems comprising only the parts most critical to the equipments' reliability, connected in series. Any maintenance carried out is assumed to take negligible time. Furthermore, it is assumed that there is only one failure mechanism present per part at any one time and that part failures are always followed by part replacement.

The basic assumptions on modelling the efficiency of maintenance are known as As Bad As Old (ABAO) and As Good As New (AGAN). In the ABAO case, each maintenance task leaves the part in the same state as it was in before the maintenance took place (e.g. minor adjustments or cleaning). In the AGAN case, each
maintenance task leaves the part in a state that is conceptually as good as new (e.g., part replacement). When modelling the effect of imperfect maintenance, which is somewhere between ABAO and AGAN, the models can generally be divided into two classes: reduction of intensity and reduction of age models [55]. Only reduction of age models are covered in this thesis.

4.3.1 Reduction of Age

The principle of the reduction of age models is that a maintenance action on part \( i \) rejuvenates it to the extent that its conditional failure intensity at time \( t \) is equal to the initial intensity at time \( V_i \), where \( V_i < t \). These type of models are commonly known as virtual age models.

Virtual Age

The concept of virtual age was introduced in [56], where two virtual age models were presented. The method presented here uses the second model commonly referred to as the Kijima II model. A new piece of equipment is put into service at \( t = 0 \) and similarly a new part has the age \( x = 0 \). At the \( m \)th maintenance action the virtual age has been accumulated to \( V_{im} + x_i \). The \( m \)th maintenance action on part \( i \) will affect the virtual age so that [56]:

\[
V_{im} = (1 - \varepsilon_{im})(V_{im-1} + x_i)
\]  

(4.2)

where \( 0 \leq \varepsilon_{im} \leq 1 \) is the degree of repair, which is a measure of how much part \( i \) is improved after maintenance action \( m \). \( \varepsilon = 0 \) is a degree of repair leaving the part in an ABAO state, \( \varepsilon = 1 \) leaves the part in an AGAN state and \( 0 < \varepsilon < 1 \) represents imperfect maintenance. A new part is assumed to have a virtual age \( V_{0i} = 0 \).

For a repairable system comprising \( n \) parts the conditional failure intensity is:

\[
\lambda(t|H^t) = \sum_{i=1}^{n} h_i (V_{im})
\]  

(4.3)

Expected Time to Next Failure

The degree of repair, \( \varepsilon \), is a qualitative measure of the instantaneous effect of a maintenance action on the part level, but for the equipment model used here this measure has no real relevance and therefore some other measure is needed. Subsequently, in order to quantitatively estimate the effect of maintenance on the equipment level the Expected Time Next Failure (ETNF) is introduced [57].

The cumulative hazard function for part \( i \) is given by:

\[
H_i(V_{im}) = \int_{0}^{V_{im}} h_i(u)du = -\ln \left[ R(V_{im}) \right]
\]  

(4.4)
For a part that has survived until the virtual age $V_{im}$ the cumulative hazard at part age $x$ is given by:

$$H_i(V_{im} + x|V_{im}) = H(V_{im} + x) - H(V_{im}) \quad (4.5)$$

For a series system comprising $n$ parts the cumulative hazard function at calendar time $t$ is:

$$H(t) = \sum_{i=1}^{n} H_i(V_{im}) \quad (4.6)$$

Similarly, for a piece of equipment modelled as a series system comprising $n$ parts, the cumulative hazard function at equipment age $T$ is given by [57]:

$$H(T + x|T) = \sum_{i=1}^{n} H_i(V_{im} + x|V_{im})$$
$$= \sum_{i=1}^{n} H_i(V_{im} + x) - \sum_{i=1}^{n} H(V_{im}) \quad (4.7)$$

The age of a part when the cumulative hazard function is equal to one is often referred to as its characteristic life. The characteristic life is defined as the point in time when approximately 63% of all parts in a population have failed if installed at the same time. For the Weibull distribution the characteristic life is also the value of the scale parameter, $\eta$, thus $F(\eta) = 0.632$ [45]. This point in time (when the cumulative hazard function is equal to one) is the Expected Time to Next Failure, $ETNF$. The $ETNF$ for a series system is given by $x$ such that [57]:

$$\sum_{i=1}^{n} H_i(V_{im} + x) - \sum_{i=1}^{n} H_i(V_{im}) = 1, \quad x = ETNF \quad (4.8)$$

The $ETNF$ can be found numerically by means of iterative numerical methods such as Newton-Raphson [57]. The effect of PM is defined as the expected increase in $ETNF$ caused by the PM action. Following this the effect of PM type $k$ on the equipment reliability, $e_k$, is estimated by:

$$e_k = ETNF_k - ETNF_0 \quad (4.9)$$

where $ETNF_0$ is the expected time to next failure without carrying out any PM action at time $T$. Note, that in this context $ETNF$ is not necessarily measured in calendar time.

**Case Study: Modelling the Effect of Maintenance for SF$_6$ Circuit-Breakers**

A method to model the effect of maintenance on equipment reliability was proposed in Paper VI. The proposed method is illustrated in a case study using real failure
and maintenance data for a specific type of SF$_6$ high voltage CBs in the Swedish and Finnish transmission systems. The hazard rates of the most critical CB parts were estimated using failure data and maintenance records, the entire CB was then modelled as a series system comprising only the critical parts using equation (3.7).

In order to illustrate the proposed method it has been applied to three 400kV SF$_6$ shunt reactor CBs in the Swedish transmission system. These CBs were selected because they have the same age ($t = 18$ years) and function in the system and since they have different maintenance histories and operating frequencies ($f_1 = 10^8$ ops./yr, $f_2 = 346$ ops./yr and $f_3 = 118$ ops./yr). The equipment reliability model for this specific CB type is made up of three parts: the Open- and Close-operation locks (both in the operating mechanism) and Remaining parts. Two of the CBs had historically been subjected to maintenance other than the regular function tests carried out on all CBs in the system. The CB labelled CB 1 had the close-operation lock correctly replaced at the age $t = 15$ years and CB 2 had the open-operation lock correctly replaced at age $t = 10$ years. CB 3 received no maintenance other than the scheduled function tests during the studied period. Figure 4.2 shows the conditional failure intensities for the CBs including the effect of historical maintenance, from Paper VI. It is assumed that all maintenance, CM or PM, on the remaining parts leave the part in an ABAO state.

The maintenance actions available for the investigation in Paper VI are listed in Table 4.1. Using equation (4.9) the resulting effect of maintenance, $e_k$, may be calculated. If a PM task for a specific part has a degree of repair $\varepsilon < 1$ (see equation (4.2)) the effectiveness of that PM task is estimated by accepting or rejecting the hypothesis that the task is more cost-effective than part replacement. Hence, no exact value is assigned to the effect of maintenance for that PM task. The expected effect of PM tasks carried out at $t = 18$ years are summarised in Table 4.2. In the table $e_k$ is the expected increase in the number of CB operations (open-close) before failure due to PM. In the calculations of $e_k$ in Table 4.1, the $ETNF_0$ for CB 1, CB 2 and CB 3 are 678, 262 and 468, respectively.

It can be seen from the tables that replacing the operating mechanism with a mechanism of the new design has the largest positive effect on the equipment reliability. Whether or not this is the PM task that should actually be carried out depends on its cost-effectiveness, see Paper VI. It is assumed that the operating mechanism of the new design is designed to last more than 10000 operations according to the norm [58], giving it a Weibull scale parameter of $\eta = 10000$. Furthermore, it is assumed that it will only have random failures, giving it a Weibull shape parameter of $\beta = 1$. 
Figure 4.2. Reliability models of circuit-breakers with different operating frequencies, including equipment failure and maintenance histories.
Table 4.1. Available circuit-breaker PM tasks

<table>
<thead>
<tr>
<th>PM task, $k$</th>
<th>PM description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Replace open-operation lock</td>
</tr>
<tr>
<td>B</td>
<td>Replace close-operation lock</td>
</tr>
<tr>
<td>C</td>
<td>Replace the operating mechanism with an identical design</td>
</tr>
<tr>
<td>D</td>
<td>Replace the operating mechanism with the new design</td>
</tr>
<tr>
<td>E</td>
<td>Circuit-breaker function test</td>
</tr>
</tbody>
</table>

Table 4.2. Estimated effect of different PM tasks on circuit-breaker reliability.

<table>
<thead>
<tr>
<th></th>
<th>CB 1</th>
<th></th>
<th>CB 2</th>
<th></th>
<th>CB 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PM task, $k$</td>
<td>$e_k$</td>
<td>#ops</td>
<td>PM task, $k$</td>
<td>$e_k$</td>
<td>#ops</td>
<td>PM task, $k$</td>
</tr>
<tr>
<td>A</td>
<td>345</td>
<td></td>
<td>A</td>
<td>86</td>
<td></td>
<td>A</td>
</tr>
<tr>
<td>B</td>
<td>52</td>
<td></td>
<td>B</td>
<td>240</td>
<td></td>
<td>B</td>
</tr>
<tr>
<td>C</td>
<td>440</td>
<td></td>
<td>C</td>
<td>733</td>
<td></td>
<td>C</td>
</tr>
<tr>
<td>D</td>
<td>992</td>
<td></td>
<td>D</td>
<td>1095</td>
<td></td>
<td>D</td>
</tr>
<tr>
<td>E</td>
<td>&lt;345</td>
<td></td>
<td>E</td>
<td>&lt;240</td>
<td></td>
<td>E</td>
</tr>
</tbody>
</table>

4.4 Conclusions

The presented case studies demonstrates that the effect of maintenance for part condition may be modelled by means of linear regression models utilising laboratory condition measurements. It has also been shown that it is possible to quantitatively model the effect of maintenance for a piece of equipment using existing failure and maintenance data by representing the equipment as a series system of its most critical parts.
Chapter 5

Closure

This thesis presents the advancements towards achieving the aim of the Ph.D. project, namely to model the effect of maintenance on reliability of power system equipment. To achieve this aim, several case studies have been carried out using different approaches on various types of power system equipment. The seven appended publications present the progress of this Ph.D. thesis work. The main findings and conclusions drawn from this work are summarised below.

5.1 Conclusions

This research has demonstrated that the effect of maintenance on power system equipment can be quantified using available data. In order to realise the full potential of these methods, the gathering and utilisation of failure and maintenance data as well as condition measurements need to be improved.

The main contribution from this work can be categorised into the three related areas of condition estimation, reliability modelling and maintenance modelling. The following paragraphs summarises the main findings for each of the areas.

Condition Estimation

- It is possible to estimate part condition based on condition measurements provided that the failure mechanism is understood and that it is practically feasible to measure the physical quantity.

- By modelling the accuracy of condition measurements it is possible to calculate the probability of making an erroneous maintenance decision based on such a measurement.
Reliability Modelling

- Equipment reliability models can be created by using information on how power system characteristics affect the stress on the equipment and the relationship between the ageing process and equipment condition.

- By saving all condition measurements of sufficient quality it is possible to estimate hazard rates for those parts that cannot be measured directly.

- Existing failure statistics and maintenance records may constitute the basis for equipment reliability models. This type of modelling requires substantial amounts of detailed failure information which is often difficult to obtain in practice.

- By implementing Bayesian statistical methods in equipment reliability modelling the problem of limited failure statistics may be partly alleviated. It has been demonstrated that these methods can be used to incorporate reliability information from the equipment design process, thereby increasing the confidence in a given reliability model.

Modelling the Effect of Maintenance

- The effect of maintenance for part condition may be modelled by means of linear regression models using laboratory condition measurements.

- It is possible to quantitatively model the effect of maintenance for a piece of equipment using existing failure and maintenance data by representing the equipment as a series system of its most critical parts.

In conclusion, even though methods that require a minimum of data have been studied and implemented and a number of different data sources have been employed, the lack of detailed, high-quality data remains a critical problem when modelling the reliability of power system equipment.

5.2 Future Work

In order to increase the proportion of factual knowledge and reduce the reliance on subjective judgement, the available methods for reliability and maintenance modelling needs to be implemented in the actual planning of electric power system equipment maintenance. To achieve this, more attention needs to be paid to the collection of high quality data. In the past there has been a great focus on analysis but without the necessary input any model will become useless. In order to realise the potential of using the condition measurements that are regularly carried out in electric power systems, all measurements of sufficient quality needs to be properly saved by default.
References


Reliability modelling of aged XLPE cables
R. Eriksson, T. Lindquist and L. Bertling
*Nordic Insulation Symposium (Nord-Is), Tampere, Finland, pp.216-224, June 2003.*
Reliability modelling of aged XLPE cables

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Abstract

Modelling of the reliability of power equipment is of crucial importance in finding the optimum maintenance solution in power systems. The problem is however complex and very little information is available on how ageing or maintenance influences the equipment reliability. This paper makes an attempt to model the reliability for the first generation of XLPE cables with respect to faults due to water treeing. The model is based upon assumptions on how the water tree length develops with time and on the relationship between water tree length and breakdown voltage determined in laboratory investigations of field aged XLPE cables. Statistical distributions of cable breakdown voltage and overvoltage distributions in the network are estimated. Following this the probability of cable failure is calculated and subsequently compared with the actual failure rate experienced from aged XLPE cables in service. The parameters of the distributions are fitted to give the same calculated failure rate and experienced failure rate.

Keywords: Reliability modelling, power systems, water trees, cables, XLPE

1. Introduction

Power System maintenance optimisation involves the finding of the minimum total costs, including preventive and corrective maintenance costs and the cost of failures considering both supplier and customer costs. Knowledge on how system reliability is affected by maintenance is crucial for the optimisation of power system maintenance.

Reliability modelling of power system components needs a substantial amount of knowledge such as design details, results from accelerated ageing tests or service experiences. Since failure statistics is normally unknown for new components the relation
between ageing, maintenance and reliability must be based upon knowledge on fundamental ageing mechanisms and assumptions.

This paper gives a short review on reliability modelling of power system components followed by case study on reliability modelling of water tree aged XLPE cables. The example has been selected since the information available is voluminous on water tree phenomena and cable failures.

2. Power equipment reliability modelling techniques

The international literature on how maintenance affects the reliability is scarce except for the conventional failure statistics reporting. Nonetheless, a limited number of papers exist.

In [6] and [7] a model for probabilistic evaluation of the effect of maintenance on reliability applied to air-blast circuit breakers was presented. The model uses life curves to represent the relationship between component condition, expressed in either financial or engineering terms, and time. The model is solved by employing the Monte Carlo-simulation technique, in order to analyse the impact of different maintenance strategies. To generate the life curves a, specially developed, software was used. The main features of the software lay in its probabilistic representation of the degradation process, carried out in discrete steps, and the link between maintenance and deterioration that the model provides.

In [8] a study on maintenance optimisation of on-load tap changers was reported. The two methods used were the non-parametric TTT-method and the analytical Weibull-method. These methods were used to estimate failure rates from censored life observations. The failure rates were subsequently used to optimise the preventive maintenance interval. The two methods were later used in [9] to optimise the maintenance interval for circuit-breakers.

A probabilistic method to establish how changes in wood pole management affects the expected costs of a line was presented in [10] and [11]. The method determines the wood pole replacement rate with respect to climatic loads, such as ice and wind, and decreasing pole strength (ageing), taking into account statistical uncertainties in pole strength and loads. All calculations, when using this analytical method, are carried directly on the statistical distributions, even though an alternative method using Monte Carlo simulation was also developed. When applied, the method produces output in the form of the expected wood pole replacement rate as a function of time and the standard deviation. Even though this methodology is based on several assumptions it proves very interesting for the purpose of reliability modelling with special reference to maintenance.

A reliability centred asset management method (RCAM) has been developed in [4, 5]. This included developing a failure rate model relating the effect of preventive maintenance to the benefit in system reliability for the XLPE cable component. To achieve this model a failure rate function was approximated with a best fit to experienced data. Figure 1 shows the functional relationships for this method.
Preventive maintenance

Stopping water tree growth

Increasing of the electrical breakdown voltage

Decreasing failure rate

Figure 1. The functional relationship of the cable reliability model with respect to preventive maintenance in [4].

3. Reliability modelling approach for XLPE cables

The derivation of the reliability model is based upon the assumption that the final failure process in water tree degraded cables start as a result of an overvoltage. The overvoltage is assumed to initiate an electrical tree, which immediately or after a short time leads to insulation breakdown. Both the breakdown of the electrical insulation and the overvoltages can be described by statistical distributions. Using the concept of Risk of failure, [12], the breakdown probability for one overvoltage event is

\[ R = \int_{0}^{\infty} P_{bd}(u) f_o(u) du \]

where \( P_{bd} \) is the breakdown probability function describing the probability of breakdown as function of voltage stress \( u \) and \( f_o \) is the density function of the overvoltages.

For the demonstration of the reliability model in this paper normal distributions are used where \( \mu \) and \( \sigma \) are the mean respectively the standard deviation. Indices \( bd \) and \( o \) are used for breakdown and overvoltage distributions respectively. \( R \) can then be found from the normal distribution \( \Phi \)

\[ R = 1 - \Phi \left( \frac{\mu_{bd} - \mu_o}{\sqrt{\sigma_{bd}^2 + \sigma_o^2}} \right) \]

The failure rate \( \lambda \) (failures/year) can then be calculated for the frequency of occurrence of overvoltages, \( N \) (events/year), as

\[ \lambda = NR \]

3.1 Overvoltage estimation

A cable distribution system is normally well protected for lightning overvoltages. The main sources of overvoltages are switching overvoltages and overvoltages caused by
faults. For single events under normal network conditions the overvoltages can be estimated by simple circuit analysis. The switching overvoltages occur when an unloaded cable is connected to the system. If the cable is uncharged, which normally is the case, the overvoltages are usually below 2 p.u. (with reference to the phase voltage peak value). If the cable is first disconnected and then connected while still charged the overvoltage may reach around 3 p.u. If a fault occurs on the cable the voltage on the unfaulented phases raises to phase voltage multiplied by the square root of three. The transient process may lead maximum voltages around 2.5.

### 3.2 Insulation breakdown characteristics

The first generation of XLPE-cables were exceptionally vulnerable to water tree degradation. When failures started to appear a lot of effort was made to clarify the phenomena and failure statistics were collected. The cable design, in particular the insulation and conductor screen material, was found to significantly influence the degradation, [1]. Figure 2, reproduced from [2], show that the breakdown voltage is in the range 6 to 10 times the normal operating voltage when no water trees could be detected. When the water trees penetrate the whole insulation the breakdown voltage is in the range 2 to 3 times the normal operating voltage.

![Figure 2. Breakdown voltage in relation to maximum detected water tree length in % of the insulation thickness, [2].](image)

The matter of water tree growth is however quite complex, [14]. For the demonstration example in this paper it is assumed that the water trees grow linearly with time until the trees bridge the whole insulation and then a relation can be set up between breakdown voltage and time. A linear growth is supported by some studies [13], [15], while the results from repeated diagnostic measurements in [16] indicate that the degradation process slows down with time.
4. Reliability model application

The example described below is based upon assumptions on a typical 11 kV system in an urban area comprising 40 km cables distributed on 6 loops with 5-10 km cables per loop. Normally, the system is operated with the loop open in one point. In case of a fault the whole system connected to the transformer is subjected to overvoltages. A typical failure rate is 1 fault per 11 kV system and year considering all types of failures, [17]. Almost all failures are single phase to ground faults. For scheduled maintenance operations each loop is disconnected approximately once per year. The network layout, the operation principles and the failure rate of the system thus determine the frequency of occurrence of overvoltages. Following the above considerations the following overvoltage characteristics in Table 1 are assumed.

Table 1. Assumed overvoltage distributions.

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean value</td>
<td>1.73</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.5</td>
</tr>
<tr>
<td>Number of overvoltages</td>
<td>1 per year</td>
</tr>
</tbody>
</table>

The breakdown function parameters in figure 3 were assumed. The water trees are expected to grow linearly from 0 to 100% of the insulation thickness in 13 years. Thereafter the breakdown function is assumed to be constant.

Figure 3. Assumed breakdown distribution as function of time
One 10 km loop with aged cables was studied for comparison between failure statistics and estimated failure rate. The probability of failure was calculated using the above assumptions and the breakdown function parameters were adjusted in order to obtain a reasonable fit (the final fit is shown in figure 3) between the estimate and experienced failure statistics on water tree degraded cables, [3]. The result in figure 4 show that it is possible to find overvoltage distributions and breakdown functions that gives a reasonable agreement.

Figure 4. Comparison between experienced and estimated failure rate for a 10 km loop.

5. Discussion

In the demonstration of a reliability model several assumptions were made. These hypotheses are not verified even if the combinations of the hypotheses give an agreement with failure statistics. A number of matters can be raised for discussion on the reliability modelling of aged XLPE cables.

The ageing process is of fundamental importance for the modelling. For the early used cable designs the semiconducting screens had a considerable influence upon the water tree development. The water tree ageing properties of these can therefore not directly be used for the XLPE cables of today with extruded semiconducting screens and dry cross-linking methods for the insulation.

The breakdown voltage was used to relate the electrical condition of the cable to the ageing process (water tree length). The water trees were assumed to grow linearly with
time. This is not a generally true statement since experiences show that for some designs or laying conditions the degradation process seems to slow down with time.

The final breakdown process and how this affects the breakdown probability function needs to be further studied. It was assumed that electrical trees are initiated as a result of overvoltages. Can several breakdown sites be initiated by one overvoltage and how does the probability function depend upon cable length? Extreme value distributions would probably be a better choice than normal distributions.

To serve condition assessment and reliability modelling more information is necessary. In a Nordic project, [18], a data base was studied and it was considered essential to build up information on laying conditions, cable design including joints and terminations, diagnostic measurements, and failure statistics

6. Conclusions

The following conclusions are drawn.

- For maintenance optimisation it is necessary to know how the maintenance affects the component reliability. This creates the need for a reliability model of the components.

- Information on system characteristics and ageing process and its relation to the component condition is needed to develop a reliability model for power components.

- From assumptions based upon the ageing process and the distribution system it was possible to find overvoltage and insulation characteristics that can be fitted to agree with the failure statistics for the water tree ageing in XLPE cables

7. References


A method for age modeling of power system components based on experiences from the design process with the purpose of maintenance optimization
T. Lindquist, L. Bertling and R. Eriksson
Reliability and Maintainability Symposium (RAMS), Alexandria, Virginia, USA, January 2005.
A Method for Age Modeling of Power System Components based on Experiences from the Design Process with the purpose of Maintenance Optimization

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Lina Bertling, Ph.D., Royal Institute of Technology
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Key Words: reliability modeling, maintenance, power system components

SUMMARY & CONCLUSIONS

This paper introduces a first step towards establishing the effect of maintenance on component reliability. The concept of relative age is introduced and defined as well as a method to establish this relative age of electric power system components for the purpose of maintenance optimization. The proposed method is demonstrated by modeling the relative age of a sub-component for a circuit breaker (CB). The modeling is based on the results from a major CB reliability study and a survey of all CB failures in the Swedish National Grid during the period from January 1st, 1999 to July 31st, 2003. The results from this application study show that it is possible to model the reliability of power system components by using results from development tests and calculations from the design process along with failure and maintenance data.

INTRODUCTION

Many of today’s electric power companies operate in a de-regulated market. The electric power distribution companies are required to provide reliable electricity to customers while maintaining cost-efficiency. This has lead to an increased attention being put on maintenance as a tool to reach both of these objectives. As a result, many companies have started to change their maintenance strategies from time-based preventing strategies to more sophisticated maintenance strategies like Reliability Centered Maintenance (RCM). In order to perform maintenance optimization at the system level, within the RCM framework, it is necessary to be able to model component behavior, with respect to reliability.

Modeling the reliability of power system components is difficult due to the lack of failure data because of high reliability components and the high cost of life tests [1].

The method proposed in this paper makes use of the different calculations and tests carried out during the development process as prior information about new components that has not yet failed, in order to model the reliability. The model is updated by means of Bayesian inference, using Markov Chain Monte Carlo (MCMC) simulations, as new information becomes available. An application example of a sub-component of a circuit breaker (CB) is presented. Switchgear in general, and CBs in particular, are important to the power system with respect to reliability and also because they consume a relatively large proportion of the total preventive maintenance.

POWER SYSTEM COMPONENT RELIABILITY MODELING

2.1 Power System Reliability Models

The aim of modeling the reliability of power system components is to be able to predict failures and thus, by applying the appropriate maintenance tasks, prevent or delay these failures. These models are probabilistic and allow the user to predict the likely future behavior of the component.

Examples of reliability measures are hazard function, availability, Mean Time To Repair (MTTR), Mean Time Between Failures (MTBF), etc. In this paper the hazard function is used as a measure of reliability.

In the past, several reliability models for power system components have been proposed [1-3]. These models are all very useful, however, they all require either failure data or other forms of operational information that are not usually stored and can therefore not easily be used for new equipment. When analyzing failure data, it is common to consider samples in which not all components have failed at time $t$. These lifetimes are then said to be right censored. If, on the other hand, the lifetime is interval censored it means that the exact lifetimes are not known; only an interval of time in which the failure occurred is recorded. Left censored data has not been considered in this work.

2.2 Circuit Breaker Failures

A CB is a highly complex piece of equipment. It has many failure modes and high reliability [4,5]. This, combined with the fact that in an electric power system there often exists CBs of many different makes, models and
generations, makes CB failures difficult to predict. In general a failure is in [6] defined as:

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

The functions that the CB is required to perform are [7]:
1. Make and break normal current.
2. Maintain electric insulation.
3. Transfer normal current.
4. Make and break all occurring short circuit currents.

2.3 Ageing

All failures depend on some sort of failure mechanism i.e. some mechanical or chemical process leading to a failure [6]. The following definitions will be used throughout this paper:

Ageing – A physical process, which involves a modification of the physical and/or chemical characteristics of the material.

Ageing failure – Failures whose probability of occurrence depends on the level of unit ageing.

Ageing Factor – Applied stress, discrete or continuous, that affects the ageing process.

Relative Age – The accumulated level of stress the sub-component has been subjected to with respect to the level of stress for which it was originally designed and built to endure.

For CBs the dominating ageing factors are time in operation, number of operating cycles and accumulated interrupted short circuits currents [4].

3. METHOD

This paper proposes a method to model the reliability of power system components, using development test data from the manufacturer. The method also provides a means of updating the model as new information becomes available. In this section a description of the method is presented along with an example applied to CBs. A flow chart describing this method is presented in Figure 1. In Figure 1 the steps 3-8 is performed for every sub-component. The two input data boxes in the figure represents input data to the reliability model and the output data box shows the resulting reliability model.

1. Component modeling

In this paper, the definition of a sub-component is the smallest replaceable item in the power system component. All sub-components in the component model are considered to be non-repairable and statistically independent.

Consider a component comprising \( m \) non-repairable sub-components. Each sub-component, \( i \), has a lifetime \( X_i \), where \( X_i \) is an independent random variable (r.v.) with a probability density function (p.d.f.) \( f(x) \), where \( x \) is an observation of \( X \).

Using the proposed method, a power system component is modeled as a serial system comprising \( m \) sub-components, each with a lifetime \( X_i \), see Figure 2.

In the CB example, the component to be modeled is the high voltage (HV) part, as presented in [4], see Figure 3. Note that the operating mechanism is not included in this example.

1. Component modeling
2. Identification of critical sub-components
3. Identification of ageing factors
4. Development data analysis
5. Age modeling
6. Reliability modeling
7. Updating data analysis
8. Updating using Bayesian inference

Figure 2. A reliability model representing the entire component, e.g. a CB.

Figure 3. A layout of the different critical CB parts [4].
critical to the component. To be useful, the failure statistics need to be very detailed. If the component to be modeled is of a new design and therefore has not yet failed, failure data or experiences from previous similar designs, or experiences from the development process may be used.

In this work the critical sub-components are defined as those sub-components that are most critical to the component with respect to some reliability importance measure. The reliability importance measures will be different depending on the component to be studied and the purpose of the study. Examples of reliability importance measures are hazard rate, availability, repair costs, etc.

The number of critical sub-components will differ depending on the component and the accepted accuracy of the model.

In the context of the CB example, a study [4] of all CB failures in the Swedish National Grid system (transmission level) during the period from January 1st, 1999 to July 31st, 2003 is used as input data. In [4] the failing sub-components were identified and the time in operation and number of operations to failure was recorded.

From [4] the critical sub-components in the HV part are identified as the operating rod and the interrupter unit.

### 3. Identification of Aging Factors

The next step is to identify what factors affect the aging of the different critical sub-components. A critical sub-component may have more than one aging factor. This approach is often referred to as using different time scales [8-10].

It is expected that the dominating age factor can be established by relying on engineering judgments and experiences from the development process. However, in cases when it is not so obvious which ageing factor is dominant the method of Lifetime Coefficient of Variation described in [8,9], may be used.

For the two critical sub-components in the CB example the ageing factors represents the number of operations for the operating rod and accumulated short circuit current for the interrupter unit [1,5,11]. However, since the number and size of the interrupted short circuits was not recorded in [4], this example will from here on only focus on the wear of the operating rod.

### 4. Development Data Analysis

This step involves the collection and analysis of development test data in order to support age models for every factor affecting the relative age of the critical sub-components. This data typically results from tests and calculations carried out by the manufacturer during the design and development process, such as reliability studies, Failure Mechanism and Effect Analysis (FMEA) and different types of mechanical strength tests and calculations.

In the CB example a reliability study [5] of a CB is used as input data. In the study several strength and endurance tests were carried out as well as dynamic simulations.

For the operating rod, a development test of the mechanical strength was carried out. The test was conducted as follows: five operating rods were subjected to 10000 operations and were afterwards examined to find out whether they had sustained wear beyond the acceptance level. From the way this particular test was conducted it is not possible to know exactly how many operations the rods have been subjected to before failure. The only information available is the number of operating rods that failed before 10000 operations. However, if the rods were inspected every 1000 operations, the failure times would be interval censored and valuable information would become available.

Because the failure times of the operating rods were not recorded in [5], the interval in which they failed will here be assumed to be known. The values marked $i$ in Table 1, were picked at random from a Weibull distribution.

### 5. Age Modeling

This step involves the modeling of the relative age of the critical sub-components for each factor critically affecting its age. The relative age is typically a value between zero to one, where zero means that the sub-component is new and one means that it has reached the accumulated stress, for which it was designed. Note that a sub-component may have a relative age, $A(y)$, larger than one,

$$A(y) = \frac{y}{c}, \quad c \neq 0 \quad (1)$$

where $y$ is the accumulated stress and $c$ is the set accumulated stress limit the sub-component was designed to withstand.

The advantage of using relative age is that it is easy to compare different sub-components with respect to their relative age, even though they might have different failure mechanisms.

In the example, the CB shall be able to withstand at least 10000 operations, according to [12], and that is what the CB is designed to do, setting $c = 10000$.

### 6. Reliability Modeling

The last stage before the updating loop starts in Figure 2 is to model the reliability of the component. In this paper the hazard function is used as a measure of reliability. The hazard function is modeled by first fitting a p.d.f. to the data, acquired in stage 4. Then, for each critical sub-component $i$, the hazard function, $h_i(x)$, is calculated as
The hazard function for the serial system, comprising \( m \) sub-components, is then

\[
h_{\text{system}}(x) = \sum_{i=1}^{m} h_i(x) \quad (3)
\]

Applied to the CB example a prior p.d.f. for \( X_i \) is formulated based on the data from the development tests. The lifetimes of the operating rod is assumed to be Weibull distributed. The Weibull distribution is used due to its flexible nature and possibility to represent a large number of failure characteristics of equipment [13]. The Weibull p.d.f. is defined as follows:

\[
f(x|a,b) = \frac{b}{a} \left( \frac{x}{a} \right)^{b-1} e^{-\left( \frac{x}{a} \right)^b}, \quad x \geq 0 \quad (4)
\]

where \( a \) and \( b \) are the scale and shape parameters.

The \( a \) and \( b \) parameters are estimated from the data in Table 2, by using the Method of Least Squares (MLS) in the statistical analysis software MINITAB [14]. The parameter estimations for the assumed data in Table 1 are \( \hat{a} = 1.0272 \) and \( \hat{b} = 2.7725 \), giving the p.d.f. in Figure 4a. The hazard function in Figure 4b is found through (2). Note that the prior p.d.f. is entirely based on development data and that, following these tests, improvements have been made to the construction in order to meet the demands in [12].

The hazard rate in Figure 4b represents the hazard rate model for the operating rod until new information becomes available.

7. Updating Data Analysis

New data needs to be collected in order to update and improve the model. This data may be failure statistics and/or maintenance records. Even if the different sub-components have not failed and no failure statistics exists, maintenance records can still contribute with important information in the form of right censored failure data.

In the CB example both failure data and maintenance history for the operating rod from [4] are found in Table 2.

<table>
<thead>
<tr>
<th>Observations (# of operations)</th>
<th>2100</th>
<th>800</th>
</tr>
</thead>
<tbody>
<tr>
<td>3900*</td>
<td>4800*</td>
<td></td>
</tr>
<tr>
<td>1350*</td>
<td>900*</td>
<td></td>
</tr>
<tr>
<td>1000*</td>
<td>300*</td>
<td></td>
</tr>
<tr>
<td>759*</td>
<td>3250*</td>
<td></td>
</tr>
<tr>
<td>400*</td>
<td>300*</td>
<td></td>
</tr>
<tr>
<td>1600*</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Observations of \( X \) where * means that the observation is right censored.

8. Updating Using Bayesian Inference

Consider a quantity \( \theta \) that we wish to estimate. In classical statistics this parameter is treated as fixed but unknown. In Bayesian statistics, on the other hand, the parameter \( \theta \) is considered to be a result of a r.v. \( \Theta \) with some p.d.f. \( f(\theta) \), called the prior p.d.f. This p.d.f. may reflect any prior knowledge we may have regarding the values of \( \theta \). The greatest advantage of using Bayesian methods is the way prior knowledge is combined with collected data into the resulting posterior distribution that can be used for inference. The computation of the posterior distribution uses Bayes’ Theorem [15-18]. A general form of Bayes’ Theorem involving data \( x \) and the parameter \( \theta \) is as follows:

\[
f(\theta | x) = \frac{f(x | \theta) \cdot f(\theta)}{\int f(x | \theta) \cdot f(\theta) \, d\theta} \quad (5)
\]

where the conditional density \( f(x|\theta) \) is the posterior distribution of \( \Theta \), given \( X \), and \( f(x|\theta) \) is a model for the observed data.
In this work the posterior expectations are evaluated using MCMC methods [17]. For evaluating the expected lifetimes of power system components the method proposed in this paper uses the Gibbs-sampling MCMC method by means of the free WinBUGS software [19].

For the CB example the relationship between the r.v. in step 1 is presented in Figure 5 as a Directed Acyclic Graph (DAG) model. Each quantity is represented as a node, the circles represent r.v., and the rectangles represent deterministic variables. In the DAG-model in Figure 5 the r.v. are distributed according to $\alpha_1 \Gamma(A, r_1)$, $B \in \Gamma(A, r_2)$ and $X \in W(A, B)$, where $\alpha_1$, $\alpha_2$, $r_1$, $r_2$ are constants. The $\Gamma$ -p.d.f. is defined as

$$f(x|\alpha, r) = \frac{a^\alpha x^{\alpha-1} e^{-ax}}{\Gamma(\alpha)}$$  \hspace{1cm} (6)

where $\alpha$ and $r$ are the scale and shape parameters.

When calculating the posterior p.d.f. the updating information in Table 2 is used as input along with the prior distribution. A total of 10000 values of $A$ and $B$ are produced using WinBUGS.

### 6. Reliability Modeling

The predictive distribution is, in this paper used to study the distribution for a new observation of $X_0$. After observing $D = (X_1, X_2, \ldots, X_n)$ the predictive density of $X_0$, given $D$, is defined as [16]

$$f(X_0 | D) = \int f(x_0 | \theta) - f(\theta | D) d\theta$$  \hspace{1cm} (7)

When the predictive distributions, and subsequently the hazard functions, are calculated for all critical sub-components in the serial system the component hazard function is obtained from (3).

In the CB example, the posterior p.d.f. was simulated, the predictive p.d.f. was also simulated, i.e. not calculated analytically using (7). The predictive p.d.f. was simulated using the last 2000 values, for $A$ and $B$, of the total of 10000 from the simulations in step 8, this was done to ensure that only values from after the Markov chain had converged were included.

In Figure 6a the updated predictive p.d.f. is demonstrated and in Figure 6b the hazard function is demonstrated (labeled Case 1). This is the updated reliability model for the operating rod.

The resulting hazard function for the CB would have been found by using (3), had there been more than one sub-component in the component model.

### 4. METHOD EVALUATION

In this section the method is evaluated using four test cases. These cases are different versions of the real data found in Table 2, all using the same prior information from Table 2. In Table 3 the different cases can be seen, * means that the lifetime is right censored.

Case 1 includes the data used in section 3. One value is an observed failure and 12 values are right censored. In case 2 all values from case 1 are assumed to be right censored. In case 3 seven of the observations are assumed to be right censored and the other six are assumed to be observed lifetimes. In case 4 all values are observed failures.

### Table 3. Lifetimes for the four different test cases

<table>
<thead>
<tr>
<th></th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
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<tr>
<td>Number of operations</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2100</td>
<td>800*</td>
<td>2100</td>
<td>800*</td>
</tr>
<tr>
<td></td>
<td>3900*</td>
<td>4800*</td>
<td>3900</td>
<td>4800*</td>
</tr>
<tr>
<td></td>
<td>1350*</td>
<td>900*</td>
<td>1350</td>
<td>900*</td>
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<td></td>
<td>1000*</td>
<td>300*</td>
<td>1000*</td>
<td>300*</td>
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<tr>
<td></td>
<td>750*</td>
<td>3250*</td>
<td>750*</td>
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<td></td>
<td>400*</td>
<td>300*</td>
<td>400*</td>
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</tr>
<tr>
<td></td>
<td>1600*</td>
<td>1600*</td>
<td>1600*</td>
<td>1600*</td>
</tr>
</tbody>
</table>

In Figure 6a the two p.d.f.s are demonstrated. In Figure 6b the hazard functions are compared. The plot in Figure 6a demonstrates that when only using failure data from [4] to estimate the Weibull parameters there is a very small probability of an operating rod lasting 10000 operations i.e. reaching the relative age 1. However, it is clear from the information in Table 2 that two out of five operating rods made 10000 operations during the development tests. When considering Case 1 it can be seen that the probability of reaching a relative age of 1 is somewhat larger, which reflects the prior information acquired from the development tests.

### 4.2 Sensitivity Analysis

In this subsection the posterior p.d.f., from Case 1, is compared to a p.d.f. based solely on the failure data in Table 2, not taking the development test data into account. For the p.d.f. with no prior information the Weibull parameters, $\hat{a} = 0.3787 \hat{b} = 2.9750$, were estimated using the Maximum Likelihood Method (MLM) in MINITAB. For Case 1 the MLS estimated the parameters to $\hat{a} = 0.3796 \hat{b} = 1.4087$, also using MINITAB.

In Figure 6a the two p.d.f.s are demonstrated. In Figure 6b the hazard functions are compared. The plot in Figure 6a demonstrates that when only using failure data from [4] to estimate the Weibull parameters there is a very small probability of an operating rod lasting 10000 operations i.e. reaching the relative age 1. However, it is clear from the information in Table 2 that two out of five operating rods made 10000 operations during the development tests. When considering Case 1 it can be seen that the probability of reaching a relative age of 1 is somewhat larger, which reflects the prior information acquired from the development tests.
In order to test the sensitivity of the method the four test cases in Table 3 were used in order to evaluate the impact of the data used in the updating process.

In Figure 7 a plot of the p.d.f. from all four cases is demonstrated. From Figure 7 it is clear that the more observations of actual lifetimes (as in case 4), the smaller variance and vice versa if all observations are right censored (as in case 2) the variance increases, which is to be expected.

Figure 6a,b) A comparison between using and not using test data as prior information, p.d.f. and hazard functions respectively.

5. CONCLUSIONS AND DISCUSSION

The proposed method provides a means of modeling the reliability of a (simplified) CB, in absence of, or with limited access to, failure statistics.

The work in this paper is based on the assumption that the lifetimes from the development tests are interval censored. This assumption is not unreasonable since it is possible for the network operators to demand this data when purchasing their power system components.

It is worth noticing that the values in Table 2 may not be representative for the entire CB population. If maintenance data would be collected for all CBs in a power system the entire population would be represented and the model would be more accurate. The example in this paper aims to show that Figure 7. Plots of the p.d.f. of the four test cases even with different sets of limited data it is possible to produce a reliability model for complex power system apparatus.

The method evaluation in section 4 provides support for the statement that the method is quite dependent on the amount and type (censored or not) of data.

Figure 7. Plots of the p.d.f. of the four test cases.

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Estimation of disconnector contact condition for modelling the effect of maintenance and ageing
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Estimation of disconnector contact condition for modelling the effect of maintenance and ageing

T.M. Lindquist, Student Member, IEEE, L. Bertling, Member, IEEE and R. Eriksson, Senior Member, IEEE

Abstract—In order to optimize the maintenance of electric power equipment, models of equipment reliability as a function of age and maintenance are necessary. As a first step towards the development of these kinds of models, this paper proposes a quantitative method for establishing the condition of disconnector contacts by the use of thermography, which is a well-established diagnostic practice used in preventive maintenance programmes. Results from two sets of thermography measurements carried out in the Swedish transmission grid are presented. Statistical distributions for the uncertainties when using the method are estimated from the measurements. A method for converting temperature rises measured at non steady state loading conditions to a corresponding steady state temperature rise have been devised using a simple thermal model. The probability of sending an unaged contact to maintenance is estimated using Monte Carlo simulations based on the statistical distributions of the uncertainties. Finally, it is shown that by using the method proposed in this paper it is possible to estimate the contact condition of disconnectors, including Monte Carlo simulated confidence intervals.

Index Terms—Disconnectors, contact condition, infrared image sensors, thermography, maintenance, ageing, reliability.

I. INTRODUCTION

In order to optimize the maintenance of electric power equipment within the framework of the reliability centred asset management (RCAM) method [1], models of equipment reliability as a function of age and maintenance are necessary. This paper proposes a first step towards the development of these kinds of models via a quantitative method for determining disconnector contact condition. The method is based on the fact that the contact temperature is a measure of the condition, hence by knowing the contact temperature rise the condition can be established. The contact temperature measurements are carried out via the use of thermography, which is a well-established diagnostic practice used in preventive maintenance programmes [2],[3],[4],[5]. The temperature measurements are here used in the modelling of contact condition as a function of age and maintenance.

Previous studies investigating thermography for disconnector contact condition monitoring include [6], where the Swedish Transmission Research Institute (STRI) carried out an extensive contact ageing study, including a long-term outdoor test on four air insulated centre break disconnector poles. STRI also performed outdoor tests on pantograph disconnector contacts in [7]. There are several case studies [4],[5],[8] and guidelines [2],[3],[9] on the use of thermography on electrical equipment. A few studies have been carried out with the aim to improve the use of thermography by better interpretation of the images [10] and improving the ability to save and compare results [11]. These guidelines and studies, with the exception of [3] and [7], focus on the benefits of thermography, making only general assumptions about the accuracy.

In this study a factorial experiment was designed to investigate what factors caused ageing in a disconnector. However, the first results of the thermography measurements were less accurate than expected and a second set of measurements was carried out in order to establish the accuracy of the proposed method.

This paper proposes a method to quantitatively determine and model the contact condition of disconnectors via the use of thermography. The accuracy of the proposed method is also investigated.

II. METHOD

1) Thermography

Thermography is a non-destructive, non-contact technique, which can be applied on electrical equipment on-line. Because of its ease of use and low cost it has become the preferred diagnostic method for assessing equipment condition on-line in the Swedish transmission system.

The thermography camera measures and images the infrared radiation in some specified spectral band. If the thermography camera was to measure the temperature of a blackbody source the camera output signal, \( V_{\text{output}} \), would be [12]:

\[
V_{\text{output}} = C \cdot W_{\text{bb}}
\]  

(1)

where \( W_{\text{bb}} \) is the radiated power of the blackbody temperature source and \( C \) is a constant. A non-blackbody radiation temperature source is always emitting less radiation than a blackbody source at the same temperature. As the blackbody concept is strictly theoretical, no true blackbody emitters exist in real life. The relationship between a blackbody source of temperature and a non-blackbody measurement object is expressed as:

\[
W_{bb} = W_{\text{obj}} \cdot e^{-\frac{T_{bb}}{T_{\text{obj}}}}
\]  

(2)

where \( W_{bb} \) is the radiation power by a blackbody temperature...
source, $c$ is the emissivity of the non-blackbody measurement object and $P_{r,0}$ is the radiation power of the object. The emissivity, $c$, is dimensionless and is in the range between zero and one and is hence a measure of a material's ability to radiate heat.

A widely used method of using thermography on electrical equipment is by employing the delta-T criteria [3]. This is a qualitative method of estimating the maintenance priorities by using tables of temperature ratings to assess the severity of overheating the equipment [2]. These tables are usually divided into three or four different categories to indicate the maintenance priority based on the equipments temperature rise with respect to a similar reference component. The reference component is typically a neighbouring phase which can, under normal circumstances in a power system, be considered to have the exact same loading conditions as the measured component. The advantage of this method is that it is a practical method to establish "failure" or "no failure" and the emissivity has only a minor impact on the result [3]. A drawback is that the temperature tables are usually only found in handbooks and guidelines and hence there is a lack of a recognised standard. Moreover, the delta-T criteria does not say anything about whether the equipment temperature limits are actually exceeded. Furthermore, using the delta-T criteria will not expose systematic failures affecting all three phases. In the delta-T method the temperature rise at phase L₁ is calculated as:

$$\Delta T_{L_1} = T_{L_1} - T_{L_1}^{amb}$$  \hspace{1cm} (3)

where $T_{L_1}$ is the hot-spot temperature of the measured object and $T_{L_1}^{amb}$ is the hot-spot temperature of the reference object.

This paper, however, proposes to use a quantitative method to establish the temperature rise at the disconnect contacts. The reference is the ambient temperature, established by measuring the absolute temperature of a de-energised contact under the same ambient conditions as the contact to be measured. Since this measurement forms the basis for subsequent calculations it is very important that it is as accurate as possible. The temperature rise is calculated as:

$$\Delta T_{L_1} = T_{L_1} - T_{L_1}^{amb}$$  \hspace{1cm} (4)

where $T_{L_1}$ is the hot-spot temperature of the measured object and $T_{L_1}^{amb}$ is the ambient temperature at the time of measuring.

2) Establishing contact condition

The proposed method uses results from the field measurements to calculate the nominal temperature rise at the contacts, $\Delta T_{nom}$, at any given load. The nominal temperature rise is the rise the contacts would have if loaded with their nominal current.

a) Measuring $\Delta T$

Firstly, the temperature rise at the disconnector contacts, $\Delta T_{nom}$, is measured using thermography. When using thermography it is very important to have suitable and stable ambient conditions such as no sunshine, no rain or snowfall and no wind.

If wind at the time of measurement cannot be avoided the measured temperature rise may be compensated for the cooling effect, however this procedure is not recommended [3],[7]. The wind compensation may be carried out by using [6]:

$$\Delta T_{c} = \Delta T_{nom} \left( \frac{v_a}{v_s} \right)^z$$  \hspace{1cm} (5)

where $\Delta T_{c}$ is the compensated temperature rise, $\Delta T_{nom}$ is the measured temperature rise, $z$ is a constant, $v_a$ is the measured average wind speed, and $v_s$ is the maximum wind speed allowed when type testing a disconnector. The constants may be selected as $v_a=0.5$ m/s and $z=0.27$, from [13] and [6] respectively. If $v_a < v_s$ there is no wind and $\Delta T_{c} = \Delta T_{nom}$.

b) Temperature rise caused by load

The next step is to calculate the nominal temperature rise by using:

$$\Delta T_{nom} = \Delta T_{c} \left( \frac{I_n}{I_{load}} \right)^\alpha$$  \hspace{1cm} (6)

where $I_n$ is the disconnectors' rated load current and $I_{load}$ is the load current at the time of measuring. According to the experimental results in [6] the exponent is $\alpha=1.4$ for the same type of disconnectors as investigated in this paper.

c) Measuring at the contact cover

When measuring the temperature rise at the terminal contacts of centre break disconnectors it is not possible to see the actual contacts with the naked eye. A way to compensate for this is by using a constant temperature rise. By adding the constant temperature rise the final nominal temperature rise is calculated as:

$$\Delta T_{nom} = \Delta T_{c} + \Delta T_{const}$$  \hspace{1cm} (7)

where $\Delta T_{const}$ is the constant temperature rise. Values for $\Delta T_{const}$ are found in the type test records from the disconnector manufacturer. Contacts that are visible to the naked eye can be measured directly, making $\Delta T_{const}=0$.

However, by using (7) it is assumed that the constant temperature rise from type tests is applicable to defect contacts. This assumption is used since no model currently exists for defect contacts.

d) Estimating contact condition

Finally, the contact condition is established by comparing the nominal temperature rise to some reference. In this paper the reference temperature is the maximum temperature rise, $\Delta T_{max}$, as defined in [13]. By using such a reference and applying the delta-T criterion as defined in [9] the condition is established from Table 1.

This method of establishing the condition is essentially comparing the nominal temperature rise of the measured contact with a new contact that has the highest temperature rise allowed.

<table>
<thead>
<tr>
<th>Condition</th>
<th>$\Delta T_{max}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ok</td>
<td>&lt;10°C</td>
</tr>
<tr>
<td>Degraded</td>
<td>10-30°C</td>
</tr>
<tr>
<td>Failed</td>
<td>&gt;30°C</td>
</tr>
</tbody>
</table>

Table 1: Delta-T Criterion
III. MEASUREMENTS

In this paper two sets of thermography measurements were carried out. In both sets the contact temperature rise was calculated using the quantitative method as in (4). All measured disconnectors were of the type horizontal centre break disconnectors, and of the same make and model with the rated current $I_n=3150\,A$. The measured points, per pole, were the contact covers of the two rotating terminal contacts and the main contacts.

A. Measurement set 1

In the first measurement set the emphasis was on establishing what factors affects the contact condition. Therefore the measurements were designed as a factorial experiment, testing the effect of the age and time since maintenance on the contact condition. The two factors were tested on two levels (+) and the disconnectors in the grid were selected so as to form combinations of the four groups in Table 2. The levels of age and time since maintenance were chosen so that a maximum of disconnectors may be measured (replications) while maintaining large enough contrasts between the levels.

<table>
<thead>
<tr>
<th>Main factors</th>
<th>+</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age [yrs]</td>
<td>&lt; 11</td>
<td>&gt; 21</td>
</tr>
<tr>
<td>Time since maintenance [months]</td>
<td>&lt; 45</td>
<td>&gt; 85</td>
</tr>
</tbody>
</table>

In the first set 21 disconnectors in the Swedish transmission system were measured. The disconnectors were distributed over five substations at 220kV and 400kV. All disconnectors were of the same make and model but had been in operation for different lengths of time. The contacts were measured only once and most of the measurements were carried out after sunset in order to avoid any disturbing reflections caused by the sun. The ambient temperature, the average wind-speed and the load currents were also registered. The emissivity was estimated by two experienced thermography technicians to be $\varepsilon = 0.76$ and $\varepsilon = 0.80$, respectively. In total 66 measurements were made. The results from these measurements are summarised in Fig. 1.

In graph a) of Fig. 1 it appears as if the temperature rise is lower at higher load currents. This unexpected result together with the extremely high values for the calculated nominal temperature rises in graph b) led to the second measurement set, aimed at investigating the accuracy of the proposed contact condition estimation method. The nominal temperature rises in graph b) were calculated using $\alpha=1.4$ from [6].

B. Measurement set 2

In the second set of measurements the emphasis was on establishing the accuracy of the measured temperature rise $\Delta T_m$ and to identify the sources of error when using thermography. Eight disconnectors in total were measured at three different sub-stations in the 400kV Swedish transmission system. The same contacts were measured repeatedly at different loads. In total 237 measurements were made.

The experience from measurement set 1 was that the following sources of error were particularly important:

- difficulties in estimating the correct emissivity, $\varepsilon$, of the object,
- lack of a reliable reference,
- unstable weather conditions while measuring (just after rainfall, ambient temperature dropping rapidly after sunset, etc.),
- low load currents while measuring.

These experiences agree with both previous [3],[6],[14] and later [7] studies. The last two difficulties were avoided in the second set by measuring during stable weather conditions and choosing the disconnectors to be measured based on their typical (high) load current. For the first two error sources the following steps were taken in order to obtain reliable measurements.

The emissivity, $\varepsilon$, was set by measuring a de-energized disconnector contact and changing the value of $\varepsilon$ while comparing the measured temperature with the ambient temperature. The estimated value for $\varepsilon$ was picked when the two temperatures were equal. When the temperatures were equal the ambient temperature was used as a reference. Note that when using this method it is extremely important to eliminate any background radiation that may otherwise cause large errors [7],[12].

The emissivity used in the second set is an average value from several estimated disconnectors. The different estimated values can be found in Table 3.

Results from the measurements in sub-station A are shown in Table 3.

<table>
<thead>
<tr>
<th>Measurement no.</th>
<th>Estimated emissivity, $\varepsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>010</td>
<td>0.72</td>
</tr>
<tr>
<td>027</td>
<td>0.80</td>
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<td>037</td>
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<tr>
<td>136</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.78</strong></td>
</tr>
</tbody>
</table>

TABLE 2. FACTORIAL EXPERIMENT DESIGN FOR DISCONNECTOR CONTACTS.

![Fig. 1. Measured temperature rises and calculated temperature rises at nominal current, from set 1.](image-url)
temperature rise on the terminal contacts of disconnector 1 as a function of the load current. Fig. 3 shows the measurement results per phase for the terminal contacts of disconnector 1 in sub-station A along with the corresponding load current and time.

IV. ANALYSIS

A. Temperature rise

It is generally accepted that the temperature rise increases with the applied steady state current $I_{load}$ as in (8), where $k$ and $a$ are object specific constants.

$$\Delta T_m = k \cdot I_{load}^a$$

(8)

For the measurements in set 2 the exponent was found to be $a=1.0$ as illustrated in Fig. 4, for phase L2 of disconnector 1 in sub-station A. Note that only the points that were measured when the current was decreasing in Fig. 3 are included in the figure.

B. Thermal model

When applying (8) it is assumed that the current is at steady state. The measurements in set 2 was carried out when the current was ramping up and down, as can be seen in graph b) of Fig. 3. In order to compensate this ramping, a simple thermal model has been developed. The disconnector contact is modelled as a thermal resistance and a thermal capacitance in parallel. It is assumed that the power flow in the circuit is:

$$p_j = d_j + b_j \cdot i$$

(9)

where $d_j$, $b_j$ and $k$ are constants. The expression for the temperature as a function of a steady state current ramp for the thermal model is then:

$$T_j(i) = d_j R + b_j R t - b_j R \tau$$

(10)

where $R$ is the unknown thermal resistance and $\tau$ is the thermal time constant. Using $j=1$ for the down-ramp and $j=2$ for the up-ramp, the thermal time constant, $\tau$, for a specific current $i_0$ is:

$$\tau = \frac{T_j(i_0) - T_j(0)}{b_j R - b_j R}$$

(11)

Getting $b_1 R = 3.6$C/h and $b_2 R = 1.9$C/h from the measurements (see Fig. 3) the time constant becomes $\tau=33$ minutes, by using (11). The steady state equivalent temperature rise is then:

$$\Delta T_m = b_j R \tau$$

(12)

In Fig. 5 the results when applying (12) on the measurement points from set 2 can be seen. Fig. 5 shows the measured temperature rises before and after they have been converted to their steady state equivalents. The dotted line connects the measurement points in time and the arrows indicate the direction of time. The last measurement point has been removed due to the ending of the down-ramp. The hysteresis looking shape of the dotted line in Fig. 5 is the effect of the load current ramping.
ing a constant temperature rise
\( \Delta T \) under contact condition. Note, that the error introduced by adding measurements and calculations for establishing the distribution of the different sources of error influencing the steady state equivalent, from set 2.

C. Sources of error

The purpose of this section is to estimate the statistical distributions of the different sources of error influencing the measurements and calculations for establishing the disconnector contact condition. Note, that the error introduced by adding a constant temperature rise \( \Delta T_{\text{const}} \) from a new contact is not considered in this paper and would require a more detailed thermal model in order to reflect how the temperature rise measured at the contact cover reflects the actual contact temperature rise of a defect contact.

a) Estimated exponent

The exponent \( a \) is object-specific and its value depends on the heat-transfer capabilities of the object [3],[7]. Establishing the value of \( a \) for all measured contacts is not practically possible and therefore a mean value is used for all contacts. The value of \( a \) is sometimes reported to be 2 [9] but several studies has shown different results [3],[6],[7]. In Table 4 a summary of exponents reported in the literature can be found.

<table>
<thead>
<tr>
<th>( a )</th>
<th>Reference</th>
<th>Object</th>
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<tbody>
<tr>
<td>1.0</td>
<td>Fig. 4</td>
<td>Centre break disconnector main and terminal contacts</td>
</tr>
<tr>
<td>1.6-2.0</td>
<td>[2]</td>
<td>General electrical equipment</td>
</tr>
<tr>
<td>2.0</td>
<td>[9]</td>
<td>Fixed electrical contacts</td>
</tr>
<tr>
<td>1.4</td>
<td>[6]</td>
<td>Centre break disconnector terminal contacts</td>
</tr>
<tr>
<td>1.5-1.7</td>
<td>[3]</td>
<td>220V electrical equipment</td>
</tr>
<tr>
<td>0.6-1.1</td>
<td>[3]</td>
<td>Disconnector terminal connections</td>
</tr>
<tr>
<td>0.80-1.58</td>
<td>[7]</td>
<td>Pantograph disconnector contacts</td>
</tr>
</tbody>
</table>

b) Estimated emissivity

Due to the relationship between a blackbody source of temperature and a non-blackbody measurement object, as expressed in (2), different emissivity settings yield different temperature readings from the thermography camera for the same object. These differences are explained by (13) which is based on (2) but does also include the interferences caused by reflections and background radiation. The radiated power from the object as measured by the thermography camera is expressed as [12]:

\[
W_{\text{obj}} = \frac{1}{\varepsilon} W_{\text{tot}} - \frac{1}{\varepsilon} W_{\text{refl}} - \frac{1}{\varepsilon} W_{\text{atm}}
\]

(13)

where \( \varepsilon \) is the emissivity of the object, \( \tau \) is the transmittance of the atmosphere, \( W_{\text{refl}}, W_{\text{atm}} \) and \( W_{\text{tot}} \) are the total received power, the received power radiated from ambient sources and the power received from the atmosphere, respectively. These powers are all assumed to be the radiation power of blackbody sources of temperature.

However, because the values of \( W_{\text{refl}}, W_{\text{atm}} \) and \( W_{\text{tot}} \) are not generally known an approximation is used, stating that a 10% change in \( \varepsilon \) yields a 10% change in the temperature rise. This approximation has shown to be adequate but depends heavily on the object temperature and the value for the estimated emissivity [12].

Given the different values of \( \varepsilon \) estimated for the energized disconnectors in Table 3 and the technicians’ estimates from measurement set 1, the emissivity is assumed to be uniformly distributed with the parameters 0.7 and 0.85 giving \( \varepsilon ~ U(0.7,0.85) \). The uniform distribution is selected because it is assumed that no value of the emissivity is more likely than any other.

c) Thermography measurement error

According to [9] thermography measurements in the field can be made with a measurement error \( \leq 1 \% \). However, the practical experiences made from the measurements carried out in [7] estimated the error to be \( \leq 5 \% \). Based on this, the assumption in this paper is that the thermography measurement error is normally distributed with an expected value of zero, i.e. there is no bias. The standard deviation is assumed to be 3.0, giving \( \text{error}_\varepsilon ~ N(0,3), [\%] \). This error includes all types of random errors such as when measuring the relative humidity, ambient temperature or background temperature.

d) Current measurement error

The method of establishing contact condition depends heavily on knowledge of the disconnector load at the time of measuring. Hence, a crucial factor is the accuracy of the current measurements. A major part of this error is caused by the fact that not all currents for all measured points were obtained at the exact moment of measuring and a only minor part is the inaccuracy of the actual measuring system. The assumption is that there is no bias; hence the expected value of the error is zero. The accuracy of the current measurements is assumed to be \( \text{error}_I ~ N(0,5), [\%] \). A measurement error of 5% is approximately the equivalent of getting a current reading 20 minutes before or after the thermography measurement when the contact is loaded with a down ramping current as in Fig. 3.
D. Method accuracy

To illustrate the importance of the sources of error, three Monte Carlo simulations have been carried out. In the first simulation the nominal temperature rise from set 1 were given simulated confidence bounds. In the second simulation the probability of sending an unaged disconnector contact to maintenance is simulated. In the third simulation confidence bounds for the contact condition of a terminal contact from set 2 are simulated.

1) Summary of uncertainties

The statistical distributions of the errors introduced when establishing the contact condition from a nominal temperature rise based on thermography measurements are summarised below:

- Exponent, \(a\) ~ U(1, 2).
- Emissivity, \(\varepsilon\) ~ U(0.7, 0.85).
- Thermography measurement error, \(\text{error}_T\) ~ N(0, 3), [°C].
- Current measurement error, \(\text{error}_I\) ~ N(0, 5), [%].

2) Confidence bounds for \(\Delta T_n\)

Using the error distributions in the section above, confidence bounds for the measured temperature rises from measurement set 1 were simulated. The Monte Carlo simulation was carried out by applying the following steps \(N\) times for each measurement.

1. Get a temperature rise \(\Delta T_m\).
2. Sample an exponent \(a\) and an emissivity \(\varepsilon\) from their distributions.
3. Sample measurement errors for the thermography and the current measurements.
4. Calculate \(\Delta T_n\).
5. GOTO step 2 (repeat \(N\) times).
6. Use the 90% percentiles for the distribution of \(\Delta T_n\) as confidence bounds.
7. GOTO 1 (for every temperature rise \(\Delta T_m\)).

Fig. 6 shows the simulated confidence bounds for the nominal temperature rises from measurements in set 1.

From the figure it is clear that the accuracy of the method is decreasing with decreasing load current. This serves as an explanation to the results in graph b) of Fig. 1.

3) Probability of maintaining healthy contacts

When using thermography to establish the contact condition it is important not to incur any unnecessary and expensive maintenance actions to healthy equipment. Therefore, the probability of appearing to have measured a failed or defect contact when in reality it is unaged and has a condition of 100%, has been simulated. This probability can be expressed as:

\[
P(\Delta T_m > \Delta T_{\text{max}} \mid \Delta T_{\text{meas}} < \Delta T_{\text{max}})
\]

where \(\Delta T_{\text{max}}\) is the maximum allowed temperature rise for a new silver plated contact from the IEC standard [13] plus the maximum temperature rise of 30°C for a failed contact and 10°C for a degraded contact, from Table 1. This gives \(\Delta T_{\text{max}}=95°C\) for a failed contact and \(\Delta T_{\text{max}}=75°C\) for a degraded contact for the terminal contacts (silver plated).

This probability is simulated using Monte Carlo as follows:

1. Get the contact temperature rise \(\Delta T_{\text{meas}}=65°C\) from [13].
2. Sample an exponent \(a\) and an emissivity \(\varepsilon\) from their distributions.
3. Sample measurement errors for the thermography and the current measurements.
4. Calculate \(\Delta T_m\).
5. GOTO step 2 (repeat \(N\) times).
6. Calculate the probability (14).

Fig. 7 shows the result from the simulation. From the figure it is clear that the probability of sending a healthy contact to maintenance, believing it to be degraded, is quite large even at high load currents. The probability of labelling a contact as failed is also quite large, at least when measuring at low load currents of less than \(I_{\text{load}}=1000A\), which is approximately 0.3 \(I_n\).

![Fig. 6. Monte Carlo simulated confidence intervals for the nominal temperature rise from set 1.](image)

![Fig. 7. Monte Carlo simulated probability of maintaining a healthy contact.](image)
establish what factors affect the contact ageing was proposed. Utilisation of this method a factorial experiment designed to condition using thermography has been derived. Based on the thermal model was used for this purpose. Temperature rise has been devised in this paper. A simple non-steady state conditions to a corresponding steady state ing an unaged contact to maintenance. These simulations pro-
simulations were also used to estimate the probability of sending an aged contact at low load currents. When calculating the nominal temperature rise in Fig. 8 the temperature constant used was \( \Delta T_{\text{max}} = 65^\circ \text{C} \), from [15].

V. CONCLUSIONS
A quantitative method of establishing disconnector contact condition using thermography has been derived. Based on the utilisation of this method a factorial experiment designed to establish what factors affect the contact ageing was proposed. Using results from the thermography measurements, estimates of the statistical distributions of the different sources of error has been produced. Based on these estimations Monte Carlo simulations were used to simulate confidence intervals. Simulations were also used to estimate the probability of sending an unaged contact to maintenance. These simulations pro-
viding a tool to fix an acceptance level on this probability.

A method for converting temperature rises measured at non-steady state conditions to a corresponding steady state temperature rise has been devised in this paper. A simple thermal model was used for this purpose.

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VII. REFERENCES

VIII. BIOGRAPHIES
Tommie Lindquist (S’01) received his B.Sc. degree in Electrical Engineering from the Mid-Sweden University, Sweden, in 2000 and his M.Sc. in Electrical Power Systems (with distinction) and M.Phil. in Electrical Power Systems from the University of Bath, UK, in 2001 and 2003, respectively. He is presently a Ph.D. student at the Royal Institute of Technology (KTH), dept. of Electrical Engineering (ETN), Stockholm, Sweden. His research interests include reliability modeling of power system components and probabilistic methods for age and maintenance modeling.

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Roland Eriksson (SM’89) received his M.Sc. and Ph.D. degrees in electrical engineering from the Royal Institute of Technology (KTH), Stockholm, Sweden, in 1969 and 1975, respectively. Since 1988, he has been a Professor at the Department of Electrical Engineering, KTH. His research interests in- clude condition-based maintenance and electrical insulation diagnostics.
Hazard rate estimation for high-voltage contacts using infrared thermography
T. Lindquist and L. Bertling
Reliability and Maintainability Symposium (RAMS), Las Vegas, Nevada, USA, January 2008.
Hazard Rate Estimation for High-Voltage Contacts using Infrared Thermography

Tommie M. Lindquist, MSc, Royal Institute of Technology (KTH)
Lina Bertling, PhD, Royal Institute of Technology (KTH)

Key Words: disconnector, electrical contacts, hazard rate, maximum likelihood

SUMMARY & CONCLUSIONS

Infrared thermography is the most common way to assess the condition of high-voltage electrical contacts in electric distribution and transmission systems. However, thermography has one major drawback as contacts carrying low or no load may not be assessed.

This paper proposes a method to save and make use of thermography measurements to estimate statistical distribution parameters for the time to failure for a population of electrical contacts. The statistical distributions may then be used to support maintenance decisions for the sometimes large proportion of contacts that may not be assessed directly due to low load. As the measurement results accumulate over the years more accurate predictions can be made.

The proposed method is illustrated using three test cases applied to a population of high-voltage disconnectors with randomly generated thermography measurements.

The main conclusion of the paper is that using the proposed method will provide maintenance decision support for high-voltage apparatus that may not be assessed directly by thermography.

1 NOMENCLATURE

- $X_{\text{max}}$: maximum allowed contact temperature rise (K)
- $X$: contact temperature rise at nominal load (K)
- $X_{\text{m}}$: measured contact temperature rise (K)
- $\mathbf{X}$: vector of contact temperature rises (at nominal load) at contact age $t$
- $I_{\text{load}}$: load current (A)
- $I_{n}$: nominal load current (A)
- $a$: object specific constant (-)
- $\eta$: Weibull scale parameter
- $\beta$: Weibull shape parameter
- $\gamma$: Weibull shift parameter
- $\mu$: expected value
- $\sigma^2$: variance
- $f(t|\mathbf{X})$: conditional probability density function given the measurements in $\mathbf{X}$
- $R(t|\mathbf{X})$: conditional reliability function given the measurements in $\mathbf{X}$
- $R(t|\mathbf{X})$: vector of conditional contact survival probabilities
- $h(t|\mathbf{X})$: contact hazard rate given the measurements in $\mathbf{X}$

2 INTRODUCTION

Maintenance planning for high-voltage equipment in electric transmission and distribution systems is a challenging task. The equipment is often distributed over large geographical areas and a combination of high equipment reliability and a large number of different manufacturers, models and generations make failure data collection difficult. This has lead to a situation where very few mathematical models on equipment reliability are being used in practice due to lack of input data. As a consequence, many companies have mainly used time based maintenance supported by Condition Based Maintenance (CBM) where possible. As competition in the industry increases and equipment populations age, more sophisticated methods such as Reliability Centered Maintenance (RCM) are being implemented [1]. Consequently, there is a need for practically applicable equipment reliability models to support maintenance decisions.

A previously untapped source of information for this purpose is the results from thermography measurements regularly carried out by most electric transmission and distribution companies. Infrared thermography is a condition assessment technique that is being used to assess the condition of electrical contacts by measuring the heat generated by the load current. One of the reasons for its popularity is the fact that it is a non-contact technique, which can be applied to high-voltage electrical equipment on-line.

An obvious weakness however, is that equipment which normally carries no or low load cannot be assessed. A survey made for this study indicates that at least 50% of all measurements of high-voltage disconnector contacts in a particular system were made at a load current too low to produce reliable results. This situation is made even more serious as some companies have decided that they will only perform contact maintenance if a failure or degradation is indicated by thermography. This means that the transmission system could be left with a large number of hidden disconnector contact failures. Hidden failures in disconnector contacts have caused the only two major blackouts in the Swedish transmission system (1983 and 2003) [2]. Measurement results that are not indicating degradation or failure are rarely saved.
This paper proposes a method to save and make use of all measurement results to estimate statistical distribution parameters for the time to failure for an equipment population. These parameters may then be used in reliability models for decision support when planning maintenance for low-load equipment that cannot be assessed directly by thermography. The aim of such a maintenance policy is to reduce the number of hidden contact failures in a disconnector population and thus reducing the risk of a catastrophic power system failure.

The proposed method will be illustrated using three test cases applied to a population of high-voltage disconnectors with randomly generated thermography measurements.

3 ELECTRICAL CONTACT MAINTENANCE

3.1 Contact Maintenance

Historically, preventive maintenance (PM) on electrical contacts has been carried out in a time based fashion. As new condition assessment techniques have been developed more sophisticated maintenance strategies, such as RCM or CBM, have been implemented. This change has been caused by increased competition among electricity distribution companies as well as demands from the regulator.

As more CBM has been introduced, the importance of infrared thermography has increased. Some companies have abolished scheduled PM altogether and will only take certain equipment off-line if a failure or degradation has been indicated by a thermography measurement.

The only two parameters that may be modified in order to increase electrical contact availability are the load current and thermography inspection frequency [3], when basing all contact maintenance on thermography. As a consequence, companies have been increasing the thermography inspection frequency. If the load is too low however, increasing the inspection frequency will only improve the contact availability marginally and will thus be very inefficient. The method proposed in this paper could be applied in those cases.

3.2 Thermography

The most common method to assess the condition and inspect electrical contacts is by infrared thermography. Infrared thermography is a non-destructive, non-contact technique, which can be applied on high-voltage electrical equipment off-line. The thermography camera measures and images the infrared radiation from the object in a specified spectral band. Because of its ease of use and low cost it has become the preferred method for assessing equipment condition on-line in many electrical transmission and distribution systems around the world.

A widely used method of using thermography on electrical equipment is by employing the delta-T criteria [4]. This is a qualitative method of estimating the maintenance priorities by using tables of temperature ratings to assess the severity of overheating the equipment [4].

This paper, however, proposes to use the quantitative method to establish the temperature rise at the disconnector contacts as presented in [3] and to save all measurement results.

A serious drawback of using thermography on electrical contacts in general is that it is heavily dependent on the load current [4]. A commonly used rule of thumb states that any measurement made at less than 30% of the rated load current is considered too inaccurate [6]. This has also been verified by Monte-Carlo simulations [3]. Nevertheless, a survey made for this paper investigated at which load all thermography measurements were made in the Swedish transmission system (220kV-400kV) during 2006. The result of the survey was that more than 50% of all thermography measurements were made at a load current of less than 30% of the rated load.

3.3 Effect of Maintenance

An electrical contact that is found to be failed is assumed to be immediately replaced with an identical one, leaving the contact in an As Good As New (AGAN) state. A common failure mode for electrical contacts is wear of the silver surface, which is there to provide a low electrical resistance. When this surface is worn the contact resistance will increase and consequently the temperature rise. Any standard maintenance tasks such as cleaning and lubricating the contacts is assumed to leave the contact in a state that is conceptually As Bad As Old (ABAO).

4 FAILURE DEFINITION

In this paper an electrical contact failure is defined as a contact having a temperature rise greater than the maximum allowed temperature rise, $X_{\text{max}}$, when loaded with its nominal load current, $I_{\text{n}}$. The value for $X_{\text{max}}$ can be found using a combination of values found in [7] and [8] as a norm, the maximum allowed temperature rise for silver coated contacts in air is then $X_{\text{max}}=95\,\text{K}$ [3].

5 HAZARD RATE ESTIMATION USING INFRARED THERMOGRAPHY

This section presents a method to save and make use of all measurement results to estimate statistical distribution parameters for the time to failure for an equipment population.

Briefly, the method involves the following steps:

1. Collect thermography measurement results.
2. Clean data and discard poor quality measurements.
3. Sort measurements by contact age into groups.
4. Fit a probability density function (p.d.f.) to the measurement results for each age group.
5. Calculate the probability of exceeding the maximum temperature rise (failure) for each age group.
6. Estimate the statistical distribution parameters by least squares fitting a reliability function to the probabilities from the previous step.

The following subsections describe the method in more detail.

5.1 Collect Measurement Results

The first step of the measurement collection procedure is...
to make sure that all measurements are normalized with respect to the nominal load of the contact, i.e. calculate what the temperature rise would be at nominal load. This is done by [3]

\[ X = X_m \left( \frac{I_m}{I_{load}} \right)^a \] (1)

where \( X_m \) [K] is the measured temperature rise when loaded with \( I_{load} \) [A]. \( I_m \) [A] is the nominal load for the contact and \( a \) is a dimensionless object specific constant.

5.2 Data cleaning

Thermography measurements are heavily dependent on the load current and measurements made at too low load are not useful and must be discarded. A rule of thumb is that any measurement made at less than \( 0.3 \cdot I_a \) is considered too inaccurate [6]. This has been verified by Monte-Carlo simulations [3].

5.3 Sorting by age

After the data has been cleaned and only accurate measurements remain they must be sorted according to the contact age. This reordering does not lead to any loss of information if the times to failure are assumed to be independent and identically distributed [9].

5.4 Fit p.d.f. to measurement results

The next step is to fit a p.d.f. for all measurements made at a certain contact age.

Let the random variable \( X_i \) be the calculated temperature rise at nominal current, using (1), for contact \( j=1,2,...,k \), where \( k \) is the number of contacts of age \( t \) and \( t=1,2,... \) is describing the contact working age in calendar years. Let \( X_i \) be a vector \( (x_i, x_{i+1}, ... x_{it}) \) for contact age \( t \). The p.d.f. describing the contact temperature rise, \( X_i \) at contact age \( t \) is \( f_i(x) \).

The measurements in \( X_i \) may then be used to fit \( f_i(x) \) to a statistical distribution using standard methods such as maximum likelihood estimation (MLE) [10]. The p.d.f. fitting procedure should be followed by a goodness-of-fit test to assess the fit of the model to the calculated values of the reliability function at different contact ages.

It is assumed that the thermography measurement errors are symmetrically distributed with an expected value of zero.

5.5 Calculation of failure probabilities

The probability of a contact surviving up to time \( t \) is described by the reliability function. Hence, the probability of a contact surviving up to time \( t \) given the thermography measurements, \( X_i \), is then given by the conditional reliability function, \( R(t | X_i) \):

\[ R(t | X_i) = P(T > t | X_i) = P(X \leq X_{max}) = \int_0^{X_{max}} f_i(x)dx \] (2)

provided that \( x > X_{max}, t \to \infty \).

5.6 Estimating statistical distribution parameters

The final step is to estimate the parameters for the statistical distribution for the conditional reliability function \( \hat{R}(t | X_i) \) by using the vector of probabilities from (2) \( R(t | X_i) = (R(t | X_1), R(t | X_2), ..., R(t | X_k)) \). The estimated conditional reliability function \( \hat{R}(t | X_i) \) is found by fitting a reliability function to the probabilities in \( R(t | X_i) \) by the Method of Least Squares (MLS). As described in subsection 5.4 there is a need to perform a goodness-of-fit test in order to assess the fit of the model to the calculated values of the reliability function at different contact ages.

The p.d.f. \( f(t | X_i) \) describes the time to failure for a disconnector contact, given the measurements in \( X_i \). The estimated p.d.f. \( \hat{f}(t | X_i) \) is found via the relationship [11]:

\[ \hat{f}(t | X_i) = \frac{d(\hat{R}(t | X_i))}{dt} \] (3)

Subsequently the estimated hazard function is found by [11]:

\[ \hat{h}(t | X_i) = \frac{\hat{f}(t | X_i)}{\hat{R}(t | X_i)} \] (4)

6 ILLUSTRATION OF HAZARD RATE ESTIMATION

The proposed method will be demonstrated by an example estimating Weibull parameters for the time to failure for the electrical contacts of horizontal centre break high-voltage disconnector switches. The service role of a disconnector in an electrical network is to provide a visual open circuit in its open position and to carry the load current in its closed position. Since no real data exists to demonstrate

<table>
<thead>
<tr>
<th>Table 1 – Test case input data.</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
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<tr>
<td>( \gamma(r)=40+2.2r )</td>
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</tr>
</tbody>
</table>
the method it is illustrated by a test case.

6.1 Test case

The test case population comprises 100 horizontal break disconnectors of different ages, see figure 1. Every disconnector comprises six rotating terminal contacts that are measured via thermography once a year; the three centre main contacts are not included in the example. In this illustration this results in 600 measurement points. If a temperature rise above $X_{\text{max}}$ is discovered the contact is considered to be failed. The maintenance action for this failure mode is to replace the entire contact leaving it in an AGAN state. It is assumed that the saving of the measurements starts at an arbitrary point in time with an existing aged contact population, see figure 1.

In this illustration example the contact temperature rises are randomly generated from three different statistical distributions in three test cases. The parameter values used are based on laboratory [11] and field measurements [3] in order to generate realistic measurements. The parameters and distributions are chosen such that the method’s sensitivity to the input data may be analyzed. Table 1 summarizes the three test cases. In brief, the three distributions are, in Case 1, a Normal distribution with a mean and variance increasing with time. In Case 2 the measurements a generated from is a right skewed Weibull distribution with a large increasing variance and finally, in Case 3 the measurements are generated from a left skewed Weibull distribution with a small increasing variance. In test cases 2 and 3 the three parameter Weibull, as defined in [6], is used.

For illustration purposes it is assumed that all measurements were made at $>0.3 \cdot I_n$ and thus no measurements will be discarded due to low load. $X_{\text{max}}$ is set to 95 K (see Section 4) in all three cases.

Figures 2abc) illustrates the randomly generated temperature rise measurements, generated using the parameters in Table 1. The figure also shows the maximum temperature rise, $X_{\text{max}}$, as a solid line. The measurements are sorted by age and all points above the maximum temperature rise, $X_{\text{max}}$, are measurements of failed contacts. The figures 2abc) represents the outcome after carrying out steps 1, 2 and 3 from Section 5, i.e. collecting, cleaning and sorting. The figures 2abc) represent test cases 1, 2 and 3 respectively.

6.2 Results

This subsection shows the results after carrying out all 6 steps in Section 5 for the test case presented above.

Figure 2. Randomly generated temperature rise measurements for: a) Case 1 b) Case 2 c) Case 3

![Figure 2](image)

Figure 3. Reliability function fitted to survival probabilities for each year, Case 1.

![Figure 3](image)
Figure 3 shows the resulting reliability function fitted to the survival probabilities for Case 1, calculated for each age. The results in figure 3 follow steps 4, 5 and 6 in Section 5. In figure 3 the circles represent the probabilities, \( R(t|X) \), of exceeding the maximum temperature rise (failure) for each age, using (2). The solid line in figure 3 represents the estimated conditional reliability function, \( \hat{R}(t|X) \).

The results from the proposed method are compared to the MLE. In figure 4 the estimated p.d.f.’s, \( f(t|X) \), for the time to failure for all three test cases are shown both using the proposed method and the MLE. The time to failure is assumed to be Weibull distributed. When implementing the MLE only right censored and actual observations of the times to failure are used in the parameter estimation. The MLE was implemented using Matlab’s statistics toolbox [14]. Table 2 summarizes the comparison of the estimated Weibull parameters for the proposed method and the MLE, including the mean and variance.

Figure 5 shows the hazard rate estimated with the proposed method as well as the MLE. For comparison the empirical hazard rate is also included. The empirical hazard is simply the quotient of the number of failed contacts of a certain age and the total number of contacts of that age.

### Table 2 – Summary of results comparing the proposed method to the MLE (Weibull parameters)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Proposed method</th>
<th>MLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASE 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale, ( \hat{\eta} )</td>
<td>17.0</td>
<td>21.1</td>
</tr>
<tr>
<td>Shape, ( \hat{\beta} )</td>
<td>7.0</td>
<td>8.3</td>
</tr>
<tr>
<td>Mean, ( \mu )</td>
<td>15.9</td>
<td>19.9</td>
</tr>
<tr>
<td>Variance, ( \sigma^2 )</td>
<td>7.1</td>
<td>8.1</td>
</tr>
<tr>
<td>CASE 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale, ( \hat{\eta} )</td>
<td>20.0</td>
<td>22.0</td>
</tr>
<tr>
<td>Shape, ( \beta )</td>
<td>6.0</td>
<td>10.6</td>
</tr>
<tr>
<td>Mean, ( \mu )</td>
<td>18.6</td>
<td>21.0</td>
</tr>
<tr>
<td>Variance, ( \sigma^2 )</td>
<td>12.9</td>
<td>5.7</td>
</tr>
<tr>
<td>CASE 3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale, ( \hat{\eta} )</td>
<td>15</td>
<td>20.3</td>
</tr>
<tr>
<td>Shape, ( \beta )</td>
<td>13</td>
<td>7.4</td>
</tr>
<tr>
<td>Mean, ( \mu )</td>
<td>14.4</td>
<td>19.1</td>
</tr>
<tr>
<td>Variance, ( \sigma^2 )</td>
<td>1.8</td>
<td>9.2</td>
</tr>
</tbody>
</table>

### 6.3 Discussion

From the results in figures 4abc) and Table 2 it appears that the proposed method will always provide a more conservative estimate of the time to failure than will the MLE. The MLE on the other hand is very consistent due to the fact that the proportion of right censored observations is very similar in all three cases. The difference in the distribution of the temperature rises in figure 2 does not, to any large extent, effect the MLE parameter estimation. As can be seen from the results in figures 4abc) the proposed method is better reflecting the real world situation in figures 2abc) than the MLE. This is because the proposed method is considering the probability of survival given the contact age whereas the MLE is treating the contact age as the actual time of failure, even though the contact may have been failed for some time. Given this situation the proposed method is hence a more suitable method for estimating the time to failure compared to the MLE.
**7 CONCLUSIONS**

The main conclusion of the paper is that the proposed method will provide decision support for PM of high-voltage apparatus that may not be assessed directly by thermography, which may constitute a large proportion of the disconnector population. The aim of such a maintenance policy is to reduce the number of hidden contact failures in a disconnector population, hence reducing the risk of a catastrophic power system failure.

The benefit of the proposed method lies in its ability to not only use information on times to failure but also the information on how close to a failure a contact may be.

The proposed method is practical because it does not require any new measurements to be made, only to save those that are being made regularly anyway. A benefit with the proposed method is that as the number of accumulated measurement results will grow. Consequently, any predictions made are expected to improve in time.

The bias introduced by only using the measurements from the contacts with the highest load will most likely only have a marginal effect in practice since these contacts are less prone to over-heating due to their low loads.

**REFERENCES**

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Circuit-breaker failure data and reliability modelling
T. Lindquist, L. Bertling and R. Eriksson
Circuit Breaker Failure Data and Reliability Modelling

T.M. Lindquist, L. Bertling, and R. Eriksson.

Abstract: This paper presents results from an extensive study of SF₆ and minimum-oil circuit breaker failures in the Swedish and Finnish transmission systems. The study includes 1546 breakers with a total operating history of 16384 years. In the study a detailed analysis of a specific SF₆ breaker type with known problems revealed which parts caused the failures and an estimation of their hazard rates was made. This paper presents a complete reliability model for this type of breaker, illustrated by operating and maintenance history from a real shunt reactor breaker.

1 Introduction

Maintenance of power system equipment has become increasingly important to power utilities following the de-regulation of the electricity industry in many countries. Several methods to optimize and prioritize maintenance on the system level have been proposed [1],[2],[3]. This optimization requires knowledge about the way in which maintenance affects equipment reliability. Failure statistics and operational data are important sources of information when analyzing this relationship.

This paper focuses on circuit breakers (CB) since they consume a large proportion of the utilities' maintenance budgets and are critical to the system reliability.

Previous studies on CB failures include two major international surveys [4],[5]. The first survey included 77892 CB-years for all types of CBs. The second survey included 70708 CB-years and did only cover single-pressure SF₆ CBs. In [6] air-blast breakers failures were divided into three categories with regard to the cause of failure. A comprehensive study on air-blast breakers was presented in [7] were the CB failure rate dependence on different factors such as equipment age, voltage level, manufacturer and number of repairs was investigated. A literature search of older CB failure studies can be found in [8]. Furthermore, studies on CB failures caused by the control system have been investigated in [9] and [10].

This paper presents the results from a study of failures of SF₆ and minimum-oil CBs in the Swedish and Finnish transmission systems. The purpose of the study was to collect failure and maintenance data to a level of detail that made it possible to model the reliability for individual CB parts, thus also enabling modelling of the effect of maintenance on the CB reliability.

The paper is organized as follows: Section II presents some important definitions. Section III introduces input data requirements for CB reliability models. Section IV presents general CB population statistics. Section V explains the procedure of selecting a CB type for more detailed studies and Section VI illustrates the CB part hazard rate estimation. Section VII presents a simple method of modelling the effect of maintenance for a CB using the part hazard rates and Section VIII presents some conclusions that can be drawn from this study.

2 Definitions

In this paper failures of different CB parts are considered to be independent and the times to failure identically distributed. It is also assumed that maintenance actions take no time to perform.

The following definitions are adopted from [5],[11],[12]:

- Part: an item which is not subject to disassembly and is therefore discarded the first time it fails.
- Sub-component: a sub-system comprising several parts that are all replaced at sub-component replacement.
- Circuit breaker (CB) failure: complete failure of the CB which causes the loss of one or more of its fundamental functions.
- Corrective maintenance (CM): maintenance carried out after a failure has been recognized with the intention to restore the part to a state in which it can perform its required function.
- Preventive maintenance (PM): maintenance carried out with the intention to reduce the probability of failure or degradation on a part.

3 Input data for reliability models

The reliability models necessary to support power system maintenance optimization can be obtained either from experimental tests or from experience data, such as failure and maintenance reports [13]. In the CB case it is difficult and expensive for a power utility to carry out any experimental tests. Consequently, it is preferred that any model intended to be used by the utility is constructed using experience data.

A method of modelling reliability of CBs was presented in [13] where the required input data was failure and maintenance information on part level. The general
methodology is to build a model of the entire CB using reliability models of a small number of parts critical to the CB reliability.

4 Circuit breaker failure statistics

Failure data and maintenance records were collected for all SF6 and minimum-oil CBs from the Finnish transmission system during the period 1994-2005, and from the Swedish transmission system during the period 1999-2006. The voltage levels in Finnish transmission system are 110, 220 and 400kV, and 220 and 400kV in the Swedish transmission system. The total population of SF6 and minimum-oil CBs is 1546 and the total operating history is 16384 years.

The CB population data, failure data and maintenance records derive from the asset management and SCADA systems of the Swedish and Finnish transmission system operators (TSO).

4.1 Circuit breaker population

The average CB age in the population is 20.2 years and in Fig.1 the CB ages are plotted and divided per equipment voltage. Fig. 2 shows the same plot as in Fig.1 but with the age plot divided into SF6 and minimum-oil type CBs. The figure clearly indicates that the SF6 CBs are replacing the minimum-oil CBs. Fig. 3 shows the number of CBs with a specific CB function in the system divided into SF6 and minimum-oil CBs. In the figure the term ‘Reactor’ includes shunt reactor breakers and ‘Capacitor’ includes both shunt capacitor breakers as well as by-pass series capacitor CBs. From the figure it can be seen that the great majority of CBs in the two transmission systems are used as line breakers. In Fig. 4 the number of CBs per Original Equipment Manufacturer (OEM) is shown per country. In the two transmission systems’ OEMs A, C and E make up over 76% of all installed CBs. Only the OEMs with more than a total of 50 installed CBs are included in Fig. 4. Eight OEMs with a total of 91 installed CBs are not included in the figure.

4.2 Circuit-breaker failures

A CB failure is in this paper only defined as a failure if it is classified as a major failure using the definition in [5], which states: “Complete failure of a circuit-breaker which causes the lack of one or more of its fundamental functions”. Furthermore, only failures on primary equipment are considered, i.e. auxiliary contacts, control systems and relays are not included. Failures on the control system are considered a separate issue and have been studied in [9] and [10]. The only sub-components considered in this paper are the interrupter, the interruptive media, the operating mechanism and the isolators.

A total of 212 CB failures occurred during the studied period. A summary of the CB failures and failure frequencies per voltage level is found in Table 1. It can be seen from the table that the failure frequency increases with the system voltage. This result was also found in [5]. The ‘Unknown’ label in the table means that no information on voltage level had been entered in the database.
Table 1. Failure frequencies by voltage level

<table>
<thead>
<tr>
<th>Voltage [kV]</th>
<th>Number of failures</th>
<th>Sample size [CBYrs]</th>
<th>Failure frequency [Failures/100CBYrs]</th>
</tr>
</thead>
<tbody>
<tr>
<td>110</td>
<td>86</td>
<td>8940</td>
<td>0.96</td>
</tr>
<tr>
<td>220</td>
<td>29</td>
<td>2512</td>
<td>1.15</td>
</tr>
<tr>
<td>400</td>
<td>97</td>
<td>4884</td>
<td>1.99</td>
</tr>
<tr>
<td>Unknown</td>
<td>0</td>
<td>48</td>
<td>0.00</td>
</tr>
<tr>
<td>Total</td>
<td>212</td>
<td>16384</td>
<td></td>
</tr>
</tbody>
</table>

5 Selecting a CB type for reliability modelling

It is very difficult to obtain all the required data for modelling the reliability of CBs and therefore this paper illustrates only one CB type. The following sub-section explains the procedure for selecting the CB to be modelled.

5.1 Selection process

Table 2 shows the number failures and the failure frequency per CB function in the system. The table indicates that the shunt reactor breakers have a significantly higher failure frequency than all other CB functions in the two studied transmission systems. The following analysis will consequently only consider shunt reactor breakers.

In addition, the shunt reactor breaker population is to 73% made up of SF6 CBs from OEM A (see Fig. 4), which is why only CBs manufactured by this company will be considered henceforth.

Fig. 5 shows the CB sub-components that caused the failures during the studied period for the selected SF6 CB by OEM A. From the figure it is clear that it is the operating mechanism that causes a majority of all failures for this type of CB. The following analysis will therefore focus on the operating mechanism. The first design of this specific operating mechanism was known to have problems and was therefore re-designed. These two designs are vastly different and need to be treated separately. However, since no failures have been reported for the new design during the studied period the following analysis will only focus on the old operating mechanism design.

It is well known that not only calendar age but also the number of operations (an operation is defined as an open-close cycle) are significant in the CB aging process, especially when it comes to the operating mechanism [15].

Table 2: Failure frequencies by CB function in the system

<table>
<thead>
<tr>
<th>CB function</th>
<th>Number of failures</th>
<th>Sample size [CBYrs]</th>
<th>Failure frequency [Failures/100CBYrs]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line</td>
<td>115</td>
<td>10992</td>
<td>1.05</td>
</tr>
<tr>
<td>Busbar</td>
<td>17</td>
<td>1688</td>
<td>1.01</td>
</tr>
<tr>
<td>Shunt reactor</td>
<td>49</td>
<td>344</td>
<td>14.24</td>
</tr>
<tr>
<td>Shunt cap.</td>
<td>8</td>
<td>332</td>
<td>2.41</td>
</tr>
<tr>
<td>Transformer</td>
<td>19</td>
<td>2796</td>
<td>0.68</td>
</tr>
<tr>
<td>Other</td>
<td>0</td>
<td>84</td>
<td>0.00</td>
</tr>
<tr>
<td>Unknown</td>
<td>4</td>
<td>148</td>
<td>2.70</td>
</tr>
<tr>
<td>Total</td>
<td>212</td>
<td>16384</td>
<td></td>
</tr>
</tbody>
</table>

This is supported by Table 3 which shows the failure frequencies of CBs with operating frequencies stratified into two groups. In the table the two CBs groups are CBs with operating frequencies: >50 operations/year and <50 operations/year. It is clear that the CBs with the higher operating frequency cause more CB failures for this CB type.

Fig. 6 shows what parts caused the operating mechanism failures for the selected CB type. It can be seen from the figure that two parts caused the majority of the operating mechanism failures, namely the open- and close-operation locks. The CB parts in the graph in Fig. 6 have been divided into two groups based on the CB operating frequency. The parts in CBs with an operating frequency of >50 operations/year caused a majority of the operating mechanism failures, motivating a further analysis focused on these. Moreover, the two groups of failures on the close-operation lock did not have the same failure mode and must therefore be treated separately. The appropriate age measure for the operating mechanisms with the higher operating frequency (>50 operations/year) is the number of operations [15].

5.2 Summary

The CB type that was selected for further investigation was an SF6 CB by OEM A with an operating mechanism of the old design. Only the CBs with an operating frequency >50 operations/year are included. In the following analysis this paper will only apply to the selected CB type.

Table 3: Failure frequencies by operating frequency

<table>
<thead>
<tr>
<th>CB operating frequency</th>
<th>Average failure frequency [Failures/100CB-years]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total CB population</td>
<td>0.5</td>
</tr>
<tr>
<td>(of the selected type from OEM A)</td>
<td></td>
</tr>
<tr>
<td>&lt; 50 operations/year</td>
<td>0.5</td>
</tr>
<tr>
<td>≥ 50 operations/year</td>
<td>26.4</td>
</tr>
</tbody>
</table>
Part reliability modelling

In this paper the hazard rate is used to quantify reliability. The hazard rate is a measure of the probability that a part, still working at age $t$, is about to fail. Applying this measure to the individual parts of the CB enables modelling of the reliability of the entire equipment.

6.1 Part hazard rate estimation

The parts identified as critical to the CB reliability in the previous section are the Open- and Close-operation locks (see Fig. 6). In order to capture and model the CB failures caused by other parts, these are grouped into one part called Remaining parts. Unlike the other two parts were it is assumed that they are replaced after failure leaving the part in an As Good As New (AGAN) state, the remaining parts are assumed to be in an As Bad As Old (ABAO) state after CM. Hence, it is assumed that maintenance on the remaining parts will have no effect on the CB reliability.

The available information obtained from the asset management databases of the Swedish and Finnish TSOs only includes information on failures and maintenance during the studied period except for the CB manufacturing year. Hence, there is a gap in the information from the CB manufacturing year up until the start of the studied period.

In this paper the start of the studied period (1999-01-01 for Sweden and 1994-01-01 for Finland) is used as the ‘beginning of time’ for the CB parts i.e. $t=0$, when the part hazard rates are estimated. This results in a conservative estimation of the time to failure. One alternative to this method is to use the CB manufacturing year as $t=0$, it is however, in this case the lesser option. During the studied period 43% of the CBs, of the selected type, had at least one failure and it is therefore reasonable to assume that they have failed previous to the start of the studied period as well. Using the manufacturing year as $t=0$ assumes no failures from that year to the start of the studied period and this would underestimate the hazard rate.

In this paper it is assumed that the times to failure for parts are Weibull distributed. This assumption is supported by findings for air-blast breakers in [7]. In order to test that assumption, the failures for each CB part are plotted using a Weibull probability plot, in which the data are assumed to be Weibull distributed if the plot is linear. Fig. 7abc) shows the probability plots for the Close- and Open operation locks and Remaining parts for the CBs of the selected type with an average operating frequency of $\geq 50$ operations/year. The remaining parts are all other parts that are not the open- or close-operation locks. From the linear plots in Fig. 7abc) we may assume that the failures are Weibull distributed. Consequently, the density function for time to failure for part $i$ is [16]

$$f_i(x_i) = \frac{\beta_i}{\eta_i} \left( \frac{x_i}{\eta_i} \right)^{\alpha_i-1} \exp \left( -\left( \frac{x_i}{\eta_i} \right)^{\alpha_i} \right) \quad \text{for } x_i \geq 0 \quad (1)$$

where $\beta>0$ and $\eta>0$ are the Weibull shape and scale parameters and $x_i$ is the part age measured in the number of accumulated operations. The hazard rate is then [16]

$$h_i(x_i) = \frac{\beta_i}{\eta_i} \left( \frac{x_i}{\eta_i} \right)^{\alpha_i-1} \quad (2)$$

The Weibull parameters were estimated by the Maximum Likelihood Method (MLM), using the Statistics Toolbox in Matlab [17]. The result from this estimation is found in Table 4, where the scale parameter is in the number of accumulated operations. The data used in the parameter estimation can be found in Appendix A.

![Fig. 6 Parts in the operating mechanism causing failures to the OEM A SF6 CB by average operating frequency](image)

![Fig. 7abc) Weibull probability plot for the critical parts of OEM A SF6 CB](image)
Table 4: Estimated Weibull parameters for the critical CB parts

<table>
<thead>
<tr>
<th>CB part</th>
<th>Shape, $\hat{\beta}$</th>
<th>Scale, $\hat{\delta}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Close-operation lock</td>
<td>1.8</td>
<td>2206</td>
</tr>
<tr>
<td>Open-operation lock</td>
<td>2.1</td>
<td>2485</td>
</tr>
<tr>
<td>Remaining</td>
<td>1.6</td>
<td>2955</td>
</tr>
</tbody>
</table>

7 Illustration of CB reliability as a function of maintenance

In order to illustrate the usefulness of the part hazard models obtained in the previous section, a complete CB reliability model will be presented in this section. The model only applies to the CBs of the type that was selected in Section 5. The aim of such a model is to model the reliability of an individual CB given its operational and maintenance history.

The purpose of this type of reliability model is to predict an increasing probability of failure so that the appropriate maintenance actions may be carried out prior to a CB failure.

7.1 Circuit-breaker reliability model

Using the estimated Weibull parameters a complete CB reliability model can be found by using the conditional failure intensity [14]

$$\dot{\lambda}(t | H^n) = \sum_{i=1}^{n} \dot{h}(x_i) + \sum_{j=1}^{m} \dot{h}(x_j)$$  \hspace{1cm} (3)

where $\dot{h}(x)$ are the part hazard rates and it is assumed that the open- and close-operation locks are considered replaceable ($n=2$) and the remaining parts are considered non-replaceable ($m=1$).

7.2 Example

This sub-section presents an example of a reliability model applied to a shunt reactor breaker in the Swedish transmission system. The CB is an SF$_6$ breaker of the type selected in Section 5. It is 18 years old and has an average operating frequency of 346 operations/year. The CB had its open-operation mechanism replaced due to a failure after 10 years. In Fig. 8 the CB conditional failure intensity from (3) is depicted. In the figure the effect of the corrective replacement of the open-operation mechanism at $t=10$ can be seen. The figure also shows the effect of carrying out a number of preventive maintenance actions at the current age of 18 years.

The PM actions are:

- Function test, including measuring of contact resistances and contact travel speeds, etc.
- Open-operation lock replacement.
- Close-operation lock replacement.
- Operating mechanism replacement, replacing the entire operating mechanism including the open- and close-operation locks.

The figure shows that replacing the entire operating mechanism has the largest impact on the CB reliability. The next best action is to replace the close-operation lock. The replacement of the open-operation lock is less effective due to the fact that it was replaced only eight years earlier. The function test does not improve the CB reliability.

In order to optimize CB PM based on this model it is necessary to include the importance of the CB to the system as well as the costs of each maintenance action.

8 Conclusions

This paper presents results from a survey on CB failures for SF$_6$ and minimum-oil CBs in the Swedish and Finnish transmission systems. General conclusions from the study are that the average failure frequency increases with the CB voltage level and that the number of operations has a large impact on CB reliability.

The detailed study of the selected SF$_6$ CB failures demonstrated that it is possible to model the reliability of both individual CB parts as well as the entire CB as a function of the number of operations. The study also shows the possibility of modelling the effect of PM on CB reliability.

Note that the CB model presented in this paper only applies to the selected SF$_6$ CB with the operating mechanism of the old design. The presented methodology may however, be applied to other CB types.

9 Appendix A

Table 5: Failure data for parts with $T=50$ ops/year for the old design operating mechanism

<table>
<thead>
<tr>
<th>Close-operation lock, [# of ops]</th>
<th>1745</th>
<th>437</th>
<th>152</th>
<th>141*</th>
<th>315*</th>
<th>944*</th>
<th>432*</th>
</tr>
</thead>
<tbody>
<tr>
<td>705</td>
<td>673</td>
<td>592*</td>
<td>2332*</td>
<td>1080*</td>
<td>1152*</td>
<td>1381*</td>
<td>1985*</td>
</tr>
<tr>
<td>1196</td>
<td>1670</td>
<td>1572*</td>
<td>151*</td>
<td>1381*</td>
<td>1985*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1892</td>
<td>1937</td>
<td>836*</td>
<td>204*</td>
<td>888*</td>
<td>2089*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Open-operation lock, [# of ops] | 606 | 511*| 1080*| 944* | 2085*||
|---------------------------------|-----|-----|------|------|------|
| 756                              | 2013| 1381*| 1152*| 432* |

<table>
<thead>
<tr>
<th>Remaining, [# of ops]</th>
<th>1328</th>
<th>1180</th>
<th>849*</th>
<th>2010*</th>
<th>1080*</th>
<th>2089*</th>
<th>1985*</th>
</tr>
</thead>
<tbody>
<tr>
<td>910</td>
<td>718</td>
<td>2280*</td>
<td>106*</td>
<td>1381*</td>
<td>432*</td>
<td>944*</td>
<td></td>
</tr>
<tr>
<td>554</td>
<td>600</td>
<td>2636*</td>
<td>1409*</td>
<td>888*</td>
<td>1366*</td>
<td>1152*</td>
<td></td>
</tr>
</tbody>
</table>

(*) right censored observation
10 Acknowledgment
The authors would like to express their gratitude to Mr. Per Larsson (Svenska Kraftnät) and Mr. Pasi Yli-Salomäki (Fingrid) for providing access to valuable data, and to Dr. Per Pettersson for interesting and helpful discussions.

11 References


A practical method for benefit/cost analysis of preventive maintenance tasks in power system equipment
T. Lindquist, L. Bertling and R. Eriksson
A practical method for benefit/cost analysis of preventive maintenance tasks in power system equipment

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Abstract—This paper proposes a practical method for prioritization of preventive maintenance tasks for power system equipment based on equipment reliability and benefit/cost analysis. The method involves a procedure to rank equipment parts by their criticality to the equipment reliability as well as a technique to quantify the effect of a preventive maintenance task on equipment reliability. The proposed method is illustrated by a case study of high-voltage circuit-breakers in the Swedish and Finnish transmission systems, in which failure statistics and maintenance records for 351 SF6 circuit-breakers with a total operating history of 3432 years are analyzed. The method is used to suggest cost-effective PM tasks for three shunt-reactor circuit-breakers in the Swedish transmission system. One of the main advantages of the method is that it does not require any quantitative assumptions regarding the effect of maintenance.

Index Terms—Circuit breakers, Cost effectiveness, Hazard rate, Maintenance modeling, Preventive maintenance, Reliability modeling, Virtual age.

I. NOMENCLATURE

$t$ Equipment age measured in appropriate units (e.g. total operating time, number of operations etc.)

$x_i(t)$ Age of part $i$ measured in appropriate units (e.g. total operating time, number of operations etc.), $x_i(t)=x_i$ for simplicity

$h(x)$ Part hazard rate

$H(x)$ Cumulative hazard function

$f(x)$ Probability density function

$F(x)$ Cumulative density function

$s(t)$ Failure intensity

$s(t|H)$ Conditional failure intensity

$N(t)$ Number of equipment failures in the interval $[0,t]$

$H$ Complete equipment history up to time $t$

$n$ Number of parts in a series equipment reliability model

$m$ Number of maintenance actions carried out on a part

$k$ Type of maintenance action (part replacement, adjusting, cleaning etc.)

$p$ Equipment critical to the power system reliability

$e_m$ Degree of repair for the $m$th maintenance task on part $i$

$v_{ai}$ Virtual age of part $i$ after the $m$th maintenance

$M_k$ Relative gain from PM task of type $k$ for part $i$

$D_i$ Necessary PM gain for PM type $k$ for part $i$

$c_k$ Effect of PM task of type $k$ on the equipment reliability

$K_{ijk}$ Impact of part $j$ on the equipment reliability including its rank $r$

$\text{ETNF}$ Expected time to failure for a piece of equipment

$\bar{f}$ Average circuit-breaker operating frequency

$C_p^M$ Cost of performing PM task of type $k$ for part $i$

$C_p^{\text{REP}}$ Cost for the power system operator of having equipment $p$ off-line

$C_p^{\text{TOT}}$ Total cost of PM task of type $k$ for part $i$

$C_i^{\text{REP}}$ Cost of the most cost-effective replacement for part $i$

$\eta$ Scale parameter for the Weibull distribution

$\beta$ Shape parameter for the Weibull distribution

II. INTRODUCTION

Preventive maintenance (PM) for power system equipment is a complex matter. Decision makers need to be able to quantify the effect and cost-effectiveness of PM, estimate equipment importance as well as prioritize different PM tasks, taking into account budget and resource constraints.

Previous research on PM decision making in electric power systems (excluding power generation plants) include studies on the impact of maintenance related to the cost and reliability of the power system [1], probabilistic evaluation of the effect of maintenance using multi-state Markov models [2], optimizing resources for power system maintenance [3], prioritizing maintenance based on power system reliability [4] and scheduling line maintenance by minimizing the transmission provider’s loss of revenue [5]. Such methods require understanding of advanced mathematical techniques and render the results difficult for maintenance engineers and
managers to interpret. Methods like these often require input information not readily available, which make them harder to implement in practice [6]. In addition, they often rely on important assumptions (e.g., that the effect of PM tasks on equipment reliability is known) that may seem unrealistic. Consequently, these methods are not regularly used for maintenance planning in power system companies [6]. Other industries also experience similar challenges where advanced mathematical techniques are not implemented in actual maintenance decision making [7][8]. Even though the existing models are perceived to be too complicated by maintenance practitioners, overly simplified models such as those considering constant hazard rates are not useful for PM planning purposes [6].

The PM prioritization method proposed in this paper provides a novel approach to the PM planning problem facing maintenance planners in the power system industry. Rather than optimizing a PM schedule, which often implies making fairly strong assumptions regarding the effect of PM tasks on equipment reliability, the proposed method provides decision support by identifying which PM tasks are most cost-effective. These results are presented to the maintenance planner who then has to make the final decision on which tasks should be carried out. Previous research shows that such methods gain more acceptance among maintenance planners than the more complex mathematical methods [9].

The proposed method is a further development of the second stage of the Reliability Asset Centered Maintenance (RCAM) method [1].

In conclusion, the method provides a practical evidence-based method of prioritizing PM tasks for power system equipment. One of the main advantages of the proposed method is that it does not require any quantitative assumptions regarding the effect of maintenance.

III. THEORY FOR RELIABILITY AND MAINTENANCE MODELING

A. Definitions

The definitions are adopted from [1],[11]:

- Part: an item which is not subject to disassembly and is therefore discarded the first time it fails.
- Sub-component: A sub-system comprising several parts that are all replaced at sub-component replacement.
- Socket: a circuit or equipment position which, at any given time, holds a part of a given type.
- System: a collection of two or more sockets and their associated parts, interconnected to perform one or more functions.
- Non-repairable system: a system which is discarded after the first time that it ceases to perform satisfactorily.
- Repairable system: a system which, after failing to perform at least one of its required functions, can be restored to performing all of its required functions by any method other than replacement of the entire system.
- Power system equipment: a functional unit with a well-defined function in a power system. (In a power system scope, equipment is the equivalent of a power system component).
- Preventive maintenance: maintenance carried out with the intention to reduce the probability of failure or degradation a part.
- Corrective maintenance: maintenance carried out after a failure has been recognized with the intention to restore the part to a state in which it can perform its required function.

B. Modeling Reliability

1) Hazard rate

The hazard function \( h(x_i) \) for part \( i \) can be written

\[
 h(x_i) = \lim_{\Delta t \to 0} \frac{P\{x_i \leq X_i < x_i + \Delta x_i \mid X_i \leq x_i \}}{\Delta x_i}, \quad x_i \geq 0
\]  

(1)

where \( x_i \) is the age of part \( i \), measured in appropriate units. The hazard function is the limit of the probability that a part fails (for the first and only time) in a small interval, given survival to the beginning of the interval.

For a series system comprising \( n \) parts, the hazard function for the time to failure of the system is

\[
 h(t) = \sum_{i=1}^{n} h_i(t)
\]  

(2)

where \( h_i(t) \) is the hazard rate of part \( i \) in the series system.

2) Failure intensity

Let \( N(t) \) be the number of failures on the equipment in the interval \((0,t)\). The intensity function for the counting process \( N(t) \) is given by

\[
 \lambda(t) = \lim_{\Delta t \to 0} \frac{P\{N(t + \Delta t) - N(t) = 1\}}{\Delta t}
\]  

(3)

The failure intensity has the simple interpretation that \( \lambda(t) \Delta t \) is approximately the probability that a failure, not necessarily the first, occurs in \((t, t + \Delta t)\).

The intensity \( \lambda(t) \) is the statistical mean of the intensity process at time \( t \) and applies primarily to reliability prediction during the system design phase. During that phase no information is available on failures or maintenance [12]. To be able to model the behavior of a specific system whilst in service, the model must include the system history. Such a model is defined by the conditional intensity process \( \lambda(t \mid \mathcal{H}) \) of the counting process \( N(t) \).

Let \( \mathcal{H} \) be the complete history of the system up to, but not including, time \( t \). This history incorporates all available information on events not fixed by time \( t \), such as maintenance activity and failures of the system up to time \( t \). This information will consist of at least two elements: the time...
elapsed since the last PM or Corrective Maintenance (CM) for all parts and the part hazard [12]. Thus, given that the system has a specific history \( H \) at time \( t \geq 0 \) (i.e. the moment just before but not including \( t \)), the probability of at least one failure occurring in \([t,t+\Delta t]\) is approximately \( \lambda(t)H \Delta t \). The conditional failure intensity process is defined as

\[
\lambda(t | H') = \lim_{\Delta t \to 0} \frac{P[N[t(t-0)+\Delta t]-N[t-0]=1 | H']}{\Delta t}
\]

The conditional intensity process is completely determined by the part ages, \( x_i \), and the parts’ different inherent hazard rates through the relation [12]

\[
\lambda(t | H') = \beta(t)
\]

The conditional intensity process may be interpreted as a sequence of truncated hazard functions updated by each CM and the principle is that a maintenance action on part \( i \) rejuvenates it to the extent that its conditional failure intensity at time \( t \) is equal to the intensity at a virtual age \( V_{im} \), where \( V_{im} \sim t \). A new piece of equipment is put into service at \( t=0 \) and similarly a new part has a specific history \( V_{t0} \) before but not including \( t \). For the Weibull distribution the characteristic life is defined as the point in time when the cumulative hazard function is equal to one for a series system is the expected time to next failure \( ETNF \). The characteristic life is also the value of the scale parameter, \( \eta \), thus \( F(n)=0.632 \) [16]. The point in time when the cumulative hazard function is equal to one for a series system is the Expected Time to Next Failure, \( ETNF \). The \( ETNF \) for a series system is given by \( t \) such that [15]

\[
\sum_{i=1}^{n} H_i(V_{im}+t) - \sum_{i=1}^{n} H_i(V_{im}) = 1, \quad t = ETNF
\]

### 3) Expected Time to Next Failure

The cumulative hazard function for part \( i \) is given by

\[
H_i(V_{im}) = \int_{0}^{t} h_i(V_{im})dV = -\ln[R(V_{im})]
\]

and for a part that has survived until the virtual age \( V_{im} \), the cumulative hazard is given by

\[
H_i(V_{im} + t | V_{im}) = H(V_{im} + t) - H(V_{im})
\]

For a series system comprising \( n \) parts at equipment age \( T \) the cumulative hazard function is given by [15]

\[
H(T+t | T) = \sum_{i=1}^{n} H_i(V_{im} + t | V_{im}) = \sum_{i=1}^{n} H_i(V_{im} + t) - \sum_{i=1}^{n} H_i(V_{im})
\]

The age of a part when the cumulative hazard function is equal to one is often referred to as the characteristic life. The characteristic life is defined as the point in time when approximately 63.2\% of all parts in a population have failed if installed at the same time. For the Weibull distribution the characteristic life is also the value of the scale parameter, \( \eta \), thus \( F(\eta)=0.632 \) [16]. The point in time when the cumulative hazard function is equal to one for a series system is the Expected Time to Next Failure, \( ETNF \). The \( ETNF \) for a series system is given by \( t \) such that [15]

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\sum_{i=1}^{n} H_i(V_{im} + t) - \sum_{i=1}^{n} H_i(V_{im}) = 1, \quad t = ETNF
\]

### 4.2 Modeling the Effect of Maintenance

#### 1) Equipment Reliability Modeling

In this paper power system equipment is modeled as a repairable system comprising only the parts most critical to the equipments’ reliability connected in series. Any maintenance carried out is assumed to take negligible time. Furthermore, it is assumed that there is only one failure mechanism per part at any one time.

#### 2) Virtual Age

The concept of virtual age was first introduced in [14], where two virtual age models were presented. The method proposed in this paper uses the second model commonly referred to as the Kijima II model.

These types of models are called reduction of age models and the principle is that a maintenance action on part \( i \) rejuvenates it to the extent that its conditional failure intensity at time \( t \) is equal to the intensity at a virtual age \( V_{im} \). For the Weibull distribution the characteristic life is defined as the point in time when approximately 63.2\% of all parts in a population have failed if installed at the same time. For the Weibull distribution the characteristic life is also the value of the scale parameter, \( \eta \), thus \( F(\eta)=0.632 \) [16]. The point in time when the cumulative hazard function is equal to one for a series system is the Expected Time to Next Failure, \( ETNF \).

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\[
\sum_{i=1}^{n} H_i(V_{im} + t) - \sum_{i=1}^{n} H_i(V_{im}) = 1, \quad t = ETNF
\]
The cost-effectiveness of PM task $k$ is

$$M_k = \frac{e_k}{C_{PM}^k + C_{OL}^k}$$

where $C_{PM}^k$ is the cost of carrying out PM task $k$ including labor and spares. $C_{OL}^k$ is the cost of taking equipment $p$ off-line during PM, which may include the cost for the reduced security in the network. The total cost of a PM task is then $C_{TOT}^k = C_{PM}^k + C_{OL}^k$.

IV. PROPOSED METHOD FOR PRIORITIZATION OF PM TASKS

A. Method Summary

The proposed method works by breaking the equipment down into critical parts and modeling the equipment as a series system comprising these parts. Each PM task for a critical part is then evaluated against part replacement, for which both the cost and effect on equipment reliability is known. Rather than estimating the quantitative impact of the PM task on equipment reliability (which is extremely difficult in most cases) the proposed method only requires qualitative engineering judgment on whether the effect of the task is greater than a minimal value or not. The result is used to accept or reject the hypothesis that the task is cost effective when compared to part replacement. If a task is found non-effective and the hypothesis is rejected, it can then be excluded from further analysis. If the hypothesis is not rejected the task is kept in the analysis and the minimum effect of the maintenance is calculated. The proposed method is a practical way of evaluating all available PM tasks (both existing and future) and provides a list of possible PM tasks for each piece of equipment in the system. The final decision on which task should be carried out is made by the maintenance engineer.

This section explains the proposed method of identifying cost-effective and non-cost-effective PM tasks in some detail. Briefly the method comprises five steps:

0. Identification of equipment critical to the power system reliability
1. Collection of data and model part reliability
2. Ranking of failed parts by their criticality
3. Definition of PM tasks and removal of all PM tasks found to be non-cost-effective
4. Ranking remaining PM tasks by their cost-effectiveness

Fig. 1 shows a detailed flowchart of the proposed method. The following subsections will explain each part of the method in detail.

Step 0. Identify equipment critical to the power system reliability

Even a relatively small power system comprises hundreds of different types of equipment. With a limited budget for PM it is important to identify the equipment most critical to the system and focus the PM on that equipment. This task, however, falls outside of the scope of this paper but there are many methods described in the literature on how to identify critical power system equipment e.g. [17],[18]. This step is labeled zero since it is to be carried out before the proposed method may be applied.

Step 1. Collect data and model part reliability

In order to develop statistical models describing the reliability of the different parts in the power system, equipment data is needed. The data should ideally comprise the complete histories of the equipment, including times of
failure and maintenance, both PM and CM. Information on which part caused each failure is also necessary. Before any modeling may take place the data needs to be cleared of errors that invariably exist. This procedure must be carried out thoroughly since data cleaning is of crucial importance to obtain accurate models.

The identification of failed parts based on failure statistics requires expert knowledge and good engineering judgment.

The reliability of each part is modeled using statistical models and may often be estimated using standard methods, such as Weibull analysis [16]. The hazard function as defined in (1) needs to be estimated for each part.

When sufficient failure data is not available e.g. in cases where a new piece of equipment has not yet failed, a methodology based on Bayesian statistics may be implemented [19]. Using such a method a prior distribution for the time to failure is estimated using results from the manufacturer during equipment development. This prior information is updated as failure data becomes available. If no prior information may be obtained a non-informative prior may be used [20].

Step 2. Rank failed parts by their criticality to the equipment reliability

When all failed parts have been identified and modeled their criticality needs to be estimated.

Fig. 2 shows a detailed flowchart of the proposed method to rank the parts by their criticality to the equipment reliability. The first step is to calculate $ETNF^{New}$ for the AGAN equipment $p$ by finding $ETNF^{New}$ such that

$$\sum_{i=1}^{N} H_i(t) = 1, t = ETNF^{New}$$

(15)

The subsequent analysis follows a “take one out” methodology. Part $l$ is removed from the analysis and $ETNF$ is calculated

$$\sum_{j \neq l} H_j(t) = 1, t = ETNF$$

(16)

The criticality for part $l$, $K_c$ is then identified by taking the difference of $ETNF$, (part $l$ removed) and $ETNF^{New}$ (with all parts included), i.e. the impact of part $l$ on the equipment $ETNF$ is calculated

$$K_l = ETNF - ETNF^{New}$$

(17)

The value of $K_l$ indicates how much the equipment $ETNF$ will increase if part $l$ does not fail in the in the interval $(0,x]$ i.e. the part cumulative hazard is $H(x) = 0$. The part criticality calculations are subsequently repeated for all parts. The final ranking of the parts are made such that

$$K^{(1)} > K^{(2)} > \ldots > K^{(n)} > ETNF^{New}$$

(18)

where $n$ is the number of critical parts in the model, the most critical part is $K^{(1)} = \max \{K_1, K_2, \ldots, K_n\}$. In case many critical parts are identified it may not be necessary to include them all to obtain an accurate equipment model. In such cases only the parts with the highest criticality ranking will be included.

Since the part hazard rates have already been estimated the conditional failure intensity of the equipment is found by (6).

Step 3. Define PM tasks and remove all PM tasks found to be non cost-effective

This step includes rejecting or not rejecting PM tasks based on their relative cost-effectiveness, $M$. This methodology is shown in detail in a flowchart in Fig. 3. First, the PM tasks are divided into two groups: replacement and non-replacement tasks. The replacement group includes all types of replacement that will affect the critical part in any way (i.e. it not only includes replacement of the actual part but also the replacement of potential sub-components in which the part may be included). The non-replacement group includes all other PM tasks such as cleaning, lubricating and adjusting, etc. The cost effectiveness of the replacement tasks is found by (14). Only the most cost-effective replacement task is kept while the others are discarded.

Consequently, all non-replacement PM tasks are evaluated with respect to the replacement task. It is assumed that a non-replacement task cannot improve the critical part to a state better than AGAN. If the total cost of a non-replacement PM task exceeds that of the replacement task, it is removed from the analysis.

The next step, in the flowchart shown in Fig. 3, is to
calculate the necessary PM gain, \( D \)

\[
D_k = \frac{\frac{C_{\text{TOT}}}{C_{\text{p}}} \cdot \frac{100}{C_{\text{p}}}}{1}
\] (19)

\( D \) is the minimum PM gain, expressed as % of the ETNF for a part replacement, in order for PM task \( k \) to be cost-effective. The maintenance engineer will then have to judge whether this PM gain is realistic or not, i.e. should the hypothesis that PM task \( k \) is cost-effective be rejected or not. If the hypothesis is rejected the PM task is removed and if it is not rejected it will be one of the recommended PM tasks on the final list.

The method assumes that a replacement task is available for every critical part. If no replacement task may be carried out for the part it cannot be evaluated using the proposed method.

**Step 4. Rank remaining PM tasks by their cost-effectiveness**

In the final step of the proposed method a list of all cost-effective PM tasks for each critical part is compiled and presented to the maintenance engineer. This list is to be used as decision support both when planning PM with established PM methods but also when deciding whether a new PM method should be introduced.

V. **CASE-STUDY FOR CIRCUIT BREAKERS**

A. **Summary**

The proposed method is illustrated in a case-study using real failure and maintenance data for a specific type of SF\(_6\) high-voltage circuit breakers (CB) in the Swedish and Finnish transmission systems. The failure data and maintenance records are used to estimate part hazards which are then used to model the entire CB. The method is used to suggest cost-effective PM tasks for three shunt-reactor CBs in the Swedish transmission system.

B. **Case description**

In order to illustrate the proposed method it has been applied to three 400kV SF\(_6\) shunt-reactor CBs in the Swedish transmission system. Table 1 shows the CB histories. These CBs were selected because they have the same age but different histories and operating frequency.

C. **CB Failure statistics**

Failure data was collected for a specific type of CB in the Swedish and Finnish transmission system. The CB is an SF\(_6\) CB and is of a make and model that is common in both Sweden and Finland. This is the only CB type treated in this paper. The failure data was collected for the years 1999 to 2006 for Sweden and from 1994 to 2005 for Finland. The voltage levels are 220 and 400kV for Sweden and 110, 220 and 400 kV for Finland. The total population of this specific CB type in the two countries consists of 351 (195 in Sweden and 156 in Finland) CBs.

![Fig. 4. Number of CB failures per sub-component and CB function in the power system.](image-url)
TABLE 1. BRIEF CB HISTORY.

<table>
<thead>
<tr>
<th>CB ID</th>
<th>Age, t [years]</th>
<th>$\tilde{f}$ [ops/year]</th>
<th>Brief CB history</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18</td>
<td>103</td>
<td>Corrective replacement of the close-operation lock at age=15</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>346</td>
<td>Corrective replacement of the open-operation lock at age=10,</td>
</tr>
<tr>
<td>3</td>
<td>18</td>
<td>118</td>
<td>Scheduled function tests only.</td>
</tr>
</tbody>
</table>

and 156 in Finland) CBs. The survey for this specific CB type comprises 3432 CB years in total and is an extension of a study of CB failures carried out in [21]. During the studied period there were a total of 31 CB failures for this CB type. The average failure frequency was 0.9 failures/100CB-years.

Fig. 4 shows the number of failures for the different CB sub-components, as well as the function of the failed CB. The Fig. shows that failures on the operating mechanism are far more common that any other type of failure. This result is in line with that of previous CB failure surveys [22],[21]. The ‘Unknown’ label indicates that it was not possible to identify what part of the CB caused the failure.

CBs manufactured from the mid-1990’s and onwards have been equipped with a new operating mechanism design. This mechanism has had no failures in the studied period hence all failures are on the old design operating mechanism. As seen in Fig. 4 all 21 operating mechanism failures have been caused by two parts: close-operation lock (17 failures) and open-operation lock (4 failures).

From Fig. 1 it can be seen that shunt-reactor CBs cause a majority of failures. This is simply due to the fact that they operate more frequently than other CBs such as line or bus-bar CBs. Therefore it makes sense to investigate the impact of the CB operating frequency on the reliability. The CB population was stratified into two groups based on their average operating frequency, $\tilde{f}$, below and above 50 operations/year, where an operation is defined as an open-close cycle. Table 2 shows the average failure frequency for each stratum. From Table 2 it is clear that the CBs with $\tilde{f}$ $\geq$ 50 ops/year are more important than the other from a PM perspective.

In the total population of 351 CBs only 24 have $\tilde{f}$ $\geq$ 50 ops/year. Of these 24 CBs, 16 are equipped with the old design operating mechanism. Of these 16 CBs, 7 have had at least one failure in the studied period. From here on this paper will only focus on those CBs with $\tilde{f}$ $\geq$ 50 ops/year equipped with the old design operating mechanism.

D. Hazard rate estimation

The final CB reliability model is made up of three critical parts: Close-operation lock, Open-operation lock and Remaining, which includes all other CB parts. Both the open- and close-operation locks are situated in the operating mechanism and for the hazard rate estimation we are only concerned with the old design of the operating mechanism.

It is assumed that the times to failure are Weibull distributed and independent. Since no data before the studied time period is known the CB age is set to the start of the studied period, with the exception of CBs that are 2 years or younger which by rule of thumb are assumed not to have failed before the start of the period. This estimation method will result in a conservative estimation of the time to failure distribution. The assumption is that standard PM leaves the equipment in an ABAO state, which in this case is reasonable since the only PM carried out on the CBs are different types of inspections. Consequently, the density function for time to failure for part i is

$$ f_i(t) = \frac{1}{\eta_i} \left( \frac{t}{\eta_i} \right)^{\beta_i - 1} \exp \left[ - \left( \frac{t}{\eta_i} \right)^{\beta_i} \right] $$

for $t \geq 0$ (20)

where $\beta_i$>0 and $\eta_i$>0 are the Weibull shape and scale parameters.

The resulting Weibull estimated parameters for the critical parts for CBs that are worked the hardest (i.e. $\geq$50ops/year) is found in Table 3, where Remaining denotes all failures not caused by the Close-operation or the Open-operation locks. The Weibull parameters are estimated using the Method of Maximum Likelihood implemented using Matlab’s Statistics Toolbox [23].

An illustration of the three CB histories, from Table 1, using their conditional failure intensity from (6) is shown in Fig. 5.

1) Reliability of new operating mechanism design

Since no failure data exist for the new operating mechanism design the hazard rate cannot be estimated using standard tools such as Weibull analysis. However, the method using Bayesian statistics presented in [19] may be used to overcome this problem. Such an analysis is outside the scope of this paper so in this example we will simply assume that the hazard rate for the new operating mechanism is constant and low. Since it is not known which parts are critical, the entire operating mechanism will be modeled as one part. The assumed Weibull parameters are $\bar{\beta}_{\text{new}} = 1.0$ and $\bar{\eta}_{\text{new}} = 4000$.

E. Criticality ranking of parts

Carrying out the ranking of the CB parts based on their criticality from (18) resulted in the most important part being the Close-operation lock ($K^{\text{CL}} = 464$ops.) followed by the

TABLE 2. AVERAGE CB FAILURE FREQUENCY W.R.T. $\tilde{f}$.

<table>
<thead>
<tr>
<th>Stratum</th>
<th>Average failure frequency [failures/100CB-years]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total CB population</td>
<td>0.9</td>
</tr>
<tr>
<td>$\tilde{f} &lt; 50$ ops/yr</td>
<td>0.5</td>
</tr>
<tr>
<td>$\tilde{f} \geq 50$ ops/yr</td>
<td>26.4</td>
</tr>
</tbody>
</table>

TABLE 3. ESTIMATED WEIBULL PARAMETERS FOR THE CRITICAL PARTS FOR CBs WITH THE OLD DESIGN OPERATING MECHANISM.

<table>
<thead>
<tr>
<th>Part</th>
<th>Shape, $\beta$</th>
<th>Scale, $\eta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Close-operation lock</td>
<td>1.8</td>
<td>2208</td>
</tr>
<tr>
<td>Open-operation lock</td>
<td>2.1</td>
<td>2485</td>
</tr>
<tr>
<td>Remaining</td>
<td>1.6</td>
<td>2955</td>
</tr>
</tbody>
</table>
Open-operation lock ($K^{295} = 295\text{ops.}$) and the Remaining parts ($K^{275} = 275\text{ops.}$).

F. CB preventive maintenance

The available PM tasks are found in Table 4, where a function test includes measurements of contact resistances, contact velocities etc. The costs in Table 4 are the actual costs for PM and include labor, spares etc. The available PM tasks for each critical part are found in Table 5.

The cost of taking the CBs off-line, $C_{OL}$, are estimated at US$10k, US$2k, US$10k for CBs 1, 2 and 3 respectively. These costs represent the reduction in voltage control that the network operator suffers due to the loss of the shunt reactor. The cost estimations are partly carried out by taking the average number of hours per year that the shunt-reactor is in operation and dividing it by the average number of CB operations per year. The results are 65h/CB operation, 13h/CB operation and 66h/CB operation for CBs 1, 2 and 3 respectively. These measures are used as an indication to estimate the importance of the shunt reactor. A large number of hours/CB operation in operation indicates that the reactor is important to the voltage stability of the power system. From the results above it can be seen that CBs 1 and 3 have the same importance to the system voltage stability and hence the same off-line cost, $C_{OL}$. CB2 on the other hand has approximately 1/5 of their cost. The level of the costs above has been estimated in co-operation with the power system operating engineers.

VI. CONCLUSIONS

Making correct preventive maintenance decisions for power system equipment is a complex matter involving many tasks, such as quantifying the effect and cost-effectiveness of maintenance as well as prioritization of different PM tasks in light of budget and resource constraints. This paper proposes a method which provides a practical evidence-based method for prioritizing PM tasks for power system equipment based on equipment reliability and benefit/cost analysis. A statistical model for the time to failure for a type of SF6 circuit-breakers has been developed based on failure statistics from the Swedish and Finnish transmission systems. A method that estimates the criticality for each part on the equipment has been developed and tested using the circuit-breaker model. Benefit/cost analysis in which a PM task is compared to part replacement has been carried out and cost-effective PM tasks have been suggested for three shunt-reactor breakers in the Swedish transmission system.

One of the main advantages of the proposed method is that it does not require any quantitative assumptions regarding the effect of maintenance.

### TABLE 4. AVAILABLE PM TASKS.

<table>
<thead>
<tr>
<th>PM task, $k$</th>
<th>PM description</th>
<th>$C_{ik}^{\text{off}}$ [US$k$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Replace the open-operation lock</td>
<td>5.5</td>
</tr>
<tr>
<td>B</td>
<td>Replace the close-operation lock</td>
<td>5.5</td>
</tr>
<tr>
<td>C</td>
<td>Replace the operating mechanism with an identical design</td>
<td>30</td>
</tr>
<tr>
<td>D</td>
<td>Replace the operating mechanism with the new design</td>
<td>60</td>
</tr>
<tr>
<td>E</td>
<td>Function test</td>
<td>1.2</td>
</tr>
</tbody>
</table>

### TABLE 5. AVAILABLE PM TASKS FOR CB CRITICAL PARTS

<table>
<thead>
<tr>
<th>Critical part</th>
<th>Available PM tasks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open-operation lock</td>
<td>A, C, D, E</td>
</tr>
<tr>
<td>Close-operation lock</td>
<td>B, C, D, E</td>
</tr>
<tr>
<td>Remaining</td>
<td>E</td>
</tr>
</tbody>
</table>

### TABLE 6. CALCULATION RESULTS.

<table>
<thead>
<tr>
<th>PM task, $k$</th>
<th>$\alpha_k$ [ops]</th>
<th>$C_{ik}^{\text{off}}$, [US$k$]</th>
<th>$M_k$, [ops/US$k$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>CB 1 A</td>
<td>345</td>
<td>15.5</td>
<td>22.3</td>
</tr>
<tr>
<td>CB 1 B</td>
<td>52</td>
<td>15.5</td>
<td>3.4</td>
</tr>
<tr>
<td>CB 1 C</td>
<td>440</td>
<td>40</td>
<td>11.0</td>
</tr>
<tr>
<td>CB 1 D</td>
<td>688</td>
<td>70</td>
<td>9.8</td>
</tr>
<tr>
<td>CB 1 E</td>
<td>&lt;345</td>
<td>11.2</td>
<td>&lt;22.3</td>
</tr>
<tr>
<td>CB 2 A</td>
<td>86</td>
<td>7.5</td>
<td>11.5</td>
</tr>
<tr>
<td>CB 2 B</td>
<td>340</td>
<td>7.5</td>
<td>32</td>
</tr>
<tr>
<td>CB 2 C</td>
<td>733</td>
<td>32.0</td>
<td>22.9</td>
</tr>
<tr>
<td>CB 2 D</td>
<td>877</td>
<td>62.0</td>
<td>14.1</td>
</tr>
<tr>
<td>CB 2 E</td>
<td>&lt;340</td>
<td>3.2</td>
<td>&lt;32</td>
</tr>
<tr>
<td>CB 3 A</td>
<td>206</td>
<td>15.5</td>
<td>13.3</td>
</tr>
<tr>
<td>CB 3 B</td>
<td>208</td>
<td>15.5</td>
<td>13.4</td>
</tr>
<tr>
<td>CB 3 C</td>
<td>624</td>
<td>40.0</td>
<td>13.6</td>
</tr>
<tr>
<td>CB 3 D</td>
<td>849</td>
<td>70.0</td>
<td>12.1</td>
</tr>
<tr>
<td>CB 3 E</td>
<td>&lt;624</td>
<td>11.2</td>
<td>&lt;15.6</td>
</tr>
</tbody>
</table>

### TABLE 7. OUTPUT FROM THE PROPOSED METHOD.

<table>
<thead>
<tr>
<th>Critical part</th>
<th>Suggested PM task, $k$</th>
<th>$\alpha_k$ [ops]</th>
<th>$C_{ik}^{\text{off}}$, [US$k$]</th>
<th>$M_k$, [ops/US$k$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>CB 1 A</td>
<td>Open-op. lock A</td>
<td>345</td>
<td>15.5</td>
<td>22.3</td>
</tr>
<tr>
<td>CB 1 B</td>
<td>Close-op. lock C</td>
<td>440</td>
<td>40.0</td>
<td>11.0</td>
</tr>
<tr>
<td>CB 1 D</td>
<td>Remaining</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CB 2 A</td>
<td>Open-op. lock C</td>
<td>733</td>
<td>32.0</td>
<td>22.9</td>
</tr>
<tr>
<td>CB 2 B</td>
<td>Close-op. lock B</td>
<td>240</td>
<td>10.5</td>
<td>32.0</td>
</tr>
<tr>
<td>CB 2 C</td>
<td>Remaining</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CB 3 A</td>
<td>Open-op. lock C</td>
<td>624</td>
<td>40.0</td>
<td>15.6</td>
</tr>
<tr>
<td>CB 3 B</td>
<td>Close-op. lock C</td>
<td>624</td>
<td>40.0</td>
<td>15.6</td>
</tr>
<tr>
<td>CB 3 C</td>
<td>Remaining</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Fig. 5. Test case CB conditional failure intensities.
VII. ACKNOWLEDGEMENT

The authors would like to express their gratitude to Mr. Per Larsson (Svenska Kraftnät) and Mr. Pasi Yli-Salomäki (Fingrid) for providing access to valuable data, and to Dr. Stefan Arnborg (Svenska Kraftnät) for interesting and helpful discussions.

VIII. REFERENCES


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Estimating the accuracy of thermography of disconnector contacts in the field
T. Lindquist
Estimating the accuracy of thermography of disconnector contacts in the field

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March 17, 2008

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Abstract

This report summarises the results from an investigation into the accuracy of condition assessment of electrical contacts via thermography measurements in the field. The investigation was carried out in Ludvika, Sweden at the Swedish Transmission Research Institute (STRI) outdoor test site during the autumn of 2007. The investigation was performed as a part of the Ph.D. project “Modelling of power equipment reliability with special reference to the impact of maintenance” carried out at the RCAM research group at the KTH School of Electrical Engineering.

Two naturally aged disconnector poles of the make ABB NSA 400/3150 was loaded up to their nominal load in three stages and the contact temperature rises were measured both using thermography and thermocouples attached to the contacts. The thermography measurements were carried out by an experienced technician from Vattenfall Service. After the first set of measurements some contacts were subjected to standard maintenance and the measurements were repeated.

The investigation resulted in statistical distribution for the errors related to the estimation of contact temperature rise at nominal load based on thermography measurements. These error distributions were used to simulate the accuracy of the estimations. Furthermore the investigation resulted in two linear regression models of the relationship between contact resistance and temperature rise as well as the effect of maintenance on contact temperature rise.

A conclusion from the measurements was that statistical models should be used to estimate the effect of maintenance on the contact condition as well as estimating the contact condition from resistance measurements.
Contents

1 Introduction ............................................. 2
   1.1 Background ........................................... 2
   1.2 Statistical models .................................... 3
   1.3 Aim .................................................. 3

2 Thermography ............................................. 5
   2.1 Introduction .......................................... 5
   2.2 Measuring temperature rise ....................... 6

3 Measurements ............................................. 8
   3.1 Measurement objects .................................. 8
   3.2 Measurement setup .................................... 8
   3.3 Measurement results .................................. 10

4 Estimating the measurement error ..................... 19
   4.1 Introduction .......................................... 19
   4.2 Thermography measurement error .................. 20
   4.3 Distribution of the exponent ....................... 21

5 Simulating measurement accuracy ..................... 22
   5.1 Method ............................................... 22
   5.2 Simulation results .................................... 22

6 Conclusions .............................................. 24

References .................................................. 24
Chapter 1

Introduction

1.1 Background

The most common method to assess the condition and inspect disconnector contacts is by infrared thermography. Infrared thermography is a non-destructive, non-contact technique, which can be applied on electrical equipment on-line. The thermography camera measures and images the infrared radiation from the object in a specified spectral band. Because of its ease of use and low cost, it has become the preferred diagnostic method for assessing equipment condition on-line in many electric transmission and distribution systems around the world. However, since a thermography measurement in a low load situation is of limited use and does not provide much information [1], this situation needs to be addressed when planning thermography inspections.

A survey presented in [2] showed that disconnector contacts constituted over 60% of the failures discovered by thermography on >20kV equipment. The survey included thermography measurements from roughly 3000 high-voltage substation bays. Furthermore, the two largest blackouts in Sweden (1983 and 2003) were both caused by overheated disconnector contacts. Subsequently, the investigation presented in this report will focus on disconnector contacts.

Previous studies investigating thermography for disconnector contact condition monitoring include [3], where the Swedish Transmission Research Institute (STRI) carried out an extensive contact ageing study, including a long-term outdoor test on four air insulated centre break disconnector poles. STRI also performed outdoor tests on pantograph disconnector contacts in [4]. There are several case studies [5],[6],[7] and guidelines [2],[8],[9] on the use of thermography on electrical equipment. A few studies have been carried
1.2 Statistical models

The physical processes of electrical contact ageing are quite well known [12],[13],[14],[15]. However, since models describing these processes are quite complex, input data is often difficult to obtain in practice. Furthermore, the relationship between resistance and temperature rise is rather complex and it is difficult to model the physical process. This makes it difficult to use any models of the physical processes to describe the effect of maintenance on electrical contacts.

Subsequently, this report proposes to use less complicated statistical models, such as linear regression models in order to model the ageing behaviour of the contacts as well as the effect of maintenance. Such models contain no information regarding the actual physical process and may thus not be transferred to a similar problem without careful consideration. In order for such a model to be accurate a large statistical sample is required.

The statistical sample used in this investigation is somewhat limited and thus the results from the statistical models presented in this report are used for demonstration only. All results from these models will have to be confirmed by other measurements.

1.3 Aim

The aim of the investigation presented in this report is to gain knowledge on

- the effect of contact maintenance,
- the accuracy and worth of contact resistance measurements,
- the accuracy and worth of thermography in the field.
Chapter 2

Thermography

2.1 Introduction

Thermography is a non-destructive, non-contact diagnostic technique, which can be applied on electrical equipment on-line. Because of its ease of use and low cost it has become the preferred diagnostic method for assessing equipment condition on-line in transmission and distribution systems all around the world. The thermography camera measures and images the infrared radiation in a specified spectral band. If the thermography camera was to measure the temperature of a blackbody source the camera output signal, $V_{out}$, would be [16]

$$V_{out} = C \cdot W_{bb}$$  \hspace{1cm} (2.1)

where $W_{bb}$ is the radiated power of the blackbody temperature source and $C$ is a constant. A non-blackbody radiation temperature source is always emitting less radiation than a blackbody source at the same temperature. As the blackbody concept is strictly theoretical, no true blackbody emitters exist in real life. The relationship between a blackbody source of temperature and a non-blackbody measurement object is expressed as

$$W_{bb} = W_{obj}/\varepsilon$$  \hspace{1cm} (2.2)

where $W_{bb}$ is the radiation power by a blackbody temperature source, $\varepsilon$ is the emissivity of the non-blackbody measurement object and $W_{obj}$ is the radiation power of the object. The emissivity, $\varepsilon$, is dimensionless and is in the range between zero and one and is a measure of a materials’ ability to radiate heat.
1.3 Aim

This knowledge is to be used in order to improve the Monte Carlo simulation method for estimating the uncertainty of thermography measurements first presented in [1].
2.2 Measuring temperature rise

When using thermography it is very important to have suitable and stable ambient conditions such as no sunshine (e.g. cloudy or during night time), no rain or snowfall and no wind. If wind at the time of measurement cannot be avoided the measured temperature rise may be compensated for the cooling effect, however this procedure is not recommended [9],[4]. No wind compensation has been carried out within the investigation presented in this report.

A widely used method of using thermography on electrical equipment is by employing the delta-T criteria [9]. This is a qualitative method of estimating the maintenance priorities by using tables of temperature ratings to assess the severity of overheating the equipment [8]. These tables are usually divided into three or four different categories to indicate the maintenance priority based on the equipment's temperature rise with respect to a similar reference component. The reference component is typically a neighbouring phase which can, under normal circumstances in a power system, be considered to have the exact same loading conditions as the measured component. The advantage of this method is that it is a practical method to establish “failure” or “no failure” and the emissivity has only a minor impact on the result [9]. A drawback is that the temperature tables are usually only found in handbooks and guidelines and hence there is a lack of a recognised international standard. Moreover, the delta-T criteria does not say anything about whether the equipment temperature limits are actually exceeded. Furthermore, using the delta-T criteria will not expose systematic failures affecting all three phases. The delta-T method calculates the temperature rise at phase $L_1$ as

$$\Delta T_{L_1} = T_{L_1} - T_{L_2}$$

(2.3)

where $T_{L_1}$ [$\degree C$] is the hot-spot temperature of the measured object and $T_{L_2}$ [$\degree C$] is the hot-spot temperature of the reference object.

The other possibility is to use a quantitative method to establish the temperature rise at the disconnector contacts. The reference is in this case the ambient temperature. The temperature rise is calculated as

$$\Delta T_{L_1} = T_{L_1} - T_{amb}$$

(2.4)

where $T_{L_1}$ [$\degree C$] is the hot-spot temperature of the measured object and $T_{amb}$ [$\degree C$] is the ambient temperature.

Since the temperature rise of a disconnector contact is a very complex phenomenon to describe using physical models, empirical models may be used instead. The drawback of implementing such models is that they cannot
2.2 Measuring temperature rise

automatically be moved to different problem without careful considerations. The most important parameter for the contact temperature rise is the voltage across the contact followed by the load current [12]. An example of an empirical model describing the temperature rise for disconnector contacts as a function of the load current is found in equation (2.5) [2]:

$$\Delta T_n = \Delta T_{\text{meas}} \left( \frac{I_n}{I_{\text{load}}} \right)^a$$ (2.5)

where $I_n$ [A] is the disconnectors’ rated load current and $I_{\text{load}}$ [A] is the load current at the time of measuring, $a$ is an object specific constant and $\Delta T_{\text{meas}}$ [K] is the temperature rise from equation 2.4.
Chapter 3

Measurements

3.1 Measurement objects

Seven scrapped 400 kV disconnector poles from a substation in south-western Sweden was available for investigation in this project. The disconnectors were all NSA 400/3150 horizontal centre break disconnectors manufactured by ABB. This disconnector type have two rotating contacts and one spring mounted main contact per pole, see figure 3.1. The rotating contacts were constructed with a rotating terminal bolt with twelve spring mounted contact rolls to carry the current.

3.2 Measurement setup

The investigation was carried out at the STRI outdoor test site in Ludvika, Sweden. Due to practical reasons only two out of the seven disconnector poles could be investigated. These two disconnector poles were, one at a time, mounted at normal height with the possibility of continuously feeding it with its nominal current of 3150A. Each disconnector pole was fitted with 16 thermocouples, 12 for the main contact and 2 for each rotating contact. Furthermore the ambient temperature, sun intensity, rain fall (no rain was present during the measurements), wind speed and wind direction was continuously measured and logged.

Before the temperature rise measurements got started the contact resistances were measured for all seven disconnectors to identify the two worst disconnectors (i.e. with the highest contact resistance) for further investigation. The contact resistances were measured using 100A DC. The results from the resistance measurements are shown in table 3.1. Table 3.1 shows that disconnector F had the highest resistance for the main contact ($R_{C_2} = 57\mu\Omega$).
3.2 Measurement setup

![Diagram](image)

Figure 3.1: Schematic picture describing one pole of the investigated disconnector type.

and that disconnector G had the highest resistance for the rotating contacts \( R_{C_3} = 80 \mu \Omega \). Consequently, disconnectors F and G were selected for the detailed investigation.

Briefly, the order in which the measurements for the two disconnectors were carried out was:

1. Load the disconnector to \( I_{load} = 1000 \text{A} \), wait for a stable temperature
2. Measure contact temperatures using thermocouples and thermography
3. Load the disconnector to \( I_{load} = 2000 \text{A} \), wait for a stable temperature
3.3 Measurement results

4. Measure contact temperatures using thermocouples and thermography
5. Load the disconnector to \( I_{load} = I_n = 3150 \text{A} \), wait for a stable temperature
6. Measure contact temperatures using thermocouples and thermography
7. Reduce the load to 0A, wait until contacts cooled down
8. Measure the contact resistances
9. Carry out standard maintenance for the main contact and for the rotating contacts only if necessary
10. Repeat steps 1–8 once.

Consequently, the two disconnector poles were loaded and measured twice, once before and once after maintenance. Only one disconnector pole could be measured at one time, this means that the disconnectors had to be mounted and then taken down after every measurement.

The thermography measurements were carried out by an experienced thermography technician from Vattenfall Service using own equipment. The thermography measurements were carried out as a normal inspection in a substation, i.e. the technician did only receive information regarding the load current and made all necessary measurements of the ambient conditions. The technician estimated the disconnector emissivity to \( \varepsilon = 0.82 \).

### Table 3.1: Contact resistance measurement results

<table>
<thead>
<tr>
<th>Disconnector pole</th>
<th>( R_{C_1} ) [( \mu \Omega )]</th>
<th>( R_{C_2} ) [( \mu \Omega )]</th>
<th>( R_{C_3} ) [( \mu \Omega )]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>8</td>
<td>11</td>
<td>2</td>
</tr>
<tr>
<td>B</td>
<td>10</td>
<td>30</td>
<td>11</td>
</tr>
<tr>
<td>C</td>
<td>4</td>
<td>21</td>
<td>8</td>
</tr>
<tr>
<td>D</td>
<td>11</td>
<td>19</td>
<td>5</td>
</tr>
<tr>
<td>E</td>
<td>9</td>
<td>15</td>
<td>14</td>
</tr>
<tr>
<td>F</td>
<td>27</td>
<td>57</td>
<td>13</td>
</tr>
<tr>
<td>G</td>
<td>9</td>
<td>24</td>
<td>80</td>
</tr>
</tbody>
</table>
3.3 Measurement results

Figure 3.2: Temperature rise measurements for disconnector pole G before maintenance

Both from the thermocouples as well as from the thermography before any maintenance was carried out. The vertical black lines in the figures indicates the instantaneous change in load. The two red asterisks seen in figure 3.3 indicates two thermography measurements made from a different angle than all the others, these measurements were not included in the following analysis.

After the two first measurement sets the thermography technician noticed a temperature rise in contact $C_3$ on disconnector pole G and made the assessment that the contact was failed and required major maintenance. The maintenance activities are divided into two categories, "Minor" and "Major" maintenance. Minor maintenance involves minor activities such as inspecting and operating the disconnector. The operating of the disconnector will, in most cases, reduce contact resistance by removal of the contact surface film. Major maintenance includes both cleaning and lubricating of the contact surfaces. Major maintenance is performed on the main contacts at every maintenance opportunity whereas only minor maintenance will be performed for the rotating contacts unless a failure have been indicated by thermogra-
3.3 Measurement results

Figure 3.3: Temperature rise measurements for disconnector pole F before maintenance

The maintenance activities in this study were carried out by the contractors that normally maintain this type of equipment. Consequently, only the rotating contact $C_3$ on disconnector pole G was subjected to major maintenance whereas both the main contacts $C_2$ were subjected to major maintenance on disconnector poles F and G. The three remaining rotating contacts had only minor maintenance. Figures 3.4 and 3.5 show the temperature rises after maintenance was carried out. Figure 3.6 shows the average temperature rises at nominal current measured by the thermocouples before and after maintenance. In Figure 3.6 the dashed line indicates that the contact was subjected to major maintenance and the solid line indicates that minor maintenance was carried out. From the figure it can be seen that in some cases the temperature rise was reduced even when only minor maintenance was carried out. This is due to the fact that the disconnectors had to be mounted and taken
down after every measurement and likely to have a similar effect as operating the disconnectors. These movements cause a breakdown of the oxidation film on the contact surface, reducing the resistance and hence the contact temperature rise. In Figure 3.6 it can also be seen that the temperature rise for contact $C_1$ on disconnector $G$ increased from the first measurement to the second. This is most likely due to a poorly fitted connection when mounting the disconnector for the second measurement causing the unexpected large temperature rise. Since the resistance measurements do not include the connection clamp this temperature rise will not be reflected in a higher contact resistance. Figure 3.7 shows a linear relationship between the contact resistance and the temperature rise as measured by the thermocouples. In the figure an “A” indicates that the measurement was made after maintenance and a “B” indicates that the measurement was made before the maintenance was carried out. The correlation between resistance and temperature rise is 0.8. In the figure the solid line is the response from the linear regression $\Delta T_n = 17.3 + 0.4R$ including a 95% prediction interval as dashed lines.

Figure 3.8 shows the effect of carrying out major maintenance on the disconnector contacts as a linear regression model. In the figure the dashed lines are 95% prediction intervals and the dash-dot line indicates extrapolation beyond the observed effects. The regression model presented in the figure is $Y = -17.8 + 3.5M + \Delta T_{before}$, where $Y$ is the reduction in the temperature rise before maintenance $\Delta T_{before}$ and $M$ is a parameter indicating whether major or minor maintenance was carried out [0 or 1], where 1 means major maintenance and 0 means minor maintenance. The statistical prediction interval in the figure is not a physical model and any extrapolation beyond the observed effects may produce unreasonable results.

The relatively high temperature rise caused by a poorly fitted connection clamp on terminal $C_1$ on disconnector pole $G$ for the measurement after maintenance was considered to be an outlier and removed in this model. The regression models presented above are only valid for the investigated contacts since the statistical sample was small.

The temperature rises reported in this work as well as in [1] are relatively low compared to the type test measurements [17]. This is most likely due to the cooling effect of the wind outdoors. Even very low wind speeds will have a great impact on the temperature rise [3]. No calculations has been made to compensate for this cooling effect in this report.
3.3 Measurement results

Figure 3.4: Temperature rise measurements for disconnector pole G after maintenance
3.3 Measurement results

Figure 3.5: Temperature rise measurements for disconnector pole F after maintenance
3.3 Measurement results

![Graph showing temperature rise differences before and after maintenance. Dashed lines indicate major maintenance, and solid lines indicate minor maintenance.](image)

Figure 3.6: Average temperature rise differences before and after maintenance. Dashed lines mean there was major maintenance and solid lines indicate minor maintenance.
3.3 Measurement results

Figure 3.7: Simple linear regression model describing the relationship between contact resistance and temperature rise, including 95% prediction intervals.
3.3 Measurement results

Figure 3.8: Linear regression model of the effect of maintenance.
Chapter 4

Estimating the measurement error

4.1 Introduction

When making any kind of measurement there will be some measurement error involved. To be able to use the measurements in order to make well informed maintenance decisions it is important that the measurement errors are quantified.

The error, $\epsilon_{\Delta T}$, when trying to estimate a contacts’ temperature rise at nominal load by using equation (2.5) and thermography is

$$\epsilon_{\Delta T} = \epsilon_{\text{thermo}} + \epsilon_{\text{calc}}$$

(4.1)

where $\epsilon_{\text{calc}}$ is the error introduced due to the uncertain value of the exponent $a$ when using equation 2.5 and $\epsilon_{\text{thermo}}$ is the thermography measurement error defined as

$$\epsilon_{\text{thermo}} = \epsilon_{z} + \epsilon_{\text{hide}} + \epsilon_{\text{rand}}$$

(4.2)

where $\epsilon_{z}$ is the influence of the uncertain object emissivity, $\epsilon_{\text{hide}}$ is the error due to the fact that the contacts are sometimes hidden under protective caps and may not be visible to the naked eye (and hence not accessible for direct thermography) and $\epsilon_{\text{rand}}$ is due to random variations (e.g., variations in the object temperature, atmosphere radiation and reflected radiation). Note that the error introduced by wind have not been treated in this investigation.

This chapter presents statistical distributions for these errors, estimated from the results of the disconnector contact investigation at STRI in Ludvika.
4.2 Thermography measurement error

![Diagram showing normal distributions for thermography measurement errors at different loads.](image)

Figure 4.1: Normal distributions fitted to thermography measurement errors at three different loads.

4.2 Thermography measurement error

In this work the thermography measurement error, $\varepsilon_{\text{thermo}}$, is estimated directly rather than estimating all of the three parts separately and adding them up.

It is assumed that the thermocouples fitted on the disconnector contacts give the true temperature and hence any deviation from this is considered an error. This error is dependent on the load current. Figure 4.1 shows normal distributions fitted to the measurement error for the thermography temperature rise measurements at stable temperature. Since error distributions are often assumed to have an expected value $\mu = 0$ this also assumed here and is shown in Figure 4.1 as dashed lines. As can be seen in the figure this assumption seems reasonable. The estimated parameters for the standard deviation are $\sigma_{1000} = 70$, $\sigma_{2000} = 33$, $\sigma_{3150} = 16$. 
4.3 Distribution of the exponent

The exponent, \( a \), from equation (2.5) is critical when calculating the temperature rise at nominal load. In this investigation, the exponent was estimated twice for the rotating contacts (before and after maintenance) by least squares fitting. Only the stable temperature rise measurements for every load were used in the exponent estimation. This resulted in eight estimations of \( a \) and when fitted to a normal distribution the parameters were \( \mu_a = 1.55 \) and \( \sigma_a = 0.07 \). Figure 4.2 shows a plot of the distribution of \( a \).

Figure 4.2: Normal distribution for the exponent \( a \) for the rotating contacts.
Chapter 5

Simulating measurement accuracy

5.1 Method

This section presents the Monte Carlo algorithm for simulating the uncertainty when making thermography measurements. This simulation method was first presented in [1] but has been improved though better knowledge of the thermography errors in this investigation.

The presented method simulates the confidence bounds for temperature rise at nominal load, $\Delta T_n$, for a measurements made at lower load. The Monte Carlo simulation was carried out by applying the following steps $N$ times for each measurement.

1. Get a temperature rise measurement $\Delta T$ made at load $I_{load}$.
2. Sample a thermography measurement error from the distribution in figure 4.1 and add error to $\Delta T$.
3. Sample an exponent $a$ from the distribution shown in figure 4.2.
4. Calculate $\Delta T_n$ using equation 2.5.
5. GOTO step 2 (repeat $N$ times).
6. Use the 95% percentiles for the distribution of $\Delta T_n$ as confidence bounds.
7. GOTO step 1 (for every measurement $\Delta T$).

5.2 Simulation results

This section presents some simulation results using the method presented above. The figure 5.1 shows (from the left) the simulated confidence bounds
5.2 Simulation results

![Disconnector F, contact C₁]

Figure 5.1: Estimations of $\Delta T_n$ including 95% confidence intervals, contact $C_1$, disconnector $F$, before maintenance.

for $\Delta T_n$ for thermography measurements made at $I = 1000A$, $I = 2000A$ and $I = 3150A$, respectively. Furthermore, $\Delta T_n$ was also estimated using only the resistance measurement (see Figure 3.7) and finally the reference temperature rise as measured by the thermocouples at $I = 3150A$ is shown.

From the figure it can be seen that all temperature rise estimates based on thermography and resistance measurements include reference measurements made by the thermocouples in the 95% confidence interval. It is also clear that the temperature rise estimation based on the resistance measurements are more accurate than those based on thermography at $I = 1000A$. This result will have to be confirmed by other measurements since the statistical sample used for the regression was somewhat limited.
Chapter 6

Conclusions

This report presents statistical distributions for the errors involved when estimating the contact temperature rise at nominal load from a thermography measurement. These distributions can successfully be used in simulations to estimate the accuracy of such measurements, when made at currents lower than the nominal.

This investigation also suggests using simple statistical models in order to model the effect of maintenance as well as estimating the contact condition using resistance measurements. The use of such models will enable a comparison of accuracy and worth of resistance measurements and thermography at different loads. However, the results from the two linear regression models proposed in this investigation are for demonstration only since the statistical sample was limited. All results from these models will have to be confirmed by other measurements.

The results from the condition estimations presented in this report (Monte Carlo simulations and regression models) suggests that resistance measurements may be a more accurate way to estimate the contact condition than thermography when disconnectors are lightly loaded. This information may prove to be important when planning disconnector maintenance.
References


REFERENCES


