On reliability modelling of ageing equipment in electric power systems with regard to the effect of maintenance

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Abstract

Power system maintenance optimisation involves obtaining the minimum total costs, including preventive and corrective maintenance costs and the cost of failures for both supplier and customer. To calculate the cost of failure, information is needed about the equipment reliability characteristics. It is also necessary to know how maintenance affects component reliability. The aim of the work leading up to this thesis has been to develop reliability models that include the effect of maintenance.

Three case studies have been carried out for different types of power system components using three distinct methods. In the first study the reliability of the first generation XLPE cables was modelled with respect to failures caused by water treeing using load–strength modelling. The model was based on assumptions of the ageing process and the distribution system characteristics. This study showed that 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. The second case study included a study of all circuit breaker failures in the Swedish transmission grid during the period from 1 January 1999 to 30 June 2003. In a subsequent investigation a method to combine information from the design process with maintenance records and failure statistics was employed using Bayesian methods. The resulting reliability model is continuously updated as more failure and maintenance data becomes available. This case study showed that it is possible to develop reliability models for components that have not yet failed by utilising information from the design process and right-censored observations from inspections. Finally, in the third case study a quantitative method for establishing the condition of disconnector contacts by the use of thermography was developed. Two sets of measurements on disconnector contacts in the Swedish transmission grid were carried out to establish the accuracy of the method. By utilising the results from the measurements estimates of the statistical distributions of the error sources were produced.

The results from the case studies show that the lack of detailed, high-quality data remains a critical problem when modelling reliability of power system equipment, even when using methods that require a minimum of data.
Sammanfattning


Resultaten från fallstudierna visar att avsaknaden av detaljerad kvalitetsdata kvarstår som ett kritiskt problem vid tillförlitlighetsmodellering även då metoder som kräver förhållandevis lite data används.
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 School of Electrical Engineering, division of Electrotechnical Design at the Royal Institute of Technology.

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List of papers


IV. T. Lindquist, L. Bertling and R. Eriksson. Estimation of disconnector contact condition for modelling the effect of maintenance and ageing. Accepted to be presented at the IEEE Power Tech conference, St. Petersburg, Russia, June, 2005.
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To Helena and Ester
Chapter 1

Introduction

This chapter provides a general background as well as problem formulation and the contribution made herein.

1.1 Background

Historically, preventive maintenance of electrical 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 has led to a shift in the utilities’ view of maintenance. Preventive maintenance has gradually become an instrument of competition focusing on cost-effectiveness. Consequently, in order to reduce costs many companies have started to change their maintenance strategies from time-based preventing strategies to more sophisticated maintenance strategies like Reliability Centred Maintenance (RCM).

At the Department of Electrical Engineering at KTH a method has been developed that takes RCM one step further deducing cost-efficient maintenance plans in which the benefit of component maintenance is related to the system reliability and total cost [1]. This method is called Reliability Centred Asset Management (RCAM). In order to carry out the maintenance optimisation within the RCAM framework, equipment reliability models that include ageing and the effect of maintenance are necessary.

The work carried out within this Ph.D. project is part of the Reliability Centred Asset Management programme at the Division of Electrotechnical Design at the Department of Electrical Engineering, KTH.
1.2 Problem formulation

The aim of this Ph.D. project is to develop equipment reliability models taking into account the effect of ageing and maintenance. These models are to be used for maintenance optimisation in power systems.

The problem of establishing how maintenance affects reliability is highly complex as each type of apparatus has its particular characteristics and failure modes. Continuous equipment development makes comparison between 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 making the population sizes limited. High reliability equipment and failure data of low detail level and varying quality together with high costs of life tests makes the use of traditional methods of reliability modelling difficult for power system equipment [2].

Many of the assumptions regarding the effectiveness of maintenance that have been used in previous work within this field have been general in nature and have often lacked theoretical background.

1.3 Contribution

The main contributions in this thesis are summarised below.

- The presentation of results from a study on high voltage circuit breaker failures, illustrating the difficulties in obtaining quality failure data at a high level of detail.

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

- The development of a quantitative method to establish the contact condition of disconnectors using thermography. This includes the investigation and quantification of the error sources when using thermography in the field.

- The presentation of an example of a reliability model for aged XLPE cables based on knowledge of the ageing process and system characteristics.

1.4 Thesis outline

This thesis constitutes an extensive summary of the results presented in the appended papers. It also provides a general background and relevant theory. In
chapter 2 different methods of modelling the reliability of power system equipment are presented in some detail. Chapter 3 presents three case studies investigating three different techniques of modelling the reliability of cables, circuit breakers and disconnectors as a means to illustrate possible solutions to the problem of reliability modelling of small populations of high reliability components. The reliability models are based on available knowledge about the fundamental failure mechanisms causing failures, information from the design process and maintenance records and information from condition estimation methods. Chapter 4 summarises the results and presents conclusions. In Chapter 5 the proposed future work is discussed.

Paper I proposes a load–strength reliability model of aged XLPE cables. Paper II presents the results from a study of circuit breaker failures in the Swedish transmission grid over a period from 1 January 1999 to 30 June 2003. In Paper III a Bayesian method to model sub-component reliability of circuit breakers is presented. The method allows the use of information from the development and design process as prior information before any field data is available. Paper IV describes a method to establish the contact condition of disconnectors using thermography. The paper also presents results from two sets of measurements carried out on disconnectors in the Swedish transmission system.
Chapter 2

Reliability modelling

This chapter presents a theoretical background to the reliability modelling techniques used in the appended papers. It also discusses some previously developed methods to model the effect of maintenance on equipment reliability.

2.1 Introduction

The purpose of modelling the reliability of aged power system components is to predict future failure behaviour. The reasons behind modelling the reliability of aged power system equipment vary depending on the application. For the electric utility there is often a need to optimise maintenance intervals and for the manufacturer of power system equipment modelling reliability may be required to comply with standards or for warranty issues.

The term reliability may be expressed as a probability or a success rate but generally, reliability is defined as:

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

This definition is generally accepted and is used in [3], [4], [5] and [6]. It is the definition used throughout this thesis.

The basis for reliability models is often some form of equipment population history such as failure statistics. However, there are many other sources that may be employed in order to predict future equipment behaviour. Eight different sources for collecting failure related data are summarised below [7]. The various sources may also be combined to make predictions with more confidence.
1. Warranty claims
2. Previous experience with similar or identical equipment
3. Repair facility records
4. Factory acceptance testing
5. Records generated during the development phase
6. Customers’ failure reporting systems
7. Tests: field demonstration, environmental qualification and field installation
8. Inspection records

2.1.1 Definitions

Some of the key terms used in this thesis are described below. The definitions all derive from [5] and [6].

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

*Failure* – The termination of a unit’s ability to perform a required function.

*Function* – The intended process for a unit that leads to a detectable, but not necessarily an acceptable, performance.

*Maintenance* – The combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.

*Sub-component* – The smallest replaceable unit in a system.

2.1.2 Maintenance effectiveness and age modelling

The effectiveness of maintenance is an important aspect when modelling reliability. A commonly used assumption in the literature is that the maintenance is perfect [8], which means that the age of the component returns to zero after maintenance. Maintenance modelled under this assumption is usually called *As Good As New* (AGAN). The opposite of this assumption is the *As Bad As Old* (ABAO) assumption, which implies that the maintenance has no effect on the reliability and that the component is in the exact same state (has the same age) as before the maintenance was carried out [9]. Between these two extremes lies the *Imperfect Maintenance* (IM) assumption. In [9] two methods of IM is used, the *Partial Age Reduction*
(PAR) and the *Proportional Age Setback* (PAS). These two methods introduce the positive effect that maintenance (usually) has on equipment reliability by assuming that it reduces the failure rate.

In [10] two simple methods were used to model the effect of maintenance. Both methods presumed that maintenance reduced the system failure rate. The first method reduced the failure rate with a fixed amount and the second let the reduction be proportional to the actual failure rate.

A large number of methods that can be used for age modelling has been proposed in the international literature. In [11] the authors used a model of IM that utilised three dimensions of time in order to measure the age of a component. The three dimensions were 1) age vs. calendar time 2) age vs. calendar time between events and 3) effective age. The effective age depended both on the time between events and on the maintenance history.

Two models to describe the ageing process of safety equipment in nuclear power plants was presented in [9]. The *Accelerated Life Model* (ALM) and the *Proportional Hazard Model* (PHM) included the effect of the components’ environmental and operating conditions.

### 2.1.3 Reliability modelling of power system equipment

The international literature on how maintenance affects reliability is scarce except for the conventional failure statistics reporting. Nonetheless, a limited number of papers exists. In [12] and [13] 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. In order to analyse the impact of different maintenance strategies the model was evaluated by employing Monte Carlo simulation. To generate the life curves a specially developed software was used. The main features of the software was its probabilistic representation of the degradation process, carried out in discrete steps, and the link between maintenance and deterioration that the model provides.

In [14] a study on maintenance optimisation of on-load tap changers was reported. Two methods were used to make optimistic and pessimistic estimations of failure rates. The optimistic estimations were derived from the analytical Weibull-analysis and the pessimistic estimates were derived from the non-parametric TTT-method. Both methods took into account the effect of censored lifetime observations. These failure rates were subsequently used to optimise the preventive maintenance interval. The same method was later used in [15] 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 [16] and [17]. The method determined 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 were carried out both analytically and by Monte Carlo simulation. When applied, the method produced output in the form of the expected wood pole replacement rate as a function of time and the standard deviation.

In [1] and [18] 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. Other work on XLPE cables include [19], where the annual failure rate was based on accelerated water tree ageing and in [20] and [21] where the insulation degradation of XLPE cables was investigated. More publications on ageing of cable insulation include a literature study on ageing phenomenon and modelling of electric insulation materials [22]. Ageing models for cable insulation based on PD detection were introduced in [23]. In [24] the main factors contributing to ageing mechanisms were discussed.

2.2 Reliability modelling methods

There are a number of methods that may be used to model reliability and each method has advantages and disadvantages. This section will discuss three different methods that can be used when modelling the reliability of aged power system components with the purpose of establishing the effect of maintenance.

In this section, all sub-components are assumed to be non-repairable i.e. the only available maintenance action is sub-component replacement, i.e. the AGAN assumption. The sub-component lifetimes\(^1\) are assumed to be statistically independent and are represented by the random variable \(X\), where \(x\) is an observation of \(X\).

2.2.1 Fit statistical distributions to data

The most straightforward and perhaps 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. This approach is referred to as an actuarial approach [3].

\(^1\)Note that the measure of lifetime, as used in this thesis may differ from calendar time (e.g. number of operations or cycles).
2.2. RELIABILITY MODELLING METHODS

Probability functions

There are four primary probability functions:

1. The probability density function (p.d.f.), \( f(x) \), indicates where in time a failure is more or less likely to occur, thus giving:

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

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

\[
P(a \leq X \leq b) = \int_a^b f(x)dx \tag{2.1}
\]

2. The cumulative distribution function (c.d.f.), is defined as:

\[
F(x) = P(X \leq x) = \int_0^x f(u)du \tag{2.2}
\]

The c.d.f. is the probability that a failure occurs prior to the time \( x \).

3. The reliability function is defined as:

\[
R(x) = P(X > x) = \int_x^\infty f(u)du \tag{2.3}
\]

This is the probability that no failure occurs prior to time \( x \).

4. The failure rate function \( \lambda(x) \) is defined as:

\[
\lambda(x) = \lim_{\Delta x \to 0} \frac{F(x + \Delta x) - F(x)}{\Delta t \cdot R(x)} = \frac{f(x)}{R(x)} \tag{2.4}
\]

and is the probability of a failure in the next instant of time, conditional of survival at time \( x \). Hence, the shape of the failure rate function is indicative of the nature of the failure [25].

If any of the four probability functions are known the remaining functions can be determined [3].

Common reliability distributions

The exponential distribution is a one parameter distribution and is the most widely used distribution in the field of reliability modelling. The reason is that it is mathematically simple but also that it often provides a realistic model [3]. One of the
main attributes of the exponential distribution is that the hazard function is constant, i.e. independent of time. It also has a related memoryless property. This property implies that if a sub-component has survived until a certain point in time, the probability of failure in some additional specified constant time interval is independent of when the interval begins [25]. Subsequently, any preventive replacement of sub-components which fail according to the exponential distribution is completely pointless [26]. If \( X \) is the exponentially distributed time to failure for a sub-component with the parameter \( \lambda \), the p.d.f. is then given by:

\[
f(x) = \lambda e^{-\lambda x}
\]

for \( x > 0 \) and \( \lambda > 0 \).

Another common distribution in reliability modelling is the Weibull distribution. The Weibull is generally a two parameter distribution, although a three parameter version exists. The parameters are the shape parameter, \( \beta \), and a scale parameter, \( \eta \). The Weibull distribution is widely used due to its ability to describe many different commonly occurring shapes [27]. The Weibull p.d.f. is defined as follows:

\[
f(x) = \frac{\beta}{\eta} \left( \frac{x}{\eta} \right)^{\beta-1} e^{-\left( \frac{x}{\eta} \right)\beta}
\]

Note that the exponential distribution constitutes a special case of the Weibull, which can be seen by setting \( \beta = 1 \).

**Goodness-of-fit tests**

When analysing failure statistics it is often necessary to establish how well the data fits the assumed distribution. This may be determined by means of goodness-of-fit tests. These tests form an extension of statistical hypothesis testing.

A versatile, commonly used and simple test is the \( \chi^2 \) goodness-of-fit test. The test is applicable to any assumed distribution, provided that a reasonable number of data points are available [28]. The test is based on the assumption that, if a sample is divided into \( n \) cells, the values within each cell are normally distributed around the expected value. If this assumption is correct, then \( x_i \) and \( \bar{x} \) are the observed and expected values for cell \( i \) [28]:

\[
\sum_{i=1}^{n} \frac{(x_i - \bar{x}_i)}{\bar{x}_i} = \chi^2
\]

Hence, with \( n - 1 \) degrees of freedom the null hypothesis will be rejected if the \( \chi^2 \) value falls outside the predetermined percentile of the \( \chi^2 \) distribution. These values are found in tables (e.g. in [28] and [29]).
Another widely used goodness-of-fit test is the Kolmogorov-Smirnov (KS) test. The KS-test tests the null hypothesis that random sample has been drawn from a specified distribution. The KS-test is simpler to use than the $\chi^2$-test and can give better results with fewer data points [28]. The procedure is as follows:

1. Tabulate the ranked failure data. Calculate the values of $|x_i - \bar{x}_i|$ where $x_i$ is the $i^{th}$ cumulative rank and $\bar{x}_i$ is the expected cumulative rank value for the assumed distribution.

2. Determine the highest single value.

3. Compare this value with the appropriate KS-value.

The KS-values are available in tables (e.g. in [7] and [28]). See [7] for a more comprehensive description of the KS-test.

### 2.2.2 Load vs. strength modelling

The use of load–strength modelling is referred to as a physical approach [3]. This approach requires detailed knowledge about component failure mechanisms and actual operating conditions. In load–strength analyses both the load, $L$, and strength, $S$, are assumed to be independent random variables with some statistical distribution. The “load” may be applied voltage, mechanical stress or temperature and the “strength” refers to any resisting physical property. A failure occurs when the load exceeds the strength.

The reliability of a component or a sub-component, subjected to a discrete load application, is represented by the probability that the strength exceeds the load. This may be written as [28]:

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

$$ = \int_0^\infty f(l) \left[ \int_l^\infty f(s)ds \right] dl \quad (2.8) $$

$$ = \int_0^\infty f(s) \left[ \int_0^s f(l)dl \right] ds \quad (2.9) $$

where $f(l)$ and $f(s)$ are the p.d.f’s for the load and strength respectively. Furthermore, by defining the random variable $Y = S - L$ with the p.d.f. [29]:

$$ f(Y) = \int_0^\infty f(l)f(y+l)dl $$

and then substituting (2.10) into (2.3) the component reliability can be written as [28]:

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

$$ = \int_0^\infty \int_0^\infty f(i)f(y+l)dl\,dy \quad (2.11) $$
For multiple load applications the reliability can be expressed as [28]:

\[
R = \int_0^\infty f(s) \left[ \int_0^s f(l) dl \right]^n ds
\]  

(2.12)

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

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

(2.13)

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

Since loads often vary with time and sub-component strength decreases as it deteriorates due to different failure mechanisms, both the sub-component strength and the applied load may be considered to be functions of time. The lifetime \( X \) of a sub-component is then represented by the shortest time until \( S(x) < L(x) \) [3]. This may be expressed as:

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

** Normally distributed load and strength **

Assuming that both the load, \( L \), and strength, \( S \), are normally distributed so that \( L \sim N(\mu_L, \sigma_L) \) and \( S \sim N(\mu_S, \sigma_S) \), the c.d.f’s are:

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

(2.14)

and

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

(2.15)

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

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

(2.16)

The above analysis may be carried out assuming any other statistical distribution. However, the integrals may then become complex and the use of numerical methods, such as Monte Carlo simulation, may be necessary.

** 2.2.3 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 2.1. In Figure 2.1, let \( x = x_1, x_2, \ldots, x_n \) be observations of \( X \) and denote this data set \( \text{DATA} \). This knowledge may derive from the sources summarised in Section 2.1.

![Diagram](image)

**Figure 2.1.** The Bayesian updating process for making inferences and predictions, based on [3] and [27].

### Censored data

Censoring is common in reliability data analysis and occurs when it is not possible to observe the time of failure for a component. Three ways in which reliability data can be censored are presented below [3], [27]:

1. **Right-censored data;** component \( i \) has not failed at time \( x_i \), giving \( X > x_i \). Such data is very often the result from 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;** component \( i \) 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;** component \( i \) 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.
Likelihood

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 [29]:

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

(2.17)

where \( x_1, x_2, \ldots, x_n \) are independent observations of the random variable \( X \), given that the p.d.f. \( f(x_i | \theta) \) is known.

However, if the component times of failure are not known the likelihood contributions have to be established separately for each censoring type [27]. For right censored failure times the contribution to the total likelihood is:

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

(2.18)

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:

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

(2.19)

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

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

(2.20)

Following (2.17) the total likelihood can then be written as the joint probability of the data, assuming \( n \) independent observations:

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

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

(2.21)

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, \( n = \sum_{j=1}^{n} (b_j + l_j + d_j + r_j) \)
Bayes’ theorem

Bayes’ theorem was first formulated by reverend Thomas Bayes and was presented posthumously in 1763 [30]. Bayes’ theorem provides a mechanism for combining prior information with sample data to make inferences on model parameters [3], [27].

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

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

$$B_i \cap B_j = \emptyset \text{ for } i \neq j$$

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

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

$$P(B_k|A) = \frac{P(A|B_k)P(B_k)}{\sum_{i=0}^{\infty} P(A|B_i)P(B_i)} \quad (2.22)$$

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:

$$f(\theta|x) = \frac{f(x, \theta)}{f(x)} \quad (2.23)$$

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

$$f(x, \theta) = f(x|\theta) \cdot f(\theta) \quad (2.24)$$

In (2.23) the marginal distribution of $X$, $f(x)$ is:

$$f(x) = \int_{0}^{\infty} f(x|\theta) \cdot f(\theta) \quad (2.25)$$

In (2.23), the denominator, as described in (2.25), is only used as a normalising constant due to the fact that when a value for $X$ has been observed (2.25) is constant [3]. Hence, $f(\theta|x)$ is always proportional to $f(x|\theta) \cdot f(\theta)$, which can be written as:

$$f(\theta|x) \propto f(x|\theta) \cdot f(\theta) \quad (2.26)$$

Furthermore, Bayesian 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 [27].
If $X_0$ represents a random variable for a new observation, the posterior predictive p.d.f. of $X_0$ is then [3]:

$$f(x_0|x) = \int_0^\infty f(x_0|\theta) \cdot f(\theta|x)$$  \hspace{1cm} (2.27)

When applying Bayesian methods for reliability data analysis the integration operation for calculating the normalising constant in (2.25) plays a critical role. This integral is rarely possible to evaluate using analytical methods, except in simple cases [31]. A way to overcome this difficulty is to use numerical techniques such as Monte Carlo simulation.

**Credibility intervals**

Credibility intervals are the Bayesian equivalent to confidence intervals. Let $x = x_1, x_2, \ldots, x_n$ be observations of $X$ and denote this data set DATA. The numerical interval $(a(x), b(x)) = (a(x_1, x_2, \ldots, x_n), b(x_1, x_2, \ldots, x_n))$ is a confidence interval for $\Theta$ with the confidence level $1 - \alpha$ if [3], [32]:

$$P(a(x) < \Theta < b(x)|\text{DATA}) = \int_{a(x)}^{b(x)} f(\theta|\text{DATA}) d\theta = 1 - \alpha$$  \hspace{1cm} (2.28)

In other words, credibility intervals are two points $a(x)$ and $b(x)$ between which $1 - \alpha$ of the probability mass is located.
Chapter 3

Case studies

This chapter presents the case studies carried out within the framework of this project. The results presented herein are based on the appended papers.

3.1 Introduction

The problem of reliability modelling of small populations of high reliability components have been dealt with in this thesis and is illustrated by case studies of specific power system equipment. Three case studies have been carried out using three distinct methods on three different types of power system components. The idea was to base the reliability models on available knowledge about the fundamental failure mechanisms causing failures, information from the design process and maintenance records and information from condition estimation methods. The components and methods presented in this chapter were selected since they constituted natural sub-problems. Furthermore, the components and methods were selected with regard to the likelihood of success as well as how useful the reliability models would be to the electrical power industry.

The greatest difficulty when modelling power equipment reliability, as mentioned in Section 1.2, is to obtain sufficient amounts of data of useful quality and detail level. Throughout this thesis work much effort has therefore been put on trying to collect data suitable for the modelling process.

3.2 Failure mechanism modelling – cables

Equipment failures are often the result of a load stress being greater than a strength. This case study deals with a reliability modelling technique based on knowledge about the actual failure mechanism. Since cables have been shown to be a critical component [1] and since the water tree phenomenon has been much researched [20],
[21], [33] an attempt was made to model the reliability for the first generation of XLPE cables with respect to faults caused by water treeing. This section is based on Paper I.

### 3.2.1 Load vs. strength modelling

This sub-section presents an example of a reliability model of aged XLPE cables based on load–strength modelling. The model is based on the fact that failure of electrical insulation occurs when the voltage stresses are higher than the insulation strength. Consequently, the load in this case is overvoltages causing breakdown of the electrical insulation and the strength 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 11 kV urban area cable distribution system. The cable length was 10 km 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 equation (2.16).

The assumed values of the breakdown voltage are presented in Figure 3.1a). In Figure 3.1b) 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 3.1. a) Variations of standard deviation and mean value of the breakdown voltage with time and b) comparisons of failure rates.
3.3 Failure statistics and design data – circuit breakers

This case study presents an attempt to model the reliability of electric power system equipment based on the information gained from failure statistics, maintenance records and design data from the manufacturing process. The aim is to base the model on existing data available from the network operator and the equipment manufacturer.

The work carried out in this case study focussed on circuit breakers for two reasons. Firstly, circuit breakers consume a large proportion of the utilities maintenance budgets. Secondly, circuit breakers are critical to the system reliability. This section is based on papers II and III.

3.3.1 Failure statistics and maintenance records

In Paper II a study of circuit breaker failures in the Swedish 220kV and 400kV transmission network, operated by the Swedish National Grid Company (SvK), was carried out in order to investigate the causes of circuit breaker failures in detail. The full report on this study can be found in [2]. Prior to this work, a number of circuit breaker studies had been carried out. Cigré conducted two major circuit breaker studies, reported in [34] and [35]. These two studies collected and compiled failure statistics for circuit breakers from around the world. In [36] Anders et al. presented a study on air blast circuit breakers. This study focussed on forced and planned outages. In addition, the study also considered the effect of different operating times, manufacturers and voltage levels. Furthermore, the Canadian Electricity Association (CEA) continuously collects failure statistics [37], not only for circuit breakers but also for other equipment in the power system. The studied failure statistics are all fairly detailed but not to the required level needed for the case study presented in this section.

The study in Paper II included all circuit breaker failures during the period from 1 January 1999 to 30 June 2003. The studied circuit breaker population included 565 circuit breakers and a total of 2588 circuit breaker-years. Table 3.1 shows the distribution of circuit breaker failures over the different functions and Table 3.2 presents the ageing factors for the different circuit breaker functions.
### Table 3.1. The circuit breaker population arranged by function.

<table>
<thead>
<tr>
<th>Function</th>
<th>Abbreviation</th>
<th>Population</th>
<th>Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reactor breaker</td>
<td>X</td>
<td>50</td>
<td>19</td>
</tr>
<tr>
<td>Line breaker</td>
<td>L</td>
<td>393</td>
<td>26</td>
</tr>
<tr>
<td>Transformer breaker</td>
<td>T</td>
<td>34</td>
<td>1</td>
</tr>
<tr>
<td>Bus-bar breaker</td>
<td>AE</td>
<td>75</td>
<td>6</td>
</tr>
<tr>
<td>Capacitor breaker</td>
<td>K</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>565</td>
<td>53</td>
</tr>
</tbody>
</table>

### Table 3.2. Mean values for the ageing factors for function $i$.

<table>
<thead>
<tr>
<th>Function $i$</th>
<th>Time in op. to failure $\ell_i$ [yr/CB]</th>
<th>Op. cycles to failure $\delta_i$ [1/CB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>10.3</td>
<td>1584</td>
</tr>
<tr>
<td>L</td>
<td>20.2</td>
<td>101</td>
</tr>
<tr>
<td>T</td>
<td>27</td>
<td>81</td>
</tr>
<tr>
<td>AE</td>
<td>26.2</td>
<td>156</td>
</tr>
<tr>
<td>K</td>
<td>13</td>
<td>65</td>
</tr>
</tbody>
</table>
The data sources were:

- **AnnaKlara (AK)** is the network failure reporting system employed by SvK. AK contains information about all equipment failures, not only those causing loss of energy supply.

- **Tifo** is the maintenance system employed by SvK. All maintenance carried out on the SvK network is outsourced to external contractors. Tifo uses a web-based interface between contractors and SvK, where the contractors report all maintenance actions for which they wish to debit the SvK. Tifo contains information on all planned and already carried out maintenance actions.

- **Internal reports.** At SvK a number of internal reports are generated when a failure occurs. These reports may be preliminary reports, VHR\(^1\)-reports, failure reports or different kinds of test records.

- **Expert estimates.** In the case of the number of operating cycles to failure, it has not been possible to obtain any exact figures. Therefore, estimates from SvK experts have been used instead.

In Figure 3.2a) the failures have been arranged with respect to the circuit breaker interrupting media. In graph b) the failures have been arranged according to their function in the network. Explanations to the keys on the x-axes are found in Table 3.3. In Figure 3.3 the number of failures are plotted as a function of time in operation. The bars are divided with respect to the faulty sub-component, graph a), and function, graph b). Figure 3.4 shows the proportion of failures, failure rate, mean time in operation and mean number of operating cycles with respect to the circuit breaker function. Figure 3.5 shows the failure rate per operating cycle as a function of operating frequency.

The results from this study cannot be used as the only source of information when establishing a relationship between ageing and failure rate. The main reason for this is that the available data does not contain enough information about the faulty sub-components, that the data is of varying quality and that the small circuit breaker population comprises many different makes and models.

\(^1\)VHR is a Swedish acronym meaning “Repair engineer on duty”
Table 3.3. Sub-component keys for figure 3.2

<table>
<thead>
<tr>
<th>Key</th>
<th>Sub-component</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Trip latch mechanism</td>
</tr>
<tr>
<td>2</td>
<td>Insulators</td>
</tr>
<tr>
<td>3</td>
<td>Operating rod</td>
</tr>
<tr>
<td>4</td>
<td>Auxiliary contacts</td>
</tr>
<tr>
<td>5</td>
<td>Other mechanical sub-components</td>
</tr>
<tr>
<td>6</td>
<td>Contacts</td>
</tr>
<tr>
<td>7</td>
<td>Chains</td>
</tr>
<tr>
<td>8</td>
<td>Not identified</td>
</tr>
<tr>
<td>9</td>
<td>Incomplete switch</td>
</tr>
<tr>
<td>10</td>
<td>Other</td>
</tr>
</tbody>
</table>

![Figure 3.2](chart1.png)  
**Figure 3.2.** Number of failures per faulty sub-component, interrupting media and function.
Figure 3.3. Number of failures w.r.t. time in operation, faulty sub-component and function.
3.3. Failure Statistics and Design Data

Figure 3.4. Proportion of failures, failure rate, mean time in operation to failure and mean number of operations to failure per function.
3.3.2 Sub-component lifetime modelling

The data presented in the study described in the previous subsection does not provide sufficient information to model the reliability by fitting a statistical distribution to the data, as described in Section 2.2.1.

In Paper III a Bayesian method was applied to combine the information from the design process with failure statistics and maintenance records. The method was applied to a circuit breaker operating rod by using the WinBUGS software, which employs Markov Chain Monte Carlo (MCMC) to calculate the integral found in equation (2.25). 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). A flow chart describing the basic steps of the method is shown in Figure 3.6.

Within the RCAM research conducted at the department of Electrical Engineering at KTH other work has been carried out within the field of Bayesian reliability modelling of power system components. In [38] a study on the use of expert knowledge as prior information for lifetime modelling of stator windings of hydro power generators was presented. In [39], a study subsequent to Paper III, the same method was implemented using a simple rejection sampling method producing comparable results.
3.3. FAILURE STATISTICS AND DESIGN DATA

![Flowchart](Figure 3.6) Flowchart describing the proposed method.

By using prior information from the design process found in [40] and updating it with the information gained from failure statistics and maintenance records presented in Paper II the posterior distribution was produced. Figure 3.7 shows the updating and the posterior predictive information used in Paper III. The curve based on the updating information is fitted to the failure and maintenance data from Paper II, which contains one actual failure and 12 right-censored observations. To predict future operating rod failures the Bayesian posterior predictive distribution was simulated by using equation (2.27).

---

2Figure 3.7 is reproduced due to typos present in Figures 4ab, 6ab) and 7 in Paper III.
In conclusion, it is possible to model sub-component reliability by adding information from the design process as well as maintenance records and by using Bayesian methods. When using Bayesian methods the access to data remains the most serious problem and more data is needed to model the reliability of a complete power apparatus.

3.4 Field measurements of condition – disconnector contacts

This case study on field measurements of condition is based on Paper IV and deals with reliability modelling based on measurements made in the field within the framework of the Ph.D. project.

Paper IV presented a quantitative method to estimate the condition of disconnector contacts using thermography. The general idea 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.

In this study two sets of thermography measurements of disconnector contacts were carried out. All measured disconnectors were of the horizontal centre break type.
of the same make and model with the rated current \( I_n = 3150 \text{A} \). The measured points, per pole, were the contact covers of the two rotating terminal contacts and the main contacts.

In the first set of measurements the emphasis was on establishing what factors affect the contact condition. Therefore, the measurements were designed as a two by two factorial experiment, testing the effect of the age and time since last maintenance activity on the contact condition. In the first set, 21 disconnectors in the Swedish transmission system were measured. The disconnectors were distributed over five substations at 220kV and 400kV. The contacts were measured only once and most of the measurements were carried out after sunset in order to avoid 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.

In the second set of measurements the emphasis was on establishing the accuracy of the measured temperature rise \( \Delta T_m \) and on identifying the error sources when using thermography. Eight disconnectors in total were measured at three different substations in the 400kV Swedish transmission system. The same contacts were measured repeatedly with different loads. For the second set more care was taken in order to produce results with higher accuracy.

From the second set of measurements estimations of the different sources of errors were investigated and as a result their statistical distributions were estimated. These distributions were subsequently used in order to simulate the accuracy of the method using Monte Carlo simulation.

Figure 3.8 shows the simulated 90% confidence intervals for the calculated nominal temperature rises from measurement set 1. From the figure it is apparent that the confidence interval for the nominal temperature rise is so large that no reliable diagnosis can be made at low load currents. In Figure 3.9 the Monte Carlo simulated probability of maintaining a healthy contact is presented. Finally, Figure 3.10 shows the calculated nominal temperature rise for a terminal contact from set 2 at different currents at the time of measuring is shown.

In conclusion, by using the proposed method to estimate contact condition it is possible to include the different sources of error to obtain Monte Carlo simulated confidence intervals.
Figure 3.8. Monte Carlo simulated confidence intervals for the calculated nominal temperature rises, from measurement set 1.

Figure 3.9. Monte Carlo simulated probability of maintaining a healthy contact.
Figure 3.10. Terminal contact nominal temperature rises at steady state with 90% confidence, from measurement set 2.
Chapter 4

Summary and conclusions

This Licentiate thesis presents the half-way progress towards achieving the aim of the Ph.D. project, which is to model the effect of maintenance on reliability of power system equipment. To achieve this aim, three case studies have been carried out using distinct approaches on different types of equipment. The four appended articles present the progress of this Licentiate thesis work. The findings and conclusions drawn from this work are summarised below.

Failure mechanism modelling

- Information on the system characteristics and the relationship between the ageing processes and the component condition is necessary for the development of reliability models for power system components.

- By using assumptions based on the ageing process and the operational environment it is possible to find load and stress characteristics that can be fitted to agree with failure statistics for power system components.

Failure statistics and design test data

- The available failure statistics is not sufficiently detailed to serve as the only basis for reliability modelling of power system equipment.

- By adding information from the design process and maintenance records as well as using Bayesian methods, it is possible to model sub-component reliability. When using Bayesian methods the access to data remains the most serious problem and more data would be needed to model the reliability of a complete power apparatus.

- The large variance of the predictive posterior distribution represents the uncertainty of the prediction and is dependent on the updating data, i.e. failure statistics and maintenance records.
By using Bayesian methods it is possible to model the reliability of new equipment.

Field measurements of condition

- Methods to estimate sub-component condition can be found and it is possible to include different sources of error to obtain Monte Carlo simulated confidence intervals.
- A key issue is to relate the measured quantities to the condition of sub-components.

Finally, 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.
Chapter 5

Future work

The work carried out in this thesis serves as a basis for subsequent research within the framework of the Ph.D project. Planned future work includes the following:

- To carry out another study on circuit breaker failures using the same sources as in Paper II in order to obtain failure and maintenance data covering a longer period of time. The study could possibly be extended to include the results from other relevant studies.

- To use failure and maintenance data to further develop the method proposed in Paper III to include the effect of maintenance on equipment reliability.

- To further investigate the use of thermography as a diagnostic tool for disconnector contacts by comparing the different thermography routines employed by the transmission grid operators in the Nordel power system.

- To further develop the method of disconnector contact condition assessment by extending it to handle covered contacts and to establish the effect of maintenance on the contact condition.

- To use the developed reliability models for input into the maintenance optimisation carried out within the RCAM framework.
References


Paper I
Reliability modelling of aged XLPE cables

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Department of Electrical Engineering
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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.
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 unfaulted 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.

| Mean value | 1.73       |
| Standard deviation | 0.5        |
| Number of overvoltages | 1 per year |

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.

![Comparison between experienced and estimated failure rate for a 10 km loop.](image)

**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


Paper II
A Feasibility Study for Probabilistic Modeling of Aging in Circuit Breakers for Maintenance Optimization

Tommie Lindquist, Student Member IEEE, Lina Bertling, Member IEEE and Roland Eriksson, Senior Member IEEE.

Abstract—To support the maintenance optimization carried out within the framework of the reliability-centered asset management (RCAM) method this paper presents a feasibility study for the probabilistic modeling of the aging of circuit-breakers (CB). The aim of the study is to investigate the possibilities of the development of a reliability model for a CB, using failure data and maintenance records. A study of such statistics was carried out on all 565 CBs in the Swedish National Grid (transmission level) during a time period ranging from 1999-01-01 to 2003-06-30. A total of 53 CB failures were identified and studied with respect to faulty subcomponent, CB function, number of operating cycles to failure and time in operation to failure. Results from this study are presented in this paper.

Index Terms—Asset management, maintenance, aging, circuit-breakers, reliability, reliability centered asset management (RCAM).

I. INTRODUCTION

Today’s electric power distribution systems operate in a deregulated market. The system operators are required to provide reliable electricity to customers and at the same time be cost-effective. This has lead to an increased attention to preventive maintenance (PM) as a tool the reach both of these objectives.

A method for providing a quantitative relationship between PM of assets and the total maintenance cost has been developed by Bertling et al. [1]. The method, called reliability-centered asset management (RCAM), has been developed from reliability-centered maintenance (RCM) principles, with the objective of reaching further in the process of relating the impact of maintenance on the cost and reliability of the system. The method has previously been applied on a cable component [2]. The outset for this study is to investigate the possibilities to model a different component. This is necessary since the RCAM method is intended to be general. Switchgear in general, and circuit-breakers (CB) in particular, are well suited since they are important with respect to reliability and also consume a relatively large proportion of the total PM.

This paper presents a study on all CBs in the Swedish transmission network administered and operated by the Swedish National Grid Company, Svenska Kraftnät (SwK). The purpose of the study is to investigate whether failure statistics and maintenance records can be used in order to develop a failure rate model for CBs.

II. METHOD

a) The stages in the RCAM method

The RCAM method provides a systematic process for deducing cost-efficient maintenance plans, where the benefit of component maintenance is related to the system reliability and total-cost. Figure 1 illustrates a central feature of the method; the analysis moves from the system level, to the component level and back to the system level.

Figure 1. Illustrates the different stages of the RCAM method [2].

In the first stage the critical components are identified, i.e. the components that have the most impact on the system reliability. In stage 2 these components are studied in greater detail with the purpose of relating failure rate change in time, to the effect of applying different PM measures. In previous studies this relationship has been achieved by studying causes of failures [2]. Finally, in the last stage different maintenance strategies are evaluated based on a system reliability and cost/benefit analysis.

In the context of the RCAM method the work carried out in this paper is focused on stage 2, i.e. the component reliability modeling.

This work was supported in part by the ELEKTRA electrical power research programme.
T. Lindquist (e-mail: tommie@kth.se), L. Bertling (e-mail: lina@kth.se) and R. Eriksson are all with the Royal Institute of Technology (KTH), Stockholm, Sweden.
b) **Approach for component reliability modeling**

The objective is to develop a model of the failure rate as a function of time $\lambda(t)$, which relates to the effect of maintenance measures. In order to model the component failure rate it is necessary to understand the characteristics of the component behavior, and how these change over time. This leads to the concept of aging. The aging phenomenon is usually considered in relation to time in operation. However, this assumption is not always suitable, as will be discussed in the following section.

The purpose of this study is to establish a general model for the quantitative relationship between reliability and the effect of PM. The reasoning in this study is based on the following two assumptions:

- **Assumption 1**: Increasing age (Age) $\Rightarrow$ Increasing $\lambda$(Age)
- **Assumption 2**: Increasing maintenance $\Rightarrow$ Decreasing $\lambda$(Age)

where $\lambda$(Age) is the failure rate as a function of age, note that age may be $\neq$ time in operation.

**III. THE CONCEPT OF AGING**

All failures depend on some sort of failure mechanism i.e. some mechanical or chemical process that leads to a failure [3]. Therefore it is, strictly speaking, incorrect to talk about ageing failures as something that depends on time, as time is nor a physical or a chemical process. The following definitions will be used throughout this paper:

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

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

In the literature there is an agreement that power system components do not only age with calendar time and that other factors come in to play as well [4,5,6]. There are several mathematical models describing the effectiveness of maintenance. One common assumption is that maintenance is considered to be perfect (replacement) [7,8], models like this are called As Good As New (AGAN). The opposite of such models are the As Bad As Old (ABAO) models [7], where maintenance has no effect on the component reliability (inspection). Between these two extremes are the Imperfect Maintenance (IM) models, where an increase (or reduction) in reliability comes with every maintenance action [7]. The increase (or reduction) in reliability may either be fixed or proportional [9].

When it comes to modeling the effect of aging Martorel et al. [6] used two different models to describe the aging process of components in nuclear power plants. In [10] Langseth and Lindqvist used a model for IM that utilized three dimensions of time to measure the age of a component. There are also several articles dealing with the aging of cable insulation. In [11] Monnari and Simoni presented a literature review of aging phenomenon and modeling for insulating materials.

Accordingly, there exists a set of mathematical models that deal with the aging as a function of operating conditions and maintenance. The problem of applying these models to real-world problems is that they all depend on the setting of one or more parameters, which may turn very difficult to ascertain. The models may be perfect but without the correct setting of the parameters they are of limited use when it comes to optimizing maintenance. The most common necessary input data is some form of failure rate, either empirical or theoretical, or some other parameters that can be derived from such data.

**IV. INPUT DATA FOR COMPONENT RELIABILITY MODELLING**

**A. Circuit-breaker data**

Data to support reliability models can be obtained either from experimental tests or from operational field data. In the CB case it is difficult to carry out any experimental tests due to the big variety of CB types, manufacturers and generations that would be needed to be tested in order to make the model general. Consequently, any model has to be constructed using operational field data. However, this presents a limitation to the model since it will then only be able to model older equipment already in use.

**B. Previous circuit-breaker studies**

In order to obtain operational field data for CBs some source of statistics is needed, this type of statistics can be obtained by carrying out a study of e.g. failure statistics. There are a number of CB studies previously carried out. Cigre has carried out two major CB studies, reported in [12,13]. These two studies collected and compiled failure statistics for CBs from around the world. Anders et al. presented a study on Air Blast CBs in [14]. This study is focused mainly on outages, both forced and planned. In addition the study also considered the effect of operating time, manufacturer and voltage level. Furthermore, the Canadian Electricity Association (CEA) collects failure statistics [15], not only for CBs but other equipment in the Power System as well. These failure statistics are fairly detailed but not to the required level needed for the purpose of this study.

**C. Conclusion**

The previously mentioned CB studies are of high quality but are of limited use when it comes to establishing a relationship between failure rate and aging since they only present mean values of failure rates. Therefore the level of detail is insufficient for the purpose of the CB reliability modeling in this study. Consequently, in order to obtain the necessary operational CB data, failure statistics and maintenance records from SvK is analyzed in greater detail.
V. THE CIRCUIT-BREAKER STUDY

A. Description of a circuit-breaker

The CB has been represented by a model, depicted in Figure 2. The model has been based on the studied SvK CB population and their failure statistics. The CB has, in the model, been divided into two major parts, the pole and the operating mechanism. These two parts have been further divided into their subcomponents and there is also a part for other mechanical subcomponents, such as shafts, shear pins and other mechanical subcomponents that may be present in both the operating mechanism and the interrupter. This model is not general in the sense that it cannot be applied to any arbitrary CB population without adjustments being made.

B. Aging factors

Aging factors are such factors that, in one way or another, affect the fundamental failure mechanisms. For CBs these factors can be summarized as:

- time in operation,
- number of operating cycles (one operating cycle is defined as an Open-Close sequence),
- accumulated interrupted short circuit current.

The reason why these factors are being considered is motivated by previous CB studies [13,14] and by information from manufacturers [16]. However, contact wear is not a problem in the SvK network and as a result no contacts are replaced due to routine PM [17]. Consequently, the third aging factor will not be considered throughout the rest of this paper.

C. The circuit-breaker population

In this study all CBs administered and operated by SvK on the 220kV and 400kV levels were included. The CBs were studied for a time period, $T$, from 1999-01-01 to 2003-06-30. The studied CB population includes 565 CBs and a total of 2588 CB-years.

SvK is using a system to label their equipment where the equipment is classified according to their function in the system. The CBs in this study has been classified in a similar manner, as presented in Table 1.

Table 2 shows the distribution of CB failures over the different CB functions.

Table 3 presents the aging factors for the different CB functions, where the time in operation, $T_i$, is the mean value of the time in operation for all CBs during the time period $T$, for the CB function $i$. Analogously for the number of operating cycles to failure, $N_i$, where the percent value is the proportion of operating cycles of which function $i$ is contributing.

Worth noticing in Table 2 is that the reactor breakers with 8.8% of the total population is causing 35.8% of the failures.

Note that there has not been any information available regarding the distribution of the time in operation or of the interrupting media for the CB population.

D. Definition of CB failures

A failure is defined as [3]:

"Termination of the ability of an item to perform a required function"

The functions that the CBs are required to perform are [18]:

1. Make and break X Ampere.
2. Maintain electric insulation.
3. Transfer X Ampere.
4. Make and break all occurring short circuit currents.
5. Keep the interrupting media in the tank.

To be considered a CB failure, the failure also had to meet at least one of the below mentioned criteria:

1. Caused or could have caused loss of energy (LOE) at the customer end.
2. Caused a disturbance in the network without any LOE.
3. Could have had major consequences had the CB been in service.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>CB function</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>Reactor breaker</td>
</tr>
<tr>
<td>L</td>
<td>Line breaker</td>
</tr>
<tr>
<td>T</td>
<td>Transformer breaker</td>
</tr>
<tr>
<td>AE</td>
<td>Bus-bar breaker</td>
</tr>
<tr>
<td>K</td>
<td>Capacitor breaker</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Function</th>
<th>Population</th>
<th>Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>$N_i$</td>
<td>$n_i$</td>
</tr>
<tr>
<td>X</td>
<td>50</td>
<td>8.8</td>
</tr>
<tr>
<td>L</td>
<td>393</td>
<td>69.6</td>
</tr>
<tr>
<td>T</td>
<td>34</td>
<td>6.0</td>
</tr>
<tr>
<td>AE</td>
<td>75</td>
<td>13.3</td>
</tr>
<tr>
<td>K</td>
<td>13</td>
<td>2.3</td>
</tr>
<tr>
<td>Total</td>
<td>565</td>
<td></td>
</tr>
</tbody>
</table>
TABLE 3. MEAN VALUES OF THE AGING FACTORS FOR FUNCTION \( i \)

<table>
<thead>
<tr>
<th>Function</th>
<th>Time in op. to failure</th>
<th>Operating cycles to failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>10.3</td>
<td>1584</td>
</tr>
<tr>
<td>L</td>
<td>20.2</td>
<td>101</td>
</tr>
<tr>
<td>T</td>
<td>27</td>
<td>81</td>
</tr>
<tr>
<td>AE</td>
<td>26.2</td>
<td>156</td>
</tr>
<tr>
<td>K</td>
<td>13</td>
<td>65</td>
</tr>
</tbody>
</table>

E. Sources of statistics

During the time period, \( T \), statistics from SvK have been studied. The sources of statistics are:

- AnnaKlara (AK) is the network disturbance system employed by SvK. AK contains information about all disturbances, not only the ones causing LOE.
- Tifo is the maintenance system employed by SvK. All maintenance on the SvK network is outsourced to external contractors. Tifo uses a web-based interface between contractor and SvK, where the contractors report all maintenance actions for which they wish to debit the SvK. Tifo contains information on all planned and already carried out maintenance actions.
- Reports. At SvK, a number of reports are generated when a failure occurs. These reports may be preliminary reports, VHR-reports, failure reports and different kinds of test records.
- Expert estimates. In the case of the number of operating cycles to failure, it has not been possible to obtain any exact figure, instead estimates from SvK experts have been used.

F. Results

a) Subcomponent failures

From the 53 recorded CB failures during the time period \( T \) the failed subcomponent has been identified for 33 of the failures. The remaining 20 failures have been labeled “Not id.” and “Incomplete operation”, as can be seen in Figure 3. For the CBs that performed incomplete operations it has not been possible to identify the faulty subcomponent, and hence it is a subset of the “Not identified” category. The term incomplete switch refers to a situation when a CB does not manage to open/close all three poles. Note that there are incomplete operations among the failures with identified faulty subcomponents as well. In Figure 3 eight failures has been labeled “Other”, which means that the faulty subcomponent has been identified but does not fit the model in Figure 2, such subcomponents are e.g. charging devices and grading capacitors.

In Figure 3a) the failures have been arranged with respect to the CB interrupting media. The label “Unknown” means that there was no record of interrupting media in SvK equipment database. From the figure it can be seen that, during the studied time period, there has been 21 failures on oil insulated CBs and 35 failures on SF\(_6\) insulated CBs. For 11 CBs the interrupting media is unknown. In Figure 3b) the CB failures have been arranged according to their function in the network.

In Figure 4 the number of failures are plotted as a function of time in operation, where time have been divided into classes of five years, the failures have been arranged both with respect to faulty subcomponents and the CB function. From Figure 4a) the only visible trend is that the insulators start to fail after about 20 years in operation. Figure 4b) shows a trend that indicates that the reactor breakers fail before the line breakers.

To summarize for the subcomponent failures, it was only possible to identify the faulty subcomponents for 63% of the CB failures. Had the failure statistics been more detailed the information from the 53 failures may have been used more efficiently.

b) Aging factors

In this section the influence of the aging factors on the failure rate will be examined.

Figure 5 shows the proportion of failures, failure rate, mean time in operation and mean number of operating cycles with respect to the CB function. From Figure 5a) it can be seen that after the line breakers, the reactor breakers cause the most failures. In Figure 5b) the relatively small reactor breaker population is taken into account and a rather high failure rate per CB for the reactor breakers can be seen. In Figure 5c) the mean time in operation is taken into account. From the figure it is clear that the reactor breakers have the shortest mean time in operation to failure with approximately 10 years. In Figure 5d) the mean number of operating cycles is plotted with respect to the CB functions. From this figure it can be seen that the reactor breakers average about 1500 operating cycles to failure and the line breakers only about 100. The results in Figure 5 may be interpreted as the operating frequency is more important than operating time when it comes to the impact on the failure rate.

The results in Figure 5 has been calculated as follows:

\[
\lambda_i = \frac{n_i \cdot 100}{\sum_{i} n_i} ; \quad \bar{t}_i = \frac{1}{N_i} \sum_{i} t_i
\]  \((1,2)\)

where \( n_i \) is the number of failures caused by CBs with function \( i \) and \( N_i \) is the number of CBs in the population with function \( i \).

\[
\bar{t}_j = \frac{1}{\sum_{i} n_i} \sum_{i} t_{ij} ; \quad \bar{x}_j = \frac{1}{\sum_{i} n_i} \sum_{i} x_{ij}
\]  \((3,4)\)

where \( t_{ij} \) is the operating time to failure for CB \( j \) with function \( i \) and \( x_{ij} \) is the number of operating cycles to failure for CB \( j \) with function \( i \).

\(^{1}\) VHR is an abbreviation meaning “Repair engineer on duty”
In Figure 6 the failure rate is plotted as a function of the operating frequency [operating cycles/year]. The operating frequency is divided into classes of 50 years and the failure rate is expressed as failures per CB and operating cycle. The result may be interpreted as the risk of failure per operating cycle is decreasing with increasing operating frequency.

The failure rate per operating cycle has been calculated as follows:

\[ \lambda_k(s) = \sum_{j=1}^{N} \frac{1}{S_j N} \]

where \( g_j \) = class for CB \( j \) and \( k_p \) = number of CBs in class \( g \).

In Figure 7a) the operating time is plotted as a function of the number of operating cycles, where a ring represents every failure. In Figure 7b) the same figure as in 7a) is plotted except that it is plotted as a 3D figure with the number of CB-failures on the z-axis.

In Table 4 the SvK total CB failure rate is compared with failure rates found by Cigré in [13]. From the table it can be seen that the SvK CB failure rate is of the same magnitude as those found by Cigré. The differences between the SvK and the Cigré failure rates are partly due to differences in the definition of CB failures.

VI. CONCLUSION

This study comprises 53 CB failures on a total of 565 CBs in the SvK network over a time period stretching from 1999-01-01 to 2003-06-30. The conclusions from the study are summarized below.

The results from this study cannot be used as the only source when establishing a relationship between aging and failure rate. The reasons for this are:

- The available data does not contain enough information about the faulty subcomponents.
- The studied CB population is not large enough.
- The available data is of varying quality.

For CBs in general the following conclusions can be drawn:

- There is a trend with increasing failure rate with time.
- The risk per operating cycle is decreasing with an increasing operating frequency.
- The failure rate per CB increases with the number of operating cycles.

<table>
<thead>
<tr>
<th>Table 4: The SvK total failure rate compared to Cigré [13]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cigré “Major failures”</td>
</tr>
<tr>
<td>200-300kV</td>
</tr>
<tr>
<td>300-500kV</td>
</tr>
<tr>
<td>Cigré “Minor failures”</td>
</tr>
<tr>
<td>200-300kV</td>
</tr>
<tr>
<td>300-500kV</td>
</tr>
<tr>
<td>Swedish National Grid</td>
</tr>
<tr>
<td>220-400kV</td>
</tr>
</tbody>
</table>

Figure 3. Number of failures per faulty subcomponent, interrupting media and function.

Figure 4. Number of failures with respect to time in operation, faulty subcomponent and function.

Figure 5. Proportion of failures, failure rate, mean time in operation to failure and mean number of operations to failure per function.
ACKNOWLEDGMENT

The authors would like to express their appreciation for the valuable comments and extensive support received from Mr. Per Larsson and Mr. Thomas Thor of the Swedish National Grid Company, Svenska Kraftnät (SwK).

REFERENCES


A. Recommendations

The study of failure statistics resulted in the following recommendations:

1. For every failure, store information regarding:
   * time from the latest operating cycle,
   * time from the latest PM action and time to the next planned PM action,
   * number of operating cycles since last PM action.
2. Create routines in order to document the faulty subcomponent and the total number of operating cycles at the time of the failure.

VII. FUTURE WORK

The collection of data, as presented in the recommendations, will provide input data for continued studies of CBs. The project will also continue with the development of a model describing the condition of disconnector contacts as a function of maintenance and aging. The purpose of such a model will be to estimate the failure probability of the disconnector with respect to contact degradation.
Paper III
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
Roland Eriksson, Ph. D., Royal Institute of Technology

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.

1. 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 led 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.

2. 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.

![Flowchart of the proposed method](image)

**Figure 1. Flowchart of the proposed method.**

**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.) $f_i(x)$, where $x$ is an observation of $X_i$.

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.

![Reliability model](image)

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

![Operating High voltage mechanism part](image)

**Figure 3. A layout of the different critical CB parts [4].**

**2. Identification of Critical Sub-components**

The second step is to collect and analyze failure statistics in order to determine which sub-components are
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.

<table>
<thead>
<tr>
<th>Real data from [5]</th>
<th>Data used</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;10000</td>
<td>&gt;10000</td>
</tr>
<tr>
<td>&gt;10000</td>
<td>&gt;10000</td>
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<tr>
<td>&lt;10000</td>
<td>8000-9000</td>
</tr>
<tr>
<td>&lt;10000</td>
<td>7000-8000</td>
</tr>
<tr>
<td>&lt;10000</td>
<td>6000-7000</td>
</tr>
</tbody>
</table>

\( i \)-failure times (assumed to be known) were picked at random from a Weibull distribution

Table 1. Real and assumed development failure data.

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,

\[
A(y) = \frac{y}{c} \quad c > 0
\]

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, \( h(x) \), is calculated as

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below

\[ h_i(x) = \frac{f_i(x)}{1 - \int_0^x f_i(t) \, dt} \quad (2) \]

The hazard function for the serial system, comprising \( m \) sub-components, is then

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

Applied to the CB example a prior p.d.f. for \( X \) 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 (No of operations)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2100</td>
</tr>
<tr>
<td>3900</td>
</tr>
<tr>
<td>1350</td>
</tr>
<tr>
<td>1000</td>
</tr>
<tr>
<td>750</td>
</tr>
<tr>
<td>400</td>
</tr>
<tr>
<td>1600</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:

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

where the conditional density \( f(x \mid \theta) \) is the posterior distribution of \( \theta \), given \( X \), and \( f(x \mid \theta) \) is a model for the observed data.
In this work the posterior expectations are evaluated using MCMC methods \cite{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 \cite{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 \( A \sim \Gamma(\alpha_1, \gamma_1) \), \( B \sim \Gamma(\alpha_2, \gamma_2) \) and \( X \sim W(A, B) \), where \( \alpha_1, \alpha_2, \gamma_1, \gamma_2 \) are constants. The \( \Gamma \)-p.d.f. is defined as

\[
f(x | \alpha, \gamma) = \frac{\alpha^{\gamma} x^{\gamma-1} e^{-\alpha x}}{\Gamma(\gamma)}
\]

where \( \alpha \) and \( \gamma \) 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 \cite{16}

\[
f(D|\theta) = \int f(x_0 | \theta) \cdot f(\theta | D) \, d\theta
\]

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 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 3). 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>
<thead>
<tr>
<th>Number of operations</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>2100 800 3900 1350 1000 750 400 1600</td>
<td>2100 800 3900 1350 1000 750 400 1600</td>
<td>2100 800 3900 1350 1000 750 400 1600</td>
<td>2100 800 3900 1350 1000 750 400 1600</td>
<td>2100 800 3900 1350 1000 750 400 1600</td>
</tr>
</tbody>
</table>

Table 3. Lifetimes for the four different test cases

4.1 The effect of using development text data

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, \( \hat{a} = 0.3787 \) \( \hat{b} = 2.0750 \), were estimated using the Maximum Likelihood Method (MLM) in MINITAB. For Case 2 the MLM 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.

4.2 Sensitivity Analysis
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](image)

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.

6. ACKNOWLEDGEMENTS

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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 loadings to 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]:

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

(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:

\[
W_{bb} = W_{obj} \cdot \varepsilon
\]  

(2)

where \( W_{bb} \) is the radiating power by a blackbody temperature
source, $\varepsilon$ is the emissivity of the non-blackbody measurement object and $W_{rad}$ is the radiation power of the object. The emissivity, $\varepsilon$, is dimensionless and is in the range between zero and one and is hence a measure of a materials’ 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 $L_t$ is calculated as:

$$\Delta T_{L_t} = T_{L_t} - T_{nab}$$  \hspace{1cm} (3)

where $T_{L_t}$ is the hot-spot temperature of the measured object and $T_{nab}$ 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 disconnector 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:

$$\Delta T_{L_t} = T_{L_t} - T_{nab}$$  \hspace{1cm} (4)

where $T_{L_t}$ is the hot-spot temperature of the measured object and $T_{nab}$ 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, $\Delta T_{nab}$, 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, $\Delta T_{nab}$, 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]:

$$\Delta T_{w} = \Delta T_{nab} \left( \frac{v_m}{v_w} \right)^\alpha$$  \hspace{1cm} (5)

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

b) Temperature rise caused by load

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

$$\Delta T_{nab} = \Delta T_{nab} \left( \frac{I_m}{I_{nab}} \right)^\alpha$$  \hspace{1cm} (6)

where $I_m$ is the disconnectors’ rated load current and $I_{nab}$ 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 adding a constant temperature rise. By adding the constant temperature rise the final nominal temperature rise is calculated as:

$$\Delta T_e = \Delta T_{nab} + \Delta T_{const}$$  \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>$\Delta T_e - \Delta T_{max}$</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>
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 $I_r=3150$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 affect 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 (1) 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 $e=0.76$ and $e=0.80$, 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 $a=1.4$ 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, $e$, 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, $e$, was set by measuring a de-energized disconnector contact and changing the value of $e$ while comparing the measured temperature with the ambient temperature. The estimated value for $e$ 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 an example in Fig. 2. The figure shows the measured contact

![Fig. 1. Measured temperature rises and calculated temperature rises at nominal current, from set 1.](image)

<table>
<thead>
<tr>
<th>Measurement no.</th>
<th>Estimated emissivity, $e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>010</td>
<td>0.72</td>
</tr>
<tr>
<td>027</td>
<td>0.80</td>
</tr>
<tr>
<td>037</td>
<td>0.82</td>
</tr>
<tr>
<td>101</td>
<td>0.77</td>
</tr>
<tr>
<td>127</td>
<td>0.76</td>
</tr>
<tr>
<td>136</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.78</strong></td>
</tr>
</tbody>
</table>
IV. ANALYSIS

A. Temperature rise

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

$$\Delta T_m = k \cdot I_{\text{med}}^a$$  (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:

$$P_j = k_i$$
$$P_j = d_j + b_jI$$

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

$$T_j(t) = d_jR + b_jRt - b_jR\tau$$  (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 $i_j$ is:

$$\tau = \frac{T_j(t_0) - T_j(t_)}{b_2R - b_1R}$$  (11)

Getting $b_1R=3.65\text{C}/\text{h}$ and $b_2R=1.98\text{C}/\text{h}$ from the measurements (see Fig. 3) the time constant becomes $\tau=33$ minutes, by using (11). The steady state equivalent temperature rise is then:

$$\Delta T_m = \Delta T_{\text{med}} + b_jR\tau$$  (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.
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 $\Delta T_{\text{conn}}$ 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 $\alpha$ is object-specific and its value depends on the heat-transfer capabilities of the object [3],[7]. Establishing the value of $\alpha$ for all measured contacts is not practically possible and therefore a mean value is used for all contacts. The value of $\alpha$ 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.

The fact that the results differ so widely and that there is an uncertainty concerning the statistical distribution of $\alpha$ leads to the assumption that the exponent $\alpha$ is uniformly distributed with the parameters 1.0 and 2.0, i.e. $\alpha \sim U(1,2)$. The uniform distribution is selected because it is assumed that no exponent value is more likely than any other.

![Image](52x4 to 543x837)

**Fig. 5.** Temperature rise measured at a ramping current converted to heir steady state equivalent, from set 2.

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>Reference</th>
<th>Object</th>
</tr>
</thead>
<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]:

$$ W_{\text{obj}} = \frac{1}{\varepsilon r} W_{\text{ref}} - \frac{1-\varepsilon}{\varepsilon} W_{\text{ref}} - \frac{1-r}{\varepsilon} W_{\text{env}} $$

(13)

where $\varepsilon$ is the emissivity of the object, $r$ is the transmittance of the atmosphere, $W_{\text{ref}}$, $W_{\text{ref}}$ and $W_{\text{env}}$ 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 $W_{\text{ref}}$, $W_{\text{ref}}$ and $W_{\text{env}}$ 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 de-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 $\varepsilon \sim U(0.7,0.85)$. 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 $\varepsilon_{\text{err}} \sim N(0,3)$, [\%]. 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 $\varepsilon_{\text{err}} \sim N(0,5)$, [%]. 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 disconnecter 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, $a - U(1, 2)$.
- Emmissivity, $e - U(0.7, 0.85)$.
- Thermography measurement error, $\text{error}_r \sim N(0, 3)$, [°C].
- Current measurement error, $\text{error}_i \sim N(0, 5)$, [%].

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 $e$ from their distributions.
3. Sample measurement errors for the thermography and the current measurements.
4. Get $\Delta T_m$.
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:

$$ P(\Delta T_m \geq \Delta T_{\text{rem}} \mid \Delta T_{\text{rem}} < \Delta T_{\text{max}}) $$

(14)

where $\Delta T_{\text{rem}}$ 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 $\Delta T_{\text{rem}} = 95$°C for a failed contact and $\Delta T_{\text{rem}} = 75$°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 $\Delta T_{\text{rem}} = 65$°C from [13].
2. Sample an exponent $a$ and an emissivity $e$ 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 $I_{\text{low}}$ less than $I_{\text{low}} = 1000$A, which is approximately $0.3I_L$. 

![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)
Fig. 8. Terminal contact nominal temperature rise at steady state with 90% confidence, from test 2.

E. Contact condition

As an example of the method presented in this paper, Fig. 8 shows the nominal temperature rise from measurement set 2 for the left terminal contact of disconnector 1, phase L2, in station A when compensated for ramping current. In this case the contact is regarded as being aged, i.e. the contact is considered bare in [13], making $\Delta T_{max} = 65^\circ C$. Using Table 1, the condition of the contact is found to be in functioning condition with 90% confidence for all measurement points except one. This again points out the danger with using thermography at low load currents. When calculating the nominal temperature rise in Fig. 8 the temperature constant used was $\Delta T_{const} = 5^\circ C$, from [15].

V. CONCLUSIONS

A quantitative method of establishing disconnector contact condition using thermography has been derived. Based on this 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 provide 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

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