Individual Failure Rate Modelling and Exploratory Failure Data Analysis for Power System Components

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Abstract

A set of vital societal functions such as health and safety are necessary for today's society to function and to secure the life of its individuals. Infrastructure is required to provide and maintain these functions. This for society critical infrastructure includes electronic communication technology, transport systems, oil & gas supply, water supply, and the supply of electric power. The electric power system plays a central role in the critical infrastructure since it is required to operate all others. Therefore, outages in the power system can have severe consequences not solely for the supply of electricity but also for the supply of water, gas, and food. To provide a reliable and safe power supply, power system operators are applying asset management strategies to investigate, plan, maintain, and utilize the system and its components while improving the performance under its own financial constraints.

One approach to increase the reliability of the power grid while decreasing costs is maintenance planning, scheduling, and optimization. To optimize maintenance, a reliability measure for power system components is required. The failure rate, which is the probability of failure in a predefined interval, is utilized in maintenance optimization. Thus far, an average failure rate has been assigned to all components of the same type due to a shortage of component failure data. However, this limits the accuracy of maintenance techniques since the component heterogeneity is neglected. Moreover, the actual failure rate is being underrated or overrated and it is a challenge to identify the impact of conducted maintenance tasks.

This thesis presents how the failure rate accuracy can be improved despite limited failure data available. Firstly, an introduction to failure rate modelling theory, concepts, and definitions is given to provide a common understanding for the later chapters and papers. Secondly, regression models are presented which can be used to model, predict, and characterise the failure rate and failure intensity for power system components. The Cox regression and regression models for count data are applied to two case studies of disconnector and circuit breaker failure data. The results contribute to an improved modelling of the failure rate on individual level but also improve the understanding of risk factor's impact on component failures. However, the aforementioned regression models have rarely been applied in the power system domain due to the limited failure data. Thirdly, the necessity to distinguish between population and individual failure rates is illustrated and risk factors and methods are presented, which are frequently used in failure rate modelling. Moreover, the thesis presents a method to calculate and predict individual failure rates despite the occurrence of actual failures which is of particular advantage for new components.

Sammanfattning

Viktiga sociala funktioner som hälsa och säkerhet är nödvändiga för dagens samhälle att fungera och för att trygga dess individers liv. Infrastrukturer tillhandahåller och behåller dessa funktioner. Elektronisk kommunikationsteknik, transportsystem, olje- och gasförsörjning, vattenförsörjning och elnätet är kritiska infrastrukturer för samhället. Elnätet spelar en central roll bland de kritiska infrastrukturerna, eftersom alla andra infrastrukturer är beroende av elnätet. Driftavbrott kan därför få allvarliga konsekvenser, inte bara för elnätet men också för leverans av vatten, gas och mat. Det är därför viktigt att det elektriska energisystemet är tillförlitligt.

För att tillhandahålla ett tillförlitlig och säkert elnät tillämpar nätoperatörerna strategier för kapitalförvaltning för att undersöka, planera, underhålla och använda systemet och dess komponenter samtidigt som prestanda förbättras enligt egna ekonomiska krav. Ett sätt att öka elnätets tillförlitlighet samtidigt som kostnaderna reduceras är underhållsplanering och optimering. För att optimera underhåll krävs en tillförlitlighetsmasstal för komponenter i elnät. Felfrekvensen, som är sannolikheten för ett driftavbrott under en fördefinierad tidsperiod, används vid underhållsoptimering.

Hittills har alla komponenter av samma typ, på grund av saknade komponentfeldata, tilldelats en genomsnittlig felfrekvens. Att försumma komponent heterogenitet begränsar dock precisionen i underhållsoptimering. Dessutom underskattas eller överskattas den faktiska felfrekvensen, vilket är en utmaning för att identifiera effekten av underhållet som utförs.

Denna avhandling presenterar hur precisionen i felfrekvensen kan förbättras trots begränsad feldata. I den första delen ges en introduktion till den allmänna teorin, begrepp och definitioner av felfrekvens-modellering för att ge läsaren en förståelse för de senare kapitlen och artiklarna. Den andra delen presenterar regressionsmodeller som kan användas för att modellera, förutsäga och karakterisera felfrekvensen och felintensiteten för komponenter. Cox regression och andra regression modeller används på två fallstudier av frånskiljare och strömbrytare feldata. Resultaten bidrar till förbättrad felfrekvens-modellering på individnivå, men förbättrar också förståelsen av riskfaktorns inverkan på komponentfel. Regressionsmodellerna används sällan i kunskapsfältet i kraftnätet på grund av den begränsade feldatan. Den tredje delen presenterar behovet av att skilja mellan genomsnittlig felfrekvensen och felfrekvensen för enskilda komponenter och introducerar riskfaktorer och metoder som vanligen används vid felmodellering. Dessutom presenterar avhandling en metod för att beräkna och förutsäga felfrekvenser för enskilda komponenter trots att det inte finns någon feldata, vilket är särskilt fördelaktigt för nya komponenter.

Zusammenfassung

Gesundheit und Sicherheit gehören zu einer Reihe wichtiger gesellschaftlicher Funktionen, welche für die heutige Gesellschaft notwendig sind, um zu funktionieren und das Leben ihrer Individuen zu sichern. Infrastrukturen haben die Aufgabe diese Funktionen bereitzustellen und aufrechtzuerhalten. Elektronische Kommunikationstechnologie, Transportsysteme, Öl- und Gasversorgung, Wasserversorgung und die elektrische Energieversorgung sind für die Gesellschaft kritische Infrastrukturen. Das Stromnetz trägt eine zentrale Rolle unter den kritischen Infrastrukturen, da alle weiteren vom Stromnetz abhängig sind. Ausfälle können daher schwerwiegende Folgen haben, nicht nur für die Stromversorgung, sondern auch für die Wasser-, Gas- und Nahrungsmittelversorgung. Um eine zuverlässige und sichere Stromversorgung bereitzustellen, wenden Stromnetzbetreiber Asset-Management-Strategien an, um das System und seine Komponenten zu untersuchen, zu planen, zu warten und zu nutzen, während die Performance unter den eigenen finanziellen Vorgaben verbessert wird. Ein Ansatz zur Erhöhung der Zuverlässigkeit des Stromnetzes bei gleichzeitiger Kostensenkung ist die Instandhaltungsplanung und -optimierung. Um Instandhaltungsmaßnahmen zu optimieren, ist eine Zuverlässigkeitskenngröße für Stromnetzkomponenten erforderlich. Die Ausfallrate, die die Wahrscheinlichkeit eines Ausfalls in einer vordefinierten Zeitspanne ist, wird in der Instandhaltungsoptimierung verwendet. Bislang wird allen Komponenten des gleichen Typs, aufgrund fehlender Komponentenausfalldaten, eine zeitlich konstante Ausfallrate zugewiesen. Die Vernachlässigung der Komponentenheterogenität begrenzt jedoch die Genauigkeit der Instandhaltungsoptimierung. Darüber hinaus wird die tatsächliche Ausfallrate oft unterschätzt oder überbewertet. In Bezug auf die Identifiztierung der Auswirkungen der durchgeführten Instandhaltungsmaßnahmen stellt dies eine besondere Herausforderung dar.

Die Arbeit zeigt, wie die Genauigkeit der Ausfallrate trotz eingeschränkter Ausfalldaten verbessert werden kann. Im ersten Teil wird eine Einführung in die generelle Theorie, Konzepte und Definitionen der Ausfallratenmodellierung gegeben, um dem Leser ein Verständnis für die späteren Kapitel und Artikel zu verschaffen. Im zweiten Teil werden Regressionsmodelle vorgestellt, mit denen die Ausfallrate und die Ausfallintensität von Stromnetzkomponenten modelliert, prognostiziert und charakterisiert werden kann. Die Cox-Regressions- und Regressionsmodelle für Zähldaten werden auf zwei Fallstudien von Trennschalter- und Leistungsschalterausfalldaten angewendet. Die Ergebnisse tragen zu einer verbesserten Modellierung der Ausfallrate auf individueller Ebene bei, verbessern aber auch das Verständnis der Auswirkungen von Risikofaktoren auf Komponentenausfälle. Die zuvor erwähnten Regressionsmodelle werden jedoch aufgrund der begrenzten Ausfalldaten selten im Forschungsgebiet des Stromnetzes angewendet. Im dritten Teil wird die

Notwendigkeit dargestellt, zwischen Populations- und individuellen Ausfallraten zu unterscheiden. Des Weiteren werden Risikofaktoren und Methoden vorgestellt, die häufig bei der Ausfallratenmodellierung verwendet werden. Darüber hinaus stellt die Arbeit eine Methode zur Berechnung und Vorhersage individueller Ausfallraten trotz des Auftretens von tatsächlichen Ausfällen vor, was insbesondere für neue Komponenten von Vorteil ist.

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List of Papers

The following papers are included in the thesis:

I **J. H. Jürgensen**, A. L. Brodersson, L. Nordström and P. Hilber, ″Impact Assessment of Remote Control and Preventive Maintenance on the Failure Rate of a Disconnector Population,″ in *IEEE Transactions on Power Delivery*, vol. 33, no. 4, pp. 1501-1509, Aug. 2018.

II **J. H. Jürgensen**, E. Andreasson, L. Nordström, P. Hilber, and A. L. Brodersson, ″Assessment of Explanatory Variables on the Failure Rate of Circuit Breakers Using the Proportional Hazard Model,″ in *2018 Power Systems Computation Conference (PSCC)*, Dublin, Ireland, 2018, pp. 1-7.

III **J. H. Jürgensen**, E. Andreasson, A. L. Brodersson, L. Nordström, P. Hilber, and L. Goel, ″Modelling of Recurrent Circuit Breaker Failures with Regression Models for Count Data,″ in *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Boise, ID, 2018, pp. 1-6.

IV **J. H. Jürgensen**, L. Nordström and P. Hilber, ″A Review and Discussion of Failure Rate Heterogeneity in Power System Reliability Assessment,″ *2016 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Beijing, 2016, pp. 1-8.

V **J. H. Jürgensen**, L. Nordström, and P. Hilber, ″Individual Failure Rates for Transformers within a Population Based on Diagnostic Measures,″ in *Electric Power Systems Research*, vol. 141, pp. 354-362, 2016.

VI **J. H. Jürgensen**, L. Nordström, and P. Hilber, ″Estimation of Individual Failure Rates for Power System Components Based on Risk Functions,″ Submitted to *IEEE Transactions on Power Delivery*, pp. 1-8, 2018.

I am the main author of **Papers I-VI** where I conducted the research and authored the papers. Hilber and Nordström supported and reviewed the research. In **Papers I-III**, Brodersson and Andreasson provided the data, which incorporated cleaning, formatting, and categorising the failure data with guidance and support from my side, and supported the problem formulation and analysis of the results.

These papers are not included in the thesis:

i N. Ekstedt, C. J. Wallnerström, S. Babu, P. Hilber, P. Westerlund, **J. H. Jürgensen**, T. Lindquist, ″Reliability Data: A Review of Importance, Use, and Availability,″ presented at the *NORDAC 2014 (Eleventh Nordic Conference on Electricity Distribution System Management and Development, Stockholm, 8 - 9 September 2014)*, 2014.

ii S. Babu, P. Hilber and **J. H. Jürgensen**, ″On the Status of Reliability Studies Involving Primary and Secondary Equipment Applied to Power System,″ *2014 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Durham, 2014, pp. 1-6.

iii C. J. Wallnerström, L. Bertling Tjernberg, P. Hilber, S. Babu, and **J. H. Jürgensen**, ″Analys av Smartaelnätsteknologier Inom Kategorin Elnätslösningar,″ Tech. Rep. 2014:036, KTH, Electromagnetic Engineering, 2014.

iv **J. H. Jürgensen**, L. Nordström, and P. Hilber, ″A Scorecard Approach to Track Reliability Performance of Distribution System Operators,″ in *CIRED 2015: 23rd International Conference on Electricity Distribution*, 2015.

v S. Babu, **J. H. Jürgensen**, C. J. Wallnerström, P. Hilber and L. Bertling Tjernberg, ″Analyses of Smart Grid Technologies and Solutions from a System Perspective,″ *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, Bangkok, 2015, pp. 1-5.

vi A. L. Brodersson, **J. H. Jürgensen** and P. Hilber, ″Towards health assessment: Failure Analysis and Recommendation of Condition Monitoring Techniques for Large Disconnector Populations,″ *CIRED Workshop 2016*, Helsinki, 2016, pp. 1-4.

vii C. J. Wallnerström, L. Bertling Tjernberg, P. Hilber and **J. H. Jürgensen**, ″Framework for System Analyses of Smart Grid Solutions with Examples from the Gotland Case,″ *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Beijing, 2016, pp. 1-9.

viii **J. H. Jürgensen**, A. Scheutz Godin, and P. Hilber, ″Health Index as Condition Estimator for Power System Equipment: A Critical Discussion and Case Study,″ in *CIRED - Congrès International des Réseaux Electriques de Distribution*, Glasgow, 2017, pp. 1-4.

ix **J. H. Jürgensen**, A. L. Brodersson, P. Hilber, and L. Nordström, ″The Proportional Hazard Model and the Modelling of Recurrent Failure Data: Analysis of a Disconnector Population in Sweden,″ in *2017 Cigré SC B3 (Substations) Colloquium*, 18 - 20 September 2017, Recife, Brazil, 2017, pp. 1-8.

x D. Sadik, J. Colmenares, **J. H. Jürgensen**, H. Nee, F. Giezendanner and P. Ranstad, ″Introduction of SiC MOSFETs in Converters Based on Si IGBTs,″ *2017 IEEE 3rd International Future Energy Electronics Conference and ECCE Asia (IFEEC 2017 - ECCE Asia)*, Kaohsiung, 2017, pp. 1680-1685.

xi H. M. Nemati, A. Sant'Anna, S. Nowaczyk, **J. H. Jürgensen**, P. Hilber, ″Reliability Evaluation of Power Cables Considering the Restoration Characteristic,″ *International Journal of Electrical Power & Energy Systems*, vol. 105, 2019, pp. 622-631.

This doctoral thesis is a revised and extended version of the Licentiate thesis:

- **J. H. Jürgensen**, ″Condition-based Failure Rate Modelling for Individual Components in the Power System,″ Licentiate dissertation, Stockholm, 2016.

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Chapter 1

Introduction

This doctoral thesis has the objective to improve power system reliability assessment by creating a better perception of how internal and external risk factors influence the probability of failure of power system components and how these can be utilized to compute a failure rate on individual component level. The thesis presents the research topic in two parts. The first part consists of Chapter 1 to 5 and the second part consists of the research papers.

Chapter 1 positions the overall context of the thesis from a societal perspective and motivates the research need. Thereafter, the research objectives are presented and a summary of the research contributions given. In Chapter 2, the theoretical background, definitions, and concepts of failure rate modelling are presented, which is an extended introduction to the topic. Chapter 3 presents exploratory failure data analysis and failure rate prediction with regression models to provide the reader with a solid background before the theory is applied to two case studies. The first case study investigates disconnector population and the second case study examines circuit breaker failures to improve the characterisation of failure rate modelling and gain knowledge for power system asset management. The ensuing Chapter 4 discusses power system component's heterogeneity in failure rate modelling and presents relevant risk factors. Moreover, the chapter presents the existing modelling techniques and gives an overview of the developed model to calculate individual failure rates with two case studies. The final Chapter 5 concludes the presented work and describes required future work.

1.1 The Electric Power System: a Critical Infrastructure

The Swedish Civil Contingencies Agency (Myndigheten för samhällsskydd och beredskap, MSB) has been instructed by the Swedish government on April 14th, 2010, to develop a unified national strategy to protect the vital societal functions [1]. These vital societal functions are defined as functions which are so critical that their failure would result in 'major risks or hazards for the life and health of the population, the functionality of society or society's fundamental values' [1, p. 10]. The first phase of this strategy includes the identification of these functions at local, regional, and national level. From the perspective of the Council of the European Union (EU) [2, p. 3], these societal functions are health, safety, security, economic and social well-being of people. MSB also uses the term critical infrastructure which is the 'physical structure' that is required to maintain the vital societal functions [1, p. 11], whereas the definition of the EU does not include the term 'physical' which results in a more general definition that also includes services [2, p. 3]. Critical infrastructure is identified in eleven sectors according to [3, p. 24]: energy, information and communication technologies, water, food, health, financial, public & legal order and safety, civil administration, transport, chemical and nuclear industry, and space and research. The technical infrastructure is power supply, electronic communications, payment systems, food supply, supply of drinking, transport system, and drug supply. These are discussed in a risk and scenario analyses in [4] for the Swedish society.

All the aforementioned technical infrastructure has all one common attribute: complexity. This infrastructure can be described as a complex system of interacting components where change primarily occurs as a result of a learning process [5]. Moreover, this infrastructure has interdependencies and bidirectional relationships, so that the state of one is dependent on the state of the other. Fig. 1.1 demonstrates in an abstract example the interdependencies between the infrastructure: electric power, natural gas, oil, telecom, water, and transportation. A specific example of an interdependency is that electric power is needed for compressors, storage, and control systems of the natural gas infrastructure but natural gas is required as a fuel for thermal electricity generation. These interdependencies can be 'tight' or 'loosely' coupled, which refers to the level of dependency [5]. The electric power supply has a central role in these interdependencies as other infrastructure has strong dependencies on it. This 'special position' is also identified by the MSB in the risk assessment of technical infrastructure in Sweden [4]. Particularly, the characteristic of no intermediate storage capacity, the electricity is consumed while it is produced, increases its importance as critical infrastructure since an outage has an instantaneous effect on all other types of infrastructure.

The electric power supply is ensured through a network of electrical components to supply, transfer, store, and use electric power. The electric generation and load centres are connected via the power grid, which is categorised into a transmission and distribution system. An additional system level is used in the terminology of the Swedish power grid. Here, the regional system level is the linkage between transmission and distribution level. The transmission power grid transfers the electric power from the generation sites to electrical substations where it gets further distributed through the regional and distribution grid to the customer. Despite their common functionality of transferring electric power, the three system levels are distinguished by voltage level and importance in descending order. The voltage level ranges from 400 kV to 200 kV on transmission level, 130-30 kV on regional level, and from 20 kV to 0,4 kV on distribution level. Since the transmission grid, also

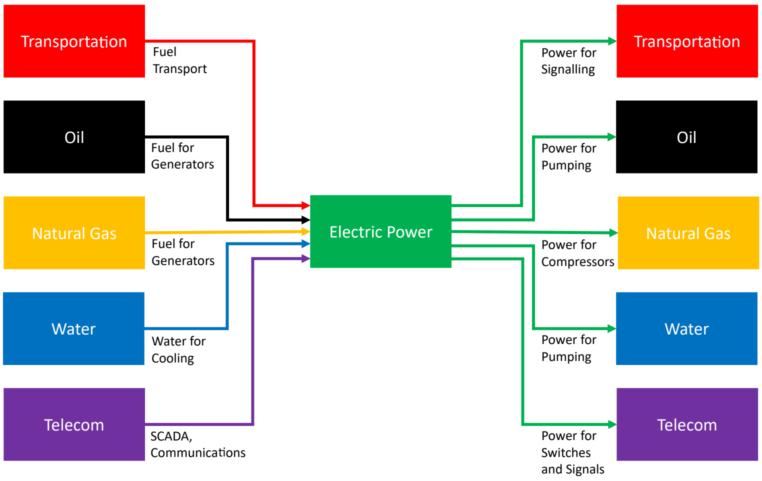


Figure 1.1: Illustration of infrastructure interdependencies in an abstract form based on [5, Fig. 3, p. 5]. Note that more interdependencies exist and that interdependencies between other types of infrastructure are neglected.

defined as bulk power system [6], supplies all regional and distribution systems, it is seen as the most important. Regardless of the importance, uninterrupted electricity supply requires high reliability on all system levels. An outage, whether it is caused by humans, technical faults, a lack of maintenance or a faulty design can therefore lead to the loss of vital societal functions [4]. Considering that an outage can have such severe impacts, the focus remains on improving the design, planning, operation, and maintenance to achieve a highly reliable and safe power grid.

1.2 Power System Asset Management

To achieve a reliable and safe power supply, a set of strategies is required to operate the power grid. Asset management involves strategies to investigate, plan, invest, utilize, maintain, replace, and dispose of components and systems while maximising the value and performance of the assets under the constraint of a utility's financial performance. The concepts and terminology of asset management have been specified in a standard [7] to achieve effective and efficient practices on an international level but also to limit the variations in the interpretation [8]. Following the business-driven approach, asset management aims to achieve the 'lifetime optimum' of components while considering the system perspective [8]. Finding the 'lifetime optimum' has its foundation on the concept of reliability-cost/reliabilityworth evaluation [9]. The resulting optimum is known as the socio-economically optimal reliability level [10]. Therefore, asset management for power grid operators has to resolve four challenges according to [11, p. 644] to remain profitable:

1. Incorporation of stakeholder values and objectives into strategy and operation of the utility
2. Achievement of reliability and safety considering financial constraints
3. Receiving the benefits of performance-based rates
4. Implementation and response to regulatory period changes

These challenges are approached by defining appropriate strategies for the components and further subdividing it into specific techniques and actions. This set of techniques and actions could include statistical failure analysis, lifetime estimation, condition assessment, and maintenance strategy decisions which are also suggested by [11]. All these techniques include the four basic parts of reliability [12]: probability, adequate performance, time, and operating conditions.

1.3 Power System Reliability Evaluation

Billinton and Allan discuss philosophical aspects of power system reliability in [13] and state that the term includes an extensive variety of aspects which have the common aim to satisfy the customer requirements. It is further described that there is the necessity to recognise the generality of the power system's ability to perform its required function. Focusing solely on the term reliability, an accepted definition is

"Reliability is the probability of a device performing its purpose adequately for the period of time intended under the operating conditions encountered." [14]

which is similar to the definition in the standard ISO 9000:2015. Applying this definition to the power system domain, we can translate device to system, a set of connected power system components, and component, a specific type of component in the system. From a societal perspective, the system reliability is of greater importance than the component reliability. However, the system is a set of components and therefore component failures could lead to system failures. This relationship is illustrated in a simplified fault tree diagram in Fig. 1.2 for one hypothetical system. Depending on the structure of the system, a component failure can lead to a system failure or not. Exploring reliability more theoretically, it is

$$\text{Reliability} = 1 - \text{Probability of Failure} \tag{1.1}$$

where the probability of failure is for a defined interval $[0, t]$. Thus, the reliability is the probability of success of a component or system to fulfil its required function in $[0, t]$. For example, a probability of failure can be assigned to an event in Fig. 1.2 and with some probability calculations, a system reliability can be calculated. Thus,

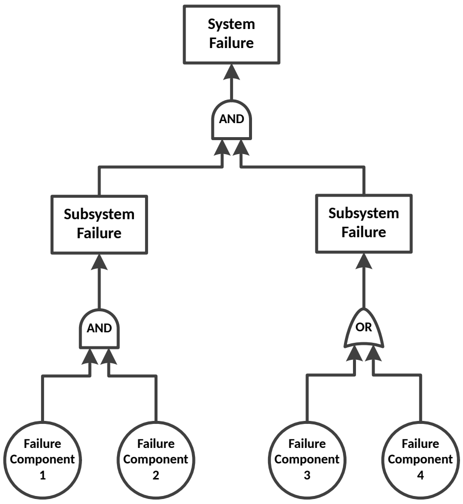


Figure 1.2: Simplified relationship between component and system reliability

it is important to precisely model the probability of failure to get the most accurate estimation of the component reliability and consequently the system reliability.

1.4 Failure Rate Accuracy and Understanding

The probability of failure for a system or component is also known as failure rate and is an essential reliability measure. It describes the conditional probability that a component will fail in the interval $(t, t+\Delta t]$ given that it has survived until t. A more detailed background of the failure rate and other reliability measures is presented in Chapter 2. The failure rate is important as a parameter in optimal maintenance planning [15], risk-based maintenance optimization [16], and to connect component reliability and maintenance in reliability-centred asset maintenance [17].

Failure data from lifetime tests is required to estimate a particular lifetime distribution $F(t) = 1-R(t)$ by using nonparametric and parametric methods. From this distribution a failure rate can be derived and is applied to all components of the same type. This requires the assumption that all components are identical and operated under equal conditions. Power system components however, are frequently designed for particular tasks and systems and are different to the tested components. Applying the same failure rate to one component type would consequently induce a bias. Moreover, primary components in power systems are designed for lifetimes typically around thirty years [18] but this might increase to forty years or more [19]. Due to these long lifetimes, experimental laboratory lifetime tests are difficult to conduct for power system components and most estimates are gained from historical operational failure data as in [19, 20]. This empirical approach is often problematic due to poor component documentation and long lifetimes cause incomplete failure data sets. This incompleteness of failure data causes censoring and truncation, see Section 2.2, which leads to large confidence intervals in the lifetime prediction. This has been shown in a study to predict the lifetime of power transformers [21], for example. Thus far, a practical solution is to assume a constant failure rate for all components of the same type [20]. This is based on the assumption of an underlying exponential distribution. This basic approach has produced reasonable results [20] since a constant failure rate reflects the useful life period of various components [22, p. 21].

Four major disadvantages remain from using this average failure rate approach. First-ly, applying one constant failure rate to each component of a type neglects the component heterogeneity. Even though all components in a population are of the same type, individual component characteristics such as size differ. This results in a failure rate which under or over estimates the actual failure rate. Secondly, the impact of maintenance activities cannot be identified from the failure rate. This is a challenge for maintenance optimization in particular. Thirdly, the failure rate estimation from empirical failure data, without considering the actual environment and stress, could cause a serious bias in the estimates [23, p. 429]. Finally, possible trends are neglected. Consequently, the constant failure rate and the universal approach of applying one failure rate to all components has a significant impact on the accuracy. This inaccuracy negatively impacts subsequent analytical methods such as network reliability modelling or optimal maintenance planning [24] and other methods discussed in chapter 2.4. This poses the question: *Can the accuracy of the failure rate be improved despite the limited historical data available?*

Generally speaking, the failure rate expresses the answer to the question: why certain components fail quicker or survive longer than others? The attempt to explain varying lifetimes demands for more information. Risk factors or explanatory variables are variables which the failure rate depend upon. Hence, [20] states that every type of component should ideally be characterised by a failure rate as a function of risk factors. The environment, component characteristics, and operational stress are such risk factors. For example, possible explanatory variables for power transformer failure rates can include:

- Continuous variables such as loading, voltage, and condition measurements.

- Categorical variables such as size, design, manufacturer, and location.

Investigating and estimating the significance and effect of explanatory variables on the failure rate can improve the understanding of risk factors which results in better decision-making within asset management. For example, in monitoring an implemented maintenance strategy.

1.5 Research Objectives

Based on the previous sections, the central research question, which is the foundation of this thesis, can be formulated as:

- Can the failure rate accuracy on an individual component level be increased despite the limited historical failure data available?

This question leads to the following research objectives (OBJ) which are to be solved with this thesis:

OBJ1: Investigate the impact of explanatory variables on the failure rate of power system components to support asset management decision-making and to improve failure rate accuracy and prediction.

OBJ2: Demonstrate that neglecting component heterogeneity leads to erroneous failure rate modelling and discuss risk factors which impact the condition and failure rate of components over time.

OBJ3: Develop and validate a method to calculate and predict failure rates for individual components without actual failure occurrence.

1.6 Summary of Research Contributions

A structured overview of the research objectives in connection to the thesis contributions is shown in Fig. 1.3.

Research Objective OBJ1

Research objective OBJ1 is addressed by the results of **Papers I-III**. These papers utilise statistical learning techniques, such as Cox regression and regression models for count data, to characterise the failure rate and rate of recurrence of failures (ROCOF) with explanatory variables for an improved failure rate accuracy and contribute to an increased understanding of failures. The papers investigate explanatory variables of solely electrical switchgear such as disconnectors and circuit breaker due to the data availability. However, the papers encourage further data analysis of other power system components for future studies. The particular results of each paper are summarised in the following.

Paper I discusses the difficulties of using regression approaches in the power system domain and illustrates how to overcome these. A population containing 1626 disconnectors is investigated to assess the impact of *preventive maintenance* (PM) and *remote control availability* on the failure rate. It is shown that *PM* has a positive impact whereas remote control availability has a negative effect. Moreover, the magnitudes of these effects are determined and can be used in further applications. The results show that single pole disconnectors have a 9.37 times

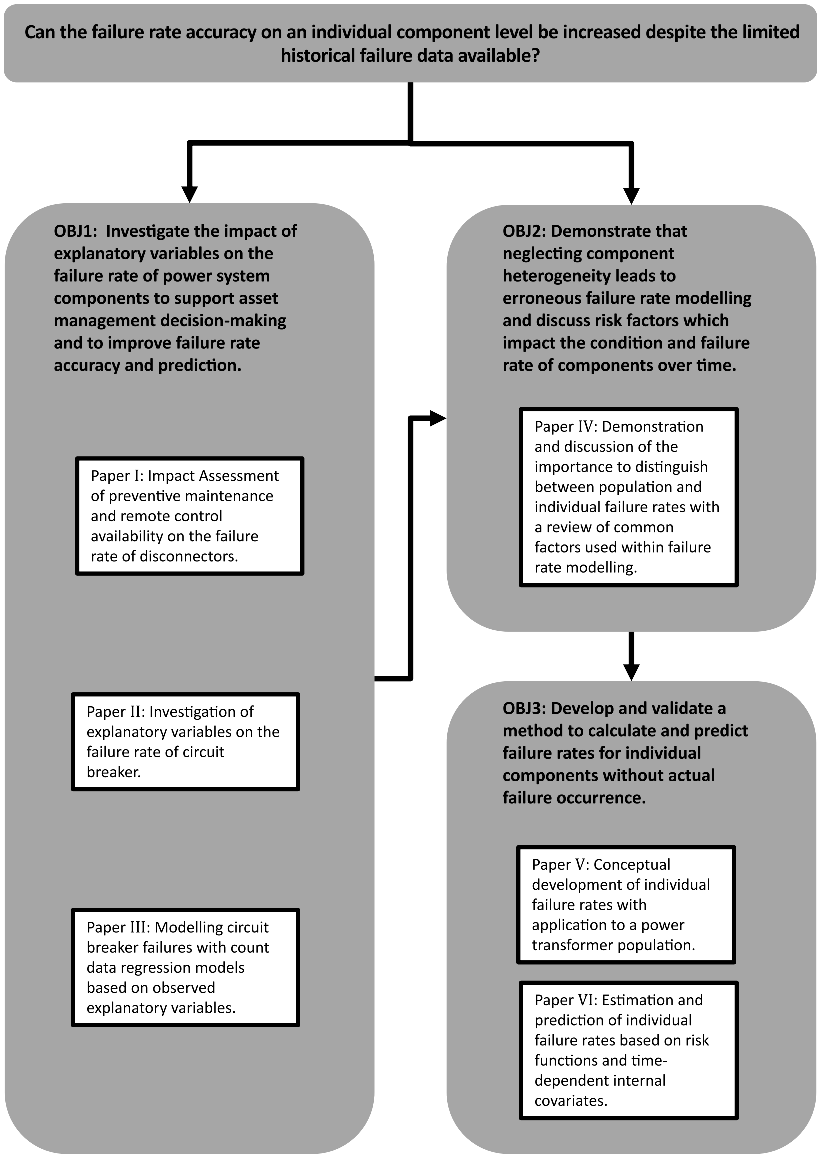


Figure 1.3: Overview of PhD thesis contributions in connection to research objectives

higher failure rate compared to the double side break disconnector. Furthermore, the competing risk approach is used to distinguish the analysis among the failure modes manoeuvrability, current carrying, and secondary functions and how this affects the results. The paper demonstrates that even though the data quality is inadequate, valuable results have been achieved.

Paper II describes exploratory failure assessment of circuit breakers (CB) by examining the impact of the explanatory variables *CB type*, *voltage level*, *operating mechanism*, *location*, *PM*, and *number of operations*. Likewise in **Paper I**, *PM* has a positive impact on the failure rate. Moreover, the study also presents that maintenance is conducted more frequently for oil CB compared to SF_6 or vacuum CB. This might be explained by the general higher age of oil CB in the population. The *number of operations within the last year before failure* has a negative impact on the failure rate. The difference between a CB operated sixty or more times compared to zero to ten times is quantified with a hazard ratio of 4.338. The age at admission is also a significant predictor and has hazard ratio of 1.038.

In contrast to **Paper II**, the analysis in **Paper III** models the recurrence of CB failure as count data. In this approach, the recurrence of failures is investigated by applying regression models such as Poisson and negative binomial regression. Likewise the results in the single failure setting, the significance of the explanatory variables is, except the CB type, similar. However, the analysis revealed that the maintenance conducted after the first failure increases the failure rate. This is due to underlying problems which have not been solved properly during repair works. *PM before the first failure*, however, has a positive effect and results in an approximately constant ROCOF over the lifetime. The negative binomial model performs better than the Poisson regression model due to the zero-inflation in the failure dataset.

Research Objective OBJ2

Addressing research objective OBJ2, **Paper IV** presents that neglected component heterogeneity in failure rate modelling leads to an erroneous failure rate estimation and understanding. To do so, two populations with different failure rates are simulated and the population failure rate, the observed failure rate, underlines that it does not reflect sufficiently the failure rate of either population. Moreover, the study in **Paper IV** explores the field of failure rate modelling in the power system domain to identify methods and explanatory variables which are commonly utilised to model the failure rate. Particularly, age and the environmental conditions have been frequently used risk factors in the literature thus far. In addition, statistical data driven approaches are still rarely used in the power system domain due to data availability and quality. Moreover, the study in **Paper IV** identifies the necessity to develop a practical method which can more accurately model the failure rate for individual components without actual failure occurrence such as for new components.

Research Objective OBJ3

Based on the findings in **Paper IV**, a method is presented in **Paper V and VI** to model individual failure rates for power system components. **Paper V** presents the general concept with solely one basic function and time independence. This method is applied to a case study of 30 power transformers to show the general suitability. **Paper VI** presents a rigorous method formulation, while considering time-dependence of explanatory variables, and suggests, with the non-linear and the cumulative risk functions, two new functions. Assuming the explanatory variables to be internal and stochastic, the individual failures rates can be predicted with some uncertainty, which is also presented in **Paper VI**. The method validation is presented in Section 4.3.3 of this thesis and the results are plausible and equivalent to expert judgement.

1.7 Thesis Outline

The thesis is structured in relation to the research objectives OBJ1 to OBJ3.

In Chapter 2, the fundamental reliability theory is presented with the required definitions, methods, and concepts necessary to provide a general understanding for the ensuing chapters and papers. Terms such as failure and time to failure are defined and it is shown how to calculate lifetime distributions for power system components. The importance to distinguish between repairable and non-repairable components is presented and challenges within lifetime modelling illustrated with particular focus on lifetime data. The failure rate is presented as an essential reliability measure and applications of the failure rate shown to underline its importance.

Research OBJ1 is addressed in Chapter 3 by introducing different explanatory variable types and presenting the theory for the regression models which are applied in **Papers I-III** and studies presented how these have been applied in the power system domain. After having presented the theoretical background, the results of **Papers I-III** are summarized in the Case Studies 1 and 2.

Individual failure rate modelling is covered in Chapter 4. This chapter addresses the research objectives OBJ2 and OBJ3 and presents the results from **Papers IV-VI**. Firstly, the necessity to distinguish between population and individual failure rates is demonstrated and common explanatory variables, which are used in failure rate modelling, are discussed. These are the results from **Paper IV** which covers the literature review and state of the art. Thereafter, the developed method is presented theoretically and validated based on a case study. Moreover, the Case Studies 3 and 4 based on **Papers V-VI** highlight the practical applicability of the method.

In the final Chapter 5, the work is concluded and possible future work is discussed.

Chapter 2

Failure Rate Modelling

This chapter provides the reader with the theoretical background, definitions, and basic concepts within the research field of reliability engineering, which this thesis is positioned in. The aim is to create a general understanding for the later chapters and research papers. Firstly, failure definitions are presented and an introduction to failure analysis is given. Secondly, this chapter presents how failures and time to failure is connected and how it can be modelled. Thirdly, reliability data is discussed along with the challenges in the process of data acquisition and modelling. This chapter presents the essential basics of reliability engineering which can be found in most textbooks. The thesis adopts the notation and definitions primarily from [25] to keep a common understanding.

2.1 Failure Definition and Classification

The essential aim of reliability engineering is the identification and prevention of possible failures by [26, p. 2]

- reducing the likelihood and frequency of failures,
- identifying the causes of failures and finding solutions to prevent it,
- developing solutions if failures occur despite the effort to prevent them,
- utilizing methods to estimate the reliability of new component and system designs and analysing historical reliability data.

Before failures can be prevented, it is necessary to understand what a failure is. To identify failures of a technical system, a clear definition of the system is required. A system consists of subsystems and components which are interconnected, see Fig. 1.2 for a simplified illustration. However, a component can be defined as a system itself. Thus, in the context of the thesis, the power system is seen as a system which is divided into several subsystems. These subsystems are an interconnection of power system components such as power transformers, circuit breakers, disconnectors, etc.. Components are specified into subcomponents to avoid any confusion. After having clarified the technical system discussed in this thesis, the term failure can be defined. A more detailed description of technical systems is provided in [25, ch. 3.2]. In the following section, the failure terminology is introduced to provide an understanding of the basic terms used in failure analysis.

2.1.1 Failure Terminology

A coherent knowledge of failures, faults, and errors is required for a general understanding. The terms are defined, according to [25], as follows:

- **Failure**: A failure is an event where a system or component loses its ability to perform a required function.
- **Fault**: A fault, on the contrary, is the state when a system or component is not able to perform one or more of its required functions. A failure is therefore the initiating event that leads to a fault state.
- **Error**: An error is defined as the deviation from an estimated, observed, or measured target value or condition. The error refers to the "true" value or condition of a component. An error becomes a failure when the measured value crosses a predefined threshold.
- **Time to failure**: The time between when a component is put into operation until it fails is the time to failure or survival time. Note that time to failure can also be measured with indirect time concepts such as the number of kilometres driven by a car or the number of circuit breaker operations.

The relationship between these terms is illustrated in Fig. 2.1 for the discrete and continuous case.

The identification and understanding of all functions is a prerequisite to the identification of failure modes which is described further in [25]. Failure mode is another important term which describes a fault, for example, how a fault is observed. Rausand and Høyland [25] recommend to use the term fault mode instead. However, the common use of failure mode in literature and practice is the reason why it is used in this thesis, primarily to avoid any confusion.

The prevention of failures requires an in-depth understanding of the failure causes. The standard IEC 60050-191:1990 defines failure causes as "the circumstances during design, manufacture or use that have led to a failure" [25]. A classification of failure causes in a life cycle context is given by [25, p. 87] with design failure, weakness failure, manufacturing failure, ageing failure, misuse failure, and mishandling failure. A strict description of these causes is important to reduce the overlaps. An example would be that the degradation of a component can be due to false design specifications or incorrect use.

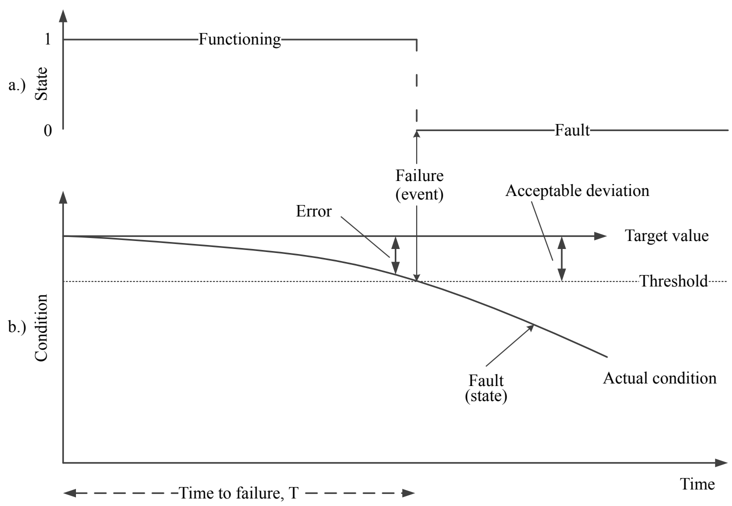


Figure 2.1: Graphical relationship between failure and fault as a discrete state variable in a.) and error, failure, and fault in a continuous setting in b.) based on [25]

A systemic approach for failure analysis is the failure mode and effects analysis (FMEA) which has been developed for military systems in the 1950s [25]. The FMEA method is used in the first phase when conducting system reliability studies and the exact procedure is described in [25]. The procedure involves studying the system and all its subsystems and components in detail to identify failure modes and causes. One particular step can be the analysis of historical work orders. The analysis of historical failure and repair data can improve the knowledge about the system or component failures and characteristics which can lead to the improvement of later design and manufacturing of future components [27]. However, one essential question remains to be answered: When are the required functions of a system or component going to be terminated?

2.1.2 Single and Multiple Failure Occurrence

One essential distinction is required before the time to failure can be measured or predicted. Systems or components can be either repairable or non-repairable. Non-repairable components have the feature that solely one failure can occur during their lifetime. The failure rate, which is defined in detail in the next section, is the probability of failure for a non-repairable system or component. The failure rate is also called the 'hazard rate' in survival analysis or 'force of mortality' in actuarial statistics. Repairable components, on the contrary, can experience multiple failures during their lifetime. Thus, the probability of failure for non-repairable components is the rate of occurrence of failures or abbreviated as ROCOF.

2.2 Failure Models for Non-Repairable Components

This section presents quantitative reliability measures to model the lifetime of non-repairable systems or components. Thus, solely the time to the first failure is studied.

2.2.1 Reliability Measures

Suppose that the random variable T denotes the time to failure of a non-repairable component. It is measured from the point $t = 0$ where the component is put into operation until it fails at time T. Assuming that T is continuously distributed with the probability density function

$$f(t) = \frac{d}{dt}F(t) = \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{P(t < T \leq t + \Delta t)}{\Delta t} \tag{2.1}$$

and the cumulative distribution function

$$F(t) = P(T \leq t) = \int_0^t f(u)du \quad \text{for } t > 0. \tag{2.2}$$

The reliability function is defined as

$$R(t) = 1 - F(t) = 1 - \int_0^t f(u)du = P(T > t) \quad \text{for } t > 0. \tag{2.3}$$

The reliability function is interpreted as the probability that a component survives the interval $(0, t]$ whereas the cumulative distribution function is the probability that the component fails within the interval $(0, t]$. These probabilities are of particular interest before the component is operated. If the component is in operation for some time t, the conditional probability that the component fails within the next interval $(t, t + \Delta t]$ is defined as the failure rate function

$$\begin{aligned} h(t) &= \lim_{\Delta t \to 0} \frac{P(t < T \leq t + \Delta t | T > t)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t} * \frac{1}{R(t)} \quad = \lim_{\Delta t \to 0} \frac{R(t) - R(t + \Delta t)}{\Delta t * R(t)} = \frac{f(t)}{R(t)} \end{aligned} \tag{2.4}$$

All four reliability measures are related and hence can be expressed by another reliability measure. These relationships are presented in [25, p. 20]. The failure rate is denoted in this chapter as $h(t)$ but has the notation $\lambda(t)$ in the research papers and the following chapters.

2.2.2 Lifetime Data Models

Life data analysis is the process of estimating a particular life distribution $F(t)$ for a component when no information about the distribution is given. A life test with

n identical components must be conducted to obtain the lifetimes necessary for the estimation. Generally, lifetimes can be either recorded in a test setting or in actual operation, which is known as field data. For the later analysis and estimation, the components must experience the same operational and environmental conditions regardless of if they are in actual operation or in a test setting [25]. The life test ends when all n components have failed and the dataset is complete. This life data analysis process can be summarised in the following three steps [26]:

1. Obtain life data for all n components.
2. Choose a suitable lifetime model and test if the data fits the model.
3. Estimate the life characteristics of the component by calculating the reliability measures.

The lifetime is denoted as T_i for component i with $i = 1, 2, \ldots, n$ and the observed value as t_i. Moreover, it is assumed that the lifetimes are independent and identically distributed with a continuous life distribution [25]. Given a complete time to failure dataset, the lifetime of all n components is analysed. However, the accuracy of estimated reliability measures depends primarily on the consistency and completeness of the obtained data. Practically speaking, recorded life data is often limited by factors such as costs, impracticality, lifetime duration, incorrect documentation, or the loss of components [25]. Thus, reliability data comes with certain challenges which need to be considered while the data is analysed.

2.2.3 Censoring

The life data is complete if all components have failed before the end of the observation which is illustrated in Fig. 2.2 a.). Due to practical reasons in the study design, the data might not always be complete. One data feature which is common in failure data is known as censoring. Generally, censoring describes the inaccuracy in the time a failure occurs and can be categorised into three different types:

Right Censoring: If a study is terminated before all components have failed, the components that remain functioning are right censored. The failure would occur after (to the right) of the end of the observation. This is shown in Fig. 2.2 b.).

Interval Censoring: When a component fails during the study within a particular interval but the exact time to failure is not known, the component is interval censored. This data occurs when components are not continuously monitored and failures are discovered during inspections, for example. Interval censoring is illustrated in Fig. 2.2 c.).

Left Censoring: A component is left censored at time t when it is included in a study, has experienced no failure before the study entry (start of the study), is in operation or at risk after the study entry, and has failed before time t but the exact time to failure is unknown [28], see Fig. 2.2 d.). This type of censoring is often confused with left truncation [28].

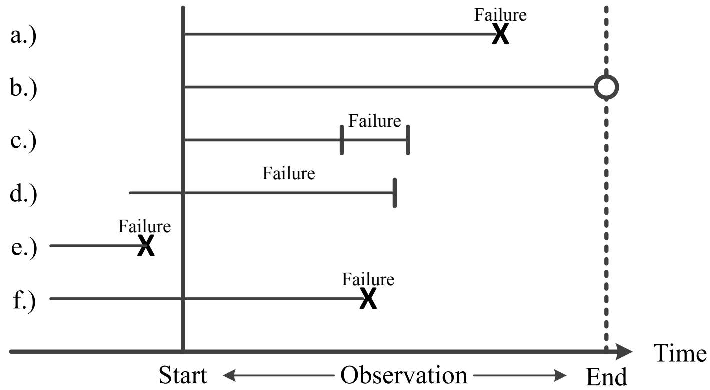


Figure 2.2: Illustration of a.) complete, b.) right-censored, c.) interval censored, d.) left censored, e.) Type 1 left truncated, and f.) Type 2 left truncated data

Another classification of censoring is presented in [25, pp. 467-469] where censoring is denoted into Type I to IV. These types are more detailed classifications of right censoring and it is referred to [25, pp. 467-469] or [29] for a description. Klein and Moeschberger only discuss Type I and II in [29].

2.2.4 Truncation

Left Truncation: Truncation occurs when components are solely observed within a certain observational interval [29]. Left truncated data can be further classified into Type 1 and Type 2 which are illustrated in Fig. 2.2 e.) and f.), respectively. Left truncation occurs when a component is not observed before a truncation variable. If the component has failed before the truncation variable, it is not included in the study and it is known to be Type 1 left truncated. When the component fails after the truncation variable and if it is assumed that the component has not been at risk before the truncation variable, the component is Type 2 left truncated. Note that left truncated components could also be censored. The truncation variable can be, for example, the study entry.

2.2.5 Tied Data

Ties: Tied data occur when the time to failure is equal for some components in the study. This scenario is common when the components are observed in intervals or in specific units such as hours or years. Considering ties is particularly important when a method, such as the proportional hazard model, is dependent on the order of the failures.

2.2.6 Non-Parametric Lifetime Models

Non-parametric lifetime models are used when no assumption about the form of the distribution $F(t)$ is made, except that it is continuous. These models provide a set of techniques for complete and censored datasets to get a non-parametric estimate of the survival function. Suppose that a complete data set without censoring is present and the n component lifetimes are sorted in ascending order such that $t_1 \leq t_2 \leq \ldots \leq t_n$. Firstly, descriptive statistics might be used to describe certain sample measures such as mean, median, and standard deviation. Afterwards, the empirical distribution function can be calculated as [25, 30]

$$F_n(t) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}\{t_i \leq t\} \tag{2.5}$$

with $\mathbb{1}$ as the indicator function which is equal to one when the condition is fulfilled and zero otherwise. Consequently, the empirical reliability function can be described as

$$R_n(t) = 1 - F_n(t) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}\{t_i > t\} \tag{2.6}$$

Recalling eq. 2.4, the failure rate is the probability density function divided by the reliability function and if Δt does not approach zero, the failure rate function can be written

$$h(t) = \frac{R(t) - R(t + \Delta t)}{\Delta t * R(t)}. \tag{2.7}$$

Assume that the study is divided into j disjoint intervals with length Δt. Now the failure rate can be computed with

$$h(j) = \frac{n_j}{\sum_{i=1}^{n} T_{ij}} \tag{2.8}$$

with n_j as the number of components which failed in interval j and T_{ij} is the functioning time for every component i in interval j. When a component has failed before time interval j the time is neglected and thus 0. The number of components at the beginning of interval j can be expressed as $m(j)$ and the failure rate might be expressed approximately as

$$h(j) \approx \frac{n_j}{\Delta t * m_j} \Rightarrow h(j)\Delta t \approx \frac{n_j}{m_j}. \tag{2.9}$$

Power system components are designed to have long lifetimes and thus a low failure rate. This becomes a particular challenge for lifetime testing and censoring since the components do not fail within the observation period. The aforementioned estimation of the reliability measures assumes a complete data set. Since this is seldom the case, methods exist which consider censoring while estimating the reliability measures.

Kaplan-Meier Estimator

An estimator for incomplete life data sets is the Kaplan-Meier estimator or product limit estimate [30] of the reliability function, which is defined as

$$\widehat{R}(t) = \begin{cases} 1 & if \quad t < t_1 \\ \prod_{t_i \leq t} (1 - \frac{d_i}{Y_i}) & if \quad t_1 \leq t \end{cases} \tag{2.10}$$

with d_i as the number of failures and Y_i as the number of components at risk at time t_i and the occurence of failures at D distinct times $t_1 < t_2 \ldots < t_D$. Since the study is not divided in j disjoint intervals, the notation is different. The resulting reliability function $\widehat{R}(t)$ is a step function with bounds at each t_i. This estimator also allows the calculation of the cumulative failure rate function $H(t) = -ln[R(t)]$ [29] and using the estimator we get

$$\widehat{H}(t) = -ln[\widehat{R}(t)]. \tag{2.11}$$

Nelson-Aalen Estimator

An alternative to the Kaplan-Meier estimator is the Nelson-Aalen estimator which estimates the cumulative failure rate with

$$\widehat{H}(t) = \begin{cases} 0 & if \quad t \leq t_1 \\ \sum_{t_i \leq t} \frac{d_i}{Y_i} & if \quad t_1 \leq t \end{cases} \tag{2.12}$$

and the reliability function $\widehat{R}(t) = -exp[-\widehat{H}(t)]$. This estimator is particularly used for parametric model identification and selection and to provide an approximate estimate of the failure rate [29]. The advantage of the Nelson-Aalen estimator compared to the Kaplan-Meier estimator is its advantage in having a better small-sample-size performance [29].

Westerlund presents in [31], two examples of the Nelson-Aalen and Kaplan-Meier estimator when applied to power system components. Firstly, the data published in [32] is analysed, which included a fuse population with 2151 components and 619 failures. Secondly, failure data of shunt reactors, which is originally provided in [33], is analysed and the reliability functions are given for both estimators.

2.2.7 Parametric Lifetime Models

In contrast to non-parametric lifetime models, parametric lifetime models assume a particular distribution for the failure data. Let us assume again that n identical and non-repairable components are in operation from time $t = 0$ and have a time to failure T. Lifetime distributions describe how the failure times of the n components are distributed over time. This section presents the exponential and Weibull distribution in more detail due to their common application in power system reliability. Other models are briefly described.

Exponential Distribution

The time to failure T is a random variable which has the probability density function

$$f(t;\lambda) = \begin{cases} 0 & \text{for } t < 0 \\ \lambda e^{-\lambda t} & \text{for } t \geq 0 \end{cases} \tag{2.13}$$

where λ is the scale parameter. Consequently, the resulting cumulative distribution function is

$$F(t;\lambda) = \begin{cases} 0 & \text{for } t < 0 \\ 1 - e^{-\lambda t} & \text{for } t \geq 0 \end{cases} \tag{2.14}$$

and the failure rate function becomes

$$h(t;\lambda) = \frac{f(t)}{R(t)} = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda. \tag{2.15}$$

This shows that the failure rate is constant. Assuming T to be exponentially distributed has the benefit that the mean time to failure can be computed as

$$MTTF = \int_0^{\infty} R(t)dt = \frac{1}{\lambda} \tag{2.16}$$

The popular use of the exponential distribution in power system reliability assessment can be explained by the detail that this failure rate accurately represents the useful life period in the bathtub curve concept [25, 34]. In Fig. 2.3, a population of power transformer lifetimes is simulated, using an underlying exponential distribution, and the non-parametric and parametric reliability measures are derived.

Weibull Distribution

Another common probability density function is the Weibull distribution with shape parameter α and scale parameter β, with the properties $\alpha > 0$ and $\beta > 0$, defined as

$$f(t;\alpha;\beta) = \begin{cases} 0 & \text{for } t < 0 \\ \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} exp\left[-\left(\frac{t}{\beta}\right)^{\alpha}\right] & \text{for } t \geq 0 \end{cases} \tag{2.17}$$

and the cumulative distribution function

$$F(t;\alpha;\beta) = \begin{cases} 0 & \text{for } t < 0 \\ 1 - exp\left[-\left(\frac{t}{\beta}\right)^{\alpha}\right] & \text{for } t \geq 0 \end{cases} \tag{2.18}$$

and the failure rate function follows with

$$h(t;\alpha;\beta) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \quad \text{for } t > 0. \tag{2.19}$$

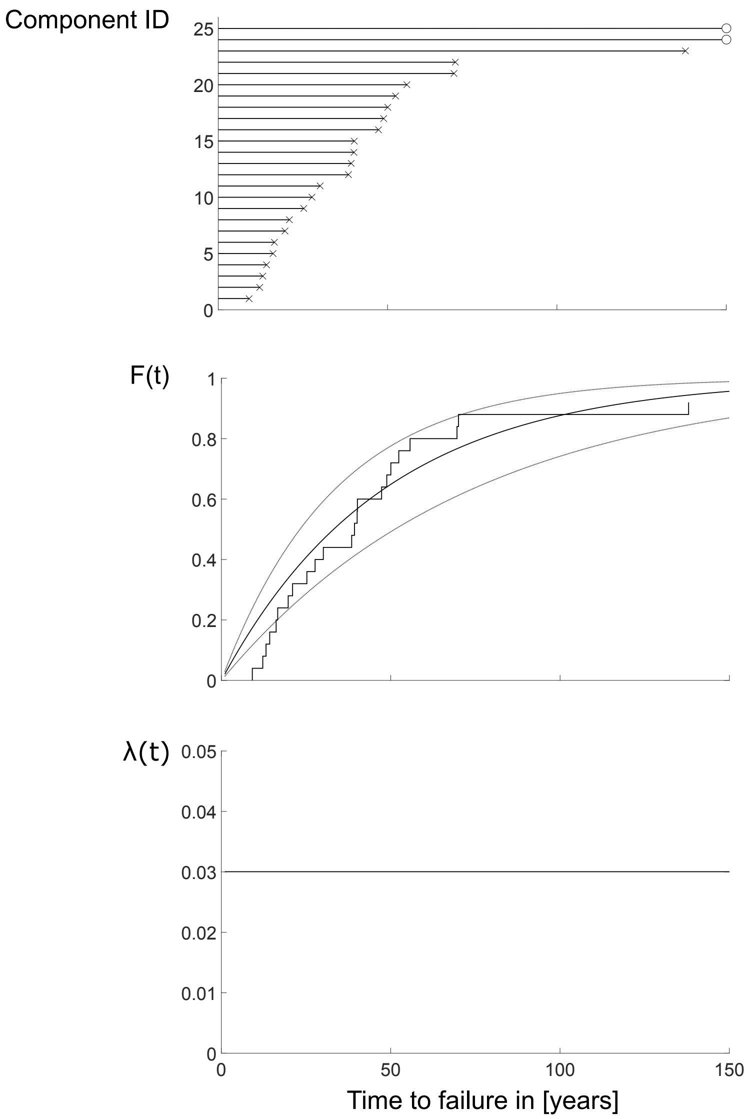


Figure 2.3: Lifetime simulation of a power transformer (> 25 MVA) population with 25 components and an average failure rate of 0.03 according to [20]

If the parameters are given with $\alpha = 1$ and $\lambda = 1/\beta = 1$, recall that the Weibull distribution is equal to the exponential distribution. Thus, the failure rate is constant. When $\lambda = 1$ and $\alpha < 1$ the failure rate decreases and for $\alpha > 1$ the failure rate increases. Particularly, this flexibility of the Weibull distribution explains the frequent use in the reliability domain [34].

Other Parametric Models

Other parametric models are the Gamma distribution, the Homogeneous Poisson Process, the normal distribution, the Lognormal distribution, extreme value distribution, and so forth. Depending on the scientific field, some distributions are preferred over others.

Estimation of Parametric Lifetime Models

To determine whether the underlying distribution $F(t)$ belongs to a specific family is not a straightforward task at the beginning. However, if the scale of the axis of the reliability function is changed accordingly, for example by taking the logarithm, the identification of the underlying distribution function becomes clear. By visualizing the reliability function in a plot, the distribution can be determined if the plot depicts a straight line. Note that each distribution has its own plotting paper. After the distribution is known, the parameter of the distribution can be calculated. Rausand and Høyland [25, ch. 11.3.4] illustrate this procedure on the example of the Weibull distribution.

2.3 Failure Intensity for Repairable Components

Thus far, it is assumed that components are non-repairable and consequently are removed from the study if a failure occurs. However, power system components are, primarily due to the high costs and long lifetimes, repaired if a failure occurs. This recurrence of failures can be seen as a stochastic process, more specifically, a counting process which is illustrated in Fig. 2.4. For reason of simplicity, the repair time is neglected. In this approach, the focus is on the random variable $N(t)$, the number of failures in time interval $(0, t]$ with t as the calendar time and S_i the sequence of calendar times with failure. Moreover, the time between failures is denoted as T_i with $i = 1, 2, \ldots$. The rate of the counting process is also known as the failure intensity or ROCOF and denoted with $\omega(t)$. This failure intensity function is defined as

$$\omega(t) = \lim_{\Delta t \to 0} \frac{\mathrm{P}(N(t + \Delta t) - N(t) = 1)}{\Delta t} \tag{2.20}$$

and having $\omega(t) * \Delta t$ as the approximated probability of failure in the time interval $(t, t + \Delta t]$. This intensity is an approximation of the mean number of failures in the time interval $(t, t + \Delta t]$. This failure intensity is often used in the design phase of a component type with no process history available. Applying Martingale theory to the counting process [25], enables to include the process history H^t, up to time t but not including time t, of a particular component. This process history is a more

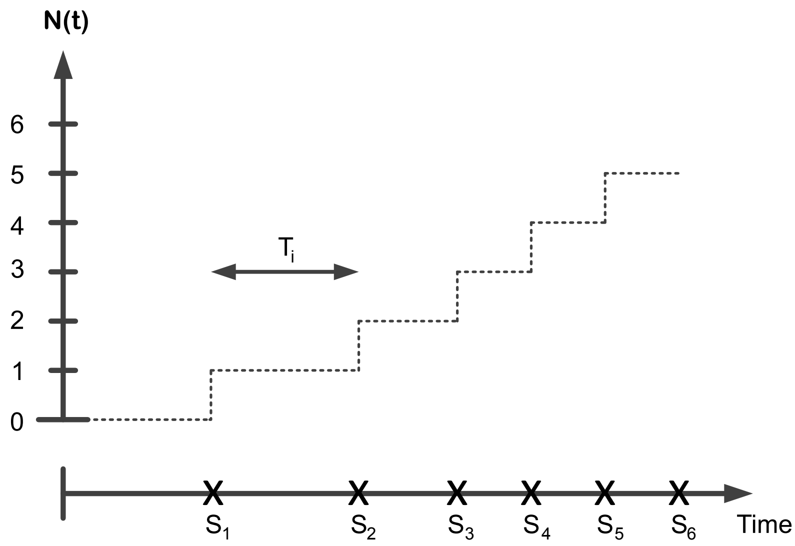


Figure 2.4: Illustration of the counting process with the number of failures $N(t)$, the time between failures T_i, and the calendar times S_i based on [25, Fig. 7.1]

appropriate estimation of the probability of failure for a component in operation. Therefore, the conditional rate of failures is defined as [25, ch. 7.1.3]

$$\omega(t|H^t) = \lim_{\Delta t \to 0} \frac{\mathrm{P}(N(t+\Delta t) - N(t) = 1|H^t)}{\Delta t}. \tag{2.21}$$

Here, $\omega(t|H^t)$ is the approximation of failure probability in $(t, t+\Delta t]$ given the failure history up to time t, but t. The failure intensity process is described in a reliability and maintenance context in [35]. Furthermore, the interrelations of the failure models are reviewed and how the maintenance task determines the relationship between ROCOF and failure rate is highlighted. For example, if the outcome of corrective maintenance is assumed to be minimal repair or the ″Bad as old″ approach, which means it is assumed that no failure occurred, hence $N(t) = 0$, the mean intensity or ROCOF is equal to the failure rate [35, pp. 75-76].

2.4 Failure Rate Applications

Failure rates are applied in many tools, methods, and calculations. Generally, the failure rate is utilised as an input parameter for the calculations of component availability, system availability with reliability block diagrams, Markov models, interruption indices, and within creating maintenance strategies, scheduling, and optimization. These applications are briefly presented in the following sections.

2.4.1 Component Availability

A component's ability to function over a stated time interval is defined as the availability [25]. The availability is hence the probability of a functioning component at time t and the average availability can be denoted as

$$A = \frac{\mu}{\lambda + \mu} \tag{2.22}$$

with μ as the repair rate in [time/failure] and λ the failure rate in [failure/time]. In contrast, unavailability is the time a component is not in operation within a stated period of time and is given by

$$U = \frac{\lambda}{\lambda + \mu}. \tag{2.23}$$

The component's availability and unavailability are used when calculating the power system reliability.

2.4.2 Reliability Block Diagrams

The probability of a system failure can be computed by using reliability block diagrams (RBD). An example of such an approach is given in [36]. RBDs are a graphical representation of all non-repairable components which combined create a system. Structure functions are used to mathematically describe the RBD. An illustration of such RBD is presented in Fig. 2.5. The system availability can be calculated with structure functions, given the availability data for each block which has been shown in the previous section. The system can be constructed with basic serial or parallel structures.

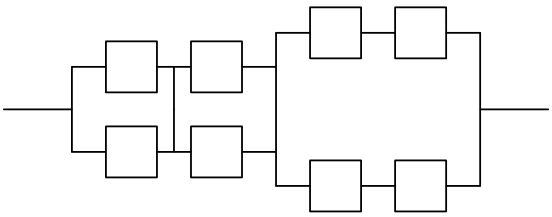


Figure 2.5: Illustration of a system in block diagram form

2.4.3 Markov Models

Markov models are the choice [25] when the ranking of failure occurrence is important or repairable components are assumed. A Markov chain is a discrete or continuous stochastic process that satisfies the Markov property. Generally, the Markov property states that future states are solely dependent on the present state and are independent of previous states, therefore it has 'no memory'.

Assume a Markov process with $\{X(t), t \geq 0\}$ with state space $\mathcal{X} = 0, 1, 2, ..., r$ where $X(t)$ denotes the random variable which is the state of the process at time t. Let a_{ij} denote the rate when the process makes a transition from state i to state j. The transition matrix is given by

$$\mathbf{P} = \begin{pmatrix} a_{00} & a_{01} & \cdots & a_{0r} \\ a_{10} & a_{11} & \cdots & a_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ a_{r0} & a_{r1} & \cdots & a_{rr} \end{pmatrix}. \tag{2.24}$$

The transition matrix can be arranged by observing the changes between the states. Note that the diagonal elements are $a_{ii} = -\sum_{j=0 \,\wedge\, j \neq i}^{r} a_{ij}$ or must be determined so that the sum in each row is zero. Considering solely a two state Markov model, with a functioning and a failed state, the transition rates are described by the failure rate and the repair rate. More extensive introductions and discussions of Markov models can be found in [12, 25].

2.4.4 Interruption Indices

The unavailability, repair rate, and failure rate are three reliability measures which have been presented previously. These measures are essential for many applications in power system reliability assessment but they do not provide a complete representation of the system behaviour [9]. For example, the load or the number of customers connected to particular load point is neglected. This leads to the development of reliability indices which can be categorised into customer-orientated indices and load- and energy-orientated indices. These are presented in a detailed form in [9] and solely a few are mentioned in this section. Let λ_i be the failure rate, N_i the number of customers, U_i is denoted as the annual unavailability, and $L_{a(i)}$ the average load connected to load point i:

- System Average Interruption Frequency Index (SAIFI)

$$SAIFI = \frac{\text{total number of customer interruptions}}{\text{total number of customers served}} = \frac{\sum \lambda_i N_i}{\sum N_i} \tag{2.25}$$

- System Average Interruption Duration Index (SADI)

$$SAIDI = \frac{\text{sum of customer interruption durations}}{\text{total number of customers}} = \frac{\sum U_i N_i}{\sum N_i} \tag{2.26}$$

- Customer Average Interruption Duration Index (CAIDI)

$$CAIDI = \frac{\text{sum of customer interruption durations}}{\text{total number of customer interruptions}} = \frac{\sum U_i N_i}{\sum \lambda_i N_i} \tag{2.27}$$

- Energy Not Supplied Index (ENS)

$$ENS = \text{total energy not supplied by the system} = \sum L_{a(i)} U_i \tag{2.28}$$

2.4.5 Maintenance of Power System Components

Asset management aims to maximise the performance of power system components with a set of different tasks such as maintenance. Classifying asset management into subcategories based on time scale, it can be separated into real time, short term, midterm, and long term. This classification has been introduced by [37, 38]. Optimal maintenance scheduling and resource allocation is a midterm, monthly or seasonal, asset management task.

The failure rate is a crucial input parameter for maintenance planning, scheduling, and optimization. Bertling et al. developed a reliability-centred asset maintenance (RCAM) method in [17] to create a functional relationship between component failure rates and maintenance. This method has been further developed in a power system context by [39] with particular focus on the failure modes of components and the improved component failure rates by using the condition score approach based on [20]. This paper also presents a criticality factor determination by using the improved failure rate data. Likewise [17], the authors of [39] use the Birka System to present the applicability of their method in paper [40]. Whereas [40] based their reliability centred maintenance method on an economic factor to prioritize the recorded maintenance strategies, Shayesteh and Hilber present in [41] a RCAM approach by minimising the total variation in all costs of component i. The result is an optimum preventive maintenance level for each component. Here, the failure rate of each component is utilized to calculate the preventive and corrective maintenance costs.

Besides the RCAM context, the failure rate has been used as input for a midterm transformer maintenance scheduler in [42] or in optimal maintenance planning for overhead lines [15]. The failure rate is also used as a model parameter for risk-based maintenance optimization in [16].

Chapter 3

Exploratory Failure Data Analysis of Power System Components with Regression Models

The preceding chapter presents definitions and concepts of reliability engineering such as failures, failure rate, and time to failure. Since the aim is to prevent failures from occurring, it is of importance to understand which explanatory variables have a significant impact on the time to failure. Regression analysis provides a set of statistical methods to estimate the relationship between explanatory variables and the outcome 'failure rate'. Regression models help to understand the relationship and can be used for failure rate modelling and prediction. All definitions and regression models presented in this chapter are applied in **Papers I-III** and knowledge of these enables a better understanding. This chapter introduces exploratory failure data analysis with regression models by (1) describing possible explanatory variable types and (2) presenting the theory of the relative risk and count response regression models which (3) are applied in the case studies 1 and 2. These case studies are summaries of **Papers I-III**.

3.1 Explanatory Variables

Explanatory variables, predictors, or covariates are variables which might affect a response variable [43], in the reliability context, mostly time to failure and a failure indicator variable, which indicates the occurrence of a failure or censoring. The term covariate is often used as an alternative name for explanatory variable [43] but the meaning might change depending on the field of application. In this thesis and the attached research **Papers I-VI**, the term covariate is primarily used due to its common use in reliability and survival analysis. Vlok [44] discusses three covariate characteristics:

1. Time dependent and time independent,

2. Internal and external, and

3. Stochastic and non-stochastic.

Understanding these covariate characteristics is essential for the selection of covariates in the later analysis and the interpretation of the results. Thus, this section gives a brief overview about covariate types and characteristics.

3.1.1 Explanatory Variable Types and Coding

Covariates are either quantitative or qualitative. Thus, a classification between the different forms is necessary. Quantitative covariates have numerical values which mostly arise when taking measurements, whereas qualitative or categorical covariates are not numerical and occur while recording features and characteristics of the components of interest. A quantitative covariate can be sub-classified into

Continuous A real number in the form of a measurement, such as oil temperature or stress of a power transformer.

Discrete An integer which is obtained as a count. For example, the number of operations of a circuit breaker.

Whereas the use of quantitative covariates is rather straightforward, more attention and preparation is required when using categorical covariates. A classification of categorical covariates is:

Nominal No natural order among the categorises exists. Examples are the distinction between manufacturer, operating mechanism, and location for example.

Ordinal A natural order exists between the categories. This is the case when sorting voltage levels in power grids in ascending or descending order.

Binary or dichotomous covariates are another type of covariate which is similar to a categorical covariate but is limited to two classes. These classes might be 'yes' and 'no' or if a particular feature is included or not. A coding into numerical values is needed when using categorical and binary covariates in regression modelling. A binary covariate might simply just be coded as an indicator variable into 1 or 0. As presented later, the value which has been coded into zero is the 'reference' value or group. Categorical covariates with more than two classes might be first translated from qualitative into numerical values such as $1, 2, 3, ...$ and a value chosen as the reference group. The indicator coding approach can be used here in an extended form. Assuming a categorical covariate with three categories, the resulting two indicator variables Z_1 and Z_2 can be introduced such that

$$Z_1 = \begin{cases} 0 & \text{otherwise} \\ 1 & \text{if the component belongs to category 1} \end{cases}$$

$$Z_2 = \begin{cases} 0 & \text{otherwise} \\ 1 & \text{if the component belongs to category 2} \end{cases}$$

To prevent dependency between the variables, the number of indicator variables is always one less than the number of categories. Note that sometimes quantitative covariates are categorised into specific groups to simplify later interpretation. A more detailed treatment of covariate coding is given by Klein and Moeschberger in [29, ch. 8.2] with several examples of coding and interpretation of covariates.

3.1.2 Time Independent and Time Dependent Covariates

The covariates of interest are usually selected before the observation period [29]. Covariates that are constant over the observation period are known as fixed or time independent covariates. Time dependent covariates, however, vary during the study period and therefore should be known before the study so that changes can be recorded. The distinction is even more important in the later regression analysis since the models differ significantly when time dependent covariates are included [29].

3.1.3 Internal and External Covariates

An essential differentiation exists for time-dependent covariates by classifying them into external and internal. External covariates might be covariates which are constant during the study period and measured in advance, with a predetermined total covariate path, or when the covariate is the result of an external stochastic process [45, ch. 6.3]. Kalbfleisch and Prentice use in [45, ch. 6.3] the example of a voltage which is applied to an electrical cable for insulation testing to illustrate an external covariate. Internal covariates are the result of a stochastic process which is generated by the component under observation [45]. An important feature is that the covariate can only be observed while the component has not failed or is uncensored. A comprehensive discussion of external and internal covariates is given in [45, ch. 6.3] and [46, ch 9.2.4] for more information.

3.1.4 Stochastic and Non-Stochastic Covariates

A time varying covariate can be seen as a collection of random variables, and in fact, as a stochastic process. Assuming the covariate to be stochastic allows its prediction with methods such as time series analysis, state space models, and Markov chains, for example. However, the prediction of the covariate path comes with some level of uncertainty. In contrast, non-stochastic covariates can be predicted with higher accuracy. Vlok presents, in the context of residual life estimation [44, ch. 4.2.5], a set of parametric functions such as a linear, quadratic, hyperbolic, exponential, and geometric curve, which can be utilized for prediction. The prediction of covariate behaviour is not directly relevant for the investigation of covariates with regression models, however, it will be utilized in the calculation of individual failure rates in Chapter 4.

3.2 Regression Models in Failure Data Analysis

One approach to investigate the relationship between an outcome Y and a set of explanatory variables X is the use of regression models. Generally, the outcome Y, the dependent variable, and the explanatory variable are related by a function f such that

$$Y = f(X) + \epsilon \tag{3.1}$$

where ϵ is the normally distributed error term with zero means and the variance σ^2. Assuming that the function f is linear, the linear regression model can be written as

$$Y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i, \qquad i = 1, \ldots, n \tag{3.2}$$

with $\mathbf{x}_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,p})$ as a row vector of p explanatory variables for the i-th component and $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_p)$ a column vector of p regression parameters. Note that this formulation includes a regression intercept such that $x_1 = 1$. A comprehensive introduction of linear regression is provided by [47], however, if the function f is not linear or the dependent variable Y is not continuous, other regression models need to be applied, such as a generalised linear regression model which has the same form as in eq. 3.2.

The choice of regression model can be made based on the data type and primarily the dependent variable. Table 3.1 shows different dependent variable types and the corresponding regression model with some examples from the power system domain. In reliability analysis, the relationship between failure or degradation and a set of explanatory variables is of interest. If the outcome is a component failure, a binary outcome, logistic regression seems a reasonable choice. However, this model would neglect the time to failure which is of particular interest. Therefore, Cox presented in [64] the proportional hazard model (PHM) or cox regression where the dependent variable is the time to failure and a censoring indicator regressed on the explanatory variables. This approach is similar to linear regression [28] and in some parts equivalent to logistic regression [65]. The failure rate and the ROCOF are in focus within power system reliability assessment, hence, regression models for these outcomes are presented in the following sections, which are the PHM and regression models for count data.

3.2.1 Relative Risk Model

The PHM is a relative risk model which is commonly applied in survival analysis with particular high frequency in the medical domain [66]. The aim is the impact assessment of explanatory variables on the failure rate. Following the notation of [45], let T be the time to failure and $\mathbf{x}_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,p})$ the vector of

Table 3.1: Choice of regression models based on type of dependent variable with examples

Type of Dependent Variable	**Regression Model**	**Applications within the Power System Domain**
Continuous	Generalised Linear Regression Models	• Condition monitoring of disconnectors with temperature sensors [48] • Prediction of circuit breaker SF_6 leakage to improve and support maintenance decisions [49]
Count	Poisson, Negative Binomial, among others	• Assessment of covariates on the number of tree-related failures on a power circuit [50, 51] • Prediction and modelling of adverse weather events [52, 53, 54, 55, 56, 57]
Binary	Logistic Regression	• Used to classify fault causes in distribution systems with a case study of tree and animal faults [58] • Power component fault diagnosis with application to power transformer faults based on gas analysis results [59] • Analysis of power system disturbances to gain an improved understanding of how these varied over time and to investigate certain characteristics which might have an impact on the outages [60]
Time to Failure and Censoring Indicator	Cox Regression	• Analysis of explanatory variables on early cable failures [61] • Investigation of covariates such as weather, season, and cause on transmission component failures in the United Kingdom [62, 63]

basic covariates for the i-th component with n as the number of components in the population. The relative risk model is defined as

$$\begin{aligned}\lambda(t;\mathbf{x}_i) &= \lim_{\Delta t \longrightarrow 0} \frac{P(t \leq T < t+\Delta t \mid T \geq t, \mathbf{x}_i)}{\Delta t} \\ &= \lambda_0(t)\, r(t,\mathbf{x}_i), \quad t > 0\end{aligned} \tag{3.3}$$

with $\lambda_0(t)$ denoted as the baseline failure rate and $r(t,\mathbf{x}_i)$ as the unspecified relative risk function. The relative risk functions can take several forms, however, the exponential is the most natural since it satisfies the property $\lambda(t;\mathbf{x}_i) \geq 0$ [45]. Note that other functional forms might be more suitable depending on the setting. Choosing the relative risk function in exponential form, the model is

$$\lambda(t;\mathbf{x}_i) = \lambda_0(t)e^{\mathbf{Z}_i(t)\boldsymbol{\beta}} \tag{3.4}$$

with $\mathbf{Z}_i(t)$ as a vector of derived and possibly time dependent covariates and $\boldsymbol{\beta}$ the vector of regression parameters as before without the regression intercept. The covariates $\mathbf{Z}_i(t)$ are obtained as functions from the basic covariates $\mathbf{x}_i$ which might be necessary for analysis or interpretation. The term PHM is generally used for the model in eq. 3.4 when the covariates are constant, thus, the relative risk function becomes proportional. The relative risk model has the advantage that the baseline failure rate $\lambda_0(t)$ can be left unspecified for the covariate assessment, hence $\lambda_0(t)$ is assumed to be non-parametric. Since the relative risk function is parametric, the overall model is semi parametric. This model has lead to the development of several other reliability models with covariates, which are presented in [44] and discussed based on their advantages and disadvantages in [67]. To apply the relative risk model, the following assumptions must hold:

- The random variable time to failure is independent and identically distributed
- Censoring must be non-informative (random) which means that components that are lost or not longer considered can solely leave the study due to unrelated reasons
- Given fixed covariates, the relative risk function is required to be proportional over time

Model Parameter

Applying the relative risk model requires the data to be available in the form of $(T_i, \delta_i, \mathbf{Z}_i(t))$. The time to failure or censoring time T_i must be given and an indicator δ_i that describes that a failure has occurred ($\delta_i = 1$) or that the component is right-censored ($\delta_i = 0$). The vector $\mathbf{Z}_i(t)$ is the vector of covariates as aforementioned. Covariates are described in more detail in section 3.1.

Estimation of Regression Parameters

The estimation of the regression parameters $\boldsymbol{\beta}$ is an inferential challenge of the relative risk model which is described in detail in [45]. Maximum likelihood methods are utilized to estimate the regression parameters, also called maximum likelihood estimates, by maximizing the partial likelihood

$$L(\beta) = \prod_{i=1}^{n} \left\{ \frac{e^{(\mathbf{Z}_i(t)\boldsymbol{\beta})}}{\sum_{k \in R_{(t_i)}} e^{(\mathbf{Z}_k(t)\boldsymbol{\beta})}} \right\}^{\delta_i} \tag{3.5}$$

with $R_{(t_i)} = \{k : t_k \geq t_i\}$ as the set of components at risk at time t_i. The likelihood function L describes the joint probability of observing the actual failures on the components in the study as a function of the unknown estimates $\boldsymbol{\beta}$ [28]. It is a partial likelihood because solely probabilities for components who fail are considered which arises due to the missing assumption about $\lambda_0(t)$. Thus, δ_i indicates whether a component contributes to the likelihood ($\delta_i = 1$) or not ($\delta_i = 0$). An illustrative example of the construction of the likelihood function is presented in [28, ch. 3.9].

The construction of the likelihood function varies depending on the data set given. The likelihood function presented in eq. 3.5 does not consider tied time to failure data as in the first relative risk model proposed by Cox in [68]. For ties in the time to failure data, several formulations of the likelihood function have been proposed such as Breslow, Elfron, or the discrete-logistic likelihood [29, ch. 8.4]. A comparison of these methods has been conducted in [69] which recommends the Elfron method due to better approximations, particularly with moderate or heavy ties in the data set.

Hypotheses Testing

After the estimation, consider testing a hypothesis about the $\boldsymbol{\beta}$ parameters. Several tests exist, however, the Wald test static, the likelihood ratio test, and the score test are mostly used, for example in [29, 70]. In general, one might be interested in testing the hypothesis of a subset of $\boldsymbol{\beta}$ parameters. Suppose that $\boldsymbol{\beta} = (\boldsymbol{\beta}_1^\intercal, \boldsymbol{\beta}_2^\intercal)^\intercal$ with $\boldsymbol{\beta}_1$ as a q-dimensional vector of the $\boldsymbol{\beta}$ parameter of interest and $\boldsymbol{\beta}_2$ as $(p-q)$-dimensional vector with the remaining parameter. Now, the null hypothesis is formulated as

$$H_0 : \boldsymbol{\beta}_1 = \mathbf{0} \tag{3.6}$$

with $\mathbf{0}$ as a vector of zeros with dimension q. In the following, the Wald test static, the likelihood ratio test, and the score test are briefly described. However, for a more profound description and derivation of the statistics the authors Klein and Moeschberger [29, ch. 8.5], Cox and Oakes [71, ch. 3.3], or Čížek, Härdle and Weron [72, ch. 5.3.3] are recommended for further reading.

Wald Test Given the maximum likelihood estimates $\widehat{\boldsymbol{\beta}} = (\widehat{\boldsymbol{\beta}}_1^\intercal, \widehat{\boldsymbol{\beta}}_2^\intercal)^\intercal$ of $\boldsymbol{\beta}$, the inverse of information matrix $\mathbf{I}(\boldsymbol{\beta})$, which is calculated while computing the maximum likelihood estimates, can be partitioned as

$$\mathbf{I}^{-1}(\boldsymbol{\beta}) = \begin{pmatrix} \mathbf{I}^{11} & \mathbf{I}^{12} \\ \mathbf{I}^{21} & \mathbf{I}^{22} \end{pmatrix}. \tag{3.7}$$

with $\mathbf{I}^{11}$ is the $q \times q$ submatrix belonging to $\boldsymbol{\beta}_1$. Thus, the Wald test statistic is given by

$$X_W^2 = \widehat{\boldsymbol{\beta}}_1^\intercal [\mathbf{I}^{11}(\widehat{\boldsymbol{\beta}})]^{-1} \widehat{\boldsymbol{\beta}}_1 \tag{3.8}$$

The distribution of the Wald test statistic, under H_0, converges for large samples to a chi-squared distribution with q degrees of freedom.

Likelihood Ratio Test The likelihood test statistic is defined as

$$X_{LR}^2 = 2[\ell(\widehat{\boldsymbol{\beta}}) - \ell(\widehat{\boldsymbol{\beta}}_0)] \tag{3.9}$$

with $\widehat{\boldsymbol{\beta}}_0 = (\mathbf{0}^\intercal, \widehat{\boldsymbol{\beta}}_2^\intercal)^\intercal$ and $\ell(\widehat{\boldsymbol{\beta}}) = ln[L(\widehat{\boldsymbol{\beta}})]$. Likewise the Wald test statistic, the likelihood ratio statistic has a chi-squared distribution for large samples and under H_0 with q degrees of freedom. The p-values are calculated as the tail probabilities of the χ_q^2-distribution.

Score Test Testing H_0 with the score statistic, suppose $U_1(\boldsymbol{\beta})$ is the subvector of the first q elements of the score function $U(\boldsymbol{\beta})$, the score statistic can be expressed by

$$X_{SC}^2 = U_1(\widehat{\boldsymbol{\beta}}_0)^\intercal \mathbf{I}^{11}(\widehat{\boldsymbol{\beta}}_0) U_1(\widehat{\boldsymbol{\beta}}_0) \tag{3.10}$$

The score test statistic also converges to a χ_q^2-distribution with a large sample under H_0.

Model Selection

Explanatory variables can be assessed in a single-variable setting individually or in a multiple-variable setting mutually. The latter is usually of greater interest to study an explanatory variable while other variables are present in the model. Consequently, a strategy is important to select a set of explanatory variables to build the best overall model. Collett discusses strategies for model selection in [73, ch. 3.6] and states that the failure rate function does not necessarily depend on a unique combination of explanatory variables. Hence, there might be a set of equally good models instead of one particular model. Both, Collett in [73, ch. 3.6] as well as Klein and Moeschberger in [29, ch. 8.7], distinguish the model selection process by the purpose of the study. Briefly, this distinction is made by whether someone has a particular hypothesis or without any specific hypothesis and solely explanatory variables are used to predict the distribution of time to failure. For the latter, the Akaike information criterion (AIC) is a useful statistic to assess the model [29]. The AIC is estimated by

$$AIC = 2c - 2ln(\hat{L}) \tag{3.11}$$

with $\hat{L}$ as the Log Likelihood and c as the number of independent parameters in the model. A lower value of AIC is preferred when comparing the fitted models to each other. This statistic rewards the goodness of fit but also securing from over-fitting by including unnecessary explanatory variables. If the number of possible explanatory variables exceeds a certain amount, automatic variable selection routines might be used. These are forward selection, backward elimination, and stepwise procedure. However, Collett in [73, ch. 3.6] discusses some disadvantages of these routines, so caution is required while applying them.

Hazard Ratio

When the covariates are constant over time, the ratio between two individuals 1 and 2 is used as a possible form of interpretation of β. This hazard ratio (HR) is defined as

$$HR = \frac{\lambda_0(t)\ e^{(Z_2(t)\beta)}}{\lambda_0(t)\ e^{(Z_1(t)\beta)}} = e^{((Z_2(t)-Z_1(t))\beta)} \tag{3.12}$$

Assuming that $Z_1(t) = 0$, the failure rate of the i-th individual is proportional to $\lambda_0(t)$ with $e^{(Z_i(t)\beta)}$. Generally, if HR $= e^{(Z_i(t)\beta)} = 1$ the covariate has no impact, HR < 1 the covariate has a positive impact, and HR > 1 has a negative impact on the failure rate. Note that the confidence interval of the HR must be considered while interpreting the results.

Competing Risks

The PHM in eq. 3.4 only considers a single failure type and thus might not be suitable in the power system domain where components can experience several failure types. Therefore, a different model, the competing risk model, is required to handle these cases. Assume that the i-th component can fail to a set of different failure types which can be denoted by the random variable J with the index $j \in 1, \ldots, m$ with m as the number of possible failure types. Let $\mathbf{Z}_i(t)$ denote the covariate vector as before. Now, the cause specific failure rate function can be defined, according to [45], as

$$\lambda_j(t; \mathbf{x}_i) = \lim_{\Delta t \longrightarrow 0} \frac{P(t \leq T < \Delta t, J = j \mid T \geq t, \mathbf{Z}_i(t))}{\Delta t} \tag{3.13}$$

which is the probability of failure that the i-th component with the covariate vector $\mathbf{Z}_i(t)$ fails in the interval $(t, t + \Delta t]$ due to the failure type j. Under the assumption that the failure types j are independent and each component can fail solely to one particular failure type can occur, it leads to

$$\lambda(t; \mathbf{x}_i) = \sum_{j=1}^{m} \lambda_j(t; \mathbf{x}_i). \tag{3.14}$$

Consequently, the occurrence of two failure types must be separately defined. The competing risk approach is discussed in theoretical form in [45, ch. 8.2] and described with more practical examples in [28, ch. 9]. Kleinbaum and Klein describe in [28, ch. 9] two different methods to for handling competing risks. Firstly, a common approach is the utilisation of the PHM to analyse the failures and hazard ratios for each failure type separately while treating all competing failures as censored. Here, separate models need to be built and analysed. The second approach is also known as Lunn-McNeil approach which requires only one model to be fitted with the PHM rather than several. This model can produce identical results when the covariates are the same [28]. Here, the data layout must be augmented to carry out the analysis. However, it is referred to [28, ch. 9] for further description of both methods.

Recurrent Failure Data

In the original formulation in eq. 3.3 of the relative risk model in [68], solely single failures are considered and a component is removed from the study after failure occurrence. This is a fair assumption in clinical studies, but technical components can be repaired after a failure. Recurrent event data analysis investigates the impact of explanatory variables on the recurrent events such as failures. Let n denote the number of recurrent failure processes components in the study over the time interval $[0, \tau]$ where τ is the total study time. Moreover, assume that $N_i(t)$ denotes the number of failures in the time interval $[0, t]$ for the i-th process or component. Now, the cumulative sample mean function is given by [74]

$$\hat{\mu}(t) = \frac{1}{n} \sum_{i=1}^{n} N_i(t). \tag{3.15}$$

Compared to the relative risk model, the pair of parameters (T_i, δ_i) is replaced with $(N_i(t), Y_i(t))$ in the counting process approach [75, p. 4] where $Y_i(t)$ equals one if the component is observed and at risk at time t and zero otherwise. This alteration in the formulation of the single-event PHM has lead to several PHM extensions for recurrent event analysis [76]. Generally, four different approaches have been developed:

1. A counting process formulation which has been developed by Andersen and Gill (AG) [77]. Thus, sometimes also called AG model.

2. Prentice, Williams, and Peterson (PWP) have developed two conditional models which differ primarily by the time scale used [78]. These are (1) the conditional probability model (PWP-CP) and (2) the gap time model (PWP-GT).

4. Wei, Lin, and Weissfeld proposed in [79] a fourth model which is a marginal event-specific model.

These models have been compared in [80] but the differences become more obvious when the time intervals used in each model are compared [81, p. 289] which is also illustrated in graphical form in [75, p. 188].

3.2.2 Count Response Regression Models

Power system components can be repaired and several failures might occur until the component is replaced. A straightforward approach is to treat failures as counts and use count response regression models such as the Poisson or negative binomial model. The next two sections present such regression models.

Poisson Regression Model

Recall the notation $\mathbf{x}_i = (x_{i,1}, \dots, x_{i,p})$ as the covariate vector with p covariates for each component i. Now, y_i denotes the number of failures for each component in an interval of length τ. Note that the assumption of event occurrence is constant for the Poisson distribution. This rate ω is known as the intensity of a process and if the event is a failure, the rate is the ROCOF describe in eq. 2.20. Therefore, the

Poisson distribution describes the probability that a failure occurs exactly k times in the interval τ with

$$P(y_i = k) = \frac{(\omega T)^k}{k!} e^{-\omega T} \quad \text{for} \quad k = 0, 1, 2, \ldots; \omega > 0. \tag{3.16}$$

A common approach for count data modelling is to use the regression model $\omega = e^{x_i \boldsymbol{\beta}}$ with $\boldsymbol{\beta}$ as vector of regression parameters as previously. Note that this basic formulation is identical to the relative risk model in eq. 3.4. However, for the Poisson model, $x_{i,1} = 1$, because an intercept β_1 is included. The regression parameters are either estimated by non-linear least squares or with the maximum likelihood method, which is the most common choice [82]. This leads to the Poisson generalised linear model (GLM) with

$$P(y_i = k) = \frac{(\omega T)^k}{k!} e^{-\omega T} \text{ for } k = 0, 1, 2, \ldots; \omega = e^{\mathbf{x}_i \boldsymbol{\beta}} > 0. \tag{3.17}$$

The Poisson GLM is a non-linear regression model which has the conditional mean function

$$E[y_i|\mathbf{x}_i] = \omega = e^{\mathbf{x}_i \boldsymbol{\beta}} \tag{3.18}$$

and the conditional variance

$$Var[y_i|\mathbf{x}_i] = \omega. \tag{3.19}$$

Obviously, it follows that $E[y_i|\mathbf{x}_i] = Var[y_i|\mathbf{x}_i]$ which means the mean is equal to the variance. To apply the Poisson GLM, this assumption must hold. However, some count data might violate this assumption. These are either under-dispersed, $Var[y_i|\mathbf{x}_i] < E[y_i|\mathbf{x}_i]$, or more commonly over-dispersed, $Var[y_i|\mathbf{x}_i] > E[y_i|\mathbf{x}_i]$. These and other count data features are more thoroughly discussed in [82, 83, 84]. To address data features such as overdispersion, other count regression models have been developed. Testing the statistical inference about the $\boldsymbol{\beta}$ parameters can be done by applying the aforementioned likelihood ratio, Wald, and score test. Likewise to the cox regression, the model selection can be done with the AIC information criterion.

Negative Binomial Regression Model

The negative binomial model is frequently used to accommodate for overdispersion in count data [82]. Given that the count data follows a NB probability density function, the NB GLM is defined as

$$P(y_i = k) = \frac{\Gamma(y_i + \frac{1}{\alpha})}{\Gamma(y_i + 1)\Gamma(\frac{1}{\alpha})} \left(\frac{1}{1 + \alpha\omega_i} \right)^{1/\alpha} \left(\frac{\alpha\omega_i}{1 + \alpha\omega_i} \right)^{y_i} \tag{3.20}$$

with α as the dispersion parameter and Γ is the gamma distribution. The conditional variance is $Var[y_i|\mathbf{x}_i] = \omega_i a + \alpha\omega_i^2$. Since $\alpha \geq 0$, the variance is greater than in the Poisson GLM. However, the conditional mean is equal $E[y_i|\mathbf{x}_i] = \omega_i$ to the Poisson model, which has the advantage that the regression parameters are calculated identically. The NB model is discussed in detail in [85].

3.3 Case Study 1: Analysis of Disconnector Failures

Disconnectors have two primary functions in the power system. Firstly, they are installed in substations to isolate other components such as circuit breakers and power transformer for maintenance purposes. Secondly, remote controlled disconnectors are installed in medium and low voltage power grids to isolate faults or for automatic network reconfiguration. In the latter function, they are an important part of automated systems or ″self-healing″ power systems to improve power system reliability and quality [86, 87]. Although disconnectors have these rather simple functionalities, failures can cause major outages as, for example, in Sweden and Denmark in 2003 [88]. The incident demonstrates that disconnectors should not be neglected in asset management. Therefore, **Paper I** presents an investigation of a non-current breaking disconnector population in Sweden to gain a better understanding of explanatory variables which impact the failure rate but also to improve the accuracy of failure rate modelling.

The investigated disconnector population is in operation on distribution and regional system levels from 6 kV to 220 kV. Totally, 1626 disconnectors with 2191 associated work orders have been analysed from a time period of 2008 to February 2015 to identify major failures in the population. This population included 36.1 % remote-controlled and 63.9 % manually operated, the disconnector is operated on-site, disconnectors. The work orders include the following information:

- Disconnector ID
- Installation year
- Voltage level
- Remote control availability
- Manufacturer
- Disconnector type
- Conducted preventive maintenance (PM)
- General description of work order

The initial failure analysis with descriptive statistics to identify failure modes, causes and location has been presented in **Paper vi**. Manoeuvrability, current carrying, and secondary functions have been identified as failure modes in both major and minor failures. To conduct the analysis with the PHM in **Paper I**, certain data features such as right censoring, left-truncation, and missing explanatory variable information, have been addressed. For example, the age was solely given for 69 % of the disconnectors. This data quality has led to assumptions to better analyse the failure data. The major findings of the study in **Paper I** include:

Single variable analysis

- The covariates *voltage level*, *remote control*, and *PM* are significant at the $\alpha = 0.05$ acceptance level.

- Remote-controlled disconnectors have a higher failure rate than manually operated disconnectors by a factor of 2.1.

- *Age at admission* is not significant.

- A significant negative effect, compared to the double side break disconnector which has been selected as reference, has the vertical break (Hazard Ratio = 5.514), knee type (Hazard Ratio = 2.960), semi-pantograph (Hazard Ratio = 2.530), and the single pole disconnector (Hazard Ratio = 9.370).

Multiple variable analysis

- The multiple variable analysis has been conducted with time on study and age, considering the left-truncation of the data set, as survival time. The significance and covariate effects are similar but differ in magnitude.

- The covariates *voltage level*, *remote control*, and *PM*, which have been selected with the stepwise regression procedure, are included in the model. *PM* has a positive and the strongest effect on the failure rate. However, the magnitude of the effect decreases with increased *PM* compared to zero PM which might be due to the smaller group size of the third *PM* category.

- The Hazard Ratio is, compared to the reference group on th 6-20 kV voltage level, 0.469 and 0.612 times lower for the 40 kV and the 220 kV voltage level, respectively.

- The competing risk approach is applied to test the covariates depending on the failure modes maneuverability, current carrying, and secondary functions. The covariate remote control has the greatest effect on secondary functions and maneuverability with 7.26 and 2.28, respectively. A reason might be the installed control equipment and the number of operations. However, unfortunately more detailed data has not been available to test these assumptions.

Remarks Exploratory failure data analysis with the PHM has been limited in the power system domain thus far due to a number of challenges in data quality and availability. These challenges are also encountered in this case study. In spite of the aforementioned statistical results to improve the failure rate prediction, **Paper I** addresses the data challenges and presents existing solutions to encourage other researchers and practitioners to apply statistical learning approaches to improve the accuracy and understanding of the failure rate. One key element in this case study, to gain the results and conduct the study, has been the strict approach to state clear assumptions, particularly in the definition and identification of failures. This is discussed in detail in **Papers I-III**.

3.4 Case Study 2: Analysis of Circuit Breaker Failures

Circuit breakers (CB) are developed to protect and control the power system by breaking the current, also when a failure occurs. Consequently, CBs have at least one more important failure mode compared to disconnectors, which is the load breaking capability. An international survey in [89] shows that around 25 % of CB applications are in transformer bays, 60 % are used in overhead lines and cable bays, 10 % as bus couplers, and the rest are used for shunt reactors, shunt capacitors, and some other minor applications. The survey showed that, in particular, the CBs in shunt reactors and capacitor applications are operated most, and that there is a connection between the average number of operating cycles per year per application and the failure rate. Another study in [33] concludes that the average failure frequency increases with the *number of operations* and *voltage level*. The demand for high reliability of CBs [89] requires a major share of the maintenance budget in utilities [33], which motivates the study of a CB population in Sweden in **Papers II and III**.

The CB population includes 2622 components which have been under observation from 2008 to 2015. The failure and maintenance information has been extracted from the internal asset management system of a utility in the form of 4496 work orders. The work orders include information such as:

- CB ID
- Installation year
- Voltage level from 40 kV to 400 kV
- Remote control availability
- Manufacturer
- CB Type: oil, SF_6, and vacuum
- Conducted preventive maintenance
- Geographical area of operation
- Number of operations in each year form 2008 to 2015
- Operating mechanism: hydraulic, mechanical spring, watch spring
- General description of work order

The population is investigated with the assumption that CBs are non-repairable in **Paper II** and that the CB are repairable in **Paper III**.

CB Failure Analysis with PHM

The findings of **Paper II** can be summarised as follows:

- A one-way analysis of variance (ANOVA) test shows that the means of the maintenance intensity (MI) in $[\frac{\#maintenancetasks}{time-on-study}]$ is different depending on the CB type. The oil type CBs experience the highest MI followed by SF_6 and vacuum CB. Moreover, age at admission and MI are moderately correlated.

- The single variable analysis shows that:

  - Age at admission is significant with a Hazard Ratio of 1.014,
  - The origin of the CB (manufacturer) has no impact on the failure rate,
  - There is no significant difference between the CB types,
  - The covariate MI has a positive and significant impact on the failure rate for all categories,
  - The operating mechanism has no significant impact on the failure rate,
  - Remote-controlled CB do not have a higher failure rate, however, the group size of manual CB is with less than 10 % very low.

- The results of covariate assessment in the multiple variable analysis are:
  - The analysis is conducted with time-on-study and age adjusting for left-truncation as survival time. The MI has a positive impact and the number of operations within the last year (#OLY) a negative impact on the failure rate in both approaches.
  - The negative impact of #OLY is increasing with the number of operations. A CB with more than 60 #OLY has a 6.322 times higher failure rate than a CB which is operated less than ten times within the last year.
  - The Hazard Ratio of age at admission is estimated with 1.038. Thus, the relative risk between two CB with an age difference of ten years would be 1.46.
  - When time-on-study is used as time to failure, the oil CB type has a positive impact compared to the SF_6 type. However, this result might be because the oil CB are generally older and more maintained.

CB Failure Analysis with Regression Models for Count Data

Since the CBs under investigation are usually repaired, a second study has been conducted in **Paper III**. If recurrent failures are treated as counts, regression models such as Poisson and negative binomial regression can be applied. The major results are:

- In general, the negative binomial regression has a better model fit, compared to the Poisson regression, primarily due to the over-dispersion and the zero-inflation in the count data.
- In the single variable setting, the *operating mechanism* and the *total number of operations* has no significant impact on the recurrence of failures, thus, they are not further considered in the multiple variable setting.
- The covariates *MI*, *age at admission*, *mean number of operations per year*, and *voltage level* are significant and included in the final model.

- The ROCOF of a CB operated more than 50 times per year is 2.33 higher compared to a CB operated less than 50 times per year.
- The *MI* is divided into *MI* before the first failure and after the first failure. The results show that there is an opposite effect. Maintenance conducted before the first failure has a positive impact and the maintenance after the first failure has a negative impact on the ROCOF. Investigating the CB with many recurrent failures revealed that an underlying problem exists which is not solved properly during the maintenance tasks.

Remarks Case Study 2 focuses less on data quality and availability challenges but explores the CB failure dataset in greater depth, primarily because more exploratory variables are given. The case study is divided by the assumption of non-repairable and repairable CB which is presented in **Papers II and III**, respectively. One important factor in analysing failure data has been found to be the variation of assumptions and the exploration of failure data by different tools instead of relying on one single analysis. This approach leads to further insight into the data and additional knowledge is gained for design and operation of the components. **Paper III** exemplifies this by the negative impact of higher frequency of maintenance after the first failure. It is shown that this is an indication of an underlying CB failure which has not been properly repaired during the first maintenance and consequently occurs again.

Chapter 4

Individual Failure Rate Modelling

The application of statical regression models in failure rate estimation and prediction in the power system domain is restricted by failure data availability and quality which has been concluded from the literature study in **Paper IV**. As a result, methods are required that improve the failure rate accuracy despite the limited failure data available. This chapter starts by demonstrating that improved failure rate accuracy can be gained through individual failure rates for components instead of using population failure rates. The concept of population and individual failure rates is presented and demonstrated based on an example. Thereafter, all relevant factors and methods which have been used to improve failure rate accuracy are shown and discussed based on the findings in **Paper IV**. These findings underline the need to develop a method which can improve failure rate accuracy without requiring actual failure data. Therefore, this chapter follows by presenting the method developed in **Papers V and VI** to calculate individual failure rates within populations without actual failure occurrence. The general method is presented and followed by a validation of the concept. The method is further applied in the Case Studies 3 and 4, which are the summarised results of **Papers V and VI**.

4.1 Population and Individual Failure Rates

Recall the definition of the failure rate $\lambda(t) = f(t)/R(t)$ in eq. 2.4 and how it is observed by testing n identical components and recoding the time to failure for each one. The failure rate is calculated from these n lifetimes, thus, it reflects the failure rate from a population perspective. This can be demonstrated with two examples. Firstly, consider the population of 25 power transformers rated greater than 25 MVA from section 2.2.7 illustrated in Fig. 2.3. The population is simulated, according to [20], with an average failure rate of $\lambda = 0.03$. In Fig. 2.3, the actual lifetimes of each component, the estimated distribution function $F(t)$ with confidence intervals, the non-parametric estimate of $F(t)$, and the failure

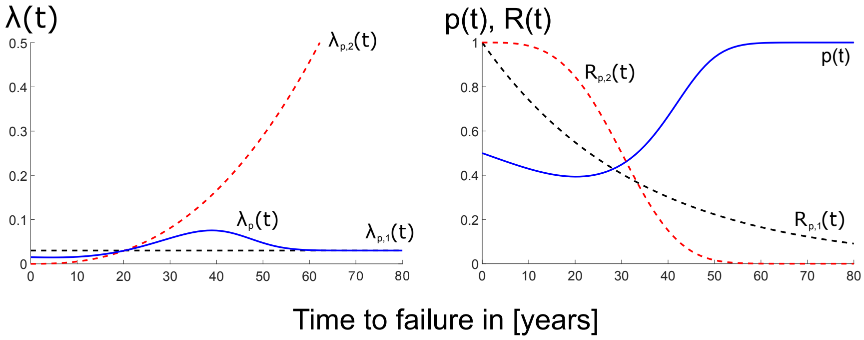


Figure 4.1: The left part of the figure depicts the population failure rate which is observed as the result of two different subpopulations with $\lambda_{p,1} = 0.03$ and $\lambda_{p,2} = 0.105 * (0.03 * t)^{3.5-1}$ for subpopulation 1 and 2, respectively. The right part of the figure shows the survival functions of both subpopulations plus the relative share $p(t)$ of the subpopulations over time.

rate $\lambda(t)$ are shown. A question to ask for the failure rate would be: "What is the probability that this component will fail in the next interval $(t, t+\Delta t]$?" [25, p. 19]. The obvious reply would be 'a constant failure rate of 0.03' because an exponential distribution is assumed. However, the previous question seems misleading since it asks for a specific component. Focusing on several components and considering being in year 40, it would be expected that the failure rate is higher for power transformer 11 to 15 which all fail soon after rather than for 23 to 25 which have a lifetime longer than 100 years. Even though the failures are often assumed to be random, the natural individual variations among the components should not be ignored [90]. Generally, [90] argues that it is tempting to consider the population failure rate as an individual failure probability over time. This becomes a particular challenge when populations have subgroups with different failure rates. This has been observed in a study regarding failure data of conductors, cables, and power transformers in [91]. Here, the observed population failure rate increases first and declines later. Particularly, this declining failure rate leads to a false perception. Let the second example illustrate this problem. For this purpose, the example from [92, 93] is used with some modifications. Suppose a population can be divided into two subpopulations which are characterised by the failure rates $\lambda_{p,1}(t)$ and $\lambda_{p,2}(t)$ and let $R_{p,1}(t)$ and $R_{p,2}(t)$ be the corresponding survival functions. Moreover, the proportion of components still operating at time t is represented by

$$p(t) = \frac{p_0 R_{p,1}(t)}{p_0 R_{p,1}(t) + (1 - p_0) R_{p,2}(t)} \tag{4.1}$$

with p_0 as the proportion of the subpopulation 1 at time $t = 0$. Now, the resulting population failure rate can be defined as

$$\lambda_p(t) = p(t)\lambda_{p,1}(t) + (1 - p(t))\lambda_{p,2}(t). \tag{4.2}$$

Here, the population is divided into two subpopulations with a constant failure rate $\lambda_{p,1} = 0.03$ and an increasing failure rate $\lambda_{p,2} = 0.105 * (0.03 * t)^{3.5-1}$ based on a Weibull distribution with scale parameter $\beta = 1/\lambda = 1/0.03 = 33.33$ and shape parameter $\alpha = 3.5$. The proportion of subpopulation 1 at $t = 0$ is $p_0 = 0.5$. The results are shown in Fig. 4.1 for the population failure rate and the corresponding survival functions. This example illustrates how the population failure rate over- or underestimates the failure rate of the subpopulations. In the first interval up to 20 years, the observed population failure rate overestimates the failure rate for subpopulation 2 but underestimates it for subpopulation 1. This changes after 20 years when $\lambda_{p,2}(t)$ further increases which results in a simultaneous increase in the population failure rate. However, after 39 years the population failure rate decreases again because the $p(t)$ increases, since more components of subpopulation 2 fail. If the population failure rate is interpreted as an individual risk, one would observe a declining failure rate even for the remaining 37 % of the subpopulation 2 components. This would lead to an incorrect perception about subpopulation 2 since these components still follow $\lambda_{p,2}(t)$.

4.1.1 Heterogeneity in Populations

The previous examples underline the importance to have a clear distinction between the population and individual failure rate and that the failure rate should be interpreted cautiously [90]. Consequently, for a measure of relative risk, it is important to describe the heterogeneity among components. To do so, the concept of heterogeneity and its source needs to be understood. Heterogeneity is the difference or diversification of components in a particular population. Therefore, the identification of component characteristics, which differentiate one component from another, is essential to understand the concept. From a survival analysis viewpoint in medical research, Aalen described three sources of heterogeneity in [90]:

1. Biological differences which are present from the beginning,
2. A weakness as the result from the stresses of life as a dynamic concept, and
3. Taking into consideration if a disease is in a early or late stage.

Unobserved individual heterogeneity is also called frailty in survival analysis [90]. However, transferring this concept to technical power system components, the sources of heterogeneity are:

1. Component specific variances from the commencement of operation (static factors),

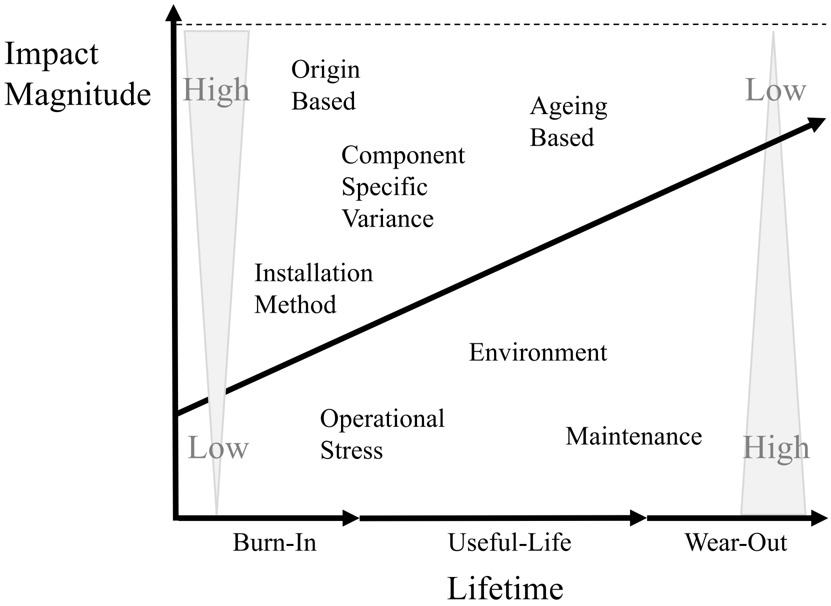


Figure 4.2: Abstract illustration of the Impact Magnitude of static and dynamic factors on a component's condition development and failure rate over time based on **Paper IV**

2. Induced frailty as the result of load and other stresses from being in operation (dynamic factors),

3. Consideration of the condition, the physical state, of a component over time which might range from "good" to "bad" and is the result of static and dynamic factors over time.

The individual failure rate is, hence, a function of the static factors, dynamic factors, and the condition which is in itself a function of the historical impact of the static and dynamic factors in the interval $(0, t]$. Consequently, the three sources static factors, dynamic factors, and the component condition are of interest to accurately model the failure rate. Note that the condition is dependent on the static and dynamic factors which are discussed in detail in **Paper IV**. Therefore, a literature study has been conducted in **Paper IV** to investigate which factors have been modelled thus far. These factors and their importance on a component's condition development are schematically illustrated in Fig. 4.2 and described in more detail in the following section.

4.1.2 Relevant Factors

The literature review in **Paper IV** revealed a set of factors which have been used in failure rate modelling of power system components. Ekstedt argued in [94] that no consistent categorization of failure rate factors exists in the literature thus far. Therefore, this section describes and categorises relevant factors which are characteristic of the population heterogeneity. The selection is based on factors used in failure rate modelling and the investigation of historical failure statistics. Generally, the factors can be categorised into static population and dynamic individual factors as aforementioned. The static population factors describe the properties which are given from the commencement and do not vary over time. Moreover, static factors cannot be controlled after the component is put into operation. On the contrary, the dynamic individual factors characterise the effect of time dependent factors on an individual component over time and consequently lead to a unique condition development. Dynamic factors can be, to some extent, controlled while the component is in operation. Even though the distinction is similar to the classification of time independent and time dependent explanatory variables in section 3.1.2, different terminology is chosen to more clearly distinguish between general population attributes and factors which impact the component condition. Primarily dynamic individual factors make a component unique in a population since these factors are difficult to control.

Static Population Factors

Component Specific Variance The term component specific variances describes the diversity of components within a population of the same type. These are attributes such as size, length, and material which describe the component. For example, overhead lines might be characterised by length and conductor type and a power transformer by power rating.

Ageing Based Power system components are built for a particular lifetime and might be modelled with a lifetime distribution under the constraint that they are operated within the predefined set of operating conditions. Hence, the general ageing can be modelled with lifetime distributions which applies to all components in the population.

Origin Based Origin or manufacturing based factors describe how a non-conformity during the design and manufacturing process impact the failure rate. For example, incorrect design or poor quality management can lead to early component failures. Typical characteristics might be model, manufacturing year, or manufacturer.

Installation Method The process of how a component is installed has an impact on early component failures or might lead to higher stress during the operation.

Dynamic Individual Factors

Environmental Impact The location and environment a power system component is operated in influences the lifetime. A general categorization of this environmental effect might be into: (1) the constant and varying impact on the wear and (2) the somewhat random appearance of certain events which cause direct failures. The surroundings such as temperature, water, wind and other weather features predominantly affect the wear. These weather related factors vary over time and hence are dynamic. On the contrary, random events which lead to direct component failures are often weather events with a higher magnitude. Other constant factors are location, usual seasonal variations, vegetation, or construction work. Vegetation or animal related factors also can cause direct failures.

Operational Stress Induced weakness resulting from operational stress in form of overload or erroneous operation increases the failure rate of components. Examples of these factors might be the current load, load history, amount of operations, and time in operation.

Maintenance Impact Maintenance activities consist of supervision, prevention and detection of failures to retain or restore the functioning state of a component [25]. Preventive maintenance, therefore can improve the condition and operating environment to decrease the failure rate. However, incorrect maintenance could have a negative impact on the failure rate. Corrective maintenance, in contrast, is conducted after component failure and restores the component to a functioning state. This type of maintenance is not considered here.

Condition-Based The physical or 'health' state of a component is the condition which is an indicator of the ability to resist operational stresses. When the condition is 'as new', the component is considered to have the strength to withstand the external forces it is designed for. During the lifetime, the preceding factors cause degradation of the condition over time and reduce its ability to withstand external forces.

4.2 Methods for Failure Rate Estimation for Individual Components

This section presents approaches to model the failure rate of components based on individual characteristics as presented in the preceding section. These consist of the PHM, Markov models, Bayesian Updating Scheme, and a practical approach based on empirical data. The presented methods are described briefly and an example of the failure rate estimation is given.

4.2.1 Proportional Hazard Model

The relative risk model or PHM, when the explanatory variables are fixed, is described in section 3.2.1. This model is primarily used to investigate the effect of explanatory variables on the failure rate. However, after the regression coefficients are estimated, the resulting risk function acts multiplicatively on the failure rate when considering the model in eq. 3.4. Therefore, the failure rate of an individual component might be computed based on the set of its explanatory variables. Let the results of Table VI in **Paper V** serve as an illustrative example. Having the three covariates *geographical area*, *maintenance intensity*, and *number of operating within the last year* to be significant, the failure rate for component i can be formulated as

$$\begin{aligned}\lambda(t;\mathbf{x}_i) &= \lambda_0(t)e^{Z_1\beta_1+Z_2\beta_2+Z_3\beta_3+Z_4\beta_4+Z_5\beta_5+Z_6\beta_6+Z_7\beta_7+Z_8\beta_8+Z_9\beta_9+Z_{10}\beta_{10}} \\ &= \lambda_0(t)e^{Z_1(-0.421)+Z_2(-0.306)+Z_3(-0.758)+Z_4(-2.482)}\times \\ &\quad e^{Z_5(-2.465)+Z_6(-1.694)+Z_7(0.731)+Z_8(1.028)+Z_9(0.965)+Z_{10}(1.468)}\end{aligned} \tag{4.3}$$

Assuming a baseline failure rate with $\lambda_0(t) = 0.01$, according to the average failure rate for CBs in [20], the failure rate of a CB within *geographical area* 3, *maintenance intensity category* 1, and *number of operations within the last year category 1* is

$$\begin{aligned}\lambda(t;\mathbf{x}_i) &= 0.01 \times e^{1*(-0.758)+1*(-2.482)+1*(0.731)} \\ &= 0.0008.\end{aligned} \tag{4.4}$$

The failure rate for the remaining $n-1$ components can be calculated likewise. Applying the relative risk model enables a better failure rate characterisation based on the investigated factors. However, this is often not feasible due to data requirements. Even though the relative risk model modifies the baseline failure rate to get an individual failure probability, the unobserved individual heterogeneity might be neglected in survival analysis which has become a major concern [90]. The argumentation and examples have been given in section 4.1.1 and the general theory is known as frailty theory and presented, for example, in [93]. Aalen discusses the topic and presents some models to consider the unobserved heterogeneity in [90]. A simplistic model is a proportional model where the individual failure rate is the product of a specific quantity $\mathcal{Q}$ and the baseline failure rate $\lambda_0(t)$ such that

$$\text{individual failure rate} = \mathcal{Q}\lambda_0(t). \tag{4.5}$$

In this basic model, $\mathcal{Q}$ is a random variable over the population. Aalen argues that the population failure rate is observed in a population, which is the result for the n number of individuals with varying values of $\mathcal{Q}$. This model primarily considers the given differences from the start and solely extracts parts, but it could give useful insights [90]. The frailty variable $\mathcal{Q}(t)$ might be modelled as a stochastic process or as a first-passage-time model. These are not further presented here and it is referred to [66, 90, 93].

Remarks Given sufficient failure data and explanatory variables, the Cox regression is the most suitable method to investigate the impact of explanatory variables on the failure rate of power system components. After developing a model, the failure rate can be more accurately modelled and predicted for each individual component under the assumption that the historical population is equal to the one in operation. If, however, a technological design change has happened and the actual components are different, then the prediction has its limitations. Furthermore, this method is especially useful to assess past asset management decisions and what impact these have on the components in operation. However, the general challenge of data quality and availability continues to be the main challenge for the application of this tool in the power system domain. It is recommended to further apply regression models to gain valuable insight into failure occurrences despite the high level of effort required to gather the data.

4.2.2 Markov Models and Hidden Markov Models

Markov models are a useful mathematical technique to model repairable components, as described in section 2.4.3. Further benefit of Markov models is the non-necessity of historical failure data as long as the failure rate and repair rate are given as transition rates. However, this applies solely to a two state Markov model and is a good application example of the failure rate. Considering a Markov model with several states to model a deterioration process of an individual component, the transition rates have to be determined differently. In this application, the transition probabilities can be computed from life-histories, manufacturer information, historical condition monitoring data, and the deterioration function [95]. Afterwards, the probability of failure in each state is determined to estimate the overall failure rate. For example, Velasquez-Contreras developed in [96] a five state Markov model, including the states new, normal, defective, faulty, and failed, to model the deterioration process of a power transformer to calculate the failure rate for an asset management framework.

In contrast to the classical Markov model, the Hidden Markov model (HMM) assumes that the state cannot be directly identified. A practical illustration is the identification of the dielectric strength of the insulation material in a power transformer. The difficulty in directly identifying the insulation material strength and diagnostic measurements such as dissolved gas analysis are applied to provide insightful information. These condition monitoring data can be utilised to calculate the states. The condition-based failure rate estimation with a discrete HMM has been demonstrated in [95]. The HMM utilizes a sequence of observations that are the result of an underlying or 'hidden' Markov process to calculate the transition rates between the condition states. The steps to determine the transition rates according to [97] are as follows:

1. Define the number of all observable and non-observable states.

2. Determine the following parameters:

a) The Markov transition matrix with state transition probabilities $A = \{a_{ij}\}, a_{ij} = P(X_{t+1} = j|X_t = i), 1 \leq i, j \leq N$ where N is the component's deterioration level and X_t is the current state.

b) The probability of obtaining an observation with a observation symbol M at a specific state is $B = \{b_j(k)\}$ with $b_j(k) = P(o_t = v_k|X_t = j, 1 \leq j \leq N, 1 \leq k \leq M$ where o_t is the current observation.

c) Suppose the latest observation is given, then the initial state distribution can be calculated with $\Pi = \pi_i$ with $\pi_i = P(X_i = i), 1 \leq i \leq N$.

3. The final step is the calculation of the optimal parameter $\lambda = \{A, B, \Pi\}$ by maximizing the likelihood of the observation $L_{tot} = p(O|\lambda)$. Here, the Baum-Welch algorithm is applied.

The transition matrix $\mathbf{P}$ can be built after the estimation of the transition rates. The state probability vector is denoted with $P(hT) = [P_1(hT) \dots P_N(hT)]$ where $h = 1, 2, 3, \dots$ and T is the time increment. The elements of the state probability vector are the probabilities that a component is in a specific deterioration state at time T. For example, when the component is in the first state at time $t = 0$ then $P(0) = [1\ 0 \dots 0]$. Now, the probability can be computed so that a component is in any deterioration level at time hT with $P(hT) = P(0) * P^h$. Finally, the failure rate is calculated as

$$P(hT \leq x \leq (h+1)T|x > hT) = \frac{P((h+1)T) - P(hT)}{1 - P(hT)}. \tag{4.6}$$

Example The HMM is applied to three power transformer case studies [96, 97, 98]. All authors utilised dissolved gas analysis results to develop the model. In [97], the authors used a sample size of 10 transformers over a time of 7 years to train the model and calculate the transition probabilities. The calculated failure rate is depicted in Fig. 4.3. One drawback of the HMM is that, to determine the transition rates, it is necessary that the component has been in all deterioration states as defined. Moreover, the definition of the states itself can be challenging when only limited knowledge about the deterioration process is available.

Remarks Event though the HMM is theoretically a method to model the failure rate on an individual level, practically this is difficult. Condition monitoring data need to be gathered over such a long interval that the component has been in all predefined stages such as a failure. Particularly, for power system transformers on transmission level, this seems to be unrealistic due to the long-lifetimes and generally low failure probability. Moreover, it is tempting from a practical perspective to apply the same model to all other components in operation instead of gathering condition monitoring data for each. Therefore, the HMM is not very suitable to model individual failure rates due to the practical implications.

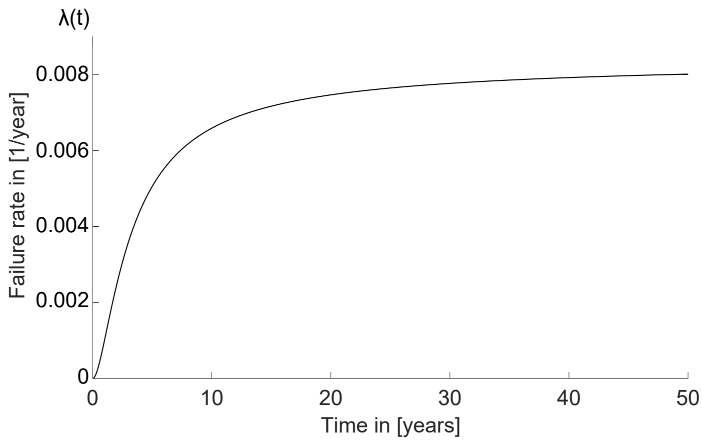


Figure 4.3: Estimated failure rate based on HMM and dissolved gas analysis data [97]

4.2.3 Bayesian Reliability Modelling

Generally, the scarcity of failure data in the power system domain creates the demand for methods which enable certain lifetime predictions with limited failure data. Bayesian methods for reliability analysis are an approach to gain additional insights by combining "prior" information with some observed data to make inferences [23]. The basic principle in a reliability context is presented in [25, ch. 13] and [23, ch. 14] and is illustrated in the following. Suppose the random variable X with the corresponding probability density function $f(x, \theta), \theta \in \Omega$ where Ω is a subspace of the r-dimensional Euclidean space. Moreover, θ is understood as the realisation of a random variable Θ with the density $f_\Theta(\theta)$ which is interpreted as the "beliefs" about the value of Θ prior to any observation. Therefore, $f_\Theta(\theta)$ is known as the prior density of Θ and let $f_{X|\Theta}(x|\theta)$ denote the conditional density of X. Following the theoretical concept in [25, ch. 13], the joint density of X and Θ is

$$f_{X,\Theta}(x, \theta) = f_{X|\Theta}(x|\theta) * f_\Theta(\theta) \tag{4.7}$$

Now, having the marginal density of X with

$$f_X(x) = \int_\Omega f_{X,\Theta}(x, \theta) d\theta \tag{4.8}$$

which leads to the conditional density of Θ, given $X = x$, is

$$f_{\Theta|X}(\theta|x) = \frac{f_{X|\Theta}(x|\theta) * f_\Theta(\theta)}{f_X(x)}. \tag{4.9}$$

This can be seen as a basic form of Bayes's theorem. Since this expression states the belief regarding the distribution of Θ, after having observed $X = x$, it is called the posterior density of Θ. Recall that when X is obtained, the density $f_X(x)$ is constant in eq. 4.9. Consequently, this resulting proportionality between $f_{X|\Theta}(x|\theta)$ and $f_{X|\Theta}(x|\theta) * f_\Theta(\theta)$ can be expressed as

$$f_{\Theta|X}(\theta|x) \propto f_{X|\Theta}(x|\theta) * f_\Theta(\theta). \tag{4.10}$$

This method is also often called the Bayesian updating scheme, which originates from the fact that the information about the parameter θ is updated. Moreover, this is an iterative process because the prior distribution of θ is updated to the posterior distribution θ, given $X = x$ as soon as new information X is obtained and the posterior distribution becomes the new prior distribution.

Bayesian methods also enable the prediction of future component failures within a particular population. These failures are predicted by using the Bayesian posterior predictive distribution [23, ch. 14.6] which is

$$f_{X_0|X}(x_0|x) = \int_0^\infty f(x_0|\theta) * f_{\Theta|X}(\theta|x) d\theta. \tag{4.11}$$

The Bayesian method as updating the prior plus predicting the future density, is illustrated in graphical form in [99, Fig. 3.2].

Examples Bayesian Updating in combination with failure rate prediction has been applied for overhead transmission [100] and distribution [15, 101] lines, and power transformers [102]. In [100], the number of overhead line failures are modelled with a Poisson process where the prior is a Gamma distribution which is updated with the number of occurred failures over a six year period. Similar, but in combination with log-linear regression, [101] is using a hierarchical Bayesian Poisson regression to estimate individual failure probabilities for distribution lines. The authors include the length, age, load and tree density as possible explanatory variables. In a rather general approach, the feasibility of Bayesian updating in power transformer failure rate estimation is shown in [102]. Here, condition monitoring information in the form of power transformer oil and gas samples over a time horizon of 8 years is used, to update the shape parameter α in the Weibull failure rate function shown in eq. 2.19 while assuming that the condition measurements follow a normal distribution.

Remarks Bayesian Updating presents accurate results, particularly, on the modelling of the failure rate of overhead lines by using historical failures of each line and external explanatory variables such as weather. However, the general approach of updating the Weibull distribution parameters based on condition monitoring data should be seen as an idea rather than a suitable method since a few simple assumptions have been made to show the idea rather than a complete method. However, more development of the general method might lead to better results.

4.2.4 Failure Rate Modelling based on Inspection Data

An empirical approach to model the failure rate based on component inspection data has been presented in [20]. Brown argued that the failure rate should be modelled ideally as a function of critical parameters. However, assessment of the failure rate with regression techniques as presented in Chapter 3 is difficult due to limited data availability and the often poor data quality. Therefore, a failure rate model has been found to empirically fit the data best with an exponential function such that

$$\lambda(\mathcal{S}) = Ae^{B\mathcal{S}} + C \tag{4.12}$$

where $\mathcal{S}$ is the condition score and A,B, and C are the function parameters which are calculated from the failure rate at the best, average, and worst inspection outcome. The condition score $\mathcal{S}$ is computed by $\mathcal{S} = \sum_{p=1}^{k} w_p r_p / \sum_{p=1}^{k} w_p$ with the relative importance weight $w_p \in \{1, 10\}$ and the inspection outcome score $r_p \in \{0, 1\}$ with 0 as the best, 0.5 the average, and 1 as the worst inspection outcome. The natural pairs are the failure rates $\lambda(0)$, $\lambda(0.5)$, and $\lambda(1)$. Having these three failure rates, the parameters for the failure rate function are determined by [20]

$$A = \frac{[\lambda(0.5) - \lambda(0)]^2}{\lambda(1) - 2\lambda(0.5) + \lambda(0)} \tag{4.13}$$

$$B = 2ln\left(\frac{\lambda(0.5) + A - \lambda(0)}{A}\right) \tag{4.14}$$

$$C = \lambda(0) - A. \tag{4.15}$$

Whereas the average failure rate $\lambda(0.5)$ is often available for different component types, the failure rates for the best and worst condition are difficult to determine [20]. Therefore, Brown presents these for a range of component types in [20] and a more detailed benchmarking in [19]. In Fig. 4.4 the component failure rates are depicted for power transformer, disconnector, and CB dependent on the condition score.

Example This method is illustrated based on 3 transmission power transformers which are used in the case study of **Paper viii** and are also part of **Paper VI**. To calculate the condition score of these power transformers, the condition ratings for gas and oil analysis and paper ageing have been utilized. Converting the condition score or health index from 0-100, from very poor to very good, to 0-1 and inverting the scale, the failure rate for these power transformers can be calculated based on 4.12. The results are shown for the period 2002 to 2016 in Fig. 4.5 and all power transformers are below $\lambda_{0.5} = 0.03$.

Remarks This method, which is based on historical component failure data, is the most practical approach. If the condition score of a component can be accurately determined, it is beneficial for power system operators. However, the condition

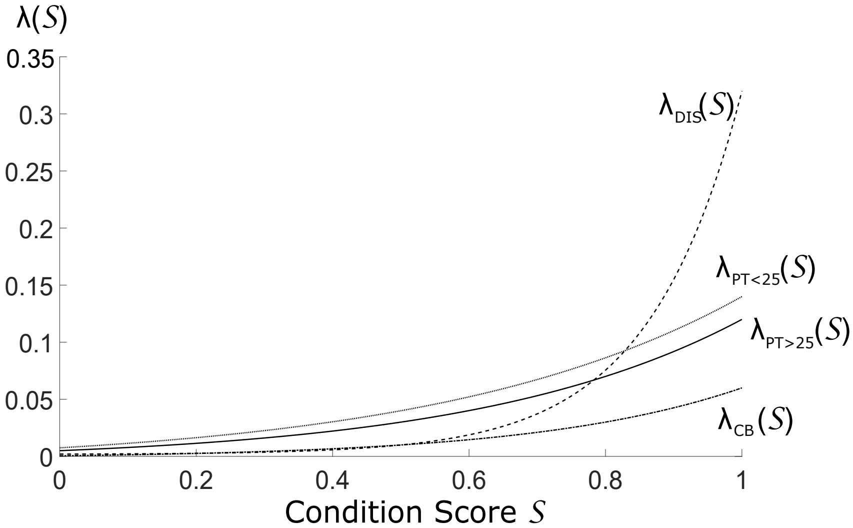


Figure 4.4: Empirical component failure rate functions based on a condition score for power transformers rated greater 25 MVA $\lambda_{PT>25}(\mathcal{S})$ and smaller 25 MVA $\lambda_{PT<25}(\mathcal{S})$, disconnectors $\lambda_{DIS}(\mathcal{S})$, and CB $\lambda_{CB}(\mathcal{S})$ which are presented in [20]

score and particularly the determination is also its weakness. Expert knowledge is required to define the criteria and importance weights for the condition score. Moreover, equal information must be gathered for all components to make the results comparable.

4.2.5 Discussion

All aforementioned methods have the mutual aim to model and predict the failure rate accurately. As Brown argued in [20, p. 783], the failure rate should be characterised preferably through a regression model which assesses each internal and external explanatory variable. Therefore, the PHM seems to be the preferable option since it not solely models the failure rate but also investigates the statistical significance of the explanatory variables. However, this requires failure data of the population of interest which is often difficult to gather due to long lifetimes and decisions to replace components before they fail. Markov and HMM estimate the failure rate depending on the deterioration state of the individual component, however, it is essential that the component has been in each deterioration state before, which makes the data requirements even higher than with the PHM.

Bayesian statistical methods, on the contrary, require less actual failure data and are therefore an alternative approach. This method combines previous process knowledge with data such as condition monitoring or failure statistics [99]. However,

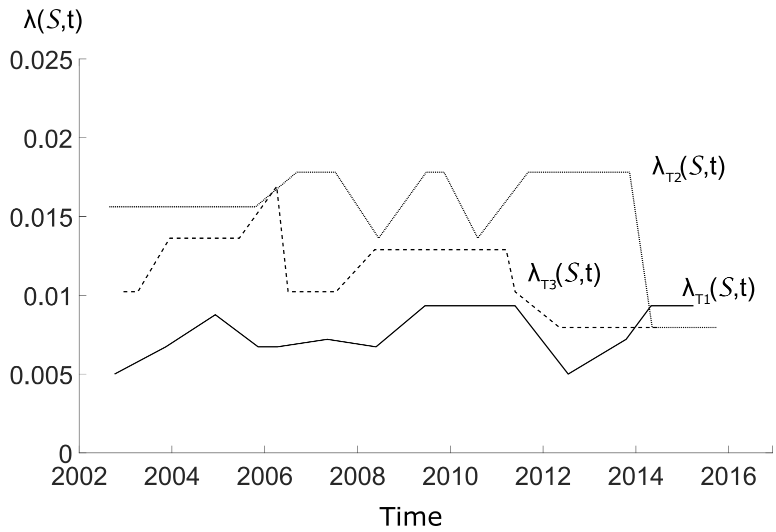


Figure 4.5: Computed failure rates for three transmission power transformers rated greater 25 MVA based on a health index score presented in **Paper viii**

an assumption about the prior distribution is required for this parametric method, which might be difficult in certain cases.

The empirical failure rate model developed by [20] and presented in the preceding section is the most straightforward method. This heuristic method combines historical failure data with expert knowledge and experience about most power system component types to model the failure rate over a condition score. Although straightforward, a challenge is the consistent definition of the condition score which the failure rate is mapped to. Depending on the criteria defined and available, the overall condition might be over- or underestimated if not a sufficient amount of criteria is selected. Moreover, the presented failure rate data in [20] for the best, average, and worst inspection outcome might be general but does not necessarily have to be accurate for the population of interest due to developments in component design, for example.

These limitations underline that a method, which does not require failure data and the parametric assumption about the sample data used, would be beneficial in improving failure rate modelling.

4.3 Individual Failure Rates within Populations

This section presents the concept of Individual Failure Rates which has been developed in the **Papers V and VI**. **Paper V** formulates the time-independent model and describes the method in a practical context of a power transformer population. The case study includes 30 power transformers with six single time condition measurements and is summarized in section 4.4. **Paper VI** presents a more rigorous formulation of the method considering time-dependence and introduces the risk functions. Furthermore, the individual failure rates are forecasted by applying time-series analysis to predict the stochastic internal covariates or condition measurements. Hence, the approach is applied to a population of twelve transmission power transformer which is presented in section 4.5.

4.3.1 Modelling Assumptions and Constraints

The preceding section presented various methods to calculate failure rates for components based on internal and external explanatory variables. However, these methods are often difficult to apply within the power system domain. From a general perspective of statistical data driven approaches, the authors of [103] conclude with a literature review that a number of challenges remain before existing methods can be applied to practical systems. The authors primarily identify that there is

1. the necessity to develop models with limited amount of data available, for example, when new components are operated,
2. the fusion of several input data sources such as condition information,
3. the investigation of how external factors can be incorporated into the models and how they impact the condition information,
4. the development of a model which considers all failure modes of a single component.

These four challenges are particularly relevant in the power system domain due to the long lifetimes of the components and poor data quality which leads to a limited amount of historical data [20]. The resulting consequences are a shortage of failure data, records of component characteristics, and long-term environmental and condition monitoring information. Therefore, the method to calculate individual failure rates is based on the limited data available considering the challenges in the power system domain. The method has been developed under the following assumptions:

1. Solely homogeneous populations are considered such as the population of a particular component type
2. No failures have occurred in the population until time t
3. The components are non-repairable
4. At least a single condition measurement has been obtained
5. The condition monitoring information is a valid failure indicator
6. The same condition monitoring information has been gathered from all components
7. The population or baseline failure rate and failure mode statistics are equal to historical data of previous populations

4.3.2 Method

Assume a homogeneous population of n non-identical power system components without failure occurrence until time t. Let $\lambda_0(t)$ be the baseline failure rate, also known as population failure rate, which is defined in eq. 2.4 and computed from historical failure data of a comparable population η with m distinct failure types $j \in \{1, \ldots, m\}$. Let $\boldsymbol{x}_{i,j}(t) = (x_{i,j_1}(t), x_{i,j_2}(t), \ldots x_{i,j_k}(t))$ be the vector of k internal covariates which are related to failure type j of the i-th component with $i \in \{1, \ldots, n\}$ and $\boldsymbol{x}_i(t)$ the vector of all d covariates of component i with $d = \sum_{j=1}^{m} k_j$. Recall the definition of the failure type specific failure rate in eq. 3.13. Following the competing risk approach in eq. 3.14, each failure type j can occur but separately, such that

$$\lambda(t; \boldsymbol{x}_i(t)) = \sum_{j=1}^{m} \lambda_j(t; \boldsymbol{x}_{i,j}(t)) = \sum_{j=1}^{m} \lambda_{0j}(t) r_j(t; \boldsymbol{x}_{i,j}(t)) \tag{4.16}$$

The method is based on the form and idea of eq. 4.16 but must be clearly distinguished from the regression model within survival analysis.

Suppose the frequency of each failure type j is known from population η, the vector $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_m)$ denotes the proportion of each failure type j with the property $\sum_{j=1}^{m} \alpha_j = 1$. Moreover, given that $\sum_{j=1}^{m} \lambda_{0j}(t) = \lambda_0(t) \sum_{j=1}^{m} \alpha_j$, the competing risk approach can then be written as

$$\lambda(t; \boldsymbol{x}_i(t)) = \lambda_0(t) \sum_{j=1}^{m} \alpha_j r_j(t; \boldsymbol{x}_{i,j}(t)) \tag{4.17}$$

Furthermore, it is assumed that each covariate is solely related to one failure type j and that the vector $\boldsymbol{x}_{i,j}(t) \in \Re_{>0}$ is assumed to be a valid failure indicator of j. Moreover, each internal covariate in vector $\boldsymbol{x}_{i,j}(t)$ has a measurement uncertainty vector $\boldsymbol{\rho} = (\rho_1, \rho_2, \ldots \rho_m)$. The measurement uncertainty ρ describes the assurance of successfully measuring the internal covariates. This leads to the time dependent model

$$\lambda(t; \boldsymbol{x}_i(t)) = \lambda_0(t) \sum_{j=1}^{m} (\alpha_j \rho_j r_j(t; \boldsymbol{Z}_{i,j}(t)) + \alpha_j(1 - \rho_j)) \tag{4.18}$$

where $\boldsymbol{Z}_{i,j}(t) = (Z_{i,j_1}(t), Z_{i,j_2}(t), \ldots Z_{i,j_k}(t))$ is a vector of time dependent covariates derived from $\boldsymbol{x}_{i,j}(t)$. This notation is useful since the basic covariates might be transformed such that $\boldsymbol{Z}_{i,j}(t) = g(\boldsymbol{x}_{i,j}(t))$ where g depends on the internal covariate data being chosen. This transformation might be needed to describe the risk functions. The model parameter ρ is described in detail in **Paper V** and the risk function in eq. 4.18 is further described in the following section.

Risk Functions

The risk function $r_j(t; \boldsymbol{Z}_{i,j}(t))$ is the factor which differentiates the i-th component from the population failure rate $\lambda_0(t)$. Since $r_j(t; \boldsymbol{Z}_{i,j}(t)) > 1$ causes an increase, $r_j(t; \boldsymbol{Z}_{i,j}(t)) < 1$ a decrease, and $r_j(t; \boldsymbol{Z}_{i,j}(t)) = 1$ an unaltered failure rate, this function is a relative risk function. Assuming that the condition of the

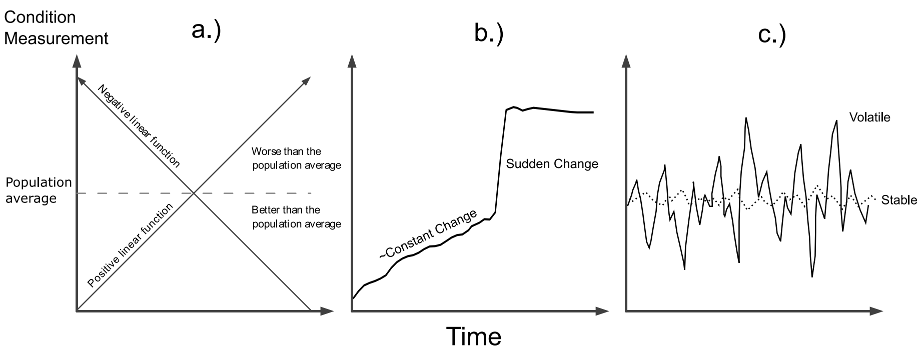


Figure 4.6: Graphical illustration of possible risk functions

i-th component is a valid risk of failure indicator, the function $r_j(t; \boldsymbol{Z}_{i,j}(t))$ adjust the population failure rate by utilizing the internal covariates $\boldsymbol{Z}_{i,j}(t)$. The initial background of the risk function is described in **Paper V** and illustrates the idea that in a homogeneous population which is operated under the same operating conditions, the component which differs from the population features has an increased or decreased failure rate. Hence, the 'reference group' required for the relative risk function, here the population reference condition, is the average population condition calculated from the internal covariates. Depending on how an internal covariate describes the failure probability, the function space is large. While **Paper V** solely introduces a positive or negative linear risk function due to the time-independence, **Paper VI** presents two additional risk functions when the covariate history $X_p(t) = \{x_p(u) : 0 \leq u < t\}$ is given. Based on these covariate histories, the vectors $\overline{\boldsymbol{C}}$ and $\overline{\boldsymbol{V}}$ are computed which are the average population condition and variance for each covariate $p \in \{1, \ldots, k\}$, respectively.

The arithmetic mean $\overline{\boldsymbol{C}}$ of all internal covariates is the reference measure and can be compared to the current measurements $\boldsymbol{Z}(t)$. Since multiple covariates can be related to failure mode j, the overall risk function is calculated by

$$r(t; \boldsymbol{Z}(t)) = \boldsymbol{S}(t; \boldsymbol{Z}(t))\mathbf{w} \tag{4.19}$$

where $\boldsymbol{S}(t; \boldsymbol{Z}(t)) = (S_1(t; Z_1(t)), \ldots S_k(t; Z_k(t)))$ is the vector of all k risk functions which are related to j, and $\mathbf{w} = (w_1, \ldots, w_k) \in \Re_{>0}$ is the weight score with the property $\mathbf{w}\mathbf{1}_{k\times 1} = 1$. The calculation is described in greater detail in **Paper VI**, which also presents the three proposed risk functions, which are the linear, non-linear, and the cumulative risk function.

Linear Risk Function This risk function can be either positive or negative and describes the relationship between covariate and failure rate as linear. An illustration of this is shown in Fig. 4.6 a.). This function can be applied in the time dependent as well as in a time independent setting. Before these function can be defined, the basic covariates need to be transformed such that

$$Z_p(t) = \begin{cases} 0 & if\ x_p(t) < 0 \\ x_p(t) & if\ x_p(t) \geq 0 \end{cases} \tag{4.20}$$

if there is a linear positive relationship and

$$Z_p(t) = \begin{cases} x_p(t) & if\ x_p(t) \leq x_{p,new}(t) \\ 0 & if\ x_p(t) > x_{p,new}(t) \end{cases} \tag{4.21}$$

if a linear negative relationship between covariate and failure rate exists. The vector $\boldsymbol{x}_{new}(t)$ describes the incipient component condition. Having transformed the basic covariates, the positive linear function is defined as

$$S_p(t; Z_p(t)) = Z_p(t)/\overline{C}_p \tag{4.22}$$

and the negative linear function as

$$S_p(t; Z_p(t)) = (x_{p,new}(t) - Z_p(t)) \,/\, \left(x_{p,new}(t) - \overline{C}_p\right) \tag{4.23}$$

Non-Linear Risk Function A possible failure indication might be the magnitude of change over time of the internal covariates. An abrupt change of the internal covariate can be an indication of an increased risk of failure, whereas a constant change over time shows normal behaviour. This is illustrated in Fig. 4.6 b.). Thus, a risk is identified when the rate of change alters over time, which is described by the second derivative of $X_p(t)$. The basic covariate $x_p(t)$ needs to be standardized such that

$$Z_p(t) = \frac{x_p(t) - \overline{C}_p}{\sigma_p}. \tag{4.24}$$

with σ_p as the standard deviation of covariate p. Now, the risk function can be modelled with

$$S_p(t; Z_p(t)) = exp(\ddot{Z}_p(t)) \tag{4.25}$$

with the exponential form to satisfy the failure rate property $\lambda(t; x(t)) \geq 0$.

Cumulative Risk Function The volatility of an internal covariate is another risk indicator which can be described by the cumulative deviation of $Z_p(t)$ from the expected condition value $\overline{C}_p$. Fig. 4.6 c.) depicts the difference between a stable and volatile covariate path over time. An example of such a covariate is the gas production in power transformers over time. Standardising the covariate with

$$Z_p(t) = \frac{x_p(t) - \overline{C}_p}{2\sigma_p} \tag{4.26}$$

first, where the common scale is two times the standard deviation to consider solely significant deviations from the mean, the cumulative risk function can be defined as

$$S_p(t; Z_p(t)) = \int_0^t |Z_p(u)|\, du. \tag{4.27}$$

Selection of Risk Function Selecting the risk function is based on the risk behaviour of the covariate. The general behaviour of different covariate risks is illustrated in Fig. 4.6. The following risk behaviours indicate which risk function to select from the set suggested.

1. **High deviation from population** The most straightforward description of risk is the deviation of one particular covariate from the population average value. Here, the linear risk function is the standard choice. Depending on the covariate this might be linear positive, the higher the measurement value is the worse the condition is, or linear negative, the lower the measurement value is the more possible it is that the covariate indicates an upcoming failure.
2. **Abrupt change** If the covariate path suddenly changes from its approximately constant path, this might be an indication for an increased probability of failure. Then the non-linear risk function is most suitable.
3. **High volatility** If a risk of failure of a component is reflected best with the volatility in a particular covariate, the cumulative risk function is suitable to describe this risk type. To identify the risk besides the general noise of the covariate, the covariate is normalised as aforementioned.

Risk Function Weight Score The k risk functions in $\boldsymbol{S}(t;\boldsymbol{Z}(t))$ must be combined with $\boldsymbol{w}$ to a single function $r(t;\boldsymbol{Z}(t))$ as shown in eq. 4.19. As described in **Paper V**, the weight w_p is calculated with

$$w_p = c_p / \sum\nolimits_{p=1}^{k} c_p \tag{4.28}$$

where $c_p \in \Re_{>0}$ is the weight score of covariate p and describes the significance as a failure indicator. Depending on the amount of historical covariate and failure data available, different approaches are possible to determine c_p, such as Cox or logistic regression or the determination by expert knowledge.

Individual Failure Rate Prediction

Given the covariate history $X_p(t)$, the covariate behaviour can be modelled with different methods to estimate the future value $X_p(t+\tau)$ with $\tau > 0$ periods ahead. This covariate behaviour is either stochastic or non-stochastic and can be modelled with time series analysis, state space models, and Markov Chains if stochastic, and parametric functions if non-stochastic, as presented in [44]. Stochastic covariate behaviour can be predicted with a certain confidence level whereas non-stochastic covariates can be predicted with a higher accuracy. **Paper VI** illustrates the prediction of individual failure rates by using univariate time series analysis to forecast the covariate behaviour. This approach can be summarised into the following steps:

1. Create a covariate behaviour model based on $X_p(t)$ using techniques for stochastic or non-stochastic covariates,

2. Forecast $X_p(t+\tau)$ with τ periods ahead,
3. Use Monte Carlo simulations to calculate c sample path of $X_p(t+\tau)$,
4. Compute an average covariate behaviour path with an upper and lower confidence level.
5. Calculate the Individual Failure Rates based on these three covariate paths.

The result is a prediction of the Individual Failure Rate with an upper and lower confidence interval which enables different interpretations and allows the selection of an Individual Failure Rate based on the operator's preferable risk behaviour. Hence, the operator can choose a risk-neutral approach by choosing the average forecasted path, and a risk-seeking or risk-averse approach by choosing the upper or lower confidence level path.

4.3.3 Validation

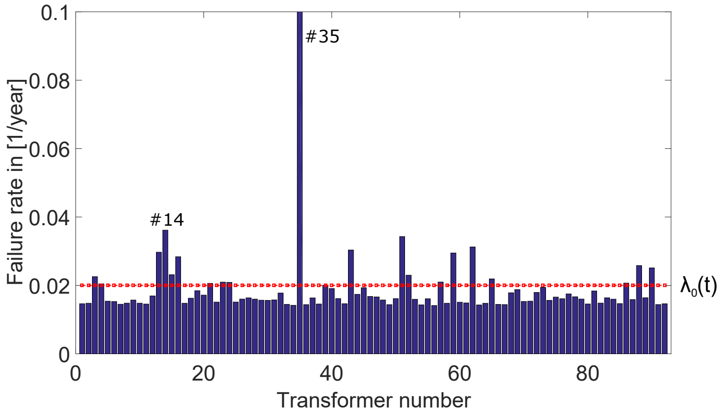
After having developed a method for failure rate estimation, validation of the results is essential to show the accuracy. Generally, the validation of component failure rates is connected to certain challenges such as the randomness of failure occurrences primarily due to environmental impacts, the lack of failure data because outages are expensive or a risk to general safety. Therefore, components are replaced before failure or controlled experiments are conducted to simulate certain failures which are imprecise due to the absence of actual operating conditions. These general challenges have been discussed in more detail for failure type detection with machine learning techniques in [104, ch. 8].

The proposed method estimates a failure probability for each component in a population and if a threshold value $\gamma \in [0,1]$ for the failure rate is set, the component might be classified as failed or near failure. Consequently, Bayes' theorem might be applied to evaluate the performance of diagnostic tests [105, ch. 1.3]. Let B denote a fault state of the component and $\bar{B}$ that the component is not in a fault state. In addition, A is the event that the method predicts a failure and $\bar{A}$ is the event that a failure is not predicted. This should describe that the method is actually able to predict positively or negatively a failure and a component actually experiencing a failure. Hence, the aim is to quantify the error of the method. To validate the proposed method, a population of power transformer in a Swedish county is investigated. General population data is given in Table 4.1, and a single time condition measurement is available in the form of gas analysis results such as the total combustible gases (TCG) which are hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), and carbon monoxide (CO). Applying the expert weights to the measurements according to [106], the failure statistics according to [107] likewise as in case study 3, setting $\lambda_0(t) = 0.02$, the individual failure rates can be computed with eq. 4.18. The results are depicted in Fig. 4.7a.

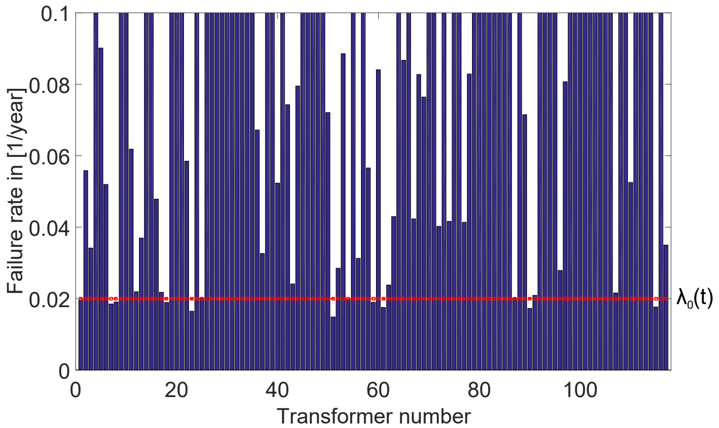
Table 4.1: Power transformer population data used in validation of individual failure rates

Number of components	92 units
Installation Year	mean 1980; standard deviation = 13; min = 1954; max=2012
Number of Producers	15 manufacturers
Voltage Levels	$6.6 \leq x \leq 230$ kV
Power Rating	$2 \leq x \leq 500$ MVA

Two power transformers have been identified with a failure in the population. Component 14 has experienced a bushing failure and has been put out of operation for some time while the component has been repaired. The gas analysis has been conducted after the failure but before it has been put in operation again. This component with $\lambda_{14} = 0.036$ still has the second highest failure rate and has been classified as a failure, even though the measurement has been taken after the failure and is not fully representative. Component 35 has been diagnosed with overheating and damaged insulation material and is classified as a failure. The estimated individual failure rate for component 35 is $\lambda_{35} = 0.210$ which is ten times higher than the population failure rate $\lambda_0 = 0.02$. Given solely the gas analysis results and no further information about other possible failure modes, the threshold value is set to $\gamma = 0.04$, which is two times higher than the population failure rate and suggests a warning for further investigation. The evaluation results of the individual failure rate method are presented in Table 4.2. Now, the two conditional probabilities $P(A|B)$ and $P(A|\bar{B})$ are calculated. $P(A|B)$ describes the positive response given that a failure has occurred, thus, the larger this conditional probability is, the more sensitive the test is [105, ch. 1.3]. In contrast, $P(A|\bar{B})$ describes the conditional probability that a positive response is detected while the component does not have a failure. Hence, the smaller $P(A|\bar{B})$ is or the larger $P(\bar{A}|\bar{B})$ is, the more specific is the method. Furthermore, the measured positive predictive rate (PPV), calculated as $PPV = P(B|A) = P(A|B) * P(B)/P(A)$, and the negative predictive value (NPV), defined as $NPV = P(\bar{B}|\bar{A}) = P(\bar{A}|\bar{B}) * [1 - P(B)]/[1 - P(A)]$, are presented in all Tables. These two criteria have also been called false positive rate and false negative rate [105, ch. 1.3]. The sensitivity for the population is with 0.5 rather low, however, the amount of failures is limited, which is similar to general component failure data as aforementioned. Therefore, known failures from other populations are utilized to validate the method further. To do so, the published gas analysis data in [108] with failure classification is utilized and the estimated individual failure rate for this components is shown in Fig. 4.7b. To compare the evaluation results, the health index method proposed in [106] is used as a benchmark. The evaluation of the individual failure rate method with additional failures



(a) Computed individual failure rates for a population of 92 units with actual failure occurence for component number 14 and 35



(b) Computed individual failure rates for 117 units with actual failure occurence based on the published data in [108]

Figure 4.7: Estimated individual failure rates for validation

is presented in Table 4.3 and the failure identification with the health index in Table 4.4. The evaluation results are similar with a sensitivity of 0.7731 and 0.7478 for the individual failure rate method and the Health Index method, respectively. This shows that the individual failure rate method is a plausible predictor of actual failures even though the failure detection with the individual failure rate method is dependent of the threshold value γ.

Table 4.2: Results of individual failure rate prediction compared to actual faults in population

Failure Status	Prediction Result (A)	$(\bar{A})$	Total	
Fault Present (B)	1	1	2	Sensitivity $= \frac{1}{2} = 0.5$
No Fault Present $(\bar{B})$	0	90	90	Specificity $= \frac{90}{90} = 1$
PPV	1			
NPV		0.9898		

Table 4.3: Results of individual failure rate prediction of population with extra added faults published in [108] with threshold value $\gamma = 0.04$

Failure Status	Prediction Result (A)	$(\bar{A})$	Total	
Fault Present (B)	92	27	119	Sensitivity $= \frac{92}{119} = 0.7731$
No Fault Present $(\bar{B})$	0	90	90	Specificity $= \frac{90}{90} = 1$
PPV	1			
NPV		0.9954		

Table 4.4: Results of individual failure rate prediction of population with additional faults published in [108] with health index gas analysis classification according to [106]

Failure Status	Prediction Result (A)	$(\bar{A})$	Total	
Fault Present (B)	89	30	119	Sensitivity $= \frac{89}{119} = 0.7478$
No Fault Present $(\bar{B})$	0	90	90	Specificity $= \frac{90}{90} = 1$
PPV	1			
NPV		0.9949		

4.3.4 Discussion

The proposed method uses the population failure rate, failure statistics, and condition monitoring data to calculate an individual failure rate. In contrast to other methods presented in section 4.2, no actual failure data, assumptions about the sample data distribution, or the definition of condition scores or thresholds is required.

Theoretical Limitations Generally, comparing the individual failure rate results to other methods as in **Paper V**, such as Health Indices, strengthens the plausibility of the concept. However, the validation of the individual failure rates remains difficult due to the limited amount of failure data in combination with an overall set of condition monitoring data. Furthermore, the fusion of multiple covariates to one failure mode and an increased set of risk functions should be improved. Whereas the set of risk functions solely needs to be extended, the weighting of covariates should be independent of expert knowledge and therefore the development of a new method is suggested. Particularly, **Paper VI** illustrated that the risk functions have an impact on the computed results and affects possible decision making or the outcome of additional system calculations. However, **Paper VI** also demonstrates that using different risk functions widen the understanding of the failure rate and consequently, provide a better risk perception.

Practical Aspects The practical aspects of the method, in an asset management context, have been primarily presented in **Paper V**. If the individual failure rates are utilised for subsequent system reliability calculations or in maintenance optimization, the additional accuracy also further improves the computations. Directly applied to maintenance and replacement decision making, the individual failure rates, generally as all failure rates, need to be correctly interpreted. To do so, thresholds might be set to support the decision making process. Since individual failure rates provide no linguistic condition classification such as Health Indices, the user is engaged to interpret and understand the individual failure rates which prevents immature decision making. Generally, the individual failure rates provide additional insights into risk management of power system components and could be especially utilised for new components. This would have great value for asset management software tools in practice.

4.4 Case Study 3: Time Independent Calculation of Individual Failure Rates for Power Transformer Populations

Paper V presents a case study of a Canadian power transformer population with 30 units based on the published condition monitoring data in [109]. The population failure rate is constant with $\lambda_0(t) = 0.02$ [1/year] and the failure statistics for vector $\boldsymbol{\alpha}$ are based on findings in [107]. The following single condition measurements have been obtained such as water content in oil, acidity, oil breakdown voltage, dissipation factor, dissolved combustible gases, and 2-Furfuraldehyde. These covariates indicate the condition of the liquid and solid insulation of a power transformer and reflect winding failures. All risk functions are calculated with the positive linear

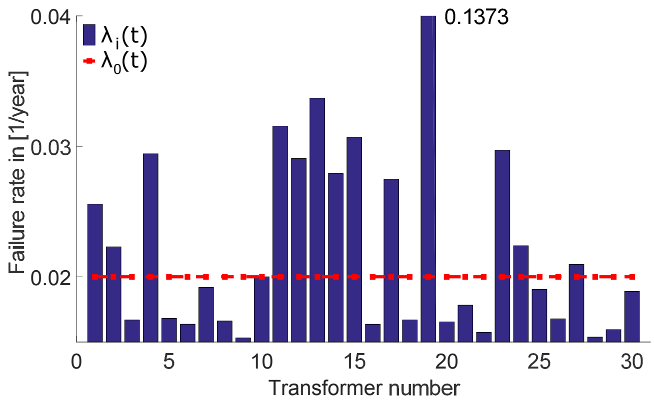


Figure 4.8: Individual failure rates for transformers 1-30 with the initial average failure rate of 0.02 and a confidence interval of 95%

function but the negative linear risk function has been chosen for the breakdown voltage. The results are presented in detail in **Paper V** but also illustrated in Fig. 4.8. Transformer 19, with $\lambda_{19}(t) = 0.1373$, the highest failure rate of the population. In [109], this transformer is determined to be in a 'very bad' condition. Comparing the value to the empirical results in [110] which provide a failure rate of 0.14 for distribution transformer under 25 MVA with a 'worst' inspection outcome, the results are plausible.

4.5 Case Study 4: Estimation and Prediction of Time Dependent Individual Failure Rates

The condition monitoring data of twelve transmission power transformers over the time period from 2002 to 2015 have been utilized to calculate Individual Failure Rates for each component in the population in **Paper VI**. The operation time of the power transformers vary between twelve and forty-five years and the basic covariates are: (1) breakdown voltage (BDV), (2) dissipation factor or tan delta, (3) water content, (4) acidity in the oil, and the (5) total combustible gases (TCG) which have been obtained in yearly intervals. The population failure rate has been assumed with $\lambda_0(t) = 0.02$ and the failure statistics for vector $\boldsymbol{\alpha}$ are based on findings in [107] as in case study 3.

The individual failure rates are computed using different risk functions. Firstly, a positive linear risk function has been chosen for measurements 1,2, and 4 and a negative linear risk function for measurement 3, because a decreasing BDV indicates a declining condition and increased probability of failure. For measurement 5, a non-linear risk function has been chosen because an abrupt increase of the TCG

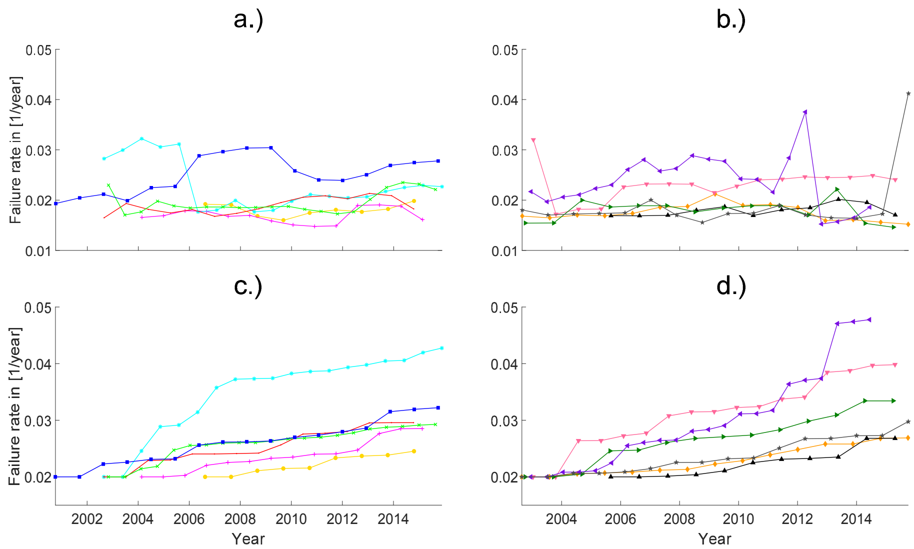


Figure 4.9: Estimated individual failure rates with suggested risk functions over the time period 2002 to 2015

is associated with a higher probability of failure. The results of the 12 power transformers are depicted in Fig. 4.9 a.) and b.). Secondly, the cumulative risk function is assigned to all covariates and the results are depicted in Fig. 4.9 c.) and d.).

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis has the objective to improve the accuracy of failure rate modelling for enhancement of power system reliability assessment tools such as maintenance optimization. Primarily, this is achieved by addressing the three research objectives presented in section 1.5.

The first objective is the investigation of the impact of risk factors or explanatory variables on the failure rate of power system components, which includes **Papers I-III**. Depending on how failures are defined and recorded, regression models such as Cox regression and regression models for count data are applied to investigate the failure rate and ROCOF of a disconnector and circuit breaker population. The studies show that preventive maintenance, remote control availability and the disconnector and circuit breaker type, among others, have a significant impact. Quantifying these effects by using regression models, the failure rate can be more precisely modelled based on external and internal risk factors but also component characteristics. Therefore, the first research objective provides enhanced understanding of the risk factors and the results can be used to gain higher failure rate accuracy.

One result of **Paper IV** is that statistical data driven methods are still rarely applied in the power system domain due to the lack of failure data. Addressed by **Paper IV**, the second research objective reviews the literature for methods and risk factors that have been frequently used in the power system domain for failure rate modelling. Primarily, the environmental impact in form of the weather is modelled. The exponential and Weibull distribution are still the most commonly used models to model the general ageing. Furthermore, the importance to distinguish between population and individual failures rates is demonstrated by an illustrative example. This shows the necessity to develop a method which is able to estimate the failure rate on an individual component level, in spite of the limited failure data.

The third research objective is the development of such a method to calculate individual failure rates by using the population failure rate, failure statistics, and condition monitoring data. This development is presented in **Papers V and VI**. The general suitability of the method is demonstrated in time-independent context in **Paper V**, whereas **Paper VI** presents the method for time-dependent cases, providing a more strict formulation, introducing into the concept of risk functions, and presenting the prediction of individual failure rates. Both case studies present accurate results. Moreover, the individual failure rates are validated on actual failure data in a time-independent setting in section 4.3.3. The results show that the individual failure rates deliver accurate estimates and could be used for failure classification with similar accuracy to health indices based on expert knowledge. Overall, the proposed method satisfies the necessity to estimate the risk of new components where little historical data is available. Even though more data might become available by the use of more Smart Grid technology and data records, power grid operators, particularly transmission system operators, have an interest to replace their components with a safety margin. Thus, failure data will constantly be rare and the individual failure rate method, a useful tool.

5.2 Future Work

Generally, the exploratory failure analysis should be applied to more power system component types. Moreover, to gain a better understanding of if the findings in **Papers I-III** are of a general nature rather than particular results of the case studies alone, more disconnector and circuit breaker populations should be examined as well as other component types. Since the applied regression models required different data types, a comparison between these methods with particular focus on power system components would be of value. This gives a better overview on which failure and condition monitoring data must be actually recorded over time.

The individual failure rate method, however, should not solely be applied to more component types, but also suggests further improvement in form of a larger set of risk functions. Moreover, there is the need of better importance quantification of condition measurements and more population data is required to further validate the method in a time-dependent setting. Thus far, the historical stress and load is considered in the actual condition measurement of the component, however, the current load should be considered in future applications as well.

Bibliography

[1] Swedish Civil Contingencies Agency (MSB), “A functioning society in a changing world,” Tech. Rep. MSB341, Swedish Civil Contingencies Agency (MSB), December 2011.

[2] Council of the European Union, “Council directive 2008/114/ec of 8 december 2008 on the identification and designation of european critical infrastructures and the assessment of the need to improve their protection (text with eea relevance),” Tech. Rep. Document 32008L0114R(01), COMMISSION OF THE EUROPEAN COMMUNITIES, December 2008.

[3] European Commission, “Green paper on a european programme for critical infrastructure protection,” Tech. Rep. COM (2005) 576 Final, COMMISSION OF THE EUROPEAN COMMUNITIES, November 2005.

[4] Swedish Civil Contingencies Agency (MSB), “A summary of risk areas and scenario analyses 2012-2015,” Tech. Rep. MSB1021, Swedish Civil Contingencies Agency (MSB), September 2016.

[5] S. M. Rinaldi, J. P. Peerenboom, and T. K. Kelly, “Identifying, understanding, and analyzing critical infrastructure interdependencies,” *IEEE Control Systems*, vol. 21, pp. 11–25, Dec 2001.

[6] NERC Legal and Standards Departments, “Use of ’bulk power system’ versus ’bulk electric system’ in reliability standards,” Tech. Rep. Document 32008L0114R(01), NERC North American Electric Reliability Corporation, April 2012.

[7] “Asset management: Overview, principles and terminology,” standard, International Organization for Standardization, Geneva, CH, 2014.

[8] H. L. Willis and R. E. Brown, *Substation Asset Management in Electric Power Substations Engineering, Third Edition.* CRC Press 20122012, 2012.

[9] R. N. Allan and R. Billinton, *Reliability evaluation of power systems.* Springer Science & Business Media, 2013.

[10] K. Alvehag and K. Awodele, "Impact of reward and penalty scheme on the incentives for distribution system reliability," *IEEE Transactions on Power Systems*, vol. 29, pp. 386–394, Jan 2014.

[11] J. Schneider, A. J. Gaul, C. Neumann, J. Hogräfer, W. Wellßow, M. Schwan, and A. Schnettler, "Asset management techniques," *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 9, pp. 643 – 654, 2006.

[12] R. Billinton and R. N. Allan, *Reliability evaluation of engineering systems.* Springer, 1992.

[13] R. Billinton and R. N. Allan, "Power-system reliability in perspective," *Electronics and Power*, vol. 30, pp. 231–236, March 1984.

[14] I. Bazovsky, *Reliability theory and practice.* Courier Corporation, 2013.

[15] A. Moradkhani, M. R. Haghifam, and M. Mohammadzadeh, "Bayesian estimation of overhead lines failure rate in electrical distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 56, pp. 220 – 227, 2014.

[16] F. Besnard and L. Bertling, "An approach for condition-based maintenance optimization applied to wind turbine blades," *IEEE Transactions on Sustainable Energy*, vol. 1, pp. 77–83, July 2010.

[17] L. Bertling, R. Allan, and R. Eriksson, "A reliability-centered asset maintenance method for assessing the impact of maintenance in power distribution systems," *IEEE Transactions on Power Systems*, vol. 20, pp. 75–82, Feb 2005.

[18] X. Zhang and E. Gockenbach, "Component reliability modeling of distribution systems based on the evaluation of failure statistics," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 14, pp. 1183–1191, October 2007.

[19] R. E. Brown, *Electric power distribution reliability.* CRC press, 2008.

[20] R. Brown, G. Frimpong, and H. Willis, "Failure rate modeling using equipment inspection data," *Power Systems, IEEE Transactions on*, vol. 19, pp. 782–787, May 2004.

[21] Y. Hong, W. Q. Meeker, and J. D. McCalley, "Prediction of remaining life of power transformers based on left truncated and right censored lifetime data," *The Annals of Applied Statistics*, vol. 3, no. 2, pp. pp. 857–879, 2009.

[22] A. Høyland and M. Rausand, *System reliability theory: models and statistical methods*, vol. 420. John Wiley & Sons, 2004.

[23] W. Q. Meeker and L. A. Escobar, *Statistical methods for reliability data.* John Wiley & Sons, 2014.

[24] A. Moradkhani, M. R. Haghifam, and M. Mohammadzadeh, "Bayesian estimation of overhead lines failure rate in electrical distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 56, pp. 220 – 227, 2014.

[25] M. Rausand and A. Høyland, *System reliability theory: models, statistical methods, and applications*, vol. 396. John Wiley & Sons, 2004.

[26] P. O'Connor and A. Kleyner, *Practical reliability engineering*. John Wiley & Sons, 2012.

[27] Cigré, "WG 12.05, an international survey on failures in large power transformers in service„" *Electra*, no. 88, pp. 21–47, 1983.

[28] D. G. Kleinbaum and M. Klein, *Survival analysis: a self-learning text*. Springer Science & Business Media, 2006.

[29] J. P. Klein and M. L. Moeschberger, *Survival analysis: techniques for censored and truncated data*. Springer Science & Business Media, 2005.

[30] G. Rodríguez, "Non-parametric estimation in survival models," Spring 2005.

[31] P. Westerlund, *Condition measuring and lifetime modelling of disconnectors, circuit breakers and other electrical power transmission equipment*. PhD thesis, KTH, Electromagnetic Engineering, 2017.

[32] W. Tippachon, R. Boonruang, S. Boonpun, C. Khamtang, N. Klairuang, D. Rerkpreedapong, and J. Hokierti, "Failure analysis of protective devices in power distribution systems for reliability purpose," in *TENCON 2006 - 2006 IEEE Region 10 Conference*, pp. 1–4, Nov 2006.

[33] T. M. Lindquist, L. Bertling, and R. Eriksson, "Circuit breaker failure data and reliability modelling," *IET Generation, Transmission Distribution*, vol. 2, pp. 813–820, November 2008.

[34] I. Bronstein, K. Semendjajew, G. Musiol, and H. Mühlig, "Taschenbuch der mathematik. verlag harri deutsch gmbh, frankfurt am 2005, 6. vollständig überarbeitete und ergänzte auflage," tech. rep., ISBN 3-8171-2006-0, 2006.

[35] P. Hokstad, "The failure intensity process and the formulation of reliability and maintenance models," *Reliability Engineering & System Safety*, vol. 58, no. 1, pp. 69 – 82, 1997.

[36] S. Babu, *Reliability Evaluation of Distribution Systems Considering Failure Modes and Network Configuration*. PhD thesis, KTH, Electromagnetic Engineering, 2017.

[37] M. Shahidehpour and R. Ferrero, "Time management for assets: chronological strategies for power system asset management," *IEEE Power and Energy Magazine*, vol. 3, pp. 32–38, May 2005.

[38] O. Tor and M. Shahidehpour, "Power distribution asset management," in *2006 IEEE Power Engineering Society General Meeting*, pp. 1–7, 2006.

[39] P. Dehghanian, M. Fotuhi-Firuzabad, F. Aminifar, and R. Billinton, "A comprehensive scheme for reliability centered maintenance in power distribution systems - part i: methodology," *IEEE Transactions on Power Delivery*, vol. 28, no. 2, pp. 761–770, 2013.

[40] P. Dehghanian, M. Fotuhi-Firuzabad, F. Aminifar, and R. Billinton, "A comprehensive scheme for reliability-centered maintenance in power distribution systems - part ii: Numerical analysis," *IEEE Transactions on Power Delivery*, vol. 28, no. 2, pp. 771–778, 2013.

[41] E. Shayesteh and P. Hilber, "Reliability-centered asset management using component reliability importance," in *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, pp. 1–6, Oct 2016.

[42] A. Abiri-Jahromi, M. Parvania, F. Bouffard, and M. Fotuhi-Firuzabad, "A two-stage framework for power transformer asset maintenance management - part i: Models and formulations," in *2013 IEEE Power Energy Society General Meeting*, pp. 1–1, July 2013.

[43] B. Everitt and A. Skrondal, *The Cambridge dictionary of statistics*, vol. 106. Cambridge University Press Cambridge, 2002.

[44] P.-J. Vlok, *Dynamic residual life estimation of industrial equipment based on failure intensity proportions*. PhD thesis, 2006.

[45] J. D. Kalbfleisch and R. L. Prentice, *The statistical analysis of failure time data*, vol. 360. John Wiley & Sons, 2011.

[46] L. Fahrmeir and G. Tutz, *Multivariate statistical modelling based on generalized linear models*. Springer Science & Business Media, 2013.

[47] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to linear regression analysis*, vol. 821. John Wiley & Sons, 2012.

[48] P. Westerlund, P. Hilber, and T. Lindquist, "Condition monitoring of disconnectors in the electric power transmission grid with temperature sensors," *International Journal of Industrial and Systems Engineering*, vol. 23, no. 1, pp. 90–110, 2016.

[49] S. E. Rudd, V. M. Catterson, S. D. J. McArthur, and C. Johnstone, "Circuit breaker prognostics using sf6 data," in *2011 IEEE Power and Energy Society General Meeting*, pp. 1–6, July 2011.

[50] S. D. Guikema, R. A. Davidson, and H. Liu, "Statistical models of the effects of tree trimming on power system outages," *IEEE Transactions on Power Delivery*, vol. 21, pp. 1549–1557, July 2006.

[51] S. D. Guikema and J. P. Goffelt, "A flexible count data regression model for risk analysis," *Risk Analysis*, vol. 28, no. 1, pp. 213–223, 2008.

[52] S.-R. Han, S. D. Guikema, S. M. Quiring, K.-H. Lee, D. Rosowsky, and R. A. Davidson, "Estimating the spatial distribution of power outages during hurricanes in the gulf coast region," *Reliability Engineering and System Safety*, vol. 94, no. 2, pp. 199 – 210, 2009.

[53] H. Liu, R. A. Davidson, D. V. Rosowsky, and J. R. Stedinger, "Negative binomial regression of electric power outages in hurricanes," *Journal of infrastructure systems*, vol. 11, no. 4, pp. 258–267, 2005.

[54] R. Z. Fanucchi, M. Bessani, M. H. M. Camillo, J. B. A. London, and C. D. Maciel, "Failure rate prediction under adverse weather conditions in an electric distribution system using negative binomial regression," in *2016 17th International Conference on Harmonics and Quality of Power (ICHQP)*, pp. 478–483, Oct 2016.

[55] D. B. McRoberts, S. M. Quiring, and S. D. Guikema, "Improving hurricane power outage prediction models through the inclusion of local environmental factors," *Risk Analysis*, 2016.

[56] Y. Zhou, A. Pahwa, and S. S. Yang, "Modeling weather-related failures of overhead distribution lines," *IEEE Transactions on Power Systems*, vol. 21, pp. 1683–1690, Nov 2006.

[57] S. Guikema and S. Quiring, "Hybrid data mining-regression for infrastructure risk assessment based on zero-inflated data," *Reliability Engineering & System Safety*, vol. 99, pp. 178 – 182, 2012.

[58] L. Xu and M.-Y. Chow, "A classification approach for power distribution systems fault cause identification," *IEEE Transactions on Power Systems*, vol. 21, pp. 53–60, Feb 2006.

[59] Z. Wang, Y. Liu, N.-C. Wang, T.-Y. Guo, F. T. C. Huang, and P. J. Griffin, "Artificial intelligence in power equipment fault diagnosis," in *PowerCon 2000. 2000 International Conference on Power System Technology. Proceedings (Cat. No.00EX409)*, vol. 1, pp. 247–252 vol.1, 2000.

[60] J. S. Simonoff, C. E. Restrepo, and R. Zimmerman, "Risk management and risk analysis based decision tools for attacks on electric power," *Risk Analysis*, vol. 27, pp. 547–570, 6 2007.

[61] Z. Tang, C. Zhou, W. Jiang, W. Zhou, X. Jing, J. Yu, B. Alkali, and B. Sheng, "Analysis of significant factors on cable failure using the cox proportional hazard model," *Power Delivery, IEEE Transactions on*, vol. 29, pp. 951–957, April 2014.

[62] S. J. Argent, A. Bendell, P. T. Manning, J. Marshall, S. G. Ryan, and D. Wightman, *Proportional hazard modelling in the analysis of transmission failure statistics*, pp. 624–633. Berlin, Heidelberg: Springer Berlin Heidelberg, 1986.

[63] M. Baxter, A. Bendell, P. Manning, and S. Ryan, "Proportional hazards modelling of transmission equipment failures," *Reliability Engineering & System Safety*, vol. 21, no. 2, pp. 129 – 144, 1988.

[64] C. R. David, "Regression models and life tables (with discussion)," *Journal of the Royal Statistical Society*, vol. 34, pp. 187–220, 1972.

[65] K. David and K. Mitchel, *Logistic regression: A self learning text.* New York: Springer–Verlag Inc, 1994.

[66] O. Aalen, O. Borgan, and H. Gjessing, *Survival and event history analysis: a process point of view.* Springer Science & Business Media, 2008.

[67] N. Gorjian, L. Ma, M. Mittinty, P. Yarlagadda, and Y. Sun, "A review on reliability models with covariates," in *Engineering Asset Lifecycle Management* (D. Kiritsis, C. Emmanouilidis, A. Koronios, and J. Mathew, eds.), pp. 385–397, Springer London, 2010.

[68] D. R. Cox, "Regression models and life-tables," *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 187–220, 1972.

[69] B. R. Irva Hertz-Picciotto, "Validity and efficiency of approximation methods for tied survival times in cox regression," *Biometrics*, vol. 53, no. 3, pp. 1151–1156, 1997.

[70] G. Rodríguez, "Linear models for continuous data," Spring 2016 2016.

[71] D. R. Cox and D. Oakes, *Analysis of survival data*, vol. 21. CRC Press, 1984.

[72] P. Čížek, W. K. Härdle, and R. Weron, *Statistical tools for finance and insurance.* 2005.

[73] D. Collett, *Modelling survival data in medical research.* CRC press, 2015.

[74] R. J. Cook and J. Lawless, *The statistical analysis of recurrent events.* Springer Science & Business Media, 2007.

[75] T. M. Therneau and P. M. Grambsch, *Modeling survival data: extending the Cox model.* Springer Science & Business Media, 2000.

[76] D. W. Hosmer, S. Lemeshow, and S. May, *Other Models and Topics*, pp. 286–354. John Wiley & Sons, Inc., 2008.

[77] P. K. Andersen and R. D. Gill, “Cox’s regression model for counting processes: A large sample study,” *The Annals of Statistics*, vol. 10, no. 4, pp. 1100–1120, 1982.

[78] R. L. Prentice, B. J. Williams, and A. V. Peterson, “On the regression analysis of multivariate failure time data,” *Biometrika*, vol. 68, no. 2, pp. 373–379, 1981.

[79] L. J. Wei, D. Y. Lin, and L. Weissfeld, “Regression analysis of multivariate incomplete failure time data by modeling marginal distributions,” *Journal of the American Statistical Association*, vol. 84, no. 408, pp. 1065–1073, 1989.

[80] L. Kuramoto, B. G. Sobolev, and M. G. Donaldson, “On reporting results from randomized controlled trials with recurrent events,” *BMC medical research methodology*, vol. 8, no. 1, p. 35, 2008.

[81] D. W. Hosmer, S. Lemeshow, and S. May, *Other Models and Topics*. John Wiley and Sons, Inc., 2008.

[82] J. M. Hilbe and W. H. Greene, “7 count response regression models,” in *Epidemiology and Medical Statistics* (C. Rao, J. Miller, and D. Rao, eds.), vol. 27 of *Handbook of Statistics*, pp. 210 – 252, Elsevier, 2007.

[83] A. C. Cameron and P. K. Trivedi, *Regression analysis of count data*, vol. 53. Cambridge university press, 2013.

[84] R. Winkelmann, *Econometric analysis of count data*. Springer Science & Business Media, 2008.

[85] J. M. Hilbe, *Negative binomial regression*. Cambridge University Press, 2011.

[86] A. Shahsavari, A. Fereidunian, and S. M. Mazhari, “A joint automatic and manual switch placement within distribution systems considering operational probabilities of control sequences,” *International Transactions on Electrical Energy Systems*, vol. 25, no. 11, pp. 2745–2768, 2015. ETEP-13-0375.R2.

[87] O. Gulich, J. Holmlund, A. Kostiainen, and T. Hakola, “Practical experience of a self-healing power system by means of the zone concept.” Company Presentation, 2013.

[88] S. Larsson and A. Danell, “The black-out in southern sweden and eastern denmark, september 23, 2003.,” in *2006 IEEE PES Power Systems Conference and Exposition*, pp. 309–313, Oct 2006.

[89] A. Janssen, D. Makareinis, and C. E. Sölver, "International surveys on circuit-breaker reliability data for substation and system studies," *IEEE Transactions on Power Delivery*, vol. 29, pp. 808–814, April 2014.

[90] O. Aalen, "Effects of frailty in survival analysis," *Statistical Methods in Medical Research*, vol. 3, no. 3, pp. 227–243, 1994.

[91] X. Zhang, E. Gockenbach, V. Wasserberg, and H. Borsi, "Estimation of the lifetime of the electrical components in distribution networks," *IEEE Transactions on Power Delivery*, vol. 22, pp. 515–522, Jan 2007.

[92] J. W. Vaupel and A. I. Yashin, "Heterogeneity's ruses: Some surprising effects of selection on population dynamics," *The American Statistician*, vol. 39, no. 3, pp. 176–185, 1985.

[93] L. Duchateau and P. Janssen, *The frailty model*. Springer Science & Business Media, 2007.

[94] N. Ekstedt and P. Hilber, "Categorization and review of failure rate factors used in power systems," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2014 International Conference on*, pp. 1–6, July 2014.

[95] J. Yong, "Condition-based hazard rate estimation and optimal maintenance scheduling for electrical transmission system," *Retrospective Theses and Dissertations. Paper 1526.*, 2006.

[96] J. L. Velasquez-Contreras, M. A. Sanz-Bobi, and S. G. Arellano, "General asset management model in the context of an electric utility: Application to power transformers," *Electric Power Systems Research*, vol. 81, no. 11, pp. 2015 – 2037, 2011.

[97] J. Pathak, Y. Jiang, V. Honavar, and J. McCalley, "Condition data aggregation with application to failure rate calculation of power transformers," in *System Sciences, 2006. HICSS'06. Proceedings of the 39th Annual Hawaii International Conference on*, vol. 10, pp. 241a–241a, IEEE, 2006.

[98] F. Sotiropoulos, P. Alefragis, and E. Housos, "A hidden markov models tool for estimating the deterioration level of a power transformer," in *2007 IEEE Conference on Emerging Technologies and Factory Automation (EFTA 2007)*, pp. 784–787, Sept 2007.

[99] T. Lindquist, *On reliability and maintenance modelling of ageing equipment in electric power systems*. PhD thesis, KTH, Electromagnetic Engineering, 2008.

[100] Ø. R. Solheim and G. Kjølle, "Wind dependent failure rates for overhead transmission lines using reanalysis data and a bayesian updating scheme," in *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, pp. 1–7, Oct 2016.

[101] M. Amin, H. M. R., and M. Mohsen, "Failure rate estimation of overhead electric distribution lines considering data deficiency and population variability," *International Transactions on Electrical Energy Systems*, vol. 25, no. 8, pp. 1452–1465.

[102] Z. Zhang, Y. Jiang, and J. D. McCalley, "Bayesian analysis of power transformer failure rate based on condition monitoring information," *Iowa State University*, 2004.

[103] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, "Remaining useful life estimation - a review on the statistical data driven approaches," *European Journal of Operational Research*, vol. 213, no. 1, pp. 1 – 14, 2011.

[104] P. Jahnke, "Machine Learning Approaches for Failure Type Detection and Predictive Maintenance," Master's thesis, Technische Universität Darmstadt, 2015.

[105] J. L. Fleiss, B. Levin, and M. C. Paik, *Statistical methods for rates and proportions.* John Wiley & Sons, 2013.

[106] A. Jahromi, R. Piercy, S. Cress, J. Service, and W. Fan, "An approach to power transformer asset management using health index," *Electrical Insulation Magazine, IEEE*, vol. 25, pp. 20–34, March 2009.

[107] S. Tenbohlen, F. Vahidi, P. Müller, J. Gebauer, and M. Krüger, "Zuverlässigkeitsbewertung von leistungstransformatoren," in *CIGRE Working Group A 2.37 Transformer Reliability Survey*, 2012.

[108] M. Duval and A. dePabla, "Interpretation of gas-in-oil analysis using new iec publication 60599 and iec tc 10 databases," *IEEE Electrical Insulation Magazine*, vol. 17, pp. 31–41, March 2001.

[109] A. Abu-Elanien, M. Salama, and M. Ibrahim, "Calculation of a health index for oil-immersed transformers rated under 69 kv using fuzzy logic," *IEEE Transactions on Power Delivery*, vol. 27, pp. 2029–2036, Oct 2012.

[110] R. E. Brown, G. Frimpong, and H. L. Willis, "Failure rate modeling using equipment inspection data," *IEEE Transactions on Power Systems*, vol. 19, pp. 782–787, May 2004.