GUIDELINES FOR THE USE OF STATISTICS AND STATISTICAL TOOLS ON LIFE DATA

Working Group D1.39

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EXECUTIVE SUMMARY

In the Western world, a growing fraction of the high voltage components in the grid have aged considerably and are considered to be close to the end of life. In fast developing countries such as China and India, most electrical infrastructures are still in their early life. Most utilities and TSO's have only recently started to collect failure data in order to obtain an indication of the future failure expectancy of their assets. It appears that there is a strong need for people "in the field" to have access to guidelines on how to deal with these failure data in a way that sound asset management decisions can be made. Further, the importance of life data requires more attention. Often, while only few (or no) failure data are available the amount of data about assets still in operation is considerable and should be used to its full extent.

Within Cigré, recently WG A3.06 "Reliability of High Voltage Equipment" has prepared a total of six Technical Brochures (509-514) that deal with an international enquiry on reliability of high voltage equipment. WG A2.37 is in the process of preparing a Technical Brochure about a survey of transformer reliability. More specifically, IEC62539 provides a guide for the statistical analysis of electrical insulation breakdown data focusing mainly on the use of the Weibull distribution.

The scope of this working group's Technical Brochure is more generic and related to failure of insulation systems, with an emphasis on the prediction of future failure rates based on the analysis of life data. This is where our work differs from the work of afore mentioned working groups that was focused on the determination of the current failure rates. The main goal of the work of this WG was to provide guidelines for the use of statistics and statistical tools to describe and analyze the failure processes for the purpose of determining future failure rates. An important challenge is how to deal with situation in which there is only very little data available. This topic will be dealt with in detail.

The guidelines will cover some specific components as examples to demonstrate the methods and the way they are best used.

In Chapter 1, first the background of the here presented work is introduced, together with the main objectives. Chapter 2 is devoted to definitions with an important discussion of the concepts of minor and major failures. In Chapter 3, the main routes to failure of electrical insulation systems are described. An overview is given of the most important parameters that affect the degradation processes and ultimately lead to failure. A distinction is made between internal and external factors that influence the degradation and failure processes.

Chapter 4 introduces the basic statistical concepts that are needed for a proper analysis of failure data and then moves on with what constitutes the core of this report and deals with the different approaches that are available for a systematic analysis of failure data. Maintenance and replacement may have a considerable effect on future failure statistics, this topic is dealt with in Chapter 5. In Chapter 6, a number of case studies is presented to illustrate the proposed approaches for failure data analysis. Chapter 7 provides guidelines for how best to collect failure data. Finally in Chapter 8 the conclusions are presented.

1 INTRODUCTION

1.1 Objectives and Motivation

Around the world, part of the utilities has already been liberalized. Consequently, the asset performance represented for example by reliability and the expectations of the asset owner and stake holders need to be balanced. Such process refers to asset management and implies optimal system operation with respect to operation, maintenance and replacement. For the latter, knowledge about the reliability of the system and individual assets is necessary. Various techniques can be used for condition assessment. All the available techniques can be subdivided into two groups; namely bottom-up and top-down approach.

The first group includes all diagnostic tools applied to an individual units in order to obtain information about the deterioration of the asset and its reliability. The output of diagnostic measurements can be used for making a decision on the maintenance actions to be performed. The second group consists of mathematical tools which can be used to analyze the data describing a given population or a system, e.g., life-data. In this case, the output of the analysis is often used to plan spare parts and replacement policies.

In recent years, a number of investigations have been undertaken to recognize the applicability of various mathematical techniques, which might help in estimating the behavior of the population of assets with respect to reliability. However, the accuracy of the analysis depends strongly on the availability and the quality of the input data. Therefore, many researchers pointed out the need for a more precise and detailed life-data registration and storage as a key factor for successful application of the mentioned methodologies.

Gradually, utilities and other asset owners are introducing systems for storing data about failures often for the purpose of assisting the asset managers in their tasks. Up to this date there is no standardized procedure that describes which data to store and how to process them to obtain most benefit. WG D1.39 has set out to structure the process of the collection and statistical treatment with the purpose of determining future reliability through a set of guidelines.

The main objective of the work of this WG is to provide guidelines for the use of statistics and statistical tools to describe the aging and failure processes, leading to reliable future failure predictions and thus facilitating the asset manager to make sound decisions. The brochure is structured such that it can be used by people in the field without an in depth knowledge of statistics and by those who want to install a systematic approach towards reliability estimation of a fleet of assets.

These guidelines will cover some specific components as examples to demonstrate the methods and their use.

1.2 Scope

In practice, the data available often is incomplete, inhomogeneous and of small quantity. The situation differs strongly between utilities but on average this is the case.

Challenging is the task of providing a sound estimation of the future failure rate when only very little failure data is available. Alternatively, data sets sometimes are incomplete, for instance in these cases where utilities started collecting data only recently. Further, one would have to consider the effect of maintenance on the outcome of the failure predictions. How can this effect be assessed and checked for its effectiveness? Finally, one often has to deal with heterogeneous data, not necessarily belonging to a single failure mechanism. How to deal with such situations?

The work of this WG is aimed at providing guidelines to tackle these questions in practice.

1.3 Relation to other Cigré Brochures / IEEE

Within Cigré, in different study committees ample attention is paid to reliability and asset management issues. In 2010, WG C1.16 published Technical Brochure 422 on Transmission Asset Risk Management. The work of this group was focused on

"...improving insight into the application of asset management in electricity transmission companies, quantifying the risk due to an ageing asset base and identifying methodologies for assessing optional asset management strategies for how these risks can be managed." In TB422 one chapter is devoted to assessing the risk of equipment performance and the use of health indexes. This chapter partly overlaps the work described in our brochure. Only recently, WG A3.06 "Reliability of High Voltage Equipment" has prepared a total of six Technical Brochures (509-514) [2] that deal with an international enquiry on the reliability of high voltage equipment. A large number of utilities were invited to fill out a specifically for this purpose developed excel sheet to obtain the current state of reliability of circuit breakers, disconnectors and earthing switches, instrument transformers and gas insulated switchgear. WG A2.37 is in the process of preparing a Technical Brochure about a survey of transformer reliability.

Within IEEE, the work of the Statistical Technical Committee of the IEEE Dielectrics and Electrical Insulation Society has led to the definition of an international standard, IEC62539 (IEEE 930) [3]. The purpose of this standard is *to define statistical methods to analyse times to breakdown and breakdown voltage data obtained from electrical testing of solid insulating materials, for purposes including characterization of the system, comparison with another insulator system, and prediction of the probability of breakdown at given times or voltages*. The focus of this standard is on the use of the Weibull distribution.

While these brochures focus on the current reliability (a snapshot in time), the scope of this working group's Technical Brochure is focused on obtaining the future failure rates based on the analysis of life data. This is where our work differs from the work of afore mentioned working groups.

2. DEFINITIONS

2.1 Definition of failure

2.1.1 Failure definitions in the literature

In order to find a proper definition of the failures we should take into account the definitions from other technical brochures. In the following part different failure definitions have been collected to cognize the different aspects from high voltage engineering primarily from cable and transformer diagnostics and high voltage asset management.

2.2.2 CIGRÉ WG B1.10, Brochure 379 Update of Service Experience of HV Underground and Cable Systems [4]

A failure is defined as "Any occurrence on a cable system which requires the circuit to be de-energized." Failures during commissioning or re-commissioning tests are excluded.

Classification of failures:

Two categories of failure are defined follows;

1. Instantaneous failure leading to automatic disconnection
2. Occurrence requiring subsequent unplanned outage

2.2.3 CIGRE WG A2.43 Bushing failures

Faulty: Can remain in service, but short-term reliability likely to be reduced. May or may not be possible to improve condition by remedial action.

Failed: Cannot continue in service. Remedial action required before equipment can be returned to service (may not be cost effective. Necessitating replacement.)

2.2.4 CIGRÉ WG C1.16, Brochure 422 Transmission asset risk management [1]

Major failure: instantaneous unplanned outage of the equipment with and without energy interruption (e.g. flashover inside the circuit-breaker due to lightning strike)

Minor failure: failure which can be repaired by a planned maintenance and does not lead to an outage of the supply.

2.2.5 CIGRÉ WG B5.20, Brochure 424 New trend for automated fault and disturbance analysis [5]

Failure: One component fails to perform its required function.

2.2.6 CIGRÉ WG B1.04, Brochure 279 Maintenance for HV Cables and Accessories [6]

Failure: the termination of the ability of an item to perform a required function.

1. After failure the item has a fault.

2. "Failure" is an event, as distinguished from "fault", which is a state.

Fault: the state of an item characterized by inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources. - A fault is often the result of a failure of the item itself, but may exist without prior failure.

2.2.7 CIGRÉ WG B1.09, Brochure 358 Remaining Life Management of Existing AC Underground Lines [7]

When applying Remaining Life Management the following terms have to be defined first.

Remaining Life The remaining life of a component at this moment is the difference between the moment when the end of life is reached and this moment.

End of Life End of life is reached if the cable system does not meet the requirements any more. Usually it involves a combination of technical, economic and strategic requirements.

Technical End of Life Technical end of life of a cable system is reached when repair does not seem to offer a reliable solution or the cable system does not meet the technical specification.

Economic End of Life Economic end of life of a cable system is reached when it becomes too costly to maintain a cable system in service in comparison to technical alternatives.

Strategic End of Life Strategic end of life of a cable system is reached when the company values are not met any more.

Remaining Life Management A combination of coherent activities, all related to remaining life issues (condition assessment, diagnostic testing, risk management, maintenance), to be applied in the framework of an exchange program for underground cables.

Critical Link A critical link is one in which there are no alternative feeding arrangements possible (e.g. a tail-fed supply to an important customer). If something goes wrong with this link, it has critical technical, economical or strategic consequences

Life Extension Life extension is a set of actions taken to prolong the expected life of a cable circuit.

Expected Life Expected life is the expected service time of a new system under normal operating conditions (equals to the remaining life of a new system).

2.2.8 CIGRÉ WG C1.1, Brochure 309 Asset management of transmission systems and associated CIGRE activities [8]

Most experts distinguish explicitly between Major Failures (MF) (or Failures) and minor failures (mf) (or defects). A defect is seen as an imperfection in the state of the equipment that increases the probability of a Failure (TB 175 [9]). A MF (TB 83 [10] and TB 150 [11]) or a Failure (TB 175) is a failure to fulfil a key function, while mf and defects are other failures. The failure data support reliability and availability calculations and are necessary to determine hazard rate curves (bath-tub curves) by means of curve fitting techniques and to perform risk analysis (criticality). To TB 211 [12], such data are used at the equipment level (both MF and mf), at the system level (MF) and at the business level (system failures only). All equipment experts and asset managers agree that constructive feedback from service experience is vital.

2.2.9 CIGRE WG A2.18, Life Management Techniques for Power Transformers

The IEC 60050 [13] definition of failure is:

The termination of the ability of an item to perform a required function.

Notes on this definition state:

1- After failure the item has a fault.

2- "Failure" is an event, as distinguished from "fault," which is a state.

For the present purposes, this definition appears acceptable as far as it goes and the distinction made in Note 2 between event and state is very important, but the implied definition of fault is not consistent with the usage suggested here (see later). The following alternative definition is suggested:

Any situation which requires the equipment to be removed from service for investigation, remedial work or replacement.

Notes:

1- After a failure the equipment can be described as being in a failed condition.

2- "Failure" is an event, as distinguished from "failed condition," which is a state.

As previously, this proposed definition of failure concentrates on the operational consequences of a problem, as required by its priority role in the discussion of reliability, rather than the state of the equipment which caused it.

This definition clearly covers a wide range of problems. In common usage the term failure usually implies a major problem, often requiring the replacement of the equipment. However, there is no intention here of restricting the definition to major failures. The common usage of the simple term failure can still be retained for major failures, provided the context is clear.

In order to distinguish between major and minor failures in terms on their effect on reliability the following definitions of failure types based on those in C57.117-1986 [14] may be used:

Failure with forced outage

Failure of an equipment that requires its immediate removal from the system. This is accomplished either automatically by the operation of protection equipment or as soon as switching operations can be performed.

Failure with scheduled/deferred outage

Failure for which the removal of the equipment from service can be deferred to some more convenient occasion, but still requires a change to planned outage programme.

Major and minor failures can also be differentiated in terms of the degree of remedial work required, either by describing the condition of the equipment, which may be described as being normal, defective or faulty, or by the use of the terms restore or continue failure (see later). Minor faults which do not require significant remedial work are often referred to by some other term, e.g. trouble. The problem with such a terminology arises when intermediate examples have to be classified.

Fault

The IEC 60050 definition is: The state of an item characterized by inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources.

This definition does not seem particularly useful in the context of life management and the proposed failure model since it ties the term too closely to failure. An alternative definition is proposed:

Any deterioration beyond normal wear or aging.

Notes:

1- A fault results in some non-reversible deterioration.

2- A fault is expected to have some impact on the short term reliability of the equipment. For example, a localized hotspot resulting in excessive local insulation aging would be considered a fault, but aged insulation resulting from service loading would not. Any discharge activity inside the transformer would also be considered a fault. A fault would normally only become apparent once it had developed to the point that it caused some abnormal change in measured parameters e.g. increases in dissolved gases. A fault therefore corresponds to a real problem with a transformer which is expected to have a significant impact on life expectancy. Therefore, the existence of a fault is expected to increase the probability of a failure, while a major failure is normally expected to occur as the result of the development of a fault. However, according to the definitions proposed here, a fault can also occur without a failure and vice versa, contrary to the IEC definition of fault.

Defect

Any non-conformance to normal condition requiring some investigative or remedial action.

Note that there is no IEC 60050 definition for this term. The IEEE C57.117-1986 definition of **'Imperfection or partial lack of performance that can be corrected without taking the transformer out of service'** is a sub-set of the above and is equivalent here to defect without failure.

The above definition is very wide, covering anything from a very minor problem with no significant impact on the life expectancy of the equipment, e.g. a broken sight glass on a conservator, to a major problem, e.g. through-fault failure. The main use of the term defect is related to maintenance reporting, but may be extended to cover any problem requiring rectification, e.g. excess moisture. In an attempt to illustrate the differences between the proposed definitions of failure, fault and defect the following examples are provided:

(i) An incident in which a Buchholz oil surge was caused by all oil pumps starting simultaneously would be classified as a defect but not a fault, and would also be counted a failure if it caused the transformer to trip during normal service.

(ii) If a confirmed unusual DGA result was obtained for a transformer, then this would be classified as a defect since it warrants further investigation. If the DGA result was subsequently determined to be caused by some abnormal deterioration within the transformer, rather than simply a response to unusual conditions, then the defect would also be a fault. If the transformer had to be removed from service to investigate the DGA result, then this would be classified also as a failure.

Restore Failure

A major end of life failure which requires the transformer to be removed from service for repairs or replacement. Where repairs are required, these involve major remedial work, usually requiring the transformer to be removed from its plinth and returned to the factory. The chief characteristic of a restore failure is that its repair would result in the transformer being returned to a substantially 'as new' state.

(For example, a three phase rewind would be considered a restore failure, while a single phase rewind of a three phase transformer would not. End of life failures of components are not in themselves considered restore failures. Therefore, a bushing failure which resulted in the loss of the transformer would be considered a restore failure, otherwise it would be considered a continue failure (see below). Note that a restore failure as defined here would often be described in common usage as simply a 'failure', but not all 'failures' would be classified restore failures as defined here.)

Continue Failure

A failure which requires the transformer to be removed from service for repairs which can usually be carried out on site, and do not involve restoring the transformer to a substantially 'as new' condition.

(A tap-changer or bushing fault, or any other component fault, which did not cause damage to the windings would be considered a continue failure.)

Failure mode

A description of a failure which illustrates what actually happened when the failure occurred.

Failure mechanism

A description of the physical processes leading up to a failure.

Failure cause

The circumstances during design, manufacture or application that led to the failure.

Contributing cause

A factor which by itself would not have resulted in a failure, but which had some influence on the progression to failure.

Condition

An expression of the state of health of an equipment which takes into account its aged state as well as any inherent faults.

Indication (of a fault)

Indirect evidence for the existence of a fault.

Through fault

An abnormal system event outside the equipment which causes high fault currents to flow through the transformer.

Examples for the extensions of the failure definitions:

The basic **failure model** proposed for consideration assumes that there are a number of key functions or parameters, such as dielectric and mechanical strength, and that:

Failure occurs when the **withstand strength** of the transformer with respect to one of these key properties is exceeded by **operational stresses**

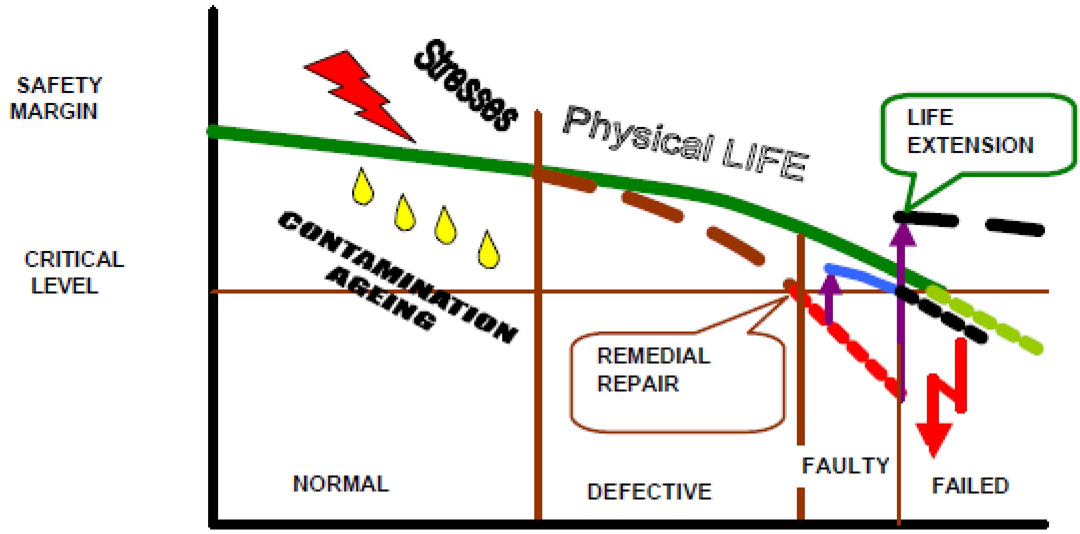


FIGURE 1 - CONDITIONS OF A TRANSFORMER IN THE COURSE OF ITS LIFE CYCLE

A failure is usually a "tuning fork" of Life Management procedures. Many failures occur due to aging phenomena:

Shortened life due to accelerated deterioration of components particularly bushings and OLTCs

Overheating of the HV winding coils due to poor cooling or excessive circulating current

Change in the condition due to ingress of water, particle contamination, aging of oil, loosening of contacts and clamping forces, vibration, unusual stresses, etc.

Latent defects of design or defects during manufacture. These may require some other factor such as aging of insulation or increase in fault level to lead to a failure.

A failure occurs when the withstand strength of the transformer with respect to one of its key properties is exceeded by operating stresses. Sometimes the transformer can keep serviceability being in a faulty condition (overheating, gassing) but it will fail immediately if a short-circuit or open-circuit happens. The withstand strength of a transformer decreases naturally over its life.

Definitions for CIGRÉ WG D1.39

The goal of this work is to provide guidelines for failure data collection and analysis in order to handle the aging power system and the expected re-investment boom. The failure data analysis aims to estimate the number of future replacement in order to determine the future operating costs of the aging power system. Inversely: the failure is an event which the life data analysis tries to quantify for the future. Thus, it has to facilitate to answer questions like “how many transformers do I have to replace in the next two or five years?" and "what is the correct balance between preventive maintenance and replacement?"

Failure data collection and analysis provide vital information that enables to classify the devices into the above groups. However, the concept of failure has to be adjusted for the purposes of life data analysis. Table I summarizes the concepts from the literature.

TABLE I – DEFINITIONS RELATED TO THE CONCEPT OF FAILURE

CONCEPT	WORDS USED IN DEFINITIONS
Failure	Termination of ability; event; operational consequences; key function
Fault	State; inability to perform; deterioration
Faulty	Short term reliability reduced
Failed	Action required; out of service
Defect	Non-conformance; requires investigation or action; imperfection
Condition	State of health; aging
End of life	Not meeting requirements; technical; economical; strategic

In this work, the failure definition is **equipment centered**, i.e. the outage that can occur is less important, but the condition of the equipment is, see Table II. This means, that the concept of failure may be supplemented with those cases, where no outage has happened, but the condition of the device was such that without preventive maintenance there would have been outage in a short time (e.g. based on diagnostic measurements or scheduled maintenance). In other words, the level of deterioration is relevant and not the moment, when the operational stresses happen to exceed the withstand strength. These cases are rarely handled by failure statistics, however, regarding life data analysis, bear with the same importance as those with the need of immediate de-energization.

TABLE II

TO CONSIDER **(device)**	**NOT TO CONSIDER** **(event, external factors)**
Condition of the equipment	Erroneous protective relay tripping
Signs of end-of-life	Operational consequences (e.g. non-sold energy or disturbed consumer number)
Maintenance that may have brought back the device from faulty to acceptably reliable (not necessary good or as new) condition	Extreme weather
Outages caused by faulty equipment	Third-party damages

Taking the above consideration into account, the following definition is proposed:

A failure is an event, which results in a component or subcomponent to stop fulfilling its function

The termination of the ability of an item to perform a required function

In particular cases the definitions could be extended for a specific asset or group of assets, according to the demands of the asset manager.

Due to aging or other factors…

…the operation of a component or subcomponent becomes life-threatening…

…the energy supply is interrupted…

…the component or subcomponent reaches the end of life condition…

…and therefore a component or subcomponent has to be replaced.

In order to justify considering cases without outage as failure, the condition for end of life has to be added. This can be devised from CIGRÉ Working Group B1.09, Brochure 358 (Remaining Life Management of Existing AC Underground Lines).

End of life is reached if the equipment does not meet the requirements any more. Usually it involves a combination of technical, economic and strategic requirements.

Technical End of Life: Technical end of life of a component or subcomponent is reached when repair does not seem to offer a reliable solution or the component or subcomponent does not meet the technical specification.

Economic End of Life: Economic end of life of a component or subcomponent is reached when it becomes too costly to maintain a component or subcomponent in service in comparison to technical alternatives.

Strategic End of Life: Strategic end of life of a component or subcomponent is reached when the company values are not met any more.

There are outages which occur because of an abrupt, external reason, e.g. failures due to extreme weather conditions. As these are not (or to a low extent) dependent on age, they should be treated differently, and not in the frames of life data analysis.

3. MAIN ROUTES TO FAILURE OF POWER SYSTEM ASSETS

3.1 Insulation in HV components

The construction of a power grid is very complex. In [14], a power grid is defined as "A system of interconnected power lines and generators that is managed so that the generators are dispatched as needed to meet the requirements of the customers connected to the grid at various points" The generation, transmission and distribution parts can be distinguished in each power grid. Despite the location and voltage level, several types of high voltage components utilizing different types of the insulation can be found in the power grid, for detail see Table III.

TABLE III - TYPES OF HIGH-VOLTAGE COMPONENTS AND APPLICABLE TYPES OF INSULATION

Type of components	Types of the insulation
• Generators • Transformers • Cable systems (cables, joints, terminations) • Overhead line systems (masts, insulators, conductors) • Switching equipment • Bushings, line and chain insulators • Capacitors	• Solid (XLPE, Resins, Rubber, porcelain composites…….) • Liquid (oil) • Mixed (mass and oil-impregnated paper) • Gaseous (SF_6, air, nitrogen etc.)

The above mentioned components are complex in their construction and consist of different subcomponents which start to age while being in service [16]. The term aging does not only refer to the elapsing of the service time, it is deterioration of the component due to service stresses in the way that the operational abilities decrease, until a failure of the component occurs [16]. The moment of failure occurrence determines the end of the useful life. A simplistic approach of the process of components aging until failure occurrence is shown in Figure 2. Note: the effect of refurbishment is not included in this schematic overview.

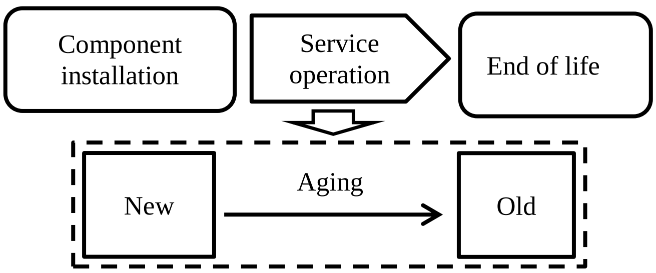


FIGURE 2 - SCHEMATIC SHOWING THE AGING OF THE COMPONENT

Next to the operational stresses which usually have been taken into account during design, multiple stresses of different nature that affect additionally the life of the component, may be found. Even in case the abnormal stresses are withstood by the component, their influence on the component deterioration is often considerable. In principle, the factors and phenomena influencing the operation and life of the high-voltage component can be divided in four main groups [17],[18],[19]. These are of electrical, thermal, mechanical and environmental nature. The deterioration of the component is a result of the action of one or more aging stresses, which might be of intrinsic or extrinsic nature [17]. A detailed categorization of stresses and a description can be seen in Figure 3.

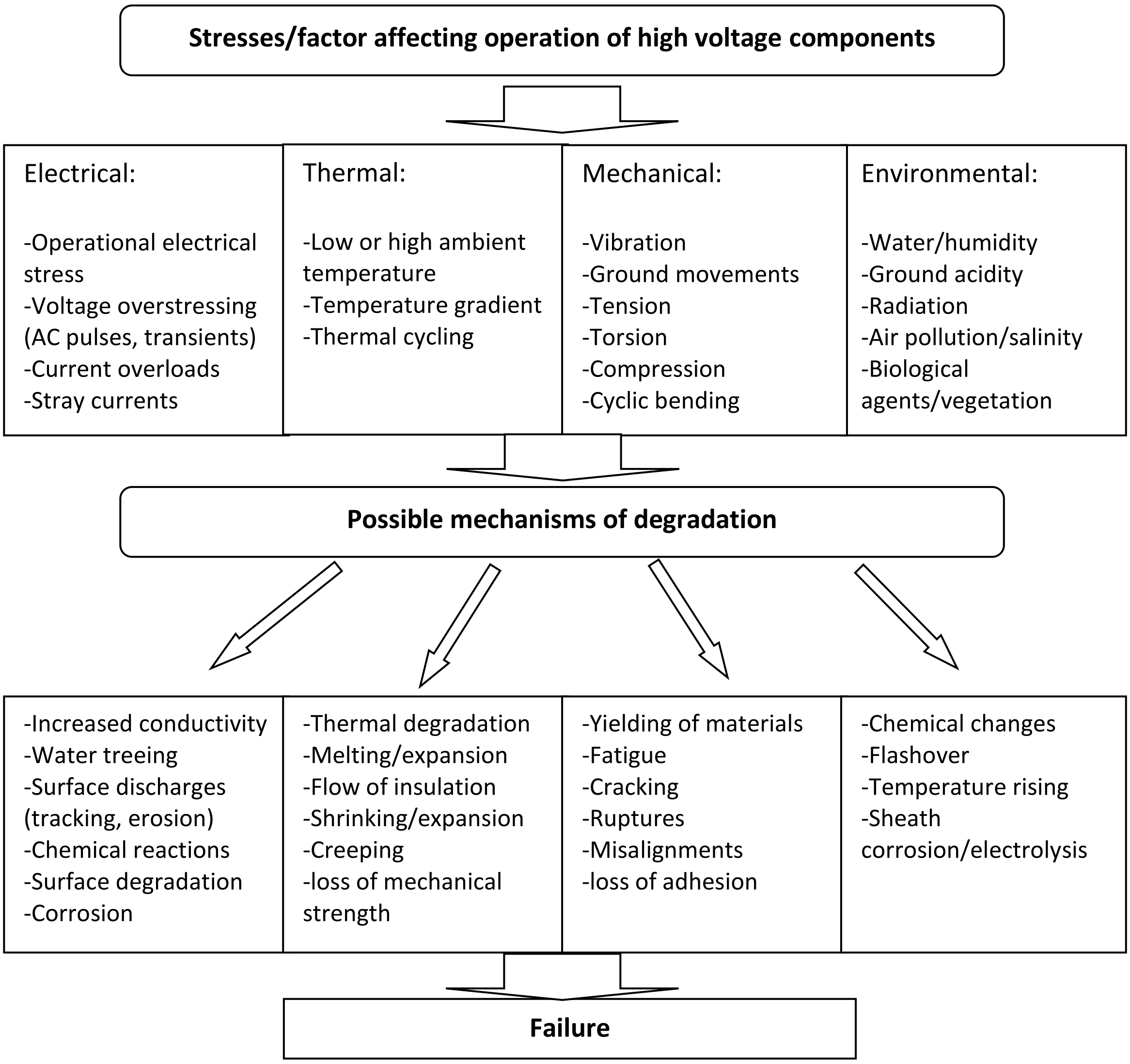


FIGURE 3 - BASIC DIVISION OF STRESSES AFFECTING HIGH VOLTAGE COMPONENTS DURING OPERATION, WITH FURTHER DEVELOPMENT INTO POSSIBLE DEGRADATION MECHANISMS

In addition, it has to be emphasized that the stresses may have sequential, simultaneous or synergistic character. Further on, a brief overview of the aging mechanisms and their characteristics will be given.

Electrical stress

Each component, particularly the insulation, is stressed electrically during the service life and, therefore; it ages electrically as well. The electrical aging includes degradation due to partial discharges, treeing, space charge, and tracking and due to electrolysis. The mentioned aging mechanism arise due to impurities, heterogeneities, protrusions, voids and inclusions on the surface and in the volume of the insulation.

Thermal stress

Service conditions of the high-voltage components require abilities to withstand elevated temperatures over long period of time. Besides thermal stressing of the insulation due to component loading, energy dissipation within the insulation due to electrical stress application, what results in heating of the insulation, might play a role.

Mechanical stress

The high-voltage components might be stressed during manufacturing, transportation, installation and operation. The operation is the most extensive period and therefore is of most interest. The continuous mechanical stressing often leads to the gradual degradation of the physical structure of the component what often accelerates the electrical and thermal aging. Practically, the mechanical aging can be very complex.

Environmental stress

The environmental stresses affecting the high-voltage components include actions of such agents as: moisture (water), high and low temperatures (thermal cycling), vegetation, radiation, biological agents. These character of stresses depends mainly on the location of the component and the character of the area (rural or urban). Therefore, it is rather difficult to find a general model taking into account all possible factors. Particularly, that the agents might interact with each other. In addition, it has to be mentioned that the environmental stresses often accelerate the electrical, thermal and mechanical aging of the component.

Each utility operates hundreds or even thousands of different components installed in the power grid. Every component is characterized by the expected lifetime, i.e. the period of time the component is expected to operate under normal conditions. This is the same as the remaining life of a new component [26]. However, any abnormal conditions occurring in the grid such as voltage transients, may accelerate the aging of the component and the real technical life might be shorter than the expected one. Moreover, depending on the component importance and network arrangement, the life of the component can be assessed on different levels taking into account different criteria [25].

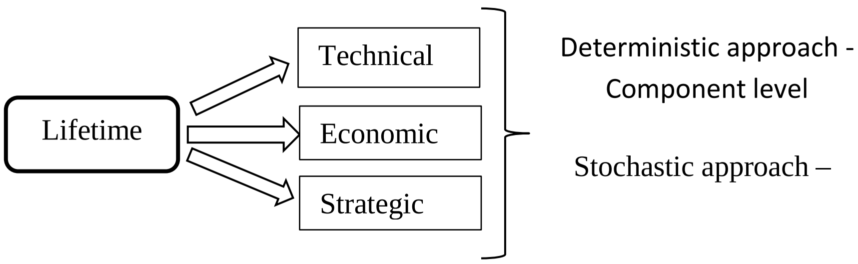


FIGURE 4 DIFFERENT ASPECTS OF THE LIFE TIME AND THE APPROACHES TO ASSESS THEM

In practice, the technical life of components can usually not be assessed without considering other aspects such as economic and strategic criteria. The challenge is to obtain a pragmatic and sufficiently robust approach to incorporate these aspects with the purpose to predict failure behavior.

In the following two approaches are described, the “bottom up” and the “top down” approach.

In the first approach, application of diagnostics on individual components provides an indication of the components condition. This bottom-up analysis follows a deterministic approach to failure prediction.

The second “top down” approach is the main focus of this brochure. In this case mathematical methods are used to predict the behavior of the population under investigation. Particularly the number and trend of the upcoming failures are of interest. This stochastic approach is aimed at providing the asset managers with data driven information needed for long term renewal and maintenance decision making.

In practice, we observe that usually both approaches are used. The determination of the condition of the components requires the application of several diagnostic methods. Based on a set of diagnostic parameters and a database that links parameter values to insulation condition, many utilities have introduced the concept of health index. The health index is often used to prioritize maintenance and replacement within a population of components. The ultimate goal is to get access to the future failure behavior of the components within the population.

3.2 Asset deterioration and Failure

Materials deteriorate as a result of their exposure to the environment, loads and other stresses, abrasion and many other factors and processes. So it is to be expected that assets in power systems which are made up from many sorts of materials will age and deteriorate and either fail in service or ultimately be replaced proactively at end of life, as illustrated in Figure 5. The aging process is influenced by the quality of the materials employed and the original design of the equipment, the quality of maintenance provided during the equipment's time in service, and the nature of the operational stresses and the environment in which the assets operate.

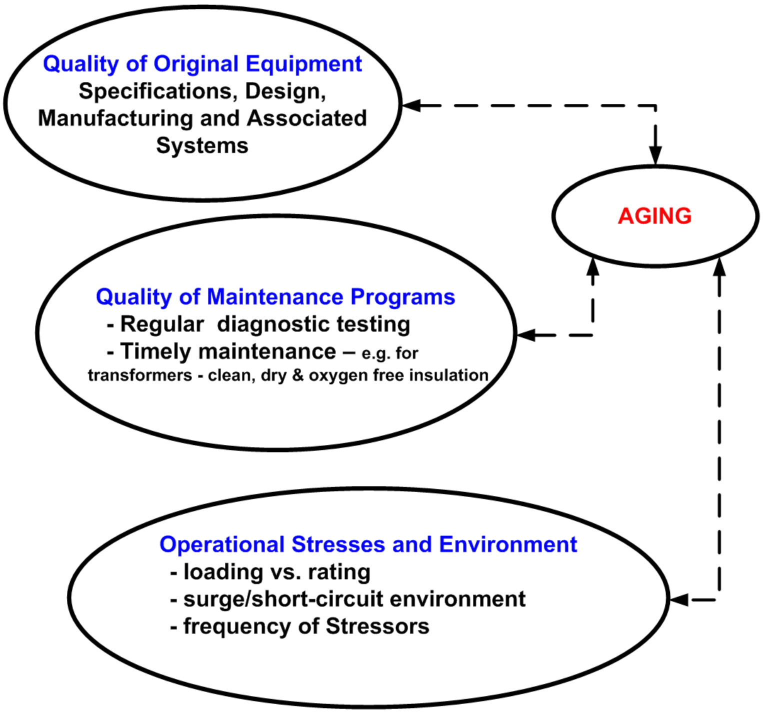


FIGURE 5 - INFLUENCES ON ASSET AGING [8]

Apart from infant mortality failures caused by defects, aging processes typically operate slowly with gradual deterioration in material strengths or electrical withstand over time frames of years or decades. Ultimately, if aging processes are not monitored or if deterioration is not detected, the remaining life or the occurrence of failure and end of life are statistically determined and dependent on the overlap between the distribution of stresses and the distribution of withstand strength as illustrated in Figure 6. The figure depicts a wide margin of safety between the withstand strength of new materials and the distribution of stresses, while over time and the action of operating and environmental stresses, the withstand strength curve moves to the left, ultimately overlapping the stress distribution. The extent of the overlap determines the probability of failure.

From the perspective of the reliability of a fleet of assets, the aging process and the effect it has on asset reliability is illustrated by Figure 7.

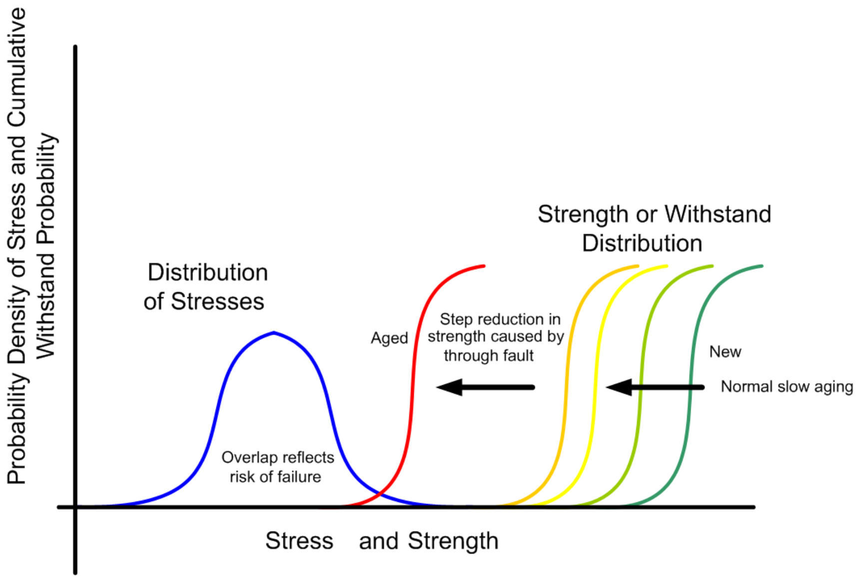


FIGURE 6 PROBABILISTIC MODEL OF MATERIAL OR ASSET AGING LEADING TO INCREASING RISK OF FAILURE [8]

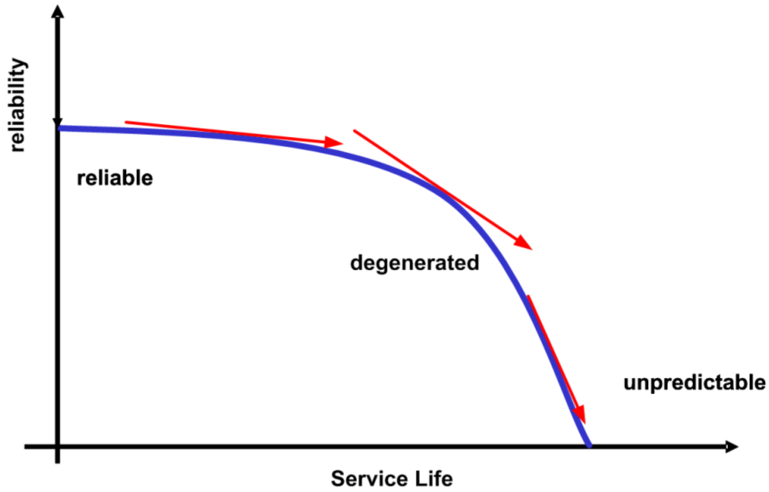


FIGURE 7 AGING AND ASSET RELIABILITY [8]

Figure 7 illustrates the steep decline in asset reliability towards end-of-life which qualitatively reflects how aging processes can interact synergistically to cause a "slippery slope". This acceleration in the rate of deterioration processes, if not detected, can lead to rapid failure. Avoidance of such situations and prevention of failures in service is the objective of utility asset inspection, monitoring and maintenance programs as illustrated below in Figure 8 [8]. This figure illustrates conceptually the periods during the service life of assets when replacement or refurbishment might be contemplated and when routine maintenance and repairs would be considered to be adequate.

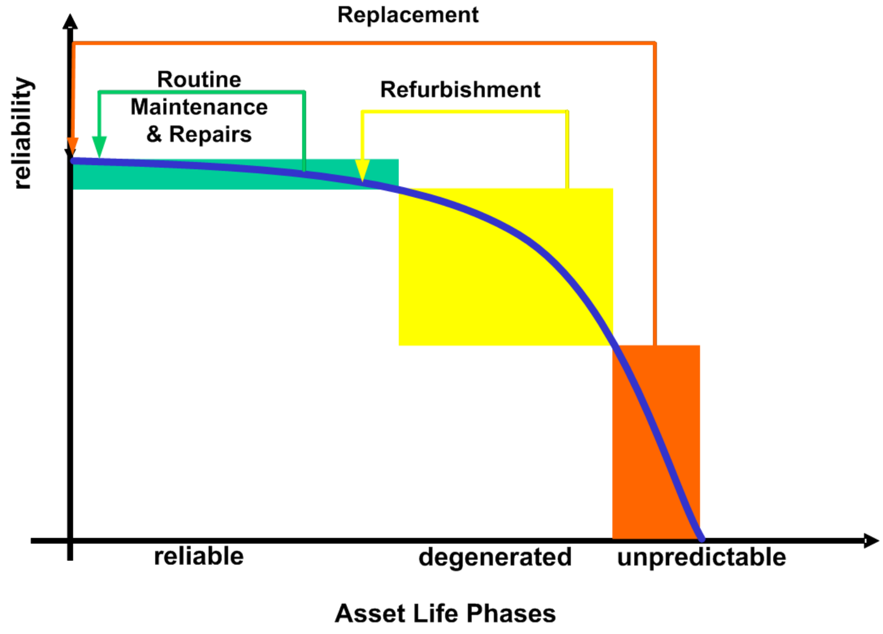


FIGURE 8 TYPICAL UTILITY INTERVENTIONS AND THE TIMING OF ROUTINE MAINTENANCE OPERATIONS, REFURBISHMENT AND REPLACEMENT [8]

3.3 Impact of Aging on Component Failure Rate

Failure rates tend to vary with time. Different causes of failure could lead to different rates of rise of the failure rate. Therefore, there is not a general consensus on the best way for modelling the wear-out period of components (aging stress factor). However, it is clear that depending on the degree of aging the slope of the failure rate curve can be large or small [27][28].

The degree of aging will eventually result in an increase of the failure rate of components (for most power system components this is the case). Much of the available data in literature [29] indicate that, inevitably, failure rates will increase when equipment are in the final stages of aging. This increase is attributed to wear and aging stress factors, and can be mitigated by maintenance. In practice, maintenance cannot be performed perfectly and often create their own temporary “infant mortality” increase in the failure rate. This can be represented by using a saw-tooth bathtub curve [28][29][30]. The reason for the temporary increases in the failure rate is due to the possibility of maintenance crews causing damage or making errors during assembly. Equipment surviving this short period of time is actually maintained properly and, therefore, the failure rates decrease accordingly. This situation is depicted in Figure 9 [27].

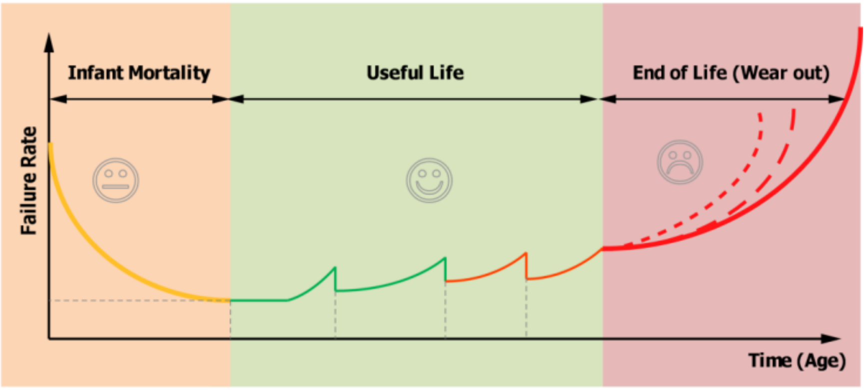


FIGURE 9 - THE SAW-TOOTH BATHTUB CURVE, WHICH MODELS THE INCREASING FAILURE RATE OF A COMPONENT BETWEEN MAINTENANCE SERVICES AND INDICATES THE RELIABILITY IMPROVEMENT AFTER EACH MAINTENANCE SERVICE. NOTE HOWEVER, THAT THE FAILURE RATE WILL LIKELY STILL INCREASE OVER TIME [27]

In Figure 10 an example, according to [28], of cable joint failure rates of different types is shown. In general, electrical equipment experience sufficient deterioration with time and therefore, failure rates do increase over time.

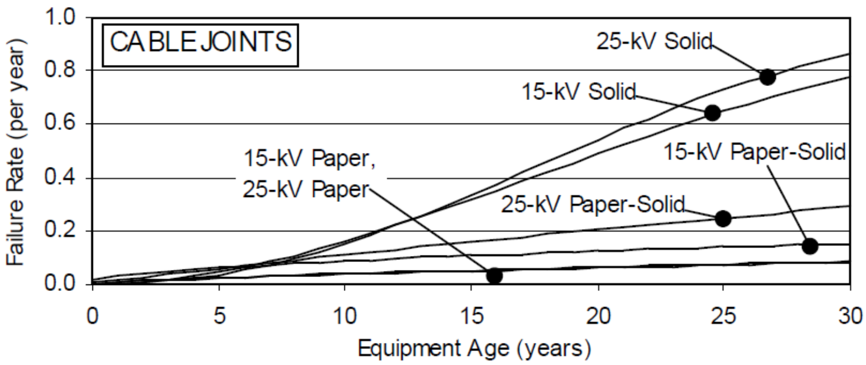


FIGURE 10 - THIS GRAPH SHOW AN EXAMPLE OF DETERIORATING FAILURE RATES FOR DIFFERENT MV CABLE JOINTS. IT ALSO SHOWS THAT JOINTS OF DIFFERENT VOLTAGE CLASSES AND WITH DIFFERENT FEATURES CAN HAVE COMPLETELY DIFFERENT FAILURE CHARACTERISTICS [28]

3.4 Asset Information Management

Generally speaking, asset intensive industries rely on asset data, information and asset knowledge as key enablers in undertaking both strategic AM activities and operational activities [1],[15]. As a consequence, in the past years, utilities have progressively created databases to record, not only, information related to network components (for example failure data, population data), but also information regarding economical, societal, and other corporate aspects. All the relevant information collected and stored should be directed in a proper way to the asset management in order to prepare the correct decision [16]. An example of a possible asset management information flowchart is given in Figure 11.

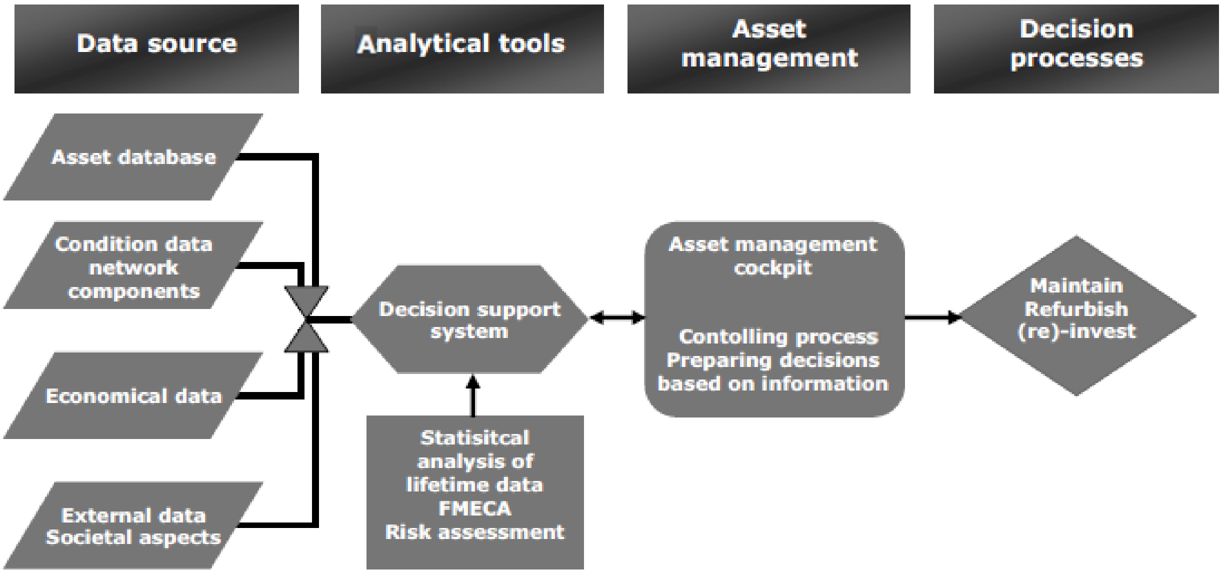


FIGURE 11 AN EXAMPLE OF THE POSSIBLE ASSET MANAGEMENT INFORMATION FLOWCHART APPLIED FOR DECISION MAKING PROCESSES [16]

As shown in Figure 11, the sources of asset data can be manifold and necessary for a thorough decision making process. It is desirable to analyze and evaluate all the input data together in an asset management decision support system. Based on the evaluated data different alternative solutions can be proposed of which a final decision is made and translated into actions.

From a statistical life data analysis point of view (with the purpose to understand and track the technical reliability of populations of components during operational lifetime) the data sources on technical level are especially of interest to provide the suitable information which is used for the input for statistical life time data analysis.

4. SYSTEMATIC APPROACH TO STATISTICS BASED ANALYSIS OF FAILURE AND LIFE DATA

4.1 Systematic Approach to Statistics Based Analysis of Failure and Life Data

A systematic approach to statistics based analysis of insulation failure and life data should encompass the following aspects:

- Raw inventory and failure event data collection
- Setting objectives and selection of statistical model
- Statistical parameter estimation and result interpretation
- Application of statistical modelling to maintenance or replacement planning

4.2 Basic Concepts and Data Collection

4.2.1 Basic concepts

Components, equipment and systems

Components, in statistics [31],[32], are not repairable and have a finite life. They usually have a dominant failure mode such as in the case of a cable joint where the dominant failure mode is insulation failure. Their life characteristics for a population of identical components can be represented fairly well by one of the standard statistical distributions.

A piece of equipment is an assembly of components that operate to provide a specific function. It will fail as a result of component failure and thus can have multiple failure modes. It can be restored to operation by replacement of the failed components (assuming no catastrophic effects such as a transformer explosion).

Systems are more complex. They generally comprise a combination of equipment and components. During the system lifetime, components may be replaced and equipment repaired in situ or replaced. Modifications can also be made to improve performance or to meet new operational requirements. Often systems are regarded as repairable and therefore not treated in terms of reliability / end of life but rather in terms of availability, unavailability, MTBF etc.

INSULATION FAILURE MODE AND FAILURE CAUSE

There is often confusion between the concepts of failure mode and failure cause. In this report failure cause defines the mechanisms that led to the failure such as manufacturing defect, aging, water ingress, third party damage and poor installation practice etc.

The failure mode is the manner in which an item fails [33] or the effect by which the failure is observed [31]. Typical failure modes may include broken conductor, thermal breakdown in cable insulation and transformer oil degradation etc.

REPAIRABLE AND NON-REPAIRABLE SYSTEMS

In power plant failure data analysis, an important distinction is to be made between repairable and non-repairable systems.

There is usually only one failure mode for each type of non-repairable power plant component or item. In comparison, equipment and systems are deemed “repairable” with the repair process involving the replacement of an integral component with a new one. Repairs are often assumed to be perfect, restoring the equipment to “As Good As New” (AGAN). This assumption of “AGAN” is very important in failure analysis because it is based on the premise that all replacement components are of the same type as those they replace and that the observed lifetimes are independent and identically distributed. An alternative concept is “As Bad As Old” (ABAO), when repairs are not assumed to be perfect. In this case, the times between failures are neither independent nor identically distributed. Different techniques are usually applied to the two scenarios.

Component lifetime is always based on time to failure and non-failure data of components in service. Repairable items are those where the occurrence of a failure does not necessarily cause “end of life” because failed component is repaired or replaced to restore the equipment or system to full operational condition.

4.2.2 Raw data collection

Majority of asset data collected from operating plant will be in the form of individual reports or data sheet. To collect data essential to statistical analysis, one may need to check both the inventory data, which comprises information defining the type of equipment in terms of its design, functional, operational and environmental characteristics, and separately, failure event data which describes each failure event containing the item’s inventory code, failure mode, failure cause and, if possible, operational and environmental conditions.

Individual inventory data sheet lodged with utility companies often contain, however, much information which is not required in statistics based analysis. Table IV illustrates an example of the data which need to be taken from the inventory and failure event data sheet of a cable circuit.

For the purpose of statistical analysis, this information will need to be interpreted to establish the failure mode, cause of failure and numerical information required by statistical models.

TABLE IV - CABLE INVENTORY FAILURE EVENT DATA SHEET REQUIRED FOR STATISTICAL ANALYSIS

	Classification	Data	Required for statistics based failure analysis (Y: essential, D: desirable)
<u>Inventory data</u>			
	Class:	HV Cable	Y
	Voltage rating	220kV	D
	Type	XLPE single core, 3-phase	Y
	Circuit length	1.0 km	Y
<u>Manufacturer/Design Data</u>			
	Manufacturer	abc	D
	Insulation	Extruded XLPE	Y
	Radial water barrier	aluminum foil laminate	D
<u>Operational and Environmental Data</u>			
	Date of commissioning	1, January 1990	Y

	Date of decommissioning	2 Sept 2013	Y
	Reason for decommissioning	failure	Y
	Cable length	3 kilometers	Y
	Number of joints and terminations in circuit	5	Y
	Installation method	Cable Duct, cross section: 0.8 X1m	D
	Design current carrying capability	2000A	D
	Average load current over service period	950A	D
	Annual ambient temperature	-10 – 45	D

Event data			
	Failure mode	Insulation breakdown	Y
	Level of Severity	Critical	D
	Cause of failure	Aging	D
	Action required	Replacement	D
	Failure detection	Date: 7th April 2013Time: 14:30	Y

For the sake of data homogeneity, it is recommended that cable joints/terminations are excluded from the cable inventory data and are registered separately. Any replacement of a cable section or cable joint/termination should be registered separately in a new inventory sheet so that time-to-failure, when failure eventually occurs, is correctly logged.

4.3 Review of Statistical Models

Models applicable to constant failure rate -- Poisson distribution and Binomial distribution
Prior to the current working group, CIGRE WG A3.06 investigated reliabilities of a number of power plant items including circuit breakers, disconnectors and earthing switches, instrument transformers and gas insulated switchgear (GIS). During an electrical equipment reliability survey conducted between 2004 and 2007, the working group (A3.06) found that both the Poisson and binomial distributions were suitable distribution models in reliability analysis when details of equipment population and failure data are at hand.

Details of the models and how they can be applied using MS Excel program can be obtained from reference [34].

Model applicable to constant and varying failure rate -- Weibull distribution
The Weibull distribution is perhaps the most widely used model in analysis of reliability and failure data. It gives the distribution of lifetimes of objects and was originally proposed to quantify fatigue data [31][32][35], but it is also used in analysis of systems involving a "weakest link" (which is also the theoretical justification for this distribution) such as insulations in power plant.

The features make it attractive to reliability and maintenance engineers include its flexibility – it can deal with decreasing, constant and increasing failure rates and consequently can model all the three phases of the reliability bathtub. It has also been shown to fit with most lifetime data better than other distributions (because it is the asymptotic correct distribution for the weakest link in a chain) and has been found particularly valuable for the relative small samples that are often the encountered by maintenance engineers.

4.3.1 The Weibull distribution

There are two versions of the Weibull model, namely the two-parameter and three-parameter models. Mathematically the probability of cumulative failure of the two-parameter model, as a function of time, is given in Equation (1). The three parameter model, as given in Equation (2) involves the introduction of a location parameter into the two parameter model.

$$F(t) = 1 - \exp(-(\frac{t}{\eta})^{\beta}) \qquad (1)$$

$$F(t) = 1 - \exp(-(\frac{t-\gamma}{\eta})^{\beta}) \qquad (2)$$

Where $F(t)$ is the cumulative distribution function for the group of assets, or the probability of failure of an individual asset before time t. The complement of $F(t)$ is the reliability, or probability of not failing up to time t, $R(t) = 1 - F(t)$. η is the scale parameter and β the shape parameter. γ in Equation (2) is the location parameter.

The probability density function (PDF) of the two parameter model, the first derivative of equation (1), is given in Equation (3).

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{t}{\eta}\right)^{\beta}\right) \qquad (3)$$

The probability density function defines the life probability distribution of a population. The area under this curve equals unity. The probability density function is similar to the Normal curve, with its typical bell shape (if β = 3). The difference between the two, which makes the Weibull better for describing the life of insulations, is that the Weibull has no negative values, and can be assigned a specific starting point (a point below which there are no failures). The normal curve, on the other hand, has values from negative to positive infinity [36]. There are also physical reasons why the Weibull distribution is adequate. It is the weakest extreme distribution for variables > 0 (so it applies to objects that can be regarded as a chain of which the strength depends on the weakest link of many).

The failure or hazard rate function is given in Equation (4).

$$h(t) = f(t)/(1 - F(t)) \qquad (4)$$

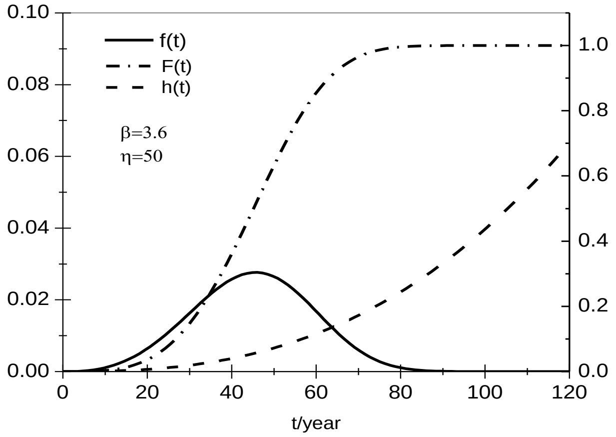
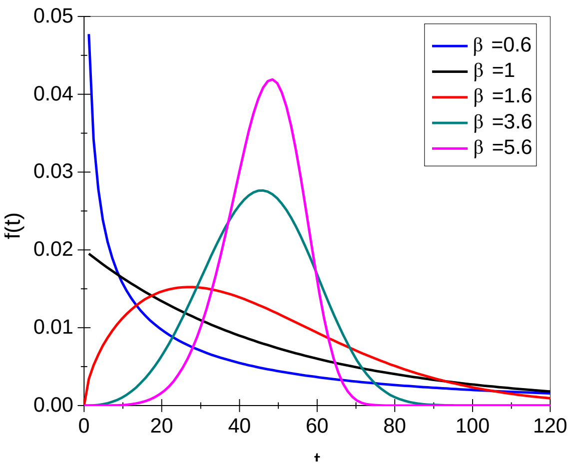
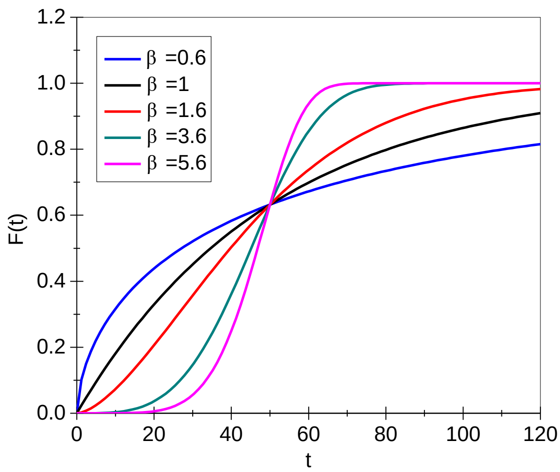


FIGURE 12 - ILLUSTRATION OF THE WEIBULL FUNCTIONS HERE THE UNIT OF HORIZONTAL AXIS IS IN CALENDAR YEAR. THE LEFT VERTICAL AXIS CORRESPONDS WITH F(t) AND THE RIGHT VERTICAL CORRESPONDS WITH H(t) AND F(t).

Figure 12 illustrates the probability of failure over time, or cumulative failure distribution function, F(t) which is superimposed with the probability density function f(t) and the hazard function. In power plant failure analysis, F(t) is the probability of failure before time t. The hazard function would be the probability of a surviving item failing in a given year and the probability density function would be the percentage of the population to fail in that year. The hazard function forces the probability density function into a bell shape because there are few failures early in life (because of the low failure rate), few failures later in life (because the chances are the individual items have already failed), and the bulk of the failures clustered in some range of central tendency [36].

4.3.2 The Weibull parameters





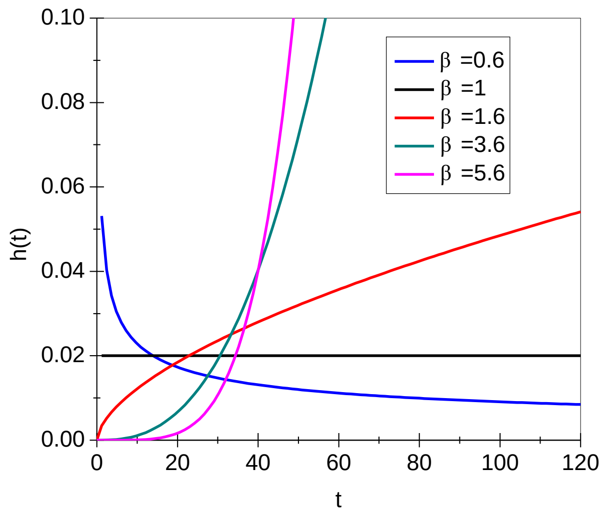


FIGURE 13 - THE CHANGE IN PROBABILITY DENSITY FUNCTION, PROBABILITY OF FAILURE AND HAZARD RATE FUNCTION WITH SHAPE PARAMETER

As shown in Figure 13, When the shape parameter β = 1, the hazard rate is a constant and the Weibull distribution is equivalent to the exponential distribution. For β > 1, the hazard rate is increasing and the greater the value of β, the more rapid is the increase in h(t). For β <1, h(t) is decreasing and, the smaller the value of β, the more rapid is the decrease in h(t).

The scale parameter η is also known as characteristic life in reliability study. It is the time for 63.2% of the original population to fail since

$$1-e^{-\left(\frac{t}{\eta}\right)^{\beta}} = 1-e^{-1} = 0.632 \qquad \text{when } t=\eta$$

The location parameter in the three parameter model signifies the period prior to the occurrence of failures.

4.3.3 Data requirement

It is well recognized that the Weibull model performs best when dealing with homogeneous life data, or data containing failures due to a single failure mode or with one dominant failure mode [37]. Life data are related to items that "age" during time to failure, which is the case in insulation systems where plant items age due to operating time and operational stresses.

To ensure that the Weibull approach in insulation failure data is valid, one needs to have time to failure for each of the failure and the survival time to date when data censorship takes place for each of the items in the population. The time to failure should include the following:

• Time to failure of a non-repairable item.

• Time to first failure of a repairable item.

• Time between two consecutive failures

This represents data that most utilities either have available, or can develop. The only other data that is pertinent would be the amount of the population replaced each year – if retirement is underway.

4.3.4 Data censoring

In terms of the way failure data are collected, they can be categorized as complete, censored on the right, censored on the left, time censored, failure censored, multiply censored, and multiply censored with mix of competing failure modes.

Censoring occurs when the value of an observation is only known to some extent. Censored data is often encountered when analysing practical life data, especially in case of electrical power systems where the majority of installed equipment is still in-service, and most of the time the exact age of equipment at the moment of failure is unknown. The following censoring schemes are possible:

1. Right censored data (suspended data): When a data set is composed of components that did not fail it may be referred to as right censored data or suspended data. The term right censored indicates that the event is located to the right of the data set, which implies that certain components are still operating.

2. Interval censored data: This reflects uncertainty as to the exact times the equipment failed or exact age of an equipment upon failure. Interval data is often encountered in asset related databases when components are not constantly monitored.

3. Left censored data: This censoring scheme in some way is similar to interval censoring, because a failure time or age is only known to be before a certain time and the starting time for the interval is zero.

4. Failure censored (or Type II) data: Failure censoring or truncation occurs when an experiment is terminated after a certain number of failures have occurred.

5. Multiply censored data: This type of censoring is relevant for field failure data where components have been installed at different times and a number of them is still in service (Multiply right censored data).

6. Multiply censored data with a mix of competing failure modes: As 5. But in addition different failure modes and or causes apply.

With insulation failures, which is the primary concern of the present Working Group, the Multiply censored with a Competing Failure Modes/failure causes provides the most complete set of information, as much data have differing running times intermixed with failure time and with different failure mode/failure causes.

Table V lists data of 31 failures which have been extracted from inventory and failure event report in order to apply Weibull analysis to failures in a HV cable population. It consists of 220 kV and 110 kV cable, cable joint and cable termination failure data which was collected, in July 2011, from an Electric Power Company in China where the cable length increased from nil to 381.8 kilometers in the period from Jan 1989 to June 2011. It was observed that, out of the 31 failures during the period, 17 incidents were associated with manufacturing and installation insulation quality problems and all these failures happened to cable joints or terminations, 9 with third party damage to cable insulations, 2 failures due to aging in cable joints and 3 with unknown reasons. No distinction has been made here between cable joints and the main XLPE cable circuits themselves in Table V. Almost all the failures due to manufacturing quality issues and poor installation practice are associated with cable joints, and the ones due to external or third party damage associated with main cables. This may be done differently if a large data sample were made available.

The most important data, when applying the Weibull model, are time to failure which enables numerical analysis, and failure causes which allows the correct rows of data to be processed. For instance, if the focus is early mortality hazard rate, then failures due to third party damage and aging should not be included. However if the contributing factors and the relative reliability of different installation methods is to be identified, then all data entries may be useful.

TABLE V – HV CABLE FAILURES WITH A UTILITY COMPANY BETWEEN 2005 AND 2011

Number i	Name of cable line	Failure causes	Date of Commission	Date of Fault	Age to failure/day

1	sd0dljn008	Quality issue	2008.01.01	2008.01.01	0
2	sd0dljb030	Quality issue	2007.06.21	2007.06.21	0
3	sd0dljn176	Quality issue	2010.06.08	2010.06.13	5
4	sd0dljb028	Installation issue	2007.10.23	2007.12.05	43
5	sd0dljb028	Installation issue	2007.10.23	2007.12.27	65
6	sd0dljn113	External damage	2007.09.30	2008.01.05	97
7	sd0dljn125	External damage	2010.04.10	2010.08.13	125
8	sd0dljn110	External damage	2008.04.18	2008.10.03	168
9	sd0dljb071	Quality issue	2009.07.01	2010.1.11	194
10	sd0dljn210	Quality issue	2008.08.02	2009.04.18	259
11	sd0dljb060	Quality issue	2007.08.21	2008.05.09	262
12	sd0dljn009	Quality issue	2008.07.12	2009.07.01	354
13	sd0dljn110	External damage	2009.09.01	2011.03.17	562
14	sd0dljn085	Quality issue	2003.06.01	2005.02.10	620
15	sd0dljn069	Quality issue	2002.01.01	2004.01.01	730
16	sd0dljb002	External damage	2008.07.01	2011.02.20	964
17	sd0dljb007	Quality issue	2008.02.04	2010.09.29	968
18	sd0dljb034	External damage	2007.01.01	2009.09.08	981
19	sd0dljn121	External damage	2008.08.30	2011.10.22	1148
20	sd0dljb020	Quality issue	1998.06.01	2004.03.01	2100
21	sd0dljb071	Quality issue	2003.05.30	2009.09.28	2313
22	sd0dljn102	Quality issue	2002.07.17	2009.09.27	2629
23	sd0dljn075	Unknown	1999.09.01	2006.12.29	2676
24	sd0dljn081	Unknown	1999.09.01	2006.12.29	
25	sd0dljn084	Quality issue	2003.05.30	2010.12.03	2744
26	sd0dljb017	Unknown	1996.06.01	2008.01.20	4250
27	sd0dljb023	Quality issue	1996.06.01	2008.10.20	
28	sd0dljn069	External damage	1997.06.01	2009.10.28	4532
29	sd0dljb054	External damage	1996.06.01	2010.09.28	5232

30	sd0dljb068	Aging	1989.01.01	2005.06.26	6020
31	sd0dljb068	Aging	1989.01.01	2005.08.31	6086

The total population of the HV cable circuit in this case is 298. Dates of commissioning of each of the circuits which survived to the date of data censoring (data collection) are also registered but have not included here due to consideration of space.

4.3.5 Model applicable to mixed failure modes – Crow-AMSAA model

The Crow-AMSAA model was originally developed to track and quantify the reliability growth of preliminary product designs or developmental manufacturing processes to help establish when a product or process has obtained adequate reliability to be put into production [31]. However, over the past several years, the Crow-AMSAA model has found increasing use as a tool to monitor reliability and forecast failures/faults in mechanical and electrical systems in the field. The advantage of the Crow-AMSAA model is that it models repairable systems, not a failure mode distribution of replaceable systems such as the Weibull distribution. This is an important distinction, as Crow-AMSAA can model a component that has failed and been repaired multiple times, while the Weibull distribution can only be used to model the first failure. The Crow-AMSAA model is also capable of handling a mixture of failure modes whereas the Weibull model works best with one, perhaps two failure modes only [37]. This reduces the requirement for detailed information of time to first failure. Instead it can make a forecast of overall failures of a type of plant based on cumulative time against cumulative failures without consideration of failure modes.

The process where repairs are assumed to return the equipment to the level at which it was operating (ABAO) before failure is known as the Non-Homogeneous Poisson Process (NHPP). In this case, the process is only time homogeneous when failure rate is a constant over a specific period of time. It can be shown, however, that, if t1 < t2 <…, are the times at which failure events occur, then failure rate is a constant between the times and the expected number of failures in a selected interval is:

$$Z(t_2) - Z(t_1) = \int_{t_1}^{t_2} z(t)dt \qquad (5)$$

Therefore, the cumulative number of failures as a function of cumulative failure time can be expressed as:

$$N(t) = \lambda t^{\beta} \qquad (6)$$

In this case, Crow AMSAA model, especially suitable for modelling reliability growth, can be applied. The failure intensity function of the model is given as:

$$\rho(t) = \lambda\beta t^{\beta-1} \qquad \lambda \text{ and } \beta > 0 \qquad (7)$$

The reciprocal of ρ(t) is the instantaneous Mean Time Between Failure (MTBF). The log of cumulative failure events N(t) (Eq.(6)) plotted against log cumulative time is therefore a linear plot, if the model applies, because taking the log of equation (6) yields a straight line as given in Equation (8).

$$\log N(t) = \log\lambda + \beta \log t \qquad (8)$$

In this model, λ is the scale parameter, or the intercept on the y-axis in the linear plot as will be shown in the case studies later in this report, and β is the growth parameter which is the slope of the line. For β < 1 the rate of failures is decreasing, for β > 1 it is increasing and for β = 1, failure rate is a constant.

From the above equations, data requirement for applying the C-A model can be deduced (see Table VI for the data format).

TABLE VI – BASIC FAILURE DATA REQUIRED FOR APPLYING THE C-A ALGORITHM

Chronological year	Cable length in kilometers installed	Cumulative cable length	Failure counts (f(t) for Weibull model)	Failures per 100 kilometers	Cumulative faults t for Crow	Cumulative Failures per 100 kilometers(H(t) for Crow model)
1989	9.48	9.48	Unknown		Unknown	
1995	5.23	14.71	Unknown		Unknown	
1996	12.577	27.29	Unknown		Unknown	
1997	7.245	34.53	Unknown		Unknown	
1998	8.26	42.79	Unknown		Unknown	
1999	10.988	53.78	Unknown		Unknown	
2000	1.181	54.96	Unknown		Unknown	
2001	23.276	78.24	Unknown		Unknown	
2002	10.762	89.00	Unknown		Unknown	
2003	14.576	103.58	Unknown		Unknown	
2004	14.592	118.17	2	1.69	2	1.69
2005	11.068	129.24	3	2.32	5	4.01
2006	12.635	141.87	2	1.41	7	5.42
2007	39.323	181.19	3	1.66	10	7.08
2008	98.539	279.73	6	2.14	16	9.22
2009	35.549	315.28	6	1.90	22	11.12
2010	31.761	347.04	6	1.72	28	12.84
2011	34.771	381.81	3	0.79	31	13.63

4.3.6 The Cox Proportional Hazard Model (PHM)

Proportional hazards models was first proposed as a class of survival models which relate the time that passes before some event occurs to one or more covariates that may be associated with that quantity of time. As shown in equation (9), mathematically PHM consists of time-dependent and time-independent covariates, along with a baseline hazard function which can be in any form such as the Weibull distribution [39][40],[41].

$$h(t,X)=h_0(t)\exp\left(\sum_{k=1}^{n_1}\delta_i\cdot X_k+\sum_{j=1}^{n_2}\gamma_j\cdot X_j\right) \qquad (9)$$

Where $h_0(t)$ is the baseline hazard function, X_k are time-dependent covariates and X_j are time-independent covariates, of which the respective coefficients, regression parameters are denoted as δ_i and γ_j respectively, n_1 and n_2 represent the number of time-dependent and time-independent covariates respectively. If the set of data under analysis obeys Weibull distribution [39],[40], then the baseline hazard function $h_0(t)$ can take the form of the Weibull model which has been a popular choice. In this case the model is known as a full parameter model. However, when the focus of an analysis is on relative importance of covariates on the hazard, then $h_0(t)$ can be hidden. In this case the model is referred to as half-parameter Cox PHM [41].

David Cox [39] observed that if the proportional hazards assumption holds (or, is assumed to hold) then it is possible to estimate the effect parameter(s) without any consideration of the hazard function. This approach to survival data is called application of the Cox proportional hazards model. Cox PHM was proposed by Cox in 1972 and widely used in medical domain to study how the influencing factors affect survival time of patients [40]. It also found applications in other areas for reliability analysis [42].

Compared with other statistical models, the greatest advantage of Cox PHM is that it can consider and quantify the effects of more than one covariate simultaneously on the failures, without the need to have information of time to failures and the failure modes. This is exactly the feature required in analyzing early mortality failures among power plant items where priority is to identify any poor manufacturing quality and poor installation practice which results in quick failures (first 5 years) instead of their effects on aging.

A case study on the detailed use of the model can be found in chapter 6 of this report.

4.3.7 Summary of statistical models for failure data analysis

For component failures, and a given specified period, if the failures are a result of Homogeneous Poisson Process (HPP) or failure events are independent of each other and independent of time, then the failure rate and the number of failures can be modelled using Poisson or binomial distribution method. Reliability growth plots known as Crow-AMSAA plots are powerful for predicting future failures for mixed failure modes. Weibull probability plots are powerful single failure mode tools for predicting the type of failure mode which guides reliability centered maintenance strategies and forecasting future failures for each failure mode. Table VII below summarizes the aforementioned models with their suitable applications, data requirements and expected outcomes.

TABLE VII – SUMMARY COMPARISON OF THE STATISTICAL MODELS FOR INSULATION FAILURE DATA ANALYSIS

Model	Conditions required	Data requirement for application	Application/Purpose
Poison Distribution	Failures independent of each other and independent of time	Failure rate during a period of time, or size of population and total failures, allow multiple failure modes	Reliability survey, probability of various reliability rate
Weibull	Single mode failures, or homogeneous data	Time to failure, and number of survivals at time of censoring, perform better with single failure mode	Failure forecasting and prediction Evaluating corrective plans Test substantiation for new designs with minimum cost

			Maintenance planning and cost effective replacement strategies Spare parts forecasting
Crow AMSAA	Non-homogeneous Poisson process, Constant failure rate at a specific time but failure rate does not have to be constant	Cumulative number of failures against cumulative time, allow multiple failure modes	Reliability growth -Reliability or failure rate as a function of time, can predict failure and evaluate effects of replacement and maintenance activities
Cox PHM	If analysis of failure as function of time is required, condition is the same as the baseline function. None otherwise.	Number of failures with information of contributing factors involved, number of survivals at time of data censoring, allow multiple failure modes	Evaluation of effects of various contributing factors, Weighting of contribution from each of the contributing factors

4.4 Systematic Approach to Statistical Modelling

4.4.1 Setting objectives

Thorough understanding of the problem at hand and identification of the purpose of the analysis is extremely important as it allows correct formulation of data and selection of the most appropriate statistical model.

It has been widely regarded that the failure rate of a class of an insulation system, as a component, in power plant items obey the “bathtub curve” which can be divided into “burn-in phase” with a decreasing rate of early mortality failures (0~5 years), “the useful life phase” with a low number of casual failures (5~20 years) and “the wear-out phase” with an increasing rate of aging related failures (>20 years) [36],[37].

Early mortality failures usually result from imperfections during manufacturing process, defects associated with poor installation practice and third party damages. During the period identifying weak areas or significant factors leading to failures may take priority so that the process of power plant procurement, design, installation and operation can be improved.

During the useful life phase, failures happen occasionally due to various reasons such as third party damage, wear-out of components and environmental stress etc. Then analysis of reliability and predicting possible failure numbers may be useful for scheduling of maintenance activities.

When age related failures start kicking in, it is important to predict the future annual failures, to evaluate the effect of various options so that operational risks can be evaluated and replacement program can be optimized.

4.4.2 Weibull plotting, statistical parameter estimation and interpretation

With insulation failure data, the best start point is the Weibull modelling. This is to represent a set of failure data using the characteristic life η and shape parameter β. From these parameters further insight can be gained into the failure rate of the case at hand such as where in the bathtub curve a particular set of plant items are situated and how maintenance and replacement would effect on the overall reliability of the plant population under analysis.

There are two ways parameters can be estimated. One is median rank regression or statistical plotting and the other is the Maximum Likelihood Estimation (MLE) via numerical iterations. Both can be carried out using specialist software packages.

The Median Rank regression method has been recognized [35] as one of the best methods to deal with large data sets. The MLE is used by many statisticians but linear regression however is considered more accurate in terms of bias and random error. The chief deficiency of the MLE method is its lack of good graphical display of data.

Weibull plotting

Weibull plotting can be carried out on a Weibull probability paper which involves transforming the cumulative distribution function by successively taking logarithms of the basic probability equation. For convenience, equation (1) is given here again:

$$F(t) = 1 - \exp(-(\frac{t}{\eta})^{\beta})$$

Taking ln of the equation once,

$$\ln\frac{1}{1-F(t)} = (\frac{t}{\eta})^{\beta} \qquad (10)$$

Taking log of equation (10) again, we have:

$$\log\ln\frac{1}{1-F(t)} = \beta(\log t - \log\eta) \qquad (11)$$

Clearly Equation (11) is a straight line when being plotted. If it is represented by *y = mx + c*, then m is the gradient of the line and c is the intercept on the y-axis. This gradient gives the β value which determines the shape of the failure distribution. Correspondingly the value η can be obtained from value c, the intercept on y-axis and β using Equation (11). Obtaining the values of m and from the plot can be achieved with visual aids or by using specialist software packages.

It is to be noted that, when the approach is applied, the plot uses the log of time to failure for each data point (t in Table V) as x-axis and F(t) is taken as the cumulative percentage failed by the end of the subinterval. For example, At the end of month 8, if 6 items of a total of 24 failed in a complete set of samples (assuming all samples failed at the time of censoring), then F(t) = 6/24 = 0.25. Similarly at the end of month 88, if 18 out of a total of 24 failed, then F(t) = 18/24 = 0.75.

Estimation of the plotting position

The IEEE 930 standard [3] recommends the use of expected plotting which is in line with parameter analysis through linear regression.

$$F(t, N) = \frac{i - 0.44}{N + 0.25} \qquad (12)$$

Where, i is the failure number or rank of the event being analyzed and N represent the total failure events under analysis. Ranking is made from event with the lowest time to failure to the one with the highest value. Table VIII below shows an example of applying the Weibull plotting method to the data given in Table V.

TABLE VIII - CABLE FAILURE (THOSE DUE TO EARLY MORTALITY) DATA FOR WEIBULL MODELING

Fault No. i	t/ days	F(t)	$\ln[\ln \frac{1}{1-F(t)}]$	$\ln t$
1	5	0.0393	-3.2166	1.6094
2	43	0.1095	-2.1547	3.7612
3	65	0.1796	-1.6194	4.1744
4	194	0.2498	-1.2467	5.2679
5	259	0.3200	-0.9528	5.5568
6	262	0.3902	-0.7040	5.5683
7	354	0.4604	-0.4832	5.8693
8	620	0.5305	-0.2795	6.4297
9	730	0.6007	-0.0855	6.5930
10	968	0.6709	0.1056	6.8752
11	2100	0.7411	0.3009	7.6497
12	2629	0.8112	0.5112	7.8744
13	2744	0.8814	0.7571	7.9171
14	4250	0.9516	1.1078	8.3547

With the table of data entries, any specialist software packages can then be applied to fit the straight line to obtain the values of slope and intercept from which both β and η can be readily obtained. Figure 14 shows the fitting results using an Excel spreadsheet.

It is to be noted that only those failures due to manufacturing quality issues and poor installation practice have been considered here. Three cases where data records were not complete were also ignored.

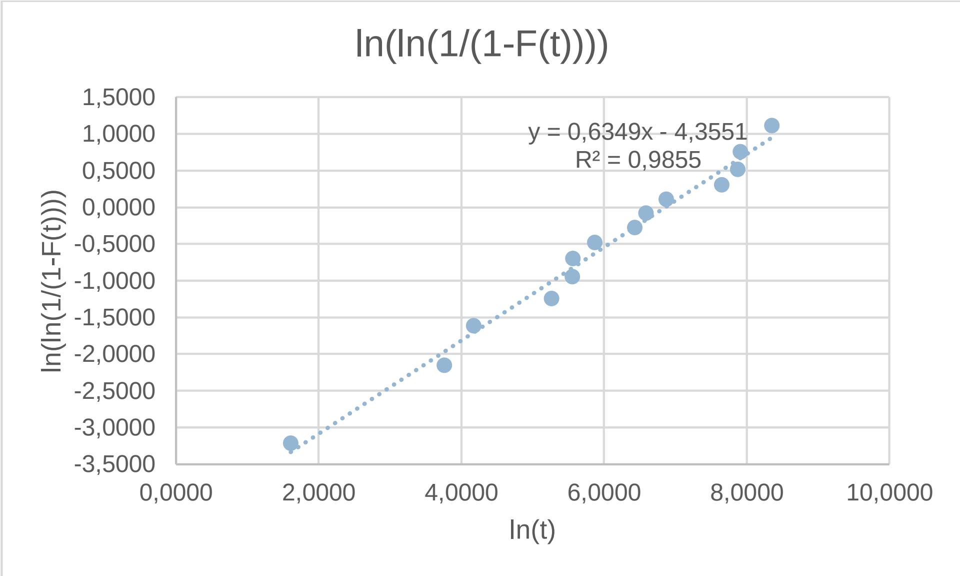


FIGURE 14 - THE FITTING RESULT OF THE WEIBULL DISTRIBUTION

The results of the model fit are shown Figure 14, with Adjusted R-square 0.9855. Here, Adjusted R^2 measures the quality of the data fitting process. The closer its value is to 1, the more accurate is the result of the curve-fitting. From the intercept of the fitting curve with y-axis and the slope of the fitting curve provided in Figure 14, the Weibull parameter estimates are obtained as β = 0.63 and η = 952 respectively. The shape parameter β < 1 indicates that the failure rate is decreasing with age for the cable population data under this analysis. The scale parameter η = 952 means that 63.2% faults happened before 952 days.

Dealing with suspended data

It is important to note that some items are removed or replaced without failure after acquiring some age and we can never know how much remaining life existed in the item as equipment fails on a probabilistic basis rather than a deterministic basis [35]. Data related to replacement without failure or failure in another failure mode are known as suspended data which is useful for reliability calculations. In statistical analysis it is better not to discard the suspended data as it can be useful to calculate more appropriate percentage of failures.

The procedure of dealing with censored data or suspended data is described in IEEE 930 [3]. For progressively censored data with a large percentage of discarded items the following approach is used.

$$I(i) = I(i-1) + \frac{n+1-I(i-1)}{n+2-C_i}$$

with $I(0) = 0$ and C_i the total number of broken down and suspended items.

The plotting position becomes:

$$F(i,n) = \frac{I(i)-0.44}{n+0.25} \qquad (13)$$

In summary, the procedure to analyze failure data with suspensions is as follows [35].

a. First rank the times, both failures and suspensions, from earlier to last.
b. Calculate the adjusted ranks for the failures (suspension data are not plotted).
c. Plot the failure times versus the median ranks on standard Weibull paper using software packages.
d. Estimate β and η.

Results shown in Figure 15, using the data of Table IX, agree with that the effect of taking into consideration of suspension data is usually an increase in the value of η, or the characteristic life, in this case from 952 to 4023, whilst β hardly changes [35], from 0.63 to 0.57.

TABLE IX – CABLE FAILURE DATA FOR WEIBULL MODELING INCLUDING SUSPENDED DATA

Fault No. *I*; *Suspension: S*	C_i	I(i)	t/ days	F(i,n)	$\ln\left[\ln\frac{1}{1-F(i,n)}\right]$	$\ln t$
S	1		0			
S	2		0			
1	3	1.0667	5	0.0201	-3.8992	1.6094
2	4	2.1333	43	0.0542	-2.8876	3.7612
3	5	3.2000	65	0.0883	-2.3809	4.1744
S	6		97			
S	7		125			
S	8		168			
4	9	4.4000	194	0.1267	-1.9988	5.2679
5	10	5.6000	259	0.1651	-1.7122	5.5568
6	11	6.8000	262	0.2035	-1.4804	5.5683
7	12	8.0000	354	0.2419	-1.2839	5.8693
S	13		562			
8	14	9.2632	620	0.2823	-1.1033	6.4297
9	15	10.5263	730	0.3228	-0.9423	6.5930
S	16		964			
10	17	11.8684	968	0.3657	-0.7869	6.8752
S	18		981			
S	19		1148			
11	20	13.4170	2100	0.4153	-0.6225	7.6497
S	21		2313			
12	22	15.1064	2629	0.4693	-0.4563	7.8744
S	23		2676			
S	24		2676			
13	25	17.2181	2744	0.5369	-0.2616	7.9172
14	26	19.3298	4250	0.6045	-0.0752	8.3547

S	27		4250			
S	28		4532			
S	29		5232			
S	30		6020			
S	31		6086			

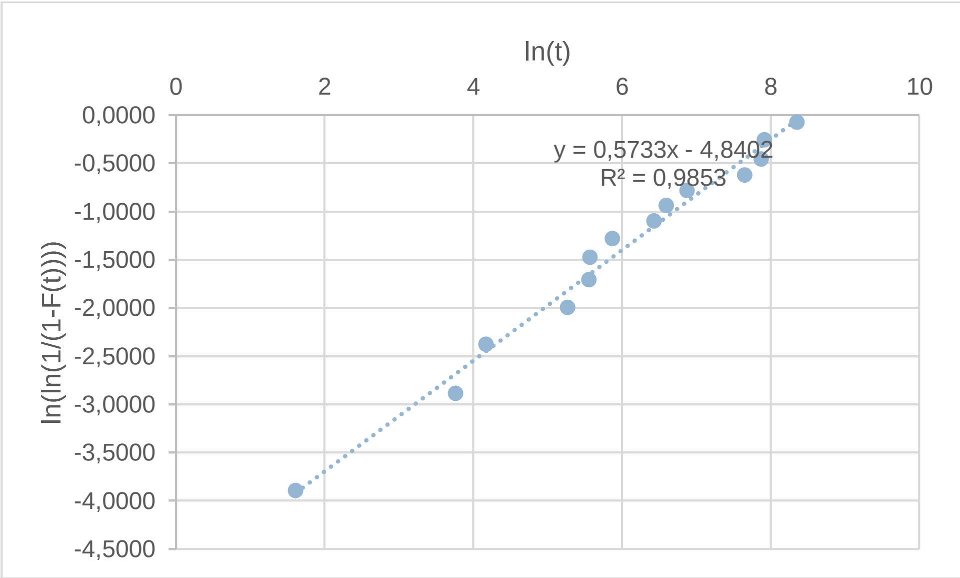


FIGURE 15 - THE FITTING RESULT OF WEIBULL DISTRIBUTION WITH SUSPENDED DATA

MLE based parameter estimation

The MLE method is to take an iterative approach to find the values of β and η which maximize the "likelihood" of obtaining the observed data. Almost all specialist probability software packages such as SPSS have the functionality of fitting the observed data to obtain the statistical parameters. With two parameters, the likelihood is a three dimensional surface shaped like a mountain. The top of the mountain locates the maximum likelihood value. The MLE values are the most likely to be the true values, as can be seen in Figure 16 where the horizontal slices through the surface represent the joint confidence regions for β and η. For example, the bottom slice might be 99% confidence, the next above 95% confidence and so on. In general, the higher up the mountain the more likely the parameters β and η coordinates are the true unknown values. This ability of produce confidence levels is an advantage of the method over the median rank.

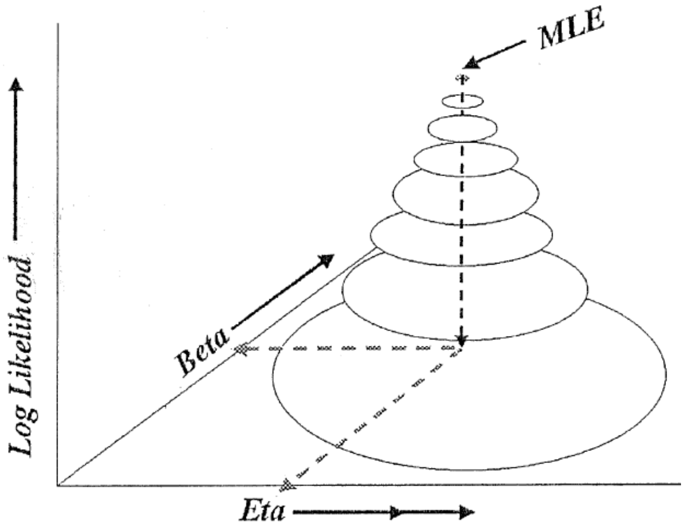


FIGURE 16 - THE WEIBULL LIKELIHOOD FUNCTION (REPRODUCED FROM [35])

Goodness-of-fit test

There are always discrepancies between the observed failure data and the statistical representations using characteristic parameters. Goodness-of-fit test is often applied to evaluate how well the chosen model has performed in fitting a set of observations.

Chi Square test is the most often applied method when the Weibull is adopted to model failure data and are used to forecast future failures. This is the technique which is often taken to determine whether the observed events data follow a specified distribution. It is a statistical hypothesis test in which the sampling distribution of the test statistic is a chi-squared distribution when the null hypothesis is true, or any in which this is asymptotically true, meaning that the sampling distribution (if the null hypothesis is true) can be made to approximate a chi-squared distribution as closely as desired by making the sample size large enough. The chi-squared distribution (also chi-square or χ^2-distribution) with k degrees of freedom is the distribution of a sum of the squares of k independent standard normal random variables. It is also applicable with the Crow-AMSAA model which will be introduced later. In both situations the test can be done using software functionalities with the result being either “Pass” or “Fail”.

In addition to the Chi-square test, many software packages such as ORIGIN or Excel provide another metric known as R^2 or adjusted R^2 which is given as a value between 0 and 1 [43]. The closer the adjusted R^2 value is to 1, the better the model is said to be a fit to the observed data.

Interpretation of results from Weibull modelling/plotting

With early mortality failures, the shape parameter $\beta < 1$ should stand, as early failures which are usually a result of manufacturing imperfection, poor installation or assembly practice and third-party damage, in normal situations, should be decreasing. The example given in Table VIII and Figure 14 belongs to early mortality failures where $\beta = 0.75$, and $\eta = 937$ days. This agrees with on-site evidences which indicate that early failures related to manufacturing and installation problems usually vanish in less than 5 year.

In the “useful life phase”, β should be approximately one, indicating a flat failure rate. Volume of failure is lowest among the three phases. The failures during the period are mainly due to overstress during operation, human errors introduced during maintenance, and third-party damages.

When $\beta > 1$, it means that failure rate is increasing. Reasons such as age-related material relaxation and moisture ingress attributes to failures in the "wear-out" phase. In mechanical plant items, $1.0 < \beta < 4.0$ implies early wear-out, covering failure modes of low cycle fatigue, bearing failures and corrosions, whilst $\beta > 4.0$ implies old age (rapid) wear-out. This may mean that failure rate increases rapidly and the entire fleet of the plant item will fail.

In electrical power systems, some plant items or equipment such as transformers and switchgears comprises many components, both mechanical and electrical ones. The overall failure rate of a plant item, which sums up that of each individual component including those replacements, tends to be more complicated in equipment unless there is a dominant failure mode. In comparison, failure rate in a system is even more complex as this is determined by the system configuration and reliabilities of individual equipment and components.

4.5 Failure forecast and predictions

In many countries, a good proportion of the power plant items were installed during 1950-1970s' economic expansion, which have expired or are fast approaching the end of their design life in some countries. A prediction of the number of failures that will occur in a fleet in the next period of time is highly desired as this allows maintenance planning and optimal replacement programme.

Failure forecast can be achieved simply using the Weibull or Crow-AMSAA (C-A) model, or via complicated analysis require Monte Carlo simulation. For both the C-A and Weibull models, the hazard function has to be monotonic, so the hazard function is either constant, increasing or decreasing. They do not apply to situations where the hazard function, say, increases with time, then decreases and then increases again. It is therefore recommended that, when statistics based analysis is carried out on insulation failure data for each individual plant items, failure events should be separated into three groups commensurate with the three phases in the "bathtub curve", namely, early mortality failures, useful life phase and age-related failures. Accordingly different models may be chosen for the prescribed purposes.

In this section, the Weibull and C-A approach will be introduced.

4.5.1 Failure forecasting based on Weibull model

Assuming that the failure functions F(t) and their parameters β, η have been obtained for a set of failure or life data. $\Sigma F(t_i)$ or the sum of the failure rate of the each plant item at current time t gives the predicted failure number at current time.

For failure numbers during a period between (t, t+k), forecasting can be made using equation (14):

$$\text{Expected failures} = \sum_{i=1}^{n} \frac{F(t_i + k) - F(t_i)}{1 - F(t_i)} \qquad (14)$$

Where $F(t_i)$ is the accumulated failure rate for the ith plant item up to time t and $F(t_i+k)$ represents the failure rate for the ith plant item at the time t+k.

Take the HV cable population as discussed earlier in the chapter as an example. Table X and Table XI below demonstrate a step-by-step procedure of making failure predictions for a period of 4 years using the Weibull model. Note that statistical parameters were obtained as β = 0.60807 and η = 937.8627 (see Figure 3). The adjusted R-square, or goodness-of-fit, was 0.98129.

TABLE X – FAILURE RATE CALCULATION FOR A PERIOD OF 4 YEARS

index	Time to failure (month)	F（t）	F（t+365）	F（t+365*2）	F（t+365*3）	F（t+365*4）
1	5	0.0021	0.0220	0.0320	0.0399	0.0466
2	43	0.0067	0.0232	0.0329	0.0406	0.0472
3	65	0.0085	0.0239	0.0334	0.0410	0.0476
4	97	0.0105	0.0249	0.0341	0.0416	0.0481
5	125	0.0121	0.0257	0.0348	0.0422	0.0486
6	131	0.0124	0.0258	0.0349	0.0423	0.0487
7	144	0.0131	0.0262	0.0352	0.0425	0.0489
8	144	0.0131	0.0262	0.0352	0.0425	0.0489

9	154	0.0136	0.0265	0.0354	0.0427	0.0491
10	154	0.0136	0.0265	0.0354	0.0427	0.0491
11	157	0.0137	0.0266	0.0355	0.0428	0.0491
12	157	0.0137	0.0266	0.0355	0.0428	0.0491
13	168	0.0143	0.0269	0.0357	0.0430	0.0493
14	170	0.0144	0.0269	0.0357	0.0430	0.0493
15	170	0.0144	0.0269	0.0357	0.0430	0.0493
16	182	0.0149	0.0273	0.0360	0.0432	0.0495
17	182	0.0149	0.0273	0.0360	0.0432	0.0495
18	194	0.0154	0.0276	0.0363	0.0434	0.0497
19	238	0.0173	0.0287	0.0372	0.0442	0.0504
20	238	0.0173	0.0287	0.0372	0.0442	0.0504
⋮	⋮	⋮	⋮	⋮	⋮	⋮
294	8369	0.1176	0.1202	0.1228	0.1254	0.1278
295	8369	0.1176	0.1202	0.1228	0.1254	0.1278
296	8369	0.1176	0.1202	0.1228	0.1254	0.1278

Further examples of the application of the Weibull model for life data analysis and replacement optimization will be provided in the chapter of case studies.

TABLE XI - PREDICTED NUMBER OF FAILURES OF THE HV CABLE POPULATION FOR A PERIOD OF 4 YEARS

year	Predicted number of failures
2012	1.940
2013	1.665
2014	1.500
2015	1.382

4.5.2 Failure forecasting based on Crow-AMSAA (C-A) model

When dealing with data of multiple failure modes, or a repairable insulation system is to be analyzed, C-A model is a better option. The model can be used to predict future failure numbers as well as evaluating optimal replacement programme

If the HV cable life data is analyzed using the C-A model, the procedure would be as follows.

TABLE XII - FAILURE DATA ANALYSIS USING C-A MODEL

Year	Number of failures in the year (N1)	Cumulative failures (N2)	Total cable length in km (L)	N1/L	$\sum$ (N1/L)
2004	2	2	118.17	1.692	1.692
2005	1	3	129.24	0.7738	2.466
2006	0	3	141.87	0	2.466
2007	2	5	181.19	1.104	3.570
2008	2	7	279.73	0.7150	4.285
2009	3	10	315.28	0.9515	5.237
2010	4	14	347.04	1.153	6.389
2011	0	14	381.81	0	6.389

Taking data regression using a software package it can be obtained that $\beta = 0.6749$ and $\lambda = 1.504$ as can be seen in Figure 17. Table XII shows that predicted total failures per year using the C-A model (Equation (15), where Δt = 1 year.) if the total cable length remains unchanged.

$$n(t+\Delta t) - n(t) = \lambda(t+\Delta t)^{\beta} - \lambda t^{\beta} \qquad (15)$$

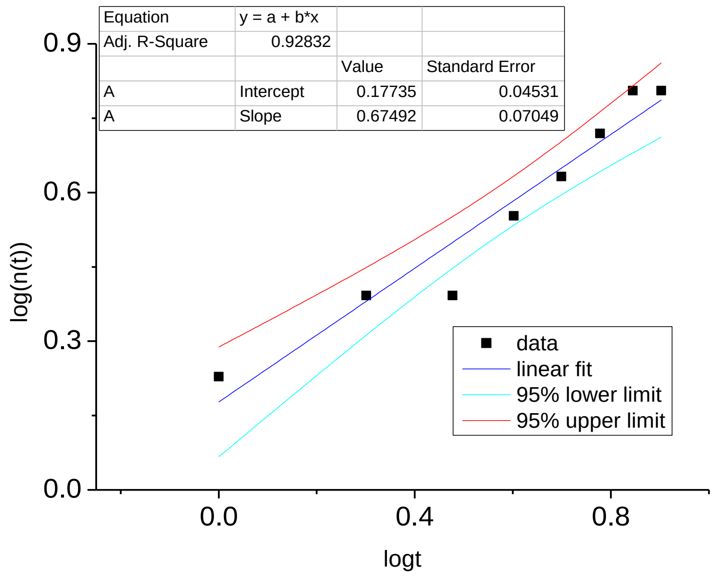


FIGURE 17 - DATA REGRESSION USING C-A MODEL

TABLE XIII - PREDICTED NUMBER OF FAILURES FOR A PERIOD OF 4 YEARS USING CROW-AMSAA

year	Predicted number of failures
2012	1.93
2013	1.87
2014	1.81
2015	1.75

It can be seen that, when comparing with the failure forecast results using the Weibull model, Table XIII resulted from the C-A model above gives a higher number. Fundamentally Weibull result is more reliable as it uses time-to-failure data in months for each individual case providing more data points when conducting data regression. In addition, the Adjusted R-square of 0.97 is better than in the case of C-A model where only 8 data points have been used with the Adjusted R-square of 0.92.

However, the C-A model can be very useful when making replacement planning as can be seen in reference [37].

4.5.3 Confidence interval

So far failure forecast has only yielded a point estimate, i.e., a single value of failure number for each given period in time given as the estimate. This may be insufficient in practical applications due to uncertainties which always exist. Hence, the concept of confidence intervals or confidence level (CI, or CL) needs to be introduced. Statistics software packages can use a given value of CI the predicted result consists of a range of values (interval) that act as good estimates. CI is usually given as

95% or 99%, meaning that there is a 95% or 99% of probability that the number of failures will fall within the predicted range of values.

This report will not go any further on the concept as CIGRE WG A3.06 and many other sources of reference can be obtained for more details. Failure forecast with introduction of CI will be demonstrated in the case study 1 in chapter 6 of the report.

4.5.4 Identification of contributing factors to failure ---The Cox-Proportional Hazard Model

The Cox-PHM can be used to identify the main factors contributing to failure. This is a good complement to the Weibull and C-A model as the results leads to improvement in design, installation and maintenance practice.

An example of how to apply the model will be provided in a case study in chapter 6.

5. THE EFFECT OF MAINTENANCE AND REPLACEMENT ON FAILURE STATISTICS

5.1 Introduction

Power equipment is designed, commissioned and goes into service and operates over long periods of time. Valuable assets of this type are important to their owners and for this reason most, if not all, utilities provide ongoing services to maintain the condition of the equipment as well as possible in order to maximize reliability and to sustain the assets for as long as economically justifiable. Maintenance services include routine checks, monitoring programs, diagnostic tests, routine maintenance, repairs, and refurbishment. Ultimately assets may be declared and end-of-life or they may fail in service and therefore need to be replaced. Figure 18 illustrates the typical asset condition/sustainment cycle [44].

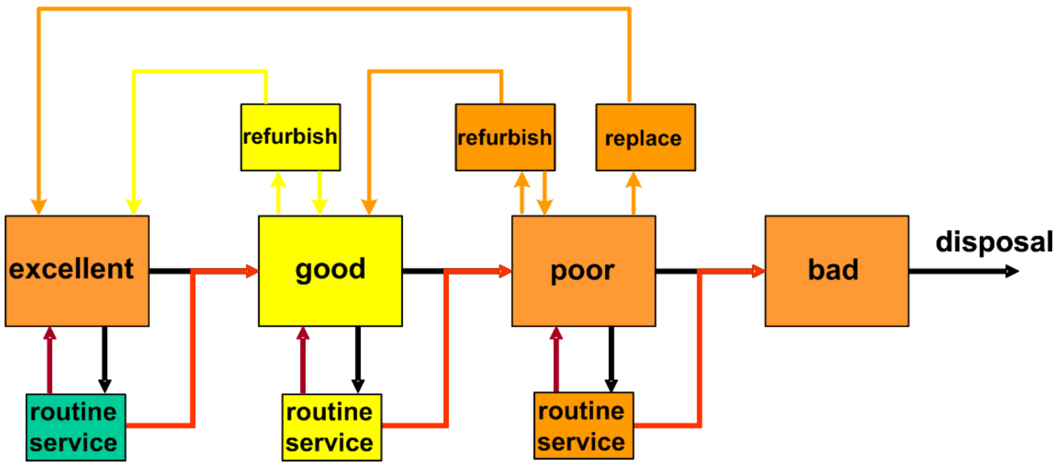


FIGURE 18 - TYPICAL ASSET CONDITION/SUSTAINMENT CYCLE

Maintenance services have a direct influence on equipment reliability, failure and failure statistics. In qualitative terms, too little maintenance, or ineffective maintenance generally will reduce asset life and increase the likelihood of premature failures. Sometimes too much maintenance or poorly performed maintenance can also increase outage statistics and in some cases, failure statistics. Replacement policies can also affect failure statistics depending on the definition of failure and the rationale for equipment replacement. For example, equipment may be replaced while its condition is good because its rating is not considered to be adequate because of growing load levels. Such an asset may be moved to another location or kept as a system spare. While on the other hand, an asset may be in poor condition serving critical loads and is replaced and scrapped because failure is considered to be imminent and the consequences of failure too severe. The former case need not be considered to contribute to failure statistics, while the latter case is effectively equivalent to a failure and therefore this replacement contributes to failure statistics. Typically, failure is defined as the state in which an asset can no longer perform its required function. This may occur when an asset fails in service and is damaged so badly that it cannot be returned to service and must be moved off site for either repairs or scrapping, or as in the latter case when an asset's condition is deemed to be such that continued operation is considered to be too risky and the asset is proactively removed from service and moved off site for repairs or scrapped. Therefore, understanding asset aging and failure processes and their interactions with maintenance, repair, refurbishment and replacement strategies is an important prerequisite for the interpretation and analysis of failure data.

In qualitative terms the effect of good maintenance practices has the effect of extending the life of assets and reducing in service failures. Routine maintenance includes such activities as visual inspections, routine diagnostic tests, lubrication of moving parts, cleaning of contaminated insulation or cooling systems, and so on. Simple visual inspections can detect such things as minor leaks, unusual noises or vibrations, contamination etc. Dissolved gas analysis, infra-red inspection, Doble testing, partial discharge testing, timing tests on breakers can detect potentially serious problems that could if not caught, result in failures. Repairs of such defects, while they may be routine, if not attended to, could lead to failures and the action of attending them results in avoided failure extended life and a corresponding effect on the failure statistics for the associated population of assets. **Fout! Verwijzingsbron niet gevonden.**Figure 19 illustrates an example from the Netherlands [44] related to failures of cable joints. An analysis of historical failure data and the population demographics provided projection of the number of failures to be expected going forward. In response the utility instituted a testing program which resulted in a significant reduction in the number of prospective failures.

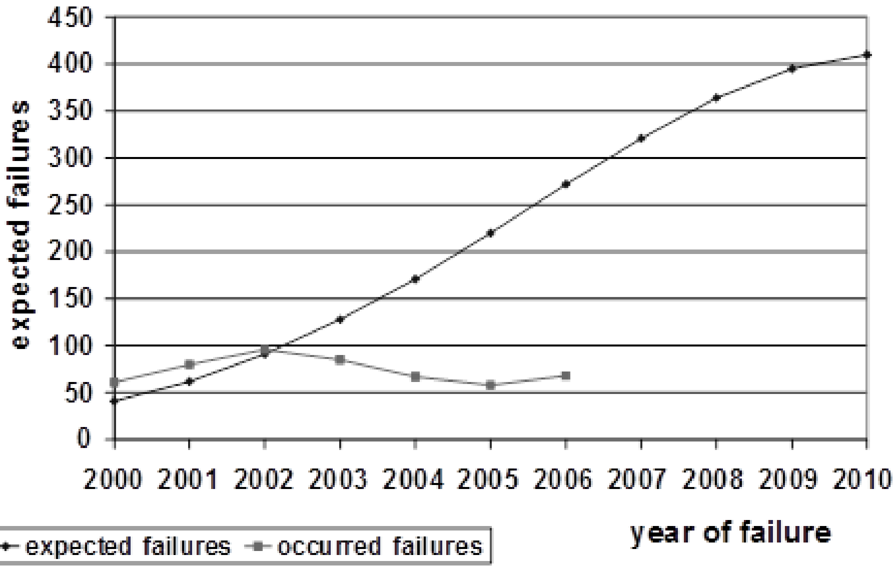


FIGURE 19 - NUMBER OF OCCURRED FAILURES AFTER INITIATING A JOINT TESTING PROGRAM COMPARED WITH THE EXPECTED NUMBER OF FAILURES BASED ON THE ANALYSIS OF THE FAILURE DATA 2000-2002

Similarly the investment in refurbishment of assets has the effect of extending life as illustrated in Figure 20**Fout! Verwijzingsbron niet gevonden.**. Refurbishment is a capital investment in an asset that is justified on the basis that it will defer the need to replace the asset by extending the life of an asset.

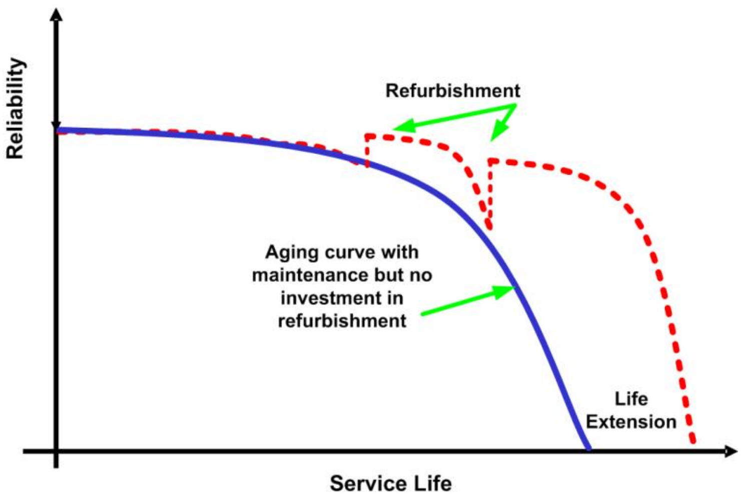


FIGURE 20 - REFURBISHMENT AS A METHOD FOR ASSET LIFE EXTENSION

Long-term transformer aging, characterized by deterioration processes in the primary insulation systems in the transformer, has been the focus of research for decades. Three interrelated stress parameters are involved. As illustrated in Figure 21, heating caused by losses under load, the and the condition of the insulation systems as related to the presence of oxygen and the presence of moisture conspire to break molecular bonds in the cellulose insulating materials and to react with the oil causing damage to the insulation system. Research on this topic, goes back to the early work of Montsinger and Dakin in the 1930's and 40's, which still forms the basis for industry standards. This well-known model can be used to illustrate the effect on failure statistics caused by the quality of maintenance provided to transformers, and as well the effect of refurbishment of transformers through drying and degassing the insulation systems.

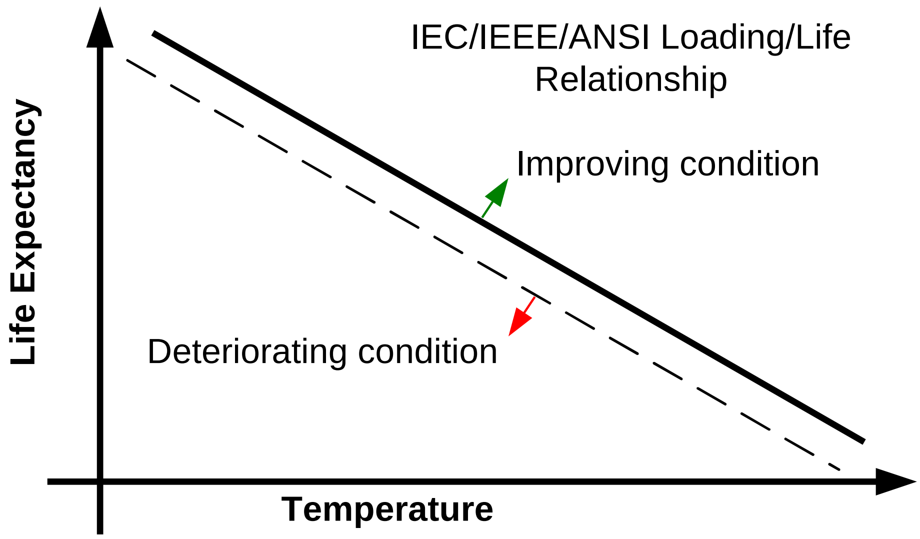


FIGURE 21 - CLASSICAL OIL/PAPER AGING CONCEPT

Based on this work, insulation life expectancy can be calculated as a function of temperature, and insulation system condition factors [49]. In practice, transformer loading varies over time and therefore the transformer insulation experiences a range of temperatures depending on the nature of the transformer application, its design and ambient conditions. Once the historical or planned statistical distributions for hot spot temperatures are determined, these can be transformed the using well known probabilistic transformation:

$$p(L) = p(T)/(dL/dT)$$

where:

$p(L)$ is the probability density distribution of expected life

$p(T)$ is the probability density distribution of hot spot temperatures

dL/dT is the derivative of the expected life expression L, with respect to T

Instead of using the relationships of Figure 21 in the usual way to transform single points, in this case, we transform the whole statistical distribution. Once the probability density distribution of expected life is obtained, the corresponding cumulative probability distribution and the hazard rate function can be obtained as shown in Figure 22 [50].

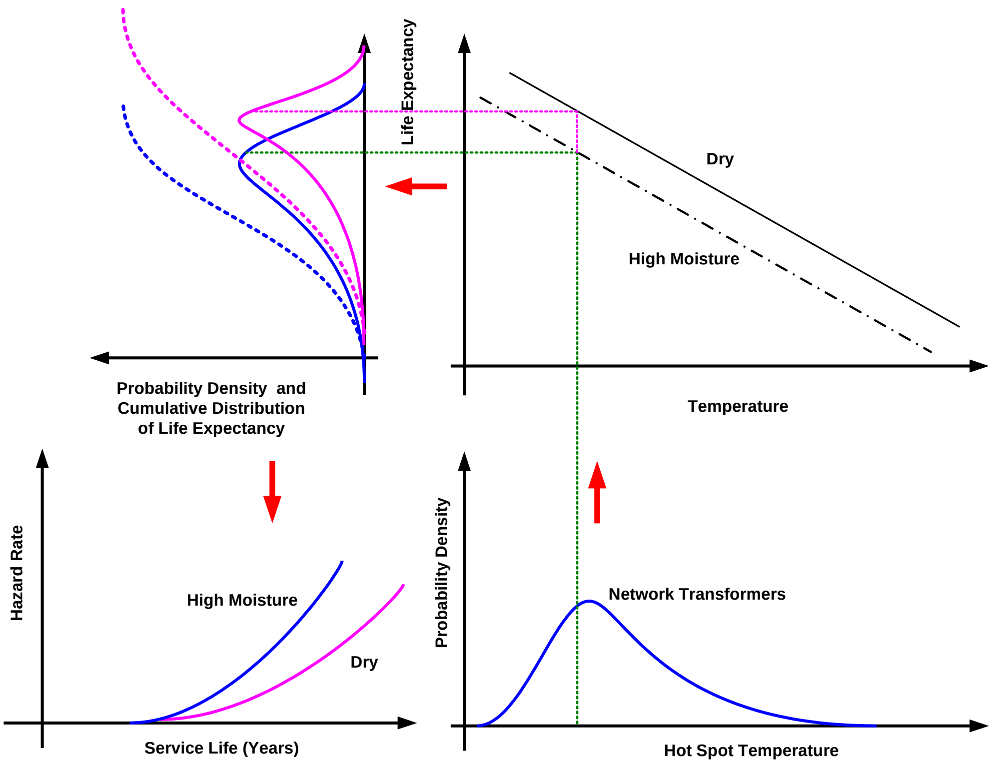


FIGURE 22 - TRANSFORMER LIFE EXPECTANCY MODEL BASED ON INDUSTRY STANDARD LOADING GUIDE, HOT SPOT TEMPERATURE DISTRIBUTION AND INSULATION CONDITION PARAMETERS

The hazard rate function is critical for subsequent business case analysis because it provides the probability of failure at each year of service, so that for a known demographic distribution of transformer ages, the expected numbers of failures or replacements for the fleet going forward in time can be calculated [51].

Analysis of typical time-based loading histories was carried out which indicated, as expected, that there is considerable variability in the statistical distributions for loading and therefore for the corresponding hot-spot temperature distribution. Overall for network transformers the data were well represented by an Extreme value Type I distribution with varying location and scale parameters. Such a distribution is illustrated in Figure 23 for a location parameter of 96 C and a shape parameter of 3 C.

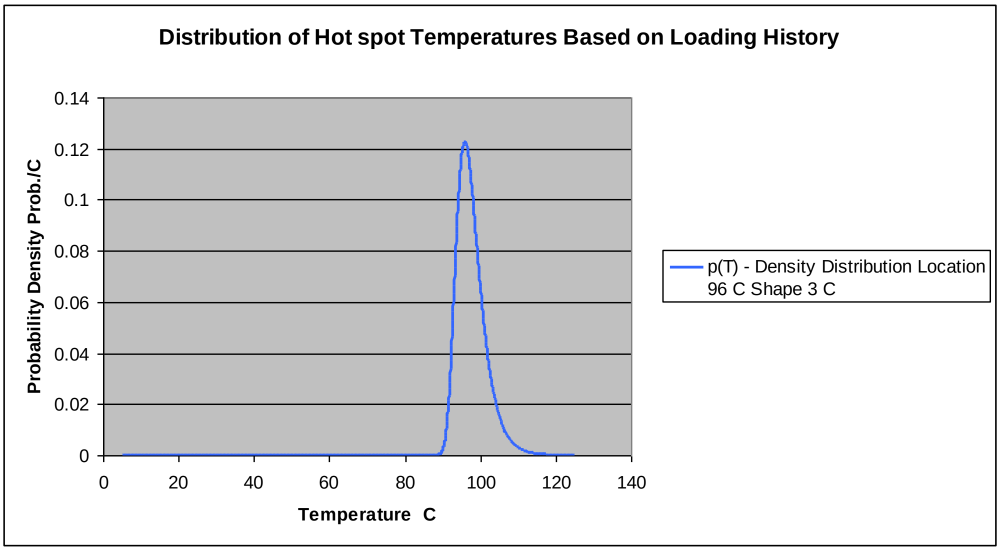


FIGURE 23 - EXAMPLE OF A TYPICAL HOT-SPOT TEMPERATURE DISTRIBUTION

The sensitivity of the condition with which a transformer fleet is maintained can be assessed by varying the insulation condition factors in the model. In this case, data on pre-exponential factors was summarized in [49] and these data have been used as a basis for the results shown in Figure 24. Again, as expected the factors associated with the condition of the insulation are significant. While it is un-realistic to expect that the insulation condition can be maintained in the clean and dry conditions which exist in the factory, utilities can employ a range of efforts to keep transformer insulation systems dry and as free of oxygen, moisture and other contaminants as possible.

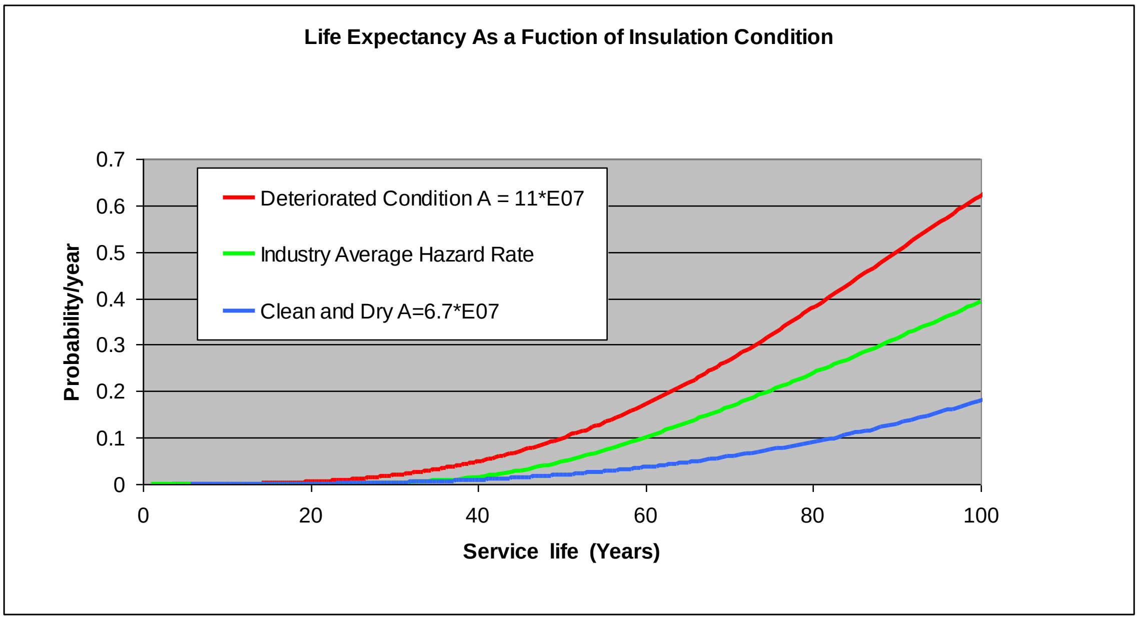


FIGURE 24 - SENSITIVITY OF HAZARD RATE FUNCTIONS WITH INSULATION SYSTEM CONDITION FACTORS

Should insulation systems be determined to be in a deteriorated state through routine testing, the question of investing in possible remediation or refurbishment becomes an option. As noted by Lundgaard et al [49] deterioration and aging processes in oil/paper insulation result in irreversible damage. The question then for asset managers is, if we invest in an insulation refurbishment program, how much improvement in reliability will be achieved and therefore is the cost justified by the savings associated with life extension? This can be assessed using the above models with a conditional probability based analysis to allow for the periods the insulation was deteriorated as opposed to a post refurbished state.

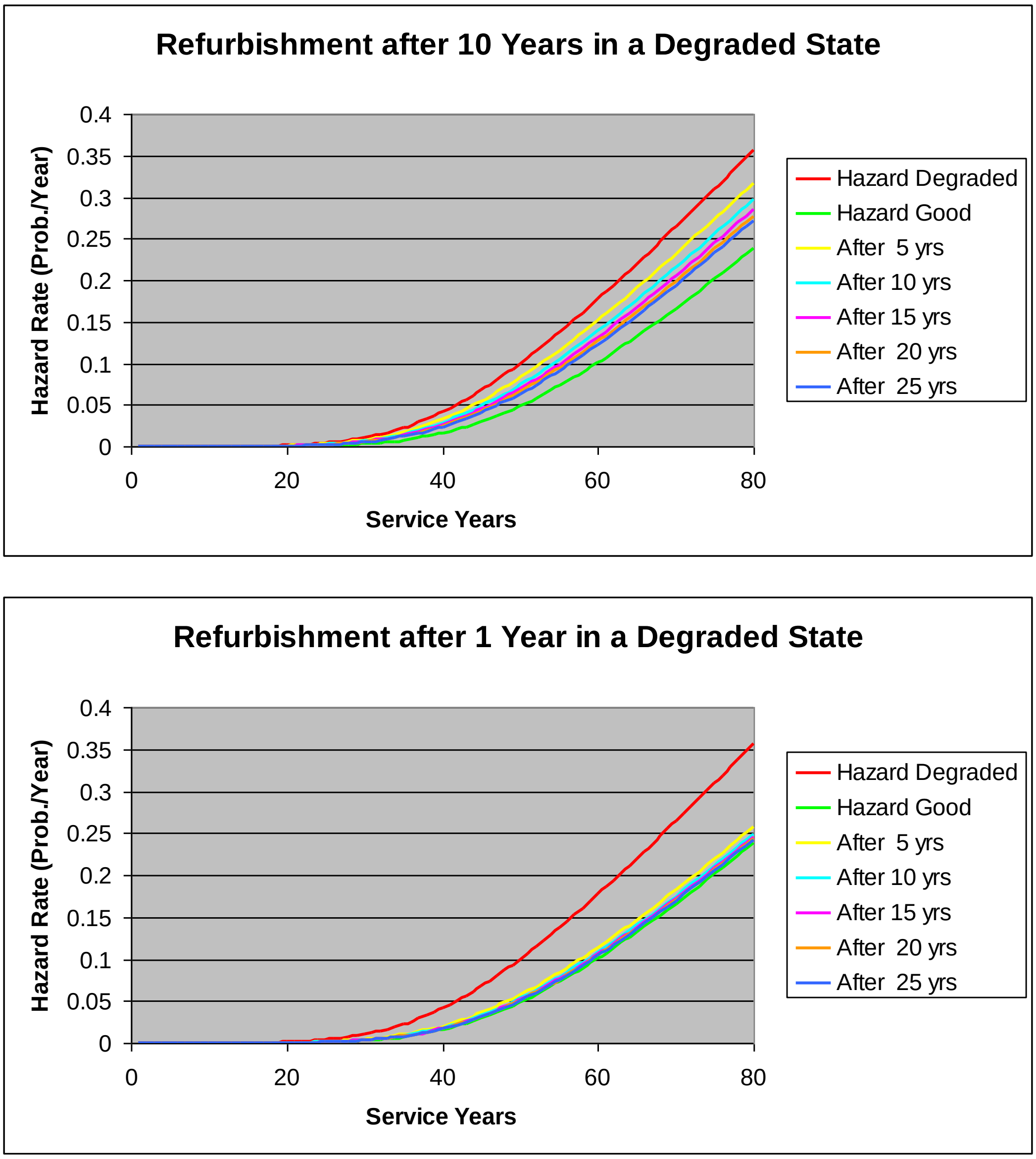


FIGURE 25 - REFURBISHMENT EFFECTIVENESS AS DETERMINED BY THE LENGTH OF THE DETERIORATED PERIOD

The results in Figure 25 illustrate the importance of maintaining insulation systems in a good state and if for some reason they become deteriorated, remediation is more effective if applied sooner rather than later. This type of analysis also of course, could be used to justify higher maintenance costs associated with procedures and/or accessories that would help prevent transformers from deteriorating to a state where refurbishment is required.

Lastly, asset managers have the option of proactively replacing assets before they fail or otherwise are deemed to be effectively at end of life. As discussed previously, proactive replacement may become an option if for example, an asset is in very poor condition and experts are of the opinion that failure is imminent, or if the costs of ongoing repairs, outages and consequential damage exceeds to incremental net present value of advancing the date of the capital investment, or if the asset can no longer be maintained because spare parts are not available or for several other reasons. Obviously maintaining a fleet of aged equipment that is near end of life and prone to failure, as compared with a fleet of relatively new assets will display differing failure statistics. An example of the effect of replacement on failure statistics is illustrated in Figure 26 [44].

This figure provides the results of an analysis of several replacement options for a population of cable joints. In this case, the analysis considered a continuation in operation of the population as is with no proactive joint replacements and this option is compared with options of replacing proactively 200, 500 or 750 joints per year over the planning period. The results indicate that the more joints are proactively replaced the lower the numbers of expected failures.

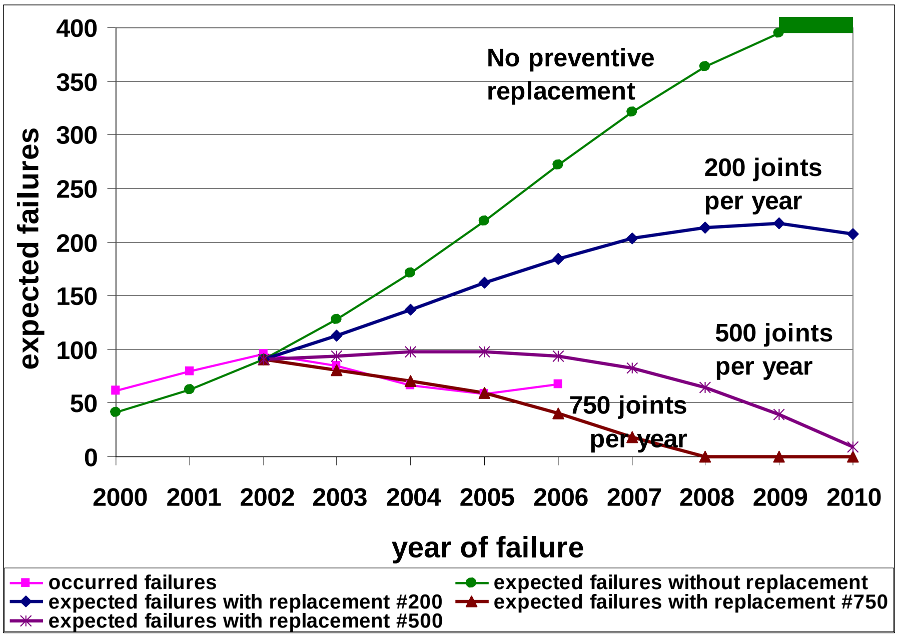


FIGURE 26 - EFFECT OF A PREVENTIVE REPLACEMENT STRATEGY OF A NUMBER OF THE OLDEST JOINTS IN SERVICE EACH YEAR ON THE EXPECTED FAILURES DEVELOPMENT FOR DIFFERENT NUMBER OF JOINT REPLACEMENTS [44]

5.2 Conclusions

There are inherent risks associated with each of the options available to asset managers. Mistakes can be made in carrying out repairs that lead to failures, refurbishment can be ineffective in reducing failure statistics, replacement with new equipment and designs can result in a whole new crop of infant mortality or generic failure modes. Fortunately, such unfortunate and inadvertent results are rare. In general, taking action through maintenance, routine repairs, refurbishment or ultimately replacement of assets, as opposed to following the "do nothing" or continue to run without risk mitigating actions options, will lead to positive effects on failure statistics.

6. CASE STUDIES OF FAILURE DATA ANALYSIS ON CRITICAL INSULATION SYSTEMS

In the following sections four case studies are described with an extensive description of the statistical approach used. This should give some guidelines on how to tackle practical situations.

6.1 Case Study 1: Analysis of Significant Factors on Cable Failure Using Cox Proportional Hazard Model

In China, the total length of power cables rated 10 kV and above has exceeded three hundred thousand kilometers, most of them being commissioned to urban power transmission and distribution systems over the last 20 years [52] due to the ever-increasing rate of urbanization. In major metropolitan cities, the hundreds of cable related failures which occur each year are mainly early mortalities.

Existing assessment and investigation of power cable failures are based on simple calculation of the number of failures per one hundred kilometers per year or number of failures per one hundred circuits, with considerations occasionally of voltage ratings, cable types [53] and cable lengths. The outcome of the analysis is often inconclusive as cable failures can be due to a number of factors such as poor practice in installation, manufacturing quality, aging and third party damage [54].

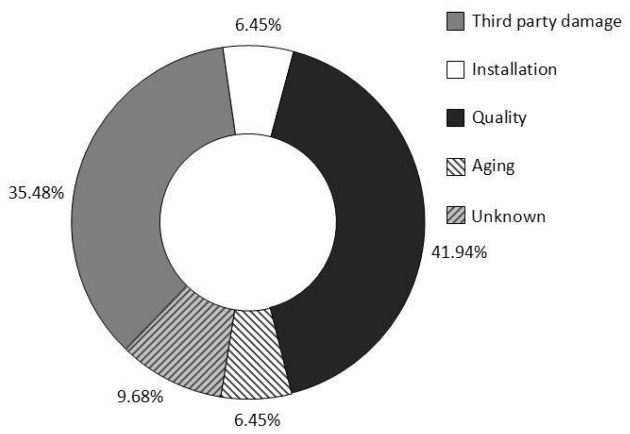
There is a strong need for a novel methodology which is capable of dealing with cable failures with which data is often inhomogeneous and associated with a number of causative mechanisms each, in turn, can attribute to a number of parties such as in a case where a manufacturing problem can be down to just one of the manufacturers. The technical advancement would provide guidance for future cable procurement, design, installation, cable asset management and maintenance. Also it would provide scientific proof in regard to who should have been responsible for the failures when legal disputes between manufacturers, installation service providers and network operators happen.

The Cox Proportional Hazard Model (PHM) was firstly proposed by Cox [59] in 1972 and widely used in the medical domain to study how influencing factors affected survival time of patients [60] and in reliability analysis [61][62]. Compared with other statistical models as mentioned above, the greatest advantage of Cox PHM is that it can consider the impact of more than one covariate simultaneously, which is exactly the feature required in analyzing those failure data related to early mortality among power cables as will be discussed in the next session.

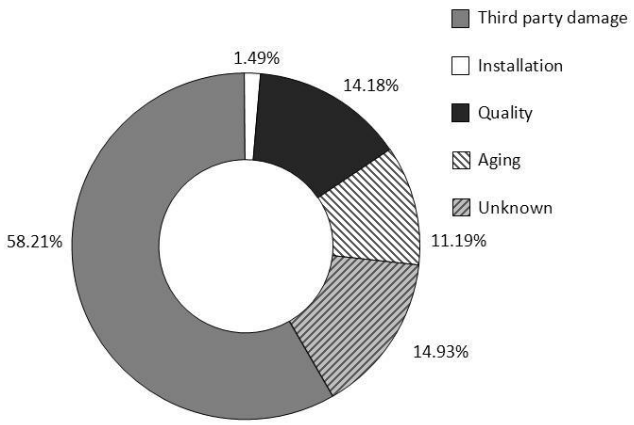
6.1.1 Cable Failure Data Collection and Analysis

Failure and life data are related to Medium Voltage (MV, rated at 10kV) distribution cables and High Voltage (HV, 110kV and 220kV) transmission cables that have been collected from a regional electricity company in China.

The HV cable data include a total of 285 cable circuits with a length of 409 kilometers and 1068 cable joints. 31 failures were registered during the period between January 2004 and December 2011.



(a) Composition of HV cable failures



(b) Composition of MV cable failures

FIGURE 27 - FAILURE DATA AND A BREAKDOWN OF FAILURE CAUSES

Among the 31 HV failures, 18 happened to cable joints with causative mechanisms being registered as manufacturing quality issues (13), poor installation practice (2) and unknown (3), whilst third party or external damage have mainly been responsible for the remaining 13 failures associated with main cables. With the MV cables, a total of 15538 MV cable circuits (10kV) with a length of 3871 kilometers. 134 failures were observed over the period from April 2011 to March 2013. There is a lack of details with regard to the number of cable joints and the number of failures which happened to cable joints.

For each of the HV cable joints, relevant information available include the date of commissioning, the manufacturer and the installer. For MV cable circuits, available information include the name of each of the circuits, the date of commissioning, the manufacturer the type of installation and the circuit length. The failure data, mostly early mortalities, include date and type (joint or main cable) of each failure and the cause of each of the failures. Further information extracted from data is presented in Figure 27 and a summary of the cable failure numbers.

With the available data records, cable failure mechanisms were categorized into poor practice in installation, manufacturing quality, aging, and third part damage [63]. However there are situations where reasons for failure were not identified and registered as “unknown”. As can be seen from Figure 27, of all the failures the percentages of unknown reasons are 14.93% and 9.68% for MV and HV cables respectively.

6.1.2 Cox Proportional Hazard Model

The Cox PHM was proposed to analyze time-dependent and time-independent covariates, along with a hazard function under analysis [65]. The Cox PHM function is given in Equation (16).

$$h(t,X) = h_0(t)\exp\left(\sum_{k=1}^{n_1}\delta_i \cdot X_k + \sum_{j=1}^{n_2}\gamma_j \cdot X_j\right) \qquad (16)$$

Where $h_0(t)$ is the baseline hazard function, X_k stand for time-dependent covariates and X_j represent time-independent covariates, whose regression parameters are denoted as δ_i and γ_j respectively, while n_1 and n_2 represent the number of time-dependent and time-independent covariates respectively. If the set of data under analysis obeys Weibull distribution [66],[67], then the baseline hazard function $h_0(t)$ can take the form of the Weibull model which has been a popular choice [66],[67]. In this case the model is known as a full parameter model. However, when the focus of an analysis is on relative importance of covariates on the hazard, then $h_0(t)$ can be hidden. In this case the model is referred to as half-parameter Cox PHM [68].

In this paper, only the half parameter Cox PHM model and time-independent covariates are considered. The objective of the current analysis is to identify those factors which are the most significant to cable failures. The mathematical expression function [68] is given in equation (17).

$$h(t,X) = h_0(t)\exp\left(\sum_{i=1}^{n}\beta_i \cdot X_i\right) \qquad (17)$$

X_i is the *ith* covariate that can have influence on cable failure, while β_i is the regression parameter that represents the weighting of the *ith* covariate on the failures. When β_i is positive, it means that *ith* covariate has a positive correlation with the failures. When β_i is negative, it means that *ith* covariate is negatively correlated with the failures. If β_i equals to 0, it means the covariate has no correlation with the failures. SPSS, a specialized statistics software, has been employed in the current work to evaluate β_i through regression analysis of the failure data. It is to be noted that although the hazard function $h_o(t)$ is still in Equation (17), it does not need to take a specific form and is ignored when failure data are analyzed in SPSS.

CABLE FAILURE DATA ANALYSIS

With cable failure data at hand, the procedure of carrying out Cox PHM based data analysis involves determination of covariates, setting of dummy variables, calculation of time-to-failures for each failed cases, and identifying significance of the influencing factors using SPSS. Further explanations of the procedures are given below in the section.

DETERMINING COVARIATES AND EVALUATION OF THEIR WEIGHTINGS IN THE COX PHM

Failure rate related to HV and MV cables have been analyzed separately. With the available data information, HV cable failures and cable joint failures can be identified, which is not the case with MV cable data.

TABLE XIV - COVARIATES TAKEN FOR

HV cable joints /covariates	Installer	Joint Manufacturer	
Covariates/symbol	HI (HI1~HI4)	HM (HM1~HM8)	

MV cable circuits/ covariates	Methods of installation	Manufacturer	Cable length
Covariates/symbol	MI (MI1~MI5)	MM (MM1~MM6)	ML (ML1~ML4)

With HV failures, only the 18 joint failures are to be dealt with. Those failures due to third party damage happen in a random nature and aging (cases are few due to the young age of the cable population) have been ignored. Further to information provided in Fig. 1, failures among HV cable joints were produced by 8 manufacturers, installed by 4 different installation companies. Information regarding the methods of installation for HV cables was unavailable and has not been considered. MV cables and cable accessories were produced by 6 manufacturers, installed in 5 different methods and cable length are divided into 0 - 0.5 km, 0.5 – 1 km, 1 - 1.5 km and >1.5 km. Methods of installation include “laid in cable trenches”, “directly buried”, “in cable conduit”, “overhead bridge” and “unknown”. The covariates of HV and MV cables are as shown in Table XIV.

SETTING DUMMY VARIABLES

A dummy variable is one that takes the value 0 or 1, indicating the absence or presence of the categorical effect of a covariate that may shift the outcome. If a covariate contains only two classes, for example, the human gender contains male and female, the dummy variable is unnecessary. In the case of, say, the covariate “length of cable” which include four classes that are (0 - 0.5 km), (0.5 -1 km), (1 - 1.5 km) and (>1.5 km), dummy variables are then necessary when SPSS is used to carry out data regression [18]-[20]. Take the covariate “cable length” as an example, cable lengths of (0 - 0.5 km), (0.5 – 1 km), (1 - 1.5 km) and (>1.5 km), are recorded as 1 to 4 respectively. According to the rules of setting dummy variable, when cables of an arbitrary length group, say, (0 - 0.5 km) or ML1, is chosen as the base for analysis, then the other three length group (ML2, ML3, ML4) are dummy variables. The codes of dummy variables can be formed for use in SPSS as given in Table XV. Although the other length group can also be chosen as the base, the results will be the same. These procedures will be applied to other covariates and will not be repeated here.

TABLE XV - CODES OF DUMMY VARIABLES IN SPSS WHEN ML1 IS ASSUMED AS THE BASE

Length of cable/km	(ML2)Length of cable(1)	(ML3)Length of cable(2)	(ML4)Length of cable(3)
0 - 0.5 (base)	0	0	0
0.5 - 1	1	0	0
1 - 1.5	0	1	0
> 1.5	0	0	1

CALCULATION OF TIME-TO-FAILURE AND CENSORED TIME

The data collected are the so-called “censored data” in statistics. This means that data include both cables with and without failures till the day data was collected. The collecting date of HV and MV cables were 1st, Dec., 2011 and 27th, Feb., 2013 respectively. If a cable had failed before the collecting date, then the time-to-failure of the cable can be calculated. With those cables still in normal operation till the collecting date, then censored life time of a cable is calculated. An example of the data set associated with HV cable joints after pre-processing of data and before carrying out regression is provided in Table A in the Appendix at the end of case study.

ANALYSIS OF SIGNIFICANCE OF INDIVIDUAL COVARIATES

When a particular covariate is analyzed to assess whether it has a significant effect on the failures, Hypothesis Test [72] is applied. The Hypothesis Test includes a null hypothesis and an alternative hypothesis. The p-value [73], a statistical tool for significance testing, is adopted here in the Hypothesis test. A predetermined significance level is set as 0.05 here, meaning that, when the p-value is below 0.05, the null hypothesis is refused because the chance of the null hypothesis being true is too small. However when p-value is greater than 0.05, null hypothesis should be accepted. Here the null hypothesis is taken as “a covariate’s β value (as shown in equation (17)) is equal to 0” and the alternative hypothesis being “the covariate’s β value does not equal to 0”. The covariate’s β value is estimated using the Maximum Likelihood Estimation method.

ANALYSIS OF HV CABLE JOINTS

Table XVI illustrates the results produced from the regression analysis of failure data using SPSS, where SE is the standard error of β. Wald is the value of Wald statistics in hypothesis test in software package SPSS. DF is the degree of freedom. SIG is the p value of hypothesis test. Exp(β) signifies the relative risk. 95% CI means 95% confidence interval. The “backward stepwise” option has been chosen in SPSS in order to delete the covariate which is not significantly correlated with failure.

TABLE XVI - ANALYSIS RESULTS OF HV CABLE JOINT

Covariate	*β*	SE	Wald	DF	SIG	Exp(*β*)	95.0% CI for Exp(*β*)	
							lower	upper
Step1 HI			4.695	3	0.196			
HI1	-2.562	1.307	3.840	1	0.050	0.077	0.006	1.00
HI2	-1.704	1.255	1.845	1	0.174	0.182	0.016	2.127
HI3	-1.354	1.235	1.202	1	0.273	0.258	0.023	2.906
HM			12.795	7	0.077			
HM1	1.867	1.376	1.842	1	0.175	6.469	0.437	95.868
HM2	2.248	0.936	5.765	1	0.016	9.471	1.511	59.35
HM3	3.533	1.172	9.087	1	0.003	34.218	3.441	340.25
HM4	-10.104	1123	0	1	0.993	0	0	
HM5	-11.365	751.2	0	1	0.988	0	0	
HM6	2.013	1.358	2.195	1	0.138	7.482	0.522	107.2
HM7	0.963	0.910	1.118	1	0.290	2.619	0.440	15.593
Step2 HM			18.218	7	0.011			
HM1	2.063	1.241	2.764	1	0.096	7.871	0.691	89.631
HM2	2.043	0.818	6.232	1	0.013	7.711	1.551	38.337
HM3	3.544	1.035	11.736	1	0.001	34.609	4.556	262.91
HM4	-10.651	1119.9	0	1	0.992	0	0	
HM5	-11.290	849.29	0	1	0.989	0	0	
HM6	1.885	1.234	2.331	1	0.127	6.584	0.586	73.99
HM7	0.611	0.837	0.533	1	0.465	1.842	0.357	9.496

Two steps have been taken in SPSS. In step 1, the significance of covariates HI and HM were analyzed simultaneously. The SIG values of covariate HI and HM were found to be 0.196 and 0.077 respectively, both being greater than 0.05. HI is ignored in the process of “backward stepwise” regression because the SIG value of HI is greater than that of HM.

In step 2, only the covariate HM was analyzed. It can be found from Table V, for HM2 and HM3, the SIG values were 0.013 and 0.001 respectively, both less than 0.05. For all the other covariates, as SIG values were greater than 0.05, their effects were assumed as insignificant and therefore ignored.

For HM2, its Exp(*β*) value was 7.711 meaning that the failure hazard of the cables manufactured by manufacturer 2 (HM2) was 7.711 times of manufacturer 8 (HM8). Meanwhile, the Exp(*β*) value of HM3 is 34.609 which means that the failure hazard using the cable joints produced by the 3rd manufacturer (HM3) was 34.069 times higher than manufacturer 8 (HM8).

It can be concluded that manufacturer 2 (HM2) and manufacturer 3 (HM3) were significantly and positively correlated with the failures. The installation companies and other manufacturers were found to be less correlated with the cable joint failures. It is worth noting that the particular cable joint manufacturer (HM3) eventually accepted its responsibility in the failures after a long standing legal dispute.

ANALYSIS OF MV CABLE CIRCUITS

As shown in Table XVII, the SIG values of covariate MI, MM and ML were all zeros. So no covariate should be ignored.

TABLE XVII - ANALYSIS RESULTS OF MV CABLE CIRCUIT

Covariate	β	SE	Wald	DF	SIG	Exp(β)	95.0% CI for Exp(β)	
							lower	upper
Step1 MI			20.155	4	0			
MI2	0.006	0.319	0	1	0.986	1.006	0.538	1.879
MI3	-2.306	0.532	18.81	1	0	0.100	0.035	0.283
MI4	0.824	0.745	1.225	1	0.268	2.280	0.530	9.816
MI5	-13.187	821.56	0	1	0.987	0	0	
MM			68.592	5	0			
MM2	0.239	0.280	0.730	1	0.393	1.270	0.734	2.199
MM3	1.445	1.032	1.960	1	0.161	4.242	0.561	32.078
MM4	2.227	0.323	47.476	1	0	9.270	4.920	17.465
MM5	-0.163	0.648	0.063	1	0.802	0.850	0.239	3.024
MM6	-12.065	176.14	0.005	1	0.945	0	0	4E144
ML			67.274	3	0			
ML2	1.022	0.279	13.389	1	0	2.778	1.607	4.802
ML3	2.094	0.279	56.136	1	0	8.118	4.694	14.039
ML4	1.191	0.393	9.177	1	0.002	3.290	1.523	7.109

It can be found that the SIG values of MI3, MM4, ML2, ML3 and ML4 were 0, 0, 0, 0 and 0.002 respectively, all being less than 0.05. In order to identify the most significant variable from ML2, ML3 and ML4, their Exp(β) values were compared. ML3 was the most relevant with failure because the Exp(β) value of ML3 was found to be the greatest.

From the above results, it can be concluded that installation method 3 (MI3), manufacturer 4 (MM4) and cable length of between 1 km and 1.5 km (ML3) were significantly correlated with failures. Cables laid in conduit should be recommended when cables are installed, while Manufacturer 4 (MM4) should be the last name to be recommended in future cable procurement. A higher failure rate has been found to be associated with cables with a length between 1 km and 1.5 km. The reason is due to the higher number of third party damages.

Discussions

1. *The Impact of Sample Size*

It was found during the investigations that PHM based analysis results depend greatly on the data sample size at hand. Take the HV cable joints as an example, the total number of cable joints was 1068, while the number of failed cable joints was 18. When the sample size of 18 was taken, i.e. only failed cable joints were considered as cable joint samples, during evaluation of covariate HM3, the significance value was found to be 0.460. While all the 1068 cable joints were taken as the data sample, the SIG value of covariate HM3 was 0.001 which was less than 0.05, meaning that the covariates had effect on failures. Clearly the correct data sample should be taken if meaningful results are to be generated.

2. *The Effect Due to Third Party Damage on Analysis Results*

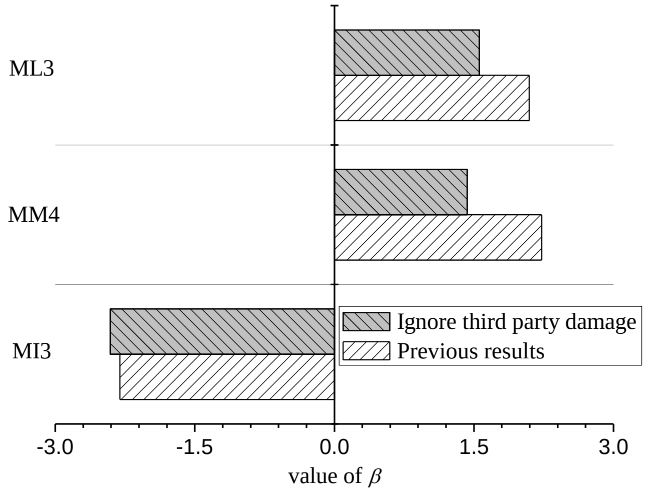


FIGURE 28 - EFFECTS OF SIGNIFICANT FACTORS WITH AND WITHOUT CONSIDERATION OF THIRD PARTY DAMAGE

Failures are occasionally caused by third party damages. However the category of failures encompass a variety of failure symptoms, with which some cables suffered instant failures and some failures occurred years after damage. The reason that cases of third party damages have been taken into consideration in the case study was because they were related with installation methods and cable length. For example, a cable is more likely to be damaged by rodents if a cable is directly buried. Also the longer the cable length, the higher is the probability of third party damages. With regard to the significance of factors such as "manufacturer", ignoring failures due to third party damage may yield more useful results.

In order to assess the effect of failures due to third party damage on analysis results, the "state" of MV cables that failed due to third party damage were changed to 0. In other words, these cables were taken as being still in normal operation. The other settings were left unchanged. The significances of covariates MI3, MM4 and ML3 were compared with previous results. As can be seen from Figure 28, the relative risk of covariates MI3, MM4 and ML3 decreased.

Conclusions

The case study presented a Cox PHM based approach to analysis of early mortality failure data and demonstrated that the model can help to quantify the degree of the effect of the selected covariates on cable and cable joint failures. It is capable of providing accurate and decisive verdict on the outstanding factors such as a particular manufacturer and/or an installation method which are responsible for the failures especially when more than one factor has influences on cable failures. The model should help asset managers to deal better with early mortality failures as the model can help to identify weak links, with scientific proof, in the procedure of procurement, design and installations.

Compared with Weibull distribution, Cox PHM is more adaptive and robust because it is a semi-parameter model which does not need to know the distribution of data. The covariates used in Cox PHM should contain the entire cable sample. Otherwise, analysis can lead to misleading results.

Appendix

Table A

Data input to SPSS (HV cable)

No	Time-to-failure/ censored time	Installer	Joint manufacturer	State of cable
1	2100	2	8	1
2	620	3	3	1
3	6020	2	2	0
4	6086	3	1	0
5	2676	3	1	1
6	2676	2	2	1
7	-19	3	5	1
8	43	3	7	1
9	65	2	7	1
10	4250	1	2	1
11	262	4	8	1
12	0	3	3	1
13	730	3	7	0
14	97	2	7	0
15	4250	3	2	1
16	168	2	4	0
17	354	3	7	1
18	981	3	7	0
19	2629	3	7	1
20	2313	1	7	0
21	4532	2	7	0
22	259	2	6	1
23	194	1	2	1
24	5	1	7	1

25	125	2	7	0
26	5232	3	2	0
27	968	3	2	1
28	2744	3	2	1
29	964	1	7	0
30	1148	2	7	0
31	562	2	7	0
⋮ ⋮	⋮ ⋮	⋮ ⋮	⋮ ⋮	⋮ ⋮
1068	1198	4	8	0

(Note: In the final column of the table, the cable has failed when its "state" is given as 1 and is still in healthy or operational condition when it is 0.)

6.2 Case Study 2: Application of statistical life data analysis for 10 kV cable joint populations in the Netherlands

6.2.1 Background

Asset failures, that need to be managed, have an uncertain behavior and therefore the analysis of uncertainty is essential for strategic, tactical and operational activities within asset management. Stedin, a Dutch Distribution Network Operator (DNO) recognized the vital role of having access to systematic techniques and guidelines on how to deal with information of equipment lifetimes. In this case study a systematic method as described in chapter 4 which deals with limited or incomplete life time data of large populations of 10 kV cable joints with the aim of obtaining an indicator of the future failure expectancy, is discussed. The methods and analytical tools developed in this contribution share a basic framework for decision-making and specify the evolution of the failure of cable joints over time.

This case study summarizes references [74][75],[77],[76].

6.2.2 Medium Voltage (MV) Distribution Network

The medium voltage (MV) infrastructure in the Netherlands is almost 100% realized by means of underground cable systems (approximately 100.000 km). Historical data indicates that the most dominating component related failures (85%) are observed for MV cable systems. A cable system consists of a cable part, cable joint and cable termination. A vast majority of the distribution grid outage times is due to failures in MV cable joints (45%). A case study for the application of statistical life data analysis was carried out for a particular region of 10 kV distribution network of Stedin. Three types of 10 kV cable joint populations are investigated. The three categories are based on the principle of joint insulation used. These three categories are:

- Mass insulated joints (liquid mixture of oil and resin)
- Oil insulated joints
- Synthetic insulated joints

Different insulating materials have different aging mechanisms, which should be distinguished when performing statistical studies (homogeneity). The number of 10 kV cable joint failures resulting in power delivery outages in this region is high compared to other regions. The available population and failure data for this region has been recorded with more accuracy in the past, which makes it useful for statistical analysis.

6.2.3 Available 10 kV Cable Joint Data

6.2.3.1 FAILURE DATA COLLECTION

Paper-based outage (failure) data recording started, partly, around 1976 in the Netherlands, followed by a database collection tool in 1991 named "Kema Nestor". At the time that this case study was performed, the available MV failure data for the period 2004 until 2009 had been consistent and could be used in a viable way. The development of failure data recording is shown in Figure 29.

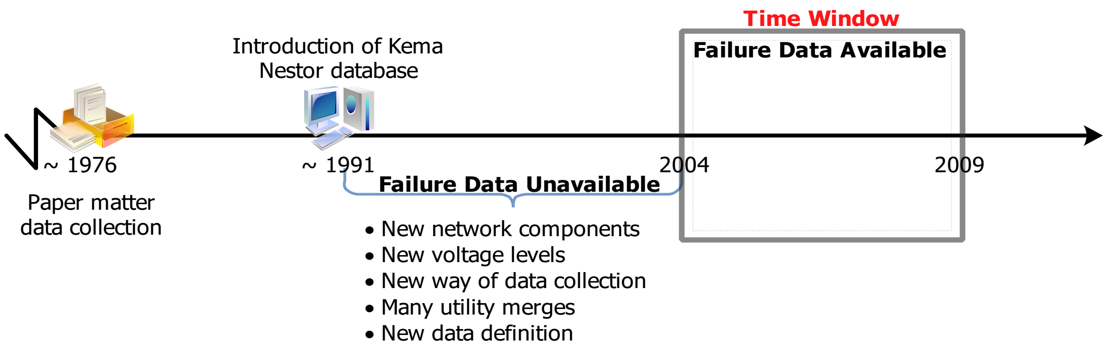


FIGURE 29 -TIMELINE SHOWING THE AVAILABILITY OF FAILURE DATA IN DISTRIBUTION NETWORK FOR THIS STUDY. THIS TIME WINDOW REFLECTS THE PERIOD WHERE FAILURE DATA IS AVAILABLE. IN BETWEEN, FAILURE DATA IS OFTEN MISSING OR INCOMPLETE

The available failure takes into account roughly 556 reported cable joint failures, within the last 6 years. It happens often that the exact age of the cable joint at the moment of failure is unknown to the utility. To be able to take these incomplete data into account, estimated age intervals for the reported failures are used to circumvent this issue. This is shown in Figure 30 for the three categories of cable joint populations.

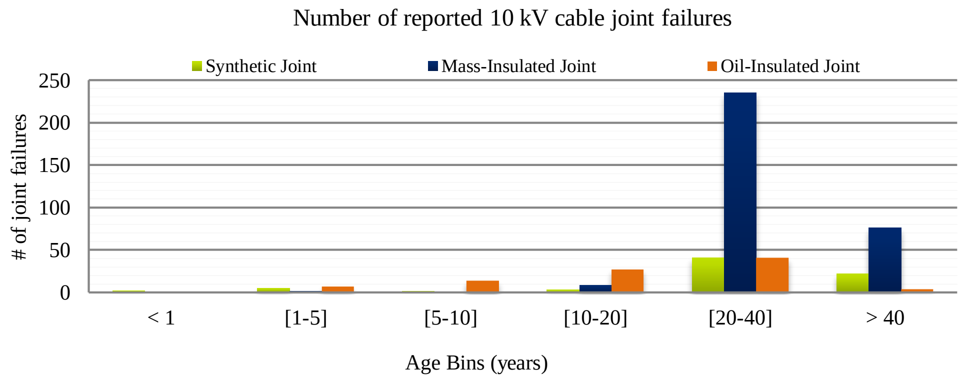


FIGURE 30 - 10 KV JOINT FAILURE RECORDS FOR THE PERIOD 2004-2009 FOR THREE CATEGORIES OF CABLE JOINTS. AS RESULT OF UNKNOWN EXACT AGE AT THE MOMENT OF FAILURE OF A COMPONENT, AGE INTERVALS ARE USED TO ESTIMATE THE AGE OF THE FAILED COMPONENTS

6.2.3.2 IN-SERVICE DATA COLLECTION

Besides failure data, information regarding the un-failed cable joints is used. The total recorded population of all three types of cable joints is roughly 31700 pieces. During this case study two issues with missing and incomplete data had to be dealt with. Firstly, for large portions of the joint population the exact age (year of installation) is not specified or unknown. Such records are often missing for assets that were installed more than 20 to 30 years ago. Secondly, for some parts of the cable joint population the corresponding joint type is unknown. The first shortcoming is dealt with by dividing the number of joints without age, proportionally, and adding these joints to the joints installed in particular years (conceptually shown in Figure 31). A formula developed for this procedure is:

$$New\ \#\ of\ joints_{age,i} = \left(\frac{recorded\ \#\ of\ joints_{age,i}}{total\ \#\ of\ joints\ with\ age} \times Total\ \#\ of\ joints\ without\ age\right) + recorded\ \#\ of\ joints_{age,i} \quad (18)$$

The second shortcoming is dealt with by using information, based on expert knowledge, regarding the historic application of certain joint types. These experts still have knowledge regarding the history of when a certain type of joint was taken into operation (conceptually illustrated in Figure 31). As a result, it was possible to make rough estimations of the missing records and incorporate these in the statistical analysis.

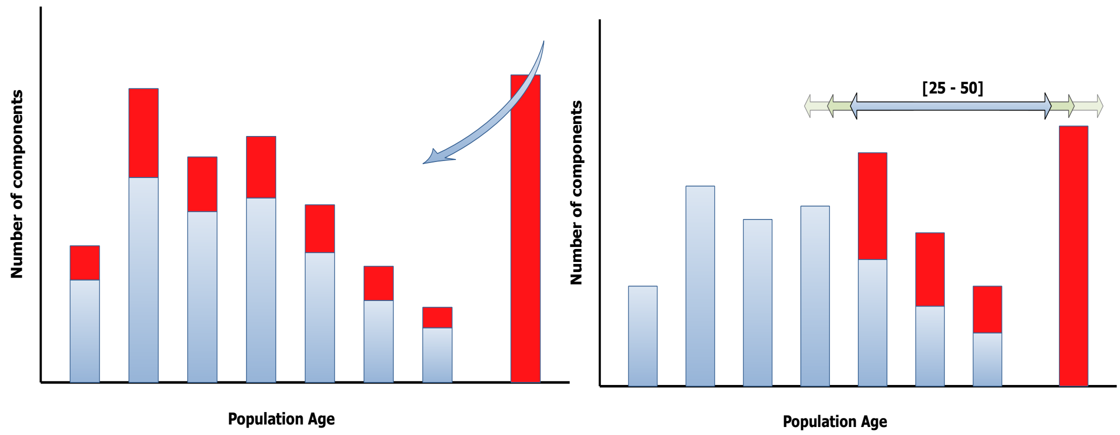


FIGURE 31 - SIMPLIFIED IMPRESSION FOR THE ESTIMATION METHODS WHICH ARE APPLIED TO INCORPORATE THE MISSING DATA (MISSING ASSET INSTALLATION YEAR)

6.2.4 Statistical Life Data Results and Interpretation

6.2.4.1 PROCEDURE

The systematic approach, which is described in chapter 4, was used for modelling the life data of this case study. The parametric distribution fitting method was applied. The available failure data and in-service data of the three types of cable joint populations was used as input. For the statistical calculations the software tool *Reliasoft Weibull++* was selected. Based on this statistical analysis of the available life time data and, not to be neglected, engineering knowledge the corresponding failure distribution (probability model) are selected.

Basically, the next straightforward steps cover the procedure for life data analysis:

1. Failure and In-service data collection and preparation for statistical analysis
2. Failure distribution parameter selection
3. Goodness-of-fit tests (used to diagnose if the fitted statistical distribution matches the data)

4. Confidence bounds (is used to indicate the estimated range of values which are likely to include an unknown population parameter)
5. Selection of the best fit (selected failure probability model)

It should be mentioned that for step (2) the Maximum Likelihood Estimation (MLE) method for parameter selection is used. MLE has the ability to take into account large numbers of suspensions (explained in chapter 4) and large data sets. It is reported, that MLE is asymptotically consistent, which means that as the data sets get larger, the estimates converge to the true value.

6.2.4.2 RESULTS FOR 10 KV CABLE JOINTS

The failure rate (*λ(t)*) and probability density function (*pdf*) allow different assets to be compared with other. In Figure 32 and Figure 33 the *pdf* curve and the failure rate curve are shown, respectively. From Figure 32, the density of failure probability can be examined for the three different cable joint groups. The peak value of the *pdf* curve for the synthetic insulated cable joint (green) is higher than the remaining ones. Typically, this illustrates that synthetic insulated cable joints have a higher probability of failure when the components age is near the peak value (mean life).

From Figure 33, it can be seen that the failure behavior is different for each population of cable joints. For all three populations their failure rates rise over years according to the increasing right wing of the bathtub curve. Additionally, it can be seen that the populations' age quite similarly, however, the rate of rise of the failure rate with equipment age differs from each other. Subsequently, the failure behavior of oil insulated joints (red line) and of mass insulated joints (blue line) differs from each other, even though they belong to the group of filled cable joints. An important reason why the failure rates for the oil insulated cable joints are higher can be the result of lower liquid levels in the oil type joints. As mentioned in [78], a lowered liquid level in joints filled with viscous material is often due to thermal heat cycles as result of daily load cycles. Basically, a lowered liquid levels results in a impaired electrical breakdown strength of the component, which leads to electrical discharges and may finally lead to breakdown of the component.

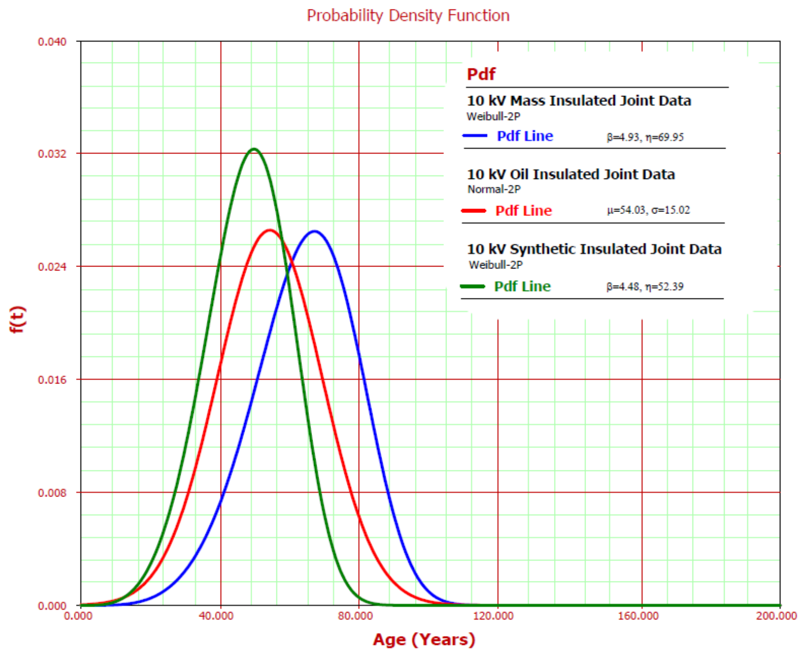


FIGURE 32 - PROBABILITY DENSITY FUNCTIONS (PDF) FOR THREE DIFFERENT TYPES OF 10 KV CABLE JOINTS

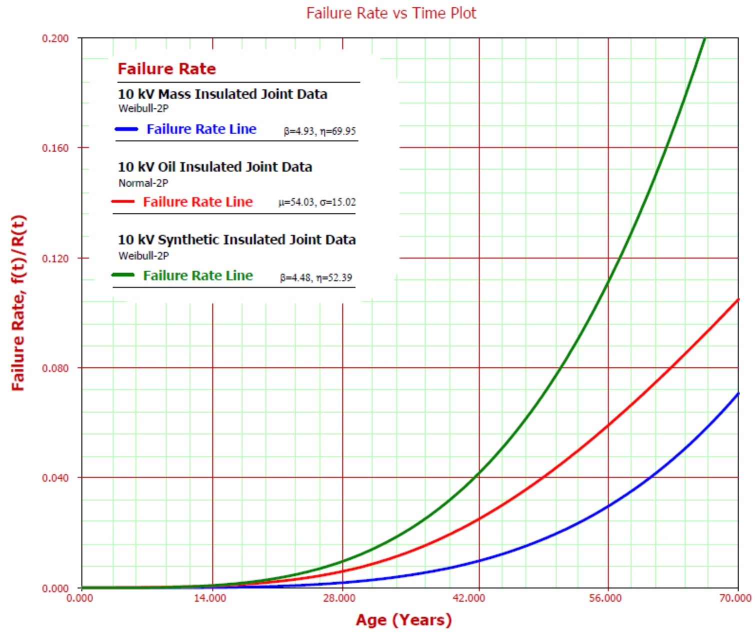


FIGURE 33 - FAILURE RATE CURVES FOR THE THREE DIFFERENT TYPES OF CABLE JOINT POPULATIONS

6.2.4.3 SENSITIVITY ANALYSIS

For the case of synthetic insulated cable joints, experts at the DNO indicated that the cable joint failures, which are reported in the age intervals [20-40] and [>40] years (see Figure 30) are probably failures of 10 kV resin joints that were installed in the 1970's. These resin joints, often referred as "Nekaldiet" joints, have resulted significantly to outages in the past years, however, are not applied anymore and replaced as much as possible. Consequently, a sensitivity analysis was performed, using the calculated failure rates, to assess the failure behavior of synthetic cable joints without the suspect "Nekaldiet" failures. For this purpose, it was required to exclude certain failure as well as appropriate in-service data records. After consulting experts at the utility, it was agreed to exclude all failures which were recorded in the age bin [> 40] years and a number of failures from the age bin [20 - 40] years. Likewise, the in-service data was adjusted. These considerations were based on the viewpoint that "Nekaldiet" joints were installed a few decades ago and, therefore it was very likely that this group of synthetic joints had operated sufficiently to have reached ages higher than 20 years. Two scenarios were analyzed, in which failure data points were removed as follows:

- All failures from age bin [> 40] year and 10 failures from age bin [20 - 40] year
- All failures from age bin [> 40] year and 20 failures from age bin [20 - 40] year.

The calculated failure rates, according to the best fit failure distribution (Weibull), are shown in Figure 34.

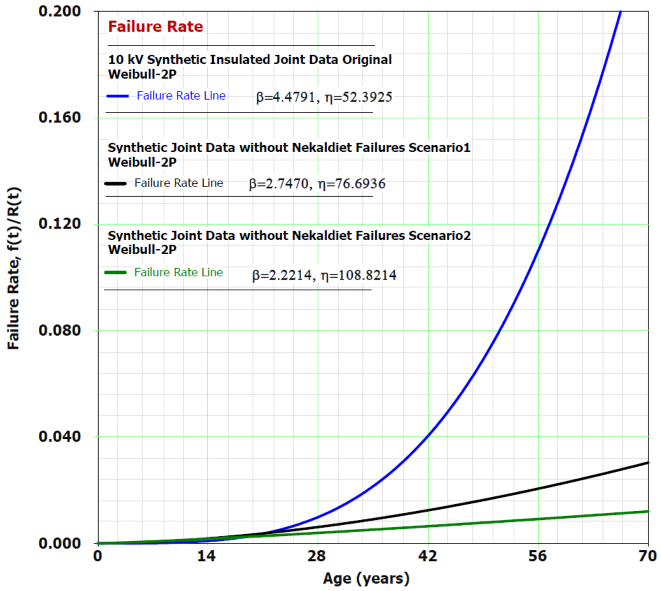


FIGURE 34 - THIS FIGURE SHOWS THE FAILURE RATE PLOTS FOR THREE SUBSETS OF LIFE DATA FOR SYNTHETIC INSULATED CABLE JOINTS. THE BLUE FAILURE RATE PLOT REPRESENTS THE ORIGINAL DATA RECORD, WHILE THE BLACK AND GREEN FAILURE PLOT REPRESENT SCENARIO 1 AND 2, RESPECTIVE

From Figure 34, it can be found that the failure rates are considerably lower for the synthetic joints when the suspect “Nekaldiet” failure records are excluded from the statistical analysis. Therefore, we may reasonably conclude that the suspect “Nekaldiet” failure records negatively impact the overall failure behavior of the synthetic insulated joint population. More specifically, the asset manager can justify, based on these results, that replacing aged “Nekaldiet” cable joints, or applying condition monitoring to cable feeders with these types of joints, can be a feasible strategy to mitigate future failures.

6.2.5 Asset Management Decision-Support

Aspects, for instance, failure probability and future failure frequency form the basis for asset management activities such as maintenance and replacement strategies. Knowledge and information of these aspects can contribute in the decision process of AM. With the results of the statistical analysis from the previous section, information regarding the failure probability and the failure frequency at a certain age f asset groups in the near future of the three types of 10 kV cable joints can be extracted.

Two possible supporting tools for asset managers are discussed here:

1. Predicting future cable joint failures
2. Failure count diagram
3. Percentile Life

6.2.5.1 PREDICTING FUTURE CABLE JOINT FAILURES

Predicting future performance is a very important objective from an AM viewpoint. The future failure predictions for all three types of investigated 10 kV cable joints are given here.

Synthetic insulated 10 kV cable joint future failures:

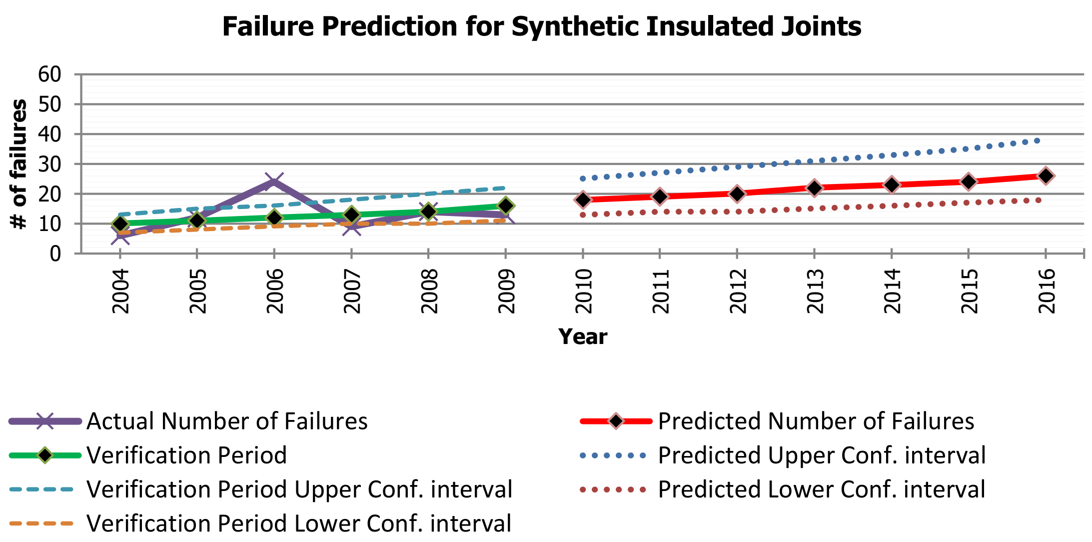


FIGURE 35 - ESTIMATION OF THE NUMBER OF TOTAL EXPECTED FAILURES FOR THE COMING SIX YEARS FOR 10 KV SYNTHETIC INSULATED JOINTS. THE RED LINE GIVES THE NUMBER OF PREDICTED FAILURE STARTING AT 2010 UNTIL 2016. THE CORRESPONDING 90% CONFIDENCE BOUNDS ARE ALSO SHOWN

From Figure 35, it can be seen that the estimated number of failure (green line) based on the analysis are comparable with the actual number of failures in the period 2004 - 2009. As result of this, it can be concluded that the developed failure rate model reasonably describes the failure behavior of the considered population.

The developed failure rate model for the synthetic joints is used together with the population of 2010 to predict the number of failures in that particular year. For 2010, a number of 18 failures are predicted with a variation between 13 and 25 when taking into account the respective 90% lower and upper confidence bounds.

From this point on, for every next year, the ages of the remaining population of joints are made one year older. At the same time, the estimated failures from the previous year are subtracted from the population. It is also taken in account that every joint failure introduces two new joints. With this information, the asset manager can determine whether the expected numbers of future failures are acceptable, or, whether structural replacement is necessary in the coming years.

Oil insulated 10 kV cable joint future failures:

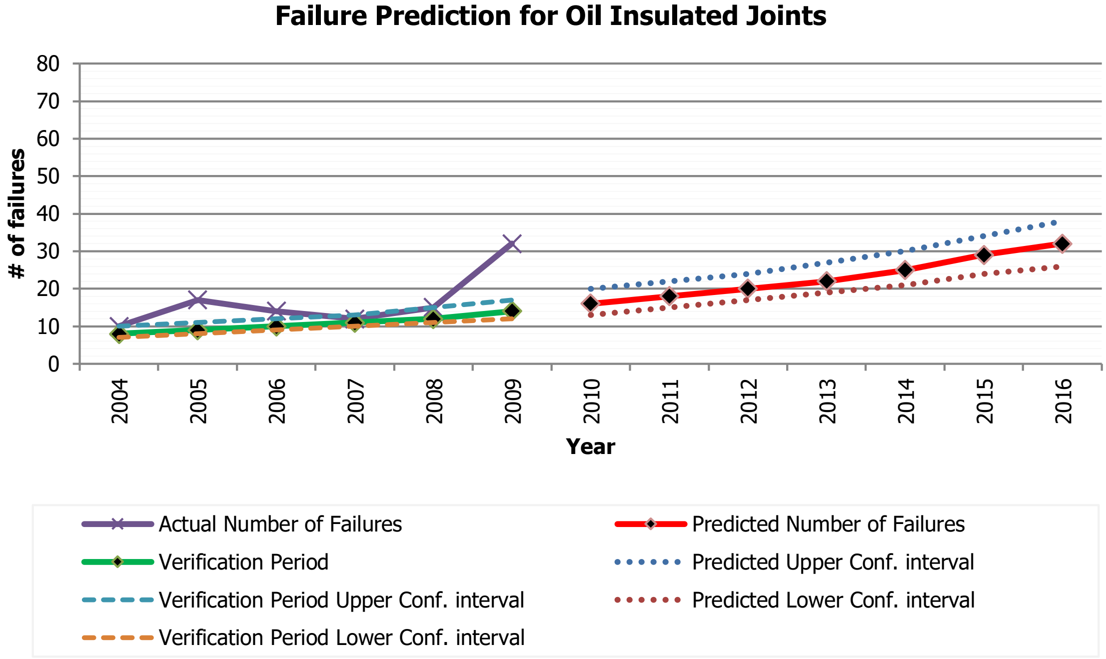


FIGURE 36 - THE NUMBER OF CALCULATED EXPECTED FAILURES FOR THE OIL INSULATED CABLE JOINTS. ALSO SHOWN ARE THE CORRESPONDING 90 % CONFIDENCE LOWER AND UPPER BOUNDS. FOR THE PERIOD 2004-2009, THE NUMBER OF CALCULATED EXPECTED FAILURES FOR THE OIL JOINTS (GREEN LINE)

Mass insulated 10 kV cable joint future failures:

For two joint populations (synthetic and oil) the validation test suggests to be in accordance with the actual occurred failures. However, for the mass-insulation cable joint population this was not the case. It is worth noting, that for almost 60% of the mass joint population no exact installation year was specified in the database. These incomplete datasets were taken into account as described earlier (Figure 34). In order to assess whether this first estimation, regarding the 60%, might be an improper estimation, a number of new estimations were examined. In a second attempt, the 60% of data was not divided proportionally, but according to a certain age interval, as shown in Figure 34. The main reason behind this second attempt was based on experts' opinions, who indicated that mass-insulated joints were mostly used a few decades ago. Thus, it was likely that the missing 60% data should be of a population which is older than roughly 20 years. Therefore, this 60% was proportionally divided in various age intervals, satisfying this assumption. Different scenarios were used namely; age intervals of [20 - 30], [20 - 40], [25 - 50], etc. The expected future failure outcomes for the interval [25 - 50] years were most in accordance with the actual occurred failures in the period 2004 - 2009. In Figure 37, two scenarios (black and blue plot) are illustrated together with the actual recorded number of failures (red plot).

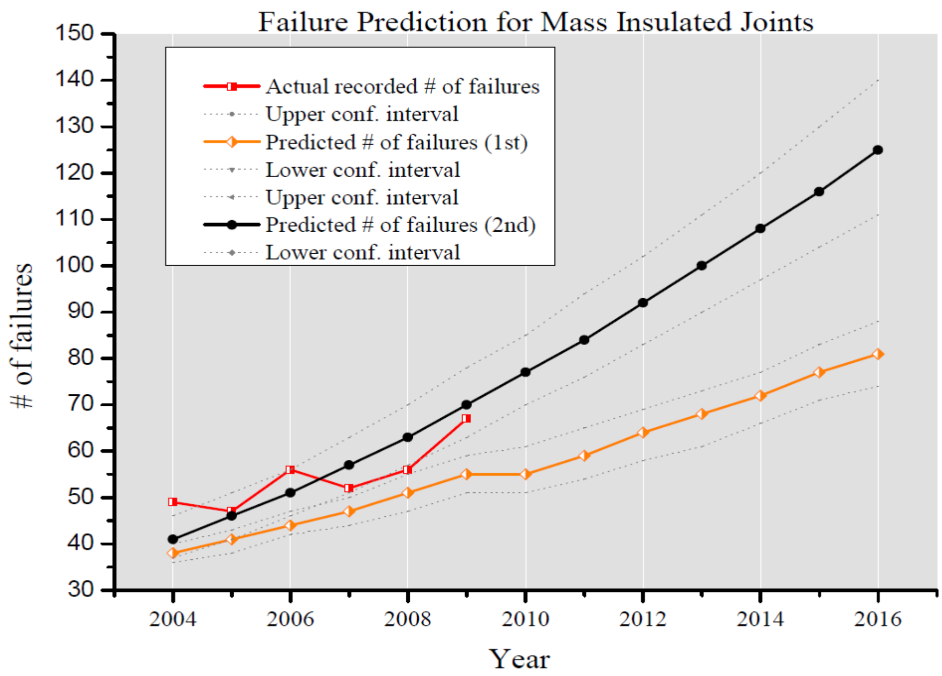


FIGURE 37 - THIS FIGURE SHOWS THE FAILURE PREDICTION FOR THE MASS INSULATED JOINTS TOGETHER WITH THE CORRESPONDING 90% CONFIDENCE INTERVALS. THE BLUE PLOT REPRESENTS THE FIRST CASE (60% OF MISSING DATA IS ESTIMATED PROPORTIONALLY), WHILE THE BLACK PLOT INDICATES THE SECOND CASE (60% OF MISSING DATA IS ESTIMATED USING SPECIFIC INTERVALS, BASED ON EXPERT JUDGEMENT).

Under these circumstances, it can be concluded that based on the analysis, it seems probable that the population of mass-insulated joints without recorded installation year (60% of the population) might be older than 25 year. However, it should be noted, that these assumptions are based on the available data at the moment of the study. Another way of reasoning might reveal that there have been more failures of mass-insulated joints in the past, of which the records are missing, and therefore the failure rates obtained here could be conservative values. Whether the mass-insulated joint population is of an older age category or the number of failures in the past are higher, in either case, the asset manager now has more knowledge on the failure behavior of the mass-insulation joint population. With this information, the asset manager can determine if the expected number of future failures are acceptable or whether structured replacement or pin-pointed condition monitoring is necessary in the coming years, as part of the AM strategic and operational policies.

6.2.5.2 FAILURE COUNT DIAGRAM

With a failure count diagram, it will be possible to assess the impact that typical increasing failure rates have on the installed equipment base. In practice, it is usually encountered that utilities do not know the exact age of a component at the moment of failure, and make estimations of the age in the failure records. With the failure count diagram it can be calculated, in relative terms, how many components of an installed population of a particular age contribute to failures [79]. The failure count diagram for the synthetic insulated cable joints is shown in Figure 38.

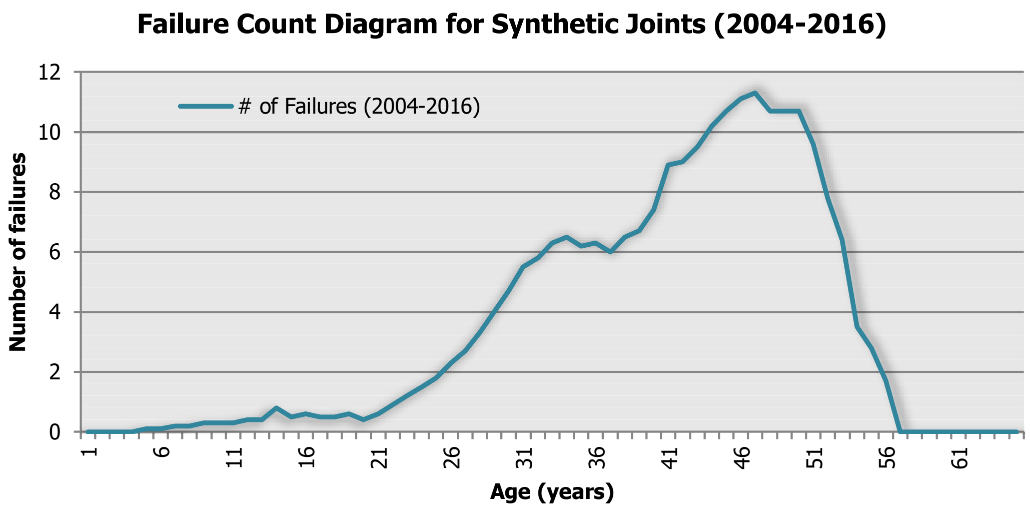


FIGURE 38 - THE TOTAL NUMBER OF FAILURES OCCURRING EACH YEAR FOR THE SYNTHETIC INSULATED CABLE JOINTS. THE MAXIMUM IS REACHED AT AGE 47, WHEN THE COMBINATION OF HIGH FAILURE RATE AND HIGH NUMBER OF REMAINING UNITS PEAK

When considering the failure rate curves shown in Figure 33, it can be seen from the failure count diagram (Figure 38) that failures in intermediate years are the real cause of the system reliability problem. More than half of the failures occur in the range of 21 and 51 years. The very old cable joints (older than 50 years) have indeed a higher failure rate, however, there are most of the time too few to generate a high total failure count. The failure count diagram is a representation of the relative contribution to failures of synthetic joints as function of their age. This diagram can be seen as an important tool in managing reliability and replacement policies. Similar analyses are performed for the oil and mass insulated joints, showing that each population have unique failure count behaviors.

6.2.5.3 PERCENTILE LIFE

The B-life or percentile life gives the estimated time when the probability of failure will reach a specific point. For instance, if 10 % of the cable joints are expected to fail by 15 years of operation, then, it can be stated that the B(10) life is 15 years. The value of the B(x)-lives can assist the asset manager in anticipating which level of reliability is acceptable and at which age this level of reliability is reached. In Table XVIII, the B(x)-lives are shown for all three types of cable joints.

TABLE XVIII - B(X)-LIVES OF SYNTHETIC, MASS AND OIL INSULATED 10 KV CABLE JOINTS. THE CORRESPONDING UPPER AND LOWER 90 % CONFIDENCE BOUNDS ARE ALSO LISTED.

	Mass Insulated Cable Joint Population		
	Component Age (year)		
	90 % Bound	*B-Life*	*90 % Bound*
B(1)-life	26	**27**	28
B(10)-life	43	**44**	45
B(25)-life	53	**54**	56
B(50)-life (mean life)	67	**65**	63

	Oil Insulated Cable Joint Population		
	Component Age (year)		
	90 % Bound	*B-life*	*90 % Bound*
B(1)-life	18	**19**	20
B(10)-life	33	**35**	37
B(25)-life	42	**44**	46
B(50)-life (mean life)	51	**54**	57

	Synthetic Insulated Cable Joint Population		
	Component Age (year)		
	90 % Bound	*B-life*	*90 % Bound*
B(1)-life	17	**19**	21
B(10)-life	30	**31**	33
B(25)-life	38	**40**	42
B(50)-life (mean life)	45	**48**	52

With the statistical information from Table XVIII, the asset manager can assess and compare the reliability of the three cable joint population with each other. Additionally, the B(x)-lives can be used to assess how many cable joints are actually older than a certain chosen B(x) level. The level of B(x)-life which the asset manager can choose for a certain population of component, depends on the network type, component, impact of failure etc. If, for example, the asset manager is interested in getting to know how many cable joints of each population are older than the B(10)-life, then the calculated B(10)-life together with the in-service cable joints can be used for this.

6.3 Case study 3: Statistical Modelling of Transformer Deterioration

6.3.1 Introduction

National Grid manages its assets on the England and Wales transmission network to ensure that an acceptable and sustainable balance is achieved between performance, costs and risks. Transmission assets are critical to secure bulk power transmission to customers and often have long repair or replacement times. The failure of an asset may result in potential safety and environmental consequences and as such National Grid takes a long term view of asset replacement strategies and uses models to predict long term asset replacement requirements for its lead assets (transformers, cables, circuit breakers and overhead lines).

National Grid experiences a relatively low number of failures on its system compared with the installed population and it is often not possible to derive strong statistical links between the failures experienced and declared asset lives; hence engineering understanding is central to the process of asset replacement and refurbishment.

This case study aims to demonstrate National Grid's approach to understanding the deterioration of its transformer assets and prioritizing their replacement and how failure information can inform this process.

6.3.2 How National Grid Prioritizes Transformer Replacement

Because of the significant consequences associated with transformer failure, asset replacement modelling is not based upon the probability of failure but is instead based on the probability of the transformer reaching a *state requiring replacement*. This is the point at which it is expected that equipment condition will have an unacceptable impact on performance or capability, and repair is either not possible or uneconomic. Assets in a state requiring replacement constitute an unacceptable risk should failure occur. However, as illustrated in Figure 6 from TB 309 [8], failure only usually occurs when an event happens (e.g. fault, switching, weather) which makes it difficult to predict asset failure. This state is defined differently for different equipment types as it is a function of the deterioration modes, safety, environmental and operational consequences of failure and the required operational duty and stresses.

To facilitate the development of an optimized replacement plan, priority ranked lists for replacement are created for each transformer. The priority ranking is achieved by applying both technical and specific business criteria to develop a series of condition based scores, Asset Health Indices (AHI), which are assigned to lists of assets that prioritize the technical requirement for replacement based on relevant performance and condition criteria. They are scored from 1 to 4, 1 being worst condition and 4 being best condition. Each asset is also assigned a Criticality score, based on the safety, operational or environmental consequences of asset unreliability or failure. Replacement Priorities are lists of assets that prioritize the requirement for replacement actions based on the Asset Health Index and Criticality (Figure 39).

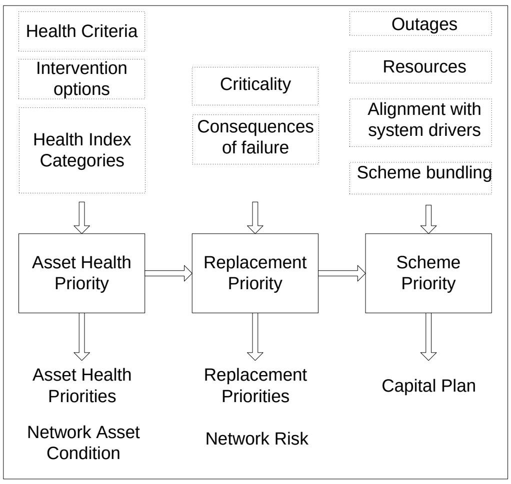


FIGURE 39 - RELATIONSHIP BETWEEN ASSET CONDITION, REPLACEMENT PRIORITIES AND INVESTMENT PROCESS

A number of criteria are used to assess transformer condition. These include consideration of the transformer design family, routine testing of aging indicators, such as chemical analysis of the oil, as well as information obtained from condition monitoring, where appropriate. A scoring system based on the condition of dielectric, thermal and mechanical elements is applied to each transformer on the National Grid Transmission System to inform its Asset Health Index and this is combined with its Criticality Score to produce a Replacement Priority.

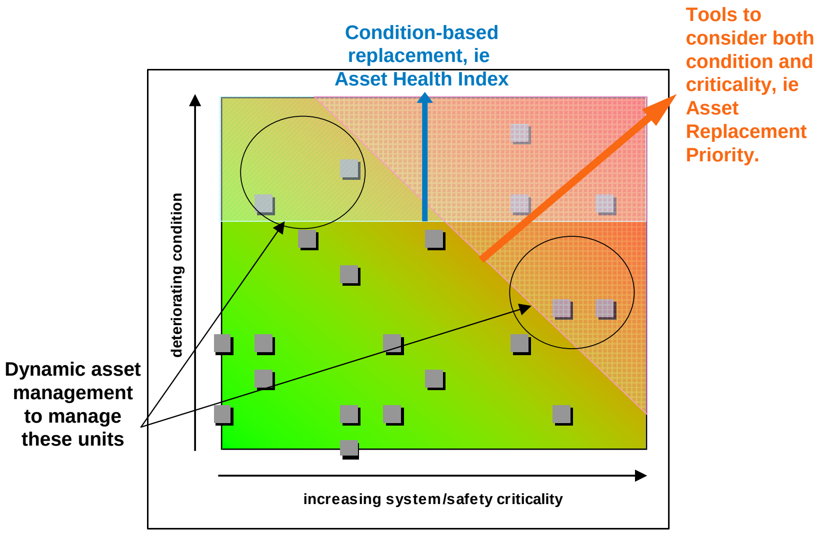


FIGURE 40 - HOW REPLACEMENT PRIORITIES INFORM ASSET MANAGEMENT DECISIONS

6.3.3 Failure Analysis

Condition monitoring and condition assessment techniques are becoming increasingly sophisticated. Monitoring of transformers that are reaching the end of their life, or are known to be in poor condition, can mitigate the risk of catastrophic failure and their replacement is planned using the Replacement Prioritization methodology.

Although National Grid plans to replace transformers at the end of life before they fail, failures have occurred on the transmission system. A transformer failure is defined as an event that requires the unit to be taken off the plinth either for replacement or factory repair. Aging alone is unlikely to cause failure but the quality of the oil or mechanical strength of the paper will deteriorate over time which means that the transformer is less able to sustain operational stresses. Usually failure is triggered by an event which will result in an alarm or protection operation, although sometimes routine or special condition monitoring, typically analysis of dissolved gas in oil or electrical testing, may indicate that the transformer needs to be removed from service for repair or emergency replacement.

National Grid has retained good records of transformer failures for many decades. The hazard rate (conditional probability of failure) curve shown in blue in Figure 41 is derived from the age at which 79 transformers have failed on the England and Wales transmission system since 1962. The failure probability per year at any particular age is conditional on the transformer having survived to that age.

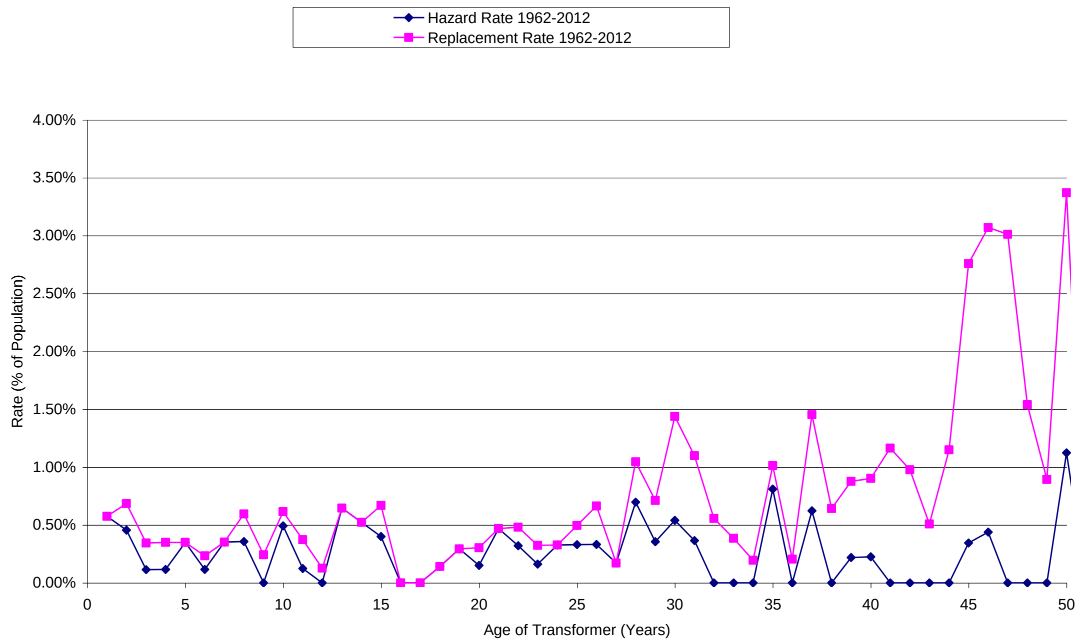


FIGURE 41 - HAZARD RATE AND REPLACEMENT RATE CURVE FOR TRANSFORMER FAILURES AND REPLACEMENTS RECORDED SINCE 1962

The average hazard rate is 0.3% per transformer per year. This is obtained by normalizing the number of transformer failures for each age with the number of service years experience at that age since 1962. It can be observed from the data that the hazard rate is stationary with a random pattern, indicating failures are independent of age. There is a peak at age 50, but this is due to a single failure and National Grid has a limited number of transformers aged 50 years or over. The theoretical higher rate of failures in early years on a standard bath-tub curve (the burn-in failures) does not appear in this data. This is likely to be a reflection of the fact that transformers undergo extensive factory testing before they are commissioned on-site, hence any potential defects are identified and rectified before the transformer begins operation.

The pink curve shows the total transformer replacement rate which includes both failures and planned replacements. This data tracks the failure rate before 30 years of age and shows an upward trend afterwards. In many respects this indicates that the failure rate has remained stationary because the asset replacement policy has ensured that poor condition transformers (which tend to be the older units) have been replaced before they fail. It should be noted that a replaced transformer could have remained in service for a longer time period before reaching the point of failure. If National Grid allowed transformers to operate to failure, the failure rate curve would be slightly to the right of the replacement rate curve. All transformers which have been replaced are forensically examined prior to their scrapping and research work has been ongoing into incorporating information about these transformers into this curve in order to derive a more accurate deterioration model.

6.3.4 Statistical Modelling of Transformer Deterioration

A model of how transformer condition changes with age has been developed which allows National Grid to forecast future network risk and plan the replacement of transformers. The assumptions underlying this model are wear out points defined by the Earliest Onset of Significant Unreliability, the age at which 2.5% of the asset population would be expect to be in a state requiring replacement, the Anticipated Asset Life, the age at which 50% of the asset population would be expect to be in a state requiring replacement and the Latest Onset of Significant Unreliability, the age at which 97.5% of the asset population would be expect to be in a state requiring replacement, i.e. Asset Health Index 1.

Work has been ongoing to use the failure information and survival statistics to model the progression of a transformer's AHI to AHI 1 and hence determine the earliest onset, latest onset and anticipated transformer lifetimes.

The survival function, $S(t)$, is the probability that a transformer will not become AHI 1 before age t. Its complement is the accumulative probability of becoming AHI 1, $F(t)$ such that:

$$F(t) + S(t) = 1 \qquad (19)$$

The corresponding probability density function, $f(t)$ is defined by:

$$f(t) = \frac{dF(t)}{dt} \qquad (20)$$

The hazard function, $H(t)$, is defined as the probability that a transformer will become AHI 1 at an age t given that is has survived up to that age.

$$H(t) = \frac{f(t)}{1 - F(t)}$$

The hazard rate for transformers can be understood from a combination of two effects:

a) A constant hazard rate defining a random failure mechanism – this is a constant rate λ from age zero.

b) A hazard rate associated with the wear out of the transformer. This can be modelled by defining a probability density function $f(t)$ using a normal distribution $g(t;\mu,\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}$ and a corresponding cumulative probability function $G(t;\mu,\sigma^2)$ where μ is the mean age before AHI 1 and σ the standard deviation (Figure 42).

A set of values for λ, μ and σ were used to model the hazard rate. These were compared with another method of defining the wear out rate, using a linearly increasing hazard rate which starts at a knee point age k and increases at a rate ρ.

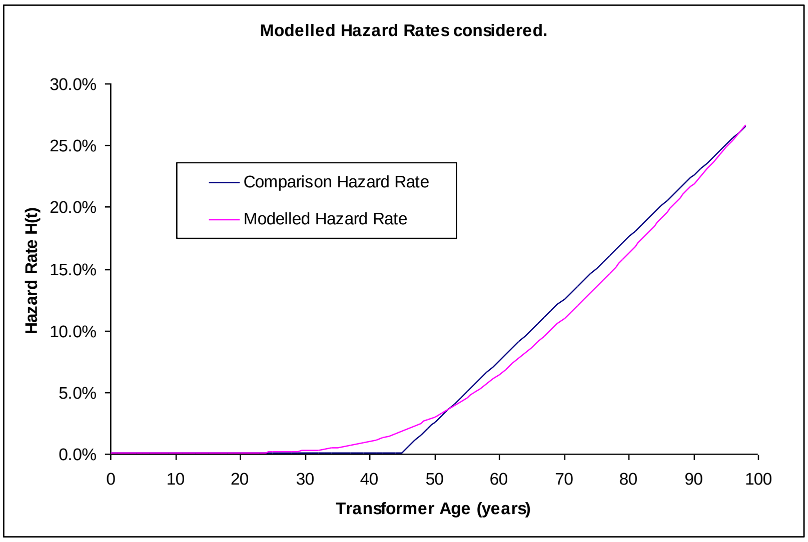


FIGURE 42 - MODELLED HAZARD RATE

The following equation was used to iteratively define the transformer survival function, starting from the defined point $S(t = 0) = 1$ alongside the modelled hazard rate, as shown by the pink curve in Figure 42.

$$\boxed{S(t+1) = S(t) - H(t)S(t)}$$

The distribution of Asset Health Indices for each transformer age group was plotted using data from the period 1990-2012. Data from 2004 onwards was based on recorded condition scores. Prior to this date condition scores were assigned retrospectively using historic test information, including dissolved gas analysis results. Transformers that had either failed or were scrapped because they were AHI 1 were included in the AHI 1 category for the age group appropriate to their number of years in service plus the years since scrapping or failure (i.e. a transformer that had failed aged 30 in 2000 was recorded as a 42 year old transformer with AHI 1 at 2012). This ensured that failures among transformers in a particular age group were assigned to the correct grouping.

Only transformers that had been replaced because of their poor condition were included in the analysis. Transformers which had been replaced in order to meet new load requirements, for example, were excluded from the data set because the asset's condition was not the primary driver for replacement.

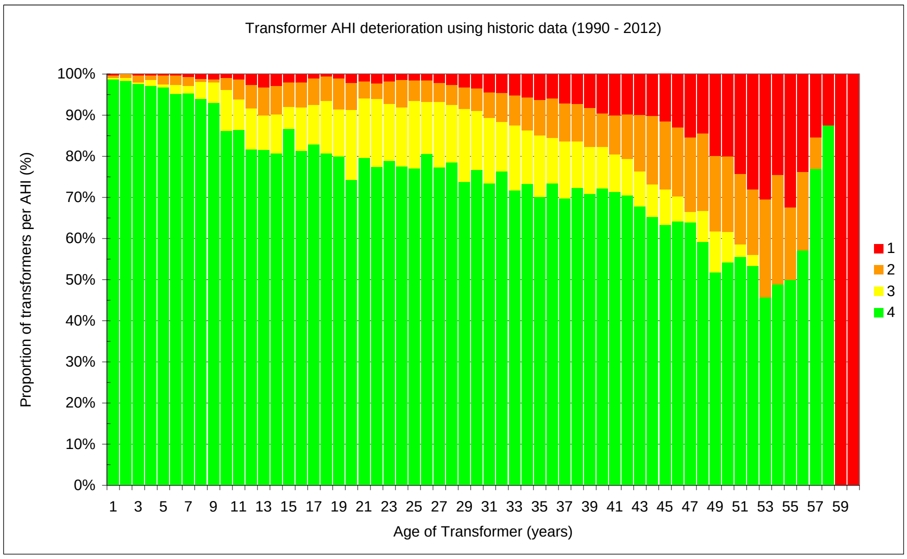


FIGURE 43 - AGE-CONDITION PROFILE FROM 1990-2012

Figure 43 shows the transformer deterioration based on historic data. It should be noted that there is a peak at years 59 and 60 due to the very small number of transformers that have reached this age compared with the rest of the population.

The empirical survival function derived from the historic data is defined as:

$$S(t) = \frac{N_s(t)}{N_F(t) + N_S(t)}$$

Where $N_F(t)$ and $N_S(t)$ denote the number of AHI 1 transformers and non-AHI 1 transformers at a given transformer age t respectively. This empirical function derived from the historic data was plotted against the modelled survival function (Figure 44).

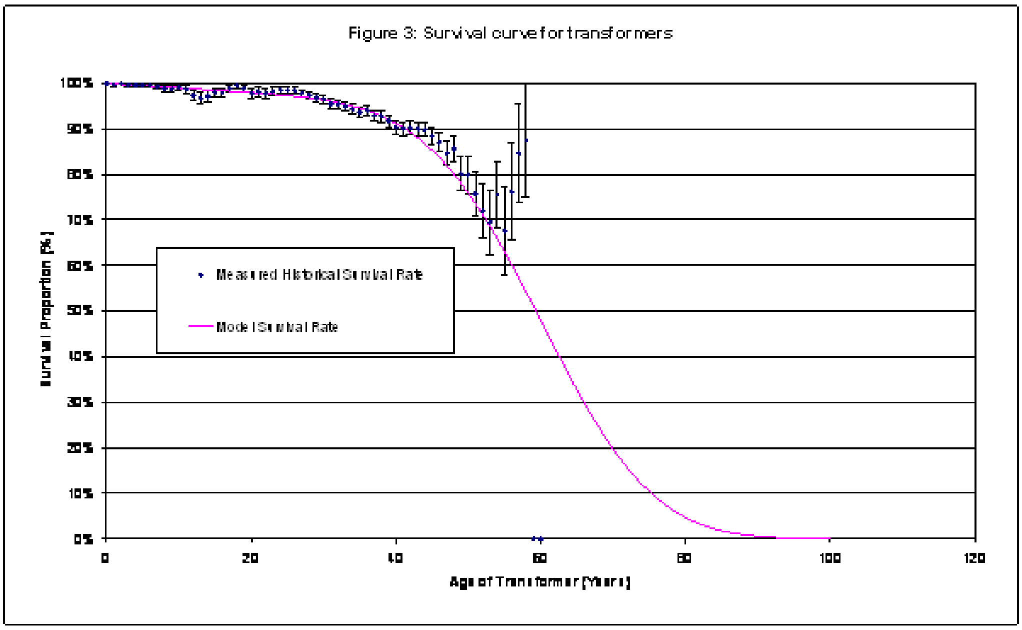


FIGURE 44 - SURVIVAL CURVE FOR TRANSFORMERS

The errors in the historic survival function are related to the number of transformers which NG has experience of, at that age. Therefore they are very large for the older transformers on the system.

The earliest and latest onset points are defined as the 2.5% and 97.5% points on the survival curve respectively and the anticipated life of the transformer is the 50% point on the curve.

Continuous development of the lifetime models that fit the available data and an appreciation of the range of expected error in lifetime prediction is the subject of ongoing research. These models are updated as more data from older transformers becomes available over time.

Acknowledgements: This case study was based upon work carried out by Paul Jarman and Ruth Hooton as well as PhD students under the supervision of Prof Zhongdong Wang from the University of Manchester.

6.4 Case Study 4 - Sensitivity of Life Data Analysis – Example of 50 kV COQ Bushings

Statistical tools play an important role in Life Data Analysis (LDA). The first step for any statistical tool is the collection of failure and in-service data, and subsequent distribution fitting allows to derive the failure rate function. The latter allows to conclude about trend and numbers of upcoming failures [45], [46]. Statistical analysis requires a sufficient amount of independent and homogeneous data, resulting in a good distribution fitting. In the here described case study on 50 kV epoxy resin bushing installed in oil-filled switchgears, the results of an investigation into the number of failures on the outcome of the analysis will be presented.

The population of investigated bushings consists of approximately 5100 units and until 2013 only 14 bushings broke down. The ratio of failed bushings to those in-service is very small, approximately 0.27%. The impact of failures on the local network reliability is significant and therefore an approach was made to perform LDA.

In 2013, the average age of the bushing was 39 years, with an age span between 21 and 57 years. Detailed information with respect to the number and age of in-service bushings and the age of failed bushings can be seen in Figure 45.

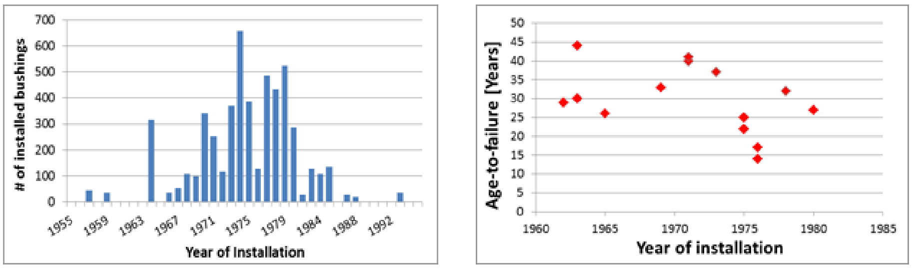


FIGURE 45 - AGE DISTRIBUTION OF INSTALLED BUSHINGS (LEFT) AND THE AGE-TO-FAILURE OF FAILED BUSHINGS (RIGHT)

To find the best fitting distribution, a goodness of fit test was performed and the 2-parameter Weibull distribution turned out to fit the data best. The fitted Cumulative Density Function (CDF) and failure rate function, together with 90% confidence bounds, can be seen in Figure 46.Figure 53

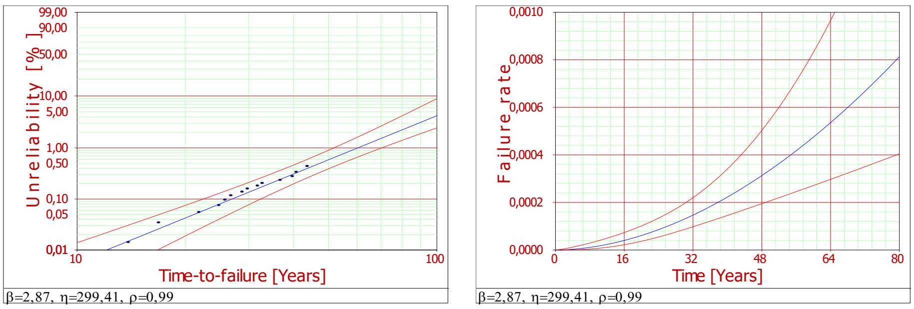


FIGURE 46 - CDF (LEFT) AND FAILURE RATE FUNCTION (RIGHT), REPRESENTING THE POPULATION OF 50 KV BUSHINGS

The value of β parameter of the Weibull distribution is close to 3 indicating aging and hence an increase of the number of failures in the future. The η parameter of the Weibull distribution equals 300 years, indicating the age at which 63.2% of the population is expected to have failed. Taking into account the time dependent failure rate function and the age and number of installed bushings, the number of upcoming failures is estimated:

$$N_{f,e} = \sum_{i=1}^{Age\ oldest} \lambda(t_i) \cdot N_i \quad (1)$$

Where $N_{f,e}$ is the number of expected failures, $\lambda(t)$ failure rate at age i and N_i is the number of components of age i.

The number of failures expected to occur in coming years, together with the 90% confidence bounds are depicted in Figure 47.

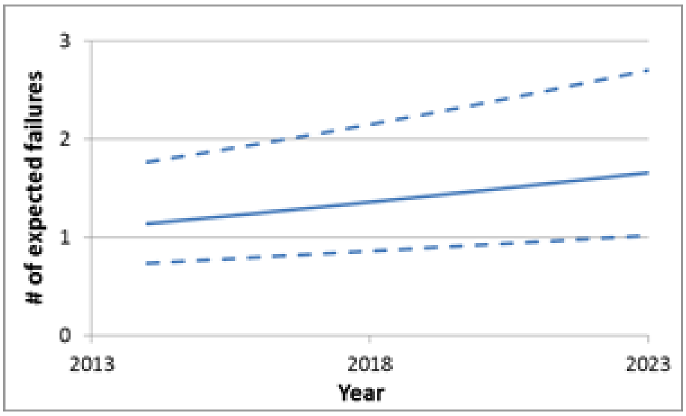


FIGURE 47 - FAILURE EXPECTANCY TOGETHER WITH 90% CONFIDENCE INTERVAL

In total, 1 to 2 bushings are expected to fail in the coming years.

Due to the small amount of failure data in comparison to in-service data, it is necessary to investigate the sensitivity of the analysis to the number of failures. For that reason, the influence of the number of failures and time at which the analysis is performed, was investigated. The results of the investigation are shown in Figure 48. The legend in this figure shows the year for which the analysis is performed and the number of failures registered till that time.

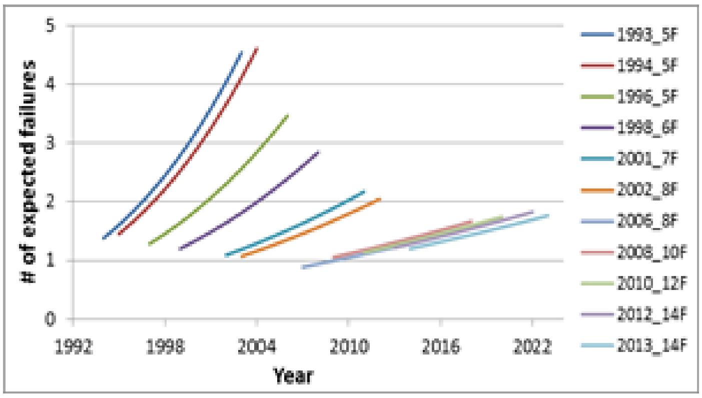


FIGURE 48 - FAILURE PREDICTION, AS OBTAINED AT DIFFERENT MOMENTS IN TIME WITH DIFFERENT NUMBER OF FAILURES REGISTERED

From the above figure it can be noticed, that until the year 2006, the number of expected failures was decreasing when the analysis was performed in different years. This might be explained by the increasing number of registered failures. However, after the year 2006 there is no clear increasing or decreasing trend. The predictions change, but in general the change is very small as the lines depicting the predictions overlap. Further on, the influence of the age of the failure that occurred as the last one was investigated. The last bushing failed in 2012, the age span of the installed bushings was between 20 and 56 years. Therefore, for the last failure, different ages from this particular interval will be assumed and the failure expectancy will be calculated. The results are presented in Figure 49, the legend shows the assumed age of the last failure.

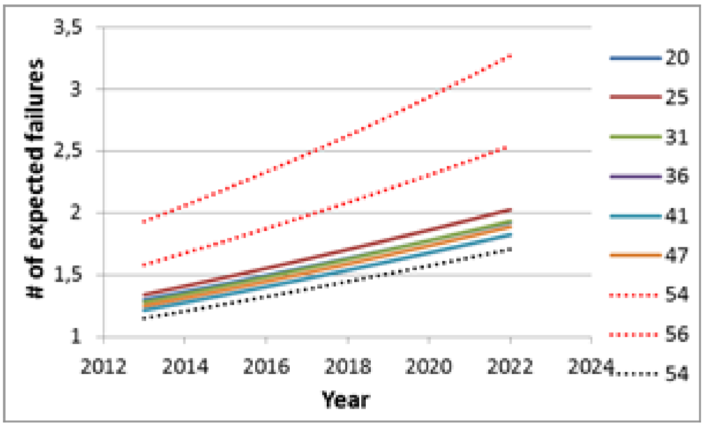


FIGURE 49 - INFLUENCE OF THE ASSUMED AGE OF THE FAILURE THAT OCCURRED IN 2012

In the above figure, the influence of the assumed age of the bushing that failed as last one is depicted. The two red dotted line (failures assumed to occur at age of 54 and 56) depict the analysis where the last failure was determined to be outlier [47], [48], the line depicts the analysis when the outlier is included. Rejection of the outlier resulted in obtaining a new distribution and the failure analysis is depicted with black dotted line. In this way, it can be noticed that the analysis, as performed in 2012 is insensitive to the age of the failure that occurred as the last one. The same approach was applied for the previous years. The details are shown in Figure 50.

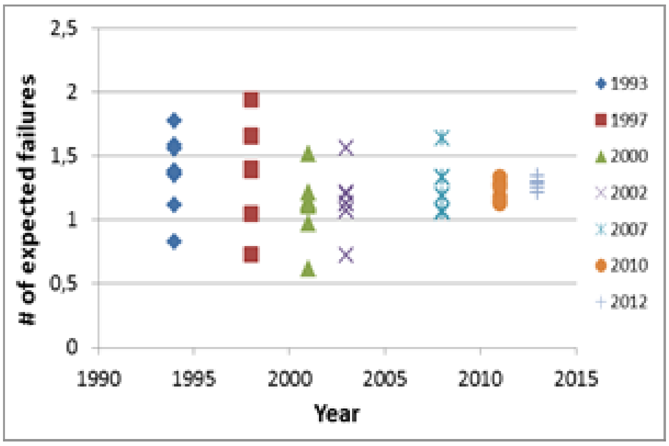


FIGURE 50 - DISCREPANCY OF THE NUMBER OF EXPECTED FAILURES, AS OBTAINED IN DIFFERENT YEARS FOR DIFFERENT AGE OF THE LAST FAILURE.

From the above figure it clearly follows that in the course of time, the scatter in the number of expected failures decreases in time. This means that the analysis becomes more insensitive as more failures are available for the analysis. In order to get a better overview of the scatter, the difference between minimal and maximal number of expected failures obtained for different years is plotted in Figure 51.

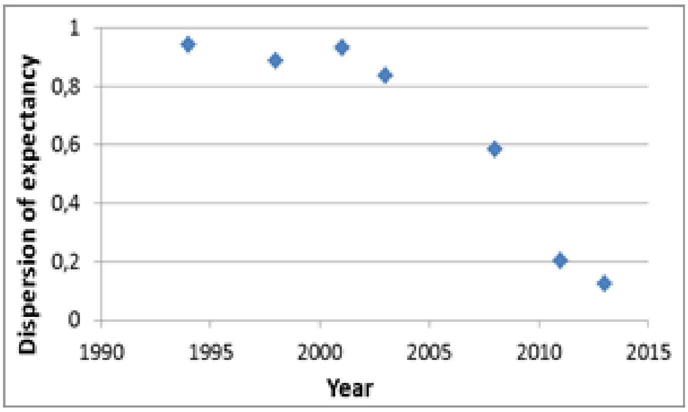


FIGURE 51 - DIFFERENCE BETWEEN MINIMAL AND MAXIMAL NUMBER OF EXPECTED FAILURES, AS INFLUENCED BY THE AGE OF LAST FAILURE FOR DIFFERENT YEARS.

From Figure 51 it can be noted that the scatter in the failure expectancy obtained for different years starts to decrease from the year 2002 onwards. This is although only 8 failures were available in the year 2002. In the course of time it decreases until the year 2012 and it is almost negligible. More details can be seen in Figure 49**Fout! Verwijzingsbron niet gevonden.**.

<u>Summary</u>

The analysis presented, shows the applicability of statistical analysis to assess the future failure behaviour of epoxy resin bushings installed in 50 kV switchgears. This includes trend and the number of failures expected to occur in coming years. Through a sensitivity analysis it has been shown that even in the case of as few as 10 failures, the statistical analysis provides robust results. The latter can be used as additional input when deciding about spare parts and investment policies.

7. GUIDELINES FOR LIFE DATA COLLECTION

7.1 Guidelines for Collecting Failure Data

For making asset management decisions, it is of great importance to have information about network components. This information will form the basis for the asset management decision process. In order to make the information applicable for decision making purposes, it is basically required to analyze and evaluate the information. This chapter describes the process of collecting life time data for network components. The purpose is to provide practical guidelines for collecting life time data to engineering and management practitioners who are preparing for performing statistical life time data analysis.

7.1.1 Data Sources

Power network utilities have, historically, recorded and stored data in a wide variety of methods, accuracy, consistency and databases. In the earlier days, most of data records was primarily paper based and utilities had their specific ways of collecting data. As a results, it is very challenging to provide general data sources from which appropriate data for statistical life data analysis can be extracted. It is found that throughout many utilities, at least, the following types of data sources (databases) can be found (useful for statistical analysis):

- Static asset information databases (providing asset data on: year of installation, type of component, number of installed components, etc.)
- Dynamic asset information databases (providing asset data on: maintenance, replacement, inspections, diagnostics, condition monitoring, etc.)
- Geographical asset information databases (providing asset information on: location and topology of the network)
- Enterprise resource planning (ERP) databases (providing information on business resources e.g. assets, materials, employees, etc.)
- Failure information databases (providing information on failures of components i.e. outage management systems)

The type of databases used extend from spread sheet type to computerized types. Recently, many utilities are gradually implementing data warehouses and enterprise asset information systems for combining asset information on many levels (such as technical, economical, and other corporate data).

For statistical life data analysis, information regarding the network component population is needed. Typically, the required life data consist failure data of the components, while it is of importance to include the data of the total population of components in service. Hence, the term LIFE instead of FAILURE data. Life data refers to failed and survived components at the moment of analysis.

The first data source that form the bases for the analysis are survived components data (usually referred to in-service data) e.g.:

- Type of equipment
- Year of installation

However, it has been reported that the availability of more detailed information gives the ability to obtain a more structures and consistent estimation [45]. The extra available information may assists in dividing the datasets in smaller (hence homogenous) datasets, depending on the goal of the analysis. Although, is could be expected that the information is available from a single database, it is found in practice that in many cases it required a multi-database approach to extract a consistent dataset for statistical analysis purposes.

The second data source which forms the most important part is the failure data collection, usually in the form of:

- Date/time of failure
- Repair time/ attempts of failure
- Cause of failure
- Component that fails
- Network level (medium voltage/high voltage/low voltage)
- Age (estimate) of the component at the moment of failure

It is useful and sometimes necessary, to be able to group data in order to obtain reasonably homogenous data sets. To do that it is useful to record information describing the operational and maintenance histories of assets. For example to separate data on network transformers which are loaded typically less than 50% from data on GSU's or autotransformers that are loaded more closely to their ratings. Similarly for breakers, some see frequent operation and are in high fault level areas of the network, while others are less frequently operated and/or are in area with low fault levels.

Basically, this information is required to perform a statistical life data analysis study.

Throughout the past decades, failure reporting and related databases have undergone many improvements, because the information stored is also applied for yearly reporting of energy regulators and for benchmarking purposes (e.g. yard-stick regulation). As a result, these databases have undergone many changes and expansions.

Based on the availability of the different levels of data within a particular database it can be made out which degree of sophistication of statistical analysis can be performed. In Figure 52 an overview [45] of the requested information on life time data.

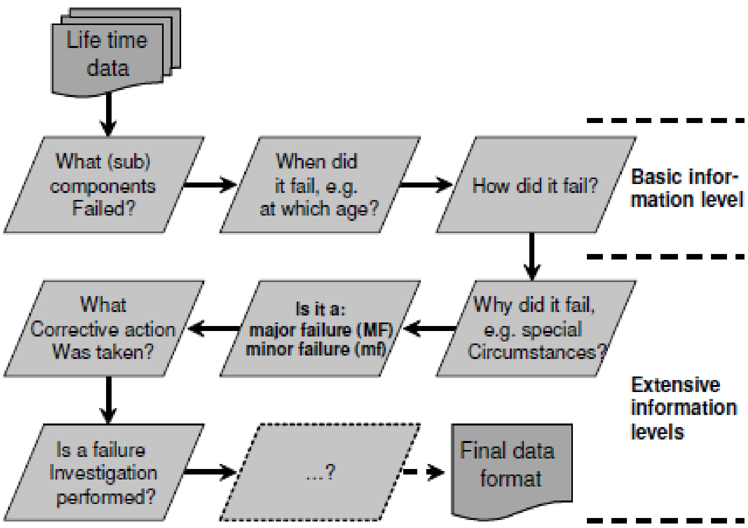


FIGURE 52 - INFORMATION WHICH IS REQUESTED FOR PERFORMING LIFE TIME DATA ANALYSIS. A POSSIBLE DISTINCTION IS MADE BETWEEN BASIC REQUIRED INFORMATION AND EXTENSIVE INFORMATION LEVELS [45]

7.1.2 Life Time Data Types

In the previous section sources of data are described. In this section the criteria and types of data are discussed. Statistical failure distribution models rely extensively on the data to make predictions. The accuracy of any prediction is directly proportional to the quality and completeness of the supplied data. The combination of good data and appropriate model choice, will usually result in acceptable predictions [35].

With regard to statistical life data analysis [35] and as explained in the previous section, the following terminology is used:

- Failure data -> component that failed (F) at the moment of analysis
- Suspended data -> component that is in-service (S) at the moment of analysis

Suspended data means that the units are still operating at the time the reliability of these units is to be determined. The life data is gathered during the whole life of a technical component, starting with the installation and ending with its disposal. Important data properties which should be fulfilled for statistical studies are:

- Randomness
- Independency
- Homogeneity
- Sufficient amount of data

In the analysis of life data it is deemed to be advisable to use all available data. In practice, however, it is hard, expensive and sometimes impossible to collect all required life data. Therefore most of the time, the available data is incomplete or includes uncertainties as to when a component failed exactly. To interpret this, life data can be separated into two categories [45]:

- Complete Data (all units have failed)
- Censored Data (not all units have failed)

Complete Data – Complete data is used when the value of an observation is known completely. For example, if the time-to-failure for a cable joint population with 200 units is observed and all 200 units have failed (and the time-to-failures has been recorded), then the complete information as to the time of each failure is known (Figure 53). It goes without saying that processing complete data is much more efficient and easier than censored data.

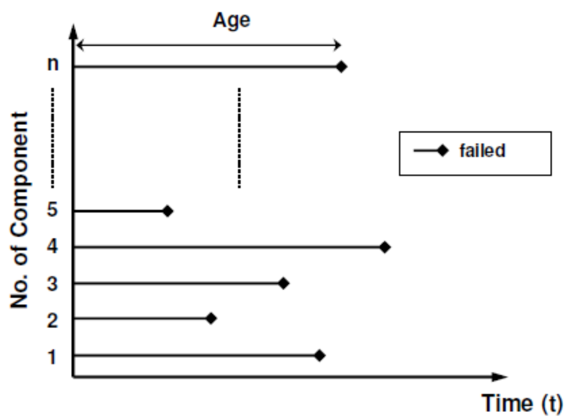


FIGURE 53 - SIMPLISTIC EXAMPLE OF A COMPLETE DATASET ILLUSTRATING ONLY FAILURE TIMES [45]

Censored Data – Censoring occurs when the value of an observation is only known to some extent. Censored data is often encountered when analyzing practical life data, especially in case of electrical power systems where the majority of installed equipment is still in-service, and most of the time the exact age of equipment at the moment of failure is unknown. Several censoring schemes are possible (see also section 4.3.4), the most often used are [74], [45]:

- Right-censored data (suspended data): When a data set is composed of components that did not fail, it can be referred to as right-censored data or suspended data. The term “right-censored” indicates that the event is located to the right of the data set, which implies that certain components are still operating (Figure 54).

- Interval-censored data: This reflects uncertainty as to the exact times the equipment failed or exact age of an equipment upon failure. Interval data is often encountered in asset related databases when components are not constantly monitored.

- Left-censored data: This censoring scheme is a special case of interval-censored data. With left-censored data the time-to-failure for a particular component is known to occur between time zero and some inspection time.

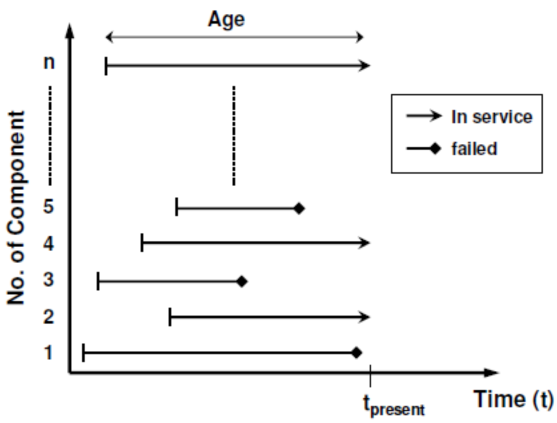


FIGURE 54 - SIMPLISTIC EXAMPLE OF RIGHT CENSORED DATA SET WITH FAILURES AND SUSPENSIONS [45]

7.1.3 Practical Guidelines for Data Issues

In this section a number of practical guidelines for dealing with data issues (during collecting and judging data) are given.

In many practical cases it should be evaluated whether the collected available data is representative for performing statistics. From experience it is found that available databases have discrepancies, missing data or incomplete data. This data can, in most cases, still be made “valuable” by consulting experts for their experts’ opinions. Usually, expert judgements can make missing data useful or at least partially useful for taking into account in further statistical analysis.

Mapping population type with its related failure types. This means, for example, that populations of a certain type of component (e.g. insulation material) should be regarded against its related failure numbers (of the same component type and insulation material type).

8. SUMMARY AND CONCLUSIONS

The current brochure presents and discusses a number of statistical of statistical tools for the analysis of life-data characterizing populations of components installed in power network. The ultimate goal is to provide asset managers with advice how to handle limited and imperfect failure data and which tool should be used to obtain a representative future failure estimation based on the historical records of the population.

At the beginning, the review of the work done by CIGRE bodies on failure occurrence issues was done. More specifically, the currently used definitions of failure has been analyzed and that led to the development of new failure definition as an event that terminates the principal functions of a given component. For better understanding of the nature of each failure, aging mechanisms leading to failure have been briefly described.

The core of this brochure is related to the collection, treatment and analysis of the life-data of high-voltage components. In the first instance, different statistical models allowing the analysis of the life-data are presented in chapter 4.

Chapter 5 treats the influence of maintenance and replacement on failure statistics.

In chapter 6, four case studies are presented. The mathematical models presented in chapter 4 are employed for the analysis of the life-data characterizing the populations of medium and high voltage components.

At the end, in chapter 7 the guidelines for data collection, types of databases as well as the limitations of the datasets are described.

Based on the presented case studies, it can be seen that the main obstacles and problems related to the life-data and its analysis are: the limited amount of life-data, its censoring and possible non-homogeneity. Further application of the mathematical tools that is presented in chapter 6 showed that the analysis of imperfect and limited data can yield a sound failure expectancy that is useful to the asset manager. Based on the amount and characteristics of the available life-data, the decision about the most suitable tool can be taken. Further on, the obtained result should be compared with past records to obtain overall impression of the outcome validity. At the end, the obtained information might be used as additional information for the asset management decision making processes.

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