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Power Transformer Reliability Modelling

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Technische Universiteit Eindhoven, op gezag van de rector magnificus, prof.dr.ir. C.J. van Duijn, voor een commissie aangewezen door het College voor Promoties in het openbaar te verdedigen op donderdag 24 juni 2010 om 14.00 uur

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Preface

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Next to my friends my ancestry should be thanked for bringing me to this point by their specific quirks and abilities brought to me through genes and nurture. I experienced this at first hand by the existence and stories told by my grandparents Adriaan and Aagje, and parents Ben and Agatha. Last, but not least, I like to acknowledge my sister, Rosemarie, for providing the most honest and best tuned feedback to me.
Curriculum vitae

Arjan van Schijndel was born in Oss, the Netherlands, on February 9, 1978. In 1996 he obtained his VWO (Athenaeum) degree at het Maaslandcollege in Oss.

His fascination in radio communication motivated him to obtain his amateur radio license (PE1PUL) in 1994 and later to start his education in electrical engineering at the Eindhoven University of Technology.

From the Eindhoven University of Technology he obtained his Master of Science degree in Electrical Engineering in October 2003, based on antenna modelling techniques during his internship and master thesis work at TNO Defence in The Hague. In October 2003 he obtained his Master of Science degree in Electrical Engineering at the Eindhoven University of Technology, his thesis dealt with antenna modelling techniques developed during his internship and master thesis work at TNO Defence in The Hague [104, 105, 119].

From 2004 to 2010 he performed his PhD research under supervision of prof.dr.ir. J.M. Wetzer, prof.dr.ir. E.F. Steennis and dr. P.A.A.F. Wouters at the Eindhoven University of Technology. His PhD research addresses a methodology to determine the reliability of a power transformer or a population of power transformers, with the aid of an integral lifetime model for the power transformer. The mechanisms to attain this model are addressed in this dissertation.

Currently, he is employed by Alliander as an asset manager policy advisor. Alliander is the largest Dutch distribution network operator, which operates and maintains about a third of the Dutch distribution grid.


Preface

List of publications

Journal papers


Conference papers


Letter

**Power transformer reliability modelling — Summary**

**Problem description**

Electrical power grids serve to transport and distribute electrical power with high reliability and availability at acceptable costs and risks. These grids play a crucial though preferably invisible role in supplying sufficient power in a convenient form. Today’s society has become increasingly dependent on the availability of power, and has become a more and more demanding "client", putting strong pressure on the reliability, availability and cost efficiency of supply.

Once the functionality of a grid is designed and the grid is constructed, it is taken into operation and expected to stay in operation for several decades. From then on the ways to control grid quality (reliability, availability, costs and risks) are operation and maintenance. The quality of the grid may be measured in terms of quality of supply (grid performance), condition (ability to perform) or costs (to ensure quality and control risks). The grid functionality may be endangered by capacity or quality limitations. In that case the grid operator needs to come up with either operational measures (maintenance, revision, load control, process improvements) or investments (replacement, extension).

For making substantiated decisions it is important to know the condition of the grid and its components. Condition information is crucial to make the expected performance quantifiable, and to make risks and costs predictable and controllable. Without condition information risks and costs may either be accepted, at the possible expense of reliability or availability, or prevented at the expense of additional safety margins and costs. Specifically, condition assessment may contribute significantly to make maintenance effective, efficient and timely, it may allow to postpone investments in a justified way and to permit controlled overloading. Moreover, it enables to justify the asset management policy to stakeholders such as clients, shareholders and regulator.

One of the key components in the grid, in terms of both reliability and investment, is the power transformer, which allows for power transmission and distribution at the required voltage level. The reliability of transformers is a prime concern to grid operators. The ultimate aim of the present study is to develop an integral transformer life time model. This model will predict the transformer reliability based on relevant degradation mechanisms. These degradation mechanisms can occur in the transformer subcomponents, i.e. tank, bushings, tapchanger, core, oil and windings. Further, the transformer life time model must be applicable to individual power transformers and to power transformer populations.

**Technical reliability**

A technical reliability model aims at supporting the asset management process by providing reliability information from a technical perspective. In most cases, technical reliability refers to the technical condition and the way it changes over time, catalysed by operational and environmental parameters. One contribution to the technical reliability, for example, is the quality of electrical insulation.

The technical reliability model predicts the technical condition of a component or system in terms of the probability that a component or system can perform its designated function. The method used to predict the reliability may depend on the topology, the life cycle stage of the component or system, the available level of information, and the type and level of the
required output. Several methods may be used to predict future technical reliability. Two basic options are distinguished, one based on statistical data analysis and one based on the understanding of degradation mechanisms.

The concept of "quality parameters" is introduced as the link between a degradation mechanism and a degradation model to predict its corresponding technical reliability. Parameters describing the condition of the system are defined as quality parameters (QP). Three different types of quality parameters (QP) are distinguished:

**Direct explicit QP**: is a measurable quantity that is directly linked to the degradation process, and is a direct measure of the degree of degradation.

**Indirect explicit QP**: is a measurable quantity as well, but it is not directly linked to a specific degradation mechanism, and may originate from various sources. As a result it requires additional processing to link it to a specific mechanism.

**Implicit QP**: is a comparative value of how well the component works in normal operating scenarios, but the result in any specific situation cannot by verified by measurement.

Three distinctive methods for predicting the QP, the rate of degradation, and the level of degradation, in an increasing order of linkage with the degradation process, are:

**Expert judgement model** An expert judgement model is a set of knowledge rules based on expert judgement. With these rules a classification of the degradation level and rate can be derived. The classification is made by defining trigger levels based on the value of the QP.

**Regression model** With a regression model observed correlations and trends are employed to match key properties of an asset. The available data is matched to a suitable mathematical relationship.

**Physical model** By understanding the physics behind the degradation process, QPs can be defined that are representative for the process. A physical model relies on accurate input data, which may be hard to obtain. Having defined explicit QPs, it allows tracing the progress of degradation. The results can even be fed back in to the physical model to improve the accuracy of the modelling.

The overall fault probability follows from a combination of the three types of information. Any of these fault probabilities can be used as input for the integral asset management decision model. For the power transformer an overview is given of the different diagnosis and monitoring tools, and the corresponding quality parameters that link observable or deducible quantities to the degradation mechanism.

**Integral transformer technical reliability model**

**Paper-oil insulation**

The power transformer is a component operating in a high voltage, high current, and consequently high power environment. Each aspect imposes its specific challenge on the transformer design. Paper-oil insulation is widely applied in power transformers. Oil has an intrinsic high insulating strength and at the same time serves as cooling medium by either passive or active flow. The paper prevents electric bridging by contaminants left behind and serves as a mechanical barrier between the windings and winding layers. The paper is a critical factor in paper-oil insulation. Bad paper quality leads to premature insulation degradation.

The technical reliability of the paper is affected mainly by the load and ambient temperature of the transformer and concerns the modelling of three phenomena: the reliability of
winding paper insulation, the temperature dependency of paper degradation and the winding hot-spot temperature. The predicted DP-value of the degradation mechanism model is in good agreement with the investigation results of a failed machine transformer.

The used paper degradation model has two benefits: it describes the degradation process from a physical perspective and it is adjustable to different end-of-life thresholds. The trade off of this approach is the need of detailed process parameters. The paper degradation model is extended to include the impact of harmonic currents on the winding hot-spot temperature.

**Bushings and tap-changer**

Transformer reliability does not only depend on the condition of the winding insulation. The most relevant other subcomponents which may contribute to the overall transformer reliability are the bushings and the tap-changer. Unfortunately, for these components easily accessible direct QPs are harder to find than for paper insulation. Conceptual ideas to predict the reliability of bushings and tap-changers are discussed according to the degradation mechanism modelling principle.

The reliability of a system depends on its subcomponents and their interaction. The interaction of subcomponent reliabilities on the overall reliability can be visualised by a fault tree analysis, a degradation mechanism tree analysis or by a reliability block diagram. An integral reliability model for power transformer is formed from combining two statistics based models for bushing and tap-changer failure with the paper degradation model.

The results of the integration of the transformer subcomponent models confirm that for European load scenarios the performance of the tap-changer endangers the performance of the transformer more than the quality of winding paper insulation.

**Transformer population reliability model**

**Modelling populations**

Typical high voltage grids may contain thousands of power transformers. The load of these transformers depends upon the number and character of the costumers connected. In heavy industry with a high power demand transformers are continuously loaded nominally, whereas in rural areas only a small fraction of the rated power needs to be delivered. A specification of all individual transformers reliabilities only does not provide a clear picture of the overall network condition. There is a need for defining properties that characterise the condition of a population of similar assets by means of a limited number of figures. Useful figures are the expected number of transformers still operational or the number of transformers expected to fail each year. Depending on past policy of installation, on present and future scenario of transformer loading, and on maintenance strategy, an increased replacement effort may be required within several decades. The projected failure rate from a population model predicts whether, and on what time scale, transformer failure is to be expected. For population analysis an alternative is provided to predict the population reliability from an individual perspective.

**Failure wave scenarios and replacement alternatives**

The transformer population reliability model is applied to two Dutch population data sets. For these populations the effects of failure wave scenarios and replacement alternatives are determined and compared. The simulations performed illustrate the importance of correct
load scenarios and the history of the individual components. The future scenario analysis and replacement alternatives show that for moderate growth scenarios the expected replacement wave will probably not start earlier than the year 2050. This implies that the majority of transformers will be replaced due to transportation capacity issues. Further, a preventive replacement of all transformers is only effective in increasing the reliability of the population as a whole if a differentiation can be made between highly loaded and moderately loaded transformers. If not, the fleet needs to be replaced completely before the failure wave will start.
Modelleren van de betrouwbaarheid van vermogenstransformatoren — Samenvatting

Probleem beschrijving

Elektriciteitsnetwerken worden gebruikt om elektrische energie te transporter en te distribueren met hoge betrouwbaarheid en beschikbaarheid, en tegen acceptabele kosten en risico's. Deze netwerken spelen een cruciale, doch onzichtbare, rol door energie in een gewenste vorm te brengen waar hij nodig. De huidige samenleving is in toenemende mate afhankelijk geworden van de beschikbaarheid van elektriciteit, en stelt daarnaast als "klant" steeds hogere eisen aan de betrouwbaarheid, beschikbaarheid en kosten van levering.

Wanneer een netwerk eenmaal is ontworpen en aangelegd, wordt het in gebruik genomen om enkele tientallen jaren probleemloos te kunnen blijven functioneren. Vanaf dat moment kan de kwaliteit van het netwerk (betrouwbaarheid, beschikbaarheid, kosten en risico's) alleen nog beïnvloed worden door bedrijfsvoering en onderhoud. De netwerk kwaliteit kan worden gemeten in termen van de kwaliteit van levering (netwerkprestatie), de conditie (het vermogen om te blijven functioneren) of de kosten (om kwaliteit te borgen en risico's te beheersen). De netwerk functionaliteit kan in gevaar komen door beperkingen in de capaciteit of in de kwaliteit. Als beperkingen zich voordoen dan is het de taak van de netwerkbeheerder om tegenmaatregelen te nemen (onderhoud, revisie, belastingsturing, proces verbeteringen) of tot investeringen over te gaan (vervanging, uitbreiding).

Om tot een onderbouwde beslissing te komen is het belangrijk om de conditie van het netwerk en haar componenten te kennen. Informatie over de conditie is nodig om het verwachte functioneren te kwantificeren, en om risico's en kosten te kunnen voorspellen en beheersen. Wanneer deze informatie ontbreekt, kunnen risico's en kosten ofwel voor lief genomen worden, ten koste van betrouwbaarheid en beschikbaarheid, of slechts tegen hoge extra kosten beheerst worden. Conditiebepaling kan er in het bijzonder toe bijdragen dat onderhoud effectief, efficiënt en op tijd wordt uitgevoerd, dat investeringen pas worden gedaan wanneer ze echt nodig zijn, en dat netdelen op een verantwoordelijke wijze kunnen worden overbelast zonder aan kwaliteit in te boeten. Tot slot geeft het de asset manager de mogelijkheid om zijn beleid inzichtelijk te maken aan de belanghebbenden, zoals klanten, aandeelhouders en de toezichthouder.

Een belangrijke component in het elektriciteitsnetwerk, in termen van betrouwbaarheid en investeringen, is de vermogenstransformator. De vermogenstransformator maakt het mogelijk dat het vermogen op elk gewenst spanningsniveau kan worden getransporteerd en gedistribueerd. De betrouwbaarheid van transformatoren is daarmee van belang voor netwerkbeheerders. Het uiteindelijke doel van dit onderzoek is om een integraal levensduurmodel van de vermogenstransformator te ontwikkelen. Dit model dient om de transformatorbetrouwbaarheid te voorspellen, op basis van relevante degradatiemekanismen. Deze degradatiemekanismen kunnen optreden in deelcomponenten van de transformator, zoals de bak, de doorvoeren, de regelschakelaar, de kern, de olie en de windingen. Doel van het model is om het te kunnen toepassen op individuele transformatoren en op populaties van transformatoren.


**Technische betrouwbaarheid**

Een technisch betrouwbaarheidsmodel ondersteunt het asset management proces met betrouwbaarheidsinformatie vanuit een technisch perspectief. In de meeste gevallen, refereert technische betrouwbaarheid aan de technische conditie als functie van de tijd, en aan de wijze waarop die beïnvloed wordt door bedrijfsvoering en omgevingsvariabelen. De kwaliteit van de elektrische isolatie, bijvoorbeeld, draagt bij aan de technische betrouwbaarheid van de transformer.

Het technische betrouwbaarheidsmodel voorspelt de conditie van een component of systeem in termen van de waarschijnlijkheid dat die component of dat systeem kan functioneren naar behoren. De gebruikte voorspelmethode kan afhangen van de topologie, het stadium in de levenscyclus, de beschikbare informatie, en het type en niveau van de benodigde voorspelling. Om de technische betrouwbaarheid te voorspellen zijn verschillende methoden beschikbaar. In de basis worden twee mogelijkheden onderscheiden, de een gebaseerd op een statistische analyse van data, de ander gebaseerd op een fysische beschrijving van degradatie mechanismen.

We introduceren het concept "kwaliteitsparameters" als de link tussen een degradatiemechanisme en een degradatiemodel, om daarmee de technische betrouwbaarheid te kunnen voorspellen. Een kwaliteitsparameter (QP) wordt gedefinieerd als een parameter die de conditie van de component of het systeem beschrijft. We onderscheiden drie verschillende soorten kwaliteitsparameters (QP):

- **Directe expliciete QP**: een meetbare grootheid die direct is gerelateerd aan het degradatieproces, en een directe maat is voor de verouderingsgraad.
- **Indirecte expliciete QP**: eveneens een meetbare grootheid, en gerelateerd aan het degradatieproces maar niet direct gerelateerd. Er is een extra vertaalslag nodig om de parameter te kunnen koppelen aan een specifiek degradatiemechanisme.
- **Impliciete QP**: een afgeleide, soms ook relatieve, waarde, die aangeeft hoe goed een component functioneert onder normale gebruiksomstandigheden. Het gedrag in een concrete situatie kan echter niet door meting geverifieerd worden.

Men kan drie verschillende methoden onderscheiden om het gedrag van kwaliteitsparameters, de degradatiesnelheid, en het niveau van degradatie, te voorspellen. In volgorde van toenemende correlatie met het degradatieproces, zijn dat:

- **Expertmodel** Een expertmodel is een set van kennisregels gebaseerd op het oordeel van deskundigen. Met deze regels kan een classificatie van degradatieniveaus worden afgeleid. De classificatie wordt gemaakt door drempelwaardes te definiëren op basis van QP.
- **Regressiemodel** Met een regressiemodel worden correlaties en trends geobserveerd, om de belangrijke asset eigenschappen te bepalen. De beschikbare data wordt "gefit" met een bruikbare wiskundige relatie.
- **Fysisch model** Door het begrijpen van de natuurkundige verschijnselen van het degradatieproces, kunnen QP’s worden gedefinieerd die representatief zijn voor het proces. Een fysisch model is afhankelijk van accurate invoer gegevens, welke soms moeilijk te verkrijgen zijn. Als er expliciete QP’s gedefinieerd zijn, geeft dat de mogelijkheid op het degradatieproces te volgen ("monitoren"). Het resultaat kan op zijn beurt als terugkoppeling gebruikt worden om de nauwkeurigheid van het fysische model verder te verbeteren.

De uiteindelijke foutkans volgt uit een combinatie van de drie voorspelmethodes. Elk van deze foutkansen kan worden gebruikt als invoer voor het integrale assetmanagement beslissingsmodel. Voor de vermogenstransformator is een overzicht gegeven van de verschillende meth-
oden van diagnose en monitoring, en van de bijbehorende kwaliteitsparameters die de verbind-
ing vormen tussen geobserveerde of afgeleide grootheden en het degradatiesproces.

**Integraal transformator betrouwbaarheidsmodel**

**Olie-papier isolatie**

De vermogenstransformator opereert onder hoge spanning, hoge stroom en, als gevolg daar-
van, hoog vermogen. Spanning, stroom en vermogen stellen elk haar eigen specifieke eisen
aan het transformatorontwerp. Olie-papier isolatie wordt veelvuldig gebruikt in vermogen-
stransformatoren. Olie heeft een hoge intrinsieke isolatie sterkte, maar fungeert tegelijkertijd
als koelmedium door actieve of passieve stroming. Het papier voorkomt elektrische doorslag
als gevolg van aanwezige vervuiling en dient als mechanische barrière tussen de windingen en
windinglagen. Het papier is een kritische factor voor olie-papier isolatie. Een slechte papier-
waarde leidt tot voortijdige degradatie van de isolatie.

De technische betrouwbaarheid van het papier wordt voornamelijk beïnvloed door de be-
lasting en omgevingstemperatuur van de transformator. Het modeleren omvat drie fenome-
nen: de betrouwbaarheid van de papierisolatie van de windingen (uitgedrukt in de kans op
een te lage DP-waarde), de temperatuur afhankelijkheid van de papierdegradatie en de wind-
ing hot-spot temperatuur. De DP-waarde zoals die wordt voorspeld met het papierdegradatie
model komt goed overeen met de meetresultaten van een gefaalde machinetransformator.

Het gebruikte papierdegradatie model heeft twee voordelen: het beschrijft het degradatiespro-
ces vanuit een fysisch perspectief en het is toepasbaar bij verschillende criteria waarmee het
einde van de levensduur kan worden gedefinieerd. Een nadeel van deze benadering is de
noodzaak om te beschikken over gedetailleerde procesparameters. Aan het papierdegradatie
model is de mogelijkheid toegevoegd om de invloed van harmonische stromen op de hot-spot
temperatuur van de windingen te beschrijven.

**Regelschakelaar en doorvoeren**

De betrouwbaarheid van de transformator hangt niet alleen af van de conditie van de windin-
gen. De deelcomponenten die daarnaast het meest bijdragen aan de totale betrouwbaarheid
van de transformator zijn de regelschakelaar en de doorvoeren. Voor deze componenten zijn
geen eenvoudig toegankelijke directe expliciete QP’s te vinden, zoals bij papierisolatie. Mo-
gelijkheden om de betrouwbaarheid van regelschakelaars en doorvoeren te voorspellen wor-
den op conceptueel niveau besproken aan de hand van modelleringprincipes voor de degra-
datiemechanismen.

De betrouwbaarheid van een systeem hangt af van de deelcomponenten en hun inter-
actie. De interactie tussen de betrouwbaarheden van de deelcomponenten en de betrouw-
baarheid van het geheel kan inzichtelijk gemaakt worden met een foutboomanalyse, met een
"degradatiemechanisme-boomanalyse" of door middel van een betrouwbaarheidsblokdia-
gram. Een integraal betrouwbaarheidsmodel voor de vermogenstransformator is opgebouwd
uit statistische modellen voor regelschakelaar en doorvoer, in combinatie met het papierdegra-
datie model.

De resultaten behaald met het integrale transformatormodel bevestigen, dat voor Europese
belastingsscenario’s de regelschakelaar een grotere bedreiging vormt voor de transformatoren
dan de kwaliteit van de papierisolatie van de windingen.
**Transformer populatie betrouwbaarheidsmodel**

**Populatie modellering**

Typische hoogspanningsnetwerken kunnen duizenden vermogenstransformatoren bevatten. De belasting van deze transformatoren is afhankelijk van het aantal klanten en het type klant dat is aangesloten. Voor zware industrie met een grote vermogensvraag zijn transformatoren continue nominaal belast, voor stedelijke gebieden wordt vaak slechts een fractie van het nominale vermogen getransporteerd. Door de betrouwbaarheid van individuele transformatoren te bepalen ontstaat nog geen overzichtelijk beeld van de toestand van het net als geheel. Er is daardoor behoefte om populatie eigenschappen te definiëren die het mogelijk maken om de conditie van een populatie met een beperkt aantal grootheden te karakteriseren. Brukbare grootheden zijn het verwachte aantal nog werkende of al gefaalde transformatoren per jaar. Afhankelijk van het historische installatiepatroon, van de huidige en toekomstige transformatorbelasting, en van de gevoerde onderhoudsstrategie, kan een toenemend vervangingsvolume verwacht worden in de komende tientallen jaren. De gepresenteerde faalsnelheid van een populatiemodel voorspelt op welke tijdschaal transformator falen verwacht kan worden. Naast de populatieanalyses bestaat er het alternatief om de populatiebetrouwbaarheid te voorspellen op basis van de individuele betrouwbaarheden.

**Faalscenario’s en vervangingsalternatieven**

Het transformator populatiemodel is toegepast op twee Nederlandse populaties van vermogenstransformatoren. Voor deze populaties en voor verschillende te verwachten faalscenario’s zijn vervangingsalternatieven vergeleken. De uitgevoerde simulaties illustreren hoe belangrijk het is om de juiste belastingsscenario’s en de historie van de individuele componenten te kennen. De scenarioanalyses en vervangingsalternatieven laten zien dat voor een matige groei van de belasting de verwachte vervangingsgolf op basis van papierdegradatie niet eerder zal plaatsvinden dan rond het jaar 2050. Dit betekent dat het merendeel van de transformatoren voordien vervangen zal zijn omwille van beperking in de transportcapaciteit. Daarbij is gebleken dat met een preventieve vervanging van transformatoren de populatiebetrouwbaarheid alleen effectief verbeterd wordt wanneer gedifferentieerd kan worden tussen zwaar belaste en matig belaste transformators. Als er niet gedifferentieerd kan worden tussen transformatoren, moet de gehele transformatorvloot preventief vervangen worden voordat de transformatoren op grote schaal gaan falen.
Chapter 1

Introduction

Electrical power grids serve to transport and distribute electrical power with high reliability and availability at acceptable costs and risks. These grids play a crucial though preferably invisible role in supplying today’s society with sufficient power in a convenient form. Today’s society has become increasingly dependent on the availability of power, and has become a more and more demanding “client”, putting strong pressure on the reliability, availability and cost efficiency of supply.

Once the functionality of a grid is designed, and the grid is constructed and taken into operation, a grid is expected to stay in operation for several decades. From then on the ways to control grid quality (reliability, availability, costs and risks) are operation and maintenance.

The quality of the grid may be measured in terms of quality of supply (grid performance), condition (ability to perform) or costs (to ensure quality and control risks). The grid functionality may be endangered by capacity or quality limitations. In that case the grid operator needs to come up with either operational measures (maintenance, revision, load control, process improvements) or investments (replacement, extension).

For making substantiated decisions it is important to know the condition of the grid and its components. Condition information is crucial to make the expected performance quantifiable, and to make risks and costs predictable and controllable. Without condition information risks and costs may either be accepted, at the possible expense of reliability or availability, or prevented at the expense of additional safety margins and costs. Specifically, condition assessment may contribute significantly to make maintenance effective, efficient and on time, allows to postpone investments in a justified way and allows controlled overloading. Moreover, it enables to justify the asset management policy to stakeholders such as clients, shareholders and regulator.

Nowadays many condition assessment techniques are available to measure and evaluate condition information. Three observations can be made:

- Most techniques provide information on the present condition. Although this does allow for some extrapolation, there is a lack of techniques that are able to accurately predict future behaviour and performance.
- Moreover, most techniques focus on a single quantity, process or defect type, and not on the equipment as a whole.
- There is an increasing need to distil from all possibilities available the most appropriate set of techniques that provides sufficient and accurate information for a specific purpose (the purpose being e.g. the need for maintenance, the optimum replacement time or strategy for an individual component or a population, the ability to endure overloading, and so on).
For this reason the ultimate aim of the work described in this thesis is to arrive at a model that will predict the future performance of an integral component in relation the specific management question to be addressed: an integral lifetime model.

The component that this effort is focused on is the power transformer. It is a crucial component of the grid and is often mentioned in relation to quality or capacity bottlenecks. Furthermore the state of the art of diagnostics and modelling suggests that an integral lifetime model is within reach.

Before the formation of an integral lifetime model for the power transformer is discussed, a general introduction is in place. Firstly, background and historical developments from social, asset management and scientific perspective are addressed in Section 1.1. Hereafter, some general assumptions and the playing field of the research will be defined in Section 1.2. The precise scope of the research is given in Section 1.3. The structure of the discussion of the research results is provided in Section 1.4.

1.1 Background of this study

The historical developments from several perspectives will show the necessity of new information in the field of reliability engineering. These information needs will be discussed from three perspectives: society (Section 1.1.1), asset management (Section 1.1.2) and scientific (Section 1.1.3).

![Figure 1.1: The yearly installed power transformers and their assumed failures for instance after fifty years for two Dutch utilities. The two Dutch utilities are Enexis and Stedin.](image-url)
1.1.1 **Society perspective**

A large scale electrification took place in the Netherlands from 1950–1970. This resulted in an installation wave of power transformers, for two Dutch utilities the yearly installed power transformers is depicted in Figure 1.1. Let us assume that these transformers have an average lifetime of fifty years. This assumption will result in an expected increase of failures in the 2000–2020 period, which can also be seen in Figure 1.1. Fortunately, these trends are not observed yet. The failure of these components is however imminent and to counter its disastrous effects, knowledge is needed about the exact distribution of the failure wave. This challenge arises not only in the Netherlands, but in most industrialised countries [12, 59, 60, 91, 122, 126].

The topology of the electricity grid installed from 1950 till 1970 was, and still is, a top down structure, i.e. energy is transported in one direction, schematically represented by Figure 1.2(a). Here, energy is produced at a power plant and transported through the grid to the customers. The future grid topology is expected to have a bidirectional energy flow, because electricity production will be dispersed, and because many customers also have production capacity, as depicted in Figure 1.2(b). Due to the uncertainty on the exact future power grid layout, the asset manager will be cautious with replacements and investments.

![Schematic layout of the current and the expected future power grid.](image)

**Figure 1.2:** Schematic layout of the current and the expected future power grid.

Power outage incidents, such as Haaksbergen 2006 and Bommelerwaard 2007 [13, 66, 89], show that in today’s society electricity is experienced as a basic life necessity. As a result, the regulator demands transparency and accountability of the decisions made by the asset manager.

1.1.2 **Asset management perspective**

The privatisation of power utilities and the introduction of competition on the electricity market changed the focus of these companies. The focus changed from reliability, availability and safety to effectiveness and accountability, i.e. from technology driven to economy/risk driven. This is, e.g., reflected in a recent standard for the asset management of infrastructures issued by the BSI: PAS55\(^1\) [9, 10]. This standard describes the different responsibilities and tasks throughout the utility. Furthermore in PAS55 the asset manager is defined as a separate

\(^1\)Strictly speaking PAS55 is not a standard but a publicly available specification (PAS).
role and is responsible for managing the assets and needs to find the optimal balance between reliability, costs and risks for the infrastructure as a whole.

The asset manager is urged by the asset owner and the regulator, to give a transparent and objective account, based on a cost-benefit and risk analysis. These risks incorporate technical and economical risks, but also legal, social, reputation and environmental risks. Due to the demand of transparent and objective accountability, the asset manager prefers a scientifically accepted basis for his decisions.

The power transformer is an important component for the asset manager, because of three reasons. Firstly, the power transformer, next to cables and switchgear, often represent a capacity and reliability bottleneck. A second factor concerns the high primary and secondary costs caused by power transformer failure, with the primary costs being the price of a new transformer and the costs of replacing the transformer. The secondary costs depend on the effect of the failure (contaminated soil, the loss of peripherals at the substation, or the outage costs caused by a substation failure). A third factor involves the long delivery time of new power transformers, presently at least two years.

1.1.3 Scientific perspective

Transformer degradation mechanism, such as, paper degradation [26, 64, 93], bushing degradation [8, 19, 47] and contact degradation [32, 62], have been extensively studied in laboratories for the last two decades. These studies have provided insight in the behaviour of these degradation processes and which conditions will accelerate the process. However, the actual condition of a transformer can not presently be predicted by these models, because the models are obtained from controlled laboratory experiments.

Failure data and expert interpretations are extensively available [2, 6, 60, 83], because the transformer operators and owners were focussing on determining the actual condition of transformer by diagnostic methods. The diagnostic methods are discussed in Section 3.4. A selection of the most common methods are: the dissolved gas analysis which determines the quality of the insulation paper and oil, furan analysis provides information about the quality of the winding insulation and the dynamic resistance measurement can be used for determining the contact quality of the tap-changer. These tools were developed for determining the actual condition and taking immediate action. A downside is that future behaviour can only be extrapolated under the assumptions that the historical conditions will remain similar in the future, e.g., the impact of a load increase due to the development of a suburb in a rural area, can not be determined from extrapolation.

The developments in the information and communication technology (ICT) field provide possibilities for reliability modelling and forecasting. The developments in ICT and their possibilities are summarised as:

- Complex real-time calculations will enable the integral transformer model parameter calculations based on historical data and extrapolate the reliability under the assumptions of future scenarios.
- With large scale data management the storage and manipulation of the historical load patterns and diagnostic results can be more efficiently put to use.
- Cheap and reliable communication may transmit the desired available information to the right location at any time.

These items increase the number of possibilities of the integral transformer reliability model. The integral transformer lifetime model may incorporate several degradation mechanism of
the transformer. The progress of the degradation mechanisms is determined from historical and future stress scenarios. Further, it has the ability to be tuned to diagnostic results.

1.2 Framework of this research

The purpose of this section is to provide a general introduction on asset management in accordance with PAS55 [9, 10] and to describe the position of the presented work on the asset management playing field.

PAS55 presents a preferred way of managing assets to achieve a desired and sustainable outcome. An asset is defined as a distinct quantifiable business function or service. Five categories of assets can be distinguished: physical, human, financial, information and intangible. Examples of these categories are presented in Table 1.1.

Table 1.1: Asset classification with examples.

<table>
<thead>
<tr>
<th>Asset classes</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical</td>
<td>natural resources, infrastructure, machinery, plant, equipment, buildings, IT systems</td>
</tr>
<tr>
<td>Human</td>
<td>leadership, management, workforce, skills, knowledge and experience</td>
</tr>
<tr>
<td>Financial</td>
<td>cash, investments, equity, credit rating</td>
</tr>
<tr>
<td>Information</td>
<td>data and information</td>
</tr>
<tr>
<td>Intangible</td>
<td>reputation, costumer and staff impression, public image/relations, brand value, licenses, patents, trademarks, copyrights and culture</td>
</tr>
</tbody>
</table>

Three major roles are defined in the management of assets, the asset owner, the asset manager and the service provider. All three have their own responsibilities in decision making and providing information, these dependencies are presented in Figure 1.3.

- The asset owner is responsible for defining and guarding the business strategies, goals and values. Further, he should safeguard that there is enough financial means and that the yield of the investment are according to agreements.
- The asset manager is responsible for transforming the business strategies and goals into policies, plans and programs. Next to this, he should control the costs and secure functionality and performance. He decides about the performance limits of the assets, service and turnover. He also controls the risks concerning technical performance, safety, economical, environment and law.
- The service provider will execute the policies in conformity with safety, planning and budget specifications.

The first communication layer is the exchange of targets and performance between the asset owner and asset manager. The second layer consists of providing work orders by the asset manager to the service provider and reporting the result of the work order execution from service provider to the asset manager supplemented with performance data of the assets. The asset manager will process the information according to his responsibilities.

We will explain the basic principles of asset management in Sections 1.2.1 and 1.2.2 according to PAS55. The dependencies of optimising the asset management process and a basic decision aid model are discussed in Sections 1.2.3 and 1.2.4, respectively. The focus of this dissertation on technical reliability is clarified in Section 1.2.5.
1.2.1 Asset management terms and definitions (PAS55)

Asset plant, machinery, property, buildings, vehicles and other items and related systems that have a distinct and quantifiable business function or service.

Asset management systematic and coordinated activities and practices through which an organisation optimally and sustainable manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organisational strategic plan.

Asset management information meaningful data relating to assets and asset management.

Asset management information system system for the storage, processing and transmission of asset management information.

Asset management objective specific and measurable outcome or achievement required of asset system(s) in order to implement the asset management policy and asset management strategy; and/or detailed and measurable level of performance or condition required of the assets; and/or specific and measurable outcome or achievement required of the asset management system.

Asset management performance measurable results of an organisation's management of its assets and/or asset system(s).

Asset management plan document specifying activities and resources, responsibilities and timescales for implementing the asset management strategy and delivering the asset management objectives.

Asset management policy principles and mandated requirements derived from, and consistent with, the organisational strategic plan, providing a framework for the development and implementation of the asset management strategy and the setting of the asset management objectives.
Asset management strategy  long-term optimised approach to management of the assets, derived from, and consistent with, the organisational strategic plan and the asset management policy.

Asset management system  organisation's asset management policy, asset management strategy, asset management objectives, asset management plan(s) and the activities, processes and organisational structures necessary for their development, implementation and continual improvement.

Asset portfolio  complete range of assets and asset systems owned by an organisation.

Asset system  set of assets that interact and/or are interrelated so as to deliver a required business function or service.

Audit  systematic, independent process for obtaining evidence and evaluating it objectively to determine the extent to which audit criteria are fulfilled.

Contracted service provider  individual(s) not directly employed by the organisation including contractors, subcontractors, service providers, consultants, agency staff and casual workers.

Corrective action  action to eliminate the cause of a detected nonconformity or other undesirable situation.

Critical assets/asset systems  assets and/or asset systems that are identified as having the greatest potential to impact on the achievement of the organisational strategic plan.

Effectiveness  extent to which planned activities are realised and planned results achieved.

Efficiency  relationship between the result achieved and the resources used.

Enablers (asset management)  supportive systems, procedures, processes, activities and resources that enable an organisation to operate its asset management system efficiently and effectively.

Functional policy  specified approach, rules and boundaries set out by an organisation, that provide direction and the framework for the control of specific asset-related processes and activities.

Life cycle  time interval that commences with the identification of the need for an asset and terminates with the decommissioning of the asset or any associated liabilities.

Nonconformity  non-fulfilment of a requirement.

Optimise  achieve by a quantitative or qualitative method, as appropriate, the best value compromise between conflicting factors such as performance, costs and retained risk within any non-negotiable constraints.

Organisation  company, corporation, firm, enterprise, authority or institution, or part or combination thereof, whether incorporated or not, public or private, that has its own functions and administration.

Organisational strategic plan  overall long-term plan for the organisation that is derived from, and embodies, its vision, mission, values, business policies, stakeholder requirements, objectives and the management of its risks.

Preventive action  action to eliminate the cause of a potential nonconformity or other undesirable potential situation.

Procedure  specified way of carrying out an activity or a process.

Process  set of interrelated or interacting activities which transforms inputs into outputs.

Record  document stating results achieved or providing evidence of activities performed.

Risk management  coordinated activities to direct and control an organisation with regard to risk.

Stakeholder  person or group having an interest in the organisation's performance, success or the impact of its activities.
**Sustainable** achieving or retaining an optimum compromise between performance, costs and risks over the asset’s life cycle, whilst avoiding adverse long-term impacts to the organisation from short-term decisions.

**Sustainable development** enduring, balanced approach to economic activity, environmental responsibility and social progress.

**Top management** appointed and authorised person, or a group of people, who direct and control an organisation at the highest level.

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**Figure 1.4:** The asset system and its elements in a cycle to ensure continual improvement [9, 10].

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### 1.2.2 Asset management system elements

The asset management system depicted in Figure 1.4 is a continues process to ensure the achievement of the organisational strategic plan. This system consists of five elements:

1. **Policy and strategy** describe the framework for the operational planning, in essence a long-term direction and plan for the organisation.

2. **Information, risk assessment and planning** In this phase, information will be gathered and stored. The information is essential to monitor risks, legislation, standards, objectives, performance, conditions and available plans.

3. **Implementation and operation** is the phase where the plans are implemented in a structured way. To get these plans implemented and in operation, training is necessary for an adequate level of awareness and competence. In this active phase, it is also essential that the gained information is again communicated and stored for future usage.

4. **Checking and corrective action** are done to get insight in the execution status of the plans and correct them if they are not on track.
5. **Management review and continual improvement** ensures that new gained information, about incomplete plans and changing situations, will improve the new formed policies and strategies.

### 1.2.3 Asset management optimisation process

The asset management optimisation process is aiming for the best compromise between expenditures, performance and risks. Where all actions should comply to the non-negotiable constraints defined by the asset owner, e.g. legislation, standards, and/or agreements with external parties. In Figure 1.5 the boundaries of the optimisation process are depicted. The life cycle phase and the optimisation horizon are two other major influencing criteria on the optimisation process.

![Figure 1.5: The domain of the asset management optimisation process.](image)

The asset life cycle, depicted in Figure 1.6, consists of six major phases: design, production, operation, maintenance, replacement and decommissioning. In the design phase of an asset, it is endorsed that the asset will live up to the demands during production and operation, i.e. easy and safe to produce, capable of performing when in operation and minimising liability risks. The asset is created in the production phase. In the operation phase the asset performs a task beneficial to the organisation strategic plan. The maintenance phase ensures that the asset will keep performing its task. If the asset is no longer able to perform its task, it is for instance replaced. During the replacement phase, it is essential that the asset gets a new destination or gets decommissioned. Decommissioning of an asset, is removing the asset from the organisation.

Three distinguishable optimisation horizons exists: strategic, tactical and operational. The strategic plan determines the long term optimisation goals of an asset, e.g. keeping the reli-
ability of a region sufficient. The tactical horizon focusses on optimising the system performance without changing the system significantly, i.e. operation guidelines, maintenance and replacement. The operational plan ensures that on hourly, daily and weekly basis the system is operating as good as possible (for example rerouting energy due to a high voltage line failure).

1.2.4 Asset management model

To support the asset manager in making optimal decisions, a methodical and systematical approach is needed to compare scenarios and their consequences. A possible approach in aiding the asset manager is presented in Figure 1.7.

Two different stages are recognised in this model, the information stage, and the decision stage. The information stage is of a "technical" nature, its task being to provide information on condition, performance, risks and costs to the decision making unit (DMU). The second stage combines the output of the technical analysis, and investigates different scenarios and their consequences to form an optimal decision for a given asset management question.

The technical analysis includes the expenditures, performance and risks. The expenditure model involves the cash flow through investments, salaries and capita, including depreciation and inflation for example. The performance model determines the change in transportation capacity, power loss and reliability. The risk of for example costumer minutes loss, safety hazard or unforeseen environment pollution is assessed by the risk model.

The models for the technical analysis are fed by three different types of input data: historical data, future scenarios and non-negotiable constraints. The historical data consist of voltages, currents, tap positions, ambient temperature, cash flow, interests rates, maintenance data, nameplate information, etc. Different future scenarios may be defined and compared. Such scenarios may vary in for example expected load growth, maintenance intensity, re-
Expenditure model
Performance model
Risk model
Evaluation of options
Decision

Figure 1.7: Integral asset management decision model.

placement volume and the like. The non-negotiable constraints, which will limit the possible number of valid solutions, consist of laws, standards, agreements with external parties, non-negotiable business values, and so on.

1.2.5 Technical reliability as a focus

The focus of this thesis is technical reliability. Basically, technical reliability describes how reliably a system or component will function over a period of time dependent on its historical and future stress. Furthermore, the reliability is the leading input in determining, for example:

- What is the possibility of losing production, i.e. customer minutes lost?
- What is the impact of overloading?
- What is the impact of maintenance?
- When do we need to replace this asset?

Technical reliability will be used in the operation, maintenance and replacement phase of the life cycle, and in all optimisation horizons, strategic, tactical and operational. The aim is to arrive at a technical reliability model which provides the input to be used in expenditure, performance and risk models. Hence, it will provide accountability on scientific basis for these models.

1.3 Scope of this thesis

The work presented will answer the research questions of Section 1.3.1. The research goal is discussed in Section 1.3.2, and is based on the framework defined in Section 1.2.

1.3.1 Research questions

The scope of this dissertation can be defined with two sets of questions. The first set of questions describes the knowledge we want to gain. The second set will narrow down the scope of our research. The questions to be addressed are:
• What is the definition of technical reliability?
• How does technical reliability relate to condition, stress, age and other parameters?
• Is it possible to model and predict technical reliability?
• Can the prediction of technical reliability be demonstrated for individual power transformers and/or a population of power transformers?

The results of our scientific quest is constrained by not focussing on the following questions:
• How does a decision process work?
• Can the decision process be automated with a transparent and objective method?
• With what diagnostic means can the detection of technical reliability be improved or extended?
• How to gain historical information?
• What is the best method for processing and storing historical information?

1.3.2 Research goal

The aim of the present study is to develop an integral transformer lifetime model. This model will predict the transformer reliability based on relevant degradation mechanisms. These degradation mechanisms can occur in the transformer subcomponents, i.e. tank, bushings, tap-changer, core, oil and windings. Further, the transformer lifetime model must be applicable to individual power transformers and to a power transformer population.

The integral transformer lifetime model as a structured method will provide objectivity, transparency and accountability in the results, even if the methods are based on expert opinions and do not have a scientific foundation. Furthermore, the accuracy of the lifetime model is explicitly dependent on the quality of the input parameters. The accuracy of the predicted values is provided by a sensitivity analysis. This sensitivity analysis can also determine the effectiveness of the available diagnostic methods and may indicate the benefits of collecting and storing data, information and knowledge.

1.4 Outline of this thesis

In Chapter 2 the working principles of technical reliability modelling and its causes and effects are explained. The reliability is limited by degradation mechanisms. Methods to model these degradation mechanisms are described in Chapter 3 and illustrated with practical examples of diagnostic methods and their degradation mechanism.

Chapters 4, 5 and 6 consist of case studies, concerning the major degradation mechanisms of the power transformer. The most discussed degradation mechanism of the power transformer, the degradation of winding paper insulation, is reassessed in Chapter 4. In Chapter 5 the method of Chapter 4 is used to demonstrate the effects of failure wave scenarios and failure wave mitigation actions, a failure wave example scenario is depicted in Figure 1.1.

Three subjects are discussed in Chapter 6. The first two subjects describe possible degradation mechanism models for the bushing and tap-changer. The third subject addresses the combination of reliabilities, related to different degradation mechanisms.

In Chapter 7 the overall conclusions and recommendations of this dissertation are summarised.
A technical reliability model aims at supporting the asset management process by providing reliability information from a technical perspective. In most cases, technical reliability refers to the technical condition and the way it changes over time, catalysed by operational parameters. One contribution to the technical reliability, for example, is the quality of electrical insulation.

The technical reliability model predicts the technical condition of a component or system in terms of the probability that a component or system can perform its designated function. The method used to predict the reliability may depend on the topology, the life cycle stage of the component or system, the available level of information, and the type and level of the required output.

In this chapter we will first introduce the condition change process, as part of the state change process. Next, we will discuss reliability topologies, i.e. the levels of aggregation at which we will address reliability: component, system and population. To conclude, we will give an overview of techniques available for reliability modelling.

### 2.1 The condition change process

The basic terminology, which will be used throughout the thesis is in accordance with the terminology used in Cigré [15] and IEC [41], except for some minor adjustments.

- **State** is a description of the present situation of a system with all accessible quantities, such as, colour, dimensions, weight, age, and manufacturer. The running mode and condition are also part of the state.

- **Running mode** is the mode of operation of the system. Examples of the running mode are:
  - in storage,
  - under transport,
  - on load / level of loading,
  - in overload / level of overloading, and
  - under maintenance.

- **Condition** is the ability of a component or system to perform its specified function. Examples of conditions are:
  - the ability to withstand the specified voltage / electric field,
  - the ability to withstand the specified current / temperature,
  - the ability to withstand the specified (electro-)mechanical forces,
  - the ability to withstand the specified ambient conditions,
Chapter 2 Technical reliability model

- the ability to provide the required voltage conversion,
- the ability to withstand the specified switching capability.

Condition parameters may directly relate to the specified functionality, i.e. measure of compliance, or to the underlying processes, such as, insulation degradation, mechanical wear. Examples of the latter are the degree of polymerisation of insulation paper, partial discharge activity and gasses dissolved in oil. An accurate reliability prediction involves both actual parameter values and their development over time.

Prior to a formal description of the state change process, four examples are given. The first example of a change in the state of a transformer is removing its transportation packaging and connecting the transformer to the energy grid. Here the state changes from a packed asset to an operational asset, this is a change in running mode. Next, the same transformer may get a paint job and its colour changes from dull grey to lovely pink. Without knowing anything better one could say that only the colour is changed and therefore it is a simple state change. The third example involves a paint job but now with an anti-corrosion paint. This is a condition improvement and may have an effect on the end of life the transformer. In the last example the transformer is placed outdoors and the condition may be effected by rain. The rain, an external stimulus, accelerates the corrosion process. This state change may thereby cause a change in condition.

The four examples can be formalised in a schematic state change model, as depicted in the diagram of Figure 2.1. The state change process is a continuous process, therefore the state at time $t$ changes in a state at time $t + dt$.

![Figure 2.1: The process of state change with time.](#)

The technical reliability is distilled from the condition quantities. These condition quantities are influenced by the condition change processes, and their outcome is the result of the previous state and the condition change process. The influence of the several actuators on the condition change process, as described in previous examples, is graphically represented in Figure 2.2. These actuators are the running mode and the external stimuli. The running mode is a subset of state, which includes operation modes relevant to the condition change. It can be controlled by operational measures. External stimuli can not be controlled continuously. Weather, short circuits and the social environment, are influences out of direct control of the asset manager. The impact however can be mitigated if needed.

In the earlier examples two directions of condition change were implicitly given. One addresses usage and loading of the asset, which may have a negative effect on the condition. On the other hand, maintenance will have a positive effect on the condition. These two condition change types, shown in Figure 2.3, are referred to as degeneration and regeneration, respectively.

Obviously, both degeneration and regeneration can act on different time scales. For the degeneration process two time dependent sub-processes can be distinguished. Continuous degeneration includes e.g. corrosion of iron, depolymerisation of paper. Under normal circumstances these are relatively slow continuous processes of degradation. Degeneration effects caused e.g. by lighting, short circuits or sabotage are intermittent. Here the stress occurs
in a limited period of time. Outside this time period there is no degeneration. Apart from external stress related stimuli for condition change we can recognise internal stimuli. These are unintentional defects that may cause or accelerate degradation. Such defects may be present initially in the form of inclusions, voids, dust or they may be the result of earlier degradation.

For the regeneration processes similar categories can be defined. Conditioning is a slow continuous process of improving the quality of the asset. Examples are the initial oxidation of aluminium or the oil settling in certain power equipment. Externally driven regeneration includes maintenance and revision, which are intermittent processes. Maintenance is a periodic, low impact, action aiming to improve or to stabilise the condition of the asset. Refurbishment or replacement on the other hand is a high impact improvement of the asset.

Figures 2.2 and 2.3 can be combined to the generic transformer condition change schematic of Figure 2.4. Here, a differentiation is made between gradual and instantaneous processes. The present state at time \( t \) consists of the running mode, the condition, and the external stimuli. Which gradual processes are on hand, is mainly determined by the present condition and external stimuli. Instantaneous processes may be triggered by gradual processes reaching a critical threshold, and by external stimuli. The evolution of the condition change processes is influenced by internal and external stimuli. The combination of the gradual and instantaneous processes results in the state at time \( t+\Delta t \).
neous processes are the basis of the new condition at time $t + dt$.

![Diagram of generic condition change model]

Figure 2.4: Generic condition change model.

In the next subsections a classification of causes and effects of condition change is made.

## 2.1.1 Causes of the condition change process

Classification of the condition change processes provides the asset manager clues on how to influence the condition change process. The causes of the condition change can be subdivided by the process mechanism or by the process trigger or actuator.

### 2.1.1.1 Subdivision by process mechanisms

Four basic condition change mechanism are distinguished:

- **Chemical**: The condition of the device changes due to chemical reactions, e.g., rusting of iron, or deterioration due to acids.

- **Electrical**: The presence of electrical stress by high voltages or high electromagnetic fields influences the condition negatively. An example is the reduction of the dielectric strength due to partial discharges.

- **Mechanical**: Mechanical forces will lead to wear and reduction of the mechanical integrity, e.g., deformation of windings due to electromagnetic forces by short-circuits currents.

- **Thermal**: Thermal energy can deform the properties of a material negatively, such as, metal fatigue, or structural deformation caused by the shrinking or expanding of the material. Degradation can be a multi-stress mechanism. For example insulating material can deteriorate under the combined action of mechanical and thermal stress during overloading. Identification of mechanisms does however provide the clues to mitigate the degradation.

### 2.1.1.2 Subdivision by process actuators

The degradation processes can also be categorised by their actuators. According to [118] three types of actuators can be distinguished, as depicted in Figure 2.5. Furthermore, Figure 2.5 shows how different failure actuators may be linked to causes and root causes.

- **Primary failure**: Failure of an entity not caused either directly or indirectly by the failure of another entity. Generally, the entity has to be repaired to be in working order. The primary failure of a component results from a cause inherent in the component and not
from the failure of another component. For a component under operation, the failure may, for instance, originate from wear problems or defects in its design, or manufacture, or due to inappropriate technical specifications. E.g. a bushing failing to withstand a voltage below the level it is designed for is considered as a primary failure.

**Secondary failure:** Failure of an entity caused either directly or indirectly by the failure of another entity that this entity was neither qualified for nor designed against. Generally, the entity has to be repaired to be in working order. Failures of other entities, particular conditions in the environment or human errors may result in the secondary failure of components. Let us take again the example of the bushing: its insulation breakdown due to an over voltage beyond the specified limits caused by the failure of another component is a secondary failure.

**Command failure:** Failure of an entity caused either directly or indirectly by the failure of another entity this entity was qualified for or designed against. Generally, the entity need not be repaired to be restored to good condition. Such a failure usually occurs when the entity changes state following inadvertent control signals. For example, a tap-changer taking a wrong tap position upon receiving an inadvertent control signal.
2.1.2 Effects of the condition change process

Different stages in the condition of an asset can be recognised. A classification based on IEC 60050 [41] with some adjustments\(^1\) identifies four classes:

**Healthy:** The device or system can perform its function.

**Defective:** The device or system deviates from its designed specifications. It can still perform it functions, but its performance is degraded.

**Faulty:** The device or system is not able to perform a critical function. This means, it can still perform basic functions. Only if one or more of them are called upon the asset will fail.

**Failure:** The device or system has ceased to perform its basic tasks.

The classification\(^2\) of an event depends on the taken perspective. An exploded transformer is a failed device from the component perspective. On the other hand, from a system perspective the exploded transformer can be a defect, fault or failure in the grid. It will be a defect if the exploded transformer was in storage as a general spare, a fault if the exploded transformer causes the inability of fulfilling a necessary \(N - x\) criterium, or a failure if the energy transportation to the connected costumers stops.

\(^{1}\)The adjustment involves defining a healthy and defective class, and differentiating between the faulty and failure classes.

\(^{2}\)In standards and specifications sometimes a failure is defined as the result of a fault, sometimes as the origin of a fault.

\[\text{Figure 2.6: Condition change versus time with classification.}\]
The condition change process

The condition change process is a representation of the condition of the asset. The lower horizontal line represents the functional requirements for fulfilling the asset's functions. The upper horizontal line represents the specifications for a manufactured and installed component. The figure illustrates the classes healthy, defective, and faulty.

A schematic representation for a defect, fault, and failure is depicted in Figure 2.7. If the condition is less than the design specifications, the component is in a defective state. A faulty state occurs if one or more functional requirements cannot be fulfilled anymore. Having a faulty state implies that it is also in a defective state. A trigger may cause a failure, depending on the force of the trigger and the gap between specified and actual condition level. Hence, a failed state is subset of a faulty state, which in turn is a subset of a defective state.

![Flowchart Diagram](image)

**Figure 2.7:** Interaction of condition change effects and their sequential appearance.

The transition from fault to failure is a transition of the fault state, where the device still operates, to a failed state where operation has ceased. The schematic representation of Figure 2.8 indicates that a failure needs two ingredients: a faulty device and a corresponding trigger. The force of the necessary trigger can be of such level that the failed state occurs simultaneously with the faulty state.

![Diagram](image)

**Figure 2.8:** A system can still perform its functions in a faulty state. The transition to the failed state is dependent on the right trigger event.

The transition from fault to failure may be more complex than suggested by Figure 2.8. With a severe trigger, for example, a component may change from a defective or healthy state directly to the failed state. The effect of the degradation mechanism determines whether a fault situation occurs. The failure mode depends on the trigger event and the degradation mechanism, as shown in Figure 2.9. With a single degradation mechanism and different triggers, the system can end up with different failure modes. On the other hand, it can end up in the same failure mode with completely different triggers and degradation mechanism.

For every degradation mechanism, we assume there is a certain condition level from which it is considered to be in a faulty state. In this faulty state, failure is imminent after a trigger.
event. In the case of reliability predictions the most plausible triggers are known and the minimum functional requirements to prevent that the trigger causes the device to transit into a failed state can be derived. With this in mind it is possible to predict when the functional requirements are no longer met, and the device is operating in a faulty state. The time at which a faulty state occurs is stochastic in nature, as is the time at which a trigger occurs. Assuming known distributions the MTTF can be found from Appendix C,

\[
MTTF = E(T_f) + E(T_T),
\]

where \(E(T_i)\) is the expected value of the stochastic parameter \(T_i\), \(T_f\) is the stochastic time to a fault, and \(T_T\) the stochastic time that an appropriate trigger occurs.

In practice one usually calculates the probability of a faulty state. This equals the probability of failure only in the worst case scenario that the repetition time of the trigger event is much shorter than the time to a fault \(T_f\). For maintenance practice it is important to know which fraction of a population is in a faulty state. For predicting the unavailability also the trigger needs to be accounted for.

### 2.2 Technical reliability topologies

Technical reliability models can be considered on various levels. In this thesis we distinguish: component, system and population. A brief description of each level is provided in the next subsections.

#### 2.2.1 Component reliability

A single component usually represents different subcomponents and functionalities, each associated with failure and degradation mechanisms. The reliability on a component level is the result of these mechanisms and represents the overall impact for the component as a whole. A component reliability model predicts the probability of fault events in all critical condition change processes for a single component.

#### 2.2.2 System reliability

A system consists of a combination of different components, working together to achieve a unified task, for example the electricity grid, or a substation. Possible system reliability questions are: Where are the bottlenecks? What will happen during an \(N - 1\) contingency? When is the substation or the system due for replacement?
Available programs to calculate power system reliability are CYMDIST, Etep, DigSilent, and Neplan. These programs are based on Markov models, as described in [73, 101]. Different indices are in use to quantify system reliability:

- **SAIFI**: System Average Interruption Frequency Index is the total number of customer interruptions divided by the total number of customers served;
- **SAIDI**: System Average Interruption Duration Index is the sum of customer hours of unavailable service divided by the total number of customers served;
- **CAIDI**: Customer Average Interruption Duration Index is the sum of customer hours of unavailable service divided by the total number of customers interruptions;
- **ASAI**: Average Service Availability Index is the customer hours of available service divided by the customer hours demanded;
- **ASUI**: Average Service Unavailability Index is the customer hours of unavailable service divided by the customer hours demanded;
- **ENS**: Energy Not Supplied is the total energy not supplied to the system;
- **AENS**: Average Energy Not Supplied is the total energy not supplied by the system divided by the total number of customers served.

The individual component reliabilities indicate the performance of each specific component. The reliability of a specific system is found from the combination of individual reliabilities, and requires a model of the system as a whole.

### 2.2.3 Component population reliability

Components having similar properties can be grouped to form a population, e.g. a fleet of power transformers. Component reliability on a population level can address questions on optimum maintenance strategy, replacement strategy or on estimating the overall reliability of a population. Based on the answers, on a management level, decisions can be made on reserves both in money and in spare parts, or spare components.

Comparing the impact of maintenance strategies, such as time based and condition based maintenance, and optimising them for best result, is a typical fleet asset management approach. The impact of these methods can be modelled with a Markov process, as described in [99, 121]. The required data involves statistical failure rates for every condition aspect, impact of maintenance at these condition aspects, and maintenance frequencies.

To determine the reliability of a population of e.g. a fleet of power transformers, two general approaches are available: statistically based forecasting and individual forecasting:

- A statistically based approach uses data available from the past to predict the short term reliability of this group of assets, [36, 55, 70–72]. Note that these methods predict the future based on only the past performance. They fail when actual and future operational and environmental parameters deviate from the historical operational and performance data or when a degradation process transforms to a next stage with higher degradation rate.
- A more flexible way of obtaining information on a fleet of components is the degradation modelling approach. In this approach the reliability of each individual item is calculated, after which the reliability of the population as a whole is derived.
- By taking a representative sample size it is possible to give an accurate prediction of a large batch of components based on only a part of the population. This is a compromise of the pure statistical forecast method and the forecasting based on individual reliabilities.

The latter two approaches are applied in this thesis.
Chapter 2  Technical reliability model

2.3  Technical reliability modelling

Several methods may be used to predict future technical reliability. We distinguish two basic options, one based on extrapolating data and one based on the understanding of mechanisms. Both approaches are discussed in this section. We will furthermore provide guidelines for selecting the appropriate approach in specific situations.

2.3.1  General reliability analysis tools

Available statistical techniques may be supported by or combined with analysis techniques, such as, a Failure Mode Effect and Criticality Analysis (FMECA), a Fault Tree Analysis (FTA), and a Reliability Block Diagram.

In a Failure Mode Effect (and Criticality) Analysis, or FME(C)A, a structured approach is followed to gather the following information:

- the functionalities ascribed to the component or system;
- possible failure modes threatening each functionality;
- the cause and the consequence of each failure mode;
- the criticality of the consequences;
- mitigation measures for each failure mode;
- the options and probability for detecting failure modes.

Statistical and historical data may then be used to assign to each failure mode the associated failure probability and frequency. By combining probability and consequence, risks may be evaluated and ranked or prioritised. FMECA and statistical analysis may provide a powerful approach to design effective and efficient maintenance and replacement programs.

Whereas in FME(C)A all possible failure modes are evaluated, Fault Tree Analysis (FTA) is a structured approach to analyse, and learn from, individual faults that have occurred. FTA is a top-down approach [23]. First the main causes of the fault are identified, consequently each main cause is analysed in more detail until eventually the root causes are found. FTA is used to analyse known faults and arrive at measures to mitigate future occurrence.

Reliability Block Diagrams are used to study and optimise the reliability of systems that consist of interconnected subsystems. Given the reliability of the subsystems, the interconnections may be designed to optimise the overall system reliability, e.g. by applying parallel and series connections and thus creating sufficient redundancy.

2.3.2  Reliability modelling based on statistical data analysis

With a statistical data analysis, available data from the past and present is extrapolated to predict future expectations. These predictions are valid, as long as future operating scenarios and environmental conditions remain within a certain bandwidth with respect to the historical operating scenarios and environmental conditions. The available data should be sufficiently large to allow for such an approach.

Future failure rates can be obtained from the data by fitting them with a probability distribution, e.g. using a least square method, or a maximum likelihood method [55]. These fitted probabilities can be applied in a Markov-type model to predict reliabilities of systems and populations of components. The major advantage of an approach based on statistical data is that no underlying physical model is required. The major drawback is its inadequacy to generalise the historical trends outside the bandwidth for which the data is valid, and the necessity of available data.
2.3.3 Reliability modelling based on degradation mechanism

Reliability predictions based on degradation mechanisms focus on critical components, such as the power transformer. It allows predictions where future scenarios deviate from the conditions for which the historical data were obtained. On the other hand, the dominant degradation mechanisms must be known and an appropriate model must be available.

In order to identify dominant degradation mechanisms, and study the interaction between mechanisms we have developed variations of the FMECA and the FTA, the Degradation Mechanism Effect and Criticality Analysis (DMECA) and the Degradation mechanism Tree Analysis (DTA), respectively.

- A DMECA is quite similar to a FMECA. The only item added is an additional column with the degradation mechanisms. The data on the degradation mechanisms includes the probability that the degradation mechanism leads to failure, its criticality, and how the present status of this degradation mechanism may be determined.
- The DTA is based on the FTA and the Reliability Block Diagram. The DTA shows which degradation mechanisms lead to which failure. Furthermore, it shows which processes may trigger or influence the degradation mechanisms. These processes may be other degradation mechanisms, or external triggers.

2.3.4 Guidelines for selecting a prediction tool

The two basic methods described in the previous subsections are either based on statistical data analysis or on a physical model of the relevant degradation mechanisms. The question: "Which of those two to choose?" can be judged after answering three basic questions:

1. What is the goal of the prediction? For example: minimise warranty costs, system design, optimise maintenance, optimise replacement strategy, etc.
2. What is the situation at hand?
   - Which topology? Individual product, population of quasi uniform products, or a system of interconnected products.
   - Which stage? Development, production, transportation, active life, or dismantling.
3. What adequate data is available? Such as failure data, diagnostic test data, historical load, in worst case: nothing.

Answers on these questions provide the first step to the solution of the asset manager's decision goal, i.e. finding the best analysis method. The consecutive step formulates the steps for obtaining the critical model parameters. E.g. a paper degradation model needs heat flow parameters of the transformer, Arrhenius parameters of the paper degradation process and the historical stress values.

An example of addressing these questions in a production environment is given by van den Boogaard in [102, Chapter 4 and 6]. The method advocated there is the Reliability Optimisation Method using Degradation Analysis, in short ROMDA. A general systematic approach of ROMDA to predict and optimise reliability in a robust way is:

1. Identify, for example with the Pareto principle, the dominant failure mechanism and relate this dominant failure mechanism to a performance characteristic.
2. Identify the design parameters influencing the performance characteristic under study dominantly.
3. Obtain time-dependent stochastic models that describe the degradation of the performance characteristic through the physical degradation of the dominant design parameters.

4. Introduce the stochastic properties of the design parameters into the performance characteristic/design parameter functional relationship to obtain a stochastic time and design parameter dependent model for the performance characteristic under study.

5. Use this functional relationship with respect to certain chosen specification limits to obtain reliability characteristics, like the mean time-to-failure (MTTF) and variance of time-to-failure (VTTF).

6. Use an optimisation method, like Robust Design, to improve or optimise these reliability characteristics by setting the nominal value of the design parameters at certain values, parameter design. The goal of this optimisation method could be to optimise the nominal values and to minimise the variance values of these reliability characteristics.

The ROMDA method presented by van den Boogaard is used to identify failure mechanisms and relate them to statistician parameters such as MTTF and VTTF.
Degradation mechanism model

The reliability is dependent on the condition of the components, which in turn is affected by degradation mechanisms. This chapter focusses on modelling degradation mechanisms.

First we will introduce the concept of "quality parameters" as the link between a degradation mechanism and a degradation model (Section 3.1). We will further distinguish different types of quality parameters (Section 3.2), dependent on how accessible the degradation process is for information extraction. Quality parameter types differ in how direct they relate to a degradation process and in how explicit the obtained information is.

Thereafter we will discuss different ways to predict the evolution of degradation mechanisms, and the use of quality parameters therein (Section 3.3). We will distinguish expert judgement models, regression models and physical models. In an actual model different prediction methods can be combined.

To conclude with, for the power transformer an overview is given of the different diagnosis and monitoring tools, and the corresponding quality parameters that link observable or deducible quantities to the degradation mechanism (Section 3.4).

3.1 Degradation process linked with measurements

Figure 3.1 shows the transition from an initial condition to an updated condition negatively influenced by one or more degradation processes.

\[
\text{Condition}(t) \xrightarrow{\text{degradation}} \text{Condition}(t + dt)
\]

Figure 3.1: The condition change process caused by a degradation process.

By monitoring condition parameters of the system we may obtain insight in the status of a degradation process. This can be done by measuring condition parameters at the initial state of the system, during operation and at its end situation. Parameters describing the condition of the system are defined as quality parameters (QP). This process of condition change due to degradation, and its accompanying diagnostic moments is depicted in Figure 3.2.

A model describing the degradation process provides insight in the functioning of the degradation process and the condition transition of a system. The use of QPs allows to trace the evolution of a degradation process. Figure 3.3 illustrates the condition change in an infinitesimal time step \(dt\), with an accompanying model based on quality parameters. The bidirectional connection between the condition and the QP represents two translations. Firstly,
Chapter 3 Degradation mechanism model

Figure 3.2: The condition change process due to degradation. The condition is measured at the initial, intermediate and end state of the system. The condition is determined by means of quality parameters (QP).

the QP can be translated in the condition. Secondly, the degradation process and its predicted values can be verified with the use of QP.

Figure 3.3: Modelling of the degradation process to predict the condition with QP as output.

3.2 Quality parameter types

Ideally the value of a quality parameter is directly linked to the actual condition of the asset. In practice such quality parameters may not be available or accessible, and information from other sources may be required.

In this study we first of all distinguish between explicit and implicit quality parameters. An explicit QP is an observable/measurable quantity, an implicit QP is not observable but is deduced from theory, modelling and supporting arguments. The explicit QPs are further divided into direct and indirect explicit QPs. Direct explicit QPs are directly linked to the degradation process, indirect explicit QPs are related but not directly linked and require additional processing to extract information on the degradation process. The three quality parameter types are summarised in Table 3.1.

Direct explicit QP: An example of a direct explicit QP is the degree of polymerisation (DP) or tensile strength in the case of insulation paper degradation of the power transformer. It is a measurable quantity that is directly linked to the degradation process, and is a direct measure of the degree of degradation.

Indirect explicit QP: Partial discharge activity is an example of an indirect explicit QP. It is again a measurable quantity, but it is not directly linked to a specific degradation mechanism, and may originate from various sources. As a result it requires additional processing to link it to a specific mechanism. The same is true for dissolved gas analysis and the tap-changer performance measurement by means of the dynamic resistance value [117, 124].

Implicit QP: An example of an implicit QP is the loss-of-life of transformer insulation paper as derived from loading guide models [44, 49]. The model is based on extensive experience, but the result in any specific situation cannot by verified by measurement. The
relative ageing impact of different loading scenarios can be determined with these loading guide models. A similar example is the remaining number of switching operations of a tap-changer. This is a comparative value of how well the switch works in normal operating scenarios. It does not quantify to the actual conditional attributes of the used materials under stress.

<table>
<thead>
<tr>
<th>QP</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explicit (observable / measurable)</td>
<td>Directly linked to degradation process</td>
</tr>
<tr>
<td>Implicit (induced / deductable)</td>
<td>Indirectly linked to degradation process</td>
</tr>
<tr>
<td>Implicit (induced / deductable)</td>
<td>Indirectly linked to degradation process</td>
</tr>
<tr>
<td>Implicit (induced / deductable)</td>
<td>Loss-of-life paper insulation</td>
</tr>
</tbody>
</table>

The choice of the QP is determined by the availability of measuring options and models, their accuracy and their representability. The more direct the QP is linked to a degradation mechanism, the better it serves its purpose. However, the choice of suitable QPs is limited to quantities which are both technically and economically feasible to obtain in practice.

An optimal scheme incorporates all available information sources and is capable to correctly weigh their relative importance. The degradation mechanism models discussed in the next section provide a generic scheme to incorporate all information sources and to translate this information to reliability estimates for the expected system behaviour.

### 3.3 Degradation mechanism prediction methods

In Figure 3.4 three distinctive methods for predicting the QP, the rate of degradation, and the level of degradation, are depicted. On basis of increasing strength of linkage with the degradation process, they are placed in order of: an expert judgement model, a regression model, and a physical model. The overall fault probability follows from a combination of the three types of information. Any of these fault probabilities can be used as input for the integral asset management decision model of Figure 1.7.

![Figure 3.4: Schematic representation of degradation mechanism modelling, relating ageing to fault probability through quality parameters.](image-url)
**Expert judgement model** An expert judgement model is a set of knowledge rules based on expert judgement. With these rules a classification of the degradation level and rate can be derived. The classification is made by defining trigger levels based on the value of the QP. The general concept of an expert judgement model is described in [5], where the available methods and their results are pairwise compared by experts to find connections between cause and effect, and their response time. For example, the five yearly power factor test on bushings, where the bushings is considered faulty if the tangent delta is higher than a predetermined threshold.

**Regression model** With a regression model observed correlations and trends are employed to match key properties of an asset. The available data is matched to a mathematical relationship. Examples of regression techniques are polynomial interpolation, artificial neural networks, and Bayesian regression. These techniques can be adopted to the previously mentioned bushings, to determine correlations between ambient temperature, applied voltage, transported current and the tangent delta. With the correlation results it is possible to predict the moment of replacement based on the specific usage of the transformer.

**Physical model** By understanding the physics behind the degradation process, QPs can be defined that are representative for the process. This physical model relies on accurate input data, which may be hard to obtain. Having defined explicit QPs, it allows tracing the progress of degradation. The results can even be fed back into the physical model to improve the accuracy of the modelling. For the bushing example, this could be developing a physical or chemical model of insulation degradation under the influence of ambient temperature, applied voltage, transported current, weather patterns, etc.

The amount of information needed increases from an expert judgement model via a regression model to a physical model. The expert judgement model and the regression model are both empirical representations of reality and both use input of experts. With a sensitivity analysis the reliability of the predictions can be indicated. In such an analysis, the dependence of the prediction on all input parameters is calculated. This does not only result in an overall reliability estimate but also provides information on most critical factors determining the prediction reliability. From this, it can be decided to perform a specific diagnosis on the asset to improve this knowledge and thereby allow an improved prediction to be made. Combining the reliability predictions of the different forecasting methods is left to the asset manager, because the combination depends highly on his or her philosophy on what level of risk is regarded acceptable.

### 3.4 Transformer diagnosing, monitoring and prediction tools

In [17, 37], the major transformer diagnosing and monitoring tools are addressed. The corresponding QP and prediction capabilities of a selection of these diagnosing and monitoring tools are discussed in this section. Monitoring methods, which give indications about the general condition of the transformer, are given first. Hereafter, an overview of monitoring methods is given for the oil quality (Section 3.4.1), paper insulation (Section 3.4.2), tap-changer (Section 3.4.3) and bushings (Section 3.4.4).

**Turns ratio** is an explicit QP, which gives direct information on the transformation ratio. This ratio provides information on magnetisation problems and deformation of the coils. The extent can be determined by comparing the measurement with the results of the commissioning test based on knowledge rules.
**Transformer losses** is a direct indication of the efficiency of the voltage transformation. It indirectly addresses problems with loose busbars, additional eddy currents and flux leakage. Based on the commissioning test and expert judgement, defects and faults can be determined.

**Infrared thermography** provides a direct explicit quality parameter. This QP provides the asset manager with insight if there is a problem with the cooling system or if there are additional losses. The determination method is the same as for the interpretation of the transformer losses.

**Dissolved gas analysis (DGA)** determines the concentration of key gases in the transformer oil, in most cases combined with moisture content. Key gases often used are hydrogen, methane, ethane, ethene, ethyne, propane, propene, carbon monoxide, carbon dioxide, oxygen, and nitrogen. The interpretation of gases is based on the knowledge rules provided by, for example, Doernenburg, Duval, Roger, Schliesing, described in [45, 52, 77]. All these methods have a similar approach, based on a set of gas ratios. If these ratios are within certain limits, conclusions can be drawn as to what kind of defect or fault is present. Some of these gasses are byproducts of the paper degradation process, and from trends the rate of paper degradation can be determined. Methods proposed in [35, 39, 85, 88], are more sophisticated: they combine the different ratio methods to improve the accuracy of the prediction. Furthermore, if historical data is available trend predictions may be performed. The end result is a derivation of the current conditional state of the transformer. The results of the DGA assist the asset manager in making short term decisions on maintenance, extensive testing and immediate risk mitigation actions.

**Partial discharges (PD)** can occur due to the presence of floating particles, cavities, or sharp points. These PD sources may be derived from their location, frequency, and charge of the occurring PD. With an adequate set of knowledge rules it is possible to determine what types of defects and faults are present, such as, loose connections, loss of insulation material, floating particles in the oil, air bubbles in the oil, voltage sparking due to eddy currents, etc. UHF PD detection method is described in [3, 33, 67, 74, 87, 124] and is particularly useful for sensitive measurements in "noisy" environments.

**Frequency response analysis (FRA)** consists of measuring the impedance of the transformer windings over a wide range of frequencies and comparing the results of these measurements with a reference set [100]. Differences may indicate damage to the transformer, such as, winding deformation, winding short circuit, core degradation, etc.

### 3.4.1 Oil quality

The transformer oil provides both cooling and electrical insulation. Its electrical insulation strength degrades in situations with high water content and acidity. Acidity will also increase the rate of oil ageing, which in turn will result in more moisture and acids. Next to this, moisture and acidity will also enhance the rate of paper ageing. The cooling properties of the oil are negatively influenced by sludge and/or bad viscosity. Hence, the oil quality is crucial for the transformer condition and can be diagnosed, next to partial discharge activity measurement, by three methods:

**Appearance, colour and solid contaminants:** The oil appearance, clarity, turbidity and the presence of particulate materials, is indicative of the presence of free water, soluble sludge, fibrous materials and other undesirable particles. With ISO 2049 or IEC 60422,
the colour number of the oil, an indirectly explicit QP, is determined by comparison against colour standards. Rapid changes in colour or a high colour number is typically associated with advanced ageing and/or serious contamination of the oil. The colour number provides a comparative assessment based on knowledge rules.

**Interface tension:** The interface tension between oil and water provides information regarding the presence of soluble polar contaminants in the oil. The value of this indirect explicit QP changes relatively quickly in the early stages of the ageing process. As ageing progresses, however, the rate of change in the interface tension slows down. This consequently makes it more difficult to interpret the test data concerning this parameter. An acceptable range of tensions is nevertheless defined in ISO 6295 and IEC 60422. Careful interpretation of test data is vital, because a low interface tension may indicate sludge deposition on the windings. This can lead to temperature management problems under heavy loads.

**Breakdown voltage:** The oil breakdown voltage is a measure of the ability to withstand electric voltages. Clean, dry oils have high breakdown voltages. The presence of moisture or solid particles reduces the breakdown voltage. Where both are present, the effect is greatly enhanced, leading to a dramatic drop in breakdown voltage. IEC 60156 provides a breakdown voltage threshold below which the oil needs to be treated or replaced.

### 3.4.2 Paper insulation

Transformer paper provides electrical insulation between windings. The quality of the electrical insulation is mainly determined by its mechanical strength, which ensures that the paper holds its position. The ageing of the paper is accelerated by high temperatures, high water content, and acidity. Whether these high impact situations have occurred can be determined by a DGA. The DGA also gives information about the level of paper ageing products. The mechanical strength, tensile strength or degree of polymerisation, can further be determined by the methods described below.

**Furan analysis** determines the level of six chemical indicators. Three are rest products related to paper ageing process: 2-furaldehyde (furfural), 5-methyl-2-furaldehyde, and 2-acetyl furan. The other three, phenol, m-cresol, and xyylene are rest products related to resin ageing process. The methods described in [14, 22, 61, 63, 69, 78, 82, 84, 92, 95, 97, 124] translate the furanic compounds into a degree of polymerisation with a best fit model, i.e. the six chemical indicators are indirect explicit quality parameters.

**Infrared spectroscopy** as described in [7], is a non-destructive method to determine the degree of polymerisation, a direct explicit QP, at the position of the measurement.

**Loading guide** is a modelling method to determine the status of paper ageing. It predicts the impact of historical load and ambient temperature. The thermal characteristics are used as transformer parameters on paper ageing. The loading guides, described in [42, 44, 49], use a regression technique to predict the behaviour of the implicit QPs, mean-residual-life and loss-of-life. The physical model provided in [106–108, 111], on the other hand predicts the behaviour of the degree of polymerisation, a direct explicit QP.

### 3.4.3 Tap-changer

With the tap-changer the output voltage of the transformer can be regulated. Its functioning may be endangered by unsynchronised switching of the tap-selector and power-switch due
to a broken paper-resin axis or malfunctioning engine. Another failure mechanism is related to polluted contacts in the tap-changer. Because of the carbon deposits on the contacts, arcs may occur upon switching, which will lead to floating copper or silver particles in the oil. Next to the DGA and PD methods, the status can be assessed with the following techniques:

**Tap-changer torque measurement** consists of two measurements [103]. The first direct explicit QP is the torque of the engine, the other is the transition time of two sequential positions, an indirect explicit QP. With an expert judgement system the condition of the engine and in some cases also of the shaft and bearings can be determined.

**Dynamic resistance measurement (DRM)** gives information about the wear of the tap-changer contacts [116, 117, 124]. The measurement system determines the contact resistance and the coil resistance by looking at the magnetic charging time of the coil. The current condition and possible mitigation action can be selected based on the dynamic resistance value, an indirect explicit QP, and a set of knowledge rules.

### 3.4.4 Bushings

The high voltage conductor is insulated from its surroundings by a bushing. Within the bushing the electrical fields are capacitively controlled to prevent breakdown. Breakdown may occur due to insulation degradation and subsequent short circuits in between the capacitive layers. Another potential hazard is explosion due to over-heating by increasing bushing losses. Early signs of possible breakdown can be provided by PD measurement. In paper-oil bushings the quality of the oil and paper can be determined through a DGA. The most common detection methods are the power factor test and the capacitance measurement, both described in [57, 96].

**Power factor test** determines the power loss of the bushing, in other words the "quality" of the capacitance. An "ideal" bushing has a purely capacitive behaviour. Deviations from the purely capacitive behaviour indicate power losses, denoted as the tangent delta. If the tangent delta surpasses a predetermined threshold, then it is advised to replace this bushing.

**Capacitance measurement** gives the capacitance of the bushing, between the outer shell and conductor. A capacitance increasing with more than a certain percentage indicates a short circuit between the capacitive layers. This knowledge method is fed by a direct explicit QP.
The power transformer is a component operating in a high voltage, high current, and consequently high power environment. Each aspect imposes its specific challenge on the transformer design. High voltage poses a need for dedicated insulation measures to prevent flashovers, especially during temporary overvoltages due to switching or lighting strokes. High currents are associated with high magnetic fields, which corresponds to strong electromagnetic forces, during high load and short-circuit situations. Although transformers are extremely efficient, in power transformers the dissipated heat must be disposed of through the insulating medium. Hence, the insulation must be capable of dealing with electric stresses, large electromechanical forces, and high temperatures.

Paper-oil insulation is widely applied in power transformers. Oil has an intrinsic high insulating strength and at the same time serves as cooling medium by either passive or active flow. The paper prevents electric bridging by contaminants left behind and serves as a mechanical barrier between the windings and winding layers. The paper is a critical factor in paper-oil insulation. A bad paper quality leads to premature insulation degradation. Rewinding the transformer, is time consuming and is an expensive job only applied as a last resort solution. Oil on the other hand is easier to replace and its quality can be monitored, as discussed in Section 3.4.

The paper insulating properties may be affected by displacement or by ageing. Displacement may occur instantaneously as a result of external mechanical forces, e.g. due to transportation or over-load situations. This causes a direct path for bridging contaminants, which can lead in turn to a winding short-circuit. In this chapter we focus on paper degradation, which describes the loss of mechanical strength of the insulating paper, and makes it vulnerable to rupture or disintegration.

The insulating paper consist of cellulose chains with their average length expressed in the degree of polymerisation (DP). The chemical formula of one cellulose unit, the monomer, is \((C_6H_{10}O_5)_n\). The chemical structure of two connected cellulose rings, i.e. one cellobiose unit, is depicted in Figure 4.1. A practical value for the DP of unaged paper is 1000–1200. The paper tensile strength is a measure for the sensitivity to paper rupture. The tensile strength is directly related to the degree of polymerisation of the insulating paper. If the mechanical strength of paper is reduced to 50% of the initial strength, its strength is considered to be in a faulty state [26, 28, 44, 49, 64]. This corresponds with a DP-value in the range of 200–300.

In this chapter two methods for predicting paper-oil insulation degradation will be discussed. The first method is the technique opted in the loading guide, which estimates the reduction of the expected remaining lifetime as function of the transformer load (Section 4.1).
The second method involves the chemical degradation process in terms of an Arrhenius like model (Section 4.2). The model is validated and its merits are discussed in Section 4.3. Possible improvements related to the effects of harmonic currents are discussed in Section 4.4.

4.1 Thermal transformer model — Loading guide

The thermal balance in the transformer is fed by the losses in both core and windings. These losses heat the transformer oil, by which convection starts, resulting in a temperature gradient along the windings. Due to the oil flow upwards the windings on the top will be at an elevated temperature. However, the cooling at the top windings is better than the windings underneath. The hot-spot, i.e. the winding location with the highest temperature, will therefore be just beneath the top windings. Since paper ageing increases with temperature, the DP-value is lowest at the hot-spot, making it a critical region for insulation integrity. The ageing process of the paper depends on the transformer load condition via the hot-spot temperature. Owing to the inertia in temperature variation, it takes time before the temperature responds to changing load conditions. Therefore, dynamic modelling is required.

In literature four ways of evaluating the oil and hot-spot temperatures for a two coil power transformer are described; two of them are employed in the IEEE loading guide [49] and two of them are owed to the work of Dejan Susa [80, 98]. The basic dynamical model from IEEE [49] takes into account the response time of the oil and the winding temperature, but omits the link between them. An increasing winding temperature is linked to a decreasing oil-viscosity, where a decreasing oil-viscosity causes a better heat transport and a decreasing response time. The MSc work of Dejan Susa [80], which is adopted in the IEC loading guide [44], not only includes the response times of the oil and the windings, but also involves a simplified relationship representing oil-viscosity. The IEEE guide [49, Annex G] and Dejan Susa’s PhD dissertation [98] evaluate the oil and hot-spot temperatures by implementing thermodynamic parameters.

The method adopted in the IEEE Annex G bases its hot-spot temperature on the bottom-oil temperature of the transformer by scaling critical parameters based on the temperature. This method circumvents the delayed response and overshoot due to oil viscosity, and provides a slightly higher estimate of the real hot-spot temperature. In the PhD work of Susa, on the other hand, the thermal model is constructed almost from scratch. His model determines the hot-spot temperature either based on the bottom-oil temperature or on the top-oil temperature. The influence of the oil viscosity and its heat transfer capabilities is incorporated by adjusting the thermal resistances and capacitances. This is a more physical representation of
the complicated thermal balance in the transformer. A drawback of IEEE Annex G and Susa’s PhD work is, that they both need detailed input data which is seldomly available, especially for older power transformers. Therefore, the dynamic model presented in IEC 60076-7 will be adopted here, which includes the simplified relationship with respect to oil-viscosity.

### 4.1.1 IEC 60076-7

According to [44, 80], the top-oil temperature, \( \theta_o \), and the hot-spot temperatures, \( \theta_h \), can be described with a set of three semi empirical differential equations. The time derivative of the top-oil temperature contains a heating part due to the current \( I \), using an average time response of the oil \( \tau_o \), and a term which involves the heat loss driven by the difference between top-oil temperature and ambient temperature \( \theta_a \). The top-oil temperature equation is given by

\[
\dot{\theta}_o = \frac{1}{c_{11} \tau_o} \left( \Delta \theta_{or} \left( \frac{1 + I^2 R}{1 + R} \right)^x - (\theta_o - \theta_a) \right), \tag{4.1a}
\]

where \( \Delta \theta_{or} \) is top-oil temperature rise in steady state for the rated current. \( R \) represents the ratio of load losses at rated current to no-load losses. Power \( x \) is the exponential power of total losses versus top-oil temperature rise in steady state, and \( c_{11} \) a thermal constant correction factor on the average oil response time \( \tau_o \). The hot-spot gradient temperatures represent the temperature rise at the windings due to heat generated in the windings and incorporate the different response times of the heat transported through the windings and by the oil under influence of a changing oil viscosity. The hot-spot gradient temperature can be split in a part describing the winding response time and a part taking the oil response time due to its viscosity into account. At rated current the hot-spot-to-top-oil gradient is \( \Delta \theta_{hr} \) and \( y \) is the power of current versus winding temperature rise in steady state. The term corresponding with the winding response \( \theta_{h1,gr} \) can be expressed as

\[
\dot{\theta}_{h1,gr} = \frac{1}{c_{22} \tau_w} \left( c_{21} \Delta \theta_{hr} I^y - \theta_{h1,gr} \right), \tag{4.1b}
\]

with \( \tau_w \) a winding response time and \( c_{21} \) a factor related to which portion of the heating is due to the winding or oil viscosity. Factor \( c_{22} \) is a general thermal correction factor. The hot-spot temperature gradient due to the oil viscosity \( \theta_{h2,gr} \) is given by

\[
\dot{\theta}_{h2,gr} = \frac{c_{21}}{\tau_o} \left( (c_{21} - 1) \Delta \theta_{hr} I^y - \theta_{h2,gr} \right). \tag{4.1c}
\]

The hot-spot temperature \( \theta_h \) can be derived from Equation (4.1) as follows,

\[
\Delta \theta_h = \theta_{h1,gr} - \theta_{h2,gr}, \tag{4.2a}
\]

\[
\theta_h = \theta_o + \Delta \theta_h, \tag{4.2b}
\]

with \( \Delta \theta_h \) as the hot-spot-to-top-oil gradient at the load considered.

### 4.1.2 Ageing rate and loss-of-life

Two types of insulation paper are applied in power transformers: Kraft paper (normal paper) and thermally upgraded paper. Kraft paper is wood pulp formed to paper strips, which are
vacuum dried. Thermally upgraded paper goes through almost the same process but is, in addition, heated during the vacuum drying process. The estimated life time in oil with low humidity for Kraft paper at 98 °C is 15 years and for thermally upgraded paper at 110 °C about 17 years, according to [44]. The thermally upgraded paper is more resistant to conditions of high humidity.

The mean-residual-life (MRL) may be determined from the loading guide by subtracting the loss-of-life (LOL) from the estimated life time under nominal conditions. The loss-of-life can be calculated with

\[ \text{LOL} = \int_{t_0}^{t} V(\tau) \, d\tau, \]  

where \( V(t) \) is the (time dependent) paper ageing rate. The integration extends from a starting time \( t_0 \) to a variable end time \( t \). The ageing rate for Kraft paper and thermally upgraded paper can be obtained from the IEC loading guide [44]. For Kraft paper the following relation is employed,

\[ V_{\text{Kraft}}(t) = 2^{\frac{\theta_h(t) - 98}{6}}, \]  

here \( \theta_h(t) \) is the time dependent hot-spot temperature of the insulation paper in degrees centigrade. Early studies by Montsinger [76] showed a doubling of the ageing rate for every 6 °C increase in temperature for a temperature range centred around 98 °C. For thermally upgraded paper the ageing rate is

\[ V_{\text{TU}}(t) = \exp\left(\frac{15000}{110 + 273} - \frac{15000}{\theta_h(t) + 273}\right), \]  

for temperatures around 110 °C. The value of 15000 K in Equation (4.5) is obtained from [49, Annex I]. For a temperature range around 110 °C this corresponds to an ageing rate doubling every 6.8 °C temperature increase.

### 4.1.3 Discussion

The commonly applied methods to predict the paper lifetime, or loss of lifetime, are obtained from the loading guide techniques, described in [42, 44, 49]. These models predict the mean-residual-life and loss-of-life, which are both implicit QPs according to the definitions in Section 3.2, because these QPs can not be obtained by measurement. The modelling of these QPs is done with a regression technique in the scheme of Figure 3.4 in Section 3.3.

Emsley et al. published their extensive studies in 1994 [26], Lundgaard et al. repeated the experiments ten years later in 2004 [64]. The latter experiments had an extended temperature range, and the influence of oil and acids were more in focus. Both research groups base their model on the Arrhenius model. Their MRL expressed in years can be calculated from (see also Section 4.2):

\[ \text{MRL} = \left(\frac{1}{DP_{\text{end}}} - \frac{1}{DP_{\text{initial}}}\right) \frac{1}{365 \cdot 24 \cdot k}, \]  

where \( k \) is the reaction rate according to an Arrhenius process, \( DP_{\text{initial}} \) is the DP-value for a new transformer, and \( DP_{\text{end}} \) the DP-value for which the insulation paper is considered to be
at its end of life. Equation (4.6) is plotted in Figure 4.2 using the parameters from Table 4.1 for both the Emsley and Lundgaard results. The mean-residual-life obtained by using the results of Emsley and Lundgaard with $DP_{end}$ values equal to either 200 or 300 are compared with the values obtained with the loading guide.

Table 4.1: Data for Equation (4.6) to calculate the mean-residual-life of Kraft and thermally upgraded paper.

<table>
<thead>
<tr>
<th>Winding insulation paper</th>
<th>$A$ in h$^{-1}$</th>
<th>$E_a$ in kJ/mol</th>
<th>$DP_{initial}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kraft</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emsley</td>
<td>1.07 $\times 10^8$</td>
<td></td>
<td>111</td>
</tr>
<tr>
<td>Lundgaard</td>
<td>2.0 $\times 10^8$</td>
<td></td>
<td>1000</td>
</tr>
<tr>
<td>Thermally upgraded</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emsley</td>
<td>0.365 $\times 10^8$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lundgaard</td>
<td>0.67 $\times 10^8$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

From the Kraft paper results in Figure 4.2(a), three observations can be made:

- At a hot-spot temperature of 98 °C, the IEC graph does not coincide with any laboratory experiment. This suggests an erroneous fit of the regression model of Equation (4.4).
- The IEC graph, generated by Equations (4.3) and (4.4), is not parallel to any of the laboratory results. This suggests that the fit is based on a different material than Emsley or Lundgaard.
- The IEC method assumes that the end of life is reached at a tensile strength corresponding to a $DP$-value of 200. In Japan for example, there is a need for a higher mechanical strength, because their transformer can suffer higher mechanical stresses due to a relatively large risk on severe earthquakes. However IEC does not directly allow to set the threshold at an arbitrary level.

The conclusions also hold for the thermally upgraded paper in Figure 4.2(b) except that at the reference hot-spot temperature of 110 °C the IEEE curve coincides with the Emsley curve for $DP_{end} = 200$. The regression method used in the loading guide can not be tuned to a specific situation like transformer insulation material containing for example moist paper or paper in acid oil. Again the model does not allow to adjust the risk on a fault to a specific situation at hand, such as, transformers in a region with a high probability of earthquakes.

In the next section a method is described to determine the fault probability by modelling the $DP$-value upon degradation. In terms of the definitions given in Chapter 3 this method gives a physical description of a directly explicit $Q_P$. The most critical $DP$-value is located near the hot-spot. The behaviour of the hot-spot temperature is based on a thermal model of the transformer, as a function of load and ambient temperature. The thermal model provides the dynamic response of the oil and hot-spot temperature, based on thermal input and individual cooling mechanism of the transformer [106–108, 111].

### 4.2 Paper degradation mechanism model

Paper ageing is an auto-accelerated process, caused by acid-hydrolysis, pyrolysis, and oxidation, and resulting in the scission of the cellulose chains [4, 16, 20, 21, 24–30, 34, 38, 64, 65, 93]. This process is catalysed by: hydrogen ions dissolved in water ($H_3O^+$), water itself and oxygen. Scission is accelerated at elevated temperature. The chemical process of cutting cellulose chains in smaller cellulose units results in byproducts, such as water, carbon monoxide.
Figure 4.2: Mean-residual-life versus hot-spot temperature for Kraft and thermally upgraded paper. The calculations are based on the results of Emsley and Lundgaard, and the IEC loading guide. $DP_{\text{end}}$ values of 200 and 300 are used in the calculations.
and furans. Diagnostic techniques are based on detection of these byproducts, as described in Section 3.4.

According to [20, 27, 28] the decline in DP-value is the result of a cascaded chemical reaction. The primary reaction creates reactants, which will interact during subsequent reactions on the linking oxygen atom in the cellulose chain. These cascaded chemical reactions can be described by a second order differential equation with the DP-value at $t_0$ and the degradation speed at $t_0$ as initial conditions. The degradation rate is, however, hard to determine in practice. A simplified temperature dependency model of the DP-value, as proposed by Emsley, Lundgaard and others in [16, 26, 64], is a first order differential equation using the Arrhenius relation, because interaction on the linking oxygen atom is dominant. The differential equation of this auto-accelerated process is

$$\frac{dDP(t)}{dt} = -k(t)[DP(t)]^2,$$

(4.7)

with $k(t)$ being the time dependent reaction rate. The DP-value as a function of time is given by

$$DP(t) = \frac{DP(t_0)}{1 + DP(t_0) \int_{t_0}^{t} k(\tau) \, d\tau},$$

(4.8)

where $DP(t_0)$ is the DP-value at some initial time $t_0$. The reaction rate $k(t)$ has the Arrhenius form

$$k(t) = A \exp \left( -\frac{E_a}{R_g T(t)} \right),$$

(4.9)

with $E_a$ being the activation energy; $R_g$ the universal gas constant; $A$ a process constant and $T(t)$ the time dependent absolute temperature, which is related to both the current load and ambient temperature. The activation energy $E_a$ and constant $A$ can, in principle, be taken time dependent to account for change in the degradation process over time.

### 4.2.1 Fault probability

A fault situation occurs when the DP-value drops below a threshold value. Both the estimate of the actual DP-value and the threshold level for possible failure are stochastic in nature and may be described by distribution functions. The parameters in the depolymerisation rate contain uncertainties which propagate to an uncertainty of the projected DP-value with time. Also the DP-threshold for possible failure should be considered as a distribution with a finite width.

The probability density function for the DP-value at time $t$ is $p_{dp}(v, t)$. The value $p_{dp}(v, t) \, dv$ is the probability that the DP-value is between $v$ and $v + dv$ at time $t$. The cumulative probability for the DP-value $v$ being below the threshold is denoted by $P_{th}(v)$. Combining $p_{dp}(v, t)$ and $P_{th}(v)$ distributions results in the fault probability at time $t$,

$$F(t) = \int_0^\infty P_{th}(v) p_{dp}(v, t) \, dv.$$

(4.10)

It must be noted that the fault probability given by Equation (4.10) is not the same as the failure probability. The transition from fault to failure requires a trigger, which may also incorporate a stochastic component.
From a decision making point of view, if $F(t)$ would result in a distribution with a steep slope, there is a well-defined moment in time where the transformer is expected to fail. A gradual slope implies a relatively large uncertainty in the predicted time to failure.

### 4.2.2 Uncertainty estimation by error bounds

Consider the error bound of a function $y = f(\bar{x})$, with a set of variables $\bar{x} = x_1, x_2, \ldots, x_n$. The error bound $\Delta f$ in the function can be obtained in first order by a linear approximation as given e.g. in [75, Chapter 10]. If all errors of the input variables $x_i$ are uncorrelated, the error bound of the function is approximately

$$
(\Delta f)^2 \approx \sum_{i=1}^{n} \left( \frac{\partial f}{\partial x_i} \Delta x_i \right)^2,
$$

(4.11)

where the $\Delta$’s are the uncertainties in the corresponding variables. The relative error in the reaction rate of Equation (4.9) then becomes

$$
\frac{\Delta k}{k} = \sqrt{\left( \frac{\Delta A}{A} \right)^2 + \left( \frac{\Delta E_a}{E_a R g T} \right)^2 + \left( \frac{E_a}{R g T} \Delta T \right)^2}.
$$

(4.12)

Small individual parameter uncertainties may be appropriately characterised by a normal distribution, with $\mu$ the expected value and $\sigma$ the estimated error bound. As long as the linearisation required for Equation (4.11) is valid, also the reaction rate may be expected to have a normal distribution. Although the effects of the contribution of $\Delta E_a$ and $\Delta A$ can be relatively large, we will assume a normal distribution to be appropriate.

Typical values for Kraft paper based on [64] are given in Table 4.2. The uncertainty in the activation energy was not specified in [64], but is estimated 1 kJ/mol for 95% of the time. For the temperature the reference value of 98 °C is taken with a chosen standard deviation of 2.5 °C. This results in a $k$ of $4.8 \times 10^{-24}$ h$^{-1}$ and $\Delta k = 1.3 \times 10^{-24}$ h$^{-1}$. All error bound values are $\sigma$ accuracy values. The normal distribution of the error bound is compared with a Monte-Carlo simulation. Figure 4.3 shows the obtained distribution, and the Monte-Carlo simulation. Both approaches are in good agreement.

### Table 4.2: Typical values for Kraft paper according to [64].

<table>
<thead>
<tr>
<th></th>
<th>$\mu$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>$2.0 \times 10^{-8}$ h$^{-1}$</td>
<td>$0.25 \times 10^{-8}$ h$^{-1}$</td>
</tr>
<tr>
<td>$E_a$</td>
<td>111 kJ/mol</td>
<td>0.5 kJ/mol</td>
</tr>
</tbody>
</table>

For the evaluation of Equation (4.10) we also need to define a distribution for the degree of polymerisation, taking into account that the DP-values are restricted to the range 1–1500 for Kraft and thermally upgraded paper [26, 64, 93]. For the upper limit a maximum of 1500 is chosen. This value is of minor importance, since the area under the normal distribution above 1500 is negligible for practical DP-values.

A truncated normal distribution was chosen (Appendix B) since it can handle a finite domain of DP-values, whereas a standard normal distribution involves values ranging from minus to plus infinity. The density and cumulative distribution functions of a truncated normal
Validation of the physical model

4.3

The sequence in calculating the hot-spot temperature, the DP-value and the fault probability is depicted in the scheme of Figure 4.4. The current, \( I \), is taken constant within each time step \( \Delta t \). The hot-spot temperature, \( \theta_h \), and the DP-value, \( DP \), need to be calculated iteratively at each time step with the differential Equations (4.1) and (4.8). The fault probability \( F(t) \) is

\[ g_T(x) = \begin{cases} g(x) / (G(X_{\text{max}}) - G(X_{\text{min}})) & X_{\text{min}} \leq x \leq X_{\text{max}}, \\ G_T(x) = (G(x) - G(X_{\text{min}})) / (G(X_{\text{max}}) - G(X_{\text{min}})) & -\infty < x < \infty \end{cases} \]  

(4.13)

in which \( g(x) \) and \( G(x) \) denote the density and cumulative functions for a normal distribution:

\[ g(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \]

\[ G(x) = \frac{1}{2} \left( 1 + \text{erf} \left( \frac{x-\mu}{\sqrt{2\sigma}} \right) \right) \]

(4.14)

**Figure 4.3:** Monte-Carlo results combined with probability density function of the calculated \( k \) values with \( \Lambda \) and \( E_a \) values from Table 4.2.
obtained from the DP-value and the threshold distribution. The input parameters required to perform the calculations are:

- The transformer nameplate information, such as rated current, rated voltage, tap positions and operating frequency.
- The thermal characteristics of the transformer for Equation (4.1).
- The Arrhenius parameters for Equation (4.9).
- A complete historical load pattern and ambient temperature.
- The uncertainty margins of the input parameters.

\[
\begin{align*}
I(t) & \quad \text{Equation (4.1)} \quad \theta_h(t) \quad \theta_h(t + \Delta t) \quad DP_{th} \\
DP(t_0) & \quad DP(t) \quad DP(t + \Delta t) \quad F(t)
\end{align*}
\]

**Figure 4.4:** Scheme to calculate the fault probability and its intermediate parameters. The intermediate parameters are hot-spot temperature and DP-value.

In Section 4.3.1 the sensitivity of the model to its input parameters is investigated. The model is also applied to an existing transformer. It is actually hard to find a transformer for which the required data is completely available. Usually dynamic data, like the loading history, is not stored. In our verification we have used KEMA data of a failed transformer with sufficient history. The results are presented in Section 4.3.2.

### 4.3.1 Sensitivity analysis

The life span of insulating paper is extremely sensitive to the operational temperature. Figure 4.2 shows that the life span varies from 1000 years for a hot-spot temperature of 60 °C to 1 year for a hot-spot temperature of 130 °C. This nonlinear behaviour has its origin in the temperature dependent reaction rate of Equation (4.9). To give an idea, the earlier assumed one percent uncertainty of the activation energy has the same effect as a one percent change in the absolute hot-spot temperature, which corresponds to about 4 °C for a nominally loaded transformer. The operational temperature and activation energy are not the only parameters with uncertainties. The sensitivity of the major model parameters will be studied in this section.

From the error bound function in Equation (4.11) a relative sensitivity ratio is defined between each variable \(x_i\) and the function value \(f(x_i)\), i.e. the MRL. The relative sensitivity ratio is defined as:

\[
c_i = \frac{\Delta f_i(x_i)}{f_i(x_i)} \frac{f_i(x_i)}{\Delta x_i} \quad x_i.
\]

The sensitivity of the MRL for an ONAN transformer using the IEC loading guide [44] is analysed for the following situation: \(\theta_a = 20 \, ^\circ\text{C}, A = 1.07 \times 10^8 \, \text{h}^{-1}, E_a = 111 \, \text{kJ/mol} \, DP_{\text{initial}} = \ldots \)
1000, \( DP_{\text{end}} = 250 \) and \( 0.2 \) p.u. \( \leq I \leq 1.2 \) p.u.. The sensitivity analysis is done using the Monte-Carlo technique, with normally distributed input parameters. The deviations are individually varied up to 5% of their nominal values. The resulting MRL is fitted on a normal distribution. From the \( \mu \) and \( \sigma \) values the correlation factors for each individual parameter are determined as function of the per unit load, \( I \), taken in the range from 0.2 p.u. to 1.2 p.u. The results are plotted in Figures 4.5, 4.6 and 4.7.

![Figure 4.5: The relative sensitivity ratio versus the current for a 5% error in paper parameters, i.e. the Arrhenius constant \( A = 1.07 \times 10^8 \) h\(^{-1}\), the activation \( E_a = 111 \) kJ/mol and the DP-value of new paper \( DP_{\text{initial}} = 1000 \).](image)

The most critical parameter for the MRL is evidently the activation energy \( E_a \), because of the exponential relationship in the reaction rate. Especially for low load the uncertainty is large. However, at low load the contribution to the loss-of-life of the transformer is negligible as compared to conditions at near or over nominal load. The high sensitivity for this quantity implies that the value must be known accurately. The value of 1% used earlier in the Monte-Carlo simulation already gives an appreciable uncertainty in the prediction. On the other hand, since the paper degradation is strongly sensitive to the activation energy \( E_a \), its value can be obtained by monitoring the DP-value as a QP. Not only the actual value for DP is obtained, but also the model parameters can be validated and fine-tuned to account for the actual paper degradation parameters. The parameter \( A \) is less critical since it is a pre-exponential factor in the Arrhenius relation. The fault probability of Equation (4.10) already incorporates the sensitivity of \( DP_{\text{end}} \) via the threshold distribution \( P_{\text{th}} \). The impact of the initial DP-value \( DP_{\text{initial}} \) is low, as long as the \( 1/DP_{\text{initial}} \) is much smaller than \( 1/DP_{\text{end}} \). For an aged transformer with e.g. an estimated DP-value of 500, it may become significant since it starts close to the critical range. The sensitivity to load and ambient temperature enters through the temperature dependency in the Arrhenius equation, as is the case for all param-
eters involved in estimating the hot-spot temperature. Clearly, load condition is most critical, indicating the importance of a good record of the dynamic load for reliable MRL estimation.

### 4.3.2 Machine transformer

In 1992 an industrial transformer was installed at an aluminium plant. The transformer parameters are a rated power of 105 MVA, a rated primary voltage of 141 kV with 6 up and 6 down taps of 1.25%, a secondary voltage of 10.5 kV, an operating frequency of 50 Hz and a Oil Natural Air Forced (ONAF) cooling. Its thermal parameters are listed in Table 4.3. The transformer suffered a fatal failure in 2007, caused by a winding short-circuit. This transformer was subjected to an extensive investigation. The presence of corrosive sulphur in the oil was identified as the failure cause. Although the transformer did not fail directly by a low tensile strength of the paper-oil insulation, data on the actual hot-spot DP-value became available and is used to evaluate the model.

<table>
<thead>
<tr>
<th>Cooling</th>
<th>$R$</th>
<th>$\Delta\theta_{or}$</th>
<th>$\Delta\theta_{hr}$</th>
<th>$x$</th>
<th>$y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ONAF</td>
<td>5.7</td>
<td>48</td>
<td>$1.3 \times 11 = 14.3$</td>
<td>0.9</td>
<td>1.6</td>
</tr>
</tbody>
</table>

The transformer winding insulation material is Kraft paper, with the depolymerisation reaction rate figures given in Table 4.1. New Kraft paper has an initial DP-value of 1200, but after
Validation of the physical model

Figure 4.7: The relative sensitivity ratio versus the current for a 5% error in the transformer parameters, which are the oil exponent \(x = 0.8\), the winding exponent \(y = 1.3\), the power loss ratio \(R = 6\), the ambient to top-oil gradient \(\Delta \theta_{or} = 52\) K and the top-oil to hot-spot gradient \(\Delta \theta_{hr} = 26\) K.

drying the DP-value drops to about 1000. For this transformer data on load pattern and ambient temperature were recorded as two hourly values measured on 24 days. This data was available for a limited number of days, spread over a period of almost 2 years. The measured daily patterns are duplicated up to the missing days till the next sample day. Both this two-yearly load pattern and the ambient temperature profile are assumed to be representative for the transformer’s complete life, and are taken also for the missing years. Their maximum and minimum values are plotted for a 2 year period in Figure 4.8.

Figure 4.9(a) shows the model results obtained with the value of the \(A\)-parameter suggested by Emsley [26]. For Figure 4.9(b) the \(A\) value suggested by Lundgaard [64] is used. The expected DP-values are represented by the solid line in Figure 4.9. The dotted lines define the one \(\sigma\) confidence bound, representing an 68% probability margin. The calculated DP-value at the time of failure, using Emsley’s data is 622 with a standard deviation of 111 (18%). Using the Lundgaard data a DP-value of 468 with a standard deviation of 116 (25%) is obtained. The actual measured DP-value of 454 with a standard deviation of 23 is indicated in the plot.

Two conclusions may be obtained from Figure 4.9. Firstly, the predicted DP-value based on the paper parameters provided by Lundgaard seems to coincide better with the measured result as compared to the figures obtained from Lundgaard. Secondly, both predicted curves have a high uncertainty. This is due to the inaccuracies in the load, ambient temperature and the transformer characteristics. The actual uncertainty may even be higher, because of the uncertainties in the extrapolation procedure of the load and ambient temperature. At first sight one might conclude that values predicted by Lundgaard agrees best with the observed value, however, due to the high uncertainty level based on only one asset, it is premature to
Figure 4.8: Load pattern and ambient temperature of the machine transformer.

Figure 4.9: The machine transformer paper degradation curve calculated for dry Kraft paper according to Emsley and Lundgaard. The circle is the lowest measured DP-value with error bar, the dotted lines are the 68% error margin of the simulated result.
4.3.3 Discussion

The proposed model includes the dynamic thermal heat cycle and the chemical model of the paper scission process. The uncertainties of the predicted values can be estimated. The uncertainty estimation together with the sensitivity analyses provides information on parameters which are most critical to improve the fault probability prediction. Feedback with the actual condition can be realised through the quality parameters. The model predicts the behaviour of top-oil, hot-spot temperatures and DP-value. Through feedback with monitored quantities, the model can be validated, fine-tuned and improved. A next logical step in verifying the model is by monitoring parameters, such as load pattern, ambient temperature, and maintenance, for a few transformers.

The paper degradation model can be extended by incorporating harmonic transformer losses, to determine the impact of ageing on traction transformers, HVDC transformers, and rectifier transformers applied in industry. A first attempt for incorporating harmonic transformer losses in the paper degradation model is given in the next section.

4.4 Harmonic transformer losses

Eddy currents from power frequency harmonics result in relative high losses in a transformer as compared to the fundamental current. Harmonic currents are of concern in transformers applied in industry, e.g. transformers feeding power electronics. For these transformers the hot-spot temperature can be significantly higher than expected on basis of the power frequency current. Eddy currents in a winding are induced by currents in neighbouring windings and depend on winding position and on the harmonic number. The current distribution will affect the hot-spot temperature. The losses in each winding increase the oil temperature and during the upward convection heat is added at each successive winding. The oil temperature gradient at each winding is proportional to the losses in the winding. Therefore the oil temperature is expected to increase proportional with the cumulative power loss from the bottom winding to the actual winding. It is assumed that a similar relation holds for the hot-spot temperature, although in reality there is a temperature gradient from the local oil temperature to the actual winding temperature. This gradient is assumed to scale with the gradient at the main power frequency.

4.4.1 Simplified coil model

The thermal model adopted in Section 4.1 assumes, that all windings equally contribute to the heating of the oil. Therefore, the winding temperature profile will be linear. The linear temperature profile should either provide the actual temperature profile or represent a worst case situation at the position of the hot-spot to prevent underestimating the effects of paper degradation. Therefore, the impact of the harmonic current on the hot-spot temperature is studied with a simplified coil model. The modelled coil exists of 25 turns with a diameter of 1.5 m, and a copper conductor diameter of 3 cm. For each winding the losses are determined by a BEM (Boundary Element Method) software ("Oersted" from "Integrated Engineering Software"). The winding losses at 50 and 500 Hz are determined for a 1 kA current, the loss per winding is plotted in Figure 4.10. The 500 Hz frequency is chosen to illustrate the effect of
harmonics of the power frequency. In Figure 4.11 the cumulative power loss distribution is plotted for DC (dotted), 50 Hz (dash-dotted) and 500 Hz (solid). All curves are normalised on the maximum cumulative loss for 500 Hz, in order to specifically show the effect of harmonics on the distributions. At higher frequency the relative contribution of the outer windings to the total power loss is higher due to the proximity effect of the windings either below or above. For the middle windings, roughly speaking, the effect of the magnetic field from windings below and above partly cancel. In Figure 4.11, we observe that the hot-spot temperature, which occurs just below the top winding, for the linear equivalent distribution (dotted) is higher than for the equivalent 50 Hz current (dash-dotted). For 500 Hz, the solid line in Figure 4.11, the hot-spot temperature will even be lower than in the 50 Hz equivalent case. Note, that situations with constant maximum power loss are compared here. Clearly, the overall higher power loss of harmonic currents will lead to a higher hot-spot temperature.

\[ I_{EQ} = \sqrt{\frac{P_{LL,H}}{P_{LL}}} \]  

(4.16)

Figure 4.10: Power loss per winding due to ohmic losses and eddy currents, plotted for 1 kA current at 50 and 500 Hz.

The simulation results of the previous paragraph indicate that the linear temperature profile gives a worse case estimate of the hot-spot temperature, because at the hot-spot the cumulative power loss is less than its linear equivalent. For this coil example the hot-spot is assumed to be located somewhere around winding 21–24, if the coil is used in a core type transformer. From this observation a model is constructed to incorporate losses due to harmonics by using the concept of an equivalent current. To this end the earlier model (Figure 4.4) for power frequency can be extended to include the effect of harmonics (Figure 4.12). The equivalent power frequency current, \( I_{EQ} \) in p.u., can be calculated from harmonic load losses, \( P_{LL,H} \),
with $P_{LL}$ being the load losses at the rated power frequency current. We suggest that this equivalent current is the current to be used in the IEC or IEEE loading guides. Note that the heat distribution in the transformer is considered to be similar to the power frequency loading. Deviations from these distributions are considered as a second order effect.

**Figure 4.11:** Cumulative power loss due to ohmic losses and eddy currents, plotted for 1 kA current at 500 Hz. The losses for the 50 Hz and DC current are normalised so the total power loss is equal to the 500 Hz situation.

**Figure 4.12:** Scheme to calculate the fault probability from the harmonic current profile, with the hot-spot temperature and DP-value as intermediate parameters.
4.4.2 Harmonic loss estimation

The transformer losses consist of the load dependent losses, $P_{LL}$, and the no-load losses, $P_{NL}$,

$$P_{tot} = P_{NL} + P_{LL}. \quad (4.17)$$

The no-load losses are made up by the core magnetisation losses. These core losses will be assumed to be constant. According to [37, 43, 50, 51] the load dependent losses consist of ohmic losses $P_{OL}$, additional losses from the eddy currents $P_{EC}$, and magnetic flux stray losses $P_{SL}$,

$$P_{LL} = P_{OL} + P_{EC} + P_{SL}. \quad (4.18)$$

Typically, the eddy current and stray losses are each in the order of 5% of the load losses for oil immersed transformers at the power frequency [40].

Harmonic currents cause the load dependent losses to increase due to eddy currents and flux leakage. The harmonic load, $I_h$, is a p.u. current depending on the rated current of the transformer. Subscript $h$ denotes the harmonic order of the current. According to [37, 43, 50, 51], the harmonic load loss $P_{LL,h}$,

$$P_{LL,h} = P_{OL,h} + P_{EC,h} + P_{SL,h}, \quad (4.19)$$

is the sum of the harmonic ohmic losses, eddy current and magnetic flux losses, given by respectively

$$P_{OL,h} = P_{OL} \sum_{h=1}^{N} I_h^2, \quad (4.20)$$

$$P_{EC,h} = P_{EC} \sum_{h=1}^{N} h^2 I_h^2, \quad (4.21)$$

$$P_{SL,h} = P_{SL} \sum_{h=1}^{N} h^{0.8} I_h^2. \quad (4.22)$$

4.4.3 Illustration of harmonic current impact

As an illustration the impact of harmonic currents is investigated for a typical ONAN transformer. It is assumed that the ohmic losses of this transformer are 90% of the load losses, the eddy current and stray losses are each 5% of the load losses. From Table 4.4 the loss equivalent fundamental current is calculated with Equation (4.16) for a theoretical and a practical six pulse DC converter [40]. This is also done for the maximum allowed harmonic currents according to the Dutch Gridcode [1]. The harmonic currents of a theoretical DC converter is

$$I_h = \frac{I_1}{h}, \quad h = pn \pm 1, \quad n \in \mathbb{N}^*, \quad (4.23)$$

with $p$ the pulse number of the bridge, in our case 6. The total harmonic distortion (THD) is calculated from the per unit harmonic currents $I_h$ as follows,

$$\text{THD} = \frac{1}{I_1} \sqrt{\sum_{h=2}^{\infty} I_h^2}. \quad (4.24)$$
Table 4.4: The harmonic currents \( I_h \) are given for a theoretical and practical six pulse DC converter [40], the last column shows the values for Dutch Gridcode [1]. The last rows give the total harmonic distortion (THD) according to Equation (4.24) and the percentage of the loss equivalent fundamental current based on Equation (4.16).

<table>
<thead>
<tr>
<th></th>
<th>Theoretical</th>
<th>Practical</th>
<th>Netcode</th>
<th></th>
<th>Theoretical</th>
<th>Practical</th>
<th>Netcode</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>14</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.037</td>
<td>16</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>3</td>
<td>0.073</td>
<td>17</td>
<td>0.059</td>
<td></td>
<td>0.030</td>
<td>0.025</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.200</td>
<td>0.290</td>
<td>0.015</td>
<td>18</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.103</td>
<td>0.074</td>
<td>0.053</td>
<td>19</td>
<td>0.030</td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.143</td>
<td>0.110</td>
<td>0.009</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.007</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>8</td>
<td>0.012</td>
<td>23</td>
<td>0.043</td>
<td></td>
<td>0.020</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.098</td>
<td>24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.060</td>
<td>0.071</td>
<td>0.040</td>
<td>25</td>
<td>0.020</td>
<td>0.013</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>0.008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>0.050</td>
<td>0.055</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>THD</td>
<td>21%</td>
<td>32%</td>
<td>18%</td>
<td></td>
<td>( \frac{I_{EQ}}{I_1} - 1 )</td>
<td>22%</td>
<td>16%</td>
</tr>
</tbody>
</table>

From the THD and the loss equivalent fundamental current provided in Table 4.4, it is observed that the THD is not an indication of the level of the loss equivalent fundamental current. Further, harmonic currents have a relatively high impact in situations of high loading. A fundamental current of 0.5 p.u. will lead to an equivalent loss current of 0.58 p.u. for the practical six pulse converter. A fundamental current of as much as 0.8 p.u. results in an equivalent loss current of 0.93 p.u.

The effect on the mean residual life (MRL) for our typical ONAN transformer are depicted in Figure 4.13, with three types of loads. The solid line corresponds to a p.u. power frequency load only. The dotted line has a load belonging to a real six pulse DC converter. The dash-dotted curve belongs to a load with the maximum harmonic values allowed by the Dutch Gridcode.

Two conclusions can be drawn from Figure 4.13. For low loads the harmonic components have relative low impact, because the contribution to the hot-spot temperature is minimal. Further, the harmonic components at a load of 0.65 p.u. of a six pulse DC converter contribute to the same MRL life as for load without harmonic components of 0.75 p.u. Hence, these harmonic currents should not be neglected for higher loads.

It should be noted that the individual construction of the transformer determines the amount of eddy current and stray losses, and thereby the level of harmonic loss, as seen in Section 4.4.2.
Figure 4.13: The mean residual life determined of a typical ONAN transformer under the influence of only the power frequency load, connected with a six pulse DC converter, and a harmonic load with the values of the Dutch Netcode.
Transformer population reliability

The Dutch high voltage grid contains over a thousand power transformers. The load of these transformers depends upon their connected costumers, such as, heavy industry with a high power demand where transformers are continuously loaded nominally, or in rural areas, where only a small fraction of the rated power needs to be delivered.

This chapter pursues the merits of a population reliability model. Specifying for all transformers individual reliabilities only, does not provide a clear picture of the complete network condition. There is a need for defining properties that characterise the condition of a population of similar assets by means of a limited number of figures. Useful figures are the expected number of transformers still operational or the number of transformers expected to fail each year.

Depending on past policy of installation, on present and future scenario of transformer loading, and on maintenance strategy, an increased replacement effort may be required within several decades. The projected failure rate from a population model predicts whether, and on what time scale transformer failure is to be expected.

Proper maintenance and proactive grid upgrading increases the expected remaining life of individual transformers, and as a consequence the reliability of the population as a whole. The individual reliabilities allow selecting the most endangered assets, and load, maintenance and replacement policy can be adjusted and fine tuned. The effectiveness of the measures taken can be extracted from the population probabilities defined in this chapter.

Section 5.1 addresses the concept of the population reliability modelling. This method is applied to determine the effects of scenarios on the failure wave (Section 5.2) and the results of the replacement alternatives (Section 5.3). In Section 5.4 the framework of determining the financial impact is discussed.

5.1 Population reliability model

The population model and the population reliability parameters used throughout the thesis are introduced in this section. The simplest method is ranking the individual calculated mean-time-to-failures (MTTF) and fit a distribution on the data [11, Chapter 3]. This method works well for populations in identical stress environments, such as mobile phones and televisions. The stress environment of individual transformers in a population can differ a lot, and hence their individual reliabilities too. To account for interdependency of the individual reliabilities on the population reliability a method in two steps is applied. First, the individual transformer reliabilities are combined (Section 5.1.1); next a population reliability parameter is extracted
and defined (Section 5.1.2). The concept is illustrated on a hypothetical transformer population with two age groups in Section 5.1.3. The conceptual method of Sections 5.1.1 and 5.1.2 combines all permutation of the individual reliability, because permutations grow factorial a computational efficient method, both in speed and memory usage, is needed (Section 5.1.4).

5.1.1 Combining reliabilities

Consider a population consisting of $N$ transformers. The individual reliabilities are denoted by $R_i(t)$, which give the probability that transformer $i$ has not failed after time $t$. Its counterpart, the failure probability is denoted by $F_i(t)$, which equals $1 - R_i(t)$. The reliability of $N$ working fleet components is given by

$$R^{(N,N)}(t) = \prod_{i=1}^{N} R_i(t),$$

i.e. the probability that no single component did fail. The left part of the superscript $R^{(i,j)}$ denotes the number of operating components, the right part denotes the size of the population.

Next, we can derive the probability $R^{(N-1,N)}$ that at least $N - 1$ out of $N$ transformers are working and proceed up to $R^{(N-k+1,N)}$, the reliability that less than $k$ transformers have failed. The probability that at least $N - 1$ components are working is the sum of probabilities that exactly one transformer failed plus the probability that less than one failed,

$$R^{(N-1,N)}(t) = \sum_{i_1 = 1}^{N} F_{i_1}(t) \prod_{\substack{l=1 \atop l \neq i_1}}^{N} R_l(t) + R^{(N,N)}(t).$$

Obviously, this is the probability that not more than one component has failed. The probability that less than $k$ transformers have failed, or in other words that at least $N - k + 1$ are functional at time $t$, is equal to

$$R^{(N-k+1,N)}(t) = R^{(N-k+2,N)}(t) + \sum_{i_1 = 1}^{N} F_{i_1}(t) \sum_{i_2 > i_1}^{N} F_{i_2}(t) \cdots$$

$$\cdots \sum_{i_{k-1} > i_{k-2}}^{N} F_{i_{k-1}}(t) \prod_{\substack{l=1 \atop l \neq \{i_1, \ldots, i_{k-1}\}}}^{N} R_l(t).$$

According to [58] the general equation for at least $N - k + 1$ components working, i.e. less than $k$ have failed, can more conveniently be rewritten as

$$R^{(N-k+1,N)}(t) = \sum_{i=N-k+1}^{N} (-1)^{i-N+k-1} \binom{i-1}{N-k} \sum_{j_1 < j_2 < \cdots < j_i} \prod_{l=1}^{i} R_{j_l}(t).$$

5.1.2 Population reliability

We can define a population reliability as the fraction of transformers operational at time $t$ being $\frac{N-k}{N}$. Since, by definition, $k$ indicates that less than $k$ transformers have failed, the population reliability is the probability that a fraction larger than $\frac{N-k}{N}$ is working. This fraction is a known number for any choice of $k$, but the time TTF$_k$ to reach this probability still has to be
determined. We can define a risk level, \( L_R \), which is regarded to be acceptable according to the asset management policy. The time to failure, \( \text{TTF}_k \), occurs at the first instance that the probability of less than \( k \) failed transformers \( R^{(N-k+1,N)} \) is equal to the chosen risk level \( L_R \), where \( R^{(N-k+1,N)} \) is either obtained from Equation (5.3), (5.4) or as shown later from Equation (5.11). Hence, it involves solving the following equation for \( k \) failed components

\[
R^{(N-k+1,N)}(\text{TTF}_k) = L_R. \tag{5.5}
\]

An average of all risk levels is represented by the mean time to failure (MTTF). The MTTF for \( k \) failed components, \( \text{MTTF}_k \), can be found according to

\[
\text{MTTF}_k = \int_0^\infty t f_k(t) \, dt \tag{5.6}
\]

with \( f_k \) the probability density function belonging to the cumulative failure distribution up to \( k \) failures. This is equal to the time derivative of \( 1 - R^{(N-k+1,N)}(t) \), the probability that \( k \) or more transformers failed,

\[
f_k(t) = -\frac{d}{dt}R^{(N-k+1,N)}(t). \tag{5.7}
\]

The corresponding MTTF is found by integrating Equation (5.6) by parts

\[
\text{MTTF}_k = -\int_0^\infty t \frac{d}{dt}R^{(N-k+1,N)}(t) \, dt = \int_0^\infty R^{(N-k+1,N)}(t) \, dt. \tag{5.8}
\]

The population reliability, \( R_P \), belonging to the MTTF \( k \) is defined as

\[
R_P(t = \text{MTTF}_k) = \frac{N - k}{N}, \tag{5.9}
\]

with the initial value \( R_P(0) \equiv 1 \).

### 5.1.3 Application to two age groups

Consider two hypothetical transformer groups each consisting of 8 transformers. The transformers in the first group are 50 years old and the transformers in the second group have reached an age of 10 years. A constant loading of 0.9 p.u. and 15 °C ambient temperature is assumed for both groups. The technical parameters of the transformers are given in Table 5.1.

**Table 5.1:** The assumed thermal (IEC 60076-7 [44]) and paper characteristics values (Emsley [26] values of Table 4.1) and their standard deviations of the transformers in both age groups.

<table>
<thead>
<tr>
<th>Cooling</th>
<th>( R )</th>
<th>( \Delta \theta_{\text{pr}} ) °C</th>
<th>( \Delta \theta_{\text{hr}} ) °C</th>
<th>( x )</th>
<th>( y )</th>
<th>( A ) h(^{-1})</th>
<th>( E_a ) kJ/mol</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>ONAN</td>
<td>5</td>
<td>55</td>
<td>23</td>
<td>0.8</td>
<td>1.6</td>
<td>1.07 \times 10^8</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>0.05</td>
<td>0.55</td>
<td>0.23</td>
<td>0.008</td>
<td>0.016</td>
<td>1.34 \times 10^7</td>
<td>0</td>
</tr>
</tbody>
</table>
For each value of \( \frac{N-k}{N} \), the corresponding MTTF\(_k \) is calculated according to Section 5.1.2. The results are depicted in Figure 5.1. Although the MTTF of individuals in the first group is 16 years and 40 years later for the second group, there is already a significant failure probability after 4 years. This is the result of the uncertainties in the individual probabilities. Another consequence is that the time separating the populations does not show an intuitively expected "quiet" period of 40 years but has a more gradual transition with a duration of about 20 years.

![Figure 5.1: The population reliability for the two age groups; the trend line is a ninth order polynomial fit.](image)

Figure 5.2 shows the number of transformers expected to fail per year. The solid line in Figure 5.2 is the failure probability density function (PDF) multiplied by the total number of transformers (16). The PDF of the population is the numerical derivative of the population failure probability, i.e., one minus the reliability given in Figure 5.1. The bars in Figure 5.2 represent the number of failed transformers on a yearly basis and are obtained as follows. The reliability data is fitted with a high order polynomial function. Next, at the beginning of every calendar year the reliability is determined. By subtracting the next year's reliability from the current year, we obtain the fraction of failed transformers in that year. Figure 5.2 can be regarded as a superposition of two distributions, each belonging to one age class. The separation between the distributions is indeed 40 years, corresponding to the age difference of both populations.

### 5.1.4 Combining reliabilities for large fleets

The straightforward approach of calculating the combined reliability given in Equations (5.3) and (5.4) becomes time consuming for large populations. Roughly speaking, the computational time scales with order \( O(N!) \), limiting the population size which can realistically be
The yearly failures in the two age groups, the solid line is the PDF of the population multiplied by the total number of transformers.

handled to a few tens of transformers. Literature [58] provides several techniques to speed up the analysis. The method we adopted in this section is a recursive method with a computational complexity of order $O(N^2)$. The intermediate results of this method directly can be used to find all relevant reliabilities without postprocessing. The computational speed can even be improved by combining the recursive algorithm with a FFT technique to order $O(N \log N)$. However, in that case the relevant reliabilities have to be determined afterwards. Also the population size must be a power of two for a FFT implementation.

Assume a population consisting of $N$ transformers as in Section 5.1. Consider a subset of $j$ of the total $N$ transformers. The probability that all transformers of subset $j$ are still in operation, is

$$R^{(j,j)}(t) = \prod_{i=1}^{j} R_i(t). \quad (5.10)$$

The left part of the superscript of $R^{(j,j)}$ denotes the number of operating components and the right part denotes the size of the population of the subset. The probability that a maximum of $i$ transformers out of $j$, $R^{(i,j)}$, are operational, can be decomposed as

$$R^{(i,j)}(t) = \left(1 - R_j(t)\right) R^{(i,j-1)}(t) + R_j(t) R^{(i-1,j-1)}(t). \quad (5.11)$$

One transformer, with index $j$, is taken apart. This transformer has either failed and at least $i$ transformers of all other $j - 1$ are operational (first term); or this component is working and up to $i - 1$ of the remaining $j - 1$ transformers are operational (second term). Therefore the probability that at least $i$ out of $j$ transformers are operational is equal to the probability that
the "last" transformer $j$ has failed $(1 - R_j)$ and from the remaining $j - 1$ at least $i$ transformers work $R^{(i,j-1)}$, plus the probability that transformer $j$ is in working order ($R_j$), and a maximum of $i - 1$ of the rest are operational $R^{(i-1,j-1)}$.

Equation (5.11) allows to construct all relevant probabilities by means of a recurrent algorithm. The computational complexity for $R^{(k,N)}$ is of the order $O(N \cdot k)$. Moreover the results for up to $k - 1$, $k - 2$, etc are directly available as intermediate results.

### 5.2 Failure wave scenarios

In this section past and future scenarios are analysed to determine the effect on the failure wave. The analysis is applied on two data sets. The first data set contains individual transformer parameters of two Dutch distribution network operators (Section 5.2.1). The second data set provides detailed information of three substations (Section 5.2.2). The conclusions of the failure wave scenario analysis are given in Section 5.2.3.

![Figure 5.3: Transformers installed per year, which are still in operation from two Dutch utilities. Enexis and Stedin own 242 and 337 power transformers, respectively.](image)

**Figure 5.3:** Transformers installed per year, which are still in operation from two Dutch utilities. Enexis and Stedin own 242 and 337 power transformers, respectively.

#### 5.2.1 The combined fleet of two utilities

A large scale electrification in the Netherlands took place between the years 1960 and 1980. The installation dates of two population subsets of high voltage to medium voltage power transformers, presently owned by Enexis and Stedin, are depicted in Figure 5.3. The Enexis selection of 242 transformers and the somewhat larger Stedin selection with 337 transformers have a similar age distribution. Therefore they will be treated as one combined population
containing a total number of 579 transformers. The installation date of the population is more or less normally distributed around 1973 with a standard deviation of 12 years.

In this section the population model is applied to investigate whether utilities have to be prepared for a failure wave of power transformers in the near future. The peaked installation distribution may result in a peaked future failure rate as well. The IEC transformer design guide [46] assumes a life span of 40 years under normal loading conditions. If this would be the case, a failure wave could be expected between 2010 and 2020 if all transformers would be nominally loaded. However, in order to make precise predictions the actual loads and load cycles of individual transformers must be incorporated. Further, the load is expected to increase in the future.

Since not all relevant input data for the transformers are recorded, assumptions have to be made, e.g. on the operational condition. These assumptions are summarised in Section 5.2.1.1. In Section 5.2.1.2 the failure wave is modelled under different scenarios e.g. regarding an expected growth in transformer load.

### 5.2.1.1 Assumptions on model parameters

As failure mechanism the paper degradation model discussed in Chapter 4 is taken for every individual transformer. Many transformers lack precise historical data and assumptions are made. For the modelling parameters, the following conditions are taken:

- installation date and cooling method is available from the database;
- ambient temperature is taken according to average values;
- historical load pattern is used and a constant percentage increase in load is assumed;
- the accuracy of all input parameters are taken 5% of their actual value, except for the load which is taken 10% of the actual value;
- all transformers are located outside, and cooled by wind;
- transformers are continuously in operation.

The year of installation and the cooling modes are extracted from the combined population database of Enexis and Stedin. These cooling modes are Oil-Natural-Air-Natural (ONAN), Oil-Natural-Air-Forced (ONAF), Oil-Forced (OF) and Oil-Directed (OD). The transformer parameters belonging to the cooling modes are derived from the current IEC loading guide [44].

The average ambient temperature is described with the temperature model of the former IEC loading-guide [42]. The ambient temperature, $\theta_a$, is given as

$$\theta_a(t) = \theta_{ya} + A \cos \left( \frac{2\pi}{24 \cdot 365} \left[ t - 24 \cdot DX \right] \right) + B \cos \left( \frac{2\pi}{24} \left[ t - TX \right] \right),$$

with time $t$ in hours. The first term is a yearly average, the second term the variation within a year and the third term describes the daily cycle. The constants used in Equation (5.12) are $\theta_{ya} \approx 9.4 \, ^\circ C$, $A \approx 7.4 \, ^\circ C$, $DX \approx 199$ days, $B \approx 13 \, ^\circ C$ and $TX \approx 15$ hours. These constants represent statistical averages of the outside temperature in the Netherlands.

To obtain the per-unit load the average for every hour in the period 2003–2006 is calculated. This average is taken for the year 2008 and every hourly value is normalised. This normalisation factor is taken as a per-unit load of 0.4 divided by the maximum hourly load occurring throughout that year. The yearly load pattern of 2008 and the load growth consequence for 1980–2040 period is plotted in Figure 5.4, for an estimated yearly average load growth of 2%. The impact of the load growth assumption and the initial load condition is demonstrated by two scenarios, where each of the parameters is varied individually.
Figure 5.4: The yearly per-unit load pattern; a) the variation within a year for e.g. 2008 and b) the trend in load assuming a load growth of 2% per year.
5.2.1.2 Failure wave of the combined fleet

Based on the assumptions made in Section 5.2.1.1 the expected failure wave can be analysed. One of the critical assumptions is the annual load growth. As a reference a value of 2% is chosen. In order to determine the sensitivity of the failure wave with respect to the load growth, this parameter is varied. The results are summarised in Table 5.2 and the corresponding graphs are plotted in Figure 5.5. A 2% load growth results in a failure peak in the year 2063. A 0.5% lower or higher value shifts the peak 10 years forward or 15 years backwards, respectively. The predicted standard deviations are of the order of 5–8 years. The shift for increasing load growth values, implies a shorter lifespan of the population. Furthermore, the peak narrows. This is related to accelerated ageing, when the rated transformer power is approached. This occurs for every transformer at the same moment, because all transformers are assumed to have equal load in the reference year.

<table>
<thead>
<tr>
<th>Load growth</th>
<th>Peak year</th>
<th>Standard deviation year</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5%</td>
<td>2079</td>
<td>8</td>
</tr>
<tr>
<td>2.0%</td>
<td>2063</td>
<td>5</td>
</tr>
<tr>
<td>2.5%</td>
<td>2053</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 5.2: The peak and the standard deviation of expected failure wave for a load growth of 1.5%, 2% and 2.5%, for a total number of installed transformers of 579.

Figure 5.5: Transformer installation dates and the expected failure waves for a load growth of 1.5%, 2% and 2.5%; the total number of installed transformers for both utilities is 579.
The sensitivity with respect to the initial load is investigated for a fixed load growth of 2%. Three load patterns were applied, the original value of 0.4 p.u. of Figure 5.4 and loads where the maximum is scaled to 0.25 p.u. and 0.5 p.u.. The results of these simulations are provided in Table 5.3 and in Figure 5.6. Next to the observation that the lifespan gets shorter with increasing load, it is observed that there is a combined effect of load growth and initial load. An exponential growth tends to disguise the original population distribution, especially at low initial load since all transformers reach their rated power in a relatively short time. If the initial load is already close to the nominal per unit load the initial age distribution is more or less conserved.

Table 5.3: The peak and the standard deviation of expected failure waves for a load of 0.25 p.u., 0.4 p.u. and 0.5 p.u., based on a total number of installed transformers of 579 and a constant load growth of 2%.

<table>
<thead>
<tr>
<th>Initial load</th>
<th>Peak year</th>
<th>Standard deviation year</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>2087</td>
<td>6</td>
</tr>
<tr>
<td>0.40</td>
<td>2063</td>
<td>5</td>
</tr>
<tr>
<td>0.50</td>
<td>2050</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 5.6: Transformer installation dates and the expected failure waves for a load of 0.25 p.u., 0.4 p.u. and 0.5 p.u.. The total number of installed transformers for both utilities is 579 and the load increase is kept constant at 2%.
5.2.2 Three substations

Detailed information on transformer load of three substations was made available by Enexis to study the effect of load changes caused by maintenance or switching. These substations are situated in Best (BT), Roosendaal (RSD) and Tilburg Noord (TBN). Each substation comprises three transformers and two medium voltage busbars.

5.2.2.1 Model assumptions

The load of every individual transformer has been logged every five minutes in the year 2008 and their monthly maximum load values are logged over twelve years. The load values, depicted in Figure 5.7, are used to determine the annual load growth percentage by linear fitting. An average of about 1% yearly load growth for the 1996–2008 period is found. The 2008 individual transformer load is extrapolated for the remaining years with a load growth of 1%, the individual load patterns are similar as the ones in Figure 5.4.

![Figure 5.7: Monthly load maxima of the three substations over a 12 year period.](image)

The transformer data as presented in Table 5.4 are extracted from the manufacturer’s test reports. The degradation parameters of the applied Kraft-paper are taken from Lundgaard, as provided in Table 4.1. The top-oil gradient and hot-spot gradient values of the transformers in substation TBN were not available for ONAF operation. Practical averages proposed by IEC 600076-7 are taken.

The ambient temperature of all transformers are assumed to follow the temperature model of the former IEC loading-guide [42], as expressed in Equation (5.12). The constants in Equation (5.12) are based on historical outside temperature averages in the Netherlands. The constants are approximately: \( \theta_{ya} \approx 9.4 \, ^\circ\text{C} \), \( A \approx 7.4 \, ^\circ\text{C} \), \( DX \approx 199 \, \text{days} \), \( B \approx 13 \, ^\circ\text{C} \) and \( TX \approx 15 \, \text{hours} \).
Table 5.4: The parameters of the transformers in the three selected Enexis substations. All transformers are assumed to be in ONAF operation, with $x = 0.8$, $y = 1.3$, $\tau_o = 150$ min, $\tau_w = 7$ min, $k_{11} = 0.5$, $k_{21} = 2$ and $k_{22} = 2$. The $\sigma$-values of all the parameters are assumed to be 5% of the mean.

<table>
<thead>
<tr>
<th>Substation Transformer</th>
<th>Installed year</th>
<th>Power MVA</th>
<th>$R$</th>
<th>$\Delta \theta_{or}$ $^\circ$C</th>
<th>$\Delta \theta_{hr}$ $^\circ$C</th>
<th>Online %</th>
</tr>
</thead>
<tbody>
<tr>
<td>BT1</td>
<td>1972</td>
<td>44</td>
<td>6.0</td>
<td>54.1</td>
<td>26.7</td>
<td>72</td>
</tr>
<tr>
<td>BT2</td>
<td>1973</td>
<td>44</td>
<td>6.1</td>
<td>54.1</td>
<td>26.7</td>
<td>58</td>
</tr>
<tr>
<td>BT3</td>
<td>1975</td>
<td>44</td>
<td>6.7</td>
<td>54.1</td>
<td>26.7</td>
<td>70</td>
</tr>
<tr>
<td>RSD1</td>
<td>1995</td>
<td>63</td>
<td>5.4</td>
<td>57.7</td>
<td>22.5</td>
<td>72</td>
</tr>
<tr>
<td>RSD2</td>
<td>1993</td>
<td>63</td>
<td>5.4</td>
<td>57.7</td>
<td>22.5</td>
<td>54</td>
</tr>
<tr>
<td>RSD3</td>
<td>1993</td>
<td>63</td>
<td>5.6</td>
<td>57.7</td>
<td>22.5</td>
<td>73</td>
</tr>
<tr>
<td>TBN1</td>
<td>1976</td>
<td>77</td>
<td>7.1</td>
<td>55.7</td>
<td>26</td>
<td>61</td>
</tr>
<tr>
<td>TBN2</td>
<td>1976</td>
<td>77</td>
<td>6.6</td>
<td>55.7</td>
<td>26</td>
<td>55</td>
</tr>
<tr>
<td>TBN3</td>
<td>1976</td>
<td>77</td>
<td>7.2</td>
<td>55.7</td>
<td>26</td>
<td>85</td>
</tr>
</tbody>
</table>

5.2.2.2 Transformer reliability

Based on the actual load data, the individual reliabilities of each transformer in the three substations are calculated. An overview of the actual load per busbar of each substation is given for 2008 in Table 5.5. The results are depicted in Figures 5.8, 5.9 and 5.10.

Figure 5.8: The reliabilities of three transformers (BT1, BT2 and BT3) located in the Best (BT) substation.

Best (BT, Figure 5.8) The Best substation consists of two busbars of which busbar A is 0.1 p.u.
Failure wave scenarios

higher loaded than busbar B. Transformer BT1 is usually connected to busbar A and transformer BT2 to busbar B. During maintenance of one of these transformers, transformer BT3 is connected, to either busbar A or B depending whether BT1 or BT2 is in maintenance. The reliability curves in Figure 5.8 show that the degradation of transformer BT1 is strongest, due to the relatively high loading. Further, it shows that occasional connection of BT3 to busbar A has a higher impact on its remaining lifetime than the almost permanent connection of BT2 to busbar B.

Roosendaal (RSD, Figure 5.9) The transformers of Roosendaal substation have an age difference of only two years. Their individual MTTFs however differ with 10–80 years. In this substation RSD1 is most of the time connected to busbar A, RSD3 to busbar B and RSD2 is used as spare transformer and for load balancing. The individual power load of busbar A is on average 0.3 p.u. higher than that of busbar B. Such a load difference has a major influence on the hot-spot temperature. The reliabilities differ strongly, because of a significantly lower load. The impact of the load of busbar B can almost be neglected.

![Figure 5.9: The reliabilities of three transformers (RSD1, RSD2 and RSD3) located in the Roosendaal (RSD) substation.](image)

Tilburg Noord (TBN, Figure 5.10) In this case the year of installation has no effect, because all the transformers are installed in 1976. Hence, we are only observing the effect of the load. TBN1 is connected to busbar A, TBN3 to busbar B, and TBN2 is used to share the load and to create a $N−1$ situation.

The population reliability belonging to all transformers in the three substations is plotted with the solid line in Figure 5.15, and the corresponding probability density function in Figure 5.16. The fleet reliability curve of Figure 5.15 starts with all transformers working in 2008. The expected year of first failure is in 2035. The slope of the reliability curve in the period
Chapter 5 Transformer population reliability

![Figure 5.10](image)  
*Figure 5.10: The reliabilities of three transformers (TBN1, TBN2 and TBN3) located in the Tilburg-Noord (TBN) substation.*

<table>
<thead>
<tr>
<th>Substation</th>
<th>Busbar A</th>
<th>Busbar B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>Roosendaal</td>
<td>0.6</td>
<td>0.3</td>
</tr>
<tr>
<td>Tilburg Noord</td>
<td>0.5</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Table 5.5: The average load of busbar A and B for the three Enexis substations in the year 2008.

2035–2075 approximates an average failure rate of one transformer every five years. The probability density function of Figure 5.16 is obtained by numerical differentiation of the failure probability. The PDF value of 0.02–0.025 in the 2040–2060 period, obviously corresponds to about one failed transformer every 5 years for that period.

5.2.3 Conclusions

The combined fleet of two utilities The sensitivity to the load growth, as depicted in Figure 5.5 of Section 5.2.1, is a result of the non-linear acceleration. Small deviations in future scenarios of the load growth have important consequences for the failure wave. Therefore, a realistic prediction should involve an accurate actual load distribution of transformers. If insufficient data is available for all transformers, loads of a representative subset can be used.

The differences in the curves of Figure 5.6 in Section 5.2.1, belonging to different initial load patterns, show that on the short term it is not essential to know the historical
load patterns for transformers being hardly pushed to their limits in the past. Only if a considerable fraction of their technical lifespan has been consumed, this becomes relevant. For a high load, the effect of exponential behaviour due to load growth does not kick in yet. With low initial load patterns, the exponential growth behaviour will take over the effects of the historical load and will result in accelerated ageing of the transformer.

**Three substations** The effect of maintenance or failure of one transformer on the remaining lifetime of others; if in a substation with three transformers maintenance is performed on one transformer, the spare transformer will temporarily experience a load. The duration of this load period will dominate to a large extent the total ageing process, as shown in Section 5.2.2. The policy of having a spare transformer results in a delayed end of life for this asset in the order of 5–10 years with respect to the transformer which is permanently connected to the busbar with higher load.

### 5.3 Replacement alternatives

The aim of the transformer population model is not only to predict future failure rates, but also to analyse the effectiveness of maintenance/replacement strategies. In determining the effect of mitigation actions on the failure wave, the replacement alternatives should incorporate: the result of supplementing annually a predefined number of transformers (Section 5.3.1); the influence of a distribution in load growth (Section 5.3.2); and the effect of sharing the load of every transformer (Section 5.3.3). Maintenance strategies are omitted, because these effects depend heavily on the status of the individual transformer. In Section 5.3.4 the conclusions of the replacement alternatives are summarised.

#### 5.3.1 Strategy based on annual supplementation

This simplified alternative addresses a mitigation action, where any endangered transformer gets assistance in the form of load sharing with an added new transformer. As an example, annually six transformers are added to the existing assets to relieve transformers that are expected to be aged considerably. The selection process takes place in the period 2009–2049. This is done for a reference population (Section 5.2.1) with an initial load of 0.4 p.u. and an annual load growth of 2% is assumed.

In the transformer failure distribution of Figure 5.11 it is seen that the replacement alternative, indicated with a solid line, result in a reduction and a slight shift of the original replacement probability, represented with a dotted line. In addition, a peak arises about 35 years later. This peak is due to end of life of the added transformers and has no relevance for the approaching replacement wave.

**Figure 5.12** shows the fraction of transformers in operation versus time. The effect on the replacement wave is of minor impact, when six transformers are replaced annually. For instance, the time of 0.9 reliability only shifts just over one year, which indicates an average lifetime improvement of only one year for 90% of the population. A larger replacement is apparently required to prevent peaks in failure rates. However, there is no preference in the order where to install the first new transformers. This is related to the equal load assumption taken for all transformers. No efficient selection of transformers to be replaced can be made. Only by an extensive monitoring program of a QP, in this case the actual DP-value, a transformer selection scheme might be possible. If not, the number of transformers to be added yearly
Figure 5.11: The replacement wave for the transformers fleet of Enexis and Stedin, with a 2% annual load growth (dotted line). The solid line marked with “Replace 6 trafos”, represents the replacement wave of the population where annually six transformers get load sharing by parallel transformers. The dash-dotted line indicates a yearly replacement of thirteen transformers.

must be of the order of the total number of transformers involved divided by the expected duration up to the expected replacement peak, i.e. about thirteen transformers per year for the 2009–2049 period, as indicated with the dash-dotted line in Figures 5.11 and 5.12.

5.3.2 Distribution of transformer load growth percentage

The load of transformers depend on the region they are situated and on the type of users which are connected. The "equal load" assumption throughout Sections 5.2.1.1, 5.2.1.2 and 5.3.1 is only achieved when transformers would be permuted between substations with relatively large and low load. Even then, the replacement wave would start earlier due to the nonlinear response of ageing upon load on as compared to constant equal loading.

In this example, the load growth percentage is varied to enforce diversity in the individual loading scenarios. Five groups of different load growth percentages are formed with an almost equal number of transformers. The load growth percentages for all transformers in the group vary now between 1.8% and 2.2% with steps of 0.1%, instead of the 2% in the alternative of Section 5.3.1. All other assumptions are kept the same as for Section 5.2.1.1. Further, annually six most aged transformers get load sharing, which reduce their load by a factor two, as in Section 5.3.1.

The results are plotted in Figures 5.13 and 5.14. The following observations can be made:

- As compared to the load growth simulation with 2% for all transformers (dashed line) the distributed growth rate (solid line) causes a broadening in Figure 5.13 and a drop
of the peak from 60 to 40 transformers per year. Transformers with high load growth tend to fail earlier and transformers with a relative low growth in load later, implying a broadened distribution.

- If the policy of six added transformers is applied again a broader distribution is obtained for the 1.8–2.2% load growth situation (dash-dotted line) as compared to the equal growth (dotted line). However, the peak is completely shifted, indicating that now transformers can effectively be selected.

- The reliability curves of Figure 5.14 confirms that in a distributed growth rate the six transformer policy is far more efficient. Consider, e.g. the 0.9 reliability level. The time to reach this level is shifted only one year for 2% load growth, whereas in case of the 1.8–2.2% distribution five years is gained.

### 5.3.3 Equal load distribution

The present policy of Section 5.2.2 is to leave assigned transformers connected to the busbars and spare transformers are only operational during maintenance of the others. An equally shared load over all transformers is expected to result in a more efficient usage of these assets. To this end, the present loading strategy is compared to a shared load.

Consider a hypothetical situation where as from 2009 the two active transformers share equally the load of both busbars. Further a rotating scheme is adopted for the third transformer such that over longer time all transformers are equally loaded. Until 2009 the substa-
Figure 5.13: The replacement wave of 579 Enexis and Stedin transformers. Dashed line: constant 2% annual load growth; dotted line: annually six added transformers at constant growth rate; solid line: load growth is varied between 1.8% and 2.2% without replacement; dash-dotted line: 1.8–2.2% variation in load growth and yearly six added transformers.

5.3.4 Conclusions

From the annual replacement strategies of Section 5.3.1 it can be observed that the equal load is most unfavourable since there is no preference in the order of replacement, except for the installation date. The installation date however may hardly be reflected in the end of life distribution. Further, it can be seen that for a preventive replacement of all transformers, the transformers need to be replaced before the beginning of the failure wave.

In the analysis of Section 5.3.2 a variation in load growth percentage between transformers is taken, which lead to an observed spread of the replacement wave. For the replacement policy an equal load is most unfavourable since again there is no preference in the order of replacement, and the end of life hardly depends on the installation date. Due to accelerated paper ageing by the exponential increase in the load.
Figure 5.14: The fleet reliability of 579 Enexis and Stedin transformers. Dashed line: constant 2% annual load growth; dotted line: annually six added transformers at constant growth rate; solid line: load growth is varied between 1.8% and 2.2% without replacement; dash-dotted line: 1.8–2.2% variation in load growth and yearly six addition transformers.

The strategy of Section 5.3.3, where the substation load is equally distributed over all substation transformers, results in a positive effect of a delayed end of life for all transformers. The negative effect is that the transformers will fail in a short period of time.

Apparently, it is more favourable to have transformers with a significant loss of life before adding an extra transformer than trying to get an equal load as much as possible. As further optimisation one could consider to have dynamic replacement strategy starting with less replacements per year, but after some time this value is increased. Judgement of these strategies not only involves a technical reliability model, but requires a complete asset management approach of which the technical model is a small, but crucial, part.

5.4 Discussion

Which future scenario is economical optimal and organisational feasible, depends on several factors. A full economic analysis is out of the scope of this thesis, but the key factors are discussed in concept. Cost reduction is either achieved by a better use of the transformer capacity leading to postponement of replacing assets or by having a transformer replaced in time preventing costs related to sudden outages.

The first factor gives a yearly profit $Y_{PR}$ which is equal to the costs of a transformer $C_{NT}$ divided by the number of years $\Delta t$ the replacement is postponed.

$$Y_{PR} \propto \frac{C_{NT}}{\Delta t}.$$  \hspace{1cm} (5.13)
Figure 5.15: The fleet reliability of all transformers in three substations: the solid line represent the original load situation; the dotted line represents the reliability of the substation, with two transformers equally loaded and using a rotation scheme.

Figure 5.16: The fleet PDF of all transformers in three substations: the solid line represent the original load situation; the dotted line represents the PDF of the three substations population with equally loaded transformers.
Of course factors like efficiency and maintenance of new versus old transformers must be accounted for, as well as change in interest rates and inflation.

The second factor is caused by the end of the bathtub curve resulting in a concentration of failures. The concentration of failures will cause a mismatch between demand and supply of available new transformers. The demand for new transformers can probably be higher than the supply, which may increase the transformer price. Even worse, this mismatch can lead to a shortage on transformers, which cause situations where failed transformers can not be replaced on short term. The costs basically have the form

$$Y_{FC} \propto \lambda (C_{RP} + C_{kWh} E_{NS})$$, \hspace{1cm} (5.14)

with \( \lambda \) the failure rate of the transformer, \( E_{NS} \) the energy not supplied during a failure period, \( C_{kWh} \) the price of energy not supplied with or without penalty, and \( C_{RP} \) the costs for fixing the failure.

The strategy of spreading the expected replacement wave over a manageable time period as analysed in Sections 5.3.1 and 5.3.2 faces a difficult selection mechanism, depending heavily on correct information. The information needed for selecting the right set of transformers to be replaced are historical load, historical fault and failure situations, future load scenarios, future stresses, and maintenance schemes to mitigate secondary failures. The benefits of this strategy is that it is relatively easy to manage. The obvious downside is the fact that the components are not used for their maximum operational life. However, depending on replacement policy, the maximum utilisation by having equal loads for all assets is not necessarily the best strategy economically.
Transformer reliability does not only depend on the condition of the winding insulation. The most relevant other subcomponents which may contribute to the overall transformer reliability are the bushings and the tap-changer. Unfortunately, for these components easily accessible direct QPs are harder to find than for paper insulation. For the physical ageing models for bushings, Section 6.1, and tap-changers, Section 6.2, no experimental data is available to verify the modelling. Therefore, the reliability will be based on a statistical analysis of available databases. In Section 6.3, the models for bushing and tap-changer failure are combined with the paper degradation model into an integral reliability model.

### 6.1 Bushing

Bushings are used to provide a safe conduit from a high voltage conductor, power line or cable, into the transformer. High electric field stresses arise inside the bushing since the conductor enters the transformer housing through a relatively narrow opening. Ohmic losses and dielectric losses can contribute to thermal degradation of the bushing insulation. Insulation materials capable to handle the combined electrical and thermal stresses are paper-oil, paper-resin, epoxy, ceramics, and combinations of these materials.

It must be noted that bushing failure can occur due to external factors as well. Transformer bushings can be exposed to severe weather conditions, depending on where they are installed. Bushings must handle snow and ice in arctic areas, salt in coastal regions, high humidity in tropical areas and pollution in densely populated or industrial places. Moreover, damage caused either by accidents or vandalism contribute to the failure rate.

These different factors complicate the design of statistical models for bushing failure. To obtain more insight in the Dutch situation a questionnaire was distributed among two utilities.

#### 6.1.1 Questionnaire

A small questionnaire was made aiming to provide information about the severity of transformer failures for different bushings types. Further, it is intended to give insight in the preventive mitigation actions and provide an overview of bushing monitoring methods used. The survey questions and answers are given in Table 6.1.

The responses on the questionnaire were discussed with maintenance experts of a Dutch transformer manufacturer. According to these experts the problems with bushings are underestimated. They observed that bushing failures have an increasing influence on the end of life
Table 6.1: The bushing questionnaire consisting of seven questions with their answers given by two Dutch network operators, Enexis and Stedin.

<table>
<thead>
<tr>
<th>Question</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Which bushing type (gas insulating, paper-oil, paper-resin, ceramic or epoxy) is mainly used and at what voltage level?</td>
<td>On medium voltage level mainly ceramic bushings are used. On high voltage level, it is a mix of paper-oil and resin impregnated paper.</td>
</tr>
<tr>
<td>2. What is known about the failure behaviour? What is the number of failures for each bushing type per year.</td>
<td>The number of failures is low. A bushing failure is most of the time due to oil leakage through the gasket. This type of failure can be detected during inspection rounds.</td>
</tr>
<tr>
<td>3. What is the major failure cause?</td>
<td>Leakage of oil due to bad gaskets. Pollution due to salt or dust on the outside. Both failure causes can be detected by regular inspection, and if necessary the bushings are cleaned. Transformers located outdoors can also fail due to vandalism.</td>
</tr>
<tr>
<td>4. Which diagnostic means are used?</td>
<td>The main method is visual inspection. In one district the inspection is extended with a partial discharge test and a power factor test to validate the credibility of these diagnostics. (A description of these tests can be found in Section 3.4.)</td>
</tr>
<tr>
<td>5. Based on what information a decision on replacement is taken?</td>
<td>Replacement is done corrective, but in some cases because of a high partial discharge activity. The power factor test is regarded as being unreliable by one of the network operators.</td>
</tr>
<tr>
<td>6. Is there a maintenance program? If so, what is the most effective maintenance measure?</td>
<td>Basically, there is no scheduled maintenance, but if necessary the bushing get cleaned.</td>
</tr>
<tr>
<td>7. Which bushing are the most interesting for a lifetime model?</td>
<td>Most interested in models for paper-oil high voltage bushing.</td>
</tr>
</tbody>
</table>
of a transformer in the USA and UK, this could imply for the Dutch situation a similar increase in bushing failures. According to their experience the impact of bushing failures on the end of life of a transformer can be managed by a structured maintenance revision regime, comparable to the regime which is applied for tap-changers. For the tap-changer the maintenance regime consists of diagnostics, expert evaluation and countermeasures.

In addition to the present maintenance actions concerning pollution and oil leakage, a maintenance and revision regime could consist of the following steps:

**Diagnose** Determine the quality of the bushing by a dissolved gas analysis on bushing oil or measuring the capacitance and tan delta of the bushing. With the aid of partial discharge detection the existence of defects and faults can be determined.

**Evaluate** Knowledge rules translate historical and condition assessment data into a priority list. This priority list is based on the condition and the countermeasure necessary to be taken.

**Mitigate** Take countermeasures, by either replacing the bushing or placing the bushing in a lower stress environment. A low stress environment can be created, for example, by preventing large (over) voltages.

### 6.1.2 Statistical bushing model

Various sources of statistical data on bushing failure have been consulted. The CenTram database incorporates information of 2383 transformers of which 2009 transformers are in operation. The active transformers have an average age of 31 years with a standard deviation of 13 years; this adds up to a cumulative operational life of 62000 years. Since 1970, nine bushing failures are reported, two of which were non repairable. Next to the CenTram database, there are two other sources of statistical failure data available which concern bushings. One describes general transformers failures [56], the other describes 50 kV switchgear bushing failures [55].

The data in the databases are converted by a least square method to fit the Weibull distribution, as described in Appendix B.2.7. The Weibull probability density function (PDF) is

\[
    f(x) = \frac{\beta}{\alpha} \left( \frac{x}{\alpha} \right)^{\beta-1} \exp \left[ -\left( \frac{x}{\alpha} \right)^\beta \right], \quad x > 0, 
\]

with scale parameter \(\alpha\) and shape parameter \(\beta\). The result of the Weibull parameter fits is presented in Table 6.2. Before interpretation of the results, the following remarks must be made. First, the failure causes are not filtered by type of failure. Therefore, failures caused by ageing are observed next to those caused by vandalism. Second, the number of failures in each data set is relatively small compared to the size of the population. This limits the accuracy of the Weibull failure parameters.

The CenTram failure data is based on bushing failures, alone. The spread in failure time and the low number of failures result in a MTTF of about 3000 years. This figure aligns with the impression expressed by Dutch utilities that bushing failures have hardly any impact on
Table 6.2: Statistical failure data summarised in Weibull scale and shape parameters and the corresponding MTTF. The parameters are derived from the CenTram database and from [54–56].

<table>
<thead>
<tr>
<th>Source</th>
<th>$\alpha$ in years</th>
<th>$\beta$</th>
<th>MTTF in years</th>
</tr>
</thead>
<tbody>
<tr>
<td>CenTram</td>
<td>2418</td>
<td>1.3</td>
<td>2243</td>
</tr>
<tr>
<td>General [54, 56]</td>
<td>70</td>
<td>3.3</td>
<td>63</td>
</tr>
<tr>
<td>Switchgear bushings [54, 55]</td>
<td>211</td>
<td>3.2</td>
<td>189</td>
</tr>
</tbody>
</table>

the overall failure rate. However, according to the CenTram database owner not all bushing incidents are documented.

As mentioned in [54, 56], the number of general failures is insufficient for an accurate statistical parameter fit. Moreover, the failure type discussed in the paper are general transformer failures, also incorporating tap-changer and winding insulation failures.

The number of switchgear bushing failures is larger than the CenTram bushing failures, but still on the low side for accurate parameter estimation. Further, the switchgear bushing failures on medium voltage level can not be expected to be similar to bushing failure for transformers on high voltage level. However, the switchgear bushing source [54, 55] is the best source at hand to get a reasonable insight of future bushing failures in the Netherlands, because it addresses only bushing failures and is the most complete data set available.

6.1.3 Long term bushing models

Regular visual inspection and proper repair can mitigate failures from causes like oil leakage or pollution. Long term degradation of bushing insulation is related to deterioration of the insulating material of the bushing. In [8, 19] it is observed that the electrical breakdown voltage and the dissipation factor of the paper insulation changes with time due to ageing. Thermal ageing gradually degrades these quality parameters and the loss of electrical insulation quality lowers the voltage withstand capability.

Thermal breakdown is either a form of self combustion or a thermal runaway process of the insulation material. If the heat dissipated in the insulation material exceeds its capacity to dispose it, temperature will rise. The access heat can lead to self combustion. In the case of thermal runaway, the heat increases the $\tan \delta$ of the insulation, resulting in an even higher heat generation. In both cases thermal breakdown occurs, if the access heat generated due to the increased losses at elevated temperature is not compensated for by a heat transfer process, i.e. conduction, convection or radiation, which increases as well with temperature.

A physical model is presented, which allows for a similar probabilistic approach as applied for paper degradation in Chapter 4. To model thermal breakdown, knowledge about the heat generated in the dielectric insulation and the conductor, and the maximum allowable temperature of the insulation material, must be known. The temperature inside a bushing can be modelled according to [48, 53, 68], where the temperature rise is contributed to conductor losses. The steady state hot-spot temperature gradient with respect to the ambient temperature $\Delta \theta_{h,b}$, according to the IEEE bushing guide [48], is described by

$$\Delta \theta_{h,b} = K_1 I^n + K_2 \Delta \theta_o,$$  \hspace{1cm} \text{(6.2)}

with $I$ the per unit rated bushing current, $\Delta \theta_o$ the oil temperature rise with respect to the ambient temperature, and $n, K_1, K_2$ bushing type dependent constants. According to the re-
views accompanying [48, 53, 68], the dielectric losses, $P_d$ can significantly contribute to the temperature rise in Equation (6.2), especially during thermal runaway. Equation (6.2) should therefore be extended with a voltage dependent term, which incorporates the tan$\delta$ losses for high voltage bushings,

$$P_d = 2\pi f CV^2 \tan\delta.$$  
(6.3)

The maximum allowable heat flow $\dot{Q}_H$ is

$$\dot{Q}_H = \frac{\Delta\theta}{R_T},$$  
(6.4)

where $R_T$ represents the thermal resistance and $\Delta\theta$ the temperature difference between the hot-spot and environment. From Equations (6.2), (6.3) and (6.4) the maximum operational values for current and voltage can be deduced for a given thermal breakdown temperature, with $\Delta\theta$ being the limiting quality parameter.

The influence of high temperatures at nominal electric field stresses were addressed in [19, 81]. Two Arrhenius type reaction rate models were proposed, which differ in the way that the electric field stress is incorporated. The rate opted in [81] involves a reduction of the activation energy with an amount proportional to the electric field,

$$k_1 = A \exp\left(-\frac{E_a-c|\mathcal{E}_e|}{k_b T}\right),$$  
(6.5)

with $E_a$ the activation energy, $\mathcal{E}_e$ the electric field strength, $T$ the temperature, $k_b$ the Boltzmann constant, and $A$, $c$ process dependent constants. The methods applied in [19] are mainly regression techniques based on statistical data. The authors refer to a model by Crine, which describes the reduction of the energy barrier controlling the process. The time $t$ to cross the barrier, which also equals the lifetime, is given as

$$t = \frac{h}{k_b T} \exp\left(\frac{\Delta G}{k_b T}\right) \cosh\left(\frac{c_e \lambda \mathcal{E}_e}{k_b T}\right)$$  
(6.6)

with $\mathcal{E}_e$ the applied electrical stress, $\Delta G$ the free energy, $\lambda$ the barrier width (or carrier mean free path), $h$ Planck’s constant, $c_e$ a model constant, and $k_b$ and $T$ as before. The $\Delta G$ and $\lambda$ parameters describe the degradation of the material used. Rewritten as rate, Equation (6.6) can be approximated by

$$k_2 \approx \frac{2k_b T}{h} \exp\left(-\frac{\Delta G - c_e \lambda|\mathcal{E}_e|}{k_b T}\right).$$  
(6.7)

The models described by Equations (6.5) and (6.6) provide similar lifetimes. The modelling techniques from Sections 4.2.1 and 5.1.2 can be adopted to obtain failure rates caused by bushing degradation.

### 6.2 Tap-changer

The transformer ratio can be adapted by the tap-change position of the transformer. Basically, two types of tap-changers can be distinguished. The most commonly used for medium voltage
transformers can only be operated off-line. High voltage transformers are equipped with on-load tap-changers (OLTC), which can be operated while the transformer remains in service.

The online tap-changer consists of two parts, a selector switch and diverter switch, see Figure 6.1. The diverter switch ensures an arc free switch operation in the selector switch compartment by controlling the voltage difference between sequential taps. The actual output voltage is controlled by selector switches, which are directly connected to the transformer coil. Both switches are energised by a single motor. Tap-changing from position 3 to 2 proceeds as follows, starting from the situation with position tap 3 and 4 closed, as shown in Figure 6.1(a):

- Tap position 2 closes and 4 opens by rotating the tap-changer axis;
- The motor powers the diverter spring and is released if the selector taps are set in their positions;
- The diverter switch equals the voltage difference of tap 3 and 2 with the voltage difference over the two resistors, through these two resistors the nominal current of the transformer flow for a small period of time;
- The end result is that the current flows only through tap 2 and tap position 2 and 3 are closed.

The tap-changer switches in Figure 6.1(b) has a combined diverter and selector switch.

Figure 6.1: *Schematic overview of two online tap-changers for a star configured transformer. The two tap-changers schematics belong to a Reinhausen and a Smit model.*
6.2.1 **Tap-changer failure modes and failure mitigation**

An online tap-changer (OLTC) is usually applied in power transformers on high voltage level. Possible failure modes of the OLTC, as reported in the CenTram database, are:

- Asynchronous operation of the selector switch and the diverter switch caused by a broken axis or a stuck diverter switch. This results in an arc in the selector switch, because the nominal current is switched and cannot be extinguished.
- Carbon layer formation on the contacts and oxidation of the contacts. The voltage difference over the carbon can cause flashovers between the different phase contacts. These flashovers result in gas forming which in the end result in a phase-phase short circuit.

An online monitoring system has been developed to detect failure of the axis[103]. It consists of two sensors, which detect synchronous operation of the cylinder alone and the combination motor and cylinder. In case of non synchronous operation, the motor stops and a warning signal is given. This system mitigates the motor spring and axis failure effects for most transformers equipped with an on load tap-changer as depicted in Figure 6.1(b).

The deterioration of the contacts can be detected by regular off-line inspection of the tap-changer. Inspection includes contact resistance measurement of the different taps of the tap-changer, as described by Verhaart in [116, 117]. This information is recorded in the form of a "fingerprint" of the current. The current is the result of switching a known resistor in series with the main transformer windings. The current response is measured at all tap positions. The evolution of the "fingerprints" can be extrapolated to predict when revision of the OLTC is needed.

6.2.2 **Tap-changer degradation model**

A malfunctioning motor and a cylinder breach are sudden events. Only the carbon formation involves gradual ageing, which can be detected in an early stage by proper diagnostics. The quality of the contacts can be determined with the dynamic resistance measurement system [116, 117]. Three degradation mechanism models are under development.

The first model has a statistical nature, similar to the statistical bushing model of Section 6.1.2. The corresponding Weibull $\alpha$ and $\beta$ parameters for the tap-changer are 109 years and 2.4, respectively, according to [56, 94]. The MTTF belonging to these Weibull parameters is 97 years.

The second model is an expert judgement model, where the set of individual resistances of every tap position is considered as an indirect explicit quality parameter of the complete tap-changer. The degradation rate of the tap-changer is derived from these values as a function of time of measurement. The mean residual life of the tap-changer is found from extrapolation on the assumption that past operation of the tap-changer will continue similarly in the future.

The third model [31, 32, 90] reintroduces the dynamic resistance measurement system of Verhaart and is combined with an oil/carbon film growth model presented in [62]. A thicker carbon film results in a larger contact resistance. The carbon film growth model can be used for copper, brass and silver contacts in combination with "Shell Diala D" oil, which has similar properties as "Shell Diala B" insulation oil used in Dutch power transformers. The oil/carbon film growth for copper contacts in the selector switch and "Shell Diala D" oil as function of temperature and time can empirically be expressed as [62]

$$ s = 1.883 \times 10^{-7} T_c^{3.862} T^{0.3559}, $$  

(6.8)
with $s$ the thickness of the oil film in nanometres, $T_c$ is the contact surface temperature in °C and $t$ is the duration of the ageing at temperature $T_c$ in hours. The model assumes a constant surface temperature. This assumption can be questioned since extra heat may be dissipated in the formed carbon film leading to an additional temperature increase.

The last two models are incomplete, but have interesting features. The expert judgement model shows that the dynamic resistance measurement has a predictive value of the quality of the tap-changer. The carbon film model provides insight in the temperature and time dependence of the carbon forming and as consequence the increase in contact resistance.

A classification of these three models can be made based on the discussion of Sections 2.3 and 3.3. The statistical model provides a quick scan of the tap-changer general failure behaviour in a transformer population. The expert judgement model determines quickly the condition of an individual tap-changer. From the determined tap-changer condition, the countermeasures can be derived to prevent further degradation and/or to upgrade the condition of the tap-changer. The degradation model not only classifies the condition of an individual tap-changer, but is also capable in predicting the effects of future scenarios and alternatives.

### 6.3 Combination of different degradation mechanisms

The reliability of a system depends on its subcomponents and their interaction. The interaction of subcomponent reliabilities on the overall reliability can be visualised, as shown in Section 2.3, by a fault tree analysis, a degradation mechanism tree analysis or by a reliability block diagram. As outcome of such analyses, subcomponents are arranged according to reliability engineering in a series system, parallel system, $k$-out-of-$N$ parallel configuration, load sharing configuration, or a combination of these arrangements. Three basic configurations will be addressed briefly in Section 6.3.1. The load sharing configuration, which deals with interdependent reliabilities, is omitted since we assume the failure mechanisms described in this thesis to be independent. Section 6.3.2 describes an example where individual subcomponent reliabilities are integrated to an overall power transformer reliability.

#### 6.3.1 Basic reliability configurations

Three basic reliability configurations are summarised below; these are a series, a parallel and a $k$-out-of-$N$ system:

**Series system** If a system of $N$ components fails due to one component failure, the system reliability is series dependent. The time dependent system reliability $R_S(t)$ is calculated by the joint individual reliabilities according to,

$$R_S(t) = \prod_{i=1}^{N} R_i(t),$$  \hspace{2cm} (6.9)

where $R_i(t)$ represents an individual reliability.

In a simplified transformer reliability model the transformer fails if either the bushings, tap-changer or winding insulation paper fails.

**Parallel system** For parallel system reliability, the system does not fail until all components have failed. The time dependent system failure probability can be calculated from the
Combination of different degradation mechanisms

In terms of the system reliability, this results in

\[ R_S(t) = \prod_{i=1}^{N} R_i(t) \equiv 1 - \prod_{i=1}^{N} F_i(t), \tag{6.10} \]

with \( F_i(t) = 1 - R_i(t) \).

A transformer example of a parallel reliability system is the combination of degraded paper and a short-circuit situation as described in Chapter 4.

**k-out-of-N system** In a k-out-of-N system, N components are placed in operation. This system fails if less than \( k \) components are in operation. To calculate the probability that a k-out-of-N system is still working, a summation has to be made over the probabilities that all components are working, all permutations of the probability that exactly one component has failed and all other are working, etcetera, till all permutations of the probability that exact \( N - k \) components have failed and all other are working. This can be written as

\[ R_{S}^{(k)}(t) = \sum_{i=k}^{N} (-1)^{i-k} \binom{i-1}{k-1} \sum_{j_1 < j_2 < \ldots < j_i} \prod_{l=1}^{i} R_{j_l}(t), \tag{6.11} \]

where the summation over the indices \( j_1, j_2, \ldots, j_i \) represents the permutation of the reliabilities. Both series and parallel system reliability are special cases of the k-out-of-N system reliability. A series system reliability is equal to an N-out-of-N parallel system and a parallel system is equal to a 1-out-of-N parallel system.

For example in a substation of three transformers, the safe transportation of power ceases when two transformers fail.

### 6.3.2 Integration of bushings, tap-changer and insulation paper reliabilities

The integration of failure probabilities of distinct subcomponents is regarded as a series system. If either paper insulation, bushing or tap-changer fails, the complete system will fail. It is assumed that the fault probability of paper degradation is the same as the failure probability. For paper degradation the model described in Chapter 4 is used. The individual failure rates for bushing and tap-changer are derived from statistics of these populations [55, 56, 94]. The subcomponent parameters are:

- The paper ageing model of Chapter 4 is applied on an ONAN transformer, with the parameters given in [44]. The paper ageing parameters for Kraft paper are as given in Table 4.1 according to Lundgaard. The ambient temperature of this transformers is 20 °C and the load is taken as 0.7 p.u. and 0.8 p.u.
- The Weibull parameters of the 50 kV switchgear bushings are taken from Section 6.1.2.
- The tap-changer Weibull parameters are taken from the statistical model of Section 6.2.2.

The individual reliabilities are depicted in Figure 6.2. Clearly bushings have a higher reliability than the other components. The tap-changer reliability in this example lies between the reliability of paper insulation with 0.7 and 0.8 p.u. load. Note, that the physical processes behind the bushing and tap-changer reliability curves are load dependent, which is not the case for the statistical based curves.
Chapter 6 Integral transformer reliability

In Figure 6.3 the combined reliability is calculated both for the 0.7 p.u. and 0.8 p.u. loaded transformer. The integral reliability is always smaller than the worst case reliability of the subcomponents, due to the series topology of the subcomponents, but is close to the worst case reliability. For loads in the order of 0.8 p.u. or higher, the paper degradation mechanism dominates the total failure rate. For a load below 0.7 p.u., the overall transformer reliability is similar to the statistical tap-changer reliability. This results aligns with the practice of power transformers in the Dutch transmission grid, where the majority of transformers fail due to tap-changer related problems [2, 18, 54, 120].

6.4 Discussion

The integral reliability of the different subcomponents is not as straightforward as suggested in Section 6.3.2. The following aspects must be considered:

- For the individual integral reliability a choice has to be made which subcomponent model to use: a statistical model or degradation mechanism model or both.
- To construct the population reliability, we can choose between extracting it from individual integral transformer reliabilities; or from censoring the failure data on failure cause and/or failed subcomponent first, and combine the subcomponent population reliabilities later.

The subcomponent reliability modelled by a degradation mechanism, such as the paper degradation model of Chapter 4, demands extensive knowledge of its historical, present and future operational parameters. The statistical data of the bushings and tap-changers on the
other hand are based on the population failure data censored on the failure cause. For instance, the bushing reliability provides insight on the quality of this subcomponent without considering its unique stress history. The statistical information does not differentiate between the probability of failure of a very polluted bushing and its clean counterpart, i.e. the subcomponent online time can only be taken into account as a useful historical parameter.

In forming a population reliability according to the method described in Chapter 5, there are two options. For the first option, the subcomponent reliabilities are combined according to Section 6.3 into integral component reliabilities. These individual reliabilities will form the population reliability as described in Chapter 5. Calculating the population reliability from the individual component perspective, provides the possibility to select transformers which are expected to fail soon, due to one of its subcomponents. The second option behaves, determining the population reliabilities filtered on failure cause and/or failed subcomponent. A worse case estimation of the population reliability can then be expressed as

\[ R_P(t) = R_{P, \text{Paper insulation}}(t) \cdot R_{P, \text{Tap-changers}}(t) \cdot R_{P, \text{Bushings}}(t), \]  

(6.12)

with \( R_{P, \text{Paper insulation}}(t) \), \( R_{P, \text{Tap-changers}}(t) \) and \( R_{P, \text{Bushings}}(t) \) the population reliabilities filtered on failures of paper insulation, tap-changers and bushings, respectively. The dominant failure causes extracted from the statistical data may aid in determining the focus of future maintenance and revision programs.
Conclusions and recommendations

The ultimate aim of the work described in this thesis is to arrive at a model for the power transformer to predict its future performance in which different degradation mechanisms are integrated. More precisely an integral remaining lifetime model is pursued for transformers to predict the effect of asset management policy on both individual as population level. Conclusions from this work are summarised in Section 7.1. Recommendations for future work are given in Section 7.2.

7.1 Conclusions

Technical reliability is defined as the probability that a component or a system performs its designated task. In Chapter 2 modelling schemes are discussed how internal and external factors affect condition. Available reliability tools are discussed and basic guidelines for their selection are given.

Further, the existing techniques: Failure Mode Effect and Criticality Analysis, Fault Tree Analysis and Reliability Block Diagram, are adapted in Chapter 2 to include the critical degradation mechanisms and their interactions. The resulting analysis tools are a Degradation Mechanism Effect and Criticality Analysis (DMECA) and a Degradation mechanism Tree Analysis (DTA), respectively.

The focus of Chapter 3 lies in determining the technical reliability from degradation processes. In combination with explicit linking the condition with a quality parameter, this provides means of monitoring the degradation processes and calibrating the model predictions. Further, the quality parameters are classified in types on the basis of their information capacity, i.e. the strength of the link with the degradation process and condition. To extrapolate the condition and fault or failure probability, three degradation modelling methods (expert judgement model, regression model and physical model) are defined with their strengths and weaknesses. The fault or failure probability is used as input for the asset management decision model.

The modelling concept of Chapters 2 and 3 is applied in Chapter 4 to predict the condition of the power transformer winding insulation paper. The accompanying degradation mechanism model consists of a physical model (Arrhenius model) and predicts the DP-value, a quality parameter directly linked to the paper degradation process. The combination with a physical model provides a means for verifying the prediction with measurements and tun-
Chapter 7 Conclusions and recommendations

The verification of the paper degradation model with measured values of a scrap transformer (Section 4.3.2) confirmed that the predicted value was within the error margins, due to parameter uncertainties. The fault probability provides the likelihood that the predicted DP-value is below the threshold value (Section 4.2.1). The probability depends on the uncertainties in the key input parameters. The uncertainties in the predicted values are extracted from an error bound estimation (Section 4.2.2). A similar estimation can be used for a sensitivity analysis (Section 4.3.1). The paper degradation model presented in this dissertation is compared with the IEC and IEEE end of life prediction methods presented in Section 4.1.3. Three observations are made:

- IEC and IEEE prediction methods have a temperature dependency not matching the paper degradation process (the Arrhenius model).
- IEC and IEEE models are only capable of predicting the degradation of dry paper and not of paper exposed to different catalysts.
- IEC and IEEE models do not directly allow to vary the end of life threshold in order to reflect specific circumstances.

The model presented in Chapter 4 overcomes these shortcomings. In Section 4.4 the IEC 60076-7 hot-spot temperature model [44] is extended to include the impact of harmonic currents on the hot-spot temperature. Model simulations point out two important effects: the total harmonic distortion is not a reliable indicator for the impact of harmonic currents on the end of life estimation of the transformer, and the impact of the harmonic currents may be significant for loads exceeding 0.8 per unit.

In Chapter 5 a method is presented to derive the transformer population reliability for a large transformer fleet (up to thousands of components). This method is applied on two existing transformer populations to analyse the impact of replacement alternatives on possible failure wave scenarios.

The conducted simulations result in three observations. The first observation addresses the importance of a correct load scenario. In general, relatively low historical loads will only marginally influence the end of life prediction. The increase in future load (by increasing load growth percentages), on the other hand, will shorten the life span for each transformer and also decrease the time window in which all transformers fail. The second observation is that the behaviour of a spare transformer, used in a substation during maintenance or during peak load sharing, reveals similar behaviour as a transformer with the highest load. The third observation shows that the predicted failure wave will not start earlier than in the year 2050, based on assumptions made in Section 5.2 concerning initial load, load growth percentage and ambient temperature. In reality the majority of the transformers will be replaced earlier, for example, because the energy transport of the substation cannot be fulfilled during maintenance or outage.

Three replacement strategies were studied (Section 5.3): i) a recurrent annual supplement with six transformers based on a fixed load growth percentage, ii) similar analysis based on a distributed load growth, and iii) equal load distribution of transformers in each substation. The first scenario faces the difficulty of determining the transformer upgrade order. A distribution of the load growth percentage spreads the transformer failures over a longer time period and causes differentiation of the transformer condition across the population. Sharing the load equally amongst the substation transformers will delay the failure moment of each transformer, but as a consequence all transformers are expected to fail within a short time
Chapter 6 provides a discussion on two other transformer failure modes: bushing and tape-changer degradation. Methods are discussed to combine different degradation mechanism models into an integral transformer model. A questionnaire was distributed among two Dutch network operators (Section 6.1.1), providing insight in the current working methods and knowledge on bushing failures. In Section 6.3.2 the paper degradation model is combined with statistical models of bushings and tape-changers into an integral reliability model for the power transformer. This simulation is based on parameters representing transformer conditions in the Netherlands. For relative low loads (below 0.7 p.u.) the integral transformer reliability is dominated by the tape-changer reliability, this is in agreement with Dutch utility experience. For loads above 0.8 p.u., paper degradation failures become dominant.

### 7.2 Recommendations

Section 7.2.1 discusses recommendations to further improve the technical reliability modelling. Recommendations in Section 7.2.2 extend and apply the modelling beyond the scope pursued in this thesis.

#### 7.2.1 Recommendations within scope

The Degradation Mechanism Effect and Criticality Analysis (DMECA) and the Degradation mechanism Tree Analysis (DTA) were discussed in Section 2.3.3 on a conceptual level. To exploit the full benefits of these techniques, a complete analysis of the DMECA and DTA techniques could be performed on for example the power transformer as a whole.

The methods for selecting the most appropriate technical reliability prediction tool are briefly discussed in Section 2.3.4. The given guidelines should be further explored to aid the asset manager in determining the best prediction tool, based on the available asset data.

The merits of the paper degradation model (Chapter 4) can be further validated by comparing model predictions with measured DP-values, either based on available data or data from additional scrap transformers. The functionality of the paper degradation model may improve by including:

1. Determining the paper ageing parameters as a function of acidity, humidity, oxygen and temperature for Kraft paper, thermal upgraded paper and Nomex paper, combined with a model based on the cascaded chemical reaction at hand. For monitoring purposes, further work should involve finding accurate and chemical related correlation between the DP-value and rest products found in the oil.
2. The thermodynamic analysis of Section 4.1 [44] may be extended to include a three winding transformer for single or three phase, i.e. a transformer with heating contributions by a primary, secondary and tertiary winding at each phase.
3. Harmonic transformer losses of Section 4.4, may be adapted to determine the impact of ageing on traction transformers, HVDC transformers, and rectifier transformers applied in industry.
4. The dynamic thermal model of Section 4.1 may be further improved with the help of a physical representation of the complex thermal balance in the transformer [98] and also extended to include shell type transformers.
5. The mathematical distribution function may be further optimised to give the best results for dealing with uncertainties and their impact. In Chapter 4 the normal distribution could be used, because the uncertainties were within acceptable limits. The use of log-normal, Beta-distribution or Monte-Carlo simulations may bring more insight in accuracy of the results.

Failure wave analysis are important for utilities to determine the expected end-of-life of their assets. Comparing the statistical techniques advocated in [54–56] with the population reliability model based on individual reliabilities (Section 5.1) for similar circumstances will provide insight in the robustness of these techniques.

In Section 6.3.1 some standard reliability configurations are discussed. The combination of interacting degradation processes, such as paper degradation and oil degradation, is omitted, but should be studied in more detail. Possible issues in this case are: the influence of moisture formed during the paper degradation process on degradation of oil or the acceleration of paper degradation by acids formed oil oxidation.

From literature presented in Section 6.3.2, it appears that tap-changer failures are the dominant failure mode in the Netherlands and in large parts of Europe at present. Tap-changer degradation mechanisms, e.g. carbon forming on the contacts of the tap-changer, could be more focussed on. The DMECA technique would be a good method in selecting the dominant degradation mechanisms, because degradation mechanisms are essential in predicting reliabilities where future scenarios deviate from historical data.

7.2.2 Recommendations outside scope

The technical reliability modelling techniques will have to be incorporated in an asset management decision procedure. This goal lies outside the scope of this thesis, and involves issues such as:

- How does a decision process work?
- Can the decision process be automated with a transparent and objective method?
- What diagnostic means can improve or extend quantification of technical reliability?
- How to gain and implement historical information?
- What is the best method for processing historical information?

Due to the large scale electrification in the Netherlands from 1950–1970, special attention is directed to the expected failure wave:

- Determining the economical impact of the replacement alternatives for individual transformers, but foremost transformer populations. A kick-off was given in Section 5.4.
- Integral asset management models and the models discussed in this thesis depend strongly on the available asset data and financial parameters. This pleads for sophisticated data management models and a well maintained data management system.
Reliability engineering definitions

The reliability of a system is defined as [58, 86]: the probability \( R(t) \) of a system to perform its intended function for a given period of time. For a large number of identical components, used under similar circumstances, this implies:

\[
R(t) = \frac{\text{# systems operational at time } t}{\text{# systems operational at time } 0}. \tag{A.1}
\]

The failure probability \( F(t) \) is related to the reliability \( R(t) \) according:

\[
F(t) = 1 - R(t). \tag{A.2}
\]

\( F(t) \) is a cumulative distribution function (CDF) that describes the probability of a failure prior to time \( t \).

The failure rate \( \lambda(t) \), also known as the hazard function \( h(t) \), used for continues functions, is defined as

\[
\lambda(t) \, dt = h(t) \, dt = \frac{\text{# of failures for time } t \leq \tau \leq t + dt}{\text{# of systems operational at time } t}. \tag{A.3}
\]

The hazard function \( h(t) \) can be obtained from \( R(t) \) by:

\[
h(t) = \frac{1}{R(t)} \frac{\partial R(t)}{\partial t} = \frac{f(t)}{R(t)}. \tag{A.4}
\]

The cumulative hazard function can be calculated from the reliability function. The cumulative hazard function, denoted as \( H(t) \), is given by

\[
H(t) = \int_0^t h(\tau) \, d\tau = -\ln(R(t)). \tag{A.5}
\]

The Mean-Time-To-Failure (MTTF) can be calculated from the failure probability density function,

\[
\text{MTTF} = E(T) = \int_0^\infty t \, f(t) \, dt = \int_0^\infty R(t) \, dt. \tag{A.6}
\]
A system with a time to failure $T$ is put into operation at $t = 0$ and is still functioning at $t$. As from $t$ a new MTTF can be defined, the Mean-Residual-Life (MRL), which is related to the reliability function according

$$\text{MRL}(t) = \frac{1}{R(t)} \int_{t}^{\infty} R(\tau) \, d\tau. \quad (A.7)$$

In similar way a distribution function for repair time, the Mean-Time-To-Repair (MTTR) can be introduced. The MTTR represent the time necessary to make the item operational again. From the MTTF and the MTTR the Mean-Time-Between-Failures (MTBF) is calculated,

$$\text{MTBF} = \text{MTTF} + \text{MTTR}. \quad (A.8)$$

The MTBF can be used to calculated the average availability, $A_{av}$,

$$A_{av} = \frac{\text{MTTF}}{\text{MTBF}}. \quad (A.9)$$
Distribution functions

In this appendix a selection of distribution functions is given, based on the information in [36, 79].

**B.1 Discrete distribution functions**

**B.1.1 Binomial distribution**

A random experiment consisting of $n$ Bernoulli trials, with the following properties
- The trials are independent;
- Each trial results in only two possible outcomes, labelled as "success" and "failure";
- The probability of a success in each trial, denoted as $p$, remains constant.

The random variable $X$ that equals the number of trials that result in a success has a binomial random variable with parameters $0 < p < 1$ and $n = 1, 2, \ldots$. The probability density function of $X$ is

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x} \quad x = 0, 1, \ldots, n.$$  \hspace{1cm} (B.1)

Respectively, the mean and variance of the binomial distribution are

$$E(X) = np,$$ \hspace{1cm} (B.2)

$$\text{var}(X) = np(1-p).$$ \hspace{1cm} (B.3)

**B.1.2 Geometric distribution**

Assume a sequence of Bernoulli trials is carried out, with probability of individual "success" $p$. What are the number of trials, $X$, until the first trial with "success" outcome. If $X = x$, this means that the first $(x-1)$ trials are "failures", and that the first "success" will occur in trial $x$. The distribution of $X$ is

$$f(x) = (1-p)^{x-1} p \quad x = 1, 2, \ldots.$$ \hspace{1cm} (B.4)

The mean value and variance of $X$ are

$$E(X) = \frac{1}{p},$$ \hspace{1cm} (B.5)

$$\text{var}(X) = \frac{1-p}{p^2}.$$ \hspace{1cm} (B.6)
B.1.3 **Negative binomial distribution**

In a series of Bernoulli trials, let the random variable $X$ denote the number of trials until $r$ successes occur. Then $X$ is a negative binomial random variable with parameters $0 < p < 1$ and $r = 1, 2, 3, \ldots$, and

$$f(x) = \binom{x-1}{r-1} (1-p)^{x-r} p^r \quad x = r, r+1, r+2, \ldots,$$

with mean value and variance

$$E(X) = \frac{r}{p},$$
$$\text{var}(X) = \frac{r}{p} \frac{1-p}{p^2}.$$  

B.1.4 **Hypergeometric distribution**

A set of $N$ objects contains

- $K$ objects classified as successes;
- $N - K$ objects classified as failures.

A sample of size $n$ objects is selected randomly, without replacement, from the $N$ objects, where $K \leq N$ and $n \leq N$.

Let the random variable $X$ denote the number of successes in the sample. Then $X$ is a hypergeometric random variable and

$$f(x) = \frac{\binom{K}{x} \binom{N-K}{n-x}}{\binom{N}{n}} \quad x = \max\{0, n + K - N\} \text{ to } \min\{K, n\}.$$  

The mean and variance of a hypergeometric random variable are

$$E(X) = np,$$
$$\text{var}(X) = np(1-p) \frac{N-n}{N-1},$$

with $p$ the probability on "success", $p = \frac{K}{N}$. The term in the variance of a hypergeometric random variable,

$$\frac{N-n}{N-1},$$

is called the finite population correction factor.

If the number of samples $n$ is less than a tenth of the total number $N$ this distribution tends to the binomial distribution. Hence, if $\frac{n}{N} < 0.1$ the hypergeometric distribution is equal to the binomial distribution.
B.1.5 Poisson distribution

Given an interval of real numbers, assume counts occur at random throughout the interval. If the interval can be partitioned into subintervals of small enough length such that

- the probability of more than one count in the subinterval is zero;
- the probability of one count in a subinterval is the same for all subintervals and proportional to the length of the subinterval; and
- the count in each subinterval is independent of other subintervals;

the random experiment is called a Poisson process. The random variable \( X \) that equals the number of counts in the interval is a Poisson random variable with parameter \( 0 < \lambda \), and the probability mass function of \( X \) is

\[
f(x) = \frac{\exp(-\lambda) \lambda^x}{x!} \quad x = 0, 1, 2, \ldots
\]

(B.13)

The Poisson distribution has mean and variance

\[
E(X) = \lambda,
\]

(B.14)

\[
\text{var}(X) = \lambda,
\]

(B.15)

respectively. The rate \( \lambda \) is sometimes called the the intensity of the process or the frequency of events, i.e. the \( \lambda \) denotes the expected number of counts in an interval.

B.2 Continues distribution functions

B.2.1 Exponential distribution

Let the random variable \( X \) denote the distance from any starting point until a flaw is detected. The probability that the number of flaws is zero in an interval \( x \), is given by

\[
P(X > x) = P(N = 0) = \frac{\exp(-\lambda x)(\lambda x)^0}{0!} = \exp(-\lambda x),
\]

(B.16)

with \( \lambda x \) the number of flaws in an interval \( x \). This equation can easily be rewritten in the cumulative distribution function of \( X \),

\[
F(x) = P(X \leq x) = 1 - \exp(-\lambda x), \quad x \geq 0.
\]

(B.17)

The random variable \( X \) that equals the distance between successive counts of a Poisson process with mean \( \lambda > 0 \) is an exponential random variable with parameter \( \lambda \). The probability density function of \( X \) is

\[
f(x) = \lambda \exp(-\lambda x), \quad x \geq 0.
\]

(B.18)

Its mean and variance are respectively,

\[
E(X) = \frac{1}{\lambda},
\]

(B.19)

\[
\text{var}(X) = \frac{1}{\lambda^2}.
\]

(B.20)
B.2.2 Erlang distribution

The random variable $X$ that equals the interval length until $r$ counts occur in a Poisson process with mean $\lambda > 0$ has an Erlang random variable with parameters $\lambda$ and $r$. The probability density function of $X$ is

$$f(x) = \frac{\lambda^r x^{r-1} \exp(-\lambda x)}{(r-1)!}, \quad x > 0 \land r = 1, 2, \ldots$$  \hspace{1cm} (B.21)

If $X$ is an Erlang random variable with parameters $\lambda$ and $r$,

$$E(X) = \frac{r}{\lambda},$$  \hspace{1cm} (B.22)  

$$\text{var}(X) = \frac{r}{\lambda^2}.$$  \hspace{1cm} (B.23)

B.2.3 Gamma distribution

The gamma distribution is a more general form of the Erlang distribution. If the parameter $r$ of an Erlang random variable is not an integer, but real constant $r > 0$, the random variable has a gamma distribution. The random variable $X$ with probability density function

$$f(x) = \frac{\lambda^r x^{r-1} \exp(-\lambda x)}{\Gamma(r)}, \quad x > 0,$$  \hspace{1cm} (B.24)

has a gamma random variable with parameters $\lambda > 0$ and $r > 0$. If $r$ is an integer, $X$ has an Erlang distribution. Its mean and variance are respectively,

$$E(X) = \frac{r}{\lambda},$$  \hspace{1cm} (B.25)  

$$\text{var}(X) = \frac{r}{\lambda^2}.$$  \hspace{1cm} (B.26)

B.2.4 Chi-squared distribution

The chi-squared is a special case of the gamma distribution in which $\lambda = \frac{1}{2}$ and $r = \frac{v}{2}$, this distribution is used extensively in interval estimation and tests of hypotheses. The distribution function is

$$f(x) = \frac{x^{v/2} \exp(-x/2)}{2^{v/2} \Gamma(v/2)}, \quad x > 0 \land v = 1, 2, \ldots$$  \hspace{1cm} (B.27)

with mean and variance,

$$E(X) = v,$$  \hspace{1cm} (B.28)  

$$\text{var}(X) = 2v,$$  \hspace{1cm} (B.29)

respectively.

If a random sample of $n$ observations is drawn from a normal distribution mean $\eta$ and variance $\sigma^2$ then:

- The distribution of $\bar{y}$ is also normal (with mean $\eta$ and variance $\sigma^2/n$).
- The sample variance is $s^2$ is distributed independently of $\bar{y}$ in a scaled $\chi^2$ (chi-square) distribution.
- The quantity $(\bar{y} - \eta) / (s/\sqrt{n})$ is distributed with $n - 1$ degrees of freedom in the $t$ distribution.
B.2.5 Normal distribution

According to the central limit theorem a combination of distribution functions tends for large numbers always to the normal distribution, with one demand that the variance of the distribution functions exist. The probability density function is

\[ f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad -\infty < x < \infty, \]  

(B.30)

with parameters \(-\infty < \mu < \infty\) and \(\sigma > 0\). Its mean and variance is given as

\[ E(X) = \mu, \quad \text{(B.31)} \]
\[ \text{var}(X) = \sigma^2, \quad \text{(B.32)} \]

respectively.

Useful results concerning a normal distribution are summarised

\[ P(X > \mu) = \frac{1}{2}, \quad \text{(B.33)} \]
\[ P(X < \mu) = \frac{1}{2}, \quad \text{(B.34)} \]
\[ P(\mu - \sigma < X < \mu + \sigma) \approx 68\%, \quad \text{(B.35)} \]
\[ P(\mu - 2\sigma < X < \mu + 2\sigma) \approx 95\%, \quad \text{(B.36)} \]
\[ P(\mu - 3\sigma < X < \mu + 3\sigma) \approx 99.7\%. \quad \text{(B.37)} \]

The binomial and Poisson distribution can be approximated by the normal distribution. To transform the normal distribution into an approximation of the binomial distribution, we substitute \(\mu = np\) and \(\sigma = \sqrt{np(1-p)}\), the mean and standard deviation of the binomial distribution, this produce valid results for \(x\) if \(np > 5\) and \(n(1-p) > 5\). A similar approximation can be done for the Poisson distribution, there we have to change \(\mu = \lambda\) and \(\sigma = \sqrt{\lambda}\). This approximation leads to useful results if \(\lambda > 5\).

The normal distribution can also be truncated to exist on a domain \(a < x < b\),

\[ f_t(x) = \frac{f(x)}{F(b) - F(a)}, \quad a < x < b. \quad \text{(B.38)} \]

B.2.6 Log-normal distribution

Variables in a system sometimes follow an exponential relationship as \(x = \exp(w)\). If the exponent is a random variable, say \(W\), \(X = \exp(W)\) is a random variable and the distribution of \(X\) is of interest. An important special case occurs when \(W\) has a normal distribution. In that case, the distribution of \(X\) is called a lognormal distribution. The name follows from the transformation \(\ln(X) = W\).

Suppose that \(W\) is normally distributed with mean \(\theta\) and variance \(\omega^2\); then the probability density function is

\[ f(x) = \frac{1}{\sqrt{2\pi}\omega} \exp\left(-\frac{(\ln(x) - \theta)^2}{2\omega^2}\right), \quad x > 0. \quad \text{(B.39)} \]
The mean and variance of the random variable $X$ is

$$E(X) = \exp\left(\theta + \frac{\omega^2}{2}\right),$$  \hspace{1cm} (B.40)

$$\text{var}(X) = \exp\left(2\theta + \omega^2\right) \left(\exp\left(\omega^2\right) - 1\right),$$  \hspace{1cm} (B.41)

respectively.

### B.2.7 Weibull distribution

The random variable $X$ with probability density function

$$f(x) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} \exp\left[-\left(\frac{x}{\lambda}\right)^k\right], \hspace{1cm} x > 0,$$  \hspace{1cm} (B.42)

is a Weibull random variable with scale parameter $\lambda > 0$ and shape parameter $k > 0$. Respectively, its mean and variance are given as

$$E(X) = \lambda \Gamma\left(1 + \frac{1}{k}\right),$$  \hspace{1cm} (B.43)

$$\text{var}(X) = \lambda^2 \Gamma\left(1 + \frac{2}{k}\right) - \lambda^2 \left[\Gamma\left(1 + \frac{1}{k}\right)\right]^2.$$  \hspace{1cm} (B.44)

The Weibull distribution is often used to model the time until failure of many physical systems. For $k = 1$ this distribution is equal to the exponential distribution, for $k \approx 3.4$ the distribution converge to a normal distribution.
The process of obtaining a component failure probability is a two step process. The first step is the transition into a faulty state. If the component is in the faulty state, the component still needs to receive a trigger to transfer to a failure mode. This process is identical to a cold standby system with ideal switching, as described in [58, Section 4.13.1], i.e. a system will only fail of all parts are failed. The time to failure, $T_F$, is given as the sum of the time to get a fault, $T_f$, added to the time to get the trigger, $T_T$, after the fault situation,

$$T_F = T_f + T_T. \quad (C.1)$$

The event that the failure time exceeds a certain time $t$ can be realised in two possible ways:

- the fault occurs after time $t$
- the fault occurs at time $x$, with $0 \leq x < t$, and the trigger does not occur for a time period longer then $t - x$.

The reliability function belonging to the failed state, $R_F(t)$, can be expressed as

$$R_F(t) = R_f(t) + \int_0^t f_f(x) R_T(t - x) \, dx, \quad (C.2)$$

where $R_T(t)$ is the reliability function belonging to the trigger, $R_f(t)$ and $f_f(t)$ are respectively the reliability function and probability density function belonging to the faulty state.

To find the component’s MTTF, we may use $R_F(t)$ in Equation (C.2). However, a simpler way is to use Equation (C.1) to find $E(T_F)$ directly

$$\text{MTTF} = E(T_F) = E(T_f) + E(T_T). \quad (C.3)$$
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