Transformer Condition Assessment & Survival Model

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by

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Abstract

Managing electrical distribution assets entails making the decision on how to proceed with an ageing asset. The three options that asset managers have are run to fail, perform maintenance or repairs and lastly to replace.

This decision making process is becoming incrementally more important due to the threat of replacement waves. This a phenomenon that comes forth from the fact that a large portion of the assets were installed around the 1970's, the so called installation wave, combined with the fact that these assets have a life expectancy of 40 to 60 years. It is up to the asset managers to accurately asses the condition of these assets and prioritize investments due to budget constrictions.

Asset management has been evolving from time based maintenance (TBM) to condition based maintenance (CBM) and reliability centered maintenance (RCM). To aid in the decision making process for the latter two methods, accurate condition assessment and failure probability methods are needed.

At Stedin, one of the three largest network operators in The Netherlands, the asset managers require a better condition assessment method for transformers, as the one being used now lacks certain capabilities; trend analyses and proper prioritization is difficult and time consuming.

Furthermore, there lies the question whether the condition of the transformer can be used to improve the failure or survival probability model. The assumption is that the condition indicators of an individual asset can be used to adjust the population based probability models, which are then comprehensive and more accurate.

In this thesis, an improvement to the transformer condition assessment is implemented and the effect of the condition indicators on the survival probability of the transformer is studied.

Several condition assessment methods were reviewed, with the chosen method being the so called health index (HI). The results from this method is accurately reflected in the transformers which are to be replaced by Stedin. However, it has become clear that using one single number for decision making is not recommended, as the subsystems that are in moderate or bad condition might be masked by those that aren't. This can be compared to the analogy that a chain is only as strong as its weakest link, and thus the condition of that link should not be masked by the condition of the rest.

For the survival model, machine learning and classic statistical methods were reviewed. The chosen method was Cox's Proportional Hazard Model, which has the advantage of being applicable to situations in which the underlying probability distribution of the events is unknown.

Due to missing failure data, the survival model was used to model the effect of

the condition indicators on the probability of corrective maintenances. Further constraints in the data quality lead to the confidence bands of the model's parameters to be relatively large. However, the univariate models do prove the significance of the effect of these condition indicators. The conclusion is that there is a relationship between the condition and the observed failures, but that proper documentation of failures is necessary to increase the accuracy of the model.

Contents

List of Abbreviations

β	covariate effect/weighting
λ	hazard function
x	covariates
AFT	accelerated failure time
AG	Andersen-Gill
AHP	analytical hierarchy process
AM	asset management
AT	accelerated time
BS	Brier score
CBM	condition based maintenance
CDF	cummulative distribution function
CPHM	Cox proportional hazard model
DB	dielectric breakdown
DDF	dielectric dissipation factor
DGA	dissolved gas analysis
DP	degree of polymerisation
DRM	dynamic resistance measurement
DSO	distribution system operator
EOL	end of life
HI	health index
HIF	healt index function
HR	hazard ratio
IFT	interfacial tension
KM	Kaplan-Meier
LL	log-likelihood
LTC	load tap changer
ML	machine learning
MLE	maximum likelihood estimator
OLTC	on load tap changer
PD	partial discharge
PDF	probability density function
PH	proportional hazard
PHM	proportional hazard model
PLE	partial likelihood estimator
POF	physics-of-failure
PWP	Prentice-Williams-Peterson

RCM	reliability centered maintenance
RSD	regelschakelaar diagnostiek
SRM	static resistance measurement
TBM	time based maintenance
TSO	transmission system operator
WLW	Wei-Lin-Weissfeld

Chapter 1

Introduction

1.1 Problem Description

Stedin is a distribution system operator (DSO) of a large part of The Netherlands. They have a big power transformer fleet that needs proper and careful management, as they can account for up to 60% of the total investment costs for substations [1]. This falls in the field of ***asset management*** (AM) and requires many diagnostic tools and strategic decisions. When a transformer is old or displaying faults, an asset manager has to make a decision; run to fail, repair or replace?

Many inputs are used in this decision making process, one of which is the transformer's condition. At the moment Stedin's AM department uses a ***condition assessment method*** which they wish to improve, as it is difficult to preform trend analysis and the data base is quite scattered.

Furthermore, the group would like to improve the information given to the risk analysis group for predicting the ***risks*** concerning transformer maintenance and replacement, and thus improve the justifications behind their decision making. This entails a transformer failure model which is specific for each individual, instead of being optimized for the whole population

The goal of this thesis is thus twofold:

- Improve the condition assessment for power transformers.
- Develop a failure model which adapts to individual transformers.

1.2 Methods

As the first objective of this thesis is to develop a condition assessment method for transformers, the characteristics that define the condition and the factors that change it, should be reviewed. This condition assessment will be used for decision making in a condition based maintenance (CBM) strategy. Prior to developing a CBM strategy, it is important to know the following [2]:

- Function and criteria of performance standards
- Failure modes
- Causes and reasons for failures
- Consequences/importance of each type of failure

- Techniques to prevent failures

Better results with higher perfomce standards can be achieved with CBM, provided the fault is detected and properly diagnosed in its early stages [2].

Achievement of the first goal will require the use of transformer (diagnostic) data that has been gathered over many years. This data can be used in existing ***deterministic models*** or a ***machine learning*** approach can be employed. There is an extensive amount of literature covering the deterministic models and there are many libraries containing deployable machine learning algorithms.

The second objective entails using an individual transformer condition assessment, and perhaps other variables, to compute the failure probability. (Un)fortunately, there are not many cases of transformer failures, especially well documented failures, and thus not much data is available. This means that information regarding transformers that have survived should also be taken into account, to augment the amount of useful data. This requires the theory of ***survival analysis***.

1.3 Research Question and Scope

From the above listed goals, the following research question is proposed:

Can the condition of transformer be used as a reliable input for transformer failure probability prediction?

Scope

- Only power transformers will be considered. These are transformers with a secondary voltage of more than 1 kV.
- Focus will lie on the individual transformer failure probability and not population failure probability.
- When considering transformer failure, the interest lies more on the failure probability (to calculate risk) instead of the "technical" end of life.

Deliverables

- Implementation in R [3] of improved condition assessment model for HV transformers compared to current model employed by Stedin.
- Improved information for risk analysis: condition based failure model for determining failure probability per transformer.

1.4 Thesis Outline

In chapter 2 an introduction is given to transformer functionality and its subsystems and furthermore a discussion of how asset management has been evolving is presented.

In chapter 3 a failure mode analysis is conducted to asses which subsystems are critical to the condition assessment. Afterwards the subsystems are selected based on its criticality and the availability of the corresponding condition data.

In chapter 4 the transformer condition indicators are discussed along with the possible measurement possibilities.

In chapter 5 a review is given on today's transformer condition assessment techniques and the choice of the health indexing method is explained.

In chapter 6 a review is given of modern survival modelling methods and the extensions of the basic models. The choice of the model is also thoroughly explained.

In chapter 7 the transformer population, input data and implementation details are discussed.

In chapter 8 the results of the health index model and the survival probability model is given.

This thesis is concluded with chapter 9 in which the research question is answered and recommendations for future work is given.

Chapter 2

Introduction to Transformers

Transformers play a crucial role in everyday power delivery to consumers. They provide a means to transfer electrical power cost efficiently over long distances to e.g. homes, businesses and factories, whose core activities are quite dependent on electricity. Without backup power, these activities would come to a standstill if the supplying transformer ceases to function.

Transformers are relatively complex systems with many subcomponents, due to the situations that can occur if they are not designed, operated or managed properly. In figure 2.1, such a situation is depicted. Transformers have multiple protection mechanisms to prevent these types of situations from happening, and furthermore manufacturers use clever mechanisms to lower the production and operating cost. All of this in combination with the fact that they are designed for lifespans of up to 40 years, makes the transformer an interesting system to manage.

This chapter is meant to give the reader, if necessary, a physical understanding of the transformer as a system and define the functions of the components. In the first section a description of transformer operation is discussed, followed by the design characteristics in the next. Transformer types will then be discussed in order to define the scope of the transformers covered by this research. The chapter will end with a discussion on some trends seen in asset management, to indicate some of the problems with managing transformers and other assets in general.

Figure 2.1: Transformer that failed [4].

2.1 Transformer Working Principle

Transformers are electrical power devices that transfers electrical energy from one circuit to another. The different circuits are magnetically coupled by a common magnetic field, but there is no direct electrical connection between the circuits (except for certain types) [5]. A formal definition of a power transformer is given in an IEC standard [6] as "a static piece of apparatus with two or more windings which, by electromagnetic induction, transforms a system of alternating voltage and current into another system of voltage and current usually of different values and at the same frequency for the purpose of transmitting electrical power". The term "static" is however not well suited for transformers that have moving parts such as the load tap changer (LTC), which will be discussed in section 2.2.3.

The phenomenon of ***magnetic coupling*** will be introduced first. When a current runs through a conductor, a magnetic field is created around the conductor. This magnetic field is a vector, thus has a magnitude and a direciton. The magnetic field density is proportional to the current, I, that runs through the conductor. For a straight wire, the magnitude is given by

$$B \propto \mu * I \tag{2.1}$$

Where μ is the magnetic permeability of the medium in which the magnetic field is present. This value varies per material and is higher in e.g. ferromagnetic metals, which means that when applying the same current, the magnetic field density will be higher in a metal compared to e.g. air. This is an important property for using metal cores in transformer design.

Magnetic fields can be used to induce voltages over a conductor. This phenomenon is used to transfer power in wound up conductors (windings). The induced voltage in a single winding depends on the rate of change of B and the area of the winding, A and is given by

$$V = \frac{d}{dt}\vec{B} \cdot \vec{A} \tag{2.2}$$

The term $\vec{B} \cdot \vec{A}$ is described as the magnetic flux Φ, which can be seen as the total magnetic field. Equation 2.2 works both ways; when an alternating voltage is applied to a coil, an alternating magnetic flux is induced. This alternating magnetic flux can consequently induce a voltage in another coil and if an eletrcal load is connected to the terminals, then a current will flow; power transfer is achieved.

Equation 2.2 decribes the voltage and flux relationship for a single winding. Should multiple windings be connected in series to form a single winding, then the equation expands to

$$V = \frac{d}{dt}\Phi N \tag{2.3}$$

where N is the number of turns. This equation describes the basic working principle for a transformer. Assuming no flux leakage, the flux Φ induced by one winding will be equal to the flux that reaches another winding and should the two windings have a different amount of turns N, the induced voltage will have a different value. The relationship between two magnetically coupled windings can be derived by using equation 2.3 for the two windings, which are indexed by the subscripts:

$$\frac{d}{dt}\Phi_1 = \frac{V_1}{N_1}$$

$$\frac{d}{dt}\Phi_2 = \frac{V_2}{N_2}$$

$$\Phi = \Phi_1 = \Phi_2$$

$$\frac{d}{dt}\Phi = \frac{V_1}{N_1} = \frac{V_2}{N_2}$$
$$\frac{V_1}{V_2} = \frac{N_1}{N_2} \tag{2.4}$$

Equation 2.4 gives the ***voltage ratio*** between magnetically coupled coils. This means that if the second coil has a higher number of the turns, the voltage will be higher. This principle is used by transformers to increase or decrease the voltage from one coil (primary side) to another coil (secondary side). The current ratio can also simply be derived assuming that the power applied to the first coil is equal to the power received by the second coil. It is given by

$$\frac{I_1}{I_2} = \frac{N_2}{N_1} \tag{2.5}$$

Thus an increase in voltage is paired with a decrease in current. This is the reason that high power is transmitted at high voltages: lower current results in lower dissipation losses as the power loss in power cables is given by $P_{loss} = I^2R$, where I is the current through the cable and R the resistance of the cable.

2.2 Transformer Components

2.2.1 Core

In transformers for high power applications, the magnetic coupling commonly happens via an ***iron or steel core***. The reason for using electrical steels is because their magnetic permeability μ can be three orders of magnitude higher than air [5]. Furthermore, the steel also provides a pathway for magnetic coupling, see figure 2.2. However, contrary to the depiction in figure 2.2, the primary and secondary windings are usually wound around the same leg of a core in order to achieve maximum magnetic coupling.

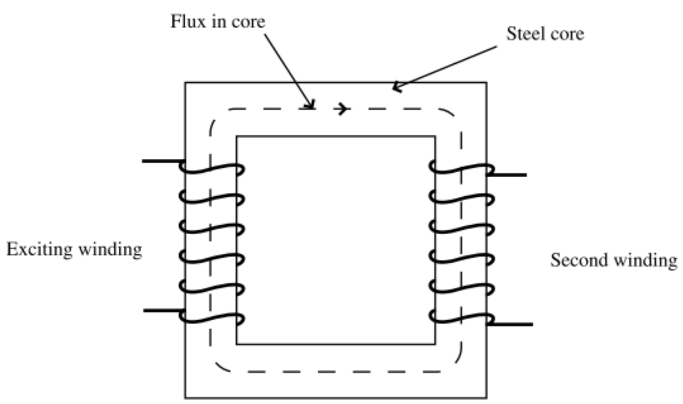


Figure 2.2: Magnetic coupling via a steel core [5].

There are differences in transformer's core and winding configuration. In common transformer design, the manufacturer has a choice between two concepts, ***core*** and ***shell*** type, which are depicted in figure 2.3.

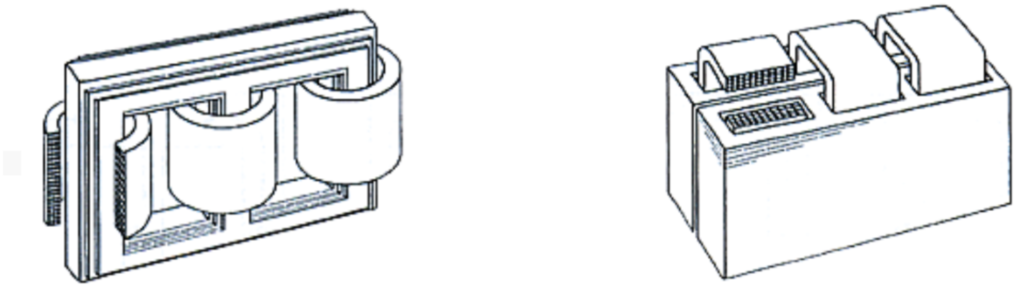


Figure 2.3: Core type (left) and shell type (right) transformers [7].

The configurations have no influence on the operational characteristics and the reliability of the transformer, the choice mainly lies in the preferred manufacturing process [7].

The alternating magnetic field in the core produces eddy currents in the core, causing losses in the form of heat. To reduce the magnitude of these currents, the cores are laminated. There are two common ways of doing this, ***wound*** and *stacked*. The configurations can be seen in figure 2.4.

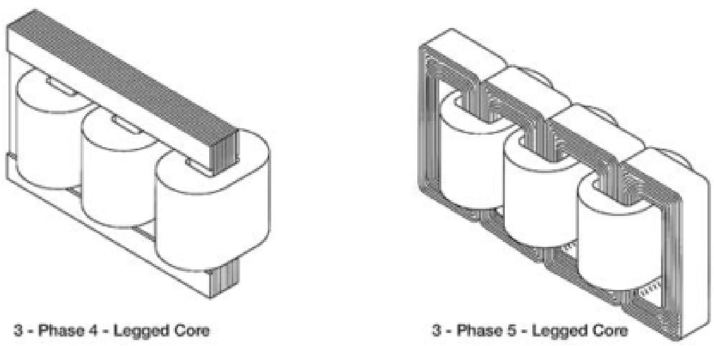


Figure 2.4: Types of core configurations [5]. Left is stacked and right is wounded

2.2.2 Insulation

In power transformers, the windings and other components are provided with electrical insulation by two components:

- **Solid insulation**: the conductors are wounded with ***high density paper*** and pressboard between the windings. Cellulose, the main component in paper, has good insulating properties [8]. The typical transformer contains 10-12 tons of paper [9].
- **Liquid insulation**: the transformer tank is filled with ***mineral oil***, which has excellent and cost effective insulating and cooling properties [10], submerging the windings and other internal subsystems. There have also been some studies on al-

ternatives to mineral oil such as vegetable oil, which is more environment-friendly and less flammable [11][12]. The typical transformer has 45 tons of oil [9].

The combination of the paper and oil results in an enhanced oil impregnated paper with respect to insulating and cooling properties. The oil eliminates air from the porous paper and pressboard to increase their resistance to dielectric breakdown [10]. However, there are also dry type transformers that use vacuum instead of oil as an insulating medium. They are usually applied in areas that require a higher fire safety rating or have environmental contamination constraints, and are less common in the transmission and distribution network.

2.2.3 On Load Tap-Changer

The winding ratio of a transformer dictates the voltage transformation, however, the output voltage will vary as the load varies. Regulation of the voltage is thus needed and this is done by changing the effective turn ratio of the transformer. The windings are equipped with different taps that make it possible to alter the amount of turns that are connected to the terminals of the transformer, see figure 2.5

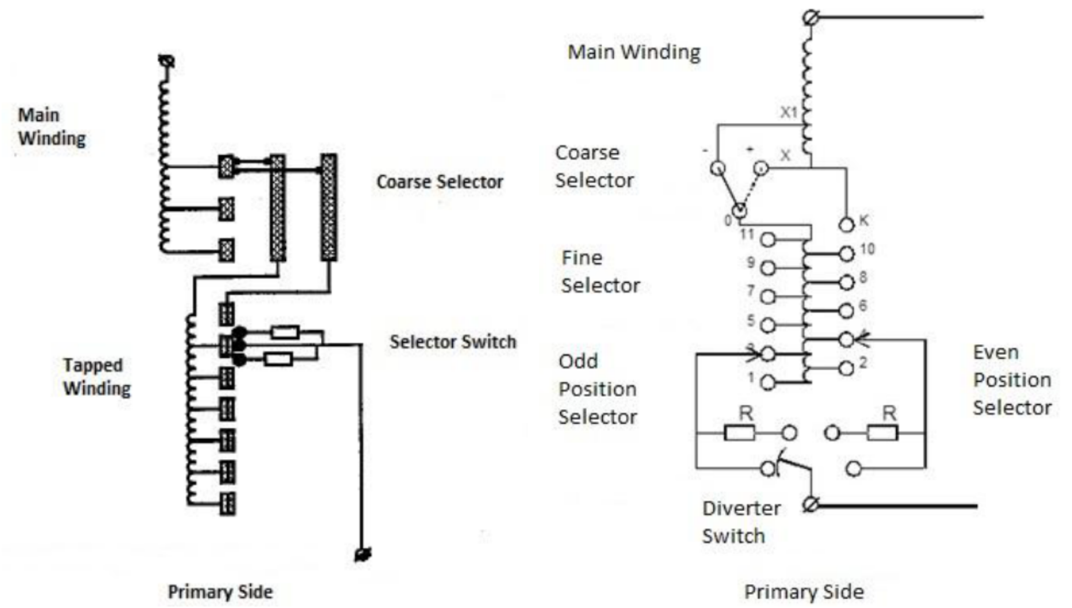
(a) Winding taps (b) Tap terminals

Figure 2.5: Winding taps for altering the effective turn ratio.

The subsystem that is responsible for selecting the taps that are connected to the output terminals is called the *on load tap changer* (LTC). This is the only actively moving part of the transformer and is the source of most of its failures [13]. The LTC selects other windings without interrupting the load and must therefore transfer the load current from one contact to another. This operation will cause arcing and thus LTC's are equipped with an *arcing switch*. How this arcing switch is implemented varies per LTC type. There are two designs of LTC switching mechanisms that are dominantly used:

- **Selector switch type**: An example of the construction of the selector switch type is given in figure 2.6a. The bottom part is called the *selector switch* and does small voltage corrections. The top part is called the *change-over selector* or *coarse selector*, which expands the regulating range and does big voltage corrections. The selector switch is the arcing switch in this design. The coarse selector doesn't break the current path during its switching cycle, by letting the selector switch do that simultaneously with its cycle.

- **Diverter switch type**: A design example of the diverter switch type is given in figure 2.6b, placed next to a selector switch type for comparison. The diverter type is the same as the selector type, but the arcing switch functionality is take over by an extra switch: the *diverter switch*. The diverter is responsible for switching the load current whenever the fine tap selector or change over selector performs a switching action.



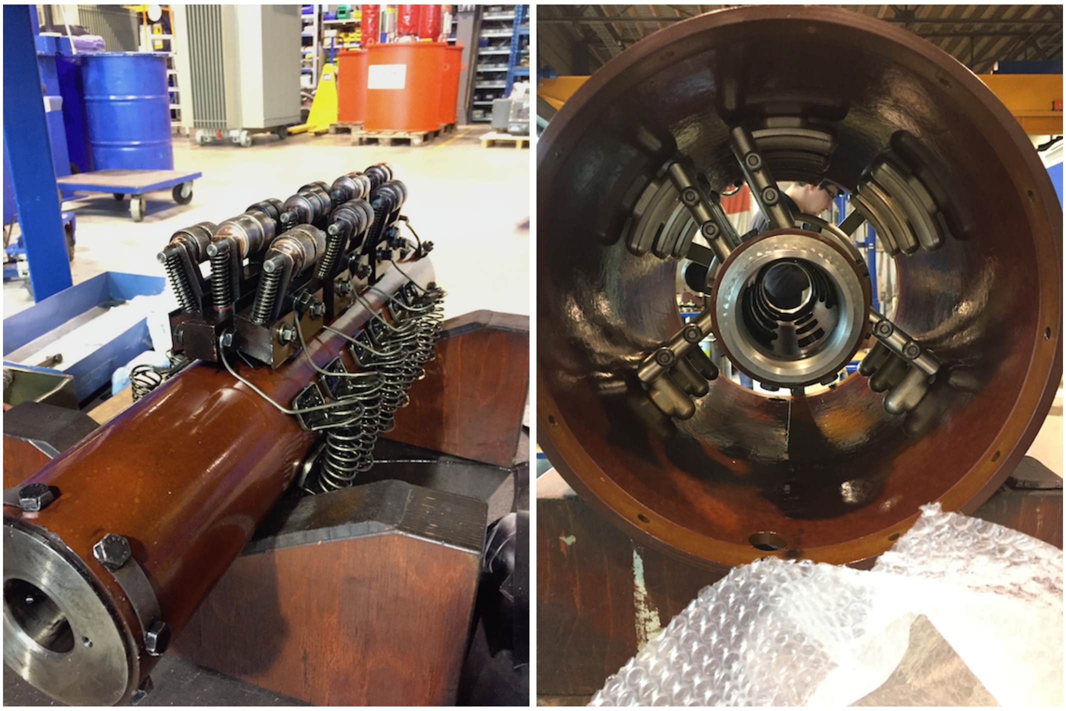
(a) Selector type

(b) Diverter type

Figure 2.6: LTC types [14].

In both designs, the movings contacts are connected by a shaft to a motor drive, which is responsible for moving the contacts. See figure 2.8 for an example of the rolling and stationary contacts.

The LTC is also submerged in transformer oil. The load switching components of the LTC are always confined in a separate compartment in the transformer tank due to the arcing. Arcing causes high temperatures and degrades the oil, resulting in contaminants that are bad for cooling and insulating properties. The non-load components are sometimes placed in a seperate compartment, but are usually placed in the main tank along with the rest of the transformer's inner parts [15][14]. There are other types of LTC that are contained in a vacuum. The vacuum types are relatively new and are not largely in use (yet).

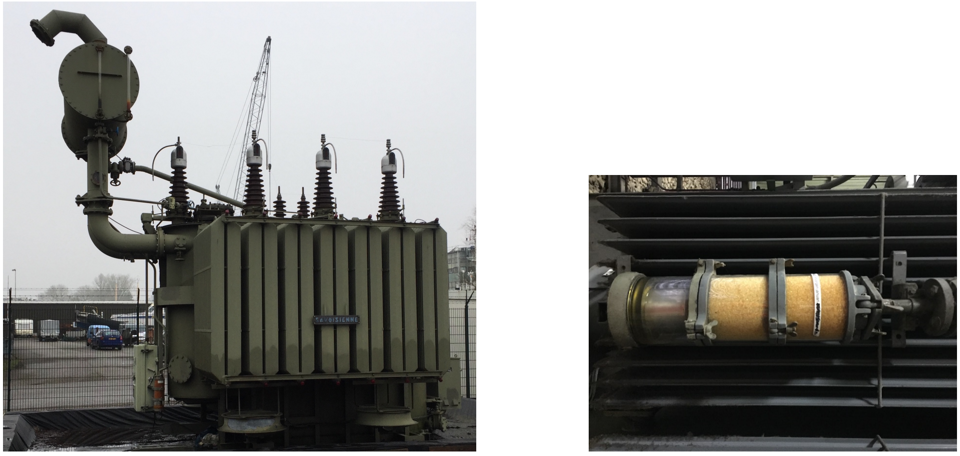


(a) Rolling contacts (b) Stationary contacts

Figure 2.7: LTC contacts.

2.2.4 Tank

As mentioned before, the transformer tank is filled with oil. One of the purposes of this oil is to cool the windings and so when the oil heats up, it expands and pressure will build up in the tank. Extra space is provided by a ***conservator tank***, which also functions as an oil reservoir. oil can expand to this conservator tank and excess air is pushed out through a valve, called a ***breather***. When the oil cools down, air enters through the same valve, however this air contains moisture and other contaminants that must be filtered out. The common filtering method is to add a silica gel compartment to the breather.



(a) Tank and conservator (out of service)

(b) Silicagel breather

Figure 2.8: Transformer tank.

2.2.5 Bushings

The cables running to the terminals of the transformer should not come into contact with the transformer housing as defects in the insulation may cause the transformer tank, which is earthed, to cause a short circuit. The cables enter the transformer through bushings, which isolate the tank from the cables. These bushings are sometimes filled with oil for its cooling and dielectric properties [16]. In figure 2.9 a transformer bushing is depicted.

Figure 2.9: Bushings

2.2.6 Protective and Auxiliary Devices

A transformer is equipped with some devices to protect it from an oncoming or ongoing fault. These devices detect an anomaly in the transformers operating conditions a corrective action. Furthermore it has some auxiliary devices for monitoring important conditions. The most common ones will be discussed here [5, 7]:

- **Buchholz**: Between the main tank and the conservator there is a relay which collects gas bubbles and detects high values of oil flow, named a Buchholz relay. An internal fault can produce free gas, due to the decomposition of the oil, and a well calibrated relay can detect early stages of a fault. A serious fault will develop gas so quickly that it will push the oil up to the conservator tank. This high rate of oil flow will trip the Buchholz.
- **Overvoltage protection**: Most common method of overvoltage protection are surge arresters. They protect the transformer from transient voltages by limiting the voltage to a level that the transformer is designed to tolerate.
- **Overcurrent protection**: These protect the transformer from the short circuits. They might be as simple as power fuses or more complex overcurrent relays.

- **Pressure relief**: These device limit the pressure built up in the tank to prevent it from rupturing. When tripped, the pressure is relieved through a valve.
- **Thermometers**: These usually measure the oil temperature in the top of the tank. This can serve as an indication of the winding hot spot temperature.
- **Oil level indicator**: Low oil levels indicate that a leakage might be present. A leakage results in not only lower oil levels, but also a pathway for moisture and other contaminants to enter the transformer.
- **Fans and pumps**: Transformers are cooled externally by air and internally by oil. The circulation of both can occur naturally, or forced. Air can circulate naturally or forced with fans, and oil can circulate either naturaly by convection or forced by pumps. The cooling types are given by ONAN (oil natural - air natural), OFAF (oil forced - air forced), and combinations thereof.

Some transformers are equipped with the ability to relay some essential measured parameters. These can be parameters such as key gases in oil, currents, voltages and partial discharge activity.

2.3 Transformer Types

Transport of energy can be distinguished in two parts: transmission and distribution. These different parts also need different transormers. Here is an overview of the most common types of transformers.

- **Distribution transformers**: transforms voltage to distribution level. These levels are suitable for connections to residential consumers.
- **Power transformers**: transforms voltage to level suitable for transportation. These levels are suitable for transmission over long distances. These transformers either increase the voltage from a generator (generator step up transformer) or lower it proportionally to the power being transmitted to a network branching from the main transmission network.
- **Autotransformers**: are placed at point in the network at which the voltage has dropped significantly due to long tranmission distances. These transformers transform the voltage back up to the nominal voltage of the network it is in.
- **Earthing transformers**: provide a ground for a network which would otherwise have no ground, e.g. a network supplied by a delta system.
- **Choke**: these transformers provide a latency effect during e.g. short circuit faults.

This thesis will focus on power transformers and autotransformers, as they are currently in the Stedin population under study.

2.4 History of Electrical Power Asset Management

The electrification of European countries grew steadily in the 20th century and by the 60's many households were dependent on electricity. This trend forced network operators to upgrade their networks and much of the electrical infrastructure was installed during the 60's and 70's. It was noticed that electrical assets were capital intensive assets, i.e. that investment costs formed most of the life cycle costs. Yearly operational costs lie between 0.1% to 0.5% of the investment and the OPEX/CAPEX ratio is between 1.3% and 11.1% [17].

The development of asset management is also dependent on the changes in the network operators themselves. In the 60's and 70's, these companies were geographically divided in smaller area's. There were specialized departments with relatively small asset data bases that were manually manageable. Much knowledge of the asset population were known by the employees and long employment periods made the transfer of knowledge simple and thus documentation was not highly needed (M. Hooijmans, private communication. October 2017).

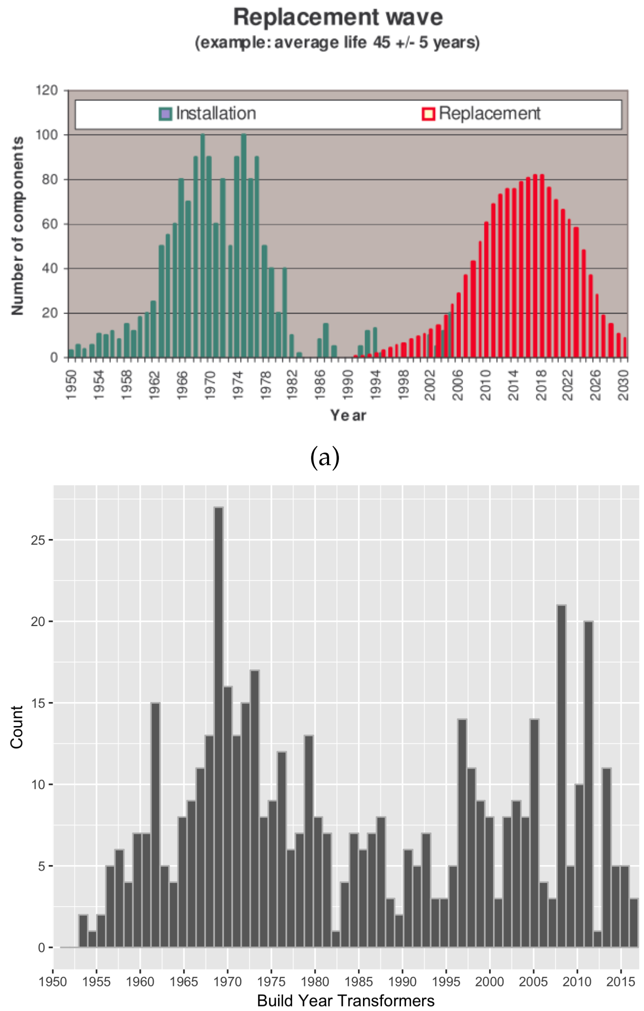
Now, many of the smaller network operators have fused and the asset data base has become too big to be managed without proper documentation. The different maintenance and design policies allow for differences between the way the assets were managed. Combining these data was not always done uniformly and to this day there are still some discrepancies in the data format for the same piece of information within the same company.

At first there was relatively little attention paid to maintenance strategy as asset life and performance up to that point were above expectations. Generally, electrical assets have a long technical lifetime due to the fact that few moving parts are used. The failure rates were low and corrective maintenance strategy was mainly used, except for switchgear, protection and substation automation; preventive maintenance was usually used for these. Furthermore, the replacement strategy was usualy run to fail and replace failed part if possible. For many years, the goal of network owners and operators was to supply electricity in the most reliable way. Although cost effiency was also taken into consideration, reliability prevailed.

This maintenance and replacement strategy has been undergoing a change to CBM and the preventive replacement of assets, respectively. This comes from the fact that a significant part of the electrical infrastucture was installed in the 60's and 70's and the average expected lifetime of the assets are 40 to 50 years. This means that many assets are now beyond their nominal design life and network operators are faced with three options for their assets:

- **Consume**: replacement after failure.
- **Prolong**: extension of the prevailing strategy with lifetime activities such as updgrading and refurbishments.
- **Replace**: preventive replacement of assets.

Replacing the assets too early results in high investments costs with neglible grid performance increase. Replacing the assets after failure results in a short period of time in which all must be replaced, which is difficult due to financial constraints (internally and due to revenue-capping regulating parties). This would result in the so called replacement wave, see figure 2.10. A similar trend can be seen between the two, and it can be assumed that a replacement wave is approaching (note that build year and installation year are approximately the same for Stedins transformers).



(a)

(b)

Figure 2.10: Comparison of typical installation/replacement waves and Stedin transformer population.

To make a better and more objective decision, precise information of asset condition is required and thus ***advanced diagnostic methods*** and ***condition assesment*** are used to study the failure behaviour. Maintenance is unified across the assets and aimed at the prevention of failures. However, there is some uncertainty in these condition assessments and thus inputting them in decision making processes results in a risk. When at first reliability prevailed, now the decision must take ***reliability***, ***costs*** and ***risks*** into account. The strategy of network operators shifts from maximizing reliability to controlled risk, optimizing reliability and costs. The considerations to achieve this can be seen in figure 2.11

Old transformers are starting to fail due to old age and the importance of replacement strategies is rising. The challenge is to optomize the replacement strategy with socially acceptable tariffs, while also pursuing the optimum from society's point of view [17]. Transformer life assessment is becoming an issue of reliability: there is no definite point at which a transformer will fail, just an increase in fail probability [18].

Presently, a program to identify transformer candidates for replacement and an action plan for each unit is a crucial element of population management. Examining the consequences of failure can make it possible to postpone the replacement of a unit, if it has a small impact in case of a failure. The balance between ***likelihood of failure*** and the ***consequences*** of that failure is at the heart of risk management [19].

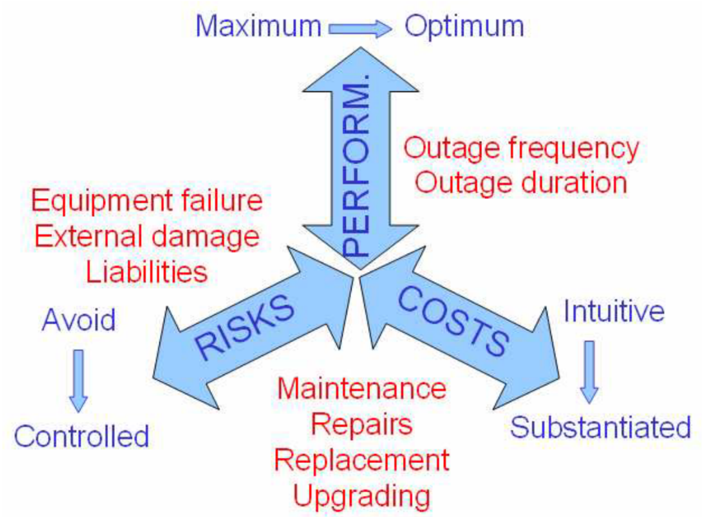


Figure 2.11: Tangeible considerations for optimizing replacement strategy [17].

Chapter 3

Failure Mode Analysis

A transformer has many components which can fail and each may have multiple failure modes. A failure mode is defined as the manner by which a failure is observed. To define, identify and eliminate these failures, a failure mode and effect analysis (FMEA) can be conducted. FMEA is a method intended to perform the following activities [20]:

1. Identify and recognize potential failures including their causes and effects.
2. Evaluate and prioritize the identified failure modes.
3. Identify and suggest actions that can eliminate or reduce the chance of the potential failures from occurring.

The goal of this FMEA is to assess which failure modes *can* and *should* be taken into account in the condition assessment. This will be based on the available data at Stedin and the consequences of the failure.

3.1 Failure Modes

Findings from [21], [22],[15] and [23] are combined in this section. The failure modes are discussed per transformer subsystem and are categorized into ***dielectric***, ***thermal***, ***mechanical*** and ***chemical*** faults.

3.1.1 Windings

A winding failure is a state in which the winding of a transformer does not effeciently conduct current for magnetic coupling. The following faults are considered:

- Dielectric faults: the insulating medium between the winding can not withstand the voltage applied, resulting in a dielectric breakdown causing a short circuit between the windings. This can be either because the insulating medium has been deteriorated or because the voltage surpasses the design specifications.

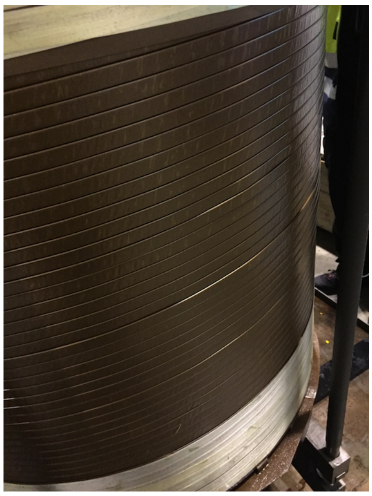


Figure 3.1: Slightly deformed windings

The presense of cavities in the solid insulation or gas bubbles in the liquid insulation decreases the dielectric strength between the conductors.

- Thermal faults: losses occur in the windings due to the resistance of the conductors. If the losses are too high, the heat might expand the conductor and deteriorate the insulating medium. This causes wear and tear of the conductor and decreases the physical strength of the conductor up to the point that it might break.
- Mechanical faults: displacement of the windings decrease the transformer performance by creating more leakage flux. These displacements may occur radially or axially due to short circuit currents introducing strong magnetic fields or during the transportation of the transformer. The displacement might also rupture the solid insulation, see figure 3.1.

3.1.2 Core

The core consists of *laminations* to reduce the eddy currents and the losses asociated with it. The lamination can become defected by poor maintenance, old oil or corrosion. When the insulating coat between the laminations is damaged, the laminations are shorted which causes larger eddy currents resulting in excesive heat. Furthermore gaps between the laminations can result in partial discharge activity, damaging the laminations. The following faults can thus occur in the core:

- Thermal faults: overheating of the core due to eddy currents heats up the solid and/or liquid insulation, which speeds up the aging process.
- Dielectric faults: partial discharges between laminations, resulting in heat. The heat might also form gases in the oil, causing damage elsewhere in the transformer.

3.1.3 Bushings

The bushings of a transformer should insulate the high and low voltage lines from the transformer tank. The *capacitance* between the tank and bushing is what should be perserved to prevent breakdowns, but this can deteriorate due to partial discharges. The faults that can occur are as follows:

- Dielectric faults: high fault voltages may cause partial discharges, damaging the bushing up to the point that complete breakdown can occur. Old oil or oil leakage may also cause internal flashovers.
- Thermal faults: explosion due to overheating of the oil and pressure build up.
- Mechanical faults: loosening of conductors caused by transformer vibrations, resulting in heat. Oil leakage due to mechanical wear.

3.1.4 Oil

Transformer oil has insulating and cooling properties which can be compromised. When these properties are below a certain threshold, a failure mode can be defined.

The electrical properties degrades when high *moisture* or *acidity* is present. This is a feedback mechanism; acidity and moisture increases the aging rate of the paper insulation, resulting in more moisture. Increased acidity will increase the ageing rate of the oil, resulting in more acid. Acid comes from oxidation of the oil and water can be introduced into the oil via the breathing system or via water holded by the cellulose in the solid insulation. The water may form vapor bubbles when heated which may come between the windings, reducing the dielectric strength between them. Gas bubbles are weak dielectrics and their presence can intensify the discharge (corona) or initiate further breakdown in highly stressed regions [10].

The cooling property is degraded when the circulation of the oil is compromised by sludge and/or bad viscosity of the oil. The following faults can thus occur:

- Dielectric faults: the dielectric properties of the oil has degraded down to the point where the probability of flashover becomes high.
- Thermal faults: the cooling properties of the oil has degraded down to the point where excessive heating is present in the transformer.
- Chemical faults: The acidity of the oil is above a treshold, which deteriorates the paper insulation excessively.

3.1.5 LTC

The LTC is in charge of regulating the output voltage and is one of the most complex part of the tranformer. Furthermore it is the only component in the main tank with moving parts. The LTC has two seperate compartments and two different failure mechanisms are dominant in each, covered in section 4.2.4. This is due to the difference in switching frequency and the presence/absence of arcing. A failure is defined as a state in which the LTC can no longer select another tap without interrupting the load current. The following failure modes are defined:

- Mechanical faults: contact interruption due to contact or spring wear. Switching failures due to low switch speed, blocking of the switch, motor failure or drive axis rupture.
- Thermal faults: contact wear, causing increased resistance and high losses, see figure 3.2.

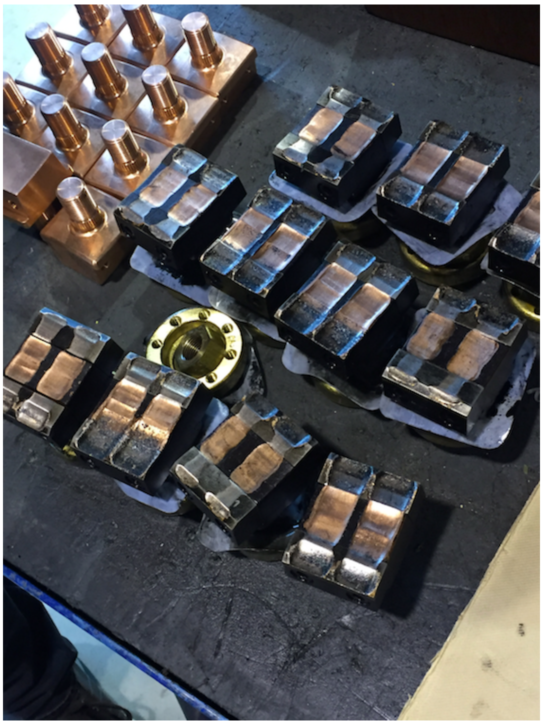


Figure 3.2: Contact wear: grooves by the rolling contacts.

3.1.6 Tank

The tank of the transformer should protect the internal systems of the transformer from mechanical damage, moisture and other contaminants. The two components of the tank that are susceptible to ageing is the outer coating and the seals and gaskets.

The ageing mechanisms are caused by environmental stresses, corrosion and high humidity. The following failures can ocur:

- Mechanical faults: cracks in the tank walls or seals and gaskets, resulting in oil leakage.
- Chemical faults: tank corrosion.

3.1.7 Protective systems

The protective systems of a transformer are devices that protect the transformer from faults by detecting the presence of a fault and taking appropiate actions. If it cannot fix a fault, it should isolate it to prevent damage to the transformer. The following protection devices and faults are identified:

- Mechanical faults: the Buchholz relay doesn't detect rapid oil expansion or low oil levels. The pressure relief valve circuitry does not release the pressure fast enough, mainly caused by the springs in the device becoming fragile over time.
- Dielectric faults: failure in the surge protector, which results in high voltages applied across the transformer, damaging it. Moisture, heat and corrosion result in overheating and short circuits in the device, which are the main reasons of failure.

3.1.8 Cooling system

The cooling system consists of fans and/or pumps, which are optional in the design of the transformer. The fans provide air circulation and the pumps circulate the oil inside the tank. The following faults can occur:

- Mechanical faults: wear-out the fan motors.
- Chemical faults: leakage in oil/water pipes due to corrosion.

3.1.9 Overview

In appendix A, an overview of the failure modes can be seen along with the effect, causes, detection method applied at Stedin, and the usual action taken by Stedin for that failure mode. The causes of the failure modes will be further elaborated in chapter 4. This table, along with the available data at stedin, will be used to select the subsystems taken into account in the condition assessment.

3.2 Failure Statistics

Failure frequency of each subsystem is essential for calculating the associated risk. In this section, some statistics are discussed.

Unfortunately, Stedin does not have a clear transformer failure data base, so instead, the *corrective maintenances* were used. Corrective maintenances are carried out after a failure has occurred, or if standard time based maintenance has pointed out an issue that needs to be corrected. These corrective maintenances entails either a repair or replacement of a subsystem.

To identify the failure cause, the data was imported in R and search terms were used to extract a categorization from the free text fields. The categories are useful for studying the effects on different subsystems, and comparing the distributions to other databases, see figure 3.3. In this case the other two databases are from a world wide Cigre survey [24] and Continuon (now Liander) [25].

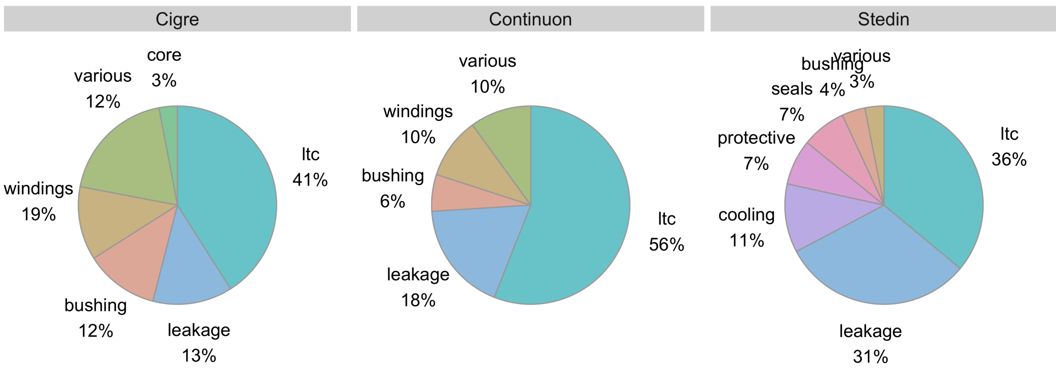


Figure 3.3: Failure cause statistics of world wide Cigre survey (±800 entries)[25], Continuon failure database (±50 entries) [24], and Stedin corrective maintenance database (470 entries).

Stedins database seems to agree with the other two distributions, with LTC and leakage failures being the most frequent problems. However, the percentage of leakages is quite higher compared to the other two. This might be due to the fact that not all the leakages from the Stedin database resulted in a failure, as it was not possible to seperate these from the data. Furthermore, Stedin transformers seem to have relatively low amount of bushing failures. This coincides with the experience of Marcel Hooijmans, Stedin's transformer asset manager, who recalls few problems with transformer bushings.

In conclusion, it can be said that the LTC and windings are the ***primary subsystems of concern***.

3.3 Failure Modes Selection

Based on the severity of a subsystem failure and the available data at Stedin, and the available condition assessment methods, the following subsystems are chosen to be considered in the developed condition assessment.

Table 3.1: Considered subsystems for condition assessment.

Subsystem	Considered	Reason
Core	Yes	DGA data present.
Windings	Yes	Furan data present. Failure effect entails transformer replacement
LTC arcing switch	Yes	LTC diagnostic data present. Failure effect is severe.
LTC off-load switch	Yes	LTC diagnostic data present. Failure effect is severe.
LTC drive	No	LTC diagnostic data present, but this only considers motor speed/switching time
Bushing	No	Although the failure effect is severe, there is insufficient diagnostic data present.
Oil	Yes	Oil diagnostic data present.
Tank	No	Oil contamination would appear in diagnostic oil data, but insufficient maintenance data present.
Cooling	No	Is corrected on sight during standard maintenance.
Protective devices	No	Are corrected on sight during standard maintenance.

Chapter 4

Transformer Condition

The condition or health of an asset is defined as its ability to perform a function, relative from its normal behaviour [23]. During a transformers lifetime it endures different kind of extrinsic stresses which contributes to its degradation, causing a change in its condition which can ultimately lead to lower performance, a fault or end of life (EOL). In this chapter, factors that affect a transformer condition and its indicators are discussed.

In section 4.1 the model of a condition change is discussed and the stresses imposed on a transformer are explored, to give an indication of what may be used as additional variables for the condition assessment.

Assessing the condition of a transformer entails understanding which characteristics of a transformer influences its functionality. These characteristics and their degradation mechanisms are presented in section 4.2.

Once these characteristics are known, the diagnostic techniques used for assessing the state of these can be discussed, as is done in section 4.3.

4.1 The Condition Change Process

The condition change process is a continous process which can describe the state of a transformer. The change process proposed in [23] will be presented. The following terms are defined to describe the process:

- The **state** of a system will be defined as a description of the current situation of a system with all accessible quantities such as e.g. colour, weight and age of a transformer.
- The **running mode** is defined as the mode of operation of a system. Examples of running mode are: under maintenance, under load, overloaded and under transport.
- The **condition** is defined as the ability of a system or component to perform its specified function.

The condition change itself is a result of the current condition undergoing the condition change process. The condition change process is a function that takes two inputs: the ***running mode*** and ***external stimuli***. The running mode includes relevant operation modes that affect the condition, e.g. the level of loading of a transformer. This factor is something which can be controlled by the system operator. The external stimuli are factors which can not be controlled continously, e.g weather, faults and social environment. A schematic of the change process is given in figure 4.1.

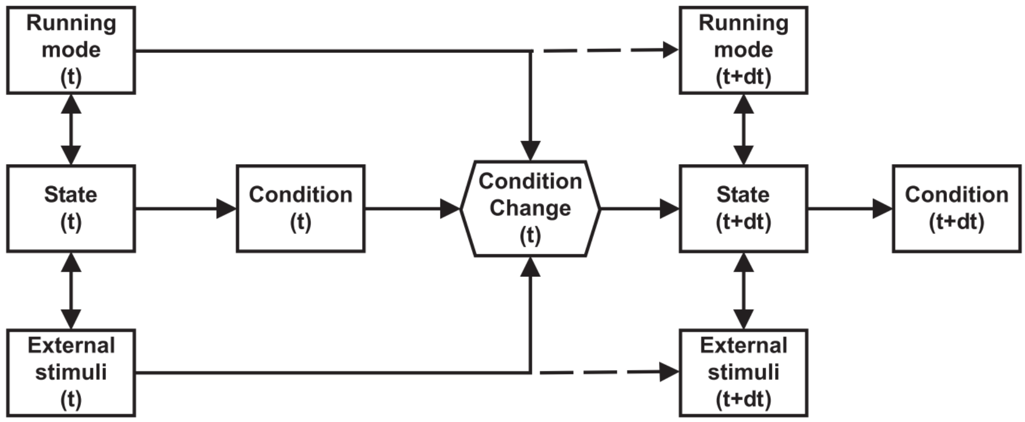


Figure 4.1: A state change process [23].

The condition change can of course either have a positive or negative effect on the condition. Maintenance work, which falls in the running mode, should improve the condition.

If this proposed change process has a probablistic input it is in essence a Markov process, specifically a Markov decision process (MDP), which can describe the change process in conjunction with maintenance actions. The property of this probablistic model is that the state change is dependent on the *current state* and *the actions applied*.

An example schematic of a MDP is given in figure 4.2, which was presented in [26]. In this schematic, D are set of system conditions, I is an inspection action, M is a minor maintenance action, MM is a major maintenance action. The transition from one state to another is probabilistic, however a maintenace action can alter the probability of going to a certain state. Not given in the schematic are the state transition probabilities.

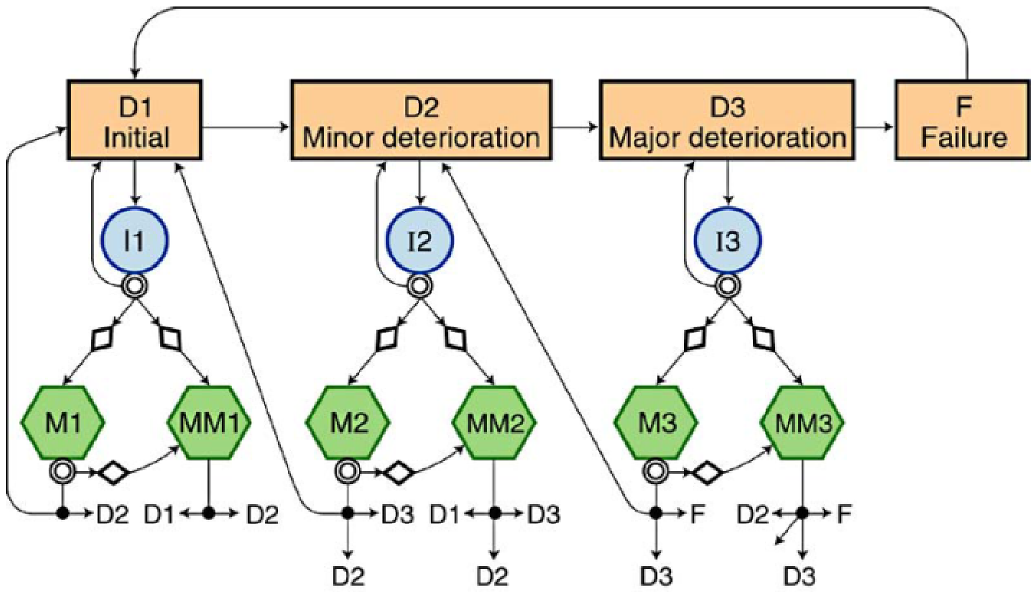


Figure 4.2: Application of the MDP [26].

4.1.1 Inputs of Condition Change Process

The changes in the condition of a transformer are a result of the stresses it endures. These stresses contribute to the change processes and can ultimately lead to a fault or end of life. The following classes are distinguished [23][27]:

1. **Electrical**: high voltage or electromagnetic fields can influence the insulation system of the transformer negatively. E.g. should the applied voltage be greater than the breakdown voltage of the insulation system, partial discharge (PD) or dielectric breakdown (DB) will occur, which degrades the dielectric properties of the insulation and cause high temperature rises.
2. **Mechanical**: the mechanical integrity of the transformer can be jeopardized due to mechanical forces such as thermal expansion or contraction and deformation of the windings due to electromagnetic forces caused by high short-circuit currents.
3. **Thermal**: thermal stresses contribute to changes in the chemical and mechanical state of the transformer. High temperatures contribute to faster chemical reactions, e.g. paper degradation, and mechanical stresses such as expansion and contraction.
4. **Chemical**: in some instances chemical reactions are separated from thermal stresses, even though thermal stress can speed up the these chemical processes. Examples of these chemical stresses are rusting of iron and oil deterioration due to acids.

These classes can influence one another and can not be seen as independent. Furthermore, a fault can be caused by a combination of these stresses, e.g insulating material can degrade due to mechanical and thermal stress. However, classification of these stresses identifies the sources of the various degradation processes and provide suggestions of mitigation measures.

4.2 Transformer Condition Indicators

The main subsystems of transformers which are exposed to degradation are [28]:

- Dielectric systems (oil, paper, windings)
- Magnetic circuit (core, clamping)
- LTC
- Mechanical parts (bushing, cooling, tank, etc.)

In this section we look further into the characteristics of a transformer that affect its operation.

4.2.1 Condition of Paper Insulation

The transformers under consideration are oil submerged type with paper insulation wrapped around the conductors. The condition of the paper depend on its ***dielectric strength*** and its ***mechanical structure***.

Its dielectric strength depends on the amount of water or other contaminants that is present within the paper. Water is a product of cellulose ageing, which if absorbed by the paper will increase its conductivity and the likelihood of forming gas bubbles, which reduces the thermal stability of the insulation system during overload conditions [9].

The insulating properties may also be affected mechanically by displacement and ageing. If the paper ruptures or disintegrates, a path for contaminants will be formed which can result in a winding short circuit.

The mechanical tensile strength of the paper depends on the composition of its molecules. The paper generally contains 90% cellulose, which is a polymer (chain) of glucose. The average units of glucose molecules (monomer) connected in a cellulose molecule (polymer) is called the ***degree of polymerisation*** (DP). In the paper change process, this oil-impregnated paper will deteriorate over time due to thermal, chemical and mechanical stresses. ***Acid-hydrolysis***, ***pyrolisis*** and ***oxidation*** result in splitting of the cellulose chains (***depolymerization***). The degradation of paper results in water, carbon monoxide, carbon dioxide and furans (chemical compound containing furan rings).

When the paper is produced, the average amount of monomer units in a cellulose molecule is 1200, however during manufacturing the structure is somewhat destructed, resulting in a DP of about 1000. For conventional Kraft paper the strength of the paper is vritualy constant for DP's between 950 to 500 , but below 500 the strength is directly porportional to the DP, see figure 4.3 [29] [9].

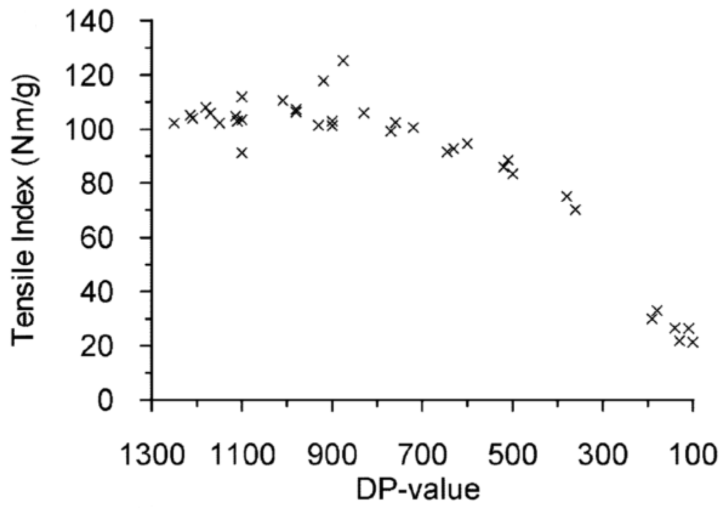


Figure 4.3: The relationship between tensile strength and the DP value of Kraft paper [29]

For the time - DP relationship, it has been shown that over most of the aging range, the relationship between time and the the logarithm of DP is linear [30]. However, increased temperature, moisture and the presence of oxygen will increase the degradation rate. The influence of temperature on the degradation rate is commonly described by a halving of life by every 10 °C rise. The presence of air accelerates the degradation by a factor of 2.5. The effect of water is a bit more complex because the introduction of water is not only due to external penetrations, but degradation of cellulose also produces water [27].

It has been found that under normal operating conditions (75 to 90 °C), the degradation of the solid insulation is more affected by moisture than temperature [31].

The reaction rate of the DP degradation can be modelled using the Arrhenius equation.

$$k(t) = Aexp(-\frac{E_a}{R_g T}) \tag{4.1}$$

Where A is a process constant expressing the probabililty that a reaction will take place and is determined by the contamination content of cellulos (moisture, acid, oxygen). E is the activation energy in kJ/mol, which determines the temperature dependece, R_g is the universal gas constant in J/K/mol. T is the absolute temperature in K.

4.2.2 Condition of Insulating Oil

The main tank of a transformer is filled with mineral oil. There are other insulating materials that may be better in terms of dielectric and thermal properties, however none achieve equal or better performance at an equal or better price. Thus mineral oil will continue to be used as a type of liquid insulation in electrical power equipment.

The function of insulating oil is to act as an insulating and cooling medium surrounding the conductors within the transformer. Heating of the windings can damage the windings and the solid insulation wrapped around it. The oil extracts heat from the windings and transfers it to the surrounding area.

The oil also serves as a ***diagnostic tool***. The chemical compounds in the oil can indicate the presence of faults within the transformer, more on this will be discussed in section 4.3.

The performance of mineral oil in an insulation system depends on some basic oil characteristics, as given in IEC 60422 [32]. The properties of the oil that it needs to posses to accomplish its tasks are:

- Sufficient dielectric strength to withstand electric stresses.
- Sufficient low viscosity to be able to circulate and transfer heat.
- Adequate low temperature properties in the lowest temperature expected at the installation site.
- Resistance to oxidation to maximize service life.

The presence of ***conducting particles*** in the oil will reduce its dielectric strength. An example of these particles is water, originating either from the breakdown of solid insulation or by ingress through breathing valves. Gas particles with a lower breakdown voltage can also come between conducting parts, causing partial discharge or short circuits[10].

The breakdown of oil due to oxidation will produce ***sludge***, which will increase the viscosity of the oil. This increase in viscosity will lower the ability of the oil to withdraw heat. High temperatures due to arcing will also produce sludge.

The oil temperature may drop to ambient temperatures when the transformer is not loaded. Should the transformer then come under load, the oil will not cool sufficiently if the temperature is below its pouring point, which is the temperature at which a liquid loses its flow characteristics.

4.2.3 Condition of Magnetic Circuit

The magnetic circuit is the driving mechanism in the transformer. Defects in the circuit will negatively impact the transformer effeciency and will lead to extra heating, which will increase the degradation of other systems. A good magnetic circuit is characterised by ***maximum magnetic coupling with minimum heating*** due to eddy currents within the core and outside of the core due to leakage flux.

The condition of te magnetic circuit changes due to the insulating layers between the laminations being damaged or by gaps between the layers, as this causes an increase in the eddy currents resulting in more heat. All types of deformations that increase the leakage flux, e.g. winding deformation, are also detrimental to the condition of the magnetic circuit [5].

4.2.4 Condition of Tap Changer

The arcing switch of an LTC experiences arcing in its normal operation and is therefore i usually placed in a seperately sealed compartment within the transformer tank to prevent damaging other components in the main tank. This separate compartment can be openend and serviced without having to open the main tank which would result in contaminants entering the main tank. The off-load switch is usually placed in the main tank. The LTC is one of the most occurring sources of failures according to multiple surveys [24][17][33] and thus it is a major condition indicator with respect to fault probability.

The condition of a tap changer is determined by the components that affect its ability to select another tap *without interrupting the load* and to conduct properly. This ability is determined by:

- The resistance of the contacts. This can be affected by contact pressure, oil deposition and contact surface and contact wear or pitting.
- The switching time. This can be affected by defects in the drive mechanism.

There are operating (running mode) differences between the arcing switch and off-load switch, and therefore there are also different degradation mechanisms for both.

One which is present in both is the so called *long term effect*: when a contact is not switched regularly, a thin film layer of oil wil deposit on it, resulting in lower conductivity and increased power losses. At an early stage of the long term effect the thin film can be wiped off by selecting the contact, however if this is not the case the layer will develop further up to the point that the high temperatures will result in oil decomposition. This will result in carbon between the contacts forming pyrolytic carbon, a phenomenon reffered to as coking. This occurs at temperatures over 300 °C. The contact material will wear off and pitted spots form on the contacts. The contact is then damaged beyond repair.

The second degradation mechanism occurs at the arcing switch, called *contact pitting*. This arcing that occurs damages the contacts, resulting in pitted spots on the contacts. The arc is usually quenched at the first zero current.

The long term effect can also occur on the arcing switch, however it does not develop as fast compared to the tap selector because of more frequent movement of the arcing switch contacts [15][34].

In figure 4.4 an overview of the degradation mechanisms and where they occur can be seen.

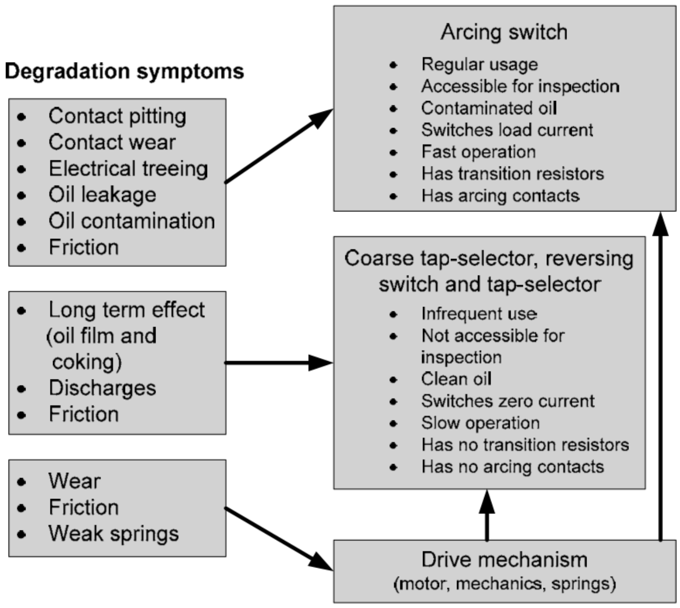


Figure 4.4: Degradation mechanisms of the LTC [15].

4.2.5 Condition of Bushings

The condition of the bushings is determined by its ability to insulate the conductor from the transformer tank. The following serve as indicators [35][22][16]:

- Contaminations on the bushing surface from the surrounding air.
- Oil contamination with water, particles and oil degradation products.
- Presence of oil leaks due to gasket aging.
- Partial discharge activity, which can develop to a dielectric breakdown.
- Bad conductor connection due to e.g. bad bushing clamp.

4.2.6 Condition of Tank

The tank protects the transformer from environmental stresses and contamination. The condition of the tank is determined by the paint/corrosion and the condition of the gasket and seals.

Environmental stresses result in paint wear and ultimately in corrosion. The position of the corrosion also determines the severity of consequences, e.g. if the corrosion occurs at the bottom of the transformer, then the transformer might have to be lifted to be serviced, which increases the costs by a lot.

The seals and gaskets should keep oil inside and moisture out, however over time they lose their elasticity and become more brittle. This might lead to cracks trough wich the oil may leak out or contaminants might enter [22].

4.3 Transformer Diagnostics

4.3.1 Insulating Oil

As mentioned in section 4.2.2, the oil has dielectric and cooling properties which prevent transformer failures. There are several properties of the oil which can be tested to assess the condition of the oil with respect to these aspects. The general routine tests, which are also employed by Stedin, are discussed below according to IEC 60422 standard [32] .

Color and appearance: the color of the oil is not a critical property, but it is useful as a comparative evaluation. Should the color change rapidly, it may be an indication of oil degradation or contamination.

Breakdown voltage: the breakdown voltage of the oil is a quantitative measure of its ability to withstand electric stress and has a high importance. Water and solid particles can reduce the breakdown voltage dramatically.

Water content: water in oil affects the breakdown voltage and the aging rate of the liquid and solid insulation. Water enters the system by ingress of moisture from the surrounding air and by degradation of insulation also produces water. The water may be present as a solution in the oil, or bonded in the solid paper insulation.

Acidity: the acidity is a measure of the acidic constituents or contaminants in the oil. The rate of increase of the acidity is a good indicator of the ageing raate. Furthermore the acidity level can be used as a general guide for determining when the oil should be replaced.

Dielectric dissipation factor (DDF) and resistivity: These parameters are quite sensitive to the presence of polar contaminants and ageing products. The general relationship between DDF and resisitivity is that resistivity decreases as DDF increases. High values of DDF, or low values of resistivity, is an indication of bad dielectric losses and/or insulation resistance.

Sediment & Sludge: Sediment is a gathering name for insolubale materials in oil. Sludge is a polymerized degradation product of solid and liquiq insulation material, which is soluble in oil up to a certain temperature limit and deposits as a solid afterwards.

The presence of sediment and sludge can change the electrical properties of the oil and degrade the cooling properties, which improves the thermal degradations of insulating materials.

Interfacial Tension (IFT): The interfacial tension between oil and and water can be used to detect soluble polar contaminants. The rate of decrease of IFT is can be an indication of compatibility problems between the oil and transformer materials, or of contamination. After a certain treshold value, the oil should be investigated further.

4.3.2 Dissolved Gas Analysis

When internal dielectric or thermal faults occur, gasses are produced as a result of oil and solid insulation decomposition, which dissolve in the oil. The composition of these gasses is dependent on the type of fault that has occurred, and thus an analysis on the amount of gas in the oil can give an indication of faults that have occured or that are still present. This diagnostic method can detect the fault type, but not the location. DGA can detect the occurence of the following faults:

- Partial discharge
- Discharges and its severity
- Thermal faults and its severity

The interpetation of these gasses are determined by standards such as IEC 60599 [32]. The amount of gas and the relative ratios can detect problems in the insulation system, however a trend analysis must be done in order to assess the severity and progression of these faults [1].

This diagnostic tool can be used for both components in the main tank and the arcing switch compartment, however some network operators (Stedin included) service the arcing switch yearly and a visual inspection can be performed instead of DGA.

At Stedin, DGA analysis is performed on a yearly basis for al transformers.

4.3.3 Furan Analysis

If the DGA analysis surpasses a treshold value of CO and CO^2, this indicates paper degradation and warrants further investigation on the condition of the paper insulation. This is done by determining the DP of the cellulose.

Taking paper samples on a regular basis is not feasible because this entails opening the whole transformer, which means high cost and a long down time of the transformer. The common way of assessing the DP is by assessing the amount of paper degradation components which is present in the oil. When paper degrades, ***furans*** are formed. The most stable and abundant furan is 2-furaldehyde (2-FAL), and thus this one is used for the analysis. Using various models found in literature, a DP value is found.

However, the determination of "the DP" of the solid insulation is not trivial because the degradation of the paper does not happen uniformly over the entire winding, and thus furan analysis determines the ***average DP***. At the top of the winding, the temperature is higher and the paper degrades faster. The scale of variations between the average DP and minimal DP were found to be as follows [36]:

$$\overline{DP_{av} - DP_{min}} = \begin{cases} 260 \pm 134 \text{ for generator step up transformers} \\ 194 \pm 75 \text{ for grid transformers} \\ 151 \pm 27 \text{ for railway transformers} \end{cases}$$

Furthermore, pressboard is also used in transformer construction which also produces furans when it decomposes, which is not distuinguishable from the furan produced from the paper insulation. One would like to know the critical DP of the furan, i.e. where the paper has degraded the most since this is the part that is the most susceptible to a fault. This spot is usually at the top of the middle low voltage winding [37]. This can not be achieved with furan analysis, resulting in significant discrepancies between the calculated average DP and the worst case DP.

The models for determining the DP from furan analysis are not always accurate. It has been shown that in old transformers, the furan and DP relationship is no longer accurate [37]. A post mortem comparison between paper samples and furan-DP models has been done in [36], see figure 4.5 for the results.

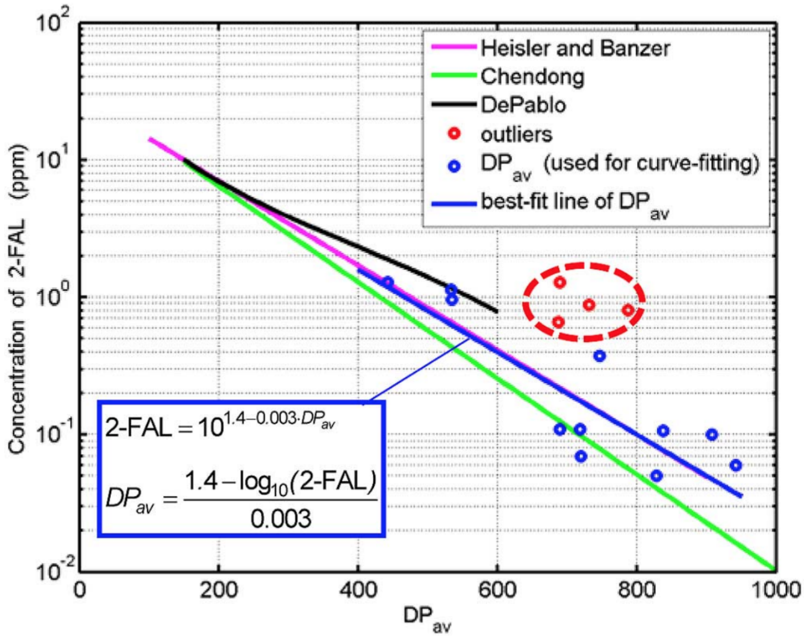


Figure 4.5: Post mortem paper sample analysis compared to furan-DP models for grid transformers[36].

Furan analysis is still a useful diagnostic tool, but care must be taken with its accuracy, especially with older transformers where high temperatures (160-200 °C) might have evaporated the furan. Furan analysis may be most useful as a troubleshooting tool, i.e. indicating high rates of ageing, rather than monitoring of normal ageing [38].

At Stedin, furan analysis is caried out after DGA indicates abnormal values of CO and CO^2 in order to save on costs.

4.3.4 Winding Diagnostics

Winding resistance can be used to indicate the condition of the tap changer contact and the winding conductor. This requires an outage and isolation of the transformer, thus it can not be done regularly. Variations of more than 5% (corrected for temperature) may indicate transformer damage[39].

The winding turn ratio test measures the voltage transformation, which can be used to derived the effective turn ratio. This test can indicate [23][39]:

- Short circuited or open windings
- Magnetisation problems such as core or winding deformation

4.3.5 Bushing Diagnostics

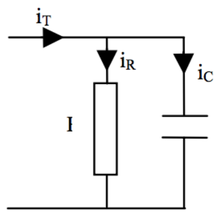


Figure 4.6: Equivalent circuit of bushing [40]

Applying an AC voltage to an insulation system causes dielectric losses regardless of the insulation condition. New insulation usually has a very low loss factor and a high loss factor might indicate aging or other problems in the insulation structure. This loss factor is usually measured in terms of ***dissipation factor*** (tan δ) or power factor [40]. In figure 4.6 the equivalent circuit is given. If there are structural changes in the insulation system, this will affect the value of the capicator and/or the resistance, resulting in a different loss factor.

A big (rate of) change in the loss factor will indicate that there are problems in the bushing such as

- High PD activity
- Problems in insulating oil or paper
- Bad conductor connection

PD activity can also be measured acoustically, with the advantage that the transformer should not have to be taken offline.

4.3.6 LTC Diagnostics

Visual inspection The condition of the contacts can be determined visually, however only the arcing switch is easily accesible for inspection as it is located in a separate compartment. The off-load switch is located in the main tank and thus not easily accessible, as the main tank should then be dismantled. The condition of the contacts of the tap selector are diagnosed with other methods.

Static resistance measurement (SRM) The condition of the LTC contacts can be measured by contact resistance measurement. This test is performed while the tap changer is motionless, hence the word static in the name. Due to the big inductance of the transformer winding, this measurement takes relatively long as the circuit must reach its steady state for each measurment.

The DC resistance of the winding and contact is measured for each tap position. If all is correct, the graph will be linearly increasing or decreasing [15].

Dynamic resistance measurement (DRM) DRM is suitable for detecting irregularies in the OLTC contacts just like the SRM, however during this measurement the tap changer is operated. The tap changers do not remain at the same position long enough for the ciruit to reach steady state. This makes the DRM less accurate than SRM, but it provides more information about the type and location of the defects, e.g. defects concerning the transistion time [15].

At Stedin the arcing switch is serviced by visual inspection yearly and replacements are done if necessary. The tap selector is diagnosed using DRM between every one and five years, depending on the results of the last test. This diagnostic tool is also referred to as "regelschakelaar diagnostiek" (RSD).

Motor and drive mechanism diagnostics The condtion of the motor can be measured by doing power measurement for the motor, as there is a relationship between the power and the delivered torque. If there is a change in the needed torque, it can be an indication of defects in the motor or the drive mechanism.

4.3.7 Infrared Thermography (IT)

IT can indicate hot spots in the transformer. The location of the hotspot can of course indicate what subsystem is experiencing a thermal fault. Examples of faults:

- Bad connection in bushing
- Faulty contact in the LTC
- High losses in magnetic core

4.3.8 Frequency Response Analysis

This test entails measuring the transformer impedance over a range of frequencies, resulting in a frequency response. This response is compared to a previous analysis or a reference set. This test can indicate damages such as [23]:

- Winding deformation
- Winding short circuit
- Core degradation

4.3.9 Visual Inspection

Visual inspection by maintenance workers is a widely used diagnostic tool, which is also very practical. It is useful for detecting aspect such as:

- Bushing surface contamination or leakage
- Arcing switch contact condition
- Tank paint and leakage

Chapter 5

Transformer Condition Assessment Techniques

In the previous chapter the condition of a transformer and its condition parameters have been discussed. The relative importance of each parameter and the methods to aggregate them into one index which describes the health of the complete transformer will be discussed in this chapter.

A quantitative measure for a transformer's condition will be refered to as its ***Health Index*** (HI). A ***HI method*** is a way of combining complex condition information to give a single numerical value as a comparative indication of overall condition [41]. There are many HI methods available in literature, thus developing a completely new one would be time consuming and probably not better than those created by experienced specialist. What should be determined however, is which (combination of) HI method(s) will be suitable to use at Stedin, considering the available data and objectives.

Choosing a HI method dependends on the objective of the condition assessments and the amount and quality of available transformer data. The objectives will be discussed in section 5.1.

How the HI methods combine the transformer data into a HI, will be discussed in section 5.2.

Reviewing the HI methods found in literature is done in section 5.3

5.1 Objective of Condition Assessment

It is important to define the purpose of the health index, because there is a considerable difference between the data requirements when assessing the condition for maintenance purposes and ***EOL*** prediction [41]. Certain subsystems of the transformer are less critical to its EOL, as it can undergo maintenance to be restored or cost-effectively replaced.

Furthermore, there are also some critical objectives for a well formulated HI. The HI should [42]:

- indicate the suitability of the asset to continue its service, and be representative of the overall asset health.

- contain objectives and verifiable measures of asset condition, as opposed to subjective observations.
- be understandabily and easily interpreted.

The objective of Stedin's HI is to aid in decision making regarding EOL of the transformer *and* maintenance planning. Stedin would like to use TF data for the following:

1. **Operational planning**: Ranking of transformers to indicate priority with respect to the attention needed to assure proper functioning of the grid. This ranking should help with short term planning and decision making (5 years).
2. **Strategic planning**: Making predictions on the moment of TF EOL/replacement. This should help with long term planning and decision making (60 years).

HI is a powerful tool for a ranking system for operational planning because it can identify investment needs, prioritize investments and furthermore the condition of each individual is assessed.

HI can be used indirectly in strategic planning as an input for e.g. a survival model. The purpose of the HI is thus to help asset management on the short term, including maintenance strategies. This means that the condition of replaceable/maintainable subsystems of the transformers must also be taken into account.

Applying transformer health and risk scores provides a basic means of asset ranking. Transformer HI is by itself not a direct indicator of a transformer's problems, but it does provide a relatively simple means for scoring a large population of transformers. HI is thus not an absolute measure, as there is still a need for engineering judgment. Combining HI with a measure of consequence allows a risk ranking that is useful to prioritize action plans for all types of risks [19].

5.2 Categorization of HI Assessment Methods

There is an extensive amount of literature regarding different HI methods, which cover different transformer condition indicators and subsystems. The HI methods will be categorised by the following properties:

1. **Input parameters**: the inputs used varies across the HI methods. These do not only include measurements on the condition indicator themselves, but also aspects that affect them, such as operating and weather conditions.
2. **Approach**: the approach describes the model that transforms the input parameters to a numerical HI. These function can be further categorised as [43]:
    - Data driven approach
    - Physical model app, the so called physics-of-failure (POF) models

5.2.1 Differences in Input Parameters

The input parameters used in HI vary based on the objective. The objective influences the parameter choice because the parameters depends on the subsystems that are taken into account, which is again dependent of the objective (e.g. for operational planning the replaceable systems with relatively low impact should on EOL also be taken into consideration).

The amount of input parameters should be comprehensive, but not redundant. Acquisition of data introduces expenses and asset managers should not carelesly request everything possible without considering its utility.

5.2.2 Difference in Approach

The PoF models are based on degradation processes that result from mechanical, chemical, electrical and thermal processes. The transformer specific change processes were discussed in section 4.1.1. The PoF approach is to calculate the cumulative damage due to these various stresses of an individual asset given the usage condition. This cumulative damage is then converted into scores used to compute the asset health.

The data driven approach estimates the health of a system by deriving relationships from the given data. This approach can be seen as a black box process, as it does not include detailed information on material properties but rather derives relationships and patterns that exist in the data based on e.g. covariance, correlation, residual and inference patterns between system variables and system stresses. The data driven approach can be further categorised into two groups: *machine learning* (ML) and *classical statistics*.

ML translates raw data to useful information by reasoning, classification and clustering. There are two types of ML algorithms; *supervised* and *unsupervised* learning. The difference is mainly in the training data that is given and the relationship that is sought. Supervised algorithms are given input data which are labelled with their corresponding outputs to derive a relationship, e.g transformer data as input and failure rate of that transformer as output. Unsupervised algorithms are given only input data and given the task to find hidden structures within the data, e.g. clustering of transformers with similar behaviour.

Statistical techniques are divided into *parametric*, *semi-parametric* and *non parametric* methods. The distinction in usage is based on whether the distribution of the data is known or not.

In table 5.1 a summary is given on the comparison between the approaches.

Table 5.1: Comparison PoF and data driven approaches[43].

Approaches	PoF approach	Data-driven approach	
		Machine Learning	Statistical
Advantages	♦ Under actual application conditions ♦ More accurate	♦ Flexible ♦ Adaptable ♦ Suitable for all levels	♦ Easy to conduct ♦ Economical
Disadvantages	♦ Sufficient product information is required ♦ Good understanding of the failure mechanisms is required ♦ Skilled personnel is required ♦ May not be quite suitable for system level analysis	♦ Training data should be preprocessed ♦ Training data are not easy to validate ♦ Computational complexity	♦ No consideration of usage environments and operation conditions, ♦ Large amount of failure data is needed

5.3 Review of Existing HI Methods

In this section previous research on the two principal approaches towards HI calculation are reviewed. These implemented HI calculation methods will be reviewed on the following criteria:

1. **Availability of required input parameters**
2. **Objectiveness**
3. **Fault mechanisms that are taken into account**
4. **Comprehensiveness**

Most likely a custom combination of HI implementations will be used to satisfy all Stedin's needs, given its data constraints.

5.3.1 PoF Approaches

Scoring method

There are numerous PoF HI methods developed which all cover different subsets of transformer health indicators [44, 1, 45, 46, 47, 48]

However, the method used to calculate the HI with the health indicators is generally the same, namely by a scoring system. The scoring system divides the HI into smaller portions (health subindices) and assigns a (discrete) score to each condition indicator based on its value, e.g. if the DP of paper insulation is between 200-300, the DP subindex receives a score of 1 out of 4. These functions will be referred to as *assessment functions* and are usually defined based on standards, guidelines, historical information and theoretical knowledge [49]. These scores are then multiplied by a weighting factor to represent the relative importance to one another. The HI is then calculated as the sum of these weighted scores, usually divided by the maximum possible score. It can be defined as

$$HI = \frac{\sum_{j=1}^{n} S_j \cdot w_j}{\sum_{j=1}^{n} S_{jmax} \cdot w_j}$$

where n is the number of condition indicators, S_j is the score resulting for the jth condition indicator, S_{jmax} the maximum possible score for the jth condition indicator, and w_j is the relative weight for the jth condition indicator. See figure 5.1 for an overview of the process.

Figure 5.1: The common HI formula.

There are some drawbacks and criticism to this approach. It can be argued that the determination of each subindex is key to the quality of the evaluation, thus the relative weighting is crucial [50]. Most of the HI methods use expert opinion for their weight determination process. These opinions are most commonly used in an analytical hierarchy process (AHP) to determine the weighting.

In the AHP, multi criteria decision making (MCDA) is approached by structuring the criteria into a hierarchy, assessing the relative importance of the criteria and then comparing the alternatives for each criterion to determine an overall ranking of the alternatives. AHP is a tool for checking the consistency of the evaluations within a team and reduces bias in decision making [51]. However, the results are to an extent still subjective and different teams will still have different results.

Other, less used, methods for determining the weighting are the Delphi method and least square method [52]. The subjective aspect in these methods, incuding AHP, will cause discrepancies between the weighting given by different experts, which makes the methods inconsistent on a wider scale.

Another point of critism is that the numerical boundaries of the assesment functions for determining the discrete scores can not be determined precisely. This means that there is a region that is not well defined. Some HI models overcome the objectiveness and boundary problem by using ***entropy weighting*** [50] and ***fuzzy logic*** [53], respectively.

Fuzzy Scoring

Fuzzy logic defines overlapping thresholds, thus instead of getting a discrete score, the condition indicator is given a level of membership to a lexigraphical value, see figure 5.2. Using this in combination with expert rules (rules in the form of "if-then"), a HI can be calculated. This method thus still uses expert opinion for formulating the rules. See fig 5.3 for a schematic of general fuzzy logic systems.

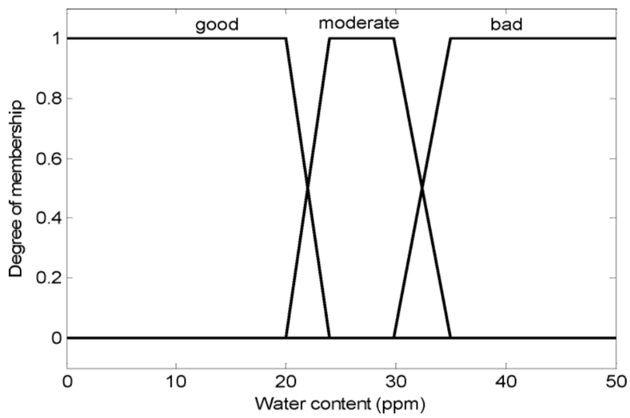


Figure 5.2: Example of water content of transformer oil being given a level of membership to a condition.

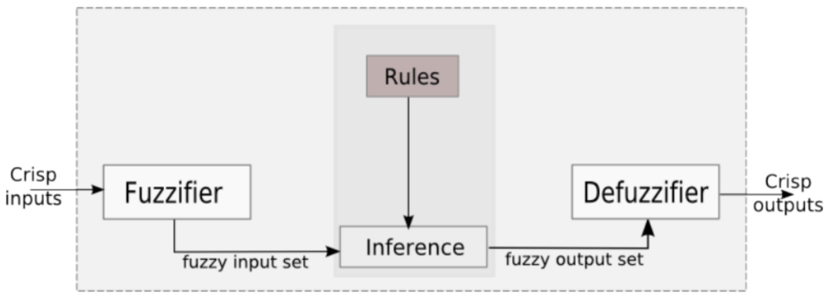


Figure 5.3: Fuzzy logic system.

Entropy Weighting

The entropy weighting method considers the level of information in a condition indicator, based on the amount that it varies within the observed period. Not only does it take care of the subjective aspect of expert weighting, it also overcomes the fact that fixed subjective weighting can not fully reflect a condition indicator's ***rate of change***, and thus omits the the fact that a condition indicator is degrading rapidly.

The basic principle of entropy weighting is to determine the weight according to its relative degree of change. This results in a dynamic weight, as the *relative* change is a measure that may vary when more data is gathered.

The algorithm takes input data into a $m \times n$ judge matrix $P = (p_{ij})_{m\times n}$, where m is the number of observations and n the number of condition indicators. This matrix is then transformed into the $m \times n$ unitary judge matrix $U = (u_{ij})_{m\times n}$ by the transformation defined as

$$u_{ij} = \frac{p_{ij} - p_{min}}{p_{max} - p_{min}}$$

where p_{min} and p_{max} are the worst and best value of the same condition indicator in all the samples. U is then used as an input to calculate the entropy H of the corresponding condition indicator as the following:

$$H_j = -(\sum_{i=1}^{m} f_{ij} \ln f_{ij}) / \ln m$$

In which

$$f_{ij} = \frac{1 + u_{ij}}{\sum_{i=1}^{m}(1 + u_{ij})}$$

The correspoding weight for the jth condition indicator is then

$$w_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}$$

However, this method only gives the health of the transformer relative to the time frame under which the condition indicators have been observed. This might pose a problem because most of the stored transformer data does not date back to the moment it entered service [50].

5.3.2 Data Driven Approaches

The statistical methods of data driven approaches are suitable for population studies, however as the goal is to find the condition of an individual transformer based on operating conditions and diagnostic results, these will not be considered further for a HI method.

Some ML approaches towards transformer HI have been found in literature [54] [55] [56] [57]. In the ML approach, the data is split into a training data set and a verification data set. The training data set is given to the algorithm to derive the model and the verification data set is used to assess the accuracy of the model. Prior to training and verifying the data, the relevantness of the input variables can be assessed in order to select the best input, this is referred to as ***feature selection***. See figure 5.4 for a overview of the application of ML for condition assessment.

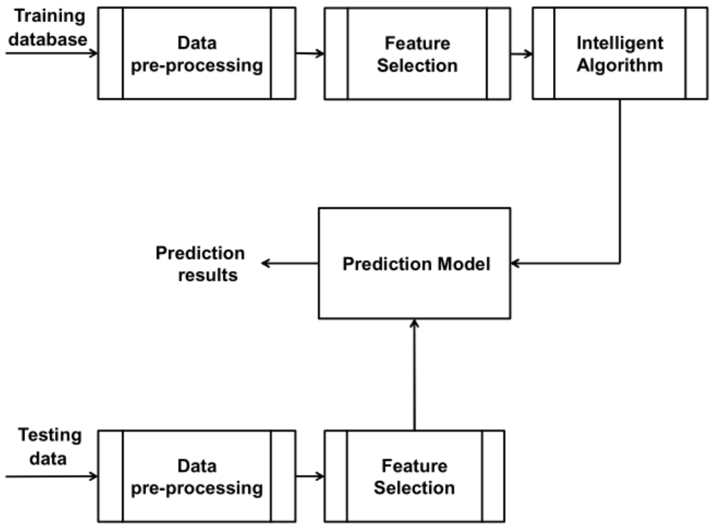


Figure 5.4: Overview of the application of ML [58].

The most common encountered ML algorithms used in transformer condition assessment literature are:

- Neural networks (NN)
- Support vector machines (SVM)

These approaches are all supervised learning algorithms when it comes to calculating a numerical HI. This means that the training data given to the algorithms is of the *labeled form* $S = (x_i, y_i)|i \in [1, c]$, where x is the vector containing data of transformer i, y is the HI of that particular transformer and c is the number of observed transformers.

Up till now, the implemented models found in literature are aimed at HI with respect to end of life assessment; they only include some oil diagnostics, while excluding other condition indicators related to maintenance. This is a gap in the research area that can be filled by this research.

Because the algorithms needs a HI labeled to the data of each transformer (not only for deriving the relationship but also for verification), a HI for each transformer must be derived prior to training the algorithm. A PoF approach is thus needed to produce training data and giving this data to a ML algorithm will just result in an approximation of the PoF model if the same input data is used. However, there are still some advantages to implementing a ML approach. ML can find a relationship between quantities for which the relationship is not yet known, e.g. weather and tank corrossion. Furthermore, by using feature selection algorithms, the most informative inputs for HI calculation can be selected. Not only can this improve the effeciency of the ML algorithm [58], but a better selection of required inputs is also created, which allows better allocation of resources in terms of data acquisition. Examples of feature selection techniques are [58][59] :

- Correlation based selection
- Minimum-redudancy-maximum-relevance (mRMR) based selection
- Forward search selection

5.3.3 Choosing a HI Method

Based on the criteria discussed in section 5.1, the chosen HI method will be that of a PoF approach. This is due to the fact that the ML approaches are done with supervised learning, for which a proper HI already needs to exist, and at the moment Stedin posesses HI categorisation that is not well suited for this. This is due to the fact that the current HI methods puts transformers with small defects in a bad category just to put it under close attention, even though it can be fixed easily. This makes it impossible to distinguish transformers which are actually in a bad condition from transformers which have a defect that can be easily repaired.

The approach in [1] will be used, as this is the most comprehensive. Although it does put carbonoxide values, which is only produced via paper degradation, under the DGA/faults subindex. The approach in [45] is also a good approach and the intention was to implement this and compare, but there was not enough time. This approach defines different assessment functions based on the condition indicator value, and also correctly puts carbonoxide values under the paper sub-health index. The data that Stedin does not have, can be left out of the scoring system, so it is possible to easily pick and choose. The objectiveness of the scoring system is less than the other methods discussed, but it was still considered the best, as there was not enough data available for the other methods or the added value did not compensate for the added complexity.

Application of the entropy weighting is not well suited because it makes a relative index based on the observed period. Stedin does not have accesible data of transformers dating back to the installation date, with the exception of newer tranformers. Furthermore, the expertise of specialists is not utilised whatsoever.

The fuzzy logic technique introduces a lot of complexity, while still needing the opinion of experts for the formulation of the expert rules, which are also not well documented in literature. Furthermore, defining the overlap of the membership functions is still a subjective matter. The added value of fuzzy logic, in this case, increases with a lesser amount of categories to apply a membership to. This is because the category choice becomes more important if the condition scale is divided into bigger intervals. In the scoring system e.g., the assessment function will divide the condition scale into six numerical categories. It then has less impact on the outcome wether the condition indicator falls e.g. into category 3 or 4.

Chapter 6

Survival Modelling

In this chapter the techniques to predict an individual transformer's probability of failure, will be discussed. The goal is to develop a model which can predict a transformers time to failure. One of the challenges when fitting such a model, is the ***absence of events*** in the data. This can be due to the fact that the subject has experienced the event outside of the observation period, or the subject dropped out of the study during this period. These type of subjects are usually present in the data, especially when the observation period is short compared to the average event time (which is the case for this study). This phenomenon is referred to as ***censoring***, and can be effectively handled using ***survival analysis techniques*** [60].

Survival analysis is a subfield of statistics, which provides a means to dealing with censored data, which is the type of data in most real-world applications. Although it has the term survival in the name, it can be used to predict the time to any type of event, alternative to death or failure. The event time will be considered to be a continuous random variable, which allows the application of statistics.

Within survival theory, several methods have been developed. A review of the methods have been given in [60], see figure 6.1 for an overview. Traditional statistical methods aim to find a function to describe the survival probabilities. The families of functions can be categorized in varying levels of parametrization:

- **non-parametric**: having no parameters.
- **parametric**: having parameters which are found by optimizing a statistical quantity.
- **semi-parametric**: a mathematical combination of a parametric and non-parametric function.

In addition to these traditional methods, machine learning tools have also been employed. When applied to survival analysis, the challenge for these algorithms is the difficulty to deal with censored information. ML algorithms are effective when there is a large number of events and a reasonable amount of variables. These algorithms differ from the traditional statistics in the fact that they are designed for higher dimensional problems and focus less on the distribution of the event times and the statistical properties of the parameter estimation [60]. However, due to time constraints and the fact that it is doubtful whether the data quality and the amount of data is up to par, these will not be explored further.

This chapter begins with general survival theory and the way it deals with cen-

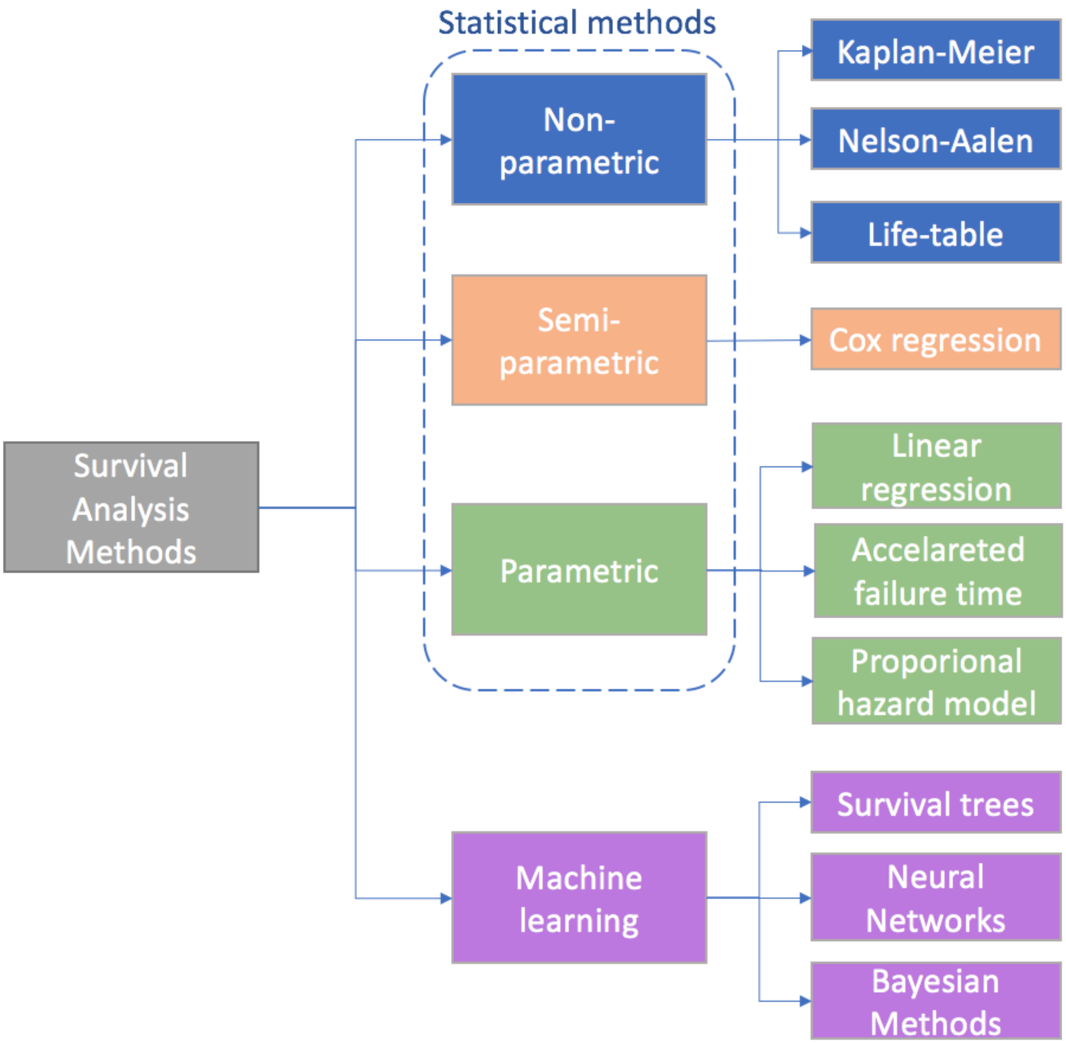


Figure 6.1: Survival analysis methods.

sored data in section 6.1. In section 6.2, the survival model types under consideration will be discussed, followed by the validation methods in section 6.3.

6.1 Survival Theory

6.1.1 Survival and Hazard Functions

Assume T to be a continuous random variable with probability density function (PDF) $f(t)$ and cumulative distribution function (CDF) $F(t)$, which gives the probability that an event has occurred by duration t. This event at time t is usually a death, e.g. a fatal transformer failure. The terms death and event will be used interchangeably from now on. For convenient purposes, the *survival function* is defined as the complement of the CDF:

$$S(t) = Pr\{T \geq t\} = 1 - F(t) = \int_t^\infty f(x)dx \tag{6.1}$$

The survival function gives the probability of being alive just before duration t, or generally, that the event of interest has not ocurred by duration t.

The *hazard function* is another characteristic of the distribution T, which can be seen as the instantaneous rate of occurrence of an event. The hazard function is defined as

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{Pr\{t \leq T < t + \Delta t | T \geq t\}}{\Delta t} \tag{6.2}$$

This expression gives the conditional probability that the event occurs in the time interval $[t, t+dt)$, given that the event has not yet occurred, divided by the width of the interval. Taking the limit of this interval to zero, results in the instantaneous rate of death. Applying the rule of conditional probability results in

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{Pr\{t \leq T < t + \Delta t\} \cap Pr\{T \geq t\}}{\Delta t \cdot Pr\{T \geq t\}}$$

The expression in the numerator is the intersection between T being in the interval $[t, t+dt)$ and $T \geq t$, which is the probability that T is in the interval; $f(t)\Delta t$ for small Δt. The probability in the denominator is by definition $S(t)$. Applying the limit produces the useful result

$$\lambda(t) = \frac{f(t)}{S(t)} \tag{6.3}$$

Considering that $f(t)$ is the negative derivative of S(t), the equation can be written as

$$\lambda(t) = -\frac{d}{dt} \log S(t) \tag{6.4}$$

This can be integrated to achieve an expression for $S(t)$, given the boundary condition $S(0) = 1$ (as the event has to occur after $t = 0$):

$$S(t) = exp\{-\int_0^t \lambda(x)dx\}$$

$$S(t) = exp\{\Lambda(t)\} \tag{6.5}$$

The integral is called the *cumulative hazard*, $\Lambda(t)$, which can be seen as the sum of risks during the time interval $[0, t)$. Equation 6.5 is an alternative but equivalent characterization of distribution T.

Another useful property of the survival function $S(t)$ is that mean or *expected life*, μ, can easily be calculated with it. Consider the definition of mean life, wich would be computed by multiplying the t by the desity $f(t)$ and integrating:

$$\mu = \int_0^\infty t f(t)dt$$

Integrating by parts and using the fact that $-f(t)$ is the derivative of S(t) with boundary conditions $S(0) = 1$ and $S(\infty) = 0$ will result in

$$\mu = \int_0^\infty S(t)dt \tag{6.6}$$

The goal of survival modelling is to fit either $S(t)$ or $\lambda(t)$ to the survival data of all the subjects [61].

6.1.2 Censoring Data

There will be cases for which the event has not yet occurred within the observation period, but this data can still be used. There are two ways of censoring the data:

- Type I: n units are followed for a fixed time τ.
- Type II: n units are followed until d units have experienced the event.

The censoring mechanisms essentially lead to the same likelihood function (see section 6.1.3), if the censoring of an observation does not provide any information regarding the survival of the unit beyond the censoring time. This is reffered to as non-informative censoring. It does affect the expected number of occured events. Furthermore, there are three types of censored data:

- Left censored: the event happened prior to the observation period. This gives an upper bound for the event time.
- Right censored: the event happened after the observation period. This gives a lower bound for the event time.
- Interval censored: the event happened within an interval, but the exact time is not known. This gives an upper and lower bound for the event time.

When under study, a subject will thus provide one of two pieces of information: a survival time or a censored time, see figure 6.2.

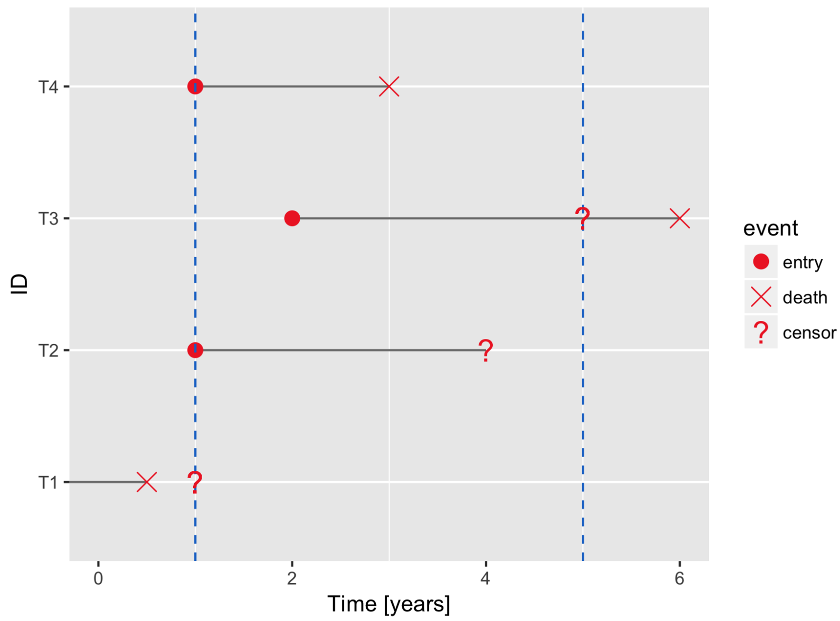


Figure 6.2: Example of survival data of four subjects; T1 - left censored, T2 - dropped out, T3 - right censored, T4 - death . The dashed lines represents the observation period and "entry" represents the point at which they entered the study.

In this study, type I censoring is applied as the observation time is fixed. Furthermore, the only censoring that is applied is right censoring; there are transformers that have not experienced a failure yet, but they will eventually fail at some point in the future.

6.1.3 Likelihood Function

The likelihood function is the cumulative probability that an amount of events have occured. This function is useful for optomization in algorithms, as it can be used to find the point at which the cumulative probability of the events is at its maximum. This can be used to e.g. find the best parameters of a hazard function that fits the observed events.

Should a unit i fail at time t_i, its contribution to the likelihood function is the probability density at that point in time

$$L_i = f(t_i) = S(t_i)\lambda(t_i) \tag{6.7}$$

However, if a unit is still alive at t_i, then under non-informative censoring the assumption is made that its lifetime exceeds t_i. Its contribution to the likelihood function is then

$$L_i = S(t_i) \tag{6.8}$$

The two mentioned units have the same survival function $S(t_i)$ and a failure/death multiplies the contribution by the hazard function $\lambda(t_i)$, but a censored unit does not. The likelihood function can then be defined as

$$L = \prod_{i=1}^{n} L_i = \prod_{i=1}^{n} \lambda(t_i)^{d_i} S(t_i) \tag{6.9}$$

where d_i is a logical value indicating wether a failure or death has occured.

Finding the maximum value of the likelihood function can pinpoint with which parameters λ will have the best fit, which can then be used to predict future failure probabilities. However, finding the maximum by equating the derivative of the likelihood function will be quite a task, as the chainrule must be applied. This can be circumvented by finding the maximum of the log of the likelihood function instead. This is called the log-likelihood function:

$$LL = \log L \tag{6.10}$$

the value will be different, but the location of the maximum is the same. The derivative will then be easier to find, as the log of the likelihood function will result in a summation instead of a multiplicative function.

6.2 Survival Models

Up to this point the survival function was assumed to be identical across the units. It is possible to define individual survival functions for each unit, based on additional information about the unit. In this section the different types of survival models will be explored.

The classification in figure 6.1 is based on the original form of the methods, but variations do exist (e.g. there is a parametric form of Cox regression)

6.2.1 Non-parametric Models

In non-parametric estimations, the survival function is estimated solely by an empirical function. The most widely used is the *Kaplan and Meier* (KM) method [62] and is also used in the survival package in R. The most popular methods will be presented.

Kaplan-Meier

This method estimates the survival function with a step-wise function. Let $T_1 < T_2 < ... < T_K$ be a set of ordered event times for $N(K \leq N)$ subjects. In addition to these event times there are also censored times. The survival function is built stepwise at each event time as follows.

For each event time $T_j (j = 1, 2, ..., K)$, the number of events is $d_j \geq 1$, as multiple events can happen at the same time. Furthermore, r_j instances will be considered at risk, meaning that they are eligible for experiencing an event (this populations event or censor time is greater than T_j). r_j is thus

$$r_j = r_{j-1} - d_{j-1} - c_{j-1} \tag{6.11}$$

where c_{j-1} is the amount of censored event times. With this, the probability of an event occurring after T_j is

$$p(T_j) = \frac{r_j - d_j}{r_j} \tag{6.12}$$

The KM method then estimates the survival probability at a given time as a product of the survival rate up to the previous time and the survival rate at that give time:

$$\hat{S}(t) = \prod_{j \in T_j < t} p(T_j) = \prod_{j \in T_j < t} (1 - \frac{d_j}{r_j}) \tag{6.13}$$

For this reason it is also reffered to as the product limit method (PLM). Note that this is an estimation, hence the hat notation. An example of such an estimation for Stedin transformers is given in figure 6.3. At each step one or more events occurred and the censor times are indicated by a short vertical line. A time tolerance may be used to consider events with a small time discrepancy to have happened simultaneously, if this provides a better fit. Furthermore the effect of different subpopulations can be compared, in this example the rated voltage.

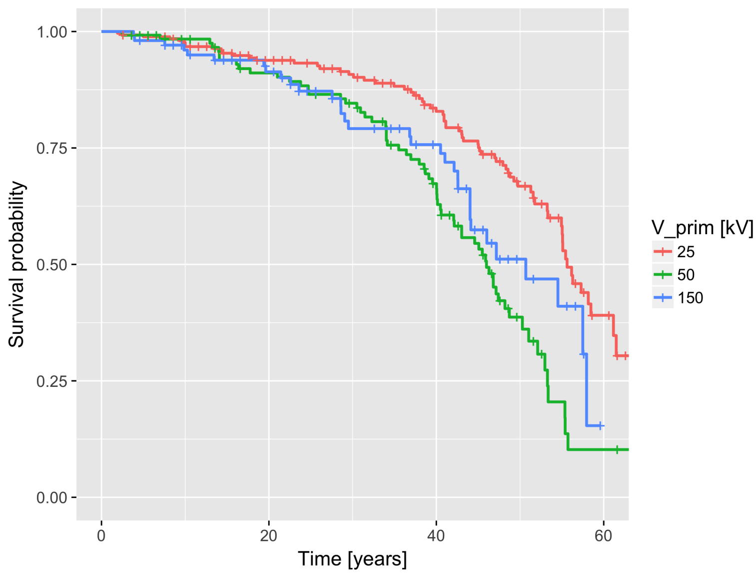


Figure 6.3: Example of a KM survival function estimation.

Nelson-Aalen

Using equation 6.5, the survival function can also be estimated by estimating the cumulative hazard function. The Nelson-Aalen (NA) method estimates this by a counting process [63]:

$$\hat{\Lambda}(t) = \sum_{j \in T_j < t} \frac{d_j}{r_j} \tag{6.14}$$

Comparison

It is a general knowledge that the NA and KM estimators are asymptotically equivalent. They appear to have negligble bias for K > 50 [64]. As the KM method is the most easily applied in R, it has the preference in case it is needed.

In both cases it is possible to study the effect of different subpopulation, e.g. 50kV and 150kV transformers, by estimating different survival functions with two seperate data sets. However, multi-variate analysis becomes complex or impossible.

6.2.2 Semi-parametric Models

Semi parametric models are a combination of a parametric and non-parametric method, hence the name. Furthermore, the distribution of the outcome of these models is unknown, even if it is based on parametric regression. The most common semi-parametric model is the Cox model.

Defining individual survival functions will be done by manipulating the ***base hazard function***, λ_0, which is the hazard function that is fitted to all subject and is thus equal for all. Choosing the correct base hazard model to describe a failure distribution is crucial to the accuracy. In semi-parametric models this base hazard function is estimated non-parametrically with the methods described in the previous section. The manipulating terms/coefficients are found by likelihood estimation, see section 6.3. The most popular methods will be presented.

Cox's Proportional Hazard Model

A large family of models which alter the hazard function where introduced by [65], referred to as Cox models. One of the models in this family is Cox's proportional hazards model (CPHM), in which a base hazard function λ_0 will be multiplied by factor which is dependent on a vector of covariates $\boldsymbol{x}_i$, which are specific for an individual subject indicated by i . Each individual can contain up to X covariates. The weight/effect of these covariates are represented by an effect vector $\boldsymbol{\beta} = [\beta_1, ..., \beta_X]$, which is identical to all individuals. This model thus assumes a proportional effect of the covariates on the hazard function, hence its name. The resulting hazard function is

$$\lambda_i(t|\boldsymbol{x}_i) = \lambda_0(t) \exp\{\boldsymbol{x}_i'\boldsymbol{\beta}\} \tag{6.15}$$

Where the apostrophe is used to indicate the transpose, resulting in the dot product. The covariates and their corresponding weighting determine the proportional factor which will thus increase or decrease the hazard function. The covariates, e.g. transformer rated voltage, will vary per subject. Note that the covariates and effect are not dependent on time in this model.

Using equation 6.15, the effect on the cumulative hazard and consequently the survival function can be found:

$$\Lambda_i(t|\boldsymbol{x}_i) = \Lambda_0(t)\exp\{\boldsymbol{x}_i'\boldsymbol{\beta}\} \tag{6.16}$$

resulting in

$$S_i(t|\boldsymbol{x}_i) = S_0(t)^{\exp\{\boldsymbol{x}_i'\boldsymbol{\beta}\}} \tag{6.17}$$

Where $S_0(t) = \exp\{-\Lambda_0(t)\}$ is the baseline survival function. The effect of the covariates on the survival function is thus multiplying the base survival function to a power of $\exp\{\boldsymbol{x}_i'\boldsymbol{\beta}\}$. An example of the survival function estimated with this model is given in figure 6.4. In this model the covariate is the HI with a weight of $-0,7$. The covariate is a continuous variable in this case, but it may also be categorical. The underlying data will be discussed later on.

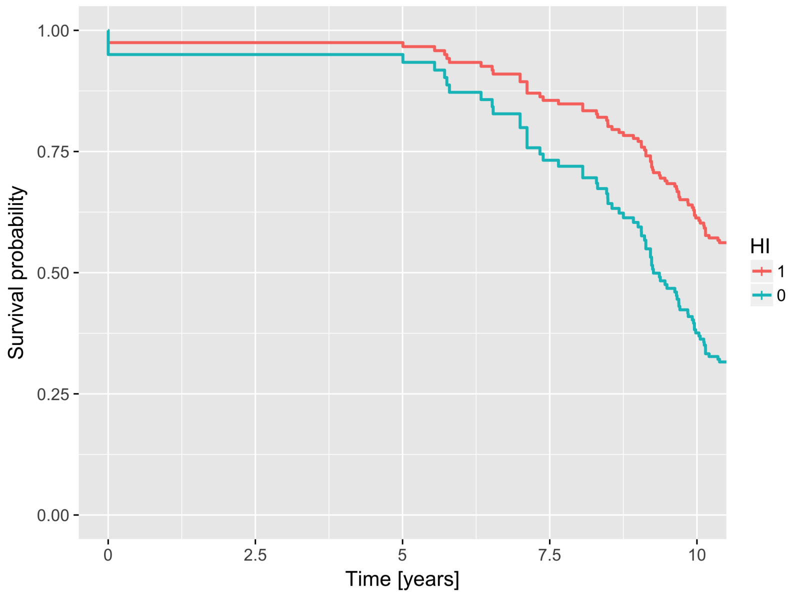


Figure 6.4: Example of a Cox survival function estimation.

An important assumption of the Cox model that must be validated, is that this proportionality is constant over time. That is, that the hazard ratio

$$HR = \frac{\lambda_i(t|\boldsymbol{x}_i)}{\lambda_0(t)} = \exp\{\boldsymbol{x}_i'\boldsymbol{\beta}\} \tag{6.18}$$

is constant over time. This also means that for different $\boldsymbol{x}_i$ the survival functions will never cross each other and will have the same starting and end points. The validation of this constant hazard ratio is discussed in section 6.3

Time Dependent Cox Model

Equation 6.15 can be extended to include time varying covariates, $x(t)$, and effects, $\beta(t)$. Example of a time varying covariate is a transformer condition indicator, e.g. the DP value of the paper insulation. The corresponding weighting of this covariate on the survival probability may also be time dependent, e.g. the DP having a bigger effect for older transformers (not necessarily true).

The two time dependent assumptions will result in the most general form of the Cox model, the time dependent Cox model (TD-Cox) [66]:

$$\lambda_i(t, \boldsymbol{x}_i(t)) = \lambda_0(t) \exp\{\boldsymbol{x}_i'(t)\boldsymbol{\beta}(t)\} \tag{6.19}$$

This extension of the base Cox model can be used to add a time correction if the constant hazard ratio assumption is invalid, or simply if there are time dependent covariates.

Comparison

The TD-Cox model is an extension of the base Cox model, and can provide a better fit, if the weights have a correlation with time. However, it does add an extra layer of complexity and should be avoided if not necessary.

6.2.3 Parametric models

These models are more accurate than the ones previously discussed, if the event times have a known underlying statistical distribution which can be specified in parameters. It also makes it easier to estimate the times to event compared to the previous methods, as now the survival function always goes asymptotically to zero [67]. The most popular methods will be presented. "The mean survival time is the average duration of the follow-up time of all observations in the study. To estimate mean survival time accurately, all individuals must have a 'complete follow-up time', i.e. all observations must be 'failures' by the closure of the study. If this condition is not met, the estimate of mean survival time will be based on incomplete observations (censored)14 and will not reflect a true picture of the data"[68].

Accelerated Failure Time Model

Consider T_i to be a random variable of the event time of unit i (assuming one event per unit). The accelerated failure time (AFT) model assumes a linear relationship between the logarithm and the covariates [69]. Assuming T_i to be non-negative, it is modeled as follows:

$$\log T_i = \boldsymbol{x}_i'\boldsymbol{\beta} + \epsilon \tag{6.20}$$

where ϵ_i is an error term which has a parametric distribution that will also determine the distribution of T_i. Solving for T_i gives

$$T_i = \exp\{\boldsymbol{x}_i'\boldsymbol{\beta}\} \cdot \exp \epsilon$$

$$T_i = \gamma_i T_0 \tag{6.21}$$

with γ_i representing the multiplicative terms and T_0 being the exponential error term. To display the effect of this modified Ti, consider the relationship between a reference group S_0 and a group under study S_1:

$$S_1(t) = S_0(t/\gamma) \tag{6.22}$$

This indicates that the study group has the same survival probability at time t, as the reference group has at time t/γ. Assume γ to be 2, this means that the reference group "ages" twice as fast as the reference group (hence "accelerated" term in the name). The corresponding hazard functions is then

$$\lambda_1 = \frac{\lambda_0(t/\gamma)}{\gamma} \tag{6.23}$$

Proportional Hazard Model

The proportional hazard model (PHM) [61] is identical to CPHM, but assumes the base hazard function λ_0 to have a known distribution function. This is somewhat contrary to the original intent of the Cox model, which is to get rid of the need to know the distribution of λ_0. However, a (completely) parametric model is more accurate if the data follows a known distribution. λ_0 can thus have e.g. an exponential, Weibull or gamma distribution.

Comparison

The choice should be to choose the model that fits the data the best, depending on whether the survival times have a time accelerated or proportional relationship with the covariates. However, there is a case for which the two models coincide [61]: if the base hazard or base survival function is chosen to be a Weibull distribution. The Weibull hazard and survival functions are as follows:

$$\lambda(t) = p\lambda(\lambda t)^{p-1} \tag{6.24}$$

$$S(t) = \exp\{-(\lambda t)^p\} \tag{6.25}$$

λ and p being the parameters. If a Weibull is picked as the baseline risk and is multiplied by the γ in the PHM model, the result is still a Weibull distribution. If the same baseline is accelerated by multiplying time with γ, the result is also a Weibull distribution.

6.2.4 Comparison of the Methods

Non-parametric methods are useful when there does not seems to be a known underlying distribution, but are not able to effectively study the effect of covariates. Semi-parametric methods combine the ease of not needing to specify the underlying distribution and the ability to effectively study the effect of covariates. Parametric methods are the most efficient when the event time has an underlying distribution. See table 6.1 for an overview of the advantages and disadvantages. The choice will lie between a Cox model or an AFT model, whichever fits best.

6.3 Model Fitting

In this section the aspects of fitting the model, i.e. finding parameter values for the (semi-) parametric methods, will be discussed. Furthermore the methods to validate the assumptions made in the model and methods to validate the model itself will be presented.

Table 6.1: Statistical method comparison

Type	Advantages	Disadvantages
Non-parametric	More efficient when no suitable theoretical distributions known	Inaccurate if data follows a distribution
Semi-parametric	No knowledge needed of distribution	Distribution still unknown; not easy to interpret
Parametric	Easy to interpret, more efficient when data follows a particular distribution	Innacurate if distribution assumption is violated

6.3.1 Parameter optimization

Finding the parameter values means finding the values of the parameters of the baseline hazard function $\boldsymbol{\theta}$, the weighting paramaters $\boldsymbol{\beta}$, or both depending if it is a semi-parametric or parametric model. Assume the hazard function of a subject to be defined as

$$\lambda(\boldsymbol{\theta}, \boldsymbol{\beta}|t) = \lambda_0(\boldsymbol{\theta}|t)\gamma(\boldsymbol{\beta})$$

Then the likelihood function (eq. 6.9) is also a function of $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$:

$$L = L(\boldsymbol{\theta}, \boldsymbol{\beta}) \tag{6.26}$$

The probability h_j that an individual of the risk set R_i has an event at T_j, given that one in the set does, can be expressed as hazard function of that individual divided by the sum of the hazard function of all other individuals in the risk set:

$$h_j = \frac{\lambda_i(\boldsymbol{\theta}, \boldsymbol{\beta}|T_j)}{\sum_{i \in R_i} \lambda_i(\boldsymbol{\theta}, \boldsymbol{\beta}|T_j)} \tag{6.27}$$

And so the likelihood function can be expressed as the multiplication of these probabilities, including a censoring exponent:

$$L = \prod_{j=1}^{K} \left(\frac{\lambda_0(\boldsymbol{\theta}|T_j) \exp\{\boldsymbol{x}_j' \boldsymbol{\beta}\}}{\sum_{i \in R_i} \lambda_0(\boldsymbol{\theta}|T_j) \exp\{\boldsymbol{x}_i' \boldsymbol{\beta}\}} \right)^{\delta_i} \tag{6.28}$$

Where x_j is the covariate vector of the unit corresponding to time T_j, and R_i is the risk set, i.e. all units which have an event time greater than T_j. By finding the values of these parameters for which the likelihood is at its maximum, the model will fit the observed data at its optimum.

$$L_{max} = L(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\beta}}) \tag{6.29}$$

with $\hat{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\beta}}$ being the values that maximizes L. Because this likelihood function contains all the parameters needed to describe the distribution, it is called the ***maximum likelihood estimator*** (MLE).

There are however cases for which λ_0 can not be specified or there is no interest in finding λ_0, resulting in a semi-parametric model.

In these cases $\boldsymbol{\theta}$ becomes nuisance parameters and to circumvent this, Cox proposed the partial likelihood estimator (PLE) [70]:

$$L_{part_{max}} = L(\hat{\boldsymbol{\beta}}) \tag{6.30}$$

Applying this to the CPHM results in

$$L_{part} = \prod_{j=1}^{K} \left(\frac{\exp\{\boldsymbol{x}_j' \boldsymbol{\beta}\}}{\sum_{i \in R_i} \exp\{\boldsymbol{x}_i' \boldsymbol{\beta}\}} \right)^{\delta_i} \tag{6.31}$$

Note that this function depends only on the order in which the events occur, not the times at which they occur. The order dictates the risk set per event.

6.3.2 Recurrent Events

Up to this point, subjects were only considered to have a maximum of one event. The conditional probability in the definition of the hazard (eq 6.2) clearly states that the event $T > t$, meaning that no previous events have occurred for that subject. However, in this study there were no fatal failures in the data, corrective maintenances and outages were used. This makes it possible for a subject to have multiple events, as a transformer may have had multiple corrective maintenance or outages within the study period.

There are different methods to extend the likelihood function to adapt to recurrent events, by adapting the risk set, R_i, in the likelihood estimator. These models assume that there are multiple states before the "death" state. There are three common methods[71]:

- Andersen and Gill (AG) [72]
- Prentice-Williams-Peterson (PWP) [73]
- Wei-Lin-Weissfeld (WLW) [74]

To explain these methods, we redefine the indices: each individual $i = 1, 2, ..., N$ can experience up to $j = 1, 2, ..., K$ events. K is thus the maximum amount of events considered per subject, and k_i is the maximum amount of events for individual i ($k_i \leq K$). Furthermore there are time dependent covariates (condition changes with time), thus $\boldsymbol{x}_{ij}$ is defined as the covariates of individual i at event time T_j. This is an extension of the time independent version proposed by the above mentioned methods.

Andersen and Gill

The AG model is the most commonly applied model for recurrent event times and is a simple extension of the Cox model. The base assumption is that the instantaneous risk, $\lambda(t)$, is not dependent on whether a previous event has occurred. This implies that subsequent events are independent, which is not always true. The likelihood function is identical to equation 6.31, with an altered risk set

$$R^{AG}(t) := \{l = 1, ..., N : \exists\, j \in \{1, ..., k_l\} : T_{ij} > t\} \tag{6.32}$$

with T_{ij} being the $j^t h$ event of individual i. This simply states that the risk group contains all the individuals that have an event time after t. It can be seen as duplicating an individual i by k_i times, and let each have one distinct event time from the set of events experienced by that individual. This results in the following likelihood function:

$$L = \prod_{i=1}^{N}\prod_{j=1}^{k_i}\left(\frac{\exp\{\boldsymbol{x}'_{ij}\boldsymbol{\beta}\}}{\sum_{l\in R^{AG}(T_{ij})}\exp\{\boldsymbol{x}'_{lj}\boldsymbol{\beta}\}}\right)^{\delta_{ij}} \tag{6.33}$$

Prentice-Williams-Peterson

The PWP model relates the hazard function to the preceding failure time history. It is a stratified model with respect to the j^{th} recurrent event time, meaning that different λ_0 and $\boldsymbol{\beta}$ are fitted for each group of all first events, for all second events and so on up to the K^{th} event. Notice that j is the recurrent event time, thus the time to the first event is not taken into account.

Regarding the time to event, there are two approaches to the time scale:

- **Total time scale**: time since study entry to the event time. The hazard functions are modelled as
$$\lambda_{ij}(t) = \lambda_{0j}(t)\exp\{\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\} \tag{6.34}$$
- **Gap time scale**: time since the previous event. The hazard functions are modelled as
$$\lambda_{ij}(t) = \lambda_{0j}(t - t_{j-1})\exp\{\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\} \tag{6.35}$$

With λ_{0j} being the base hazard function for each $j = 1, 2, ...K$ recurrent event with its corresponding coeffecients $\boldsymbol{\beta}_j$.

The risk set for the j^{th} event consists of only individuals who have experienced a previous $(j-1)^{th}$ event. The likelihood function can be written as a product of all the event specific likelihoods

$$L = \prod_{j=1}^{K} L_j \tag{6.36}$$

with

$$L_j = \prod_{i=1}^{N}\left(\frac{\exp\{\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\}}{\sum_{l\in R_j^{PWP}(T_{ij})}\exp\{\boldsymbol{x}'_{lj}\boldsymbol{\beta}_j\}}\right)^{\delta_{ij}} \tag{6.37}$$

The risk sets for the the total time model is

$$R_j^{PWP}(t) := \{l = 1, .., N : T_{ij-1} < t \leq T_{ij}\} \tag{6.38}$$

and for the gap time model the risk set is

$$R_j^{PWP}(t) := \{l = 1, .., N : (T_{ij} - T_{ij-1}) \geq t\} \tag{6.39}$$

The model makes it possible to derive strata specific weights β_j, however it might be possible to be interested in a single effect estimator, quantifying the net effect. This can be done by setting $\beta_1 = \beta_2 = ... = \beta_K = \beta$ in equation 6.37 to estimate a common β.

Wei-Lin-Weissfeld

The WLW model is also a stratified model as the PWP model and the hazard function is identical to that of the total time model as given in 6.34. The difference is in the risk set, in this case an individual is at risk even though no prior events have occurred. Stratum specific weights $\boldsymbol{\beta}_j$ can be estimated by the same PLE as in equation 6.37 with an altered risk set

$$R_j^{WLW}(t) := \{l = 1, .., N : \exists\, j \in \{1, ..., K\} : T_{lj} \geq t\} \tag{6.40}$$

Notice that this model assumes that all individuals observe K number of events, and should $k_l < K$, then "artificial" censored events will be added until $k_l = K$. This makes it necessary to carefully choose the maximum number K, because if it is too high then many artificial censored data will be added, weakening its precision.

Comparison

If the recurrent events are independent, then the AG model is the most straightforward one to use. If this method does not provide satisfactory results which might indicate that the events are not independent, then an PWP or WLW model can be used. The PWP model is focuses on relating the hazard function to the preceding failure time history. The WLW does the same, but takes the first event into account and also assumes that all individuals will have K events, censored or not.

6.3.3 Validation

There are some assumptions of the previously mentioned methods that needs to be validated, and furthermore the accuracy of the model should also be measured.

For either a CPHM, PHM or AFT model , there are some aspects that must be validated in order to consider the model suitable [75]:

- Significance of covariates, i.e. the significance of the effect of the covariate.
- Proportional hazard (PH) or accelerated time (AT) assumption. These assumption state that the hazard functions of different individuals have either a proportional or accelerated relationship at all points in time.

Validating the Significance of a Covariate

The significance of the covariates x_n with $n = \{1, ..., X\}$ can be tested by the corresponding optomized coefficients $\hat{\beta}_n$.The significance can proved by rejecting the null hypothesis in the following statements

$$\begin{aligned} H_0 &: \hat{\beta}_n = 0 \\ H_1 &: \hat{\beta}_n \neq 0 \end{aligned} \tag{6.41}$$

The region for rejecting H_0 is usually a probability of less than 5%, but this is of course up to the choice of the user [76]. This probability is referred to as the p-value

$$p = Pr\{\hat{\beta}_n | H_0\} \tag{6.42}$$

Note that if $\hat{\beta}_n = 0$, then $HR = 1$ (eq. 6.18), meaning that the addition of the covariates had no effect on the hazard function. The following statements can thus also be used as a test statistic

$$\begin{aligned} H_0 &: HR = 1 \\ H_1 &: HR \neq 1 \end{aligned} \tag{6.43}$$

Another way of testing for significance is the Wald test, which tests the amount that the optomized parameter β_n deviates from the initial value β_{n0} (the value at the start of the iteration for finding $\hat{\beta}$), which is in this case equal to 0. The Wald statistic is defined as

$$z = \frac{(\beta_{n0} - \hat{\beta}_n)^2}{\mathrm{var}(\hat{\beta}_n)} \tag{6.44}$$

Validating the Constant PH and AT Assumption

The PH assumption states that the hazard ratio should be constant with time, however, models with time varying covariates can not fulfill this requirement as the hazard ratio varies with time due to a varying covariate $x_i(t)$. The same is true for the AT assumption, which states that the hazard of one group at any time t is equal to the survival of another group at time γt (eq 6.22).

Since the model we want to use has time varying covariates, there is no need to validate these assumptions for those covariates.

Goodness of Fit

The goodness of fit of a survival model indicates to what degree it can represent the survival patterns. In survival analysis it is common to evaluate a model by considering the relative risk of an event for different instances, instead of the absolute survival times for each instance. In some cases it is also not possible to predict the exact survival time, which makes a goodness of fit test with absolute survival times unsuitable.

A goodness of fit test that considers the relative risk is the ***concordance probability*** or concordance index (C-index) [77]. This method compares the survival times of all possible pairs to check whether the instance with the lower survival rate indeed have a lower survival time. The survival times of two instances can only be compared if both are uncensored, or if the censored event occurred later than the uncensored one. A representation of these two scenarios is given in figure 6.5

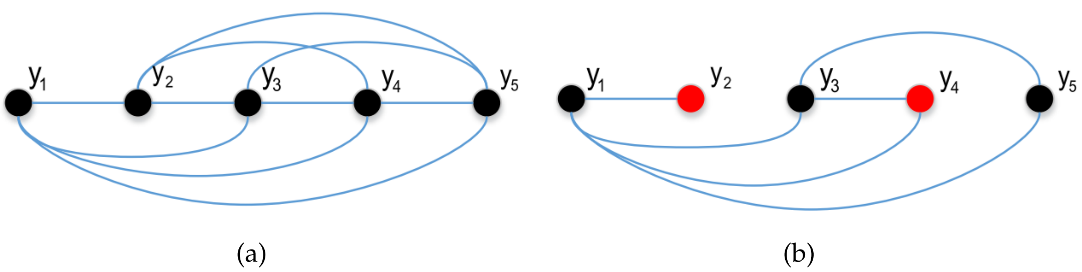


Figure 6.5: Time pairs in case of uncensored (a) and censored (b) events. Black circles indicate an event and red circles indicate a censored time [60].

The c-index is the ratio between the amount of time pairs that have been "correctly" predicted and the amount of comparable pairs.

$$C = \frac{P}{num} = \frac{1}{num} \sum_{i:\delta_i=1} \sum_{b:T_i<T_b} I\left[S_i < S_b\right] \tag{6.45}$$

Where num is the number of comparable pairs, δ_i the death indicator for instance i, I is the indicator function, P is the amount of pairs for which instance i had a lower survival time than instance b, and S_i and S_b are the corresponding survival probability at that time.

Another validation method is the ***Brier score***[78], which is a measure of error prediction for probabilistic outcomes. It is defined as

$$BS = \frac{1}{N} \sum_{i=1}^{N} (S_i - o_i) \tag{6.46}$$

Where N is the amount of instances, S_i is the survival probability of instance i at the time of the event, and o_t is the event outcome (0 for death, 1 for censoring). The BS is ranged between $[0, 1]$ where 0 is a perfect score and 1 the worst.

6.4 Conclusion

In this chapter various survival model methods were discussed. The methods that will be used and the reasoning behind it will conclude this chapter.

Machine learning methods were ruled out due to time constraints and the doubt of sufficient data quality. These methods can perform better than traditional statistical methods, but need much more data.

The model shall thus be a semi-parametric or parametric model, as non-parametric models are not adequate for studying the effects of multiple variables. The performance of a semi-parametric or parametric model can not be determined before implementation, because the performace depends on whether the events have a known underlying distribution or not. It can be assumed that the underlying distribution is a Weibull distribution, as this is the most common one used in failure analysis, but it is just a hypothesis.

Whether to use a PH or AFT model can also not be determined beforehand, as the relationship between the different hazard functions is not known yet. In case of a parametric Weibull approach, the choice does not have to be made, as the models are the same.

Furthermore, the model will have time dependent covariates, as the condition information of transformers vary with time. This affects how the data table which is passed onto the modelling function will have multiple rows per event, in order to change the value of the covariates.

To model recurrent events, a choice must also be made in the type of recurrent analysis. If independence between events is assumed, the AG model can be applied. If not, then the PWP or WLW can be used to make different survival functions for each group of recurrent events. However, the PWP does not include the first event, which is the biggest portion of events in the data. The AG and WLW models were chosen to compare.

To avoid the effects of biasing, enough data must be available. Simulation work has suggested that a minimum of 10 events are needed for each covariate considered, otherwise this will lead to problems such as the regression coeffecients becoming biased [79].

Lastly, the models should be tested for:

- Covariance significance using the p-value.
- PH or AT assumption, in case of time independent covariates.
- Goodness of fit using the C-index and/or Brier score.

Chapter 7

Data & Modelling

In this chapter the data structure and some important modelling details will be discussed. Stedin has many databases for each type of data, thus they were all imported into R to bind all of the data to each other.

In section 7.1 the data model is presented, followed by the HI model in section 7.2 and some implementation details of the failure model in section 7.3. This chapter ends with a description of the transformer population in section 7.4.

7.1 Data Model

Various data was gathered for all in-service transformers in the Stedin population, which amounted to 501. These were imported into R then joined per transformer in a nested `list` structure, with each enclosing element representing a unique transformer with a unique serial number. A `list` is an array with each element having the property that it can be data of any type and length. An overview of this structure is shown in figure 7.1.

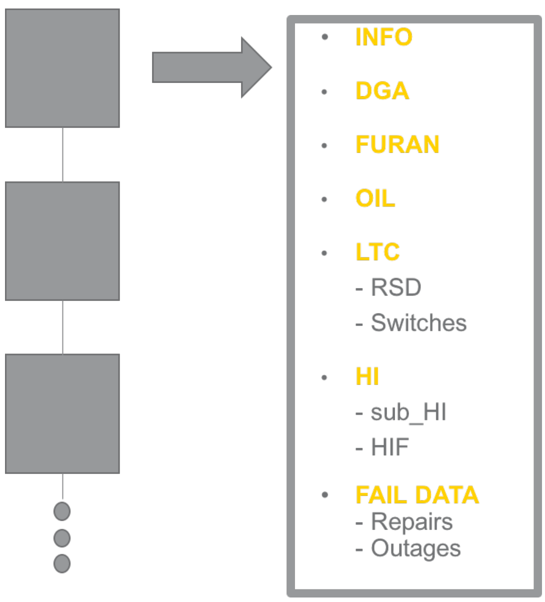


Figure 7.1: Data structure.

The chained blocks represent the top level list, with each block/element representing a unique transformer. Inside each block there is another list, containing four data frames and three lists. A `data frame` is an array in which each column can have a different data type, but must have the same length as all other columns. It is essentially a `list` with a length constraint.

Each element contains the following transformer specific data, provided that it was possible to join it from the databases:

- **INFO**: A data frame containing all static data of the transformer such as serial number, location, brand and nameplate ratings
- **DGA**: A data frame containing the DGA measurements.
- **FURAN**: A data frame containing the furan measurements.
- **OIL**: A data frame containing the physical oil properties measurements.
- **LTC**: A list containing two data frames. RSD contains the numeric diagnostic results of the LTC diagnostic. The other one contains the amount of switching actions in 2017.
- **HI**: A list containing two data frames. sub_HI contains the dates and sub health indices, which are the values outputted by the assessment functions. HIF (health index factors) contains the HI calculation for each transformer year.
- **FAIL DATA**: A list containing two data frames. Repairs contains the corrective maintenances of the transformer between 2008 and 2017. Outages contains information on the outage caused by the transformer between 2000 and 2017.

Joining the data from the different databases was not very trivial, as there are multiple ways to identify a transformer and these identifiers (keys) can differ slightly per database. A transformer can be identified by one of the following keys:

- Serial number
- Station ID in combination with transformer number

Care must be taken when using the latter because replaced transformers might have the same keys as the new transformer. Serial number, station ID and transformer numbers may differ (slightly) per database, but these are the keys used to join all the data. The data was checked manually to validate the joining, but there might still be a small amount of errors.

7.2 HI Model

7.2.1 Absence of Data

The HI will be computed once per year over the transformer's lifetime, because diagnostic values usually change at most once per year. However, these values are not available for every year because:

- Measurement orders were simply not carried out.
- The measurement frequency is set to be lower, e.g. every 5 years.
- The data could not be joined to a transformer.

In order to increase the amount of years that have a comprehensive HI, the values will be held for a period of time. Interpolation was also an option, but for long time spans this would be a big guess which is assumed to be valid. More complex missing data augmentation for transformer diagnostics is presented in [80], which can be used in future work.

The method to fill in the gaps is quite simple: for each year, the measurement with the closest date is selected and is considered to be valid only if the absolute difference is lower than half the time of the measurement frequency. To illustrate, consider the following example: furan diagnostic occurs every five years, so the measurement done within 2.5 years before or after the health index calculation date is considered to be valid.

Once the validity of a measurement point is decided, it enters the calculation for the level of ***completeness***. This is a self-defined term, which indicates how much of the data was available for a HI calculation. It can be written as

$$Compl = \frac{\sum_{i=1}^{i=N} w_i \cdot valid_i \cdot compl_i}{\sum_{i=1}^{i=N} w_i} \tag{7.1}$$

where i is the indicator of the sub HI, w_i is the weighting of that sub HI, $valid_i$ is the binary value that indicates the validity of that sub HI for that year, N is the maximum number of sub HI, and $compl_i$ is the completeness of that sub HI w.r.t. all the inputs needed for that assessment function.

7.2.2 HI Calculation

The HI is computed for each year by running the closest measurement points in time through the assessment functions, which calculates the sub HI. A weighted sum of these averages then forms the HI, while an added validity term selects the valid measurement points.

$$HI = \frac{\sum_{i=1}^{i=N} w_i \cdot S_i \cdot valid_i}{\sum_{i=1}^{i=N} w_i \cdot S_{max} \cdot valid_i} \tag{7.2}$$

Where S_i is the score of sub HI i and S_{max} is the maximum attainable score, in this case 4. w_i are the weights of the sub HI, which is determined by experts in a decision making process. Note that missing data is thus excluded from the calculation, but its absence is given by the level of completeness (eq 7.1).

The sub HI that are taken into account for the main tank are:

- HI_{DGA}, which indicates the severity of faults, but not the fault types.
- HI_{OIL}, which indicates the condition of the insulating and cooling properties of the oil.
- HI_{FURAN}, which indicates the condition of the paper insulation based on furan values.

The sub HI above form the ***HI of the main tank***. The LTC is also taken into account, but because of the high probability of failure, it's weight is taken to be 40% of the total. The total HI is thus given by

$$HI = 40\% \cdot HI_{LTC} + 60\% \cdot HI_{tank} \tag{7.3}$$

Top oil temperature and loading data were also acquired, but time constraints prevented this from being incorporated in this HI model. Furthermore the maintenance data up to 2017 was not in a suitable form to be incorporated.

7.3 Failure Probability Model

7.3.1 Model description

Due to time constraints, only a time dependent CPHM was implemented with the AG and WLW approach. However, after realizing a crucial error in the models, there was only enough time to correct the AG model and thus only the this model is presented. The model was implemented in R with the `survival` package, which provides helpful functions for survival analysis.

As mentioned before, there are no fatal failure records in the data. Instead, corrective maintenances were used as an event. A corrective maintenance is carried out due to a failure, or because inspection results during regular maintenance indicated the necessity for replacement or revision of a subsystem. This model thus computes the probability of a corrective maintenance, and (if valid) can be used to:

- Decide when to replace a transformer once it is no longer financially attractive to prolong its lifetime by repairs.
- Estimate corrective maintenance budgets per year.

Outtage data was also available, however these were not used because it only includes transformer outtages that included customer black outs. Due to network redundancy, many transformer outtages are thus not present in this data set and thus it would lead to incorrect results.

7.3.2 Event Table

The first step in analyzing time-varying covariates in survival analysis is to reshape the data frame so that there are multiple rows (time intervals) for each subject, along with covariate values that apply across these intervals [81]. This data frame will be referred to as an event table. The event table for two transformers (A and B) are given in table 7.1. The definition of the columns are as follows:

- date: the date that a need for a corrective maintenance was detected
- event_num: the n^{th} event for the same transformer during the total observation period
- status: binary event indicator (1 for an observation with an event, 0 for a censored observation)
- id: transformer ID
- tstart, tstop: starting and stopping time of the event period in years (notice that this is the time relative to the start of the observation period (2008), not the age of the transformer)
- age: age of the transformer in years at the beginning of the interval

The age and scores are the time varying covariates. The static covariates, e.g. voltage rating or manufacturer , are not displayed.

Table 7.1

date	event_num	event	id	tstart	tstop	age	score_dga	score_furan	score_oil	score_ltc
-	1	0	A	0.00	2.00	33	2	-	-	-
-	1	0	A	2.00	4.00	35	2	*4*	-	-
10-07-2014	1	1	A	4.00	6.53	37	2	4	*3*	-
21-07-2014	2	1	A	6.53	6.56	37	2	4	3	-
-	*3*	0	A	6.56	7.01	37	2	4	3	-
-	3	0	A	7.01	8.01	40	3	4	-	-
24-08-2017	3	1	A	8.01	9.65	41	3	4	*2*	-
-	*4*	0	A	9.65	10.60	41	3	4	2	-
-	1	0	*B*	0.00	1.00	47	2	4	-	-
-	1	0	B	1.00	5.01	48	*4*	4	-	-
-	1	0	B	5.01	8.01	52	4	4	*1*	-
-	1	0	B	8.01	9.01	55	4	*3*	-	-
-	1	0	B	9.01	10.00	56	*3*	3	*1*	-
-	1	0	B	10.00	10.60	57	*4*	3	1	-

The events must be divided into multiple observations to adjust the values of the covariates. The colored entries indicate the reason that a new interval was triggered. Take event 1 of trafo A as an example: in the first two years only the dga score is known, in year 2 to 4 the furan score is added and in year 4 to 6.5 the oil score is added. At the end of the 4 to 6.5 year period an event occurs. Transformer A has 3 corrective maintenances and a censored period from the last event to the end of the observation period. This last censored interval is necessary as recurrent events are considered, meaning that the transformer is still in the risk set.

Transformer B has no events and therefore has only a censored observation, but this must be distributed among multiple intervals for the time dependent covariates. The age only varies when the other covariates vary because the model should use the age at the entry of the time interval.

7.3.3 Failure types

Table 7.1 contains the event data for all failure types. When making a subset of failure types, this table must be completely constructed again, as the length of intervals and event numbers will change. The failures were divided into events concerning the following subsystems:

- Bucholz
- Seals
- LTC
- LTC Drive
- Leakage
- Bushing
- Protective
- Cooling equipment
- Various (multiple problems, but poorly described)

See figure 7.2 for the distribution of the failure types. There were 306 corrective maintenance entries, however one entry may contain multiple categories, which thus increases the amount of data points to 439.

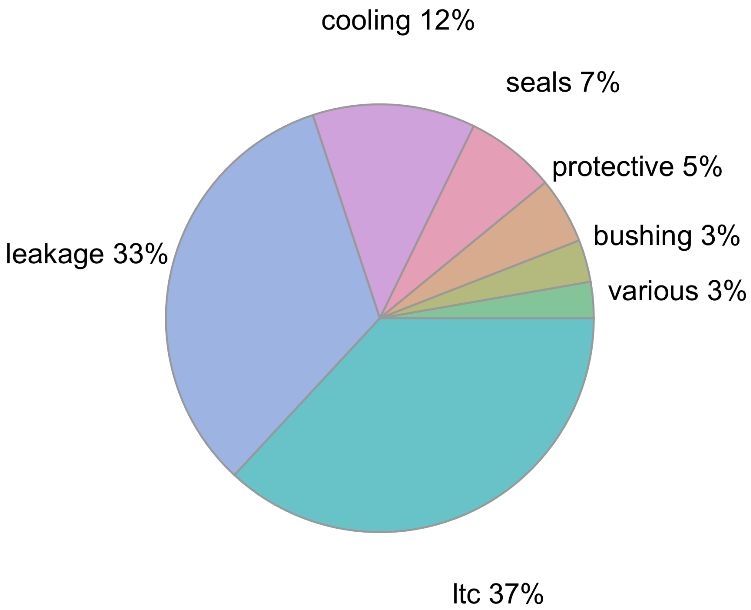


Figure 7.2: Distribution of corrective maintenances that were also identified to a transformer. n = 439

7.3.4 Implementing the Cox model

The code for constructing the event table can be found in listing C.1 in appendix C. It makes an event table for each transformer using the corrective maintenances or a censored observations as a starting point, after which the different intervals for the time varying covariates are constructed from this starting point using the `survival::tmerge` function. It thus uses information from the "INFO", "HI" and "FAIL DATA" lists, as displayed in fig 7.1.

Once the event table is constructed, it can be used as an input for fitting the Cox model. See listing 7.1 for a code snippet in which a Cox model is fitted using the `survival::coxph` function. The `Surv` function converts the event table to a survival object, using `tstart`, `tstop` and `event` from the event table. The covariates are in this case the age and sub health indices (scores). A subset is made from the event table to filter out the rows that have missing covariates. The subsetting is more applicable for the case that the HI is used as a covariate, because the `coxph` function automatically filters out rows with missing covariates.

Listing 7.1: fitting the cox model using the event table.

```
cox_sub <- coxph( Surv(tstart, tstop, event) ~  age +
                  score_dga + score_furan +
                  score_oil + score_ltc + cluster(id),
                  data = subset(event_table, compl_tot > 0.9)
                  )
```

7.4 Transformer population

The transformers that were taken into account are high voltage power transformers, meaning a secondary voltage higher than 1 kV. The distribution of the voltage, age and manufacturer can be found in figure 7.3, 7.4 and 7.5, respectively.

As expected, the amount of transformers increases as the rated voltage drops, due to the central generation structure. The age distribution seems to follow an installation and replacement wave, as discussed in section 2.4. The data regarding the manufacturers is quite incomplete, as can be seen by the high number of NA's (not available). The dominant brand is Smit, with Pauwels in second.

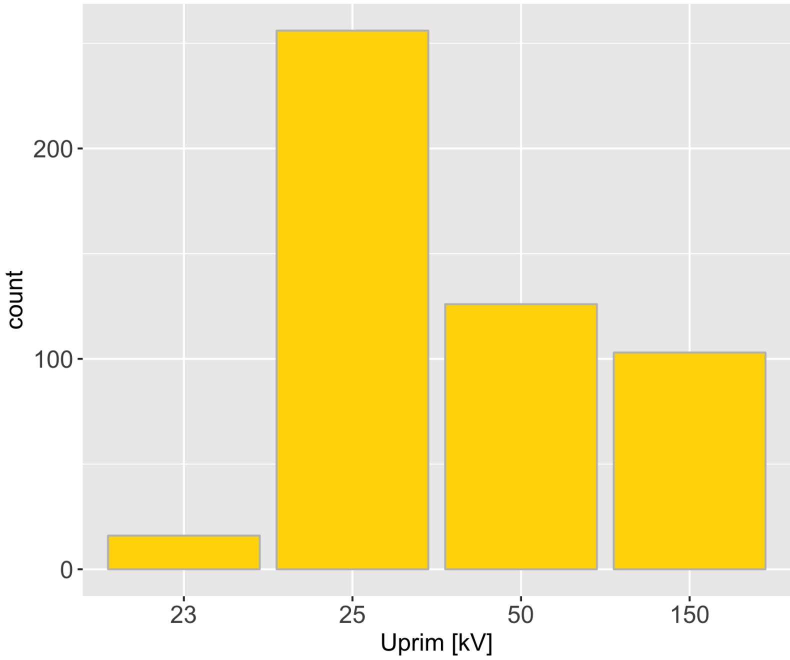


Figure 7.3: Voltage distribution of the transformer population. n = 498

Figure 7.4: Age distribution of the transformer population. n = 498

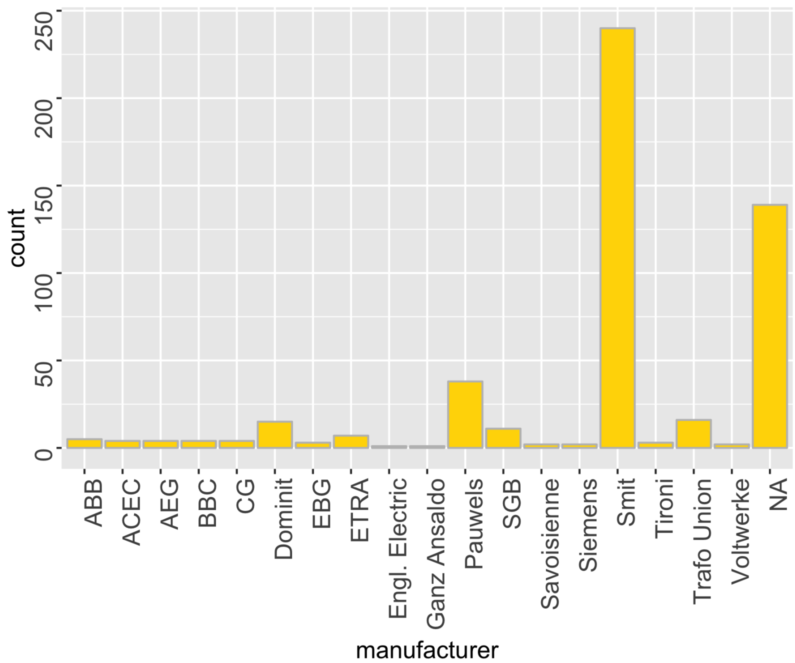


Figure 7.5: Manufacturer distribution of the transformer population. n = 498

Chapter 8

Results

In this chapter the results of the HI and failure probability models are discussed. The results of the HI model is discussed in section 8.1, in which the input data is reviewed and some exploratory data analysis is performed to find a relation between the HI and other variables. This is followed by the results of the survival model in section 8.2, in which the effect of the covariates and their significance on the accuracy of the model is studied.

8.1 Results of the HI Model

8.1.1 Review of Input Data

To check whether the input values are within reason of the treshold values proposed in [1], and to have a general overview of the problems in the population, boxplots were made to see in which category the quantiles fall. These plots for DGA, oil, and furan measurements can be seen in figure 8.1 to 8.3. The colored horizontal lines are the threshold values used by the assessment functions to score the condition indicators. These figures are based on the entire measurement history, and thus contain transformers that are no longer in service. Keep in mind that only in service transformers are used for the HI and survival models. From these figures it can be concluded that the values are correct in terms of scale. Outliers are not displayed, as they extend the scales extensively. See figure B.1 to B.3 in appendix B for the plots with outliers.

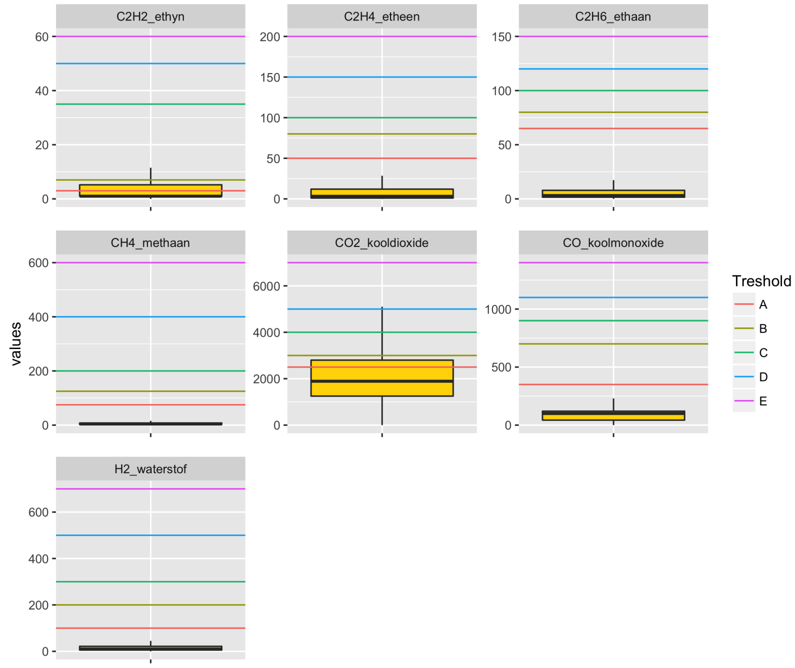


Figure 8.1: DGA data plotted with assessment function tresholds. n = 84k.

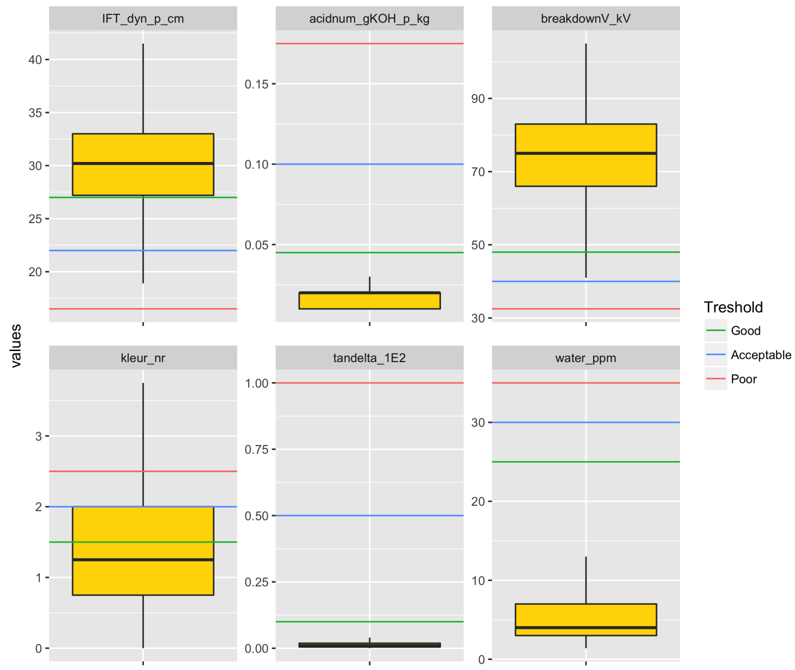


Figure 8.2: Oil properties data plotted with assessment function tresholds. n = 12k

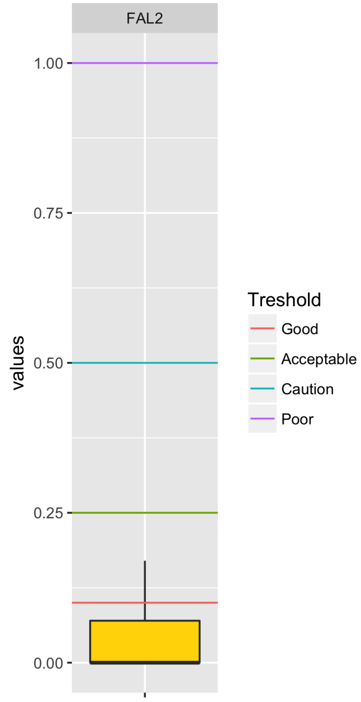


Figure 8.3: Furan data plotted with assessment function tresholds. n = 1361.

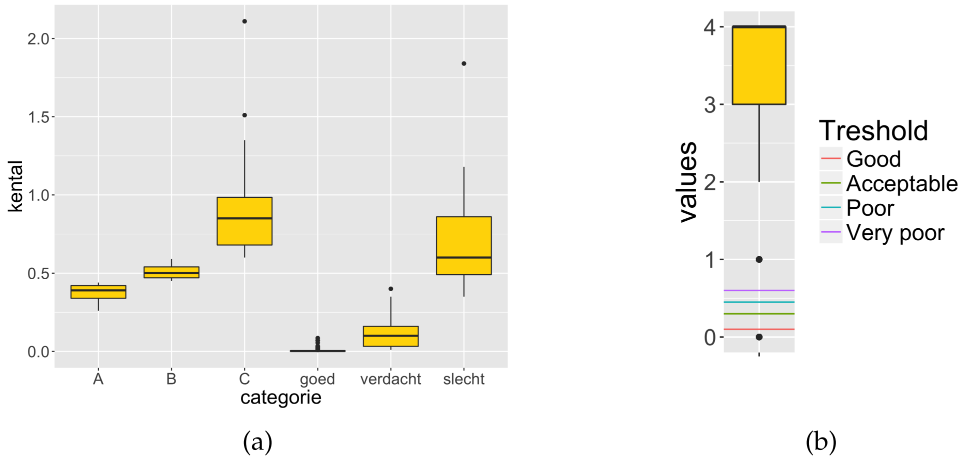


Figure 8.4: LTC data plotted with assessment function tresholds. n = 572

The treshold values for the LTC assessment function are the same as those used by the company that does the LTC diagnostic. This was not given however, and thus a categorical boxplot was made to find the tresholds, see figure 8.4a. In figure 8.4b the boxplot with the tresholds can be seen.

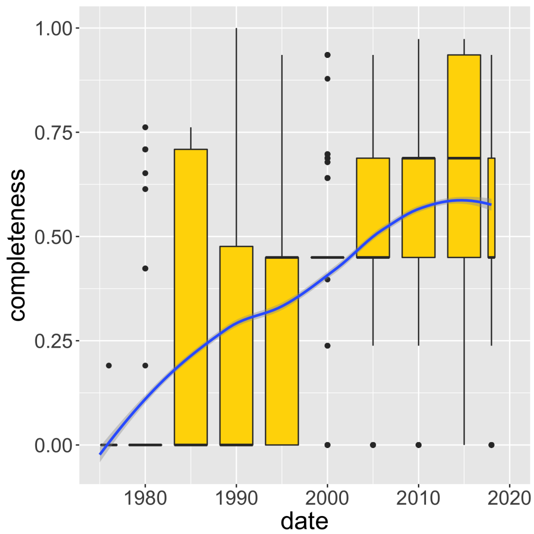


Figure 8.5: Higher completeness can be seen for more recent years. n = 15.4k.

To show any trends in the availability of data over time, the completeness of the data over time was plotted, see figure 8.5. The line is a result of a local regression smoothing function (loess). As expected, for more recent years the completeness is higher. The flattening at the end is probably caused by work orders that still need to be carried out, or the fact that the bin width is smaller at the end.

In table 8.1 the amount of measurements for each condition indicator can be seen. This only entails data that has been joined to individual transformers and actually form a part of the HI calculation later on.

Table 8.1

	dga	furan	oil	ltc
n	10232	1069	1755	629

8.1.2 HI output

Behaviour with Age

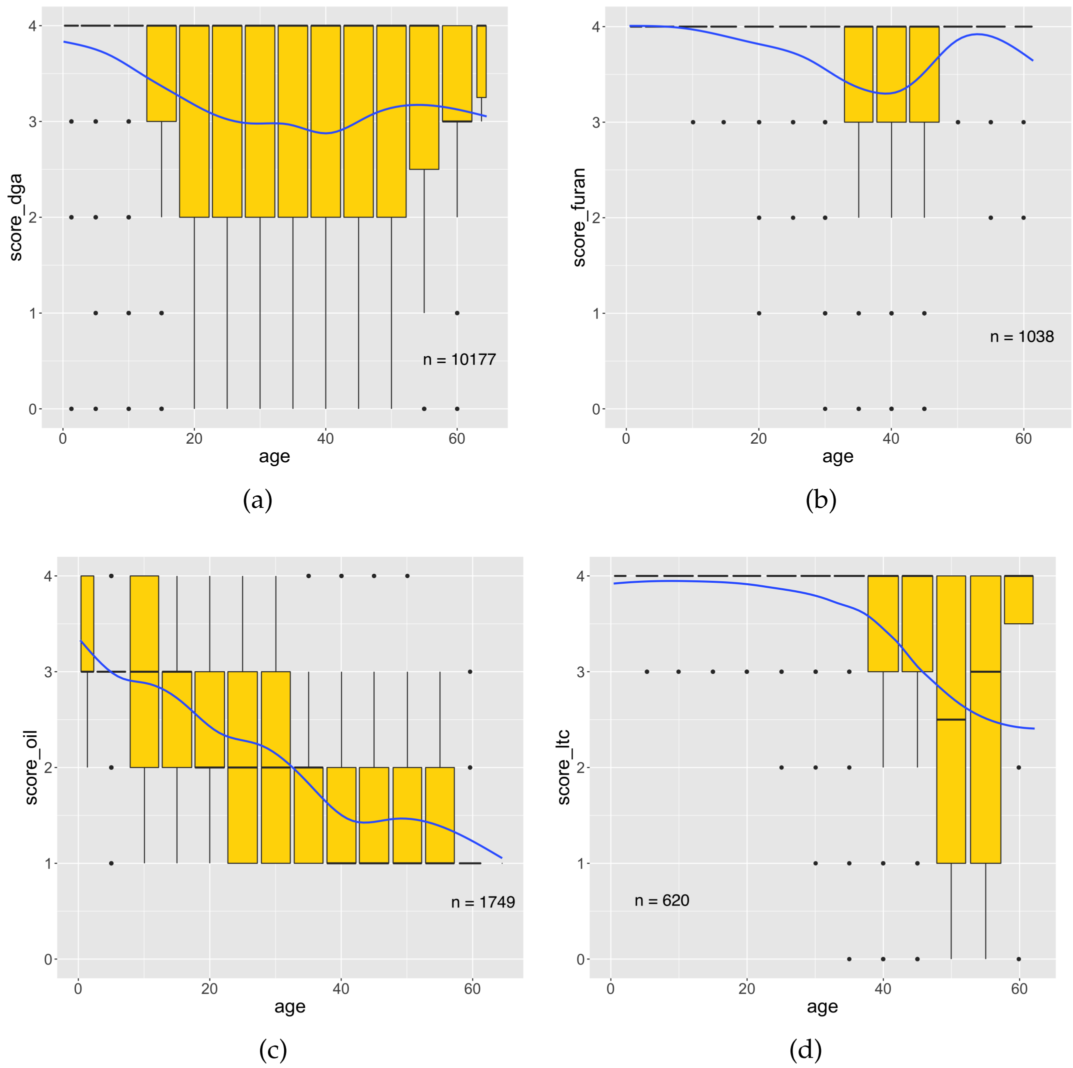


Figure 8.6: Boxplots of scores for different age groups.

Some data exploration is performed in order to get an idea of how the HI behaves and for which additional purposes it can be used. Relation with time, brand and voltage rating is performed.

In order to get an idea of how the scores behave with time, boxplots of different age groups were made, which can be seen in figure 8.6. The line is again a local regression which eases the interpretation of the results. For the DGA and furan scores, there is a clear reverse in the slope at around the 40 year age mark. Assumption is that old transformers with bad condition indicators are taken out of service if they are passed the expected lifetime of 40 years, which is typical expectancy given by manufacturers. In future work, these type of plots can be used to estimate missing values based on time.

Moving on to the relationship between the HI and time, similair observations can be made. As there is a relatively low amount of LTC measurements, HI_{tank} will be studied first. The HI is computed for each year in the transformer's current lifetime, but the completeness indicates how accurate or trustworthy that HI is. See figure 8.7 for a plot of the HI computed for each year of the whole transformer population. The color scale indicates the level of completeness, which is unfiltered in this case.

A linear regression indicates a low coeffecient, but this is to be expected as the transformer condition is not a function age but of endured stress. In figure 8.8 the points are filtered for a completeness of higher than 90%. This reduces the prediction bounds and has a slightly higher coefficient.

In figure 8.9 an example of HI calculations can be seen, which was given in [1]. This also indicates a low correlation coefficient, see table 8.2 for a comparison of the correlation coefficients (r). It seems that increasing the completeness results in a bigger correlation coefficient. They are all negative, indicating the decay of the HI with age.

Table 8.2: HI-age correlation coefficients.

Dataset	r
compl > 0%	-0.21
compl > 90%	-0.46
example [1]	-0.13

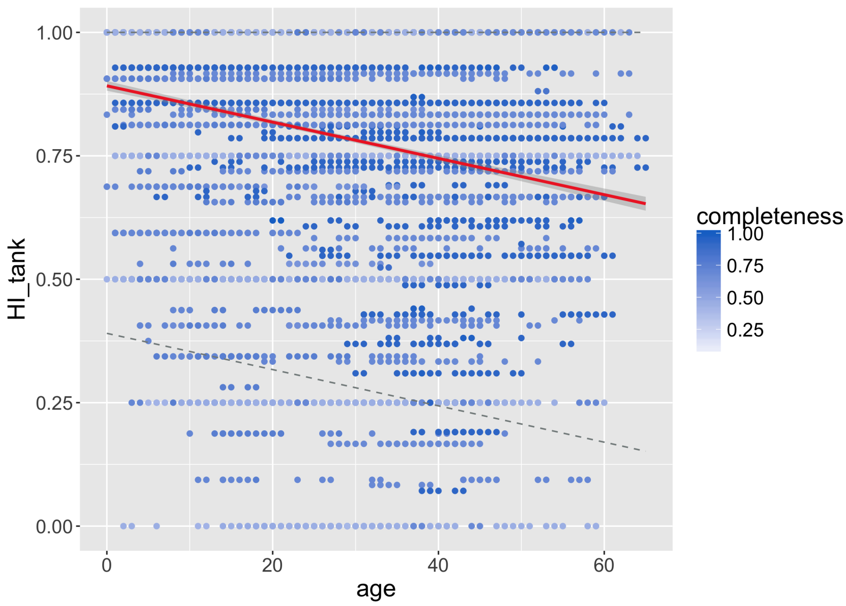


Figure 8.7: HI_{tank} of whole transformer population plotted against the age. Dashed line represents the prediction interval and the grey area the confidence interval. n = 10k

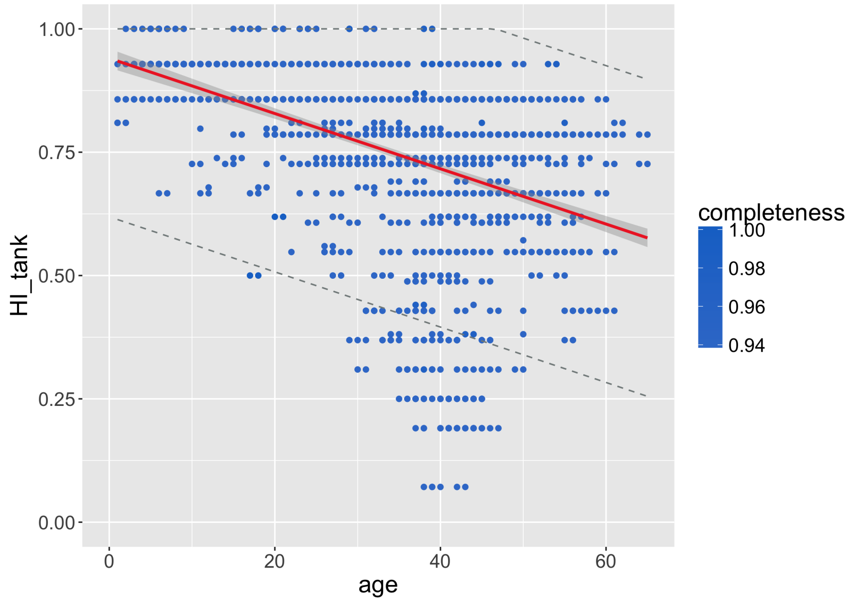


Figure 8.8: HI_{tank} of whole transformer population plotted against the age for completeness > 90%. Dashed line represents the prediction interval and the grey area the confidence interval. n = 1557

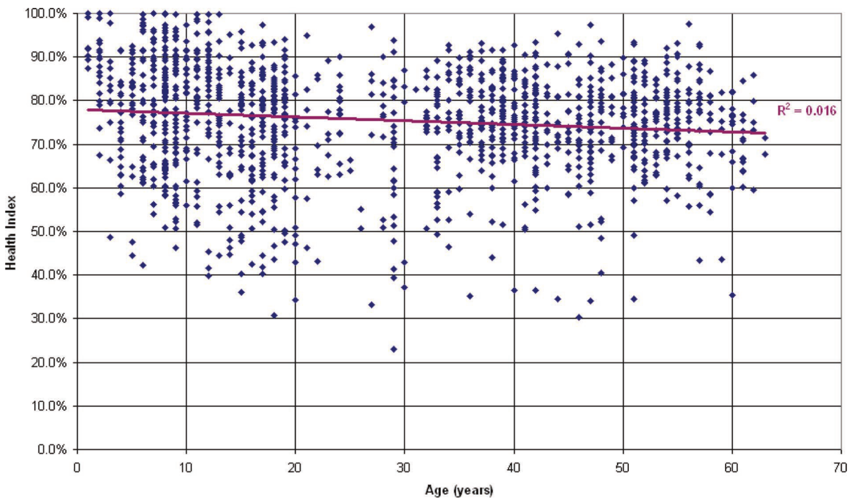


Figure 8.9: Example of HI calculation for a large transformer population taken from [1].

An important note is that after the 40 age year mark, the HI seems to increase. This is probably due to the fact that only in-service transformers are present in the data set. Old transformers with a low HI are probably taken out of service while old and good transformers are kept in service. See figure 8.10 for a smoothed regression in which this increase can be seen.

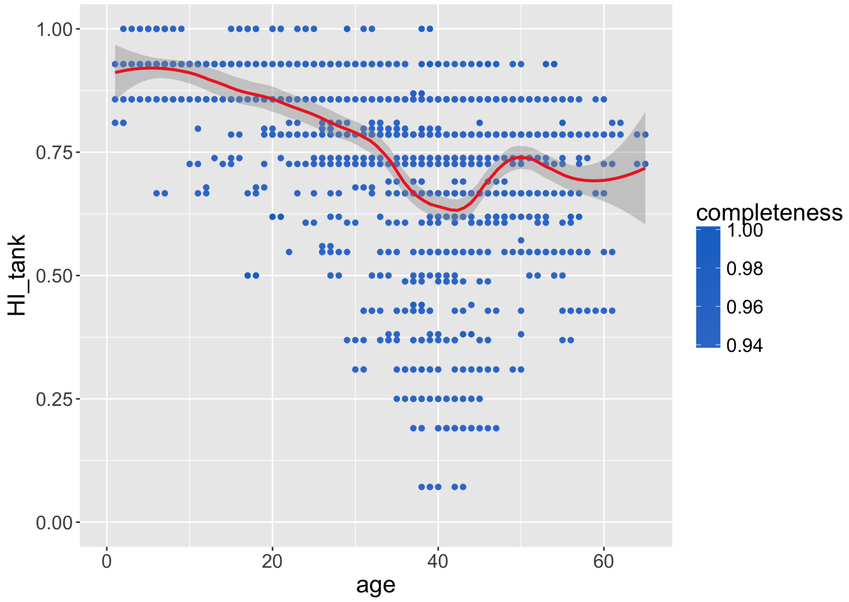


Figure 8.10: Nonparametric regression of HI_{tank} over time. Grey area is the confidence interval. n = 1557.

Introducing the LTC in the HI equation results in figure 8.11. Here the upward trend is not seen, because it is somewhat masked by the high weighting of the LTC sub health index, which does not display the trend.

Figure 8.11: Nonparametric regression of total HI over time. Grey area is the confidence interval. n = 732.

It can be concluded that the time dependency of the HI is not large, but this is to be expected as the age of a transformer is not necessarily a good measure of its condition. If this was the case then there would be no need for condition based maintenance. A transformer's condition change process has a time dependency, but it is hugely influenced by its operating conditions. Furthermore it can be concluded that the completeness index is quite usefull in filtering out highly uncertain values.

Behaviour with Voltage Rating

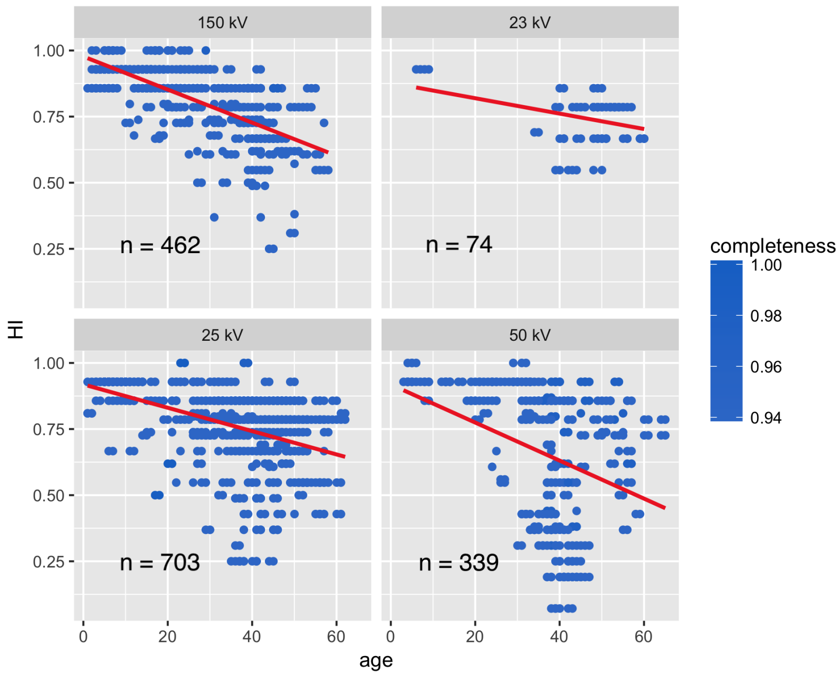


Figure 8.12: Regression for different voltage ratings.

In figure 8.12 the health index development over time can be seen for different voltage ratings. It appears that the 150 kV transformer deteriorate less that the others, but no other conclusions can be made.

Behaviour with Brands

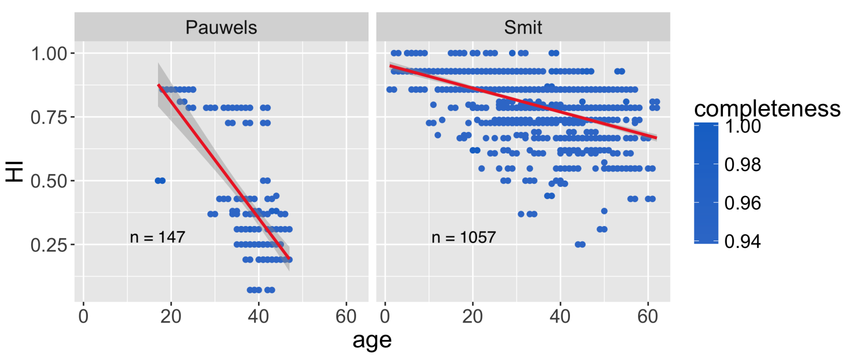


Figure 8.13: Regression for different voltage ratings.

The two most representative brands in the data were compared and it appears that Smit transformers outperform the Pauwels. This agrees with the experience of the asset manager in charge of transformers.

8.1.3 HI validation and conclusion

To verify the HI, which has the goal to identify and prioritize replacements, the HI of the tranformers on Stedin's replacement list were compared. In table B.1 in appendix B these transformers can be seen. This table includes only transformers that are to be replaced based on quality assessments.

The planned replacement year, scores and corresponding evaluation date of those scores are given. Furthermore HI_{TANK} and HI_{TOT} are also given along with the corresponding level of completeness.

Some HI are still relatively high, but this is paired with a low completeness. Those that have a high completeness display reasons for replacement; either the HI is low or one subcomponent is critical and not worth a revision.

This does display a problem with using a single number for a condition assessment, namely that if only one subcomponent is scored badly, it can be masked by other components that are scored well.

8.2 Results of the Failure Probability Model

A time dependent cox model was implemented and the effects of various covariates were studied. Univariate models were made to indicate which covariates might be useful in a multivariate model, which was implemented afterwards. The model is based on corrective maintenance events, which will be seen as a failure. The results of the failure probability model will be discussed by:

- Covariate effect β: whether it impacts the hazard function as expected, i.e. increasingly or decreasingly.
- p value: whether the covariate is statistically significant. 5% is usually used as the threshold for significance, however in the univariate models a significance level of about 20% can be used to select a covariate for a multivariate model.
- Log likelihood ratio: whether and by how much the covariate increases the likelihood of the model compared to the base model.
- Concordance: 0.75 being the average for Cox models and 0.5 being no better than a coin flip [82].

Furthermore, the amount of events per covariate should be at least 10. There were in total 306 corrective maintenances that could be matched to a transformer ID, however there was no clear measure on the severity of the situation. Furthermore the type of failure (which subsystem and cause of failure) is not well defined in some cases and can thus not always be correctly identified by the search terms used in the R script. On top of this there is also the issue of missing condition data at the time of the failure.

By distinguishing the type of failure on which the models are derived, the covariate effects can be more specific towards a failure type. This makes the contribution of the covariates to each type of failure more clear. Three subsets are made:

- LTC failures
- Leakages (seals, tank corrosion)
- Miscellaneous (bushing, cooling, protective devices)

The last group contains events that could not be categorized or are a part of small category groups.

For each event type, a univariate and multivariate model will be created. In subsection 8.2.1 the model of all events will be presented, followed by the LTC event types in subsection 8.2.2, leakage event types in 8.2.3, and miscellaneous events in subsection 8.2.4. This section ends with a conclusion in subsection 8.2.5.

8.2.1 All Event Types

Univariate models

In table 8.3 the results of the univariate models are given. These models were based on all failures while the rows containing missing covariate data were filtered out. *HR* is the hazard ratio, which is given along with the confidence intervals, and the log likelihood ratio is given by *LL.ratio*. Significant p values are followed by an asterisk or two; one for the 20% threshold and two for the 5% threshold. As these are univariate models, the C index will not be discussed as it assumed to be low for univariate models. The amount of censored and non-censored observations is given by n, while the amount of events (failures) are given by *n.event*. Note that the observations are spread across multiple rows due to time dependent covariates, which is why n is multiple times higher than the amount of transformers. *n.event* has been corrected for this and gives the actual amount of events.

Table 8.3: Univariate models for all failures

covariate	beta	HR (95% CI)	wald.test	p.value	LL.ratio	C index	n	n.event
HI	-0.53	0.591 (0.33-1.06)	3.13	0.077*	4.03	0.53	2286	272
age	0.02	1.02 (1.01-1.03)	26.60	2.5e-07**	40.18	0.60	2484	306
uprim50	0.76	2.15 (1.58-2.91)	27.10	8.2e-07**	38.18	0.58	2486	306
uprim150	0.10	1.1 (0.728-1.66)	27.10	0.65	38.18	0.58	2486	306
score_dga	-0.10	0.903 (0.797-1.02)	2.56	0.11*	3.39	0.53	2276	272
score_furan	-0.13	0.88 (0.735-1.05)	1.92	0.17*	2.23	0.52	1540	168
score_oil	-0.11	0.896 (0.735-1.09)	1.17	0.28	1.66	0.52	959	154
HI_tot	-0.17	0.84 (0.449-1.57)	0.30	0.58	0.45	0.51	2286	272
score_ltc	-0.11	0.897 (0.744-1.08)	1.29	0.26	1.48	0.51	1081	150

The significant covariates are the age and primary voltage of 50 kV. An increase in age increases the hazard, which was as expected. The primary voltage is a categorical variable and is thus compared to the reference case of 25 kV. Notably, the only voltage level that significantly impacts the hazard is the 50 kV level.

The rest of the covariates do effect the hazard as expected, i.e. lowering the hazard with the negative covariate effect, but the p values are not low enough to be considered significant in the univariate case. However, the HI, dga score and furan score are significant enough to be considered for a multivariate model.

Because these models were not based on a subset of the data, the cases with low completeness were also included in the derivation of the HI and HI_{tot} covariate effect. In table 8.4 and 8.5 these covariates were evaluated again for a subset of completeness > 0.85 and $completeness_{tot}$ > 0.80 respectively, which then includes a measurement of all sub HI.

A bigger effect is observed with an increased significance for the HI and for HI_{tot} and the significance is quite higher. This shows the importance of using the completeness index and that excessive interpolation of the data may lead to incorrect results.

Table 8.4: Univariate model of HI for all fails with completeness subset

covariate	beta	HR (95% CI)	wald.test	p.value	LL.ratio	C index	n	n.event
HI	-1.14	0.321 (0.114-0.903)	4.64	0.031**	5.71	0.56	763	109
age	0.02	1.02 (1-1.04)	4.62	0.032**	9.59	0.58	763	109
uprim50	1.18	3.25 (1.77-5.97)	29.80	0.00015**	44.05	0.67	763	109
uprim150	-0.29	0.745 (0.344-1.62)	29.80	0.46	44.05	0.67	763	109

Table 8.5: Univariate model of HI_{tot} for all fails with completeness subset

covariate	beta	HR (95% CI)	wald.test	p.value	LL.ratio	C index	n	n.event
HI_tot	-0.51	0.599 (0.166-2.16)	0.61	0.43	0.80	0.51	844	105
age	0.03	1.03 (1.01-1.05)	10.90	0.00098**	18.64	0.61	844	105
uprim50	0.87	2.4 (1.34-4.3)	13.50	0.0034**	21.09	0.61	844	105
uprim150	-0.10	0.902 (0.446-1.83)	13.50	0.78	21.09	0.61	844	105

Multivariate model

According to table 8.3 the relevant covariates are HI, age, uprim50, furan score and oil score. Using all of these results in the model in table 8.6. Many of the covariates have a low significance and so another method, backward selection, is used to find the best model. Backward selection removes covariates from the complete model by comparing the Aikake information criteria (AIC) to select the best covariates for the model [82]. The AIC is one of the most used criteria in model selection and is a trade of between the amount of parameters and the resulting likelihood. This can be implemented with the `step` function from the `rms` package. The results of the backward selection can be seen in table 8.7 and the final results, which is uses all the available data, can be seen in table 8.8. The final model also narrows down the confidence interval for the hazard ratio.

Unfortunately, the health indices were not significant enough in combination with the age and voltage level. The final model also has a below average concordance, although it is higher than the univariate models.

Because these are not time dependent covariates, a test must be done for the PH assumption. In figure 8.14 the Schoenfeld residual plots are given, along with an estimation of $\beta(t)$. This tests whether the slope of residuals are zero and from this

Table 8.6: Multivariate model for all fails based on univariate significance

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
uprim50TRUE	1.19	3.28 (1.94-5.53)	27.00	8.6e-06**	49.70	0.69	763	109
age	0.02	1.02 (0.996-1.04)	27.00	0.1	49.70	0.69	763	109
HI	1.01	2.75 (0.0251-302)	27.00	0.67	49.70	0.69	763	109
score_oil	0.00	1 (0.528-1.91)	27.00	0.99	49.70	0.69	763	109
score_dga	-0.20	0.817 (0.417-1.6)	27.00	0.56	49.70	0.69	763	109

Table 8.7: Multivariate model for all fails by backward selection

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
uprim50TRUE	1.23	3.41 (2.31-5.02)	47.10	6.2e-10	48.69	0.67	763	109
age	0.02	1.02 (1-1.03)	47.10	0.022	48.69	0.67	763	109

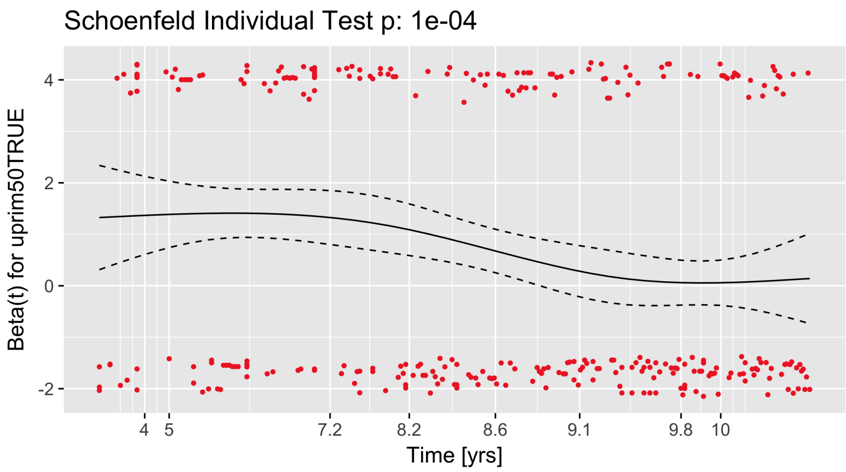
it can be concluded that the PH assumption is only valid for the age covariate. This means that the model might be improved by [79]:

- adding a omitted covariate that corrects this non-proportionality
- transforming the covariate effect to be time dependent
- the use of an non-PH model such as AFT

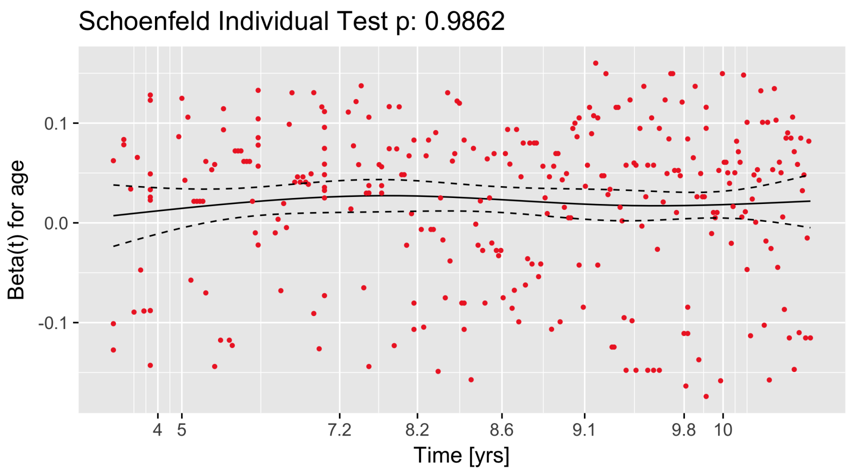
Note that the test for proportionality should be done with the multivariate models, as omitted covariates will result in a high propotion of non-proportional covariates.

Table 8.8: Final multivariate model for all fails

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
uprim50TRUE	0.68	1.97 (1.51-2.57)	45.50	6.9e-07	72.37	0.63	2484	306
age	0.02	1.02 (1.01-1.03)	45.50	8.5e-07	72.37	0.63	2484	306



(a)



(b)

Figure 8.14: Schoenfeld test for proportional hazard assumption of voltage (a) and age (b).

8.2.2 LTC Event Types

Univariate models

See table 8.9 for the univariate models based on LTC failures. In this table and the following ones, the appropriate completeness was used for the HI and HI_{tot} models. For this case no significant covariates other than the voltage and age could be found. The ltc score is on the edge of the 20% threshold and might still prove useful in a multivariate model.

Table 8.9: Univariate models for LTC fails

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
HI	-1.00	0.369 (0.0658-2.07)	1.29	0.26	1.67	0.57	605	47
age	0.03	1.03 (1.02-1.04)	27.50	1.6e-07**	34.19	0.64	1994	144
uprim50	0.79	2.2 (1.42-3.42)	16.50	0.00045**	22.59	0.59	1995	144
uprim150	-0.15	0.859 (0.488-1.51)	16.50	0.60	22.59	0.59	1995	144
score_dga	-0.00	0.997 (0.809-1.23)	0.00	0.98	0.00	0.50	1817	124
score_furan	0.06	1.06 (0.708-1.6)	0.09	0.77	0.15	0.52	1226	82
score_oil	-0.08	0.921 (0.665-1.28)	0.25	0.62	0.40	0.52	760	63
HI_tot	-0.16	0.85 (0.12-5.99)	0.03	0.87	0.05	0.48	664	61
score_ltc	-0.15	0.86 (0.671-1.1)	1.42	0.23	1.88	0.53	854	85

Multivariate models

According to table 8.9, the significant covariates with respect to LTC events are the age and uprim50. The LTC score is on the verge of being significant for the univariate case and thus a multivariate model is built with it, to see if it will increase. The result can be seen in table 8.10. It is clear that the significance of the LTC score is not increased.

Table 8.10: Multivariate model for LTC fails based on univariate significance

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
age	0.03	1.03 (1.01-1.05)	30.10	0.00044	42.97	0.70	854	85
uprim50TRUE	1.07	2.92 (1.67-5.09)	30.10	0.00016	42.97	0.70	854	85
score_ltc	-0.08	0.925 (0.697-1.23)	30.10	0.59	42.97	0.70	854	85

The result of performing backward selection can be seen in table 8.11. The significance did not increase and the effect is positive, which is in contrast with the expectation of it being negative. Furthermore there are only 30 events, which is not enough for 4 covariates. The concordance is higher, but this is quite certain a result of overfitting because according to this model a better condition of the LTC and paper leads to higher hazard rate. Therefore this model will not be developed further.

Table 8.11: Multivariate model for LTC fails by backward selection

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
uprim50TRUE	1.92	6.83 (3.01-15.5)	22.90	4.3e-06	26.27	0.76	314	30
score_oil	-0.65	0.524 (0.321-0.854)	22.90	0.0095	26.27	0.76	314	30
score_furan	0.38	1.46 (0.943-2.27)	22.90	0.089	26.27	0.76	314	30
score_ltc	0.52	1.68 (0.746-3.8)	22.90	0.21	26.27	0.76	314	30

8.2.3 Leakage Event Types

Univariate models

For the leakage events, the HI, dga score and furan score are significant covariates, see table 8.12. The score of the oil might also prove useful in a multivariate model.

Table 8.12: Univariate model for leakage related events

covariate	beta	HR (95% CI)	wald.test	p.value	LL.ratio	C index	n	n.event
HI	-1.96	0.14 (0.0441-0.447)	11.00	0.0009**	9.77	0.61	619	53
age	0.03	1.03 (1.01-1.04)	19.30	1.1e-05**	28.01	0.62	2015	149
uprim50	1.06	2.89 (1.9-4.38)	27.00	6.8e-07**	34.15	0.62	2017	149
uprim150	0.29	1.33 (0.766-2.32)	27.00	0.31	34.15	0.62	2017	149
score_dga	-0.18	0.838 (0.718-0.978)	5.04	0.025**	5.57	0.54	1842	135
score_furan	-0.30	0.739 (0.623-0.876)	12.10	0.00049**	8.28	0.56	1239	79
score_oil	-0.23	0.79 (0.618-1.01)	3.51	0.061*	3.76	0.56	785	79
HI_tot	-1.27	0.28 (0.068-1.16)	3.10	0.078*	2.60	0.56	659	50
score_ltc	-0.10	0.905 (0.694-1.18)	0.54	0.46	0.54	0.52	840	70

Multivariate models

Table 8.13: Multivariate model for leakage events based on univariate significance

covariate	beta	HR (95% CI for HR)	wald.test	p.value	LL.ratio	C index	n	n.event
age	0.04	1.04 (1.01-1.06)	41.10	0.0034	50.60	0.75	622	53
uprim50TRUE	1.57	4.78 (2.53-9.05)	41.10	1.5e-06	50.60	0.75	622	53
score_furan	-0.13	0.876 (0.655-1.17)	41.10	0.37	50.60	0.75	622	53
score_dga	-0.02	0.983 (0.736-1.31)	41.10	0.91	50.60	0.75	622	53
score_oil	0.19	1.21 (0.757-1.94)	41.10	0.42	50.60	0.75	622	53

Using the significant covariates in table 8.12, the model in table 8.13 was made. Although the concordance is average, the scores are not contributing much to this due to the low significance of it.

8.2.4 Misc Event Types

Univariate models

For the miscellaneous events there are no useful significant covariates. There are not enough events to support the use of a multivariate model, and furthermore the ones that are below the 20% threshold do not effect the hazard rate in the expected way. Therefore this event type can not be analyzed further.

Table 8.14: Univariate model for misc events

covariate	beta	HR (95% CI)	wald.test	p.value	LL.ratio	C index	n	n.event
HI	0.64	1.89 (0.395-9.05)	0.63	0.43	0.30	0.56	40	18
age	0.00	1 (0.975-1.03)	0.04	0.84	0.07	0.50	125	42
uprim50	0.66	1.93 (0.826-4.49)	2.30	0.13	2.60	0.58	125	42
uprim150	0.27	1.31 (0.532-3.22)	2.30	0.56	2.60	0.58	125	42
score_dga	-0.05	0.953 (0.707-1.28)	0.10	0.75	0.14	0.52	118	39
score_furan	0.18	1.2 (0.731-1.96)	0.51	0.47	0.36	0.54	76	23
score_oil	0.36	1.43 (0.86-2.37)	1.89	0.17*	2.39	0.62	45	22
HI_tot	1.26	3.53 (0.00562-2220)	0.15	0.70	0.16	0.57	41	7
score_ltc	0.86	2.35 (0.834-6.65)	2.62	0.11*	0.82	0.57	56	13

8.2.5 Conclusion

It can be concluded that the condition indicators do have an effect on the failure probability in the univariate cases, but when they are used in a multivariate model they are masked by the significance of the age and voltage covariates.

Comparison of the models based on event types demonstrates the need to specify the type of failure, as the size and significance of the covariate effect can vary considerably.

Another problem is that not all events could be joined to a transformer ID, which makes the model imprecise. There were in total 785 transformer related corrective maintenances, but only 306 could be joined. This results in transformers that have experienced a failure with indication thereof in its condition data, to be inaccurately represented in the likelihood estimator. This is also the reason that the outage data was not used: from the 387 transformer related outages, only 71 could be identified and these only included outages with customer interruptions.

Furthermore, the severity is not taken into account which means that small events which might not even be relevant are also present in the data.

Lastly, the voltage level does not seem to hold up to the proportional hazard assumption which indicates that there is room for improvement.

Chapter 9

Conclusion and Recommendations

9.1 Conclusion

In this thesis a HI model was built based on condition indicators. Afterwards, the HI model and its condition indicators were used as an input for the survival models.

It can be concluded that the HI method can identify transformers that need attention, however that one numerical index should only be used as a guideline, and that the sub health indices should also trigger concerns. Analogous to the weakest link in a chain, the weakest subsystems should trigger actions.

The implemented HI method is an improvement from the previous, as trend analyses is now possible due to the added quantization levels. Furthermore it is now possible to quickly create an overview of a transformer's data, which is an improvement compared to the previous situation in which the data was scattered in multiple data bases.

The survival model was used to answer the main research question: ***Can the condition of transformer be used as a reliable input for transformer failure probability prediction?*** The univariate models indicate that there is a significant effect of the condition indicators on the survival probability, however the concordance of these models were below average (~0.6). Therefore it can be concluded that there is an affect, but due to lacking data quality it can not yet be concluded whether it can be used as a reliable input (i.e. increasing the prediction accuracy of the model).

9.2 Recommendations

In order to make predictions based on the history, it is necessary to have the historical data quality up to par. The recommendation towards Stedin is to improve the outage data base by:

- Including a unique key per transformer and using this in all databases. This increases the ease of joining data and increases the amount of available data per transformer. The condition indicators of the transformers is dispersed in multiple systems which is not a problem if there was a unique key to join all the data. Joining the data took a significant amount of time and of course multiple attempts were made to join data that was not identified by a clear key.
- Adding predefined failure modes to the outage and maintenance forms provides

a better means for categorizing the events that occured. Adding both a unique key and a failure modes might also reduce the time needed for filling in forms by the electricians, as many of columns can be filled automatically if these two are known.

Future work on improving the HI should look into using the maintenance and loading data of transformers. Furthermore, it would make more sense to move the CO and CO2 assessment from the DGA sub health index to the sub health index concerning the insulation of the transformer, as paper degradation is what primarily forms these gasses and not the internal faults.

Another important aspect is that at this moment the bushings are not taken into account, which is a component that can have fatal injuries as a result, should someone be in the area. However, the asset manager stated that current condition indicator standards would dissaprove the use of a quite large portion of the bushing population, but the amount of faults do not reflect this. A study is being carried out to study the condition indicators and acceptable thresholds.

Lastly on the HI model, it might be worth while to fill in the missing data using advanced methods as described in [80]. Of course, the best solution is to improve the data acquistion and storage, but it would also take years before a significant amount of new data has been acquired. Filling in missing data by interpolation and other techniques might improve the current models, which might prove themselves useful for the replacement wave.

To increase the accuracy of the survival model, it is worthwhile to implement a fully parametric proportional hazard or AFT model. Research must be done on which base hazard function, e.g. Weibull, will fit the observations the best. The added advantage of this is that not only will it provide a better fit if the underlying distribution is chosen correctly, but it provides the means to calculate the actual survival time instead of only the probability.

Adding more relevant covariates might also improve the accuracy of the model, e.g. loading, temperature and weather conditions. The challenge is to gather as much possible while trading off the costs of acquiring and storing the data.

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Appendix A

FMEA

Table A.1: Action definitions

Action	Description
1	Monitor fault development up to point of replacement
2	Repair if possible, otherwise replace component
3	Replace component
4	Repair/replace if costeffecient, otherwise replace transformer
5	Replace transformer

Table A.2: Transformer FMEA

Subsystem	**Failure mode**	**Effect**	**Causes**	**Stress**	**Detection**	**Action**
Core	Insulating layers between lamination damaged	• Overheating due to eddy currents • Performance loss	• Transportation • Eddy currents	MT	Thermo scan, DGA	1
	Gaps between de laminations	• Partial discharges • Overheating due to eddy currents • Performance loss	• Transportation • Gas bubbles in oil	CM	Thermo scan, DGA	1
Windings	Deformation of windings axially or radially	• Rupture solid insulation • Overheating due to leakage flux • Performance loss	• Electromagnetic forces due to fault currents • Transportation • Thermal expansion/compression	EMT	Winding ratio	1
	Dielectric breakdown insulating medium	• Short circuit of windings: incorrect turn ratio • Overheating if short circuit to ground	• Fault voltages • Lightning impulse • Ruptured solid insulation • Degraded or contaminated oil	CET	DGA, resistance measurement, furan analysis	Oil:2 Paper: 5
	Conductor rupture	Interuption of load	• Mechanical wear due to thermal expansion • Deformation	MT	Transformer not functioning	4
LTC arcing switch	Bad/interupted contact	• Interuption of load • Performance loss • Overheating due high resistivity	• Low contact pressure due to spring wear • Long term effect • Operational arcing causes pitting • Mechanical wear contacts due to switching	CEMT	Visual	2
	Open or short circuited transition impedance	• High circulating current during transition • Arcing on main contact	• Bad/interupted contact • Burnt resistor	ET	Visual, DRM	2
	Switching time too large	• Interuption of load	• Faulty motor drive • Spring wear	EMT	Switch time measurements, DRM	2
LTC off load switch	Bad/interupted contact	• Interuption of load • Performance loss • High temperatures due to high resistivity	Long term effect	CET	DRM, SRM, DGA	4

Subsystem	Failure mode	Effect	Causes	Stress	Detection	Action
LTC drive	Motor failure	Unable to switch taps	Overuse	EMT	Visual	2
	Shaft rupture	Catastrophic failure	Mechanical load or fatigue	M		5
Bushing	Oil leaks	• Overheating • Flashover • Performance loss	• Environmental stresses	CMT	Visual	4
	High partial discharge activity	• Overheating • Flashover • Performance loss	• High voltages • Presence of floating particles • Presence of sharp points	EM	PD activity measurement, Acoustic, thermo scan	3
	Bad connection within bushing, local temperature increase	• Explosion due to high oil expansion • Overheating • Performance loss	Mechanical stresses	M	Thermo scan	2
Oil	Cooling properties reduced	Overheating	Oxidation results in sludge deposits on winding and cooling ducts, reducing cooling.	CT	DGA, physical oil properties	2
	Insulating properties reduced	• Partial discharges • Flashover	• Oxidation results in acid degrading paper insulation • Water content: water might be released in oil and vapor occurs.	CT	DGA, physical oil properties	2
	Reaction with copper or silver forming semi-conducting compounds	Short circuits	Presence of corrosive sulphur in oil	C	DGA, physical oil properties	2
Tank	Gaskets and seals damage	Oil contamination	Aging of seals and gaskets	CM	Visual	2
	Paint wear off and corrosion	Oil leakage	Environmental stresses	CMT	Visual	4
Cooling	Pump failure	Overheating	Pump wear/overuse	M	Visual	2
	Fan failure	Overheating	Fan wear/overuse	M	Visual	2
Protective devices	Bucholz failure	Catastrophic failure		MC	Visual	3
	Pressure relief circuitry failure	Catastrophic failure	Springs in device becoming fragile	MC	Visual	3
	Surge protector failure	High voltage applied over transformer	• Moisture • Heat • Corossion	CT	Visual	3

Appendix B

HI

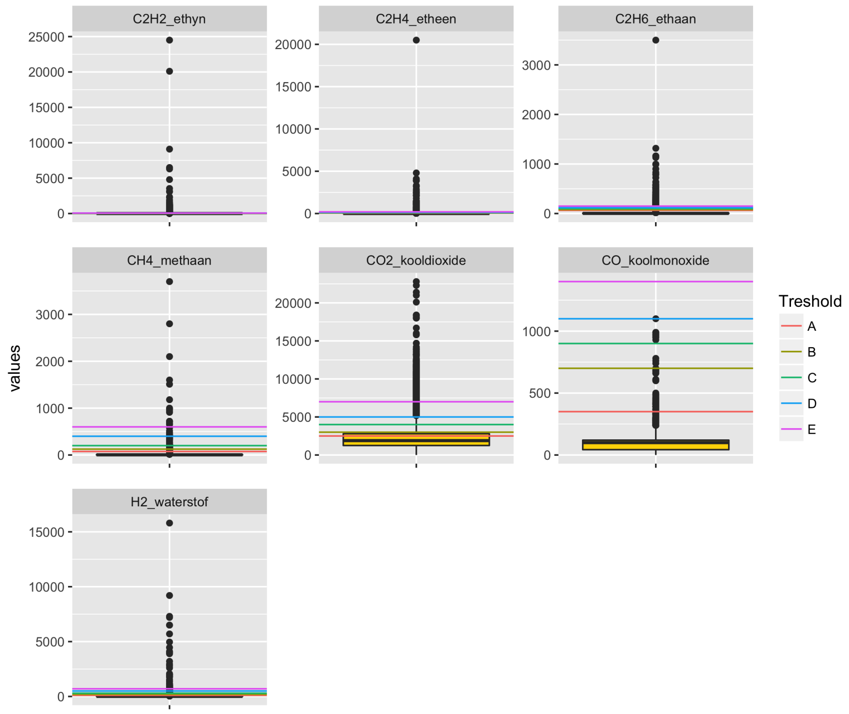

Figure B.1: DGA data plotted with assessment function tresholds.

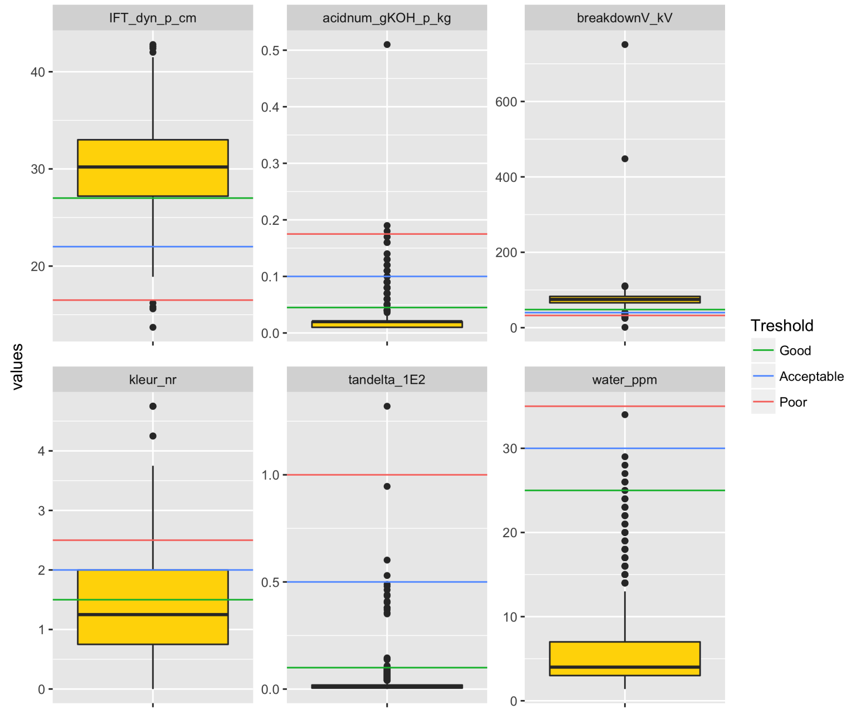

Figure B.2: Oil properties data plotted with assessment function tresholds.

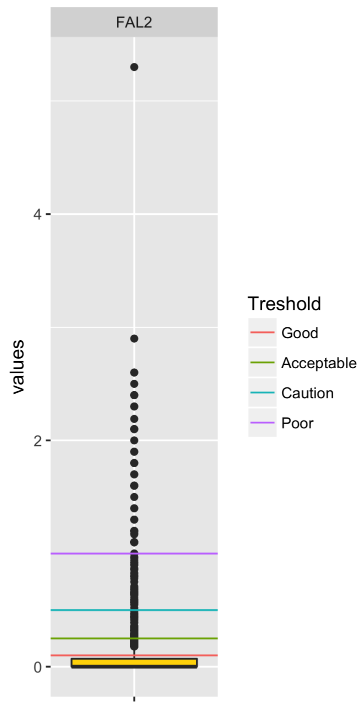

Figure B.3: Furan data plotted with assessment function tresholds.

Table B.1: HI of transformers to be replaced

ID	build year	replacing	date_ltc	ltc	date_dga	dga	date_furan	furan	date_oil	oil	HI	completeness	HI_tot	compl_tot
1	1958	2017	2015-01-23	1	2017-05-30	3	2014-04-29	4	2014-04-30	1	0.75	0.45	0.45	0
2	1962	2017	2016-07-27	0	2017-05-30	2	2017-05-23	4	2017-05-30	1	0.55	0.94	0.33	0.96
3	1958	2017	2014-04-16	1	2017-10-02	1	2012-03-06	4	2016-09-23	1	0.25	0.45	0.15	0
4	1960	2017	2016-05-12	1	2017-10-02	4	2008-07-17	4	2016-09-23	1	1	0.45	0.7	0.67
5	1965	2018	2016-07-22	1	2017-06-13	3	2017-06-07	4	2017-06-13	4	0.88	0.82	0.63	0.89
6	1957	2018	2015-08-14	0	2017-05-19	1	2017-05-16	4	2017-05-19	1	0.43	0.94	0.26	0.96
7	1960	2018	2016-07-28	1	2017-05-19	2	2017-05-16	4	2017-05-19	1	0.55	0.94	0.43	0.96
8	1966	2018	2014-06-20	1	2017-05-19	3	2017-05-16	4	2017-05-19	2	0.74	0.94	0.44	0
9	1957	2019	2015-08-13	2	2017-05-19	2	2017-05-16	4	2017-05-19	1	0.55	0.94	0.53	0.96
10	1967	2019	2014-06-20	2	2017-05-19	4	2017-05-16	4	2017-05-19	2	0.86	0.94	0.51	0
11	1962	2019	2016-04-05	0	2017-10-02	4	2005-08-16	4	2016-09-23	1	1	0.45	0.6	0.67
12	1962	2019			2015-11-06	4					NaN	0	NaN	0
13	1958	2019	2014-02-18	1	2017-09-19	3	2013-03-05	4	2016-09-23	2	0.75	0.45	0.45	0
14	1956	2020	2015-01-15	2	2017-05-19	4	2017-05-16	4	2017-05-19	1	0.79	0.94	0.47	0
15	1966	2020	2014-06-23	2	2017-05-19	4	2017-05-16	4	2017-05-19	2	0.86	0.94	0.51	0
16	1968	2020			2017-09-19	3	2009-04-24	4	2016-09-23	3	0.75	0.45	0.45	0
17	1970	2020			2017-06-13	4	2017-06-07	4	2017-06-13	4	1	0.82	0.6	0
18	1975	2021	2015-06-26	3	2017-10-03	4	2017-04-21	4	2017-04-26	2	0.86	0.94	0.51	0
19	1969	2021			2017-10-02	4			2016-09-23	2	1	0.45	0.6	0
20	1969	2021			2017-10-02	3	2008-07-16	4	2016-09-23	2	0.75	0.45	0.45	0
21	1969	2021			2017-10-02	4	2008-07-16	4	2016-08-26	2	1	0.45	0.6	0
22	1969	2021			2017-10-02	4			2016-09-23	2	1	0.45	0.6	0
23	1969	2021			2017-10-02	3	2008-07-16	4	2016-09-23	2	0.75	0.45	0.45	0
24	1969	2021			2017-10-02	4	2008-07-16	4	2016-08-26	3	1	0.45	0.6	0
25	1966	2021			2017-09-12	2	2013-03-06	4	2016-09-23	2	0.5	0.45	0.3	0
26	1992	2021	2014-03-27	3	2017-09-12	4	2015-11-16	4	2016-09-23	2	1	0.69	0.6	0
27	1965	2022			2017-10-02	4	2012-03-07	4	2016-09-23	2	1	0.45	0.6	0
28	1972	2022			2017-09-19	1	2012-03-08	1	2016-09-23	1	0.25	0.45	0.15	0
29	1972	2022			2017-10-02	4					1	0.45	0.6	0
30	1984	2022	2016-05-27	3	2017-09-19	4	2015-11-12	3	2016-09-23	2	0.92	0.69	0.85	0.81

Appendix C

R Code

Listing C.1: Constructing the event tables

```
# DATA PREP REPAIRS -------------------------------------------------------------
# Get serie_nr, HI's, bouwjaar, dates, failures
# Get these from tf list, then make life table

tfs <- list.select(tf,
                   "INFO" = INFO[c("serie_nr", "bouw jaar trafo", "regio",
                                   "fabrikant trafo", "uprim")],
                   "HIF" = select(HI$HIF, "date", "age", "HI", "completeness",
                                  starts_with("score"),
                                  starts_with("valid"), ends_with("tot")),
                   "REPAIRS" = FAILS$REPAIRS[c(1, 9, 36:48)]
)
tf_info <- list.select(tfs, INFO) %>% do.call(what = "rbind") %>% do.call(what = "rbind")
tf_info$uprim[tf_info$uprim == 2.3] <- 2.5
tf_info$uprim <- (tf_info$uprim *10) %>% as.factor()

valid_NA <- function(x,y){ # Helper function
  x*(y|NA)
}

# Define function to make an event table
make_life_table <- function(tf, method,
                            considered_fails = NULL,
                            unvalid_to_NA = FALSE){
  # Use repairs as events for life table and merge duplicates
  trafo_bouwjaar <- tf$INFO$"bouw jaar trafo" # called a lot, reduce runtime
  entry_date <- max(as_date("2008-01-01"), trafo_bouwjaar) # 2008 = studystart
  study_start_date <- as_date("2008-01-01")
  end_time <- difftime(as_date("2018-08-01"), as_date("2008-01-01")) %>%
            time_length("years") # same for all
  max_events <- 3 # max amount of considered event
  ltable <- tibble()
  { #1
    if(nrow(tf$REPAIRS)){#2
      # Create life table, fix duplicate times, add event number stratum

      #create table
      ltable <- tf$REPAIRS
      ltable <- ltable[order(ltable$"Aanmaak Datum"),]
      ltable$serie_nr <- tf$INFO$serie_nr
      #ltable <- uniw(ltable, serie_nr, "Aanmaak Datum", .keep_all = T)
      ltable$duptime_correction <- F

      #filter relevant fails
      if(!is.null(considered_fails)){
```

```
      ltable <- subset(ltable, eval(parse(text = considered_fails)))
    }

    #merge duplicate times
    duplidates <- subset(ltable, ltable$"Aanmaak Datum" %>% duplicated2())
    if(nrow(duplidates) != 0){
      ltable <- subset(ltable, !duplicated2(ltable$"Aanmaak Datum"))

      correction <- duplidates[1,]
      correction[,failtypes] <- colSums(duplidates[, failtypes]) %>% as.logical()
      correction$duptime_correction <- T

      ltable <- rbind(ltable, correction)
      ltable <- ltable[order(ltable$"Aanmaak Datum"),]
    }
    #add event number stratum
    ltable$eventnum <- seq_len(nrow(ltable))

    # Make start and stop times
    # takes study time (2008) as starting point, or build year if it entered the
        study later
    ltable$status <-  c(rep(1, nrow(ltable)))

    stop <- difftime(ltable$"Aanmaak Datum", study_start_date) %>%
              time_length("years")
    default_start <- difftime(entry_date, study_start_date)  %>%
                        time_length("years")
    start <- lag(stop, default = default_start )
    ltable$start2 <- start
    ltable$stop2 <- stop

  }#2

  # Add censored row if there were no failures to begin with,
  # or if they were all filtered out by failure type selection.
  if((nrow(tf$REPAIRS) == 0 ) | (nrow(ltable) == 0)){
    if(method == "WLW"){
      ltable <- censored_ltable[c(rep(1,max_events)),] # add presaved censor row
      ltable$eventnum <- c(1:max_events)
    }
    if(method == "AG"){
      ltable <- censored_ltable[1,] # add presaved censor row
      ltable$eventnum <- 1
    }
    ltable$serie_nr <- tf$INFO$serie_nr
    ltable$start2 <- difftime( entry_date, study_start_date) %>%
                      time_length("years")
    ltable$stop2 <- end_time
  }#1
  ltable1 <<- ltable

  # Add censored events depending on recurrence type
  if(method == "WLW"){#wlw
    if(max(ltable$eventnum) < max_events){
    event_count <- max(ltable$eventnum) # amount of events
    for(i in (event_count+1):max_events){ # add "artificial events"
      ltable[i,] <- censored_ltable[1,]
      ltable$serie_nr[i] <- tf$INFO$serie_nr
      ltable$eventnum[i] <- i
      ltable$start2[i] <- ltable$stop2[event_count]
      ltable$stop2[i] <- difftime(as_date("2018-08-01"), as_date("2008-01-01"))
          %>% time_length("years")
      }
    }else{
     ltable <- ltabe[1:max_events,]
    }
  }#wlw
```

```
    if( (method == "AG") & (tail(ltable$stop2,1) != end_time ) ){#ag add one
        censoring
        i <- nrow(ltable)+1
        ltable[i,] <- censored_ltable[1,]
        ltable$serie_nr[i] <- tf$INFO$serie_nr
        ltable$eventnum[i] <- i
        ltable$start2[i] <- ltable$stop2[i-1]
        ltable$stop2[i] <- difftime(as_date("2018-08-01"), as_date("2008-01-01"))
            %>% time_length("years")
    }#ag

  } #1


  # Add time dependent covariates with tmerge()
  # Covariates come from HIF.Not all HIF have all scores, causes problems.
  # Quick fix is adding all variables as NA with fix_missing_scores
  HIF <- tf$HIF
  HIF <- rbind.fill(HIF, fix_missing_scores)
  HIF <- HIF[-nrow(HIF),] # remove fixing row

  # Create output container
  output <- tibble()
  # Add td covariates
  for(i in ltable$eventnum){ # i for each eventnum, tmerge ltable$eventnum
    fail <<- ltable[i,]
    HIF <- subset(HIF, date >= entry_date )
    HIF$HI_stops <- difftime(HIF$date, as_date("2008-01-01")) %>% time_length("years
        ")
    scores <- select(HIF,starts_with("score"), starts_with("valid"))
    if(scores %>% is.na %>% all){return()}
    scores$serie_nr <- tf$INFO$serie_nr
    HIF <- subset(HIF, !duplicated(scores))
    HIF <- mutate(HIF, serie_nr = tf$INFO$serie_nr)

    if(unvalid_to_NA){
      HIF <- mutate(HIF, score_dga = valid_NA(score_dga,valid_dga),
                    score_furan = valid_NA(score_furan, valid_furan),
                    score_oil = valid_NA(score_oil, valid_oil),
                    score_ltc = valid_NA(score_ltc, valid_ltc) )
    }


    if(fail$start2 > fail$stop2){next} # start must be later than stop, otherwise
        error
    newfail <- tmerge(fail, fail, id = serie_nr, tstart = start2, tstop = stop2)
    for(j in 1:nrow(HIF)){ # j for each change in HIF table (change in covariates)
        #3
      newfail <- tmerge(newfail, HIF[j,], id = serie_nr,
                        age = tdc(HI_stops, age),
                        score_dga = tdc(HI_stops, score_dga),
                        score_furan = tdc(HI_stops, score_furan),
                        score_oil = tdc(HI_stops, score_oil),
                        score_ltc = tdc(HI_stops, score_ltc),
                        completeness = tdc(HI_stops, completeness),
                        HI = tdc(HI_stops, HI),
                        HI_tot = tdc(HI_stops, HI_tot),
                        compl_tot = tdc(HI_stops, compl_tot),
                        event = event(ltable$stop2[i], ltable$status[i]),
                        options = list(na.rm = F) )
    }#3

    output <- rbind.fill(output, newfail)
  }
  return(output)
}

```

```
# RUN AND SAVE VARIOUS FAILTYPES AG WITH NA  ------------------------------

life_tables <- vector("list",length = length(failtypes) )

for(i in 1:length(failtypes)){
  life_tables[[i]] <-  lapply(tfs, make_life_table,
                              considered_fails = failtypes[i],
                              method = "AG",
                              unvalid_to_NA = T
                             ) %>% do.call(what = "rbind.fill")
}

life_table_all_fails <-  lapply(tfs, make_life_table,
                                method = "AG", unvalid_to_NA = T
                               ) %>% do.call(what = "rbind.fill")

if(0){
  save(life_tables, file = "R_objects/Fail_model/life_tables_AG_failsubsets_withNA.
      RData")
  save(life_table_all_fails, file = "R_objects/Fail_model/life_table_AG_allfails_
      withNA.RData")
}
```