HIGH VOLTAGE ASSET PERFORMANCE MODELING

EVERT J. DE HAAN, BSC

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UNIVERSITY	Delft University of Technology
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DEPARTMENT	Electrical Sustainable Energy
GROUP	High-Voltage Technology & Management

Evert J. de Haan, BSc: *High Voltage Asset Performance Modeling*

For further information, contact the author: evertjdehaan@gmail.com

To Lyanne

SUMMARY

Many of the assets managed by TenneT TSO have been installed in the sixties and seventies of the previous century. Consequently, 50% of their assets will reach their designed lifetime within ten years. Due to financial and technical restrictions not all the asset can be replaced based on their age. Hence, TenneT TSO developed a *Health index tool* together with KEMA to translate measurements from inspection and maintenance to the health (technical condition) of an asset. In that way the maintenance and replacement planning can be adjusted for the health of all the assets. The outcome of the health index tool was a four-class scale. The asset could either be good, fair, moderate or poor. However, these four categories were not enough for the replacement planning and maintenance prioritization within the asset management department.

The goal of this research is to determine the current technical state of an asset in more detail. Furthermore, the derived tool or model should be capable of determining the technical state of the asset after the planning period.

In this research an asset performance estimation model has been derived. The model links inputs measured during inspection and maintenance to performance indicators. The model is based upon the failure modes of an asset and acknowledges various subpopulations of an asset with different failure rates and/or failure impacts. The more specific the subpopulations are, the more detailed the performance estimations become. A few possible performance indicator outputs of the model are failure rate, reliability and remaining lifetime. The model, which is built out of a few layers, will be explained based on the failure rate as performance indicator.

First the inputs from inspection and maintenance are translated to a failure rate by an input function. The input function uses an input failure rate distribution to perform this transformation. Next, all the input failure rates that belong to the same failure mode are combined by a failure mode function. If input failure rates are missing, a failure mode failure rate distribution is used as a reference. Lastly, all failure mode failure rates are combined to yield the asset failure rate. This is done in the asset function. In case not all failure mode failure rates are presented to the asset function, it uses an asset failure rate distribution as a reference. This model, with all its backup failure rate distributions, is capable of yielding an accurate asset failure rate both of the current and of the future. Since the failure rates are all based on continuous distributions the output of the model will be a failure rate that can be defined on a continuous scale. Compared this with the health index tool, which could only give one out of four results, the asset performance estimation model shows a large improvement in detail.

When the model was implemented for a circuit breaker, though, some issues arose. First of all, about half of the inputs were measured on a *Good–Fair–Moderate–Poor* scale. This scale is discontinuous, which results in discrete failure rate distributions. The drawback thereof is that a discrete failure rate distribution cannot be used to determine the development of the failure rate over time. Hence it is recommended that asset managers seek alternatives for the inputs that are solely defined by that scale to improve the calculation of the asset failure rate. Furthermore, several input failure rate distributions were defined

based on tacit knowledge of asset managers. Input measurements are required to improve these distributions. Finally, the dependencies between the input failure rates belonging to one failure mode function and the failure mode failure rates with respect to each other have not been modeled. More research is required to model these dependencies in detail.

ACKNOWLEDGMENTS

Although an MSc graduation project might seem a solo effort, this thesis would not have lain in your hands without the help of others. In this section I would like to thank several people that helped me in the completion of the performed research.

First of all I want to acknowledge the aid of dr.ir. S. Meijer. Foremost for arranging the MSc graduation project position at TenneT TSO within the Asset Management department. Moreover, from his position as supervisor, his thorough reading of the many draft versions of this thesis greatly improved its quality.

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Furthermore my thanks go out to dr.ir. F.H. van der Meulen who was a great help in the derivation of the likelihood function used in this research to derive the failure rate distributions. Without his expertise on statistics the implementation of a large part of the last chapter would have been much harder.

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Second to last I want to show my sincere appreciation for everything my parents, Johan and Joke de Haan, have done for me. Their support — both financial and physical — allowed me to receive education the past twenty years. Without their efforts I would not have been able to present you this thesis as a completion of my master studies Electrical Power Engineering at the Delft University of Technology.

Finally I want to express my gratitude to my fiancé, Lyanne Wilts. Although she says she does not understand a thing of my thesis, her support was indispensable. Her patience and understanding gave me the ability to keep on working on my thesis during hardships. Her kind and soothing words made me forget the encountered issues.

Although you might think your contribution was not that big, without your help and support this thesis would not have been here. I wish you all especially, and all others, joy in reading this thesis.

CONTENTS

NOMENCLATURE

ANSI	American National Standards Institute.
Asset	In general: anything, tangible or intangible, that can create a positive economic value which makes it worthwhile to monitor or control it. In this context: components of the high voltage electricity grid.
Cigré	International Council on Large Electric Systems (French: Conseil International des Grands Réseaux Électriques).
Failure	The termination of the ability of a component or system to perform a required function [1].
Failure data	Information about when and why (and sometimes how) an asset failed.
FMEA	Failure mode and effects analysis.
GIS	Gas-insulated switchgear.
Health	Technical condition.
IEEE	Institute of Electrical and Electronics Engineers.
Major failure	Failure which causes the loss of one or more of the fundamental functions of an asset, which either requires backup equipment to take over or immediate unscheduled maintenance [2].
Minor failure	Any failure of a part of the asset which does not cause a major failure [2].
Planning period	The time span for which asset managers have to prioritize and optimize maintenance and replacement.
SF_6	Sulphur hexafluoride.
Suspension data	Information about an asset that did not yet fail.
TOR	Technical maintenance directive (Dutch: Technische onderhoudsrichtlijn).

CHAPTER 1

INTRODUCTION

The present day society heavily relies on the supply of electricity. Without a steady electricity supply much of the luxurious life we live will cease to exist. Therefore much effort is being put into maintaining and upgrading the electricity grid.

The larger part of the electricity grid has been established in the sixties and seventies of the twentieth century. Having a designed lifetime of about forty years, many components in the transmission and distribution networks have reached the lifetime they were designed for or will reach it within the coming decade [3]. Consequently, many of those components, or assets, will need to be replaced. This requirement for a large scale asset replacement is also known as the *replacement wave*.

A clear visual example of the upcoming replacement wave can be seen in Figure 1.1. Figure 1.1 shows the age distribution of the assets owned by TenneT TSO (the Dutch transmission system operator). Of all the components, over 50% is older than 30 years (right of the red line) and more than 20% is even older than 40 years (right of the blue line). This means that within ten years over 50% of the current assets will have reached their designed lifetime. As all these assets will sooner or later require replacement, a replacement strategy has to be designed.

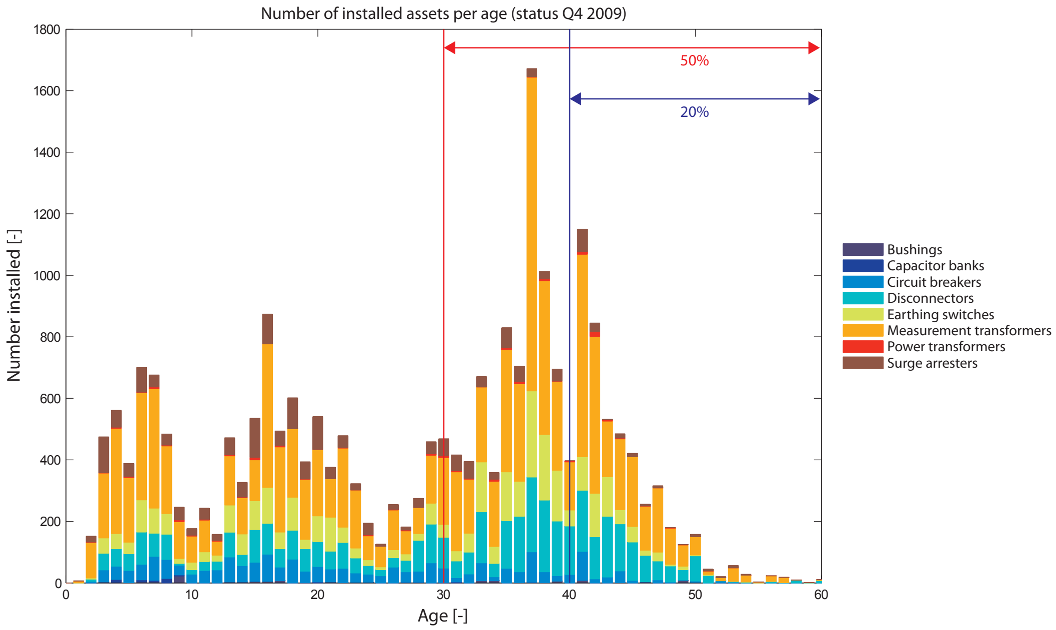

Figure 1.1: Age distribution of the high voltage assets managed by TenneT TSO (Q4 2009)

1.1 Asset replacement

An important part of asset management is replacing assets. Planning the replacement of an asset may sound easy, but optimal timing of the replacement is no sinecure. Each asset has its own technical condition and expected remaining technical lifetime due to the different manufacturing processes, operating conditions, environmental conditions and maintenance histories [4]. When an asset manager would merely look at the asset's designed lifetime when considering replacement, the asset is likely to be replaced at the wrong instant. Therefore, replacing an asset solely based on its age should be avoided as much as possible as both replacing an asset too early and too late is a waste of money. Replacing too early since the asset had a remaining reliability and lifetime that in that case go unused. Replacing too late for its decreased reliability might result in increasing maintenance requirements, increasing costs related to failure and a decreasing security of supply [5, 6]. Consequently, when it comes to asset replacement, an assessment of the technical condition of the assets is important.

1.2 Health assessment

Designing an optimal replacement strategy that maximizes the security of supply while minimizing the operating and maintenance costs requires knowledge about the current technical condition of the assets in the electricity grid [4, 7, 8]. The technical condition of an asset is often called *health* in literature. Many assets turn out to be quite healthy even though they have reached their designed lifetime. Therefore the health of an asset cannot be determined by its age alone, since that will yield the health of the average asset at the given age and not the health of the asset at hand. Knowledge on the health of the assets enables an asset manager to order the assets according to it. Subsequently he can first replace the assets whose health exceeds a certain specified minimal health. Other assets can remain operational until they start deteriorating.

To improve the prediction of the remaining life of an asset, the health needs to be specified more clearly. As many quantifiable parameters as possible that can be linked to failure of an asset need to be obtained. During inspection and maintenance these parameters should be gathered so asset managers can use these, combined with (their) expert knowledge on aging, failure modes and failure rates [8], to plan asset maintenance and replacement.

To get a clear overview of the health of the assets they manage, TenneT TSO asked KEMA to design a method which defines the health of an asset or an asset group as an index. TenneT TSO defined the health index as being the degree to which a component complies to its initial specifications when using regular maintenance in the coming seven years [9]. The health index of a single asset is calculated by combining general information (like age and grid location) and information on the asset's technical condition [7].

Once the health of the asset is determined it needs to be put into context. The health index provides much information on the current condition of an asset. However, the health index is merely an indication of the health of the asset. It will not be a hundred percent accurate on the remaining health and the time of failure of the asset. Consequently, it will not give an asset manager all the information he needs to make a well-founded decision with respect to the replacement of assets. Therefore, the risks associated with failure of the assets need to be accounted for in the maintenance and replacement decisions [10, 11]. The next section goes into risk assessment and the intended model used by TenneT TSO to perform this assessment.

1.3 Risk modeling

Risk can be seen as a combination of the probability of failure and the consequences of the occurrence of the failure [12, 13]. More precisely, within TenneT TSO the failure risk, or risk position, is defined as

$$\textit{Failure risk} = \textit{Failure rate} \times \textit{Failure impact}$$

So, to calculate the risk associated with the failure of an asset both the failure rate and the failure impact have to be known.

Basing decisions on risk instead of on a health index can make quite a difference. For example, an asset with a poor health and a small impact associated with failure may have a smaller failure risk than an asset with a fair health and a large failure impact. At the start of this research TenneT TSO intended to make a model to not only incorporate the health index but also calculate the failure risk. With risk depending on failure rate and impact, both of them would be determined in the model. The model can be seen in Figure 1.2. The blocks and arrows with low opacity had not been implemented at the start of this research but a start was made with the development thereof.

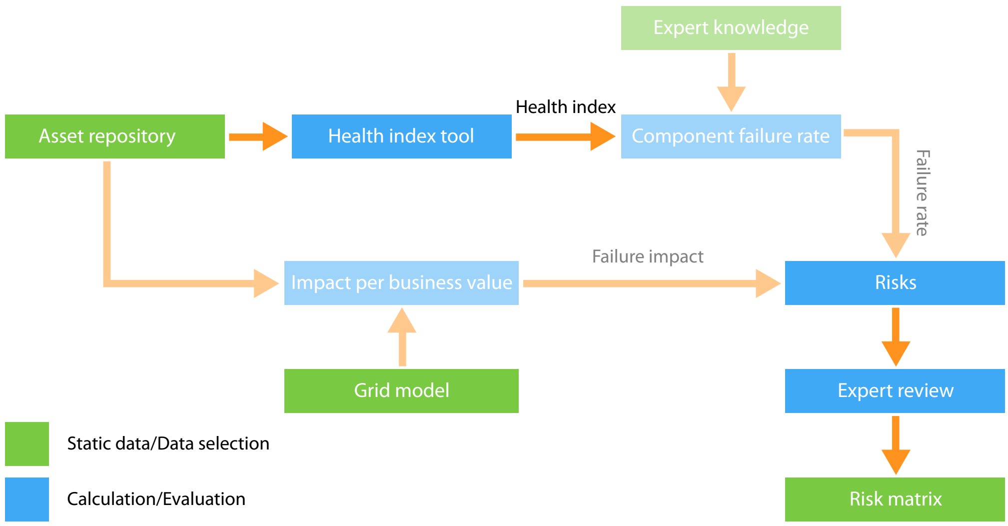

Figure 1.2: The intended model within TenneT TSO at the start of this research for linking the technical condition of an asset to failure risks (low opacity: uninplemented)

The failure rate can be derived from the current technical condition of an asset. This derivation is done in three steps. First of all, the data of an asset is taken from the *Asset repository*. The *Asset repository* is a database comprising all the available data on all the assets. Subsequently, the selected data is fed into the *Health index tool*, which determines a health index for a specific asset. (The working of the *Health index tool* at the start of this research is shown in Appendix A.) Thereafter, the health index is converted to a failure rate by using expert knowledge.

The impact of failure of an asset is determined based on the business values and corresponding effects that might endanger them. Furthermore, data from the *Asset repository* and the *Grid model* is used. The *Asset repository* is used to base the impacts on the type of asset and to select the right asset location from the *Grid model*. The *Grid model* is a model of the electricity grid which shows how the assets are connected to one another. It is used to indicate the importance of assets with respect to the security of electricity supply.

Although the intended risk model that has just been explained might seem fit, it has some flaws. Therefore some changes to the model were suggested at the start of this research.

1.4 Proposed risk model

The intended risk model of Figure 1.2 that was presented in the previous section was altered in a few ways at the start of this thesis project. Some changes are quite substantial, while others are merely for the sake of visualization. The proposed risk model is shown in Figure 1.3. This model will be the basis for the further research in this thesis. The changes made to the risk model are explained in the following sections. First of all there is a rather important change: the model is centered around failure modes.

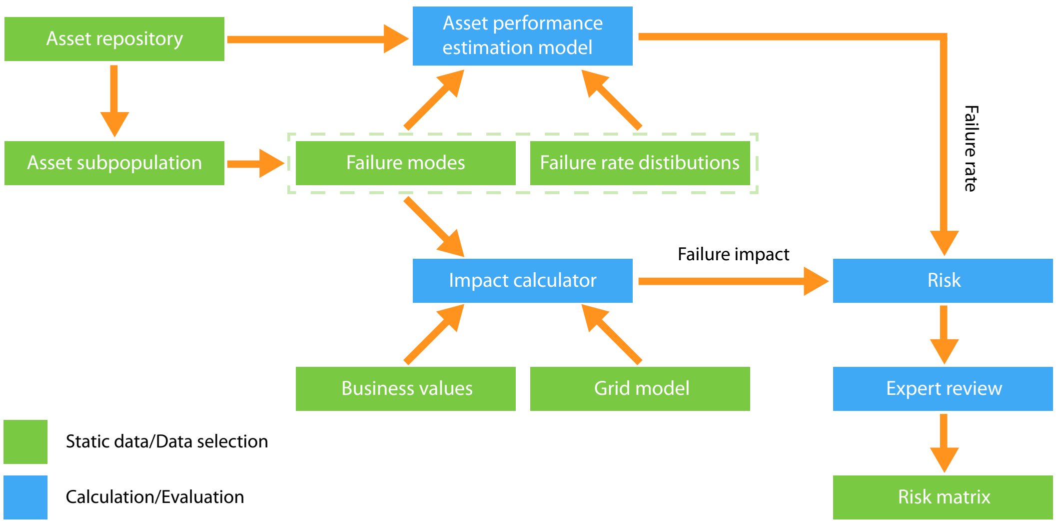

Figure 1.3: The proposed model for linking the technical condition of an asset to failure risks

1.4.1 Failure modes

Every asset type has different ways in which it commonly fails: failure modes [11]. Performing a *failure mode and effects analysis*, or FMEA, helps to identify the dominant and important failure modes [4, 14]. The failure modes might be determined from failure data from assets that are managed by the asset manager himself. Notwithstanding the fact that an asset manager requires failure data to derive health models, his goal is to prevent those failures to occur in the first place, so he probably will not own a representative database of failure data (the Resnikoff conundrum) [15]. Therefore it is recommended to retrieve data on failures and failure modes from papers, publications and inquiries from large international organisations such as Cigré or IEEE to be able to make accurate calculations [14].

In turn, each failure mode has its own failure rate and failure impacts. The combination of these two yields the failure risk for the given failure mode. The FMEA is used to initialize the risk model. The failure modes following from the FMEA, incorporated in the *Failure modes* block, form the basis for the *Asset performance estimation model* and the *Impact calculator*. The failure modes are used in the *Impact calculator* to calculate the impacts of failure of an asset based on the failure modes. In the *Asset performance estimation model* the failure modes are used to calculate the failure rate of each failure mode. How the failure modes and failure rates are linked in the *Asset performance estimation model* will be explained in Chapter 2.

1.4.2 Asset subpopulations

Failure modes do not only differ per asset type. Failure modes also change with different designs of the same asset type. Data obtained during inspection and maintenance consequently will have a different meaning for the health of different asset designs. To account for these differences, the data processing should acknowledge different categories the asset belongs to, as is depicted in Figure 1.4. These categories could e.g. be the rated voltage class or the insulating medium. In this way the total asset population is divided into subpopulations. All members of such a subpopulation will have about equal failure modes.

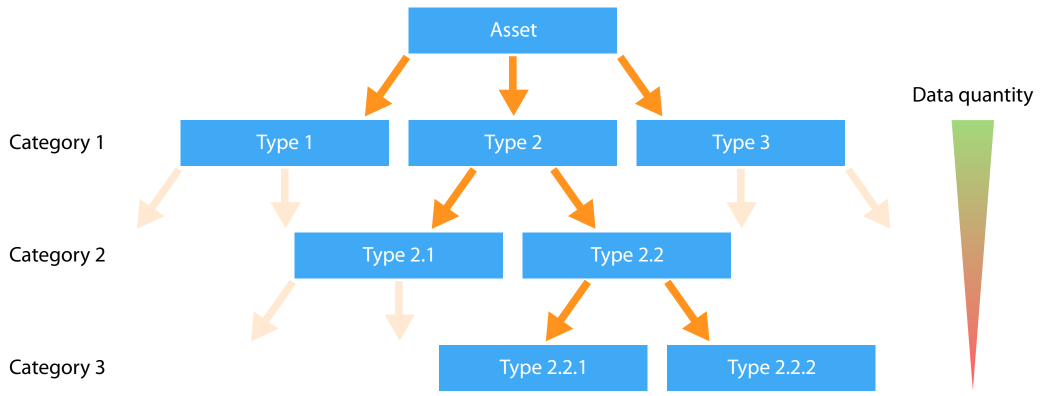

Figure 1.4: Dividing an asset into subpopulations

This differentiation amongst asset designs was already partly present in the intended risk model. In the proposed risk model, however, this process is made more explicit, both visually and in the implementation. The different subpopulations are accounted for in the *Asset subpopulation* block. This block is used to, given asset data from the *Asset repository*, determine the subpopulation it belongs to and select the relevant failure modes and failure rate distributions.

As more and more categories are used, there is an increasing differentiation amongst the asset designs and an increasing applicability of the failure modes for a given asset subpopulation. On the other hand, the more categories are defined, the smaller the data quantity will be for modeling the failure modes of a specific asset subpopulation (see Figure 1.4). Therefore the categories should not just be any identifying category, but categories of which the types have distinctive failure modes, failure rates or failure impacts.

1.4.3 Failure rate calculation

A second major change is the way the failure rate is calculated. Previously, the intention was to calculate the failure rate based on the health index of an asset. However, this reduces the level of detail since the health index already is an abstraction of the health of an asset. Inherently, the failure rate will not be as accurate as it would be if it were determined based on parameters indicating the current technical state of the asset. Therefore, the *Health index tool* in Figure 1.2 is replaced.

To overcome this lack of detail, the failure rate is calculated based on the current technical condition of the asset. This is done in three steps. First of all, data on one asset is taken from the *Asset repository* and used by the *Asset subpopulation* block to determine the subpopulation the asset belongs to. Secondly, the failure modes and failure rate distributions corresponding with the asset subpopulation are selected. Thirdly, the failure modes and failure rate distributions are combined with technical condition data from the *Asset repository*. These inputs are combined in a new block called *Asset performance estimation model* (see Figure 1.3). The calculation steps in the *Asset performance estimation model* yield the failure rate for the asset.

1.4.4 Asset performance estimation model outputs

The failure rate, though, is not the only possible output of the *Asset performance estimation model*. Therefore the name of the model is rather general. Since the calculations within this block are generally based on probability theory, the output can be all sorts of statistical measures, like failure rate and reliability. Furthermore the remaining lifetime can be assessed. It might seem that the remaining lifetime is also a statistical metric, however, it is e.g. also based on company regulations for replacement and the available amount of spare parts. Besides those, the health index is one of the possible outputs. The health index can still be used as a trigger for asset managers to indicate that the asset may need maintenance and/or replacement in the near future. A visualization of possible outputs of the *Asset performance estimation model* can be seen in Figure 1.5.

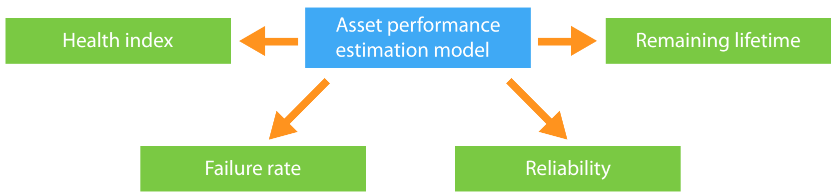

Figure 1.5: Possible outputs for the asset performance estimation model

1.4.5 Failure impact calculation

The calculation of the failure impacts has not changed much, aside from the fact that it is now based on the failure modes of the assets (as was already suggested in [16]). Furthermore, the *Business values* are shown more clearly as an input to the calculation of the failure impacts. Since the calculation of the failure impacts has not drastically changed, and since the scope of this research is the asset health rather than the asset failure impact, the calculation of the failure impacts will not be treated.

1.5 Scope of research

The current health index tool, based on knowledge rules defined by KEMA, does not offer the asset managers of TenneT TSO enough information regarding failure rates. Consequently, it does not make a perfect fit into the risk model. In this research a generic method is presented to derive a model for an asset type that links parameters from inspection and maintenance to failure rates: the asset performance estimation model. The failure rates can be used to estimate the failure risk and determine the best maintenance strategy.

Asset managers do not merely have to deal with the health of the assets and failure risks, but also with financial restrictions. Consequently, not every asset with a fair health can or will be refurbished or replaced immediately. This requires them to plan replacement of assets. When an asset manager wants to postpone maintenance on or replacement of an asset, he wants to be sure it will not fail until the next replacement decision moment. As such, asset managers are interested to know the development of failure rates over time. In this research attention will be paid to deriving these characteristics.

In the process of managing the assets, circuit breakers usually get much attention. Circuit breakers are considered the most complex high voltage assets that exist. Because they are so technically complex they have numerous ways in which they fail [17]. At the same time circuit breakers are essential to the reliability of the electricity grid [18, 19, 20]. These facts make them interesting assets to manage by estimating the performance of the asset. Therefore, after the asset performance estimation model is derived, a circuit breaker will be used as exemplary asset to illustrate the working of the model.

1.6 Thesis outline

First of all the asset performance estimation model, which has already briefly been introduced in this chapter, is defined. Chapter 2 systematically shows how the performance of an asset can be determined based on inputs from inspection and maintenance. In this model the failure rate is used as performance indicator since the asset failure rate will be used in the risk model. That specific implementation of the asset performance estimation model is called the asset failure rate estimation model.

The asset failure rate estimation model is based upon failure rate distributions. How these distributions should be derived is shown in Chapter 3. Besides instructions on the derivation of the distributions, techniques are discussed to assess the accuracy of the failure rate distributions.

In Chapter 4 is explained how the failure rates in the different layers of the asset failure rate estimation model can be calculated and combined. Furthermore, insight is given in how to calculate the change of the failure rate over time.

After the asset failure rate estimation model is defined and chapters on the derivation and calculation of (the change of) failure rates are concluded, a real life application of the model is given. As the model will be implemented for circuit breakers, Chapter 5 starts with a brief introduction into what a circuit breaker is, how it works and which types of circuit breakers there are. Next, the database used for the derivation of the failure rate distributions in the asset failure rate estimation model is introduced. Thereafter, data from the database is used to derive different important subpopulations of a circuit breaker.

Chapter 6, finally, implements the asset failure rate estimation model. Step by step the layers in the model are functionally implemented by defining the required failure rate distributions and probability theory functions. Along the way issues that arise upon implementation of the model are identified and coped with where possible.

CHAPTER 2

ASSET PERFORMANCE ESTIMATION MODEL DERIVATION

Knowing the remaining technical lifetime of an asset is desired by asset managers, yet virtually impossible. However, based on failure knowledge a good estimate can be made. In this chapter a model is derived that can be used to combine knowledge on failure modes and failure rates with inspection and maintenance data to deduce data specifying the performance of an asset. During the derivation of the model the emphasis will lie on the failure rate. The reason therefore is twofold: it keeps the process clear, and, more importantly, the proposed risk model (Figure 1.3) requires failure rates. Other performance indicators like e.g. reliability and remaining lifetime can be deduced in a similar matter.

In each section of this chapter a part of the asset performance estimation model is described. The number of inputs, functions and failure modes used is chosen such that the visualizations are clear. Their number can be increased or decreased if the asset type being modeled requires so. The last paragraph will go further into the failure rate as performance indicator, for it will be used in the rest of the research.

2.1 Failure modes

The asset performance estimation model determines how likely it is that an asset will fail. To do this, the model first needs to know in which ways the asset can fail. Therefore, FMEA forms the basis of the modeling of the asset health. The FMEA identifies several failure modes specific to the asset type of interest. The resulting failure modes are shown in Figure 2.1.

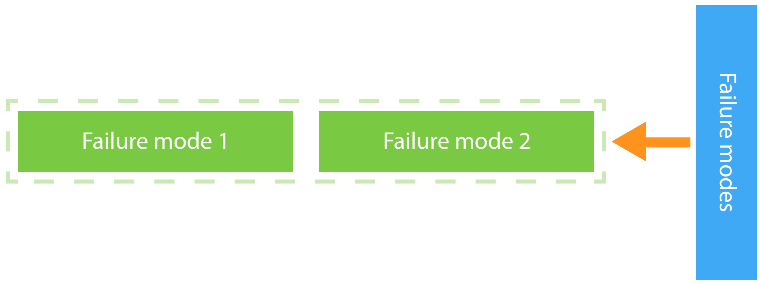

Figure 2.1: Asset performance estimation model, step 1: failure modes are selected

Section 1.4.2 focused on making distinctions between different subpopulations of the same asset type. The different subpopulations of one asset type might have different failure modes, as is illustrated in Table 2.1. Consequently, not every failure mode is applicable to each subpopulation. To select the applicable failure modes for each asset subpopulation, for example Subpopulation A, the *Failure modes* block (see Figure 1.3) is used as input.

Table 2.1: Failure modes for different asset subpopulations

	Failure modes	
Subpopulation	Mode 1	Mode 2
Subpopulation A	X	X
Subpopulation B		X
Subpopulation C	X	

With the failure modes defined and selected, the next step in the model derivation can be made. Although the failure modes indicate how an asset can fail, they do not say anything about the health of the asset or the likeliness of occurrence of failure according to the failure modes. This extra detail can be offered by using input parameters.

2.2 Model inputs

Determining the performance of an asset requires input data that specifies the technical condition. Without this input data the estimated performance of the asset would equal the performance of the average asset of that type. Input data from an asset itself is therefore used to make the asset performance specific for the selected asset. Besides static asset data, like its year of manufacturing, its year of installation, its rated voltage and its location, inspections and maintenance activities provide dynamic data that can be used as input to the model. The input data is obtained from the *Asset repository* (see Figure 1.3).

Like knowing just the failure modes, knowing just the inputs is not enough. Only when the failure modes and inputs are combined one can calculate the failure rate of the asset based on the failure modes. Therefore, asset managers need to determine relationships between the possible inputs and the failure modes based on FMEA research and (their) expert knowledge. An example of an outcome thereof is depicted in Table 2.2.

Table 2.2: The link between possible inputs and failure modes

	Failure modes		
Possible inputs	Mode 1	Mode 2	Measured
Input 1	X		Yes
Input 2		X	Yes
Input 3		X	No
Input 4			Yes

After the relationships have been determined some possible inputs might remain unused, like Input 4. On the other hand, there might be some failure modes that require possible inputs that are not measured yet, like Input 3. The result of this analysis can be used to update the inspection and maintenance directives to include only relevant inputs [14]. The relevant possible inputs are used as inputs to the model and shown in Figure 2.2.

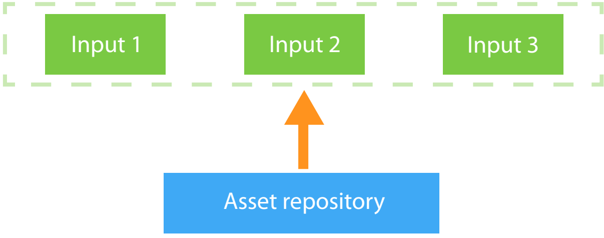

Figure 2.2: Asset performance estimation model, step 2: inputs are selected

Once the relevant inputs are known, and they are linked to the failure modes, they can almost be combined. But first each input is fed into an input function to make a uniform link between the inputs and the failure modes.

2.3 Input function

The asset performance estimation model that is being derived is based on several different inputs. The inputs are often based on data from inspection and maintenance which have widely varying units. The input functions convert an input to a failure rate to provide more unity. Moreover, the inputs by themselves do actually not measure or indicate the performance of the asset [10]. The conversion to a failure rate can provide this indication. After all the inputs are converted to a failure rate, they can be compared and combined. The appended model can be seen in Figure 2.3.

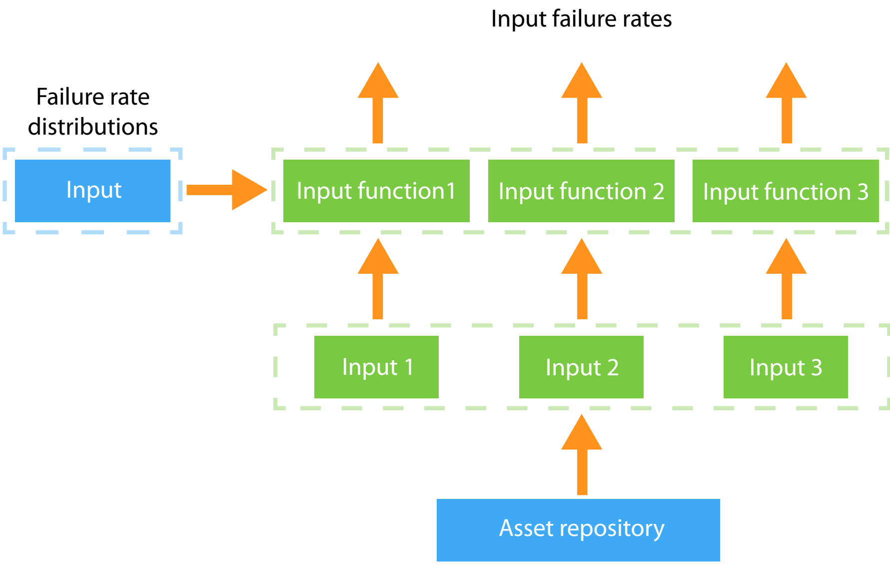

Figure 2.3: Asset performance estimation model, step 3: input functions transform input values to failure rates

The conversion from the input to a failure rate is done based on a failure rate distribution for each input, visualized by the blue *Input* block. The *Input* block is a part of the *Failure rate distributions* block (see Figure 1.3). It contains all relevant failure rate distributions for the inputs given the subpopulation the asset belongs to. The current value of the input is looked up in the distribution and the corresponding failure rate is the output of the input function. This is visualized in Figure 2.4.

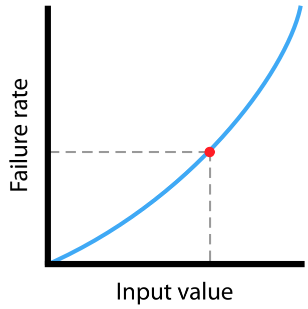

Figure 2.4: Input failure rate distribution

At this stage the inputs are converted to the same data type: failure rates. Next, the input functions can be connected to the failure modes which they affect.

2.4 Failure mode function

As of now the failure modes and the inputs can be linked to one another in the model. This is done based on the failure modes shown in Section 2.1 and their relationship to the inputs listed in Table 2.2. Next, each failure mode is assigned a function to process the input failure rates. A failure mode function combines the failure rates from the associated inputs to yield a single failure rate for the failure mode. The updated model can be seen in Figure 2.5.

Ideally the failure mode failure rate is a function of the failure rates of its inputs. The input failure rates are used to calculate the failure mode failure rate. In case the values of the inputs of a failure mode function are not or insufficiently specified, the failure rate cannot be calculated based on them. As an alternative the failure rate distribution for a failure mode itself can be used as a reference. This is visualized by the blue *Failure mode* block in the model. The *Failure mode* block is a part of the *Failure rate distributions* block (see Figure 1.3). The *Failure mode* block contains the failure mode failure rate distribution specific to the given subpopulation the current asset belongs to. The failure mode failure rate distribution is generally based on the age of the asset, because that metric is often available.

This decision is summarized in the scheme in Figure 2.6. If the values of the inputs associated with a failure mode are known, the input failure rate distributions for all the inputs (Figure 2.6a) are used to determine the failure mode failure rate (upper path of Figure 2.6c). In case one or more of the input failure rates is unknown, the failure mode failure rate distribution (Figure 2.6b) is used as a reference to determine the failure rate for the failure mode (lower path of Figure 2.6c). The decision shown in Figure 2.6c is made for each failure mode.

Figure 2.6c indicates that when all input failure rates $(h_{IF1}, h_{IF2}, \ldots, h_{IFn})$ are known the failure mode failure rate is calculated by the combination of those failure rates. The resulting failure rate is h_{IFs}. If not all inputs are known, the calculation of h_{IFs} will be incomplete. One could in that case revert to the failure rate indicated by the failure mode failure rate distribution, h_{FMFRD} (Figure 2.6b). However, if the incomplete calculation of the failure rate based on the input failure rates, h_{IFs}, is larger than h_{FMFRD}, the failure

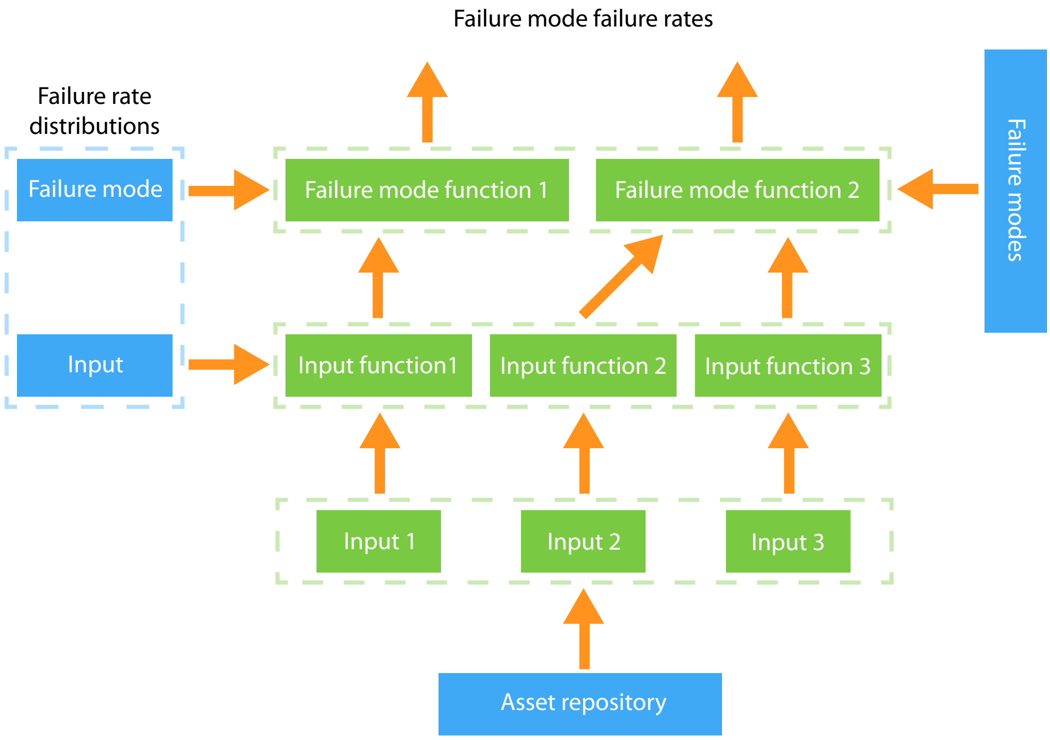

Figure 2.5: Asset performance estimation model, step 4: failure mode failure rates are calculated

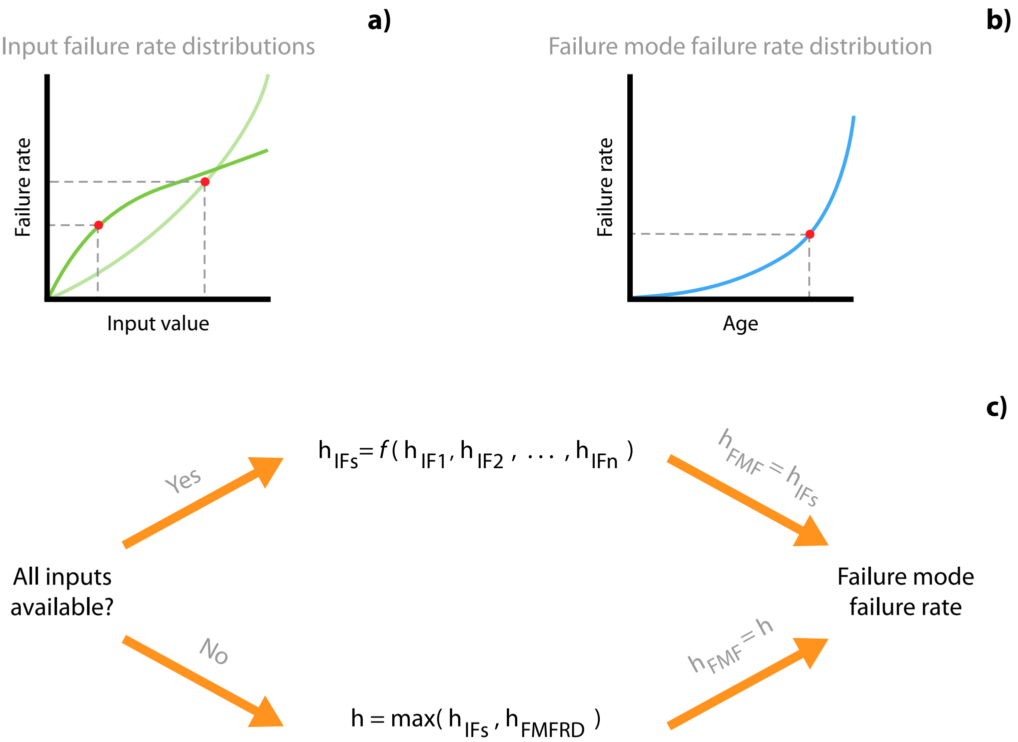

Figure 2.6: Decision scheme to calculate the failure mode failure rate

mode failure rate would be underestimated. That is why the maximum of those two rates is taken in Figure 2.6c. This maximum operation also means that when $h_{IFs} < h_{FMFRD}$, h_{FMFRD} is taken as the failure mode failure rate. Since it is unknown how much the failure rate of the missing input(s) would have increased h_{IFs}, h_{FMFRD} is taken as an estimate for the failure mode failure rate. In this case the failure mode failure rate of the asset is likely to be an overestimate. Bearing in mind that h_{FMFRD} is the average failure rate of the asset subpopulation for that failure mode, it is unlikely that taking h_{FMFRD} over h_{IFs} in that case will result in an alarming failure risk of the asset. The failure mode failure rate is still just the average failure mode failure rate for that asset subpopulation. However, since missing one of the inputs will never improve the accuracy of the calculation of the failure mode failure rate, a flag has to be set indicating that one or more inputs are missing. The asset manager can now see that the calculation of the failure rate is not fully based on the inputs.

At this stage the failure rates of each failure mode are defined. To yield a failure rate for an asset, the failure rates are fed into the asset function.

2.5 Asset function

Finally, the failure rates of the failure modes are combined to one failure rate: the failure rate of the asset. This is done in the asset function. The final addition to the model changes the last version of the model (Figure 2.5) to Figure 2.8.

Preferably the failure rate of the asset is based on the failure mode failure rates. So if they are available they should be used to calculate the asset failure rate, as also shown in Figure 2.7. They follow from the decision diagram shown in Figure 2.6.

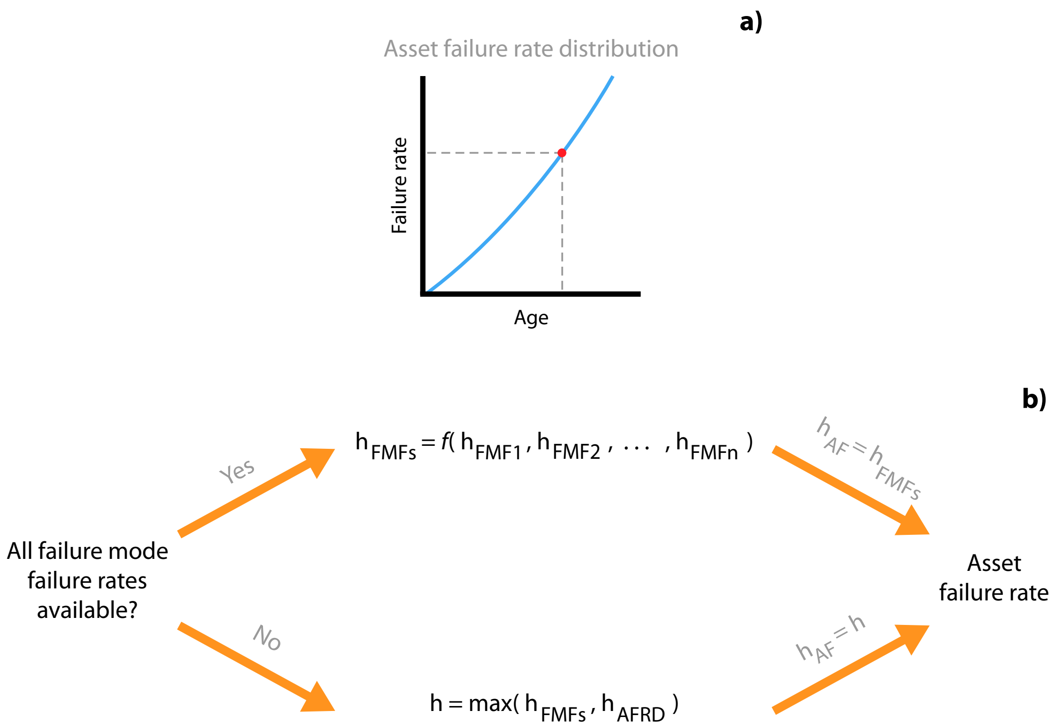

Figure 2.7: Decision scheme to calculate the asset failure rate

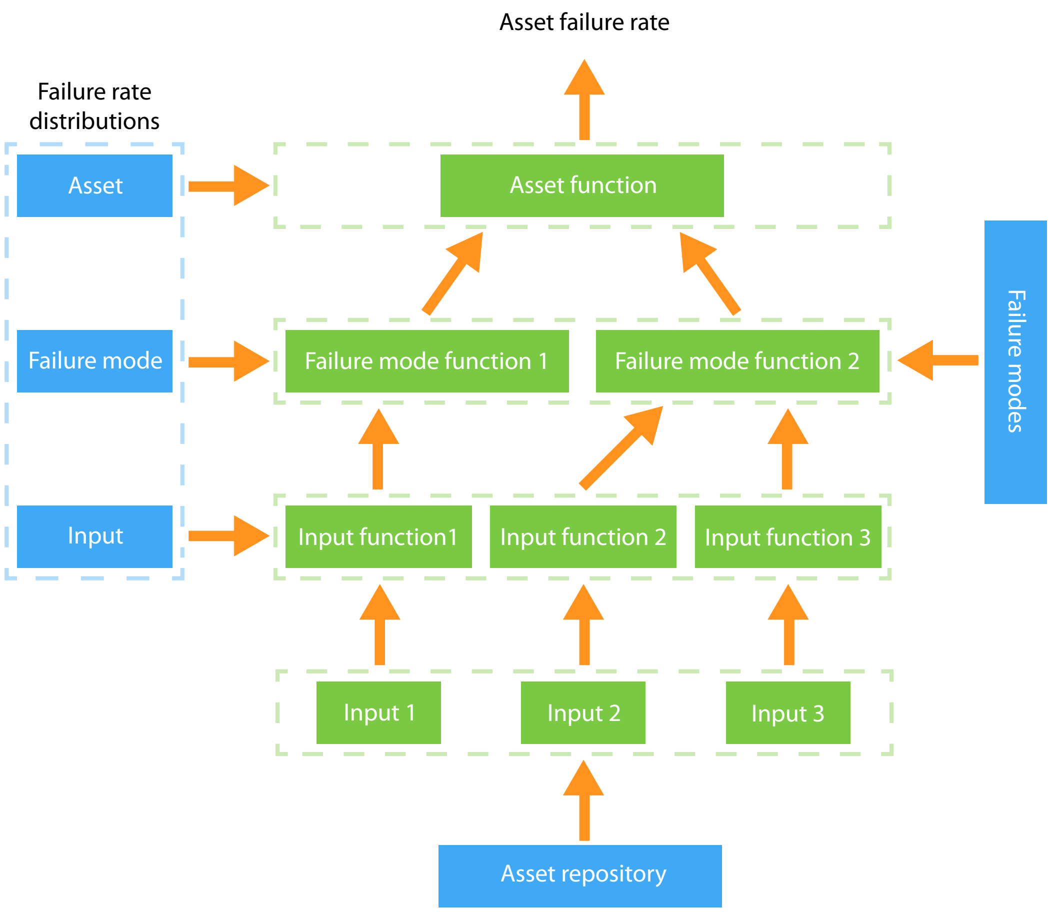

Figure 2.8: Asset performance estimation model, step 5: asset failure rate is calculated

In the highly undesirable case that the failure mode failure rates could not be calculated properly, the asset failure rate distribution can be reverted to (see Figure 2.7a). The asset failure rate distribution is contained in the blue *Asset* block. This block represents the asset failure rate distribution for the subpopulation the asset belongs to. The *Asset* block is a part of the *Failure rate distributions* block (see Figure 1.3). Just as the failure mode failure rate distribution, the asset failure rate distribution is generally based on the best available metric for an asset: its age.

The asset failure rate distribution in Figure 2.7a is used for the same purpose as the failure mode failure rate distribution in Figure 2.6. In the ideal case the asset failure rate is calculated by the failure rates of all the failure modes ($h_{FMF1}, h_{FMF2}, \ldots, h_{FMFn}$), see the upper path of Figure 2.7b. In case one or more of the failure mode failure rates is not available the failure rate according to the asset failure rate distribution, h_{AFRD}, is used as a reference, see the lower path of Figure 2.7b. The maximum of the failure rate according to the failure modes, h_{FMFs}, and h_{AFRD} is taken. The outcome of the asset failure rate calculation, h_{AF}, is equal to the asset failure rate of the average asset of that asset subpopulation (h_{AFRD}), unless $h_{FMFs} > h_{AFRD}$. In the latter case the incomplete calculation of the asset failure rate according to the failure modes results in a failure rate that is above average. As this indicates that the asset performance, given its age, is below average h_{FMFs} will be taken as asset failure rate.

Missing one of the failure mode failure rates will not improve the accuracy of the calculation of the asset failure rate. Therefore a flag has to be set indicating that one or more failure mode failure rates are missing. The asset manager can now see that the calculation of the failure rate is not fully based on the failure mode failure rates.

2.6 Asset failure rate estimation model

In the previous paragraphs the asset performance estimation model was derived. The failure rate was used as an exemplary performance indicator. The defined hierarchy and functions could just as well be used for other performance indicators like, e.g. reliability and remaining lifetime. This specific implementation of the asset performance estimation model, using the failure rate, will be called *asset failure rate estimation model* from now on. This to avoid confusion with the generic setup of the asset performance estimation model.

CHAPTER 3

FAILURE RATE DISTRIBUTION DERIVATION

In the previous chapter the asset performance estimation model was derived with failure rate as exemplary performance indicator. Several stages of the asset failure rate estimation model require failure rate distributions. This chapter shows how these distributions can be derived and how their accuracy can be assessed. Acquiring a failure rate distribution that accurately describes the asset of interest is done in a few steps, as shown in Figure 3.1. First of all, only the data relevant to the specific asset at hand needs to be selected. Thereafter, a statistical distribution needs to be chosen to describe the selected data, resulting in a model that describes the failure rate of the asset. Subsequently, the accuracy of the model with respect to the selected data needs to be assessed. If the accuracy is insufficient, another distribution might be chosen to describe the data. If the current model describes the selected data accurately enough, it can be used as a part of the asset failure rate estimation model. These steps in acquiring an accurate model are each treated in a section in this chapter, starting with selecting the data. However, first a brief introduction into the most important probability functions is given.

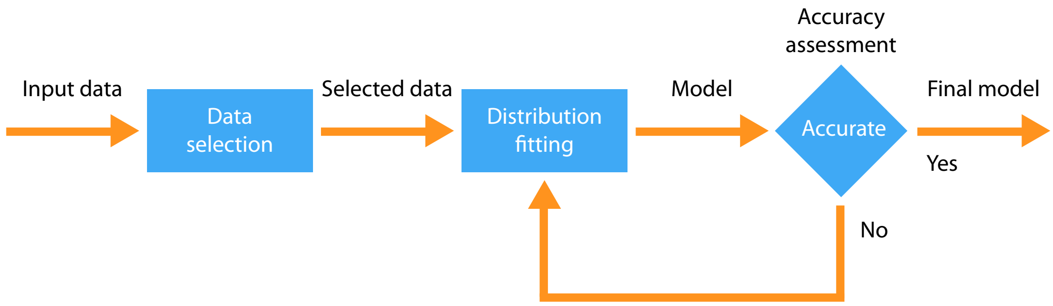

Figure 3.1: Steps in deriving an accurate failure rate distribution

3.1 Probability functions

There are several ways in which probabilities can be presented. Generally, probabilities are presented by their probability density function $f(t)$. This function returns the probability of occurrence of t. A second common distribution is the cumulative density function. This function, $F(t)$, is the probability of occurrence of t or lower, or mathematically

$$F(t) = \int_{-\infty}^{t} f(t)\,\mathrm{d}t$$

The cumulative density function is closely related to the reliability. The reliability $R(t)$ is defined as

$$R(t) = 1 - F(t) = 1 - \int_{-\infty}^{t} f(t)\,\mathrm{d}t = \int_{t}^{\infty} f(t)\,\mathrm{d}t$$

Consequently one could also think of $F(t)$ as the unreliability. With the probability density function and reliability known, the failure rate can be defined. The failure rate $h(t)$ is

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

The failure rate normalizes the probability by the remaining reliability. Hence, the failure rate indicates the number of failures that can be expected per unit of t.

Although the asset failure rate estimation model focuses on failure rates, the unreliability is generally used for accuracy assessments. Furthermore, failure data is often fitted most easy by probability density functions. How this data should be selected, filtered and grouped is explained in the next section.

3.2 Data selection

Failure rate distributions can be derived from failure and suspension data on the asset type of interest. The failure data ideally contains information about the age, the model and inspection parameters, so it can be used to derive the relationships between inspection parameters and failure rates. Suspension data is data on assets that are still operational. The fact that an asset did not fail can provide more detail on the failure rates [12, 21], as this puts the failure data in perspective. Opposed to failure data, suspension data is not per definition required. As long as the data set of failures is large and representative enough, one could do without suspension data. However, since asset managers normally prevent their assets from failing, suspension data is generally required [22].

It is important that the selected data is representative for the asset that is analyzed. For example, when deriving a failure rate distribution with respect to the asset age, the failure and suspension data should not contain assets that all have the same age. Thereby it would be impossible to deduce a relationship between failure rate and age. Furthermore, 'unnatural' causes of failure need to be removed from the data set. In this context unnatural means that the asset failed not because of normal aging but because of an incident that caused the asset to fail prematurely. Examples hereof are flooding and earthquakes. If and when an asset may fail because of these causes is highly unpredictable. Therefore failure because of those incidents cannot be modeled. Moreover, because of their premature failure these failures do not contain information about the natural failure of an asset. Consequently, they would disturb the failure rate distribution. Therefore they should be removed from the data that is used as input for the derivation [23].

Preferably an asset manager has a failure rate distribution for every different asset make and model. However, the population for a specific asset model is often very small. Therefore, the assets need to be grouped to yield large enough data sets [3], as already shown in Section 1.4.2. The grouping is done based on a few categories that influence the failure rate of the asset. This was visualized in Figure 1.4, here repeated as Figure 3.2. For the modeling of failure data at least five, and preferably more than ten, failure data points should be available per subpopulation [24]. This requirement might not be met when too many categories are defined. In those cases the number of categories should be decreased until a sufficient amount of data is available in each subpopulation of interest. Decreasing the number of categories increases the amount of data points available per subpopulation. Although ten data points is considered the minimum, larger quantities of data are recommended [3], as it will make the distribution more representative.

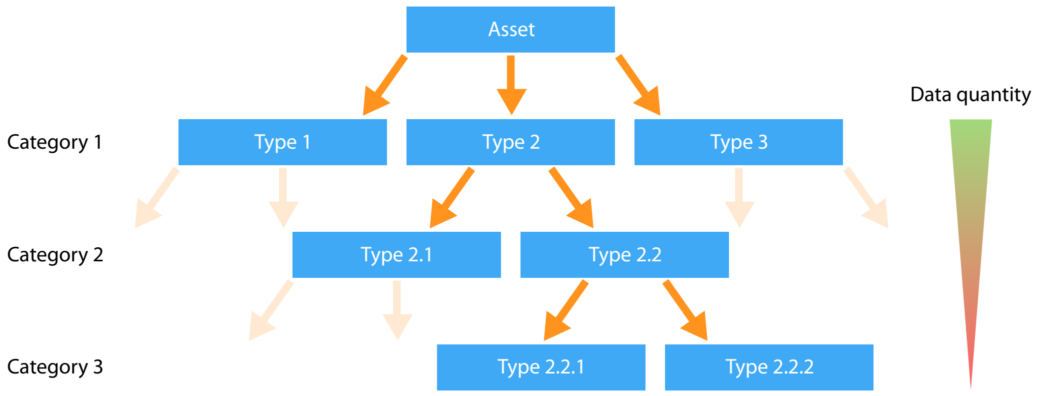

Figure 3.2: Dividing an asset into subpopulations

When enough data is available for each subpopulation of interest, a distribution type can be selected to model it.

3.3 Distribution fitting

Modeling the selected data can be done with various distributions, like: Gumbel, lognormal and Weibull [24, 25]. A good fit of the data by a distribution does, however, not just depend on the data quantity, but also on its quality. The higher the quality of the data, the better a model can be fitted to it and the better the failure rate can be estimated. In Figure 3.3 an example is shown why the data quality is important.

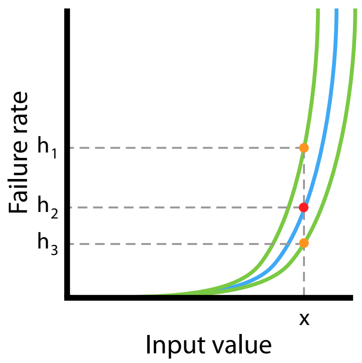

Figure 3.3: Uncertainty in failure rate given a parameter value

Say a set of data points on a specific inspection parameter is used to determine the relation of that inspection parameter to a failure rate. The blue characteristic in the Figure 3.3 is the best model fitted based on the input data. However, because of a large spread in the input data either of the green characteristics could also be regarded as an accurate approximation of the data. Say an asset manager wants to determine the failure rate for an asset based on the inspection parameter and uses the derived blue model. During the next inspection he measures the value for the specific inspection parameter, x, and sees that the corresponding failure rate of this asset equals h_2. However, it could also be as much as h_1 or as little as h_3 because of the inaccuracy of the model.

This example shows that the input data set cannot be fitted mindlessly, as the resulting distribution is not of much use if its accuracy is low. Therefore the accuracy of the model needs to be assessed before it is put into use.

3.4 Accuracy assessment

Two methods are commonly used to assess the accuracy of a statistical distribution with respect to the input data: goodness-of-fit parameters and confidence intervals [24, 25]. These two methods will be introduced in the two following sections. Thereafter will be explained what to do if it turns out the accuracy of the fit is low. Finally, the required accuracy will be put into the perspective of the risk model (Figure 1.3).

3.4.1 Goodness-of-fit parameter

The goodness-of-fit parameter is a number calculated to indicate the accuracy of the model with respect to the input data. This parameter is often defined on a zero-to-one scale, one indicating a perfect fit. The goodness-of-fit parameter is used to select the statistical distribution that fits the data best by selecting the distribution with the largest goodness-of-fit with respect to the selected data. However, the best fit is not necessarily a good fit. Therefore, it is also important to look at the absolute value of the goodness-of-fit parameter. In [24] the IEEE defined a critical correlation coefficient, i.e. the minimal value for the goodness-of-fit parameter for a good fit. That definition is displayed in Figure 3.4.

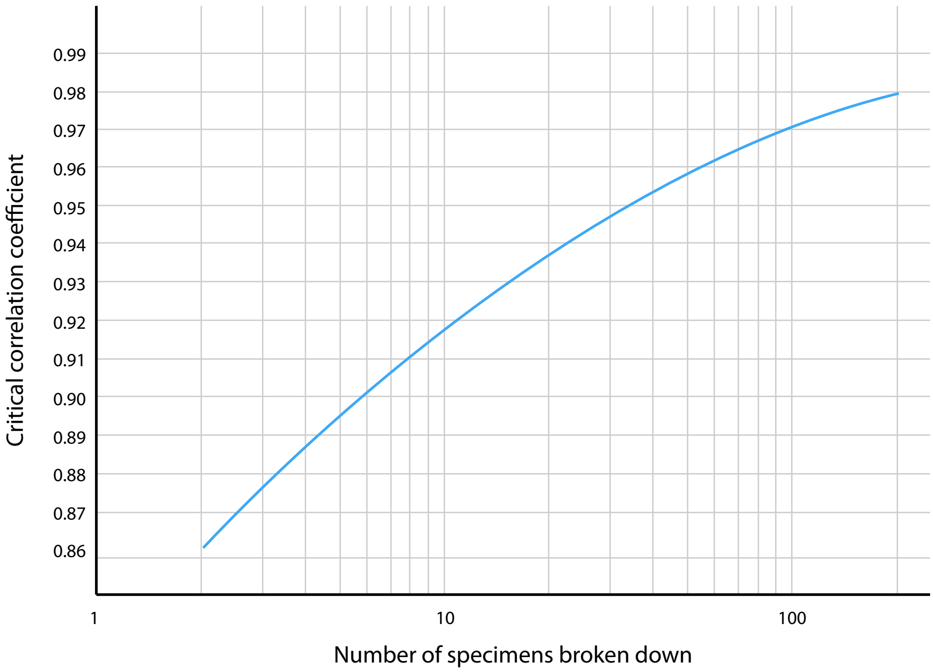

Figure 3.4: Critical correlation coefficient of a two-parameter Weibull distribution (based on [24])

Figure 3.4 shows the critical correlation coefficient relationship for a two-parameter Weibull distribution. It can be used to determine whether the selected distribution fits the data well enough. When the goodness-of-fit parameter, given the number of failure data points (number of specimens broken down), is larger than indicated by the blue curve, the fit is deemed a good fit. On the other hand, when the goodness-of-fit parameter lies below the blue curve the fit is a bad fit.

3.4.2 Confidence intervals

Unlike the goodness-of-fit parameter, confidence intervals (or confidence bounds) are a visual tool, of which an example is shown in Figure 3.5. Confidence bounds are most often plotted alongside an unreliability plot of the fitted distribution. (An unreliability characteristic is the same as a cumulative density function [25].) The unreliability is plotted versus the parameter of interest with such axes that the characteristic (blue line) is linear. Confidence bounds (red lines) have been drawn on both sides of the characteristic. The confidence bounds are defined by a percentage, indicating the percentage of data between them. For example, 90% confidence bounds depict the area in which 90% of the data points of that model lie. Consequently, if the model that is fitted on the data is accurate, and if the data is randomly distributed, 90% of the data lies between the 90% confidence bounds.[1]

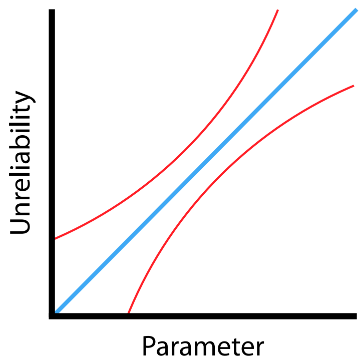

Figure 3.5: Unreliability plot with confidence bounds

On the one hand the confidence bounds can be used to inspect the dispersion of the data. Plotting the fitted model and the used data points does not tell much about the accuracy of the data points with respect to the model. Confidence bounds can be used to put it more into perspective. When looking at the example in Figure 3.6 this becomes more clear. Assume that the solid (red) lines are the 90% confidence bounds belonging to the model. That being the case, one might have some concerns regarding the accuracy of the model, for quite some data points lie outside the confidence bounds. However, when the dotted (orange) lines are the 90% confidence bounds corresponding to the model there is no reason to be concerned at all. In the latter case all data points lie between the confidence bounds.

On the other hand confidence bounds serve as a tool to assess whether a combination of distributions should be used to model the data. This is visualized in Figure 3.7. Say that

[1]One needs to keep in mind that not necessarily 90% of the data points have to lie within the 90% confidence bounds to indicate a good fit. Compare it with tossing a coin: the rate of getting heads is 50%, however, after ten tosses one might get eight tails. Only when the coin is tossed an infinite amount of times one can be sure that heads will be tossed in 50% of the cases. Similarly, 90% of the data points will lie within the 90% confidence bounds if infinitely many random data points belonging to that model are used. Consequently, the confidence bounds are merely to be used as a guide line to indicate the quality of the fit.

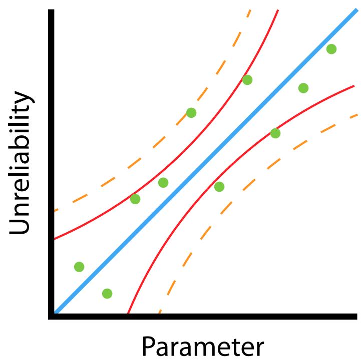

Figure 3.6: Unreliability plot with two possible confidence bound pairs and dispersed data

the solid (red) lines are the 90% confidence bounds belonging to the model. A few data points are lying outside the confidence bounds. Furthermore, two different effects seem to be present in determining the unreliability of the modeled asset — the gray data points show a different behavior than the green data points. One should consider using two distributions that each model a part of the data points. One distribution for the gray data points and one distribution for the green data points. Again, if the dotted (orange) lines are the 90% confidence bounds corresponding to the model, no action has to be taken. The data points all lie within the confidence bounds, so the spread in the data can be seen as the natural spread of the data points belonging to the model.

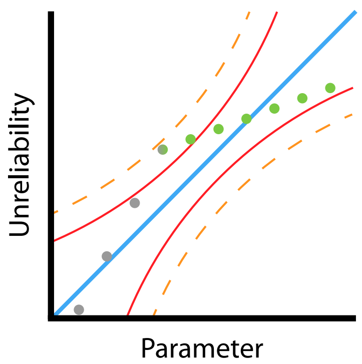

Figure 3.7: Unreliability plot with two possible confidence bound pairs and mixed data

3.4.3 Bad fit indication

When either the goodness-of-fit parameter or the confidence intervals show that the distribution is not accurately fitted to the input data, the data can be checked for outliers. Outliers are data points that do not seem to belong to the distribution that is fitted to the data. However, the outliers disturb the accuracy of the fit, since the distribution is shifted towards them. Assessing whether there are outliers present in the dataset can be done visually. An example hereof is shown in Figure 3.8.

The gray data points do not seem to belong to the model. They might for example have been measured wrongly. When the gray outliers are removed, the model will better fit the remaining data points. However, not just any data point that seems unfit can be removed

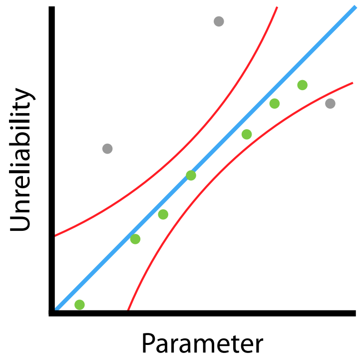

Figure 3.8: Unreliability plot of data with outliers

to make the model more accurate. The data point must clearly not belong to the model. In case the number of outliers is very large, the data quality apparently is low and the data is unrepresentative for modeling failure of the asset. After the outliers are removed from the dataset, the goodness-of-fit parameter and the confidence intervals can be recalculated. In case either of the two is still indicating a bad fit, the relationship between the parameter and the failure rate is inaccurate. Hence, the failure rate distribution will not be accurate in determining the failure rate of the assets of the asset type the distribution is meant for. Therefore, one should seriously consider leaving such a distribution out of the asset failure rate estimation model and determining the asset failure rate in another way.

3.4.4 Accuracy in the risk model

In Section 1.3 the relevance and necessity of failure risk was addressed. Also, the failure risk was defined, being

$$\textit{Failure risk} = \textit{Failure rate} \times \textit{Failure impact} \tag{3.1}$$

The failure impacts are defined on a logarithmic scale. This means that two subsequent failure impacts differ a factor ten. So if there are two assets with the same failure rate, but the one has a failure impact that is one class higher, its failure risk will be a factor ten larger.

Defining a logarithmic scale for the failure rate does not make sense. During its lifetime the failure rate of an asset will be less than, equal to or a little larger than one. Hence, the difference between the highest and the lowest failure rate will not be large and the failure rate will certainly not traverse multiple usable decades. As a result, the difference between a low failure rate and a high failure rate might not even cause the failure risk to change between classes. A solution can be found by using a risk matrix instead of a risk equation.

Table 3.1 shows an example of a risk matrix. The columns indicate the various failure impact categories. They are each separated by a factor ten. The rows are formed by the failure rate, which are not defined on a logarithmic scale. The failure rates are for example defined as low when $h(t) < 0.2$, as medium when $0.2 < h(t) < 0.5$, and as high when $h(t) > 0.5$. Such a definition corresponds more to reality and the linguistic meanings of the words low, medium and high than a logarithmic definition. The color scheme indicates the failure risk: the greener the color the lower the risk and the redder the color the higher the risk. This risk matrix does not base the risk upon Equation 3.1. It considers the failure impact and the failure rate separately. For example, when the failure impact for a certain asset is high, and the failure rate falls in the medium category, the output will be on the intersection of the high failure impact column and the medium failure rate row. In this case this means that the failure risk is orange.

Table 3.1: Example of a risk matrix

	Failure impact			
Failure rate	Low	Medium	High	Very high
Low				
Medium				
High				

Looking back at Figure 3.3, as long as h_1 and h_3 fall in the same failure rate class as h_2 the uncertainty in the distribution will not negatively influence the calculated risk. So, a certain uncertainty is allowed. However, if either of them does exceed one of the failure rate class boundaries the indicated risk will either be an underestimation or an overestimation. Concluding, uncertainty is allowed just as long as it will not cause the risk matrix to indicate a wrong risk.

CHAPTER 4

FAILURE RATE CALCULATION AND DEVELOPMENT

The previous chapter shows how the failure rate distributions are derived and which aspects should be taken into consideration in their derivation. The next step is to use these distributions to calculate the failure rates in the model. This chapter will show how the several failure rates are calculated and how they can be merged into one failure rate for an asset.

The asset failure rate estimation model is based on several functions. All these functions are used to, in the end, calculate the failure rate of the asset. The first section describes the (mathematical) implementation of the functions. The second section shows how the asset failure rate estimation model with its failure rate distributions can be used to derive a development of a failure rate over time.

4.1 Asset failure rate estimation model functions implementation

The asset failure rate estimation model has several functions that have not yet been functionally described. The following sections show how the input function, the failure mode function and the asset function are implemented.

4.1.1 Input function implementation

In an input function an input is linked to a failure rate. Ideally the relationship between them is known (as in Figure 2.4). However, the relationship is not always available from (previous) research. In that case the relationship between an input and its failure rate needs to be deduced. For example by using a variable of which the relationships to both the input and the failure rate are known. Examples hereof are the age of the asset and the degree to which the asset is used. The latter could for example be the number of operations in service of a circuit breaker.

The use of an intermediate variable requires two characteristics to be specified. Taking time as an example, first of all the failure rate with respect to time needs to be known. This distribution is shown in Figure 4.1a. Secondly, a relationship between the input and the time has to be determined, which can be seen in Figure 4.1b. Combining the two aforementioned characteristics yields the required failure rate versus input relationship shown in Figure 4.1c.

4.1.2 Failure mode function implementation

As can be seen in the asset failure rate estimation model (Figure 2.8), the major function of the failure mode function is to 'combine' the input failure rates. The first section shows how the several input failure rates should be combined into one failure mode failure rate.

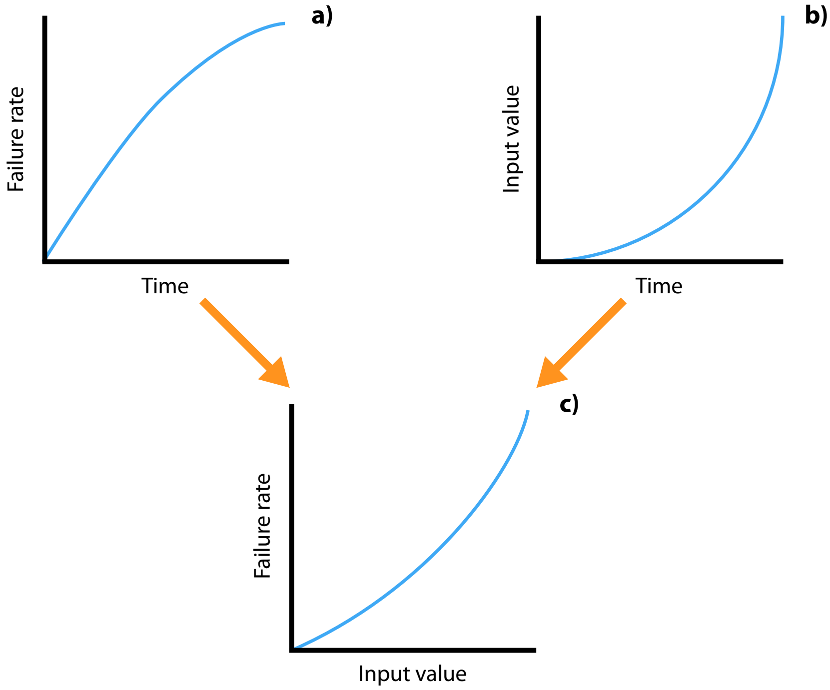

Figure 4.1: Combining failure rate and input characteristics into one relationship

The second section elaborates how probability theory can be of help in determining dependencies between various inputs.

Combining input failure rates

The failure mode function has to merge multiple input failure rates into one failure mode failure rate. In literature several ways are proposed to achieve this goal.

A first strategy is defining all the failure rates as independent exponentially distributed failure rates [12, 26]. The failure mode failure rate distribution can then be defined as the sum of all the input failure rates. The input failure rates are determined by evaluating the input failure probability distributions $(h_{IF1}, h_{IF2}, \ldots, h_{IFn})$ at the values of the inputs $(x_1, x_2, \ldots, x_n)$.

$$h_{FMF} = \sum_{i=1}^{n} h_{IFi}(x_i) = h_{IF1}(x_1) + h_{IF2}(x_2) + \ldots + h_{IFn}(x_n) \tag{4.1}$$

A drawback of Equation 4.1 is that it does not account for any dependencies between the input failure rate distributions. Since the inputs describe the same failure mode, however, they are likely to be dependent. Moreover, literature shows that when it comes to aging, lognormal, Gumbel and Weibull distributions offer a better description than exponential distributions. On the other hand, the main advantage of this approach is its simplicity. However, that is also its main drawback. Exponential failure rates are by definition constant, so Equation 4.1 actually is

$$h_{FMF} = \sum_{i=1}^{n} h_{IFi} = h_{IF1} + h_{IF2} + \ldots + h_{IFn}$$

As a result the failure mode failure rate is not input value dependent anymore. This consequence renders the use of independent exponentially distributed failure rates completely useless for application in the asset failure rate estimation model. The model is after all used to assess the time-varying behavior of the failure rates.

Another suggested method is to assign weights to every input and consequently to their failure rate distributions [27, 28]. The failure mode failure rate would then look something like

$$h_{FMF} = \sum_{i=1}^{n} w_i h_{IFi}(x_i) = w_1 h_{IF1}(x_1) + w_2 h_{IF2}(x_2) + \ldots + w_n h_{IFn}(x_n) \quad (4.2)$$

An advantage of this method with respect to the previous one is that where Equation 4.1 only allowed for exponential failure rates, Equation 4.2 can contain failure rates of any distribution. However, defining a weight for each failure rate distribution is both time consuming and requires extensive expert knowledge. Besides, say one would monitor h_{FMF} in order to determine the weights in Equation 4.2, this would be impossible as there is just one equation with n unknowns. Furthermore Equation 4.2, just as Equation 4.1, does not allow for dependencies between inputs to be taken into account properly.

A last common approach is to use Markov models to assess the technical state the asset is in [29, 30]. This state representation requires a matrix in which the probabilities that the system will traverse from the one to the next state are defined. Just as the previous method, this requires many constants to be determined. Another drawback of the Markov model is that the failure rate is made discrete instead of continuous, whereby the development of the failure rate over time is hard if not impossible to define.

In literature, no method was found that used non-weighted dependent failure rate distributions to determine the combined failure rate of a few subsystems or subcomponents. Hence, a method to calculate the failure mode failure rate was assumed. The failure mode function will contain a $\max$ function which makes the failure mode failure rate equal to the largest input failure rate. This method is both chosen because it allows for any type of failure rate distribution to be used and because it does not just concern independent input failure rate distributions.

$$h_{FMF} = \max[h_{IF1}(x_1), h_{IF2}(x_2), \ldots, h_{IFn}(x_n)] \quad (4.3)$$

Since this method may introduce an error in the failure mode failure rate, further research into modeling input failure rate distribution dependencies is recommended.

In the past few paragraphs the importance of the dependability between the input failure rate distributions has been stressed. The next section indicates the probability theory required to help determine the dependabilities between the inputs.

Support from probability theory

The failure probability of an asset is closely related to its failure rate, as shown in Section 3.1. In contrast to failure rates, failure probabilities can be added, subtracted and multiplied with ease.

The input failure probabilities are combined by using probability theory [12]. The determination of the failure probability of failure mode 2 in Figure 2.8 is graphically represented by using Venn diagrams. Such a diagram shows in this case which inputs describe which failure causes of the failure mode function. The Venn diagram for failure mode function 2 is shown in Figure 4.2.

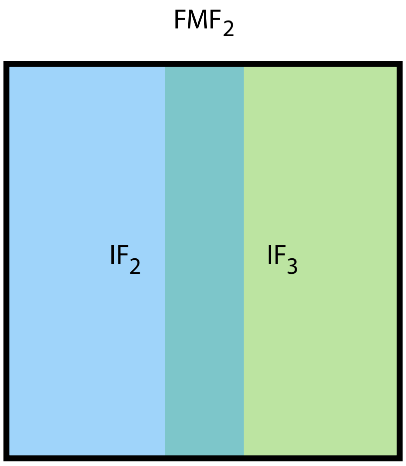

Figure 4.2: Venn diagram of FMF_2

In this figure FMF_2 stands for *Failure mode function 2* and IF_2 and IF_3 are the outcomes of its underlying *Input functions 2* and *3* (see Figure 2.8). Figure 4.2 first of all shows a black square, containing all the failure causes of FMF_2. These failure causes are described by the inputs IF_2 through the blue (and turquoise) area and IF_3 through the green (and turquoise) area. The failure probability of the failure mode function can then be described by a failure of either IF_2 or IF_3. Therefore the failure probabilities of IF_2 and IF_3 can be taken together. However, since the failure causes described by IF_2 or IF_3 partly overlap, the probability that both IF_2 and IF_3 fail (represented by the turquoise area) needs to be subtracted. Mathematically this is represented as

$$P(FMF_2) = P(IF_2 \cup IF_3) = P(IF_2) + P(IF_3) - P(IF_2 \cap IF_3) \tag{4.4}$$

The probability that both IF_2 and IF_3 fail equals

$$P(IF_2 \cap IF_3) = P(IF_2)P(IF_3|IF_2) = P(IF_3)P(IF_2|IF_3) \tag{4.5}$$

In this equation $P(IF_3|IF_2)$ represents the probability that IF_3 will fail, given that IF_2 has already failed. $P(IF_2|IF_3)$ is the probability of failure for IF_2 given that IF_3 has failed. These probabilities play a role when the inputs are dependent.

Dependent inputs The input failure probabilities can be dependent. Dependency means that the inputs are linked to each other — that the failure of one of the inputs tells something about the failure of the other input. When two inputs are dependent they (partly) describe the same failure causes of the failure mode. Graphically this means that the areas of IF_2 and IF_3 need to overlap, as shown in Figure 4.2.

Mathematically the probability of failure for FMF_2 equals Equation 4.5 substituted in Equation 4.4, being

$$P(FMF_2) = P(IF_2 \cup IF_3) = P(IF_2) + P(IF_3) - P(IF_2)P(IF_3|IF_2) \tag{4.6}$$

When the inputs are dependent, which is likely because they describe the same failure mode, the dependent probability $P(IF_3|IF_2)$ needs to be determined. Deriving this probability can be hard, as there is not always enough measurement data available to calculate this probability. Defining $P(IF_3|IF_2)$ will either require correlation calculations between the two inspection parameters (using inspection data from similar assets) or expert review.

A way to circumvent having to calculate this probability is selecting just one of the inputs to determine the failure probability for the failure modes, although that will almost certainly cause a loss of accuracy. If this approach is used, the input that most accurately describes the health of the asset should be used and the other should be removed from under the failure mode function.

Independent inputs Independency is both linguistically and mathematically the opposite of dependency. Therefore, when two inputs are independent the failure of the one does *not* yield extra information about the failure of the other. On the one hand this can be because the inputs describe the same failure causes, but belong to different subcomponents of the asset. That way the inputs do not have to be physically and probabilistically related. The areas of IF_2 and IF_3 in the Venn diagram can therefore still overlap [31] (see Figure 4.3). On the other hand it can be caused by the fact that the inputs do not describe the same failure causes, so the areas of IF_2 and IF_3 do not overlap at all, as shown in Figure 4.3

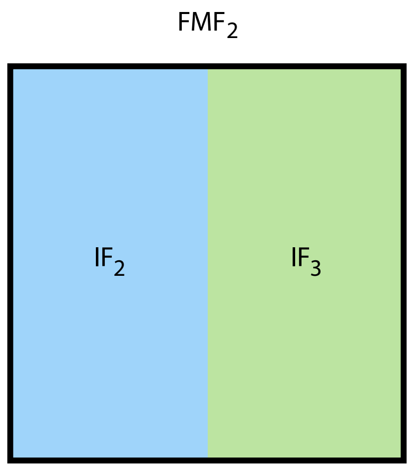

Figure 4.3: Venn diagram of FMF_2: IF_2 and IF_3 are clearly independent

As stated before, when the inputs are independent, a failure of the one does not tell anything about the failure of the other. Mathematically this comes down to

$$P(IF_2|IF_3) = IF_2$$
$$P(IF_3|IF_2) = IF_3$$

which changes Equation 4.5 to

$$P(IF_2 \cap IF_3) = P(IF_2)P(IF_3|IF_2) = P(IF_3)P(IF_2|IF_3) = P(IF_2)P(IF_3)$$

and Equation 4.4 becomes

$$P(FMF_2) = P(IF_2 \cup IF_3) = P(IF_2) + P(IF_3) - P(IF_2)P(IF_3) \tag{4.7}$$

Contrary to the case with dependent inputs, there is no probability $P(IF_3|IF_2)$ that needs to be defined. Unfortunately, it is most likely that the inputs are dependent as they describe the same failure mode.

Fully dependent inputs Independency is one extreme case of the failure probabilities, being fully dependent is another. Full dependency means that if either IF_2 or IF_3 fails the other will also fail. Graphically this comes down to a full overlap of IF_2 and IF_3, as shown in Figure 4.4.

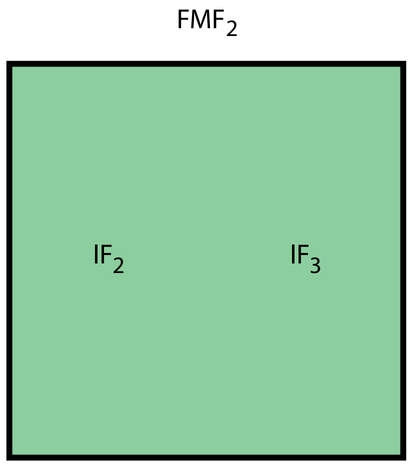

Figure 4.4: Venn diagram of FMF_2: IF_2 and IF_3 are fully dependent

Mathematically the joint failure means

$$P(IF_2|IF_3) = 1$$
$$P(IF_3|IF_2) = 1$$

Equation 4.5 consequently changes as follows

$$P(IF_2 \cap IF_3) = P(IF_2)P(IF_3|IF_2) = P(IF_3)P(IF_2|IF_3) = P(IF_2) = P(IF_3)$$

Substituting this in Equation 4.4 yields

$$P(FMF_2) = P(IF_2) + P(IF_3) - P(IF_2) = P(IF_2) = P(IF_3) \tag{4.8}$$

and the failure probability of FMF_2 would be clear. However, if IF_2 and IF_3 are fully dependent there is no use in measuring them both in the first place.

Collectively exhaustive Ideally the inputs describe all the failure causes of a failure mode, or visually, fill the entire black FMF_2 square. When IF_2 and IF_3 together cover all the failure causes, they are called collectively exhaustive [31]. An example of IF_2 and IF_3 not being collectively exhaustive is shown in Figure 4.5. Being non-exhaustive, represented by the white part, means that not all the failure causes of FMF_2 can be described by a failure indicated by IF_2 or IF_3. For the asset failure rate estimation model this means that the failure mode is not fully modeled by the inputs IF_2 and IF_3. Depending on the degree of non-exhaustivity and the influence of the undescribed failure causes, an asset manager may want to look for another parameter that also describes failure of the asset by that failure mode to make the inputs more collectively exhaustive.

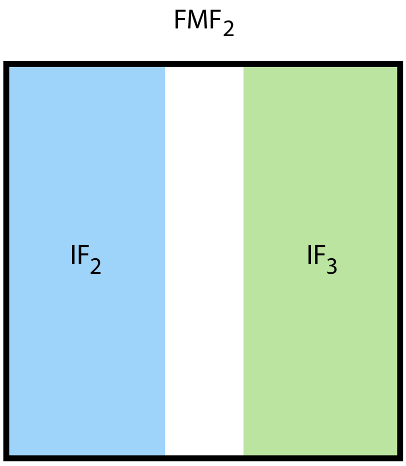

Figure 4.5: Venn diagram of FMF_2: IF_2 and IF_3 are non-exhaustive

4.1.3 Asset function implementation

Combining the failure rates of the failure modes into one is analogous to combining the input failure rates. Consequently, the formulas for calculating the asset failure rate based on the failure modes failure rates ($h_{FMF1}, h_{FMF2}, \ldots, h_{FMFn}$) follows the definition of the failure mode function failure rate in Section 4.1.2. The asset failure rate h_{AF} equals

$$h_{AF} = \max[h_{FMF1}, h_{FMF2}, \ldots, h_{FMFn}] \tag{4.9}$$

Again, the dependability amongst the failure modes can be determined by probability theory. The asset failure probability (according to Figure 2.8) is equal to

$$P(AF) = P(FMF_1) + P(FMF_2) - P(FMF_1)P(FMF_2|FMF_1) \tag{4.10}$$

where AF stands for *Asset function* and FMF_1 and FMF_2 are the underlying *Failure mode functions 1* and *2*. If the failure modes are independent, use

$$P(AF) = P(FMF_1) + P(FMF_2) - P(FMF_1)P(FMF_2) \tag{4.11}$$

If the failure modes are fully dependent, use

$$P(AF) = P(FMF_1) = P(FMF_2) \tag{4.12}$$

In any other case Equation 4.10 itself should be used and combined with correlations or expert opinions that define the dependent probability $P(FMF_2|FMF_1)$.

4.2 Failure rate development

Asset managers usually have a certain time period in which they need to both technically and economically optimize the maintenance and replacement of the assets: the planning period. Within the planning period priorities have to be set as to which assets to replace and which assets do not (yet) require maintenance. This distinction can be made when the asset manager knows how the failure rate and the corresponding failure risk of the asset will evolve during the planning period.

The change of the failure rate during the planning period can be calculated with the use of the failure rate distributions. The failure mode failure rate distributions and asset failure rate distributions are already defined with respect to time. Hence the change of the failure rate during the planning period according to those distributions can be determined with ease. For doing the same with input failure rate distributions an extra step is required.

Since the planning period is a measure of time, the change of the inputs with respect to time needs to be known to be able to tell a future failure rate with a input failure rate distribution. In the case that the change of the input was defined with respect to time and combined with a failure rate distribution based on time, as shown in Section 4.1.1, no extra distribution needs to be defined. If the failure rate distribution was defined with respect to an input different from time, another distribution linking either the failure rate (Figure 4.1a) or the input (Figure 4.1b) to time needs to be determined.

There are several ways to determine the change of the failure rate over time. The first section will cover an input-time based approach. The consecutive section shows a method to use the dependency between the input and another parameter. The third section indicates an alternative using a time based failure rate distribution.

It might occur that the required distributions for the multiple assessment techniques can be calculated. In that case the technique that performs best with respect to accuracy and ease of implementation should be adopted.

4.2.1 Input-time based assessment

With the input versus time distribution present, the calculation of the future failure rate can be calculated as is shown in Figure 4.6. The calculation of the future failure rate is based on the current value for the input, I, and the duration of the planning period, ΔT. Indicated by the green dot in Figure 4.6a, I corresponds with a certain value for the time, T — an approximation of the technical age of the asset based on the input. Adding the planning period to T yields an approximation of the change in the input during the planning period, ΔI. Next, I and ΔI are used to derive the failure rate according to the input after the planning period has expired: $h + \Delta h$ (see Figure 4.6b).

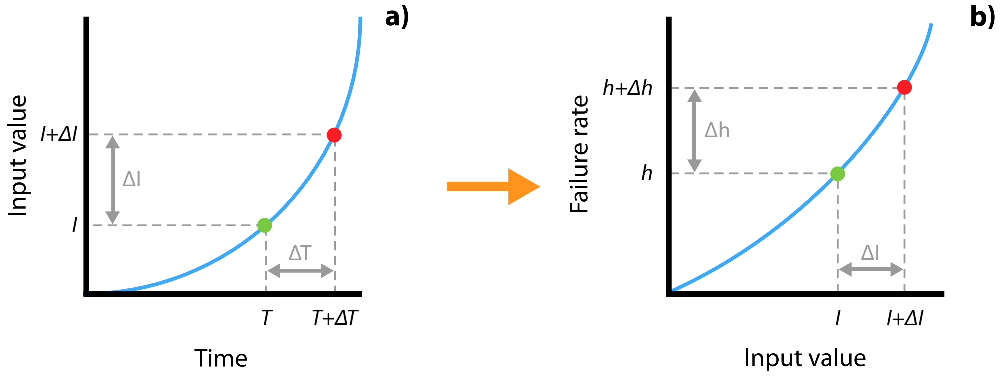

Figure 4.6: Assessing the change of the failure rate during the planning period through an input-time relationship

4.2.2 Input-parameter based assessment

In case the input is not known with respect to time, but with respect to another parameter, the approach described in this section can be adopted. The required steps are shown in Figure 4.7, given that the common parameter was the number of switching events of a circuit breaker.

The starting point is Figure 4.7a, a known relationship between the input and the number of switching events. In order to be able to see the development of the failure rate over time, the *Switching events* axis will have to be changed to a *Time* axis. This is done by combining Figure 4.7a with Figure 4.7b, a relationship between time and the number of switching events. These two taken together yield the relationship between the input and time, as shown in Figure 4.7c. This relationship corresponds with the one shown in Figure 4.6a.

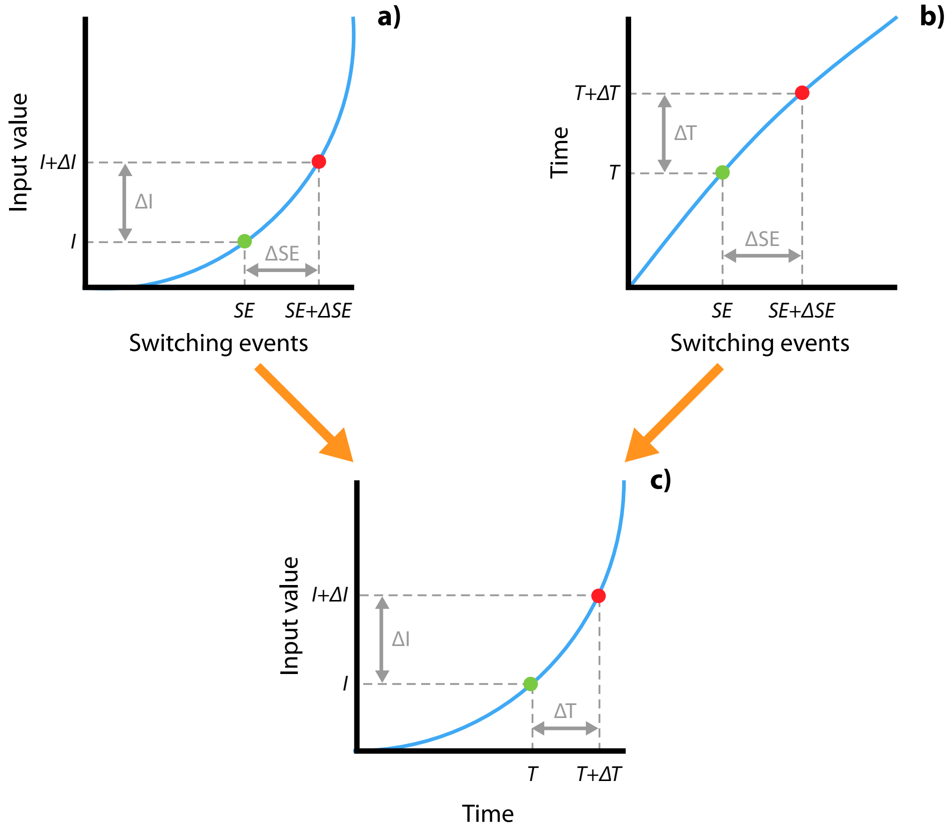

Figure 4.7: Assessing the change of the failure rate during the planning period based on a common parameter other than time

When the failure rate needs to be assessed, the input value I shown in Figure 4.7c is matched to a time T. Since the input versus time distribution is known, $T + \Delta T$ and $I + \Delta I$ can easily be calculated. However, the other distributions may still be of interest. For example, when an asset manager wants to know what the failure rate of the asset is based on the number of switching events, he can use the $I + \Delta I$ or $T + \Delta T$ to derive the current number of switching events SE and the expected number of switching events during the planning period ΔSE from Figure 4.7a or Figure 4.7b respectively.

4.2.3 Failure rate-time based assessment

Besides using the relationship between the input (x-axis of Figure 2.4) and time to assess the development of the failure rate, a relationship between the failure rate (y-axis of Figure 2.4) and time can be used.

The development of the failure rate during the planning period can be assessed in a similar matter as was done in the previous section. Starting with the current value of the input, I, one can find a corresponding failure rate h in Figure 4.8b. This failure rate is then converted to a technical age of the asset, T, using the failure rate versus time distribution in Figure 4.8a. After adding the planning period ΔT, the failure rate after the planning period $(h + \Delta h)$ is obtained. Looking for $h + \Delta h$ in the failure rate distribution in Figure 4.8b will show the corresponding input value after the planning period is over $(I + \Delta I)$.

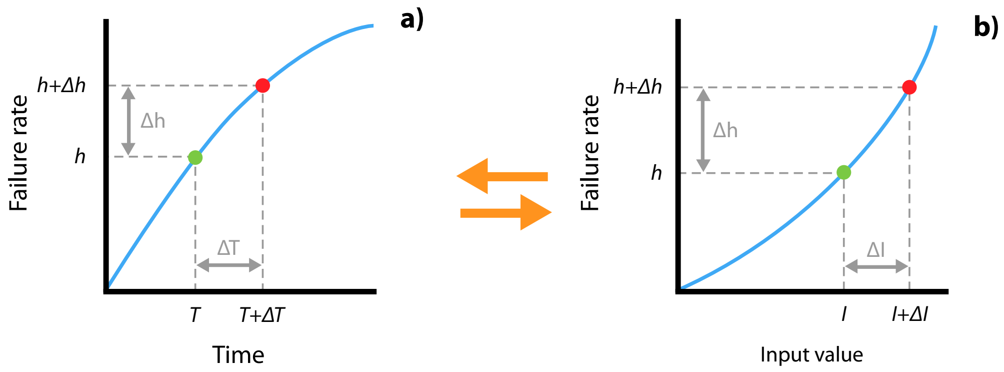

Figure 4.8: Assessing the change of the failure rate during the planning period through a failure rate-time relationship

CHAPTER 5

CIRCUIT BREAKER FAILURE

Now the asset failure rate estimation model is defined and the derivation of failure rate distributions is explained, it is time to focus on an application. The asset failure rate estimation model will be implemented for circuit breakers to show some additional considerations that come into play when the model is implemented. First of all a small introduction into circuit breakers will be given. Thereafter a section will introduce the database on circuit breaker failure that will be used for the derivation of some of the failure rate distributions. The last paragraph will use this data to determine the circuit breaker subpopulations that will be used.

5.1 The circuit breaker

A circuit breaker is a component that is used in the high voltage electricity grid to separate two parts of the grid from each other. In the very basis it is a switch that can switch on or off assets or parts of the electricity grid. However, since the circuit breaker is operating at a very high voltage level and needs to conduct or insulate large currents it is a complex asset. A simplified cross section of a circuit breaker and its stages of operation are depicted in Figure 5.1

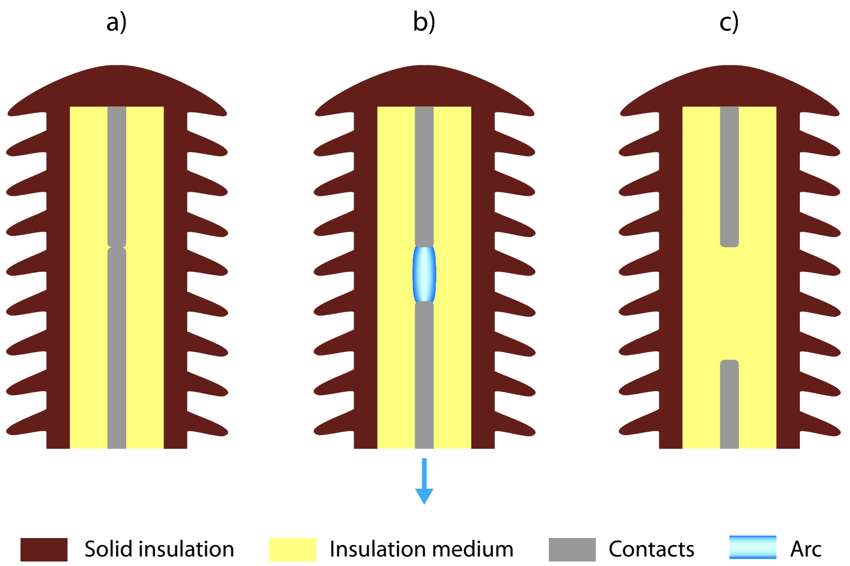

Figure 5.1: Simplified schematic cross section of a circuit breaker in several stages of operation

Basically a circuit breaker consists of two opposing contacts that touch each other when the current needs to be conducted and move apart when the current needs to be interrupted, shown in see Figure 5.1a and Figure 5.1b respectively. One of the contacts (top contact in Figure 5.1) is stationary and the other is movable (bottom contact in Figure 5.1). The contacts of the circuit breaker need to be separated quickly to interrupt the current. This requires a lot of energy. Therefore, energy is stored in a circuit breaker and all at once released when the circuit breaker needs to operate. There are different operating mechanisms in use to drive the contact which are based on different ways of energy storage. The most common operating mechanism principles are [32]

- Hydraulic
- Pneumatic
- Spring

When a circuit breaker is given a command to open, by separating its contacts, the voltage will not be immediately be isolated. The high voltage level over a small distance between the contacts will cause an electric arc to be established, as is depicted in Figure 5.1b. This arc is a plasma which is able to conduct the current. An insulating medium is often used to extinguish this arc. Another use of an insulating medium comes along when the circuit breaker is open. When the contacts are separated they still need to be able to isolate the voltage, as shown in Figure 5.1c. The high voltage circuit breakers are designed to isolate voltage levels in the order of hundreds of kilovolts. Isolating these voltages in open air would require large distances between the contacts. Therefore the contacts are contained in a chamber with an insulating medium. The insulating media that are currently used are [33]

- Compressed air
- Oil
- SF_6
- Vacuum

Vacuum, however, is not used in high voltage circuit breakers managed by TenneT TSO, so they will not be discussed in this research.

Circuit breakers are often characterized by their operating mechanism and insulating medium. Though, not all combinations of the aforementioned operating mechanisms and insulating media are used. Table 5.1 shows all the combinations of the circuit breakers managed by TenneT TSO.

Table 5.1: Available combinations of operating mechanisms and insulating media for circuit breakers managed by TenneT TSO [34]

	Operating mechanism		
Insulating medium	Hydraulic	Pneumatic	Spring
Air		X	
Oil	X		X
SF_6	X	X	X

For a more extensive introduction into circuit breakers and their operation one is referred to Appendix B. Knowing the basis about the operation of a circuit breaker, the next step is knowing how a circuit breaker fails.

5.2 Failure data

In order to assess and predict the failure rate of the circuit breakers currently in operation, failure rate distributions are required. For the failure mode failure rate distributions and asset failure rate distributions, which are based on the age of the asset, historic failure data can be used. Information about when, why and how comparable circuit breakers failed can be translated to failure rate distributions.

During the rest of this research a provided failure database will be used. The database contains both failure and suspension data of circuit breakers. For the failure data the age at failure, the failure mode (according to [35]), the operating mechanism and the main kind of service of the circuit breaker were provided. The main kind of service indicates the component the circuit breaker is meant to switch off. Those components can be one of the following

- Busbar
- Cable
- Capacitor
- Overhead line
- Reactor
- Transformer

Each suspension data point indicates an age category and the operating mechanism and the main kind of service of the circuit breaker. An age category is a group that spans five ages. To an age category belong all the suspended circuit breakers whose age equals one of the ages in the category. For example, if a suspension data point indicates that a circuit breaker was three years old it will belong to the age category that spans from zero to four years.

The data from the database is used to calculate the failure rate distributions. Fitting failure rate distributions to the data is most easily done with commercially available reliability programs such as Weibull++. Unfortunately, since the suspension data is not listed per age but per age category, this will not be possible. The suspension data age categories cannot be entered in a straightforward way into the software. Instead of using commercial software, the failure rate distributions will be estimated by using a likelihood function. The likelihood function calculates the model parameters that approximate the input data best. The derivation and working of this likelihood function is explained Appendix C.

Whereas with commercial software the accuracy of the fitted failure rate distribution can be calculated quite fast, the likelihood function (Equation C.1) does not allow for that. For example assessing the accuracy via the goodness-of-fit parameter ρ (as suggested in Section 3.4) would require a non-parametric estimation of the failure rate distribution [36]. Performing such an estimation is very complex and does not lie within the scope of this research. To overcome this issue it is recommended to use databases in which both the failure and suspension data are provided with the age of the asset at that point.

The distribution that will be used to determine the failure rate is the two-parameter Weibull distribution. This distribution is chosen for Weibull distributions are generally used to describe aging effects [24] and because of its versatility in shape. The two-parameter Weibull distribution is chosen rather than the three-parameter version for that will greatly reduce the arithmetic power required to determine the model parameters. The Weibull cumulative density function equals

$$F_{\beta,\eta}(t) = 1 - \exp\left\{-\left(\frac{t}{\eta}\right)^{\beta}\right\}$$

The parameters in this distribution are [12, 24]

t is the measured variable, here the age

β is the shape parameter, determining a constant ($\beta = 1$), increasing ($\beta > 1$) or decreasing ($\beta < 1$) failure rate

η is the scale parameter, influencing the horizontal spread

Figure 5.2 depicts the influence of various β and η values on the shape and scale of the cumulative density function. The first conclusion that can be drawn from Figure 5.2 is that when β is increased while η is kept constant, the cumulative density function will more and more resemble a step function. This is visualized by the solid lines. Furthermore, it becomes clear that the various distributions all cross the $F = 1 - \frac{1}{e}$ at their value for η. This is how η has been defined. Increasing η with a constant β will therefore decrease the slope of the distribution, as visualized by the various blue lines.

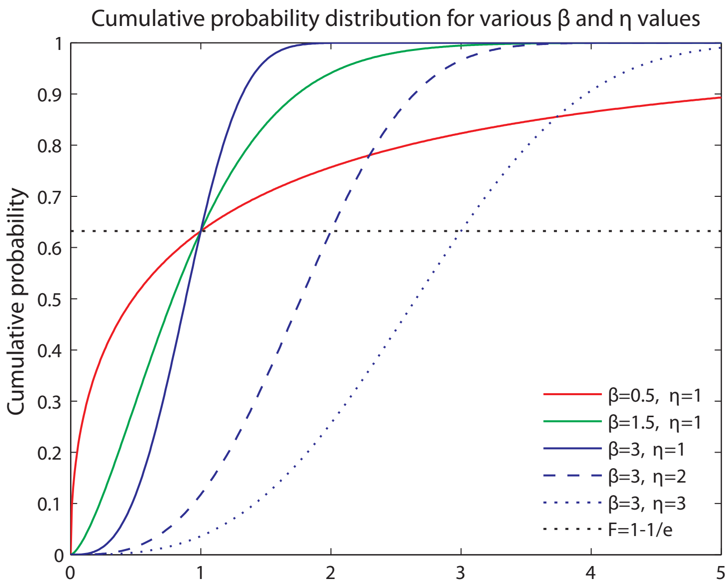

Figure 5.2: Cumulative density function for various β and η values

The likelihood function described in Appendix C will be used to determine the values for β and η that most accurately describe the data for which the failure rate distribution is determined.

The shape and scale of a failure rate distribution depend on the design of the circuit breaker and the way it is used. The next section selects the circuit breaker subpopulations that will be used in the asset failure rate estimation model of the circuit breaker.

5.3 Circuit breaker subpopulations

In Section 1.4.2 the importance of acknowledging different asset subpopulations was addressed. Based on the data in the database and the different aspects a circuit breaker can be characterized by, the subpopulations will be determined. The following sections will assess the influence of the insulating medium, the operating mechanism and the main kind of service on the failure rate distribution of a circuit breaker. The last section will summarize which subpopulations will be used.

5.3.1 Insulating medium

The first logical choice is to differentiate based on the insulating medium of the circuit breaker. Since the insulating medium had a large influence on the design, it will have largely differing failure rate distributions. Cigré inquiries confirm that for different insulating media the failure rates differ [35]. However, the database only contains data about SF_6 circuit breakers. Hence the difference in the failure rate distributions based on the insulating medium cannot be shown. The rest of the research will consequently focus on SF_6 circuit breakers only. Table 5.1 shows all three operating mechanism types exist in combination with SF_6 as an insulating medium, so no operating mechanism has to be neglected based on that knowledge.

5.3.2 Operating mechanism

Between the different operating mechanisms there are large mechanical differences. Hence it is likely that the failure rate distributions will also be different. This assumption is supported by the failure rates for operating mechanisms listed in Cigré publications [35]. The result of the calculation of the failure rate distributions is shown in Figure 5.3. The parameters for the Weibull distributions for the operating mechanisms are shown in Table 5.2.

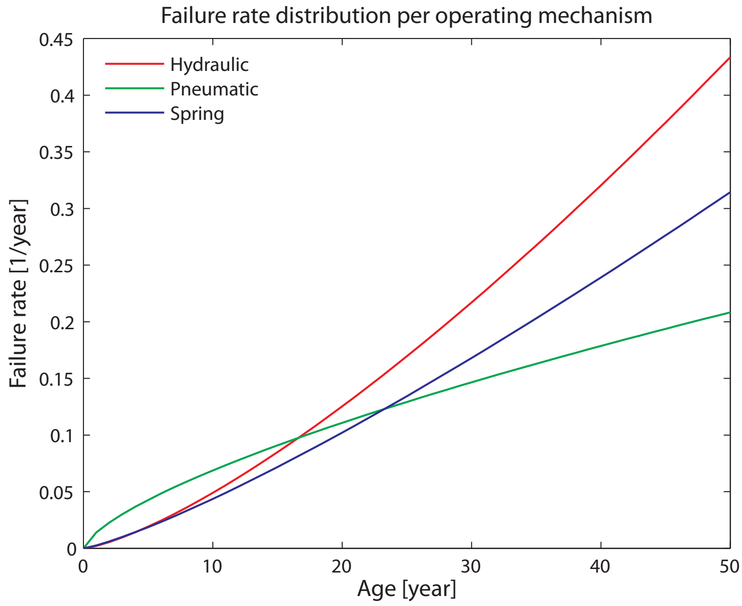

Figure 5.3: Failure rate distributions of the operating mechanisms

Table 5.2: Weibull model parameters for the operating mechanisms

Operating mechanism	β	η
Hydraulic	2.355	19.48
Pneumatic	1.689	17.03
Spring	2.227	20.79

Figure 5.3 clearly shows that the failure rate of a pneumatic-driven circuit breaker increases much faster in the beginning than that of a hydraulic- or spring-driven one. This indicates that pneumatic circuit breakers fail more at a low age. Inherently the reliability of a spring and hydraulic mechanism are higher than that of a pneumatic one. Since there is such a discernible difference between the operating mechanisms they will be used in dividing the circuit breaker into subpopulations.

5.3.3 Main kind of service

Unlike the insulating medium and the operating mechanism, the main kind of service does not depend on the design of the circuit breaker but on the use. However, it almost certainly influences the failure probability distribution.

When an overhead line carries a current it behaves inductively. Therefore a capacitor bank is added at the end of the line to compensate for the inductance and to make sure the voltage level remains within the specified limits. When an overhead line caries less and less current, it behaves as a capacitor. In that case a shunt reactor is connected to the end of the line for the same reason. The magnitude of the current that flows through an overhead line depends on the power demand. Therefore, capacitor banks and shunt reactors are generally switched on and off at least once a day, when the power demand drops at nightfall and increases again in the morning. Circuit breakers with an other main kind of service do not switch that often. Hence, the capacitor and shunt reactor circuit breakers are above averagely mechanically stressed, which might translate in a higher failure rate.

Figure 5.4 shows the failure rate distributions for all the main kinds of service. The parameters for the Weibull distributions for the main kinds of service are shown in Table 5.3.

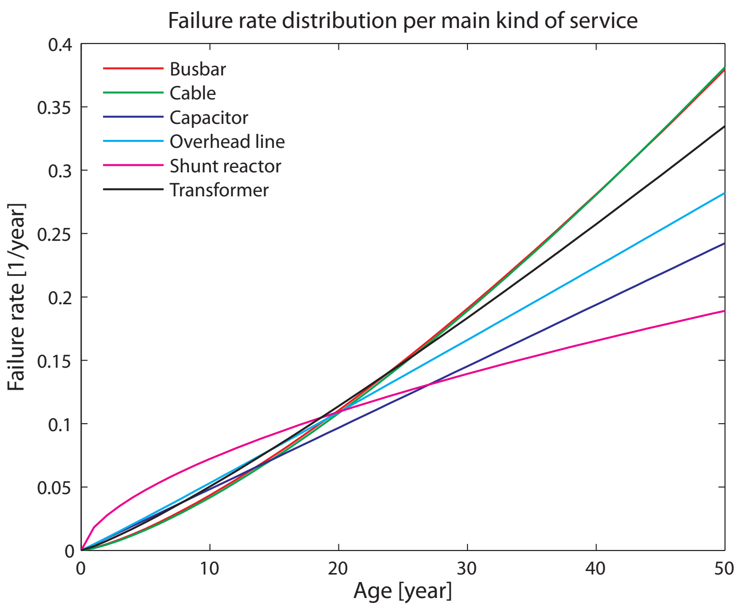

Figure 5.4: Failure rate distributions of the main kinds of service

Differences between the distributions are clearly present in Figure 5.4. Most obvious is the shunt reactor circuit breaker which failure rate indeed increases very fast in the beginning, much faster than all the others. But also amongst the other service kinds there are some differences. The capacitor circuit breaker for example has a lower failure rate then the rest.

Table 5.3: Weibull model parameters for the main kinds of service

Service kind	β	η
Busbar	2.346	20.51
Cable	2.374	20.79
Capacitor	2.002	20.34
Overhead line	2.037	19.34
Shunt reactor	1.598	16.44
Transformer	2.177	19.59

Because of the differences in the distributions, the main kind of service is also used as category for the subpopulations.

5.3.4 Chosen subpopulations

The previous paragraphs showed that amongst both operating mechanisms and main kinds of service there where quite some differences in failure rate distributions. They fulfill the demand set in Section 1.4.2 to have distinctive failure rates. Therefore every unique combination of an operating mechanism and a main kind of service will be a subpopulation.

However, as was stressed in Section 3.2, the data quantity must be large enough in order to make a justifiable fit. Table 5.4 shows the amount of failure data points per combination of operating mechanism and service kind. Clearly, the number of failure data points for the cable circuit breaker is too low to base a failure rate distribution upon. Therefore it will not be considered as a separate subpopulation. When the failure rate of a cable circuit breaker has to be calculated later on, it will be based on the failure rate distribution for its operating mechanism.

Table 5.4: Number of failure data points given per main kind of service and operating mechanism

	Operating mechanism		
Service kind	Hydraulic	Pneumatic	Spring
Busbar	39	20	13
Cable	3	1	4
Capacitor	9	13	29
Overhead line	122	64	110
Shunt reactor	7	8	42
Transformer	58	10	40

CHAPTER 6

CIRCUIT BREAKER FAILURE RATE ESTIMATION MODEL

In the past chapters the asset performance estimation model was derived, failure rate distributions and failure probability theory were treated and the circuit breaker was introduced. With all this information the asset failure rate estimation model can be implemented for a circuit breaker.

As mentioned before, a circuit breaker is a complex asset with many failure modes. Since the time for this research is limited, not all failure modes will be considered in the circuit breaker failure rate estimation model. Visualizing it, the opaque green part of the model shown in Figure 6.1 will be implemented. This chapter will follow the same steps as the model derivation in Chapter 2. Hence, the first step is to select the failure modes.

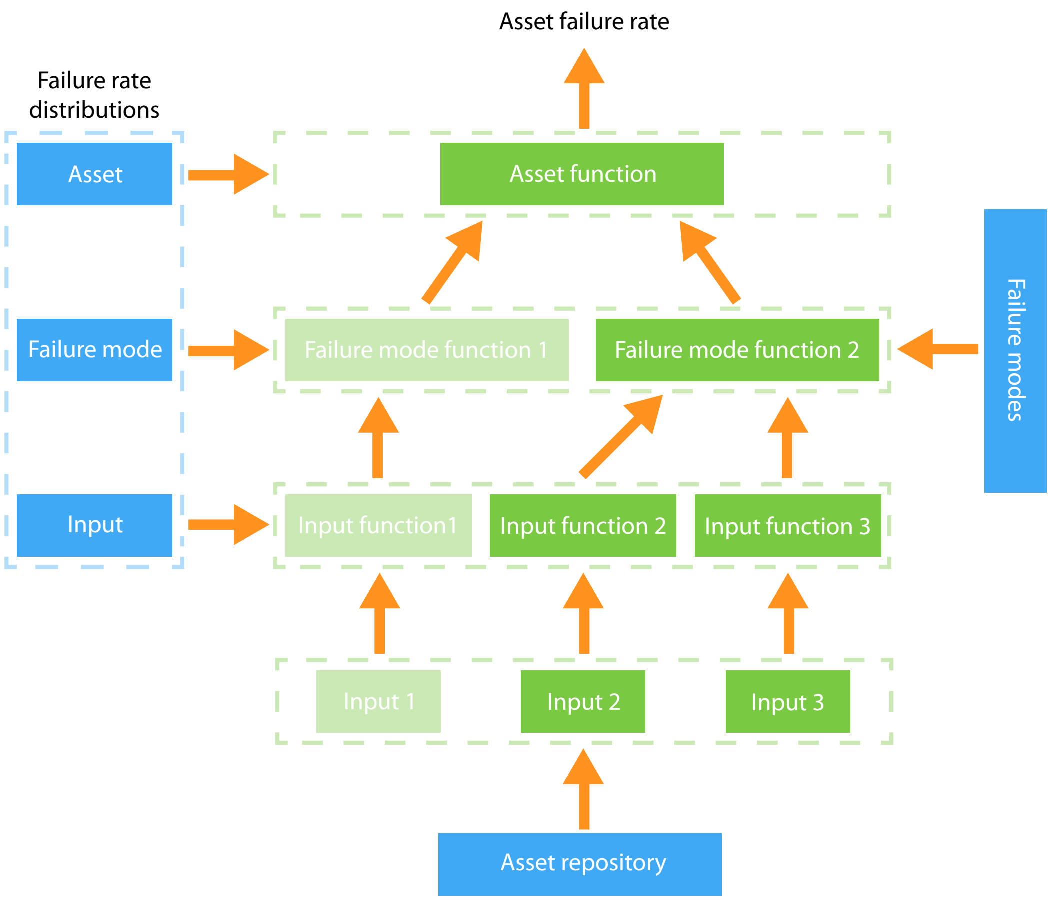

Figure 6.1: Part of the asset failure rate estimation model that will be implemented

6.1 Failure modes

In general there are two types of failures: major and minor failures. When a major failure occurs, the circuit breaker loses one or more of its fundamental functions and either backup equipment needs to take over or immediate unscheduled maintenance is required [2]. A minor failure is every failure that does not classify as a major failure. Since minor failures occur more often than major failures [35], they might be of more interest for modeling the failure rate of the asset. However, keeping in mind that the asset failure rate estimation model is meant to calculate the failure rate, which will be used to calculate a failure risk, the major failures are of more interest. As major failures are most detrimental to the proper functioning of a circuit breaker and will cause a larger failure impact than minor faults, the emphasis is on them.

Within the set of major failures there are several failure modes: major failure modes. During the second international inquiry on high voltage circuit breaker failures and defects in service Cigré held ([35]), they asked respondents to indicate by which failure mode the circuit breaker failed. The frequency distribution for major failure modes is shown in Table 6.1.

Table 6.1: Percentage of failures per circuit breaker major failure mode [35]

Failure mode	Percentage
Does not close on command	24.6 %
Does not open on command	8.3 %
Closes without command	1.1 %
Opens without command	7.0 %
Fails to carry the current	1.5 %
Breakdown to earth	3.2 %
Breakdown between poles	1.5 %
Does not make the current	1.7 %
Breakdown across open pole (internal)	3.6 %
Does not break the current	3.0 %
Breakdown across open pole (external)	1.5 %
Locking in open or closed position	28.4 %
Others	14.6 %

Table 6.1 shows that *Does not close on command*, *Does not open on command* and *Locking in open or closed position* are the most common major failure modes for a circuit breaker. Since the latter occurs most often, using that failure mode will result in the largest amount of failure data which is beneficial when deriving the failure rate distributions.

In Section 1.4.2 was stated that an increasing number of asset subpopulations decreases the number of failure data points per subpopulation. Likewise, a large amount of failure modes results in a low amount of data available per failure mode. To increase the number of failure data points per failure mode, the failure modes can be divided into groups which have about the same behavior. The behavior should both with respect to failure rates and with respect to failure impacts be about the same. Else the failure risk that would be calculated based on them would not be an accurate representation of reality.

Whether the failure rate behavior of the failure modes is alike is normally assessed in the asset function. If the failure modes describe the same asset failure causes their areas in a

Venn diagram would overlap in (just like the inputs in Figure 4.2). When two failure modes overlap the asset failure probability would become (see Section 4.1.3)

$$P(AF) = P(FMF_1) + P(FMF_2) - P(FMF_1)P(FMF_2|FMF_1)$$

and the probability $P(FMF_2|FMF_1)$ would have to be defined. In Section 4.1.3 it was suggested to do this either by correlation calculations or expert knowledge. Because of a lack of appropriate data, correlation calculations cannot be performed at this point in the research. Expert knowledge, however, suggests that these three failure modes can be taken together when it comes to failure probability and thus failure rate calculations.

When it comes to the failure impact of the three most common failure modes they are not the same. For example, if a circuit breaker fails to open on command after lightning stuck an overhead line, the lightning surge will travel further into the grid and might damage components. When a circuit breaker does not close on command the impact is generally less for by redundancy the current can often flow via another circuit breaker. Therefore, contrary to the failure rates, the failure impacts are not alike. Consequently the failure risk will differ for the three failure modes. However, the three failure modes are alike when it comes to failure rates. Therefore, for the failure rate calculations the three failure modes will be taken together as one failure mode, named *Does not switch*, and for the failure impact calculation they will be taken apart. The failure risk can then still be calculated by the product of the failure rate and the failure impact.

As stated before, the advantage thereof is that the population of failure data increases. Consequently the number of data points on which the failure rate distributions later on will fitted will increase. The *Does not switch* failure mode covers over 60% of the failure data points (see Table 6.1).

Although over 60% of the data points in the database are used, inherently almost 40% does not belong to the *Does not switch* failure mode. This may have an influence on the failure rate distributions that can be made for the subcategories as specified in Section 5.3.4. With almost 40% of the data points unused in this failure mode, the tabulation of the number of failure data points available per subpopulation (Table 5.4) changes to Table 6.2.

Table 6.2 shows that, besides the cable circuit breakers, also the hydraulic and pneumatic shunt reactor circuit breakers are not represented by enough failure data to be able to model them. A solution hereto is offered later on in this chapter.

Table 6.2: Number of failure data points given per main kind of service and operating mechanism given for the *Does not switch* failure mode

	Operating mechanism		
Service kind	Hydraulic	Pneumatic	Spring
Busbar	28	13	10
Cable	3	1	2
Capacitor	8	9	22
Overhead line	79	36	72
Shunt reactor	0	4	34
Transformer	43	6	24

Now the failure mode is selected, the next step is to select inputs that describe this failure mode.

6.2 Model inputs

The inputs for the model are inputs that are measured during inspection and maintenance. Only by using circuit breaker specific data the model will be able to indicate the right failure rate for that specific circuit breaker. For all asset types TenneT TSO manages they have written a *technical maintenance directive*, or TOR (Dutch: technische onderhoudsrichtlijn). In those maintenance directives they included a list with parameters that need to be evaluated during inspection and maintenance actions. Also for circuit breakers TenneT TSO has made such a list of parameters [34].

A next step would be linking the parameters from the circuit breaker TOR to the failure modes chosen in the previous section. Fortunately, IEEE published a *Guide for the Selection of Monitoring for Circuit Breakers* ([14]) wherein they define failure effects and failure causes for each failure mode. Furthermore they suggest monitoring options for each failure cause. By combining these failure modes with the circuit breaker TOR, a list of inputs per failure mode could be made. The extensive derivation hereof is shown in Appendix D.

The analysis in Appendix D confirms the conclusion based on expert knowledge made in the previous section: the *Does not close on command* and *Does not open on command* failure modes are very alike. Appendix D shows that the inputs that can be used to monitor these two failure modes are practically the same. The failure mode *Locking in open or closed position* is not explicitly contained in the failure mode list of the IEEE. It is implicitly contained within the does not open or close on command failure modes. Hence, the inputs will be representative for *Locking in open or closed position* as well. The inputs to the joint *Does not switch* failure mode are listed in Table 6.3 (taken from Table D.4 in Appendix D).

Table 6.3: Input parameters linked to the *Does not switch* failure mode

Input parameter	Unit
Leakage rate mechanism	{Good, Fair, Moderate, Poor}
Average number of startups hydraulic pump	[1/month]
Average number of pneumatic fills	[1/month]
Condition of accumulator & high pressure circuit	{Good, Fair, Moderate, Poor}
Open time	[%]
Close time	[%]
Contact bounce	[ms]
Simultaneous closing of pools	[%]
Maximum motor current during loading of spring	[%]
Condition of open, close and tripping coils and relays	{Good, Fair, Moderate, Poor}
Condition of secondary circuits	{Good, Fair, Moderate, Poor}
Condition of mechanic drive parts	{Good, Fair, Moderate, Poor}

Using all these inputs to describe the failure mode is not necessary for indicating how the circuit breaker failure rate estimation model should be implemented. Therefore the focus will be on a subset of the inputs. Since faults that are mechanical in nature occur in almost 70% of the cases [35] the subset will only contain the parameters that concern the mechanical parts of the circuit breaker. This limits the inputs to the list shown in Table 6.4.

Not every input is applicable to every subpopulation chosen in Section 5.3.4. Since the main kind of service of a circuit breaker does not depend on its design, it does not define

Table 6.4: Mechanical input parameters linked to the *Does not switch* failure mode

Input parameter	Unit
Leakage rate mechanism	{Good, Fair, Moderate, Poor}
Average number of startups hydraulic pump	[1/month]
Average number of pneumatic fills	[1/month]
Maximum motor current during loading of spring	[%]
Condition of accumulator & high pressure circuit	{Good, Fair, Moderate, Poor}
Condition of mechanic drive parts	{Good, Fair, Moderate, Poor}

the inputs that apply to a specific circuit breaker. The inputs do change, though, per operating mechanism. The link between the operating mechanisms and the inputs is shown in Table 6.5.

Table 6.5: Mechanical input parameters linked to the operating mechanisms

	Operating mechanism		
Input parameter	Hydraulic	Pneumatic	Spring
Leakage rate mechanism	X	X	
Average number of startups hydraulic pump	X		
Average number of pneumatic fills		X	
Maximum motor current during loading of spring			X
Condition of accumulator & high pressure circuit	X	X	
Condition of mechanic drive parts	X	X	X

With the inputs selected and knowing which subpopulations they describe, the next step is to define the input functions.

6.3 Input functions

The purpose of the input functions is to convert the inputs to failure rates. These functions make those conversions based on an input parameter and an input failure rate distribution. This part of the asset failure rate estimation model (Figure 6.1) is shown in Figure 6.2.

To translate the value of an input to a failure rate, the relationship between them has to be derived. When that relationship is known, another distribution is required to be able to assess the development of the failure rate over time (as explained in Section 4.2). In the following sections, these two distributions will be derived for all the selected inputs.

6.3.1 Leakage rate mechanism

The operating mechanism of a circuit breaker needs to be able to move the contacts. In case of a hydraulic or a pneumatic operating mechanism the movement is driven by oil and/or a pressurized gas. Leaking of the operating gas/liquid leads to a decreasing pressure which may cease the operation of the circuit breaker. The circuit breaker might not be able to

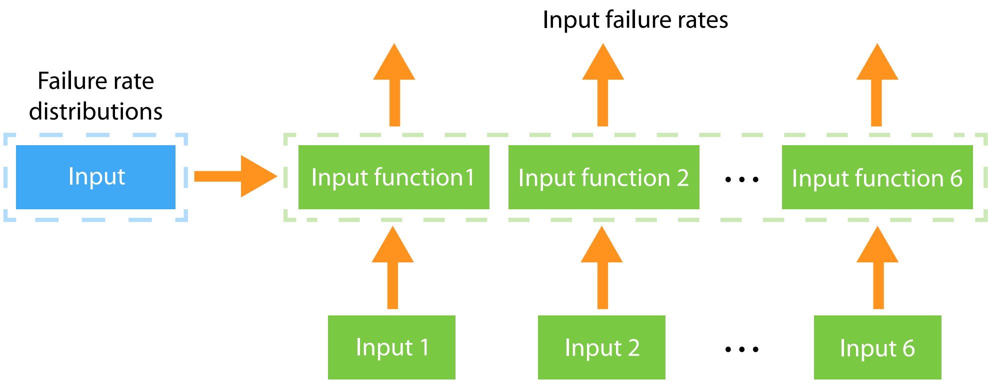

Figure 6.2: Input function section of the asset failure rate estimation model

switch anymore in case of a decrease in the amount of available gas or liquid, leading to a failure.

Input failure rate distribution

The leakage rate of the mechanism is evaluated on a *Good–Fair–Moderate–Poor* scale. Since the *Good*, *Fair*, *Moderate* and *Poor* classes are defined by TenneT TSO, the interpretation of those classes with respect to failure rates were defined in cooperation with them [37]. This was done based on the average failure rate distribution for a circuit breaker, which is shown in Figure 6.3.

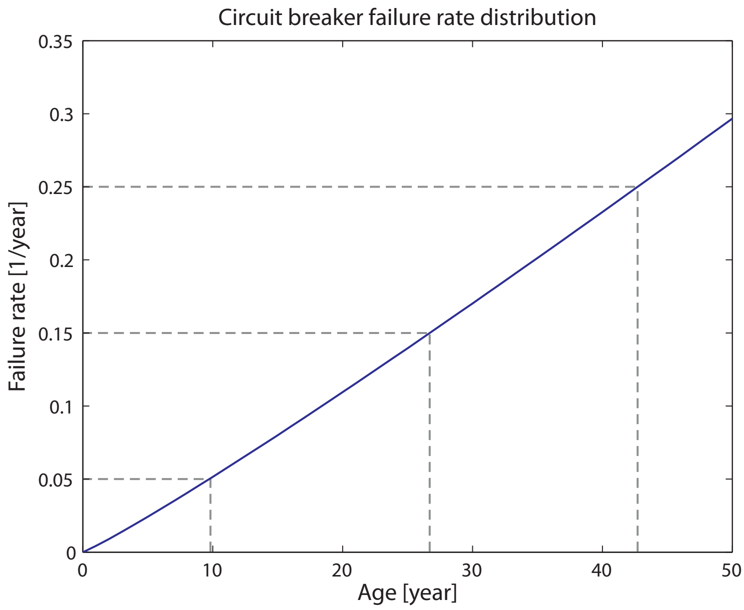

Figure 6.3: Circuit breaker failure rate distribution

A circuit breaker at TenneT TSO is considered as *Good* for about the first twelve years. Thereafter a circuit breaker gets its first scheduled maintenance. After a little less than twelve years the failure rate in Figure 6.3 is 0.05. In the next twelve years, until twenty four after the circuit breaker is installed the failure rate is considered *Fair*. Figure 6.3 shows that the failure rate at the end of that period is about 0.15. Up until the designed lifetime of a circuit breaker, which is about forty years, the circuit breaker is considered in a *Moderate* state. At that point the failure rate according to Figure 6.3 is 0.25. After that point, the state of the circuit breaker considered *Poor*. These sections of the failure rate function are translated to bounds for the definition of the *Good*, *Fair*, *Moderate* and *Poor* classes, as is shown in Table 6.6. Taking a look at these bounds indicates that the decision to use a risk matrix rather than a risk equation was a good decision (see Section 3.4.4).

Table 6.6: Failure rate distribution bounds for the *Good–Fair–Moderate–Poor* scale

	Failure rate	
Class	Lower bound	Upper bound
Good	0	0.05
Fair	0.05	0.15
Moderate	0.15	0.25
Poor	0.25	∞

As the *Good–Fair–Moderate–Poor* scale does not allow for an input value to take values from a continuous scale, the failure rate distribution will be discontinuous. The failure rate distribution for the leakage rate of the mechanism based on the class medians of the bounds listed in Table 6.6 is shown in Figure 6.4.

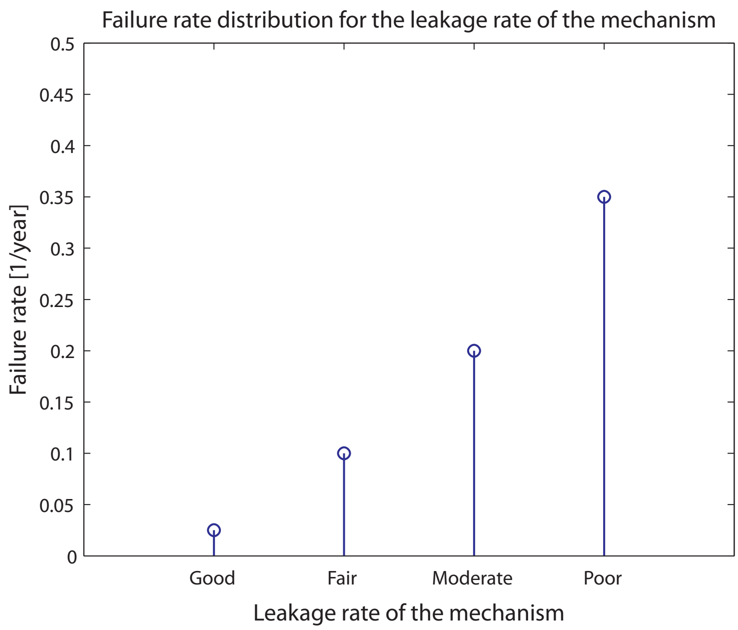

Figure 6.4: Failure rate distribution for the leakage rate of the mechanism

Failure rate development

In Section 4.2, different strategies were shown to assess the development of the failure rate over time. The suggested approaches require either an input-time distribution or a failure rate-time distribution. Figure 6.5 and Figure 6.6 show examples of these distributions for an input that is defined on a *Good–Fair–Moderate–Poor* scale.

In Figure 6.5 the vertical axis shows different pieces of possible input values that are taken up by the *Good*, *Fair*, *Moderate* and *Poor* classes. For the input-time distribution is not actually known, it is displayed as a dashed line. A low input value corresponds with the *Good* class, a higher input value with *Fair*, an even higher value with *Moderate* and the highest value range corresponds with the *Poor* class. The translation from input value to time shows that, e.g., if the input value belongs to the *Fair* class $T_1 < T < T_2$. Since this is a range of time values, e.g. years, and not a single year, it is impossible to determine which specific year would correspond to the condition of the asset as indicated by the input. It can be every year between T_1 and T_2. Consequently it is nearly impossible to tell how the failure rate will develop over time. Say an asset manager wants to assess the development of a failure rate during a planning period based on Figure 6.5. The length of the planning period is ΔT. Assume furthermore that the current input value class is *Fair*, so $T_1 < T < T_2$. The range for the time at the end of the planning period would then be $T_1 + \Delta T < T < T_2 + \Delta T$. The largest time in this range, $T_2 + \Delta T$, is a time that will lay somewhere between T_2 and $T = \infty$, so in the *Moderate* or *Poor* class. $T_1 + \Delta T$ can belong to the *Fair* moderate (if $T_2 - T_1 > \Delta T$), to the *Moderate* class and in exceptional cases to the *Poor* class. Consequently the classification for the input value after the planning period is uncertain. Hence it will be impossible to determine the development of the failure rate during the planning period.

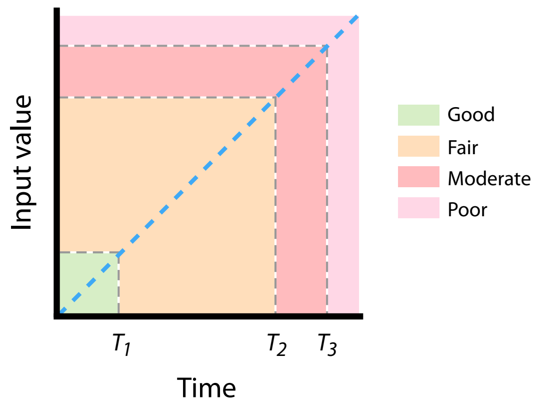

Figure 6.5: Input-time distribution for an input defined by a *Good–Fair–Moderate–Poor* scale

For the failure rate-time distribution shown in Figure 6.6 holds a similar story. The *Good*, *Fair*, *Moderate* and *Poor* classes are determined by the transitions between them as defined in Table 6.6. Again, the different input classes do not match to a single time value. Hence, based on this graph also no conclusions can be drawn regarding the development of the failure rate over time.

Section 4.2 showed that either an input-time distribution or a failure rate-time distribution is required to be able to assess the change of the failure rate over time. Since neither of them can be defined on a continuous scale, the failure rate development cannot be determined for an input defined by a *Good–Fair–Moderate–Poor* scale. Hence, it is recommended to define

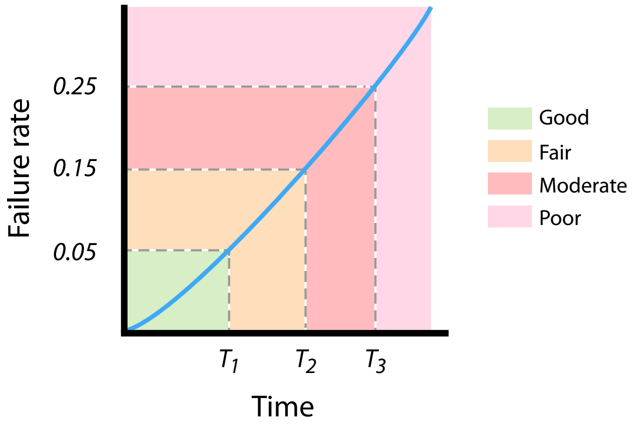

Figure 6.6: Failure rate-time distribution for an input defined by a *Good–Fair–Moderate–Poor* scale

as few inputs as possible on such a scale.

6.3.2 Average number of startups hydraulic pump

A hydraulic pump is installed in a hydraulic circuit breaker to pressurize the operating mechanism. Normally, the pump is only started after a switching event to restore the pressure. When oil is leaking from the system the pump has to be started more often to keep the pressure up. Therefore, the number of startups of the hydraulic pump can tell something about the tightness of the energy storage system. In case too much hydraulic oil is lost for the pump to fill, there is not enough energy stored to operate the circuit breaker when it is given a command to switch, resulting in a failure. So the larger the number of hydraulic pump startups, the larger the failure rate.

Input failure rate distribution

The number of hydraulic pump starts has not been monitored. Therefore, a hydraulic pump starts failure rate distribution cannot be made from inspection and maintenance data. However, the *Good–Fair–Moderate–Poor* scale has been introduced in the previous paragraph. Within TenneT TSO definitions were made connecting the number of hydraulic pump starts to the aforementioned scale. This definition is shown in Table 6.7.

Table 6.7: Initial failure rate bounds for the hydraulic pump startups based on the *Good–Fair–Moderate–Poor* scale

	Failure rate		Hydr. pump starts [1/month]	
Class	Lower bound	Upper bound	Lower bound	Upper bound
Good	0	0.05	0	60
Fair	0.05	0.15	60	125
Moderate	0.15	0.25	125	250
Poor	0.25	∞	250	∞

These upper and lower bounds can be used to define a failure rate distribution. However, as the caption of Table 6.7 indicates, the bounds are estimations that are based on the little knowledge currently available on the matter. When the upper bounds of the failure rate and the number of hydraulic pump starts are plotted, the plus signs in Figure 6.7 appear. When a least squares estimating algorithm (which is explained in detail in Appendix E) is used to approximate these points by a two-parameter Weibull failure rate distribution, the red line is added to Figure 6.7. Clearly the current transitions between the *Good*, *Fair*, *Moderate* and *Poor* classes cannot be described accurately by a two-parameter Weibull distribution.

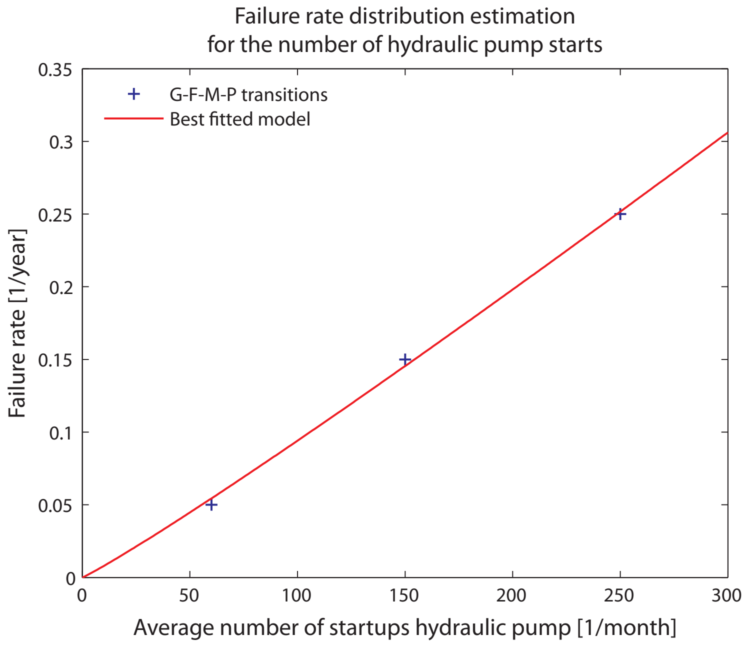

Figure 6.7: Failure rate distribution estimation for the number of hydraulic pump starts

As mentioned before, the connection between the *Good–Fair–Moderate–Poor* scale and the number of startups of the hydraulic pump is based on an estimation. Looking at how the Weibull distribution approximates the transitions in Figure 6.7, a change in the second transition could result in a better fit. When the maximum number of hydraulic pump startups that belongs to the *Fair* class and the minimum number of hydraulic pump startups that belongs to the *Moderate* class is changed from 125 to 159 a better fit results. This changes Table 6.7 to Table 6.8.

Table 6.8: Failure rate bounds for the hydraulic pump startups based on the *Good–Fair–Moderate–Poor* scale

	Failure rate		Hydr. pump starts [1/month]	
Class	Lower bound	Upper bound	Lower bound	Upper bound
Good	0	0.05	0	60
Fair	0.05	0.15	60	159
Moderate	0.15	0.25	159	250
Poor	0.25	∞	250	∞

When the new transitions from Table 6.8 are inserted into the least square estimation algorithm, Figure 6.8 results. This figure shows that the failure rate based on the number of hydraulic starts can be modeled by a two-parameter Weibull distribution with $\beta = 2.128$ and $\eta = 51.08$.

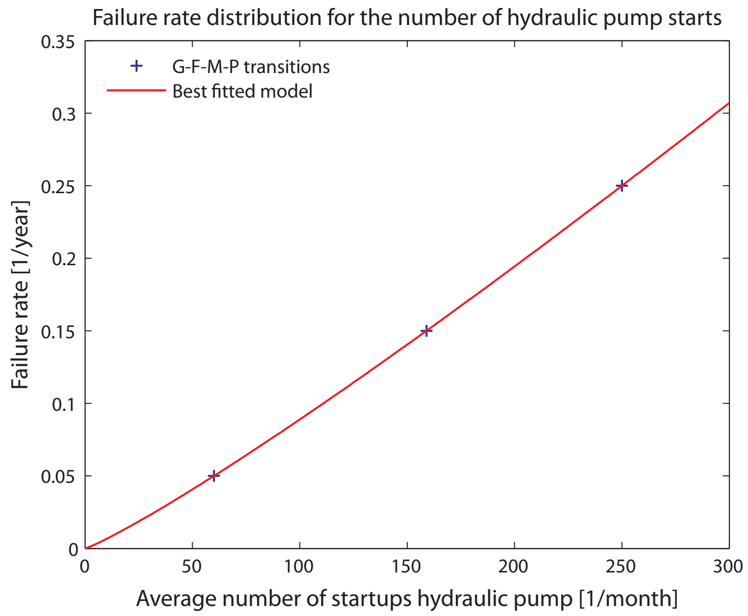

Figure 6.8: Failure rate distribution for the number of hydraulic pump starts; $\beta = 2.128, \eta = 51.08$

Failure rate development

The average number of hydraulic pump starts has not yet been monitored over time. This has, however, been signaled within TenneT TSO and it is likely to be monitored in the future. When this monitoring is performed, an input versus time distribution can be used to investigate the development of the failure rate over time (as shown in Section 4.2.1 and Section 4.2.2). Furthermore, those measurements can be used to fine-tune the hydraulic pump startups failure rate distribution.

Until then, the approach with the failure rate versus time distribution can be used (as shown in Section 4.2.3). The failure mode failure rate distribution for the subpopulation the circuit breaker belongs to can be used as failure rate distribution that is required for this approach. This distribution will be specified in Section 6.4.

6.3.3 Average number of pneumatic fills

The average number of times a pneumatic pump is started to fill the tank with compressed air is very similar the average number of hydraulic pump starts. A pneumatic circuit breaker has a pneumatic pump to compress air to drive the operating mechanism. The pump is started after a switching event to restore the pressure that was lost to drive the mechanism. However, as air leaks from the driving mechanism, the pump will start more often in order to restore the pressure. Therefore, the number of pneumatic fills can indicate a decreasing air tightness of the tank, valves and/or piping. When the pump is started more often there are more or larger leaks in the system. When the resulting leakage becomes too large, there might not be enough pressure left when the circuit breaker needs to operate, which will cause a failure.

Input failure rate distribution

Since the pneumatic pump and the hydraulic pump have the same functionality, their failure rate distributions were assumed equal. Hence, the transition points for the *Good*, *Fair*, *Moderate* and *Poor* classes were defined the same. Taking into account the change to the upper and lower bounds for the classes as shown for the hydraulic pump starts, the failure rate bounds for the average number of pneumatic fills are the ones listed in Table 6.9.

Table 6.9: Failure rate bounds for the pneumatic fills based on the *Good–Fair–Moderate–Poor* scale

	Failure rate		Pneumatic fills [1/month]	
Class	Lower bound	Upper bound	Lower bound	Upper bound
Good	0	0.05	0	60
Fair	0.05	0.15	60	159
Moderate	0.15	0.25	159	250
Poor	0.25	∞	250	∞

When the transition points from Table 6.9 are inserted into the least square estimation algorithm, Figure 6.9 results. This figure shows that the failure rate based on the number of pneumatic fills can be modeled by a two-parameter Weibull distribution with $\beta = 2.128$ and $\eta = 51.08$.

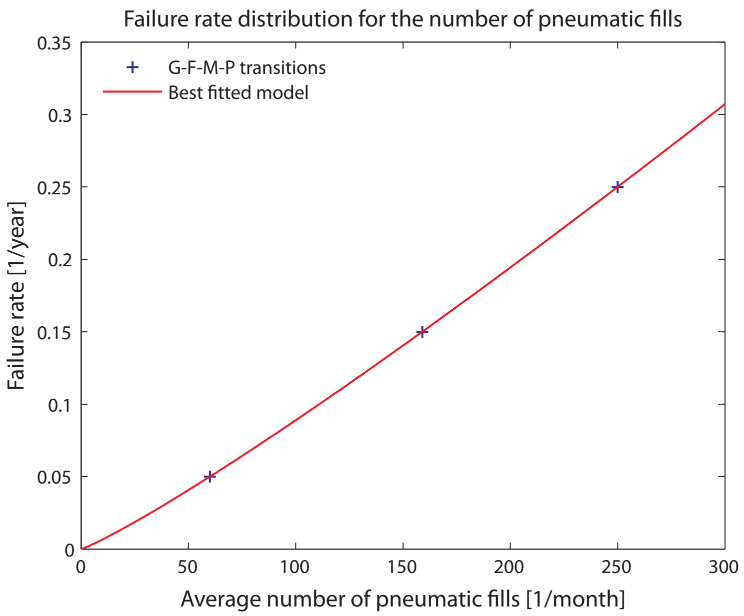

Figure 6.9: Failure rate distribution for the number of pneumatic fills; $\beta = 2.128, \eta = 51.08$

Failure rate development

As mentioned for the hydraulic pump starts, none of the inputs has yet been monitored over time. Therefore, to assess the development of the failure rate over time a failure rate versus time distribution can be used (as shown in Section 4.2.3). This approach requires a failure rate distribution. The failure mode failure rate distribution for the subpopulation the circuit breaker belongs to fulfills this demand. This distribution will be specified in Section 6.4.

6.3.4 Maximum motor current during loading of spring

In a spring circuit breaker a motor is used to compress a spring. A latch is released when the circuit breaker has to operate so the spring can deliver the required energy to move the contacts. After a switching event, the spring has to be compressed again. The amplitude of the current drawn by the motor that compresses the spring is monitored. When this amplitude increases the friction forces on the spring have increased. From a certain point on this friction may become so large that the energy transferred to the contacts during a switching operation is too small, which causes improper operation: a failure.

Input failure rate distribution

As with the number of hydraulic pump starts and the number of pneumatic fills, the maximum motor current is also matched to a *Good–Fair–Moderate–Poor* scale. The maximum motor current is compared to the rating of the maximum motor current. So a maximum motor current of 125% indicates that the largest current the motor draws is 25% higher than the rated value. The initial upper and lower bounds for the *Good*, *Fair*, *Moderate* and *Poor* classes are shown in Table 6.10.

Table 6.10: Initial failure rate bounds for the maximum motor current based on the *Good–Fair–Moderate–Poor* scale

	Failure rate		Maximum motor current [%]	
Class	Lower bound	Upper bound	Lower bound	Upper bound
Good	0	0.05	0	110
Fair	0.05	0.15	110	125
Moderate	0.15	0.25	125	150
Poor	0.25	∞	150	∞

A failure rate distribution was fit to these upper and lower bounds. This was performed by the least squares algorithm explained in Appendix E. The resulting distribution, together with the *Good*, *Fair*, *Moderate* and *Poor* class transition points are shown in Figure 6.10. In Figure 6.10 all the percentages are decreased by 100% for the ease of visualization.

In Figure 6.10 there is a substantial discrepancy between the transition points and the best fitted two-parameter Weibull failure rate distribution. For the upper and lower bounds, as listed in Table 6.10, were merely an initial class determination they can be altered so they can be more accurately modeled by a Weibull distribution. The upper bound of the *Fair* class and the lower bound of the *Moderate* class are changed from 125% to 130%. This updates Table 6.10 to Table 6.11.

When the new upper and lower bounds are approximated by a two-parameter Weibull distribution, Figure 6.11 results. Figure 6.11 shows a much larger correspondence between the

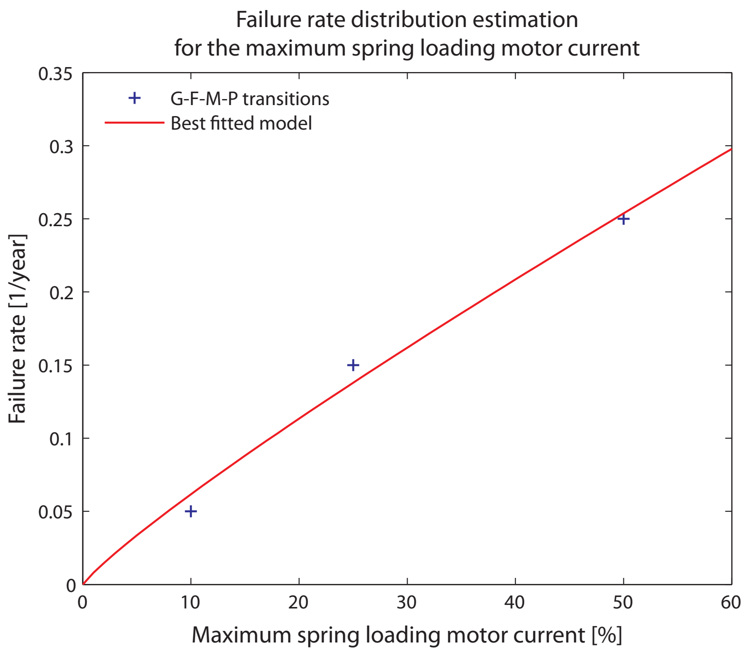

Figure 6.10: Failure rate distribution estimation for the maximum motor current

Table 6.11: Failure rate bounds for the maximum motor current based on the *Good–Fair–Moderate–Poor* scale

	Failure rate		Maximum motor current [%]	
Class	Lower bound	Upper bound	Lower bound	Upper bound
Good	0	0.05	0	110
Fair	0.05	0.15	110	130
Moderate	0.15	0.25	130	150
Poor	0.25	∞	150	∞

Weibull distribution and the transition points. Furthermore it indicates that the failure rate based on the maximum spring charging motor current can be modeled by a two-parameter Weibull distribution with $\beta = 2.000$ and $\eta = 20.00$.

Failure rate development

The development of the failure rate of the circuit breaker over time is to be determined next. The assessment thereof either requires an input-time distribution or a failure rate-time distribution (see Section 4.2). However, as explained before, the input-time distributions are not available. Hence, the failure rate-time distribution will be used. The failure rate distribution that is required for this approach will be provided by the failure mode failure rate distribution for the subpopulation the circuit breaker belongs to. This distribution will be specified in Section 6.4.

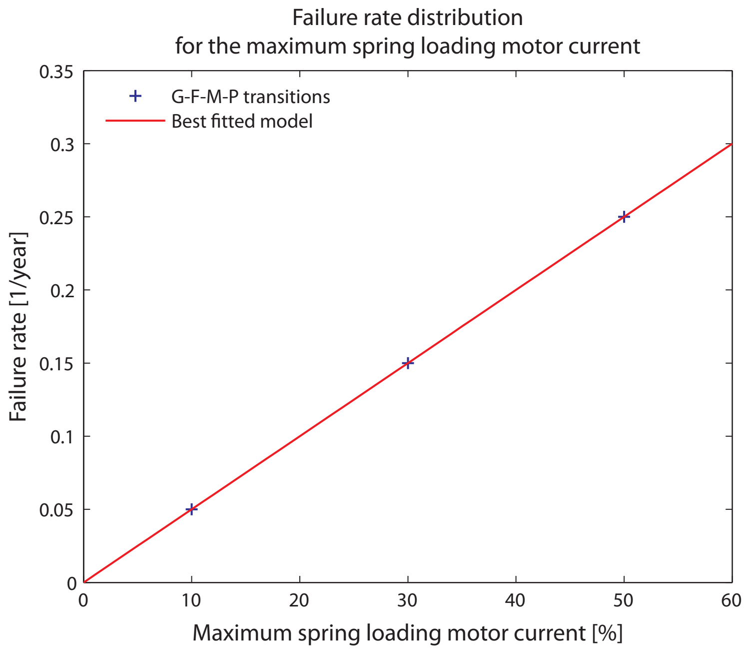

Figure 6.11: Failure rate distribution for the maximum motor current; $\beta = 2.000, \eta = 20.00$

6.3.5 Condition of accumulator & high pressure circuit

Hydraulic and pneumatic circuit breakers are operated by a high pressure gas. The condition of the tank with the pressurized gas (accumulator) and the valves and piping (high pressure circuit) the gas is contained in is monitored by this input. The accumulator and high pressure circuit are visually inspected to find corrosion, leakage and other defects that influence the mechanical integrity. Furthermore the pressure in the tank is measured right before and after a switching event to check whether the pressures are still at the required levels. With a worsening condition of the accumulator or high pressure circuit either of them may become unable to contain the operating gas/liquid. As the circuit breaker will fail to switch when too much operating gas/liquid has leaked away, this input is monitored.

Input failure rate distribution

The condition of the accumulator and the high pressure circuit is determined on a *Good–Fair–Moderate–Poor* scale. The meaning of this scale with respect to failure rates has been specified in Section 6.3.1. Using the class bounds listed in Table 6.6 results in the failure rate distribution shown in Figure 6.12.

Failure rate development

As was already shown in Section 6.3.1 the failure rate development cannot be calculated for an input that is defined on a *Good–Fair–Moderate–Poor* scale. Hence, the future failure rate of the accumulator and high pressure circuit is undefined.

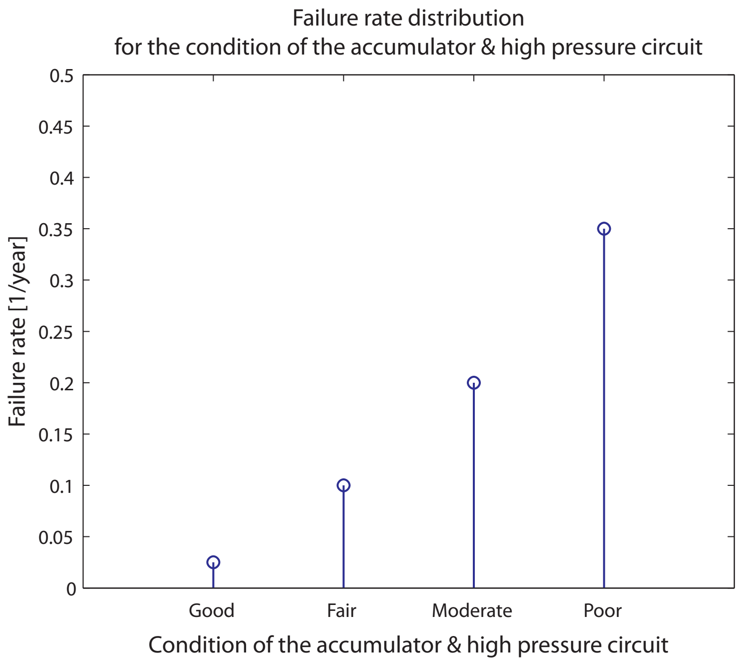

Figure 6.12: Failure rate distribution for the condition of the accumulator & high pressure circuit

6.3.6 Condition of mechanic drive parts

The condition of the mechanic drive parts is assessed by a visual inspection of all the moving parts in the circuit breakers. Examples hereof are the wear and deformation of bearings and pivot points and the deformation and corrosion to the driving rods. When the mechanic drive parts wear too much or are too deformed they will not be able to comply to a switch command given to the circuit breaker. A failure will inherently result.

Input failure rate distribution

During inspection and maintenance the condition of the mechanic drive parts is defined by a *Good*, *Fair*, *Moderate* or *Poor* classification. In Table 6.6 in Section 6.3.1 the different parts of the failure rate distribution that are represented by the aforementioned classes are listed. Those parts translate to the failure rate distribution shown in Figure 6.13.

Failure rate development

For the condition of the mechanic drive parts is defined on a *Good–Fair–Moderate–Poor* scale, the failure rate development cannot be calculated (as shown in Section 6.3.1). As a result, the future failure rate of this input parameter is undefined.

When the condition of the mechanic drive parts would be assessed in more detail, one could consider using the number of switching events to determine the development of the failure rate over time (as shown in Section 4.2.2). As the mechanic drive parts are contained in a sealed environment, corrosion will not be the major failure cause. Instead, the drive parts will age most when they are operated.

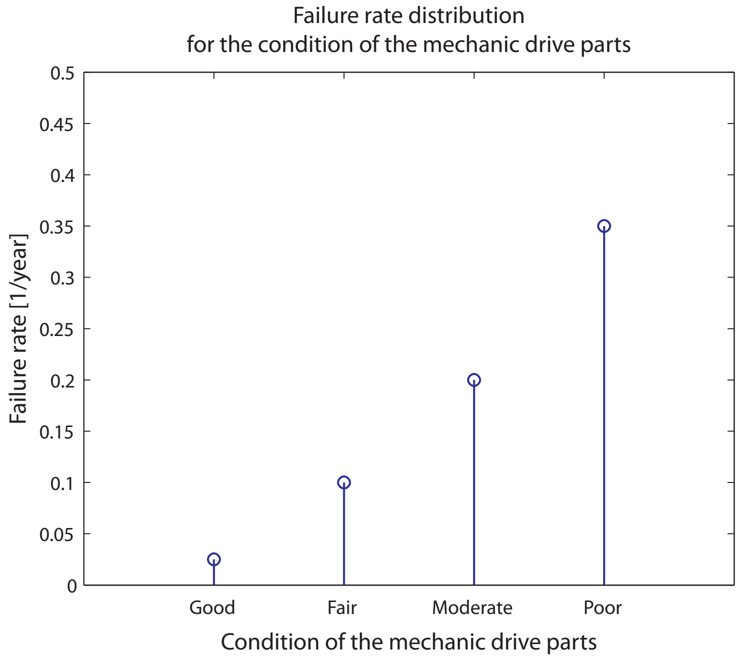

Figure 6.13: Failure rate distribution for the condition of the mechanic drive parts

6.4 Failure mode function

After the failure rates based on the inputs are calculated, the failure mode function will group them into one failure rate for the failure mode. Input failure rates are the ideal inputs for the failure mode function. In case a required input failure rate is unknown, the failure mode function will use a failure mode failure rate distribution in addition to calculate the failure mode failure rate. This part of the asset failure rate estimation model (Figure 6.1) is shown in Figure 6.14.

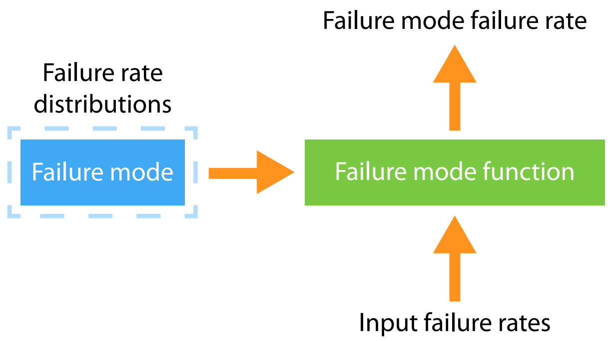

Figure 6.14: Failure mode function section of the asset failure rate estimation model

In the first section the implementation of the failure mode function based on the input failure rates will be addressed. The failure mode failure rate distributions that will be used as a backup are derived in the second section.

6.4.1 Input failure rates

As mentioned before, the failure mode failure rate is ideally based on the input failure rates (see Section 2.4). This is because the input failure rates are based on the inputs of the specific asset and therewith on the technical condition of that specific asset. The task of the failure mode function is to add together the failure rates of its inputs. Table 6.5 showed that the inputs required by the failure mode function differ per operating mechanism. Therefore the failure mode failure rate calculation will be performed per operating mechanism. Since the names of the inputs are quite long, shorthand notations for them will be used, as listed in Table 6.12.

Table 6.12: Abbreviations for the input parameters

Abbreviation	Input parameter
LM	Leakage rate mechanism
HP	Average number of startups hydraulic pump
PF	Average number of pneumatic fills
MC	Maximum motor current during loading of spring
AH	Condition of accumulator & high pressure circuit
MD	Condition of mechanic drive parts

As explained in Section 4.1.2, probability theory can be used to determine the dependencies between the inputs. All sections will start with the probability theory to study these dependencies. The failure probability of the failure mode based on the input failure probabilities is in the following sections denoted by $P_{IFPs}(FMF)$. When all the input failure probabilities are available, $P(FMF) = P_{IFPs}(FMF)$. When the failure mode failure probability equations are known, the failure mode failure rate functions are implemented.

Hydraulic operating mechanism

Table 6.5 shows that the failure mode failure probability of a hydraulic operated circuit breaker depends on four different inputs. The failure mode function has to indicate a failure if either of the inputs indicates a failure. Hence, the input failure probabilities taken together by an OR-operator. In mathematics this comes down to

$$\begin{aligned}
P_{IFPs}(FMF) &= P(LM \cup HP \cup AH \cup MD) \\
&= P(LM \cup HP) + P(AH \cup MD) \\
&\quad - P([LM \cup HP] \cap [AH \cup MD]) \\
\\
&= [P(LM) + P(HP) - P(LM)P(HP|LM)] \\
&\quad + [P(AH) + P(MD) - P(AH)P(MD|AH)] \\
&\quad - P(LM \cup HP)P(AH \cup MD|LM \cup HP) \\
\\
&= [P(LM) + P(HP) - P(LM)P(HP|LM)] \\
&\quad \times [1 - P(AH \cup MD|LM \cup HP)] \\
&\quad + [P(AH) + P(MD) - P(AH)P(MD|AH)]
\end{aligned} \tag{6.1}$$

Of all the probabilities shown in Equation 6.1 $P(LM)$, $P(HP)$, $P(AH)$ and $P(MD)$ are defined by the input functions. The unknown probabilities are $P(HP|LM)$, $P(MD|AH)$ and $P(AH \cup MD|LM \cup HP)$. The Venn diagram of this failure mode is visualized by Figure 6.15.

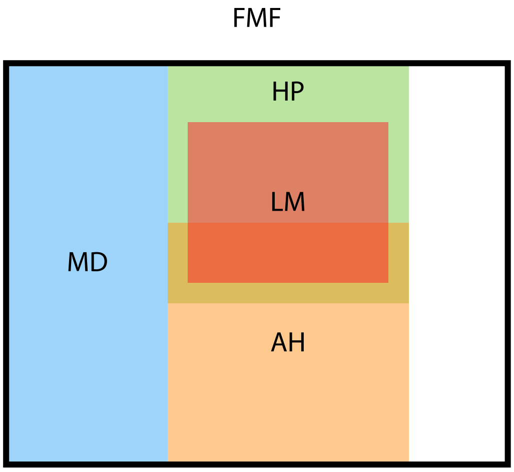

Figure 6.15: Venn diagram of the failure mode function for a hydraulically operated circuit breaker

What stands out in Figure 6.15 is that all rectangles overlap, except for the MD rectangle. The MD rectangle is mutually exclusive from the rest, as the condition of the mechanic drive parts does not describe any failure causes that are related to leakage of the driving mechanism. Because MD is independent from the other inputs, the probability $P(MD|AH)$ can be simplified. This probability concerns the dependency between the condition of the mechanic drive parts and the condition of the accumulator and the high pressure circuit. As there is no dependency between them, $P(MD|AH)$ can be substituted by $P(MD)$.

Furthermore, Figure 6.15 shows that the LM rectangle fully lies within the HP rectangle. This implicates that the leakage rate of the mechanism describes a subset of the failure causes described by the number of hydraulic pump starts. This can be explained as follows. As the number of hydraulic pump starts will increase when the leakage rate of the mechanism increases these two inputs are dependent. However, the number of hydraulic pump starts will also increase when the circuit breaker is simply operated more often. In Figure 6.15 this can be seen by the fact that the HP rectangle not only fully covers the LM rectangle, but is larger. For the number of hydraulic pump starts describes all the failure causes described by the leakage rate of the mechanism, monitoring the leakage rate of the mechanism as input becomes superfluous. The fact that the leakage rate of the mechanism is superfluous has a positive effect on $P(FMF)$. Not only because Equation 6.1 will become simpler, but also because the leakage rate of the mechanism was defined by a *Good–Fair–Moderate–Poor* scale which made failure probability assessments hard. Knowing that LM is not required as an input, the probability that the leakage rate of the mechanism or the number of hydraulic pump starts indicates a failure, $P(LM \cup HP)$, changes to $P(HP)$.

One of the three unknown failure probabilities has not yet been addressed: $P(AH \cup MD|LM \cup HP)$. This probability indicates the probability that AH or MD indicates a failure, given that LM or HP already indicates a failure. Bearing in mind that the leakage rate of the mechanism is a subset of the number of hydraulic pump starts (LM is overlapped by HP in Figure 6.15), the probability can be simplified to $P(AH \cup MD|HP)$. Furthermore, as the condition of the mechanic drive parts and the number of hydraulic pump starts are independent (MD and HP do not overlap in Figure 6.15) the probability changes to $P(AH|HP)$. Now the probability that the condition of the accumulator and high pressure circuits indicates a failure, given that the number of hydraulic pump startups already indicates one, remains. When the number of hydraulic pump starts indicates a poor condition of the circuit breaker, there is only a small probability that it is a result from a large number of switching events of the circuit breaker and not because of a poor condition of the accumulator and high pressure circuits. Consequently, the probability $P(AH|HP)$ is smaller than one. However, as there is a large correlation between the number of hydraulic pump starts and the condition of the accumulator and the high pressure circuits, $P(AH|HP)$ will be defined as 0.8.

Figure 6.15 also shows a piece of white. In Section 6.2 a subset of all the inputs describing this failure mode were selected. Consequently, the chosen inputs will not describe all failure causes of the failure mode function: they are not collectively exhaustive. Hence the white area.

When all these changes to Equation 6.1 are implemented it changes to Equation 6.2

$$\begin{aligned} P_{IFPs}(FMF) &= P(HP) \times [1 - 0.8] \\ &\quad + [P(AH) + P(MD) - P(AH)P(MD)] \\ &= 0.2P(HP) + P(AH) + P(MD) - P(AH)P(MD) \end{aligned} \tag{6.2}$$

Probability theory indicates that the leakage rate of the mechanism does not have to be an input into the failure mode function. Furthermore several dependencies are worked out and estimated. The failure mode failure rate can consequently be calculated by

$$h_{FMF} = h_{IFs} = \max[h_{AH}(x_{AH}), h_{HP}(x_{HP}), h_{MD}(x_{MD})] \tag{6.3}$$

In Section 4.1.2 was stated that this function does not take into account dependencies, but further research might result in a function that does account for dependencies. With that in mind, the derivation shown above can shed light on the dependencies between the inputs.

Pneumatic operating mechanism

The failure mode failure probability for the selected failure modes for a pneumatic circuit breaker constitutes of four input failure probabilities. The inputs applicable for a pneumatic circuit breaker are listed in Table 6.5. There is a great resemblance between the inputs used for a hydraulic circuit breaker and the ones used for a pneumatic circuit breaker. Three of the four inputs are exactly the same, and the number of pneumatic fills is the pneumatic equivalent of the number of hydraulic pump starts for a hydraulic circuit breaker. Hence, the failure mode failure probability equation for a pneumatic circuit breaker equals the one for a hydraulic circuit breaker with the number of hydraulic pump starts replaced by the number of pneumatic fills.

$$
\begin{aligned}
P_{IFPs}(FMF) &= P(LM \cup PF \cup AH \cup MD) \\
&= P(LM \cup PF) + P(AH \cup MD) \\
&\quad - P([LM \cup PF] \cap [AH \cup MD]) \\
\\
&= [P(LM) + P(PF) - P(LM)P(PF|LM)] \\
&\quad \times [1 - P(AH \cup MD|LM \cup PF)] \\
&\quad + [P(AH) + P(MD) - P(AH)P(MD|AH)] \qquad (6.4)
\end{aligned}
$$

Because of the large resemblance between the inputs used for the hydraulic and pneumatic circuit breakers, the simplification of Equation 6.4 is analogous to the simplifications made to Equation 6.1. The Venn diagram of this failure mode is visualized by Figure 6.16.

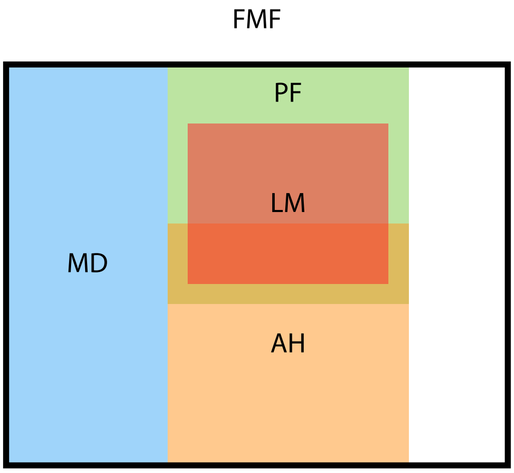

Figure 6.16: Venn diagram of the failure mode function for a pneumatically operated circuit breaker

The first change is that $P(LM \cup PF)$ reduces to $P(PF)$ (just as $P(LM \cup HP)$ reduced to $P(HP)$). This is a result of the fact that the LM rectangle is fully covered by the PF square in Figure 6.16. Furthermore, as shown for a hydraulic operating mechanism, $P(MD|AH)$ can be simplified to $P(MD)$ because MD and AH do not overlap in Figure 6.16. Lastly $P(AH \cup MD|LM \cup PF)$ reduces to $P(AH|PF)$ and is also made equal to 0.8. Again, the white space in Figure 6.16 symbolizes the fact that the subset of inputs does not describe all the failure causes of the failure mode function. Due to all these changes to the probabilities, Equation 6.4 changes to Equation 6.5.

$$
\begin{aligned}
P_{IFPs}(FMF) &= P(PF) \times [1 - 0.8] \\
&\quad + [P(AH) + P(MD) - P(AH)P(MD)] \\
&= 0.2P(PF) + P(AH) + P(MD) - P(AH)P(MD) \qquad (6.5)
\end{aligned}
$$

Again, probability theory indicates that the leakage rate of the mechanism can be left out of the equations in the failure mode function. Hence, the failure mode failure rate formula equals

$$h_{FMF} = h_{IFs} = \max[h_{AH}(x_{AH}), h_{MD}(x_{MD}), h_{PF}(x_{PF})] \qquad (6.6)$$

This formula does not take into account dependencies, as stated in Section 4.1.2. However, a future study might use a function that does take these dependencies into account. The derivation shown above can in that case be used to implement the dependencies between the inputs in that function.

Spring operating mechanism

The failure mode function of a spring operated circuit breaker depends on the maximum spring-charging motor current and the condition of the mechanic drive parts, as shown in Table 6.5. The failure probability for the failure mode consequently becomes

$$\begin{aligned} P_{IFPs}(FMF) &= P(MC \cup MD) \\ &= P(MC) + P(MD) - P(MC \cap MD) \\ &= P(MC) + P(MD) - P(MC)P(MD|MC) \end{aligned} \tag{6.7}$$

In Equation 6.7 the $P(MC)$ and $P(MD)$ probabilities are defined by the corresponding input functions. The probability that the mechanic drive parts fail given that the motor current indicates a failure, or $P(MD|MC)$ is the only unknown in this equation. The failure mode function Venn diagram is depicted in Figure 6.17.

Figure 6.17: Venn diagram of the failure mode function for a spring operated circuit breaker

Since there is no obvious dependence between the condition of the mechanic drive parts and maximum motor current $P(MD|MC)$ reduces to $P(MD)$. In Figure 6.17 this is depicted by the fact that MC and MD do not overlap: they are mutually exclusive. Figure 6.17 also shows a white space, indicating the failure causes covered by the inputs that were not selected. The simplification of $P(MD|MC)$ changes Equation 6.7 to Equation 6.8.

$$P_{IFPs}(FMF) = P(MC) + P(MD) - P(MC)P(MD) \tag{6.8}$$

According to the analysis above, the failure mode failure rate equals

$$h_{FMF} = h_{IFs} = \max[h_{MC}(x_{MC}), h_{MD}(x_{MD})] \tag{6.9}$$

6.4.2 Failure mode failure rate distributions

If one of the input failure rates is unavailable, a failure mode failure rate distribution is used in addition as was described in Section 2.4. This distribution is indicated by the blue *Failure mode* block in Figure 6.14. A failure mode failure rate distribution calculates the average failure rate for a certain failure mode of an asset based on its age. In contrast to the input failure rates, the failure mode failure rate distributions are based on a distribution for the average asset rather than on the inputs. Since the asset failure rate estimation model accounts for different subpopulations of an asset, there are multiple failure mode failure rate distributions that need to be derived.

The Weibull distribution β and η parameters are determined based on the failure and suspension database. The likelihood function is used to model the data by a two-parameter Weibull distribution (see Appendix C). The parameters for all the circuit breaker subpopulations are shown in Table 6.13. The corresponding graphs are listed in Section F.1 of Appendix F.

Table 6.13: Weibull parameters per main kind of service and operating mechanism for the failure mode failure rate distributions

		Operating mechanism		
Service kind		Hydraulic	Pneumatic	Spring
Busbar	β	2.645	1.937	2.564
	η	21.03	18.62	21.49
Cable	β	-	-	-
	η	-	-	-
Capacitor	β	3.330	1.368	2.207
	η	22.62	18.94	20.44
Overhead line	β	2.313	1.591	2.184
	η	18.94	16.05	20.84
Shunt reactor	β	-	-	1.567
	η	-	-	17.54
Transformer	β	2.345	1.801	2.391
	η	19.40	17.02	20.94

When one of the input failure rates is unknown the outcome of the failure mode failure rate equations derived in the previous section will inevitably change. Say for example that a spring-driven capacitor circuit breaker is considered and $h_{MD}(x_{MD})$ in Equation 6.9 is unknown, e.g. because the condition of the mechanic drive parts have not been assessed during inspection or maintenance. In that case the maximum of h_{IFs} and h_{FMFRD} will be calculated as was proposed in Section 2.4. The latter failure rate, h_{FMFRD}, is the failure mode failure rate based on the failure mode failure rate distribution. This is mathematically represented in Equation 6.10.

$$h_{FMF} = \max[h_{IFs}, h_{FMFRD}] \tag{6.10}$$

The part in Equation 6.10 representing the inputs, h_{IFs}, is equal to Equation 6.9. However, since $h_{MD}(x_{MD})$ is unknown, $h_{MD}(x_{MD})$ is set to zero and h_{IFs} becomes

$$h_{FMF} = h_{IFs} = \max[h_{MC}(x_{MC})] = h_{MC}(x_{MC}) \tag{6.11}$$

The failure mode failure rate according to the failure mode failure rate distribution (h_{FMFRD} in Equation 6.10) is a two-parameter Weibull distribution, $h_{\beta,\eta}(t)$. Using the parameters from Table 6.13, h_{FMFRD} becomes

$$h_{FMFRD} = h_{\beta=2.207,\eta=20.44}(t) \tag{6.12}$$

where t is the age of the circuit breaker. When Equation 6.11 and Equation 6.12 substituted in Equation 6.10, Equation 6.13 results

$$h_{FMF} = \max[h_{MC}(x_{MC}), f_{\beta=2.207,\eta=20.44}(t)] \tag{6.13}$$

As already indicated by Table 6.2, there are not enough failure data points to make accurate distributions for the cable circuit breakers and the hydraulic and pneumatic driven shunt reactor circuit breakers. So when for such a circuit breaker the input failure rate is unknown, the failure mode failure rate cannot be calculated. This problem is, however, solved by the asset function.

6.5 Asset function

The asset function is the last function in the model. The asset function has failure mode failure rates as primary input. The output is a failure rate for the asset as a whole. In case the failure mode failure rates are not available, the asset function will revert to the asset failure rate distribution. This part of the asset failure rate estimation model (Figure 6.1) is shown in Figure 6.18.

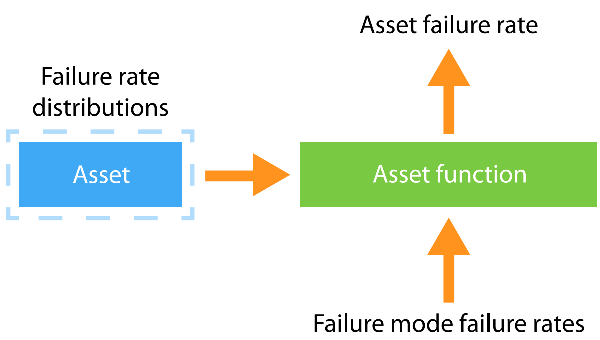

Figure 6.18: Asset function section of the asset failure rate estimation model

The first section will address how the failure mode failure rates can be converted to an asset failure rate. The next section explains how asset failure rate distributions are applied when the failure mode failure rates are not available.

6.5.1 Failure mode failure rates

Ideally, the asset failure rate is based on the failure mode failure rates, or $h_{AF} = h_{FMFs}$ (see Section 2.5). Since the asset function in this case has only one failure mode failure rate as input, the calculation of the asset failure rate would be quite simple:

$$h_{AF} = h_{FMFs} = h_{FMF} \tag{6.14}$$

When the model is also implemented for the other failure modes, the number of failure modes and the complexity of the calculation of the asset failure rate increase. Ideally, the failure modes are mathematically independent for that would make the calculations easier. Unfortunately, as can be concluded from the failure mode analysis in Appendix D they are dependent for they partly depend on the same input parameters. Hence a similar approach as in Section 6.4.1 is required to find the formula that has to be implemented in the asset function.

6.5.2 Asset failure rate distributions

When the failure rate of one or more failure modes is unavailable, the asset failure rate distribution can be used. This distribution is indicated by the blue *Asset* block in Figure 6.18. This last resort is the failure rate distribution for the average circuit breaker, as the failure rate distribution is based on the age of the circuit breaker. Since the asset failure rate estimation model accounts for different subpopulations of an asset, there are multiple asset failure rate distributions that need to be derived.

Deriving the failure rate distributions for the asset function is done in a similar matter as for the failure mode failure rate distributions. The difference between them is that in this case all the failure data is taken into account, not just the failure data of the *Does not switch* failure mode. The resulting Weibull parameters are tabulated in Table 6.14. The corresponding graphs are listed in Section F.2 of Appendix F.

As was already shown in Section 5.3.4, the number of failure data points per operating mechanism for a cable circuit breaker is too low to base a failure rate distribution upon. Since the asset failure rate estimation model is developed to model all the asset types and asset subpopulations, the cable circuit breaker has to be modeled. Therefore, the Weibull parameters for the cable circuit breakers are the Weibull parameters for the hydraulic, pneumatic and spring operating mechanisms in general.

Table 6.14: Weibull parameters per main kind of service and operating mechanism for the asset failure rate distributions

		Operating mechanism		
Service kind		Hydraulic	Pneumatic	Spring
Busbar	β	2.646	1.935	2.563
	η	21.03	18.61	21.49
Cable	β	2.355	1.689	2.227
	η	19.48	17.03	20.79
Capacitor	β	3.320	1.368	2.203
	η	22.60	18.94	20.43
Overhead line	β	2.312	1.592	2.182
	η	18.94	16.05	20.84
Shunt reactor	β	3.157	1.299	1.573
	η	20.43	11.72	17.55
Transformer	β	2.343	1.801	2.390
	η	19.39	17.02	20.94

When one of the failure mode failure rates is unavailable the asset failure rate h_{AF} is equal to Equation 6.15, as proposed in Section 2.5.

$$h_{AF} = \max[h_{FMFs}, h_{AFRD}] \tag{6.15}$$

In this equation h_{FMFs} is the incomplete calculation of the failure rate of the asset based on the failure mode failure rates. For the investigated part of the asset failure rate estimation model this equation equals

$$h_{FMFs} = h_{FMF} \tag{6.16}$$

Note that as the number of implemented failure modes increases, the complexity of this equation will inherently increase.

The second part of Equation 6.15, h_{AFRD},is the failure rate of the asset according to its asset failure rate distribution. For a hydraulic cable circuit breaker this would come down to

$$h_{AFRD} = h_{\beta=2.355,\eta=19.49}(t) \tag{6.17}$$

where $h_{\beta=2.355,\eta=19.49}(t)$ is a two-parameter Weibull distribution with the β and η parameters as determined for a hydraulic cable circuit breaker in Table 6.14.
Substituting Equation 6.16 and Equation 6.17 in Equation 6.15 yields Equation 6.18.

$$h_{AF} = \max[h_{FMF}, h_{\beta=2.355,\eta=19.49}(t)] \tag{6.18}$$

6.6 Modeling other assets

In this chapter a failure rate estimation model for a circuit breaker was worked out. The circuit breaker served as an exemplary asset in showing how to implement an asset failure rate estimation model. To be able to use the risk model for maintenance and replacement decisions all the assets types TenneT TSO manages have to be modeled by a failure rate estimation model.

An accurate implementation of such a model takes some time. Hence not all the components can be modeled simultaneously. In choosing which asset type should be modeled first, one should look at the importance of the asset type with respect to grid reliability and the predictability of failures of the asset type. One should also consider the availability of research and failure data to derive the failure rate distributions. Since circuit breakers are important to the reliability of the grid, many publications have been written about them. For other assets it may be harder to find enough data to implement all the functions in the model. However, all backups in the model (failure mode failure rate distributions and asset failure rate distributions) largely overcome this issue.

CHAPTER 7

CONCLUSIONS & RECOMMENDATIONS

In this chapter the formulated scope of the research is compared with the results thereof. The first part of this chapter briefly summarizes the outcomes of the research. Secondly some recommendations based on the performed research are presented.

7.1 Conclusions

The conclusions of the research are presented in three parts. The first part considers the development of the asset performance model and its application with respect to determining the risk of failure. Next, the change of the failure rate over time is considered. Finally, conclusions regarding the circuit breaker failure rate estimation model are drawn.

Asset performance and risk modeling

The derived asset performance estimation model has a large potential increase in detail with respect to the health index tool. The latter could only give one out of four results. The former, however, has an output that can be defined on a continuous scale.

For the assessment of the failure risk a risk matrix should be used instead of a risk equation. Due to the fact that the failure rate does not ascertain values in multiple useful decades, a risk equation will not return useful failure risks. In a risk matrix the failure rate does not have to be defined by a logarithmic scale, whereby the failure risk can be determined more precisely.

Development of failure rates over time

The asset failure rate estimation model, the implementation of the asset performance estimation model for failure rates, is largely based on failure rate distributions. Most of these failure rate distributions are continuous and have an axis that equals or is linked to time. Hence, by changing the value of the time the change of the failure rate over time can be determined.

For inputs defined by the *Good–Fair–Moderate–Poor* scale the development of the failure rate over time cannot be deduced. This is due to the fact that *Good*, *Fair*, *Moderate* and *Poor* are discrete classes and no continuous failure rate distribution can describe their behavior without extra knowledge. Hence the use of this type of inputs should be prevented as much as possible.

Circuit breaker failure rate estimation model

When an input to one of the model functions of the circuit breaker failure rate estimation model is unavailable, the model uses a backup failure rate distribution as a reference. Hence all inputs should be present from inspection and maintenance for the optimal result.

The database containing circuit breaker failure data has been split into groups according to the operating mechanism and the main kind of service. Because large differences in failure rate distributions for these categories were found, these subpopulations were formed.

7.2 Recommendations

Not all aspects of high voltage asset performance modeling could be addressed within the time span of this research. Hence a few recommendations are given for improvement of the asset performance modeling. Two types of recommendations come forth from this research. First there are recommendations for TenneT TSO. These suggest how the asset failure rate estimation model can be improved by changes in the inspection and maintenance strategies. Secondly there are recommendations for further research. For the asset failure rate estimation model could not be implemented for all the asset types, recommendations for research topics are given.

Recommendations for TenneT TSO

The asset performance estimation model encompasses different asset subpopulations which all have their own set of failure modes. In order to perform proper failure risk calculations, it is recommended to define the failure impacts per asset subpopulation.

Focusing on the asset failure rate estimation model, half of the inputs of the failure mode function are defined by the *Good–Fair–Moderate–Poor* scale during inspection and maintenance. As this research showed, not only will this result in a coarse failure rate, this classification also makes it impossible to determine the development of the failure rate over time. Furthermore, a *Good–Fair–Moderate–Poor* scale is susceptible to mistakes. The interpretation of the meaning of the classes is subjective. Consequently, they are susceptible to misinterpretation by the inspection and maintenance crew, which may lead to misclassification of the technical condition. For these two reasons it is recommended to replace this type of inputs by inputs which are defined by a unit (e.g. volt or ampere) where possible.

The other half of the inputs is assessed based on a unit. However, no input versus time measurements have been undertaken so far. Therefore, the inputs have been defined with the help of the *Good–Fair–Moderate–Poor* scale. The translation of this scale to failure rate distributions of the inputs were based on expert knowledge. However, they require confirmation by input measurements during inspection and maintenance. Hence the advise is to measure the inputs and compare them with derived the failure rate distributions.

Recommendations for future research

In this research, a part of the asset failure rate estimation model was implemented for different types of SF_6 circuit breakers. The most important and most frequently occurring failure modes are already modeled. It is recommended that similar research is done for the neglected failure modes to complete the model for the SF_6 circuit breakers.

As said, the model implementation only concerned SF_6 circuit breakers. SF_6 is currently the most used insulating medium in new circuit breakers. However, a few decades ago oil and air-blast circuit breakers dominated the market. Consequently there are many of those circuit breakers still in use today. Since those circuit breakers are older they are closer to end of life and will have to be replaced sooner. Modeling their failure rate can help in maintenance and replacement strategies, however further research is required to model those circuit breaker types.

When the two previous research topics are addressed all circuit breaker types are fully modeled. Since circuit breakers are not the only assets in electricity grids, the model also has to be implemented for the remaining asset types. It is recommended that future research first focuses on transformers since they are, just as circuit breakers, very expensive and vital to the reliability of the grid.

Lastly, the failure mode functions and asset functions in the model use an algorithm to add the various failure rates that they receive as inputs. In this research the largest failure rate was assumed dominant and failure mode functions and asset functions selecting the largest failure rate were adopted. It is recommended to undertake more in-depth mathematical research to improve this assumption.

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APPENDIX A

HEALTH INDEX TOOL

On the first of January 2008 the *Wet Onafhankelijk Netbeheer* (independent grid administration act) took effect [38, 39]. An important part of this law states that the transportation network should not be owned by commercial parties which also trade energy, but by an independent institution. As a consequence TenneT TSO now also manages the 110 kV and 150 kV parts of the Dutch electricity grid, and not just the parts with a voltage rating of 220 kV and above as they did before.

TenneT TSO needs to show all the stakeholders (connected parties, Ministry of Economic Affairs and the Office of Energy Regulation) that the managed grids — everything with a voltage rating of 110 kV and above — are in good hands. The extra voltage levels TenneT TSO has to manage makes them responsible for a largely increased number of assets. However, the technical condition of the assets in the acquired grids is not fully known, so they cannot proof and show that the grids are well-managed. Therefore TenneT TSO asked KEMA to assess the condition of the entire grid owned by TenneT TSO [40]. As long term degradation processes cannot easily be recognized during maintenance or inspection [11], KEMA defined a method to deduce a health index for an asset. TenneT TSO converted this method into their health index tool.

A health index is an index that indicates the current state of an asset with respect to the design specifications. By comparing the current state with the design specifications an estimation of the remaining life can be made. When the health index is calculated for every asset they can be ranked by their expected remaining life [3, 11].

Although the health index might seem the holy grail for an asset manager, it does not replace the need of expert knowledge. The health index calculations are based on knowledge rules defined to the best of the designers' knowledge, though they will never fully accurate indicate the moment an asset will fail. Hence a health index application should be regarded as an aid in asset management to support decision making [3, 40].

A.1 Hierarchy

The hierarchy of the health index tool TenneT TSO uses is based on the method designed by KEMA [40]. KEMA calculated the health index in two steps. First, condition functions combine measurements from maintenance and inspection and yield condition indicators. Secondly, the condition indicators are converted to a health index by a health function which weights all the condition indicators. This hierarchy, visually represented in Figure A.1, will be explained in the following sections.

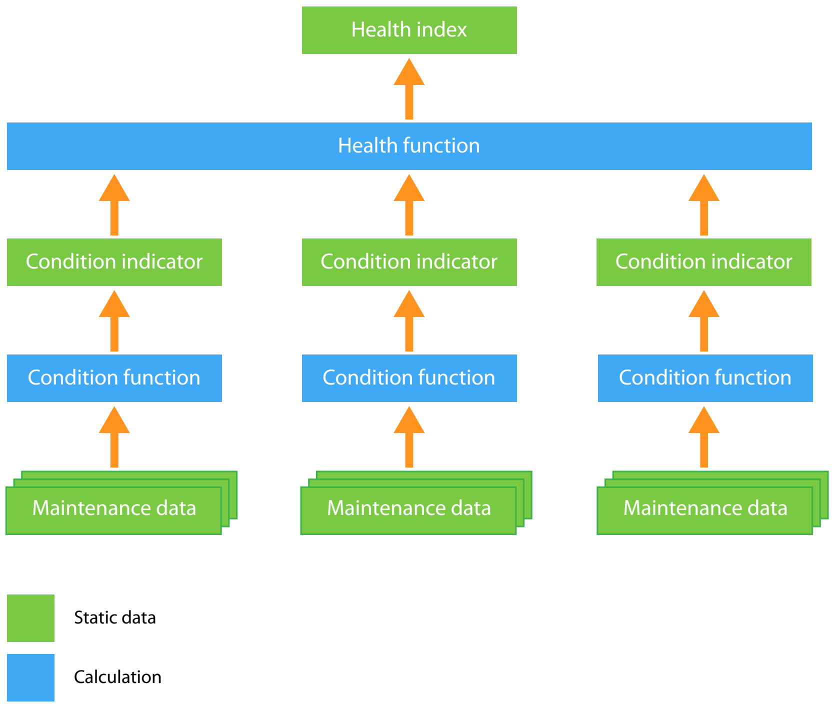

Figure A.1: Health index tool hierarchy

A.1.1 Maintenance data

The health index tool takes into account various asset types, being [9]:

- Bushings
- Cables
- Capacitor banks
- Circuit breakers
- Disconnectors
- Earthing switches
- High voltage towers
- Lines
- Measurement transformers
- Power transformers
- Rails
- Surge arresters

Every asset type has different parameters that are of interest when it comes to aging and determining the asset's health. Each maintenance parameter represents a parameter measured during maintenance or inspection. This data is used as input to the health index tool.

A.1.2 Condition function

The maintenance data is fed into condition functions. A condition function is defined by using knowledge and expertise regarding aging and failures. The condition function combines expected remaining useful life (based on population information) with measurement results from maintenance and general information about the component to determine its technical condition [9, 40]. The output of the condition function is a condition indicator, indicating the current technical condition of the asset.

A.1.3 Health function

The health function combines all the condition indicators to yield one indication of the technical condition of the asset: the health index. The health index is calculated by using rules based on expert knowledge.

The health index is defined by a color. This color indicates the amount of maintenance the asset will require in the next seven years. The colors used and their meaning are listed in Table A.1. These color groups, representing the health of the asset, are within TenneT TSO commonly visualized as in Figure A.2.

Table A.1: Meaning of the health index color groups [9, 40]

Color	Status	Explanation
Green	Good	The asset complies with its design specifications during the next seven years without additional maintenance.
Orange	Fair	The asset requires extra maintenance during the next seven years to comply with its design specifications.
Red	Poor	The asset does not comply with its specifications from some point in the next seven years on. Maintenance is either not possible or not sufficient, so the asset must be replaced.
Purple	End of Life	The asset does not comply with its specifications from some point in the next three years on. Maintenance is either not possible or not sufficient, so the asset must be replaced.

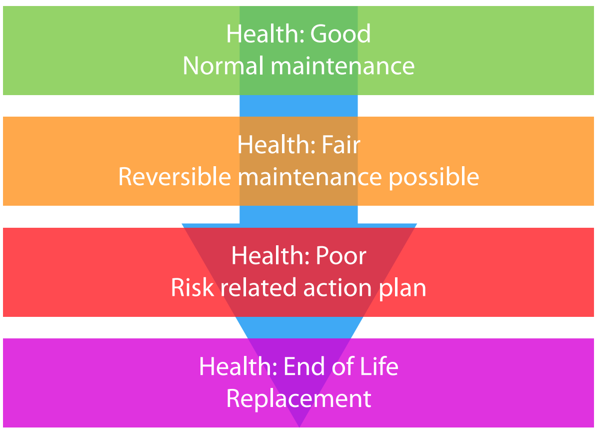

Figure A.2: Health index color group visualization (based on [9])

When looking at the change of the health index over the course of time, all the health index groups are traversed. Mapping these groups on a reliability plot results in Figure A.3.

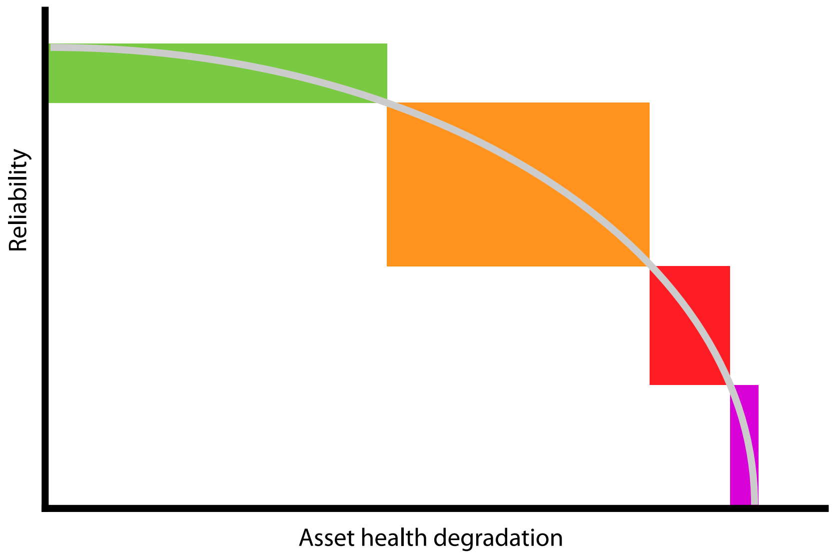

Figure A.3: Asset reliability versus life phases (based on [8])

Calculating the health index relies on the presence of input data. The less data is available, the more uncertain the outcome of the calculation. Therefore the asset's color rating changes in opacity to show the uncertainty involved in the calculations: the less data available the less opaque the health index color [9, 40]. Furthermore, the application will give a fair — or orange — result by default. When there is an absolute lack of information, one cannot assume a certain component health. The fair outcome shows that the component needs some additional maintenance, which in this case means that more information needs to be gathered [40].

A.2 Application

The health index is first of all used to indicate the health of an individual component and to determine whether the asset requires maintenance or replacement or neither of them within the next few years. Next, a list is made of the assets that will require maintenance or replacement. This list is sorted by the improvement in health index that could result from the maintenance or replacement and the monetary cost required to perform that action. Finally, the list is held against the budget for maintenance and replacement and from the top of the list downward assets are maintained or replaced until the budget is spent. Of course there are some exceptions to the rule, but this is the general approach.

Furthermore the health index can also be calculated for several defined groups, which is mostly done for management purposes. The components can be grouped by [40]:

- Grid link
- Component type
- Former grid owner (Delta, Enexis, Liander, TenneT TSO or TZH)

Besides the management purposes, these lists are also used to report to the regulator (Energiekamer) to show the current status of the assets managed by TenneT TSO and to convince them TenneT TSO is performing well.

A.3 Improvement

The four asset health color categories in the health index application assist the asset manager to quickly select the assets that need more attention. However, especially since they deal with many assets, it would be practical for the asset managers if the health index application would give a more detailed verdict about the state of the component.

As each color group represents quite a large part of the asset life (see Figure A.3), it does not clearly describe the health of the asset. For example, when a certain asset is labeled orange this can still mean that it just was in the green category or that it is almost in the red category. (This issue is less important with the other three colors, since they require either no action or immediate action [41].) Hence a more detailed determination of the health of the assets is required.

APPENDIX B

INTRODUCTION TO CIRCUIT BREAKERS

According to standards of ANSI and IEEE a circuit breaker is: *"A mechanical switching device capable of making, carrying, and breaking currents under normal circuit conditions and also, making and carrying for a specified time and breaking currents under specified abnormal circuit conditions such as those of short circuit."* [42]

Circuit breakers are available for many voltage and current ranges. The interruption voltage of circuit breakers ranges from a few hundred volts used in domestic applications to hundreds of kilovolts in the electricity grid. Since the research is specific to the asset base of TenneT TSO, only high voltage circuit breakers are of interest.

The main task of a circuit breaker is to interrupt fault currents and to isolate faulted parts of the system [43]. Faults can e.g. occur after a lightning stroke, an over-voltage or a short circuit. To interrupt the current all circuit breakers consist of two contacts: one of which is movable and the other is stationary [44]. When the movable contact is in closed position, i.e. touching the stationary contact, the circuit breaker is in conduction mode. As the movable contact separates from the stationary contact the circuit breaker becomes an isolator.

B.1 Switching arc

In case the current needs to be interrupted, the movable contact is mechanically distanced from the stationary contact. Although the contacts separate, the current continues to flow through an (electric) arc that is formed between the contacts [43]. The formation of an arc prevents abrupt current interruption and the over-voltages that would be induced [32].

B.1.1 Arc formation

When the circuit breaker opens, the contacts touch each other at a very small surface right before the circuit breaker contacts separate. As the magnitude of the current remains unchanged and the inductive grid wants to sustain the current, the current density at the contact area is very high, causing the contact material to melt. The rapidly increasing local temperature causes a fast volume increase of the molten contact material, leading to a gas discharge in the medium surrounding the contacts [43].

Because of the high current density and the increasing temperature caused by the gas discharge, the insulating medium locally changes to a plasma state. A plasma state can be reached from a gas state when the temperature is increased. First molecules to dissociate into atoms and subsequently orbital electrons are separated from atoms, leaving positive ions [43, 45]. Since in a plasma state the electrons and ions are free to move (now being free charge carriers) the plasma channel is highly conductive and the current will continue to flow. It is not yet effectively interrupted.

B.1.2 Arc properties

The formed arc has some interesting characteristics. First of all an electric arc is, aside from power semiconductors, the only known element able to quickly change from a conducting to a non-conducting state [43]. This property is essential to be able to quickly interrupt the current. Secondly, an arc is formed in plasma, so its length and volume are not predefined. As a consequence an arc can be stretched and its resistance can be increased both by length and by confinement [46]. Moreover the arc current has virtually no upper limit [45, 46] as the volume, density and degree of ionization are free to increase.

B.1.3 Arc interruption

When an arc is formed, the current is conducted between the two breaker contacts by the plasma between them. Interrupting the high current flowing through the plasma is hard, so some tricks are used to be able to interrupt the current after all.

The advantage of interrupting an alternating (50 Hz) current is that the current crosses zero twice per period [47]. As the current crosses zero, the current will stop to flow through the plasma and arc extinction becomes much easier. Since the arc is absent at and around current zero, the temperature in the medium between the contacts will decrease, which decreases the degree of ionization of the medium [45]. However, the temperature of the highly ionized medium between the contacts is still high [47]. As the conditions in the gap are still quite ideal for an arc to reside in, a re-ignition of the plasma after the current zero needs to be prevented. A re-ignition will occur when the gap between the contacts is still ionized to such a degree that the withstand strength in the gap is not high enough to prevent the rising voltage across the gap from re-establishing the arc after current zero [44, 45, 46].

Preventing a re-ignition and thus successfully interrupting a current can be done in various ways. The way an arc is interrupted differs per circuit breaker design. However, generally there are three ways to interrupt the arc [48].

Stretching the arc

Just as with every other conductor, the resistance of the arc channel is proportional to its length. By increasing the arc channel resistance the probability of a re-ignition can be decreased [46]. Hence the arc length can be increased to limit the re-ignition probability. Since the arc is drawn between two separating contacts, increasing the arc length is an integral part of the design [48].

Cooling

Most of the circuit breakers use a cooling mechanism. Cooling the arc channel limits the cross section of the arc, increasing the resistance [45]. The increased resistance will make it harder for the current to conduct again after current zero. The cooling of the arc is effective when it is stronger than the thermal heating after current zero, turning the conducting plasma back into an insulating state [47].

One would also expect that cooling would cause a part of the plasma to return to the gaseous state. Consequently there would be less free charge carriers to conduct the arc current, which would increase the arc resistance. However, by confining the arc its resistance, and thus its temperature, increases [45].

Removing charge carriers

Conduction is based on the principle that charge carriers are free to move from a start point to an end point in a certain medium (e.g. copper or plasma). Disabling the charge carriers to move as the voltage difference forces them to, causes the current to stop flowing. There are generally two ways in which the charge carriers can be removed from the conducting path, extinguishing the arc.

The first method is to physically remove the particles from the arc path [48]. This method is used by gas-blast circuit breakers, which blow away the charge carriers like one blows out a candle.

The second method uses a magnetic field to bend the arc. The arc is mostly bended into an arc chute, a set of metal plates used to further stretch the arc. By bending the arc its length and thus its resistance increase [48].

B.2 Insulating mediua

The arc can be cooled and extinguished in various ways. The way it is cooled and extinguished depends on the insulating medium that is used. High voltage circuit breakers are often categorized according to the insulating medium in the interrupting chamber in which the arc is formed. This section gives an overview of the most commonly used insulating media in high voltage circuit breakers.

Figure B.1 shows the breakdown voltage of the most common insulating media at various pressures for a sphere to plane configuration. Both the diameter of the sphere and the distance of the sphere to the plane are 12.5 mm. The line for oil is dashed, because oil is a fluid and cannot be compressed.

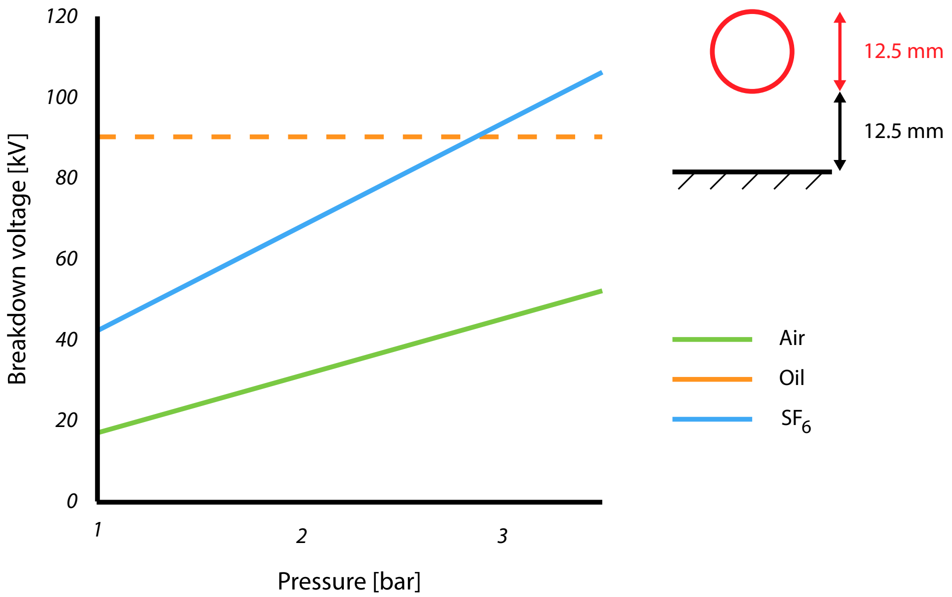

Figure B.1: Breakdown voltage of insulating media for a 12.5 mm sphere to plane configuration (based on [47])

B.2.1 Oil circuit breakers

Nowadays (minimum-)oil circuit breakers still operate in various parts of the world but they left the scene of circuit breaker development [43, 45]. Even though oil circuit breaker manufacturing has stopped about 25 years back [33], many of the circuit breakers still in use are of the minimum-oil type.

Oil characteristics

Oil in itself is an isolating medium. As Figure B.1 already showed, at atmospheric pressure ($\approx$1 bar) oil is the best insulator [45]. However, oil can also be used to conduct the arc. When the contacts of the circuit breaker separate, an arc forms between them, increasing the temperature. The increase in temperature vaporizes the oil, creating a gas bubble between the contacts [44, 45, 47]. This bubble is shown in Figure B.2.

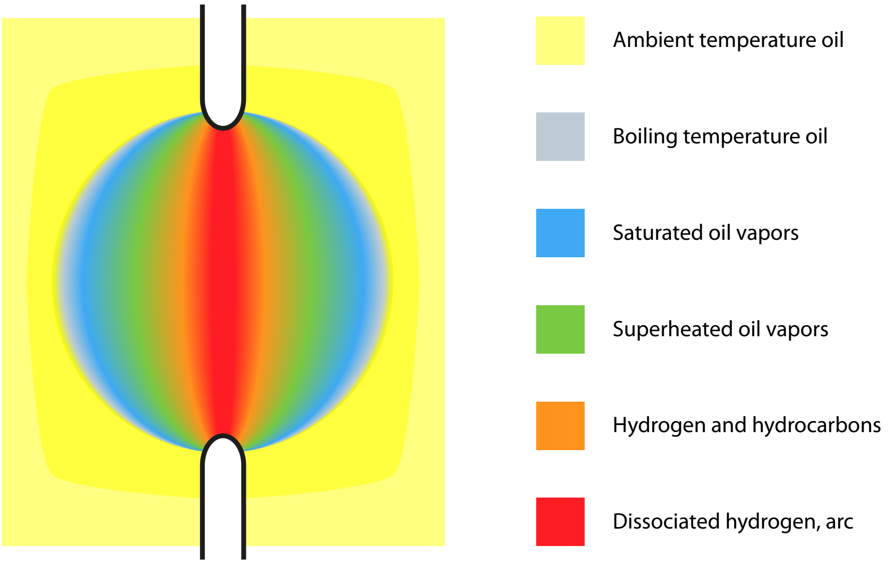

Figure B.2: Gas bubble composition created by an arc in oil (based on [45, 47])

Outside of the gas bubble is the regular insulating oil at ambient temperature. Moving towards the center of the gas bubble, are subsequently layers of boiling oil, saturated oil vapor (oil that just vaporized) and superheated oil vapor. Superheated oil vapor is vaporized oil which temperature is larger than the boiling point. According to the combined gas law, which states

$$\frac{pV}{T} = k$$

where
p is the pressure in Pascal
V is the volume in cubic meter
T is the temperature in Kelvin
k is a constant in Joule per Kelvin
the oil vapor temperature can increase by an increase in pressure. With a further increase in temperature the oil molecules start to break down into hydrogen and hydrocarbons. In the very center is a hot layer of dissociated hydrogen molecules. Each hydrogen molecule

dissociates into two protons and two electrons. The protons and electrons are the charge carries for the arc current. In this way insulating oil also serves as a conductor for the arc [44].

Arc interruption

The hydrogen in the core of the gas bubble has a high heat conductivity [48]. At a current zero the hydrogen rapidly cools down and recovers its dielectric strength [44]. So, effectively the hydrogen is the extinguishing medium [44, 46]. Through the hydrogen the insulating oil can become conductive and insulating again quite rapidly after another.

Drawbacks of oil

In general the oil is highly flammable. However, the oil will not be able to burn because of the absence of oxygen in the oil. Consequently it is very important that the housing of an oil circuit breaker is airtight. Ingress of air (oxygen) and moisture will cause a degradation of the dielectric withstand strength of the oil [45, 47] and may cause the circuit breaker to catch fire or explode. Besides that, oil might seem an ideal insulating medium. However, it is not. As the oil vapors dissociate, not only hydrogen and hydrocarbons are created. Especially when high currents are interrupted, the dissociation also results in carbon [45, 47]. As air, carbon and moisture pollute the oil, frequent maintenance is needed to check its purity [47]. Hence it has been taken out of production and replaced by air and SF_6 circuit breakers.

B.2.2 Air-blast circuit breakers

At atmospheric pressure, the interrupting capability of air is limited to low voltage and medium voltage only [43]. To be able to use the circuit breakers at a higher voltage level, the pressure of the air inside them is increased (see also Figure B.1).

Advantages of air

The main advantage of air as an insulating medium is that it is readily available [46]. There is no need to worry about availability of the insulating medium or its environmental effects. Furthermore it is practically chemically inert [46], which is another advantage of using air.

Arc interruption

To be able to interrupt the arc the air is compressed, often at pressures over 10 bar [46]. The air is dehumidified so there is no water that can cause corrosion or initiate a breakdown [46]. When the contacts separate a valve is opened and the compressed air is blown across the arc to cool it down and to remove charged particles from it [32, 45, 47].

Drawbacks of air

As stated before, the air needs to be compressed for the proper functioning of the air-blast circuit breaker. This requires powerful compressors. Besides the obvious negative effect of extra costs [46], the compressors also inevitably cause noise [47]. Furthermore, in some air-blast circuit breakers the air that blew along the arc is released in free air. This happens with such a force and speed that it causes a lot of noise [47] which leads to a need for a silencer, which is expensive [46] required.

Besides the financial and noise related drawbacks a disadvantage is that the air-blast circuit breakers are not suitable for ultra high voltages [47].

B.2.3 SF_6 circuit breakers

Sulphur hexafluoride (SF_6) is a colorless, odorless and tasteless inert gas [46, 47, 48, 49] that is used as insulating medium in circuit breakers since the 1960's [33]. SF_6 as insulation medium in circuit breakers has several advantages over using oil or gas.

Advantages of SF_6

The SF_6 circuit breaker is comparable to the air-blast circuit breaker. Both extinct the arc by using compressed gas. However, as already shown in Figure B.1, SF_6 has superior dielectrical and thermal properties at the same pressure [47, 50]. With respect to oil SF_6 has the advantage that it is non-toxic, non-explosive and inflammable [47, 50]. Furthermore SF_6 can easily be compressed since it is a gas. As such it can achieve dielectric strengths exceeding that of oil, given the same volume (see Figure B.1) [50, 51]. The higher dielectric strength of compressed SF_6 compared to compressed air and oil allows for more compact installations [32]. Besides being a good insulator, SF_6 is a very good conductor at high temperatures [48]. At 8000 K it has a conductivity equal to that of copper [49].

Arc interruption

The most used design of a SF_6 circuit breaker is the SF_6 puffer circuit breaker. When the contacts retract to interrupt the current, a chamber filled with SF_6 is compressed by a piston connected to the movable contact. When the arc is established and the contact gap is large enough the compressed SF_6 is released and blown across the arc. Thereby the arc is cooled and extinguished.

Electronegativity

Part of the increased dielectric strength is achieved by the electronegativity of SF_6 [51]. Electronegativity means that an SF_6 molecule can capture free electrons. This can be done by either of the two following chemical reactions [47]

$$\mathrm{SF_6} + \mathrm{e}^- \rightarrow \mathrm{SF_6^-}$$
$$\mathrm{SF_6} + \mathrm{e}^- \rightarrow \mathrm{SF_5^-} + F$$

The reactions create negative ions, however, their mobility is much lower than the mobility of the electrons. Consequently, the capturing of electrons decreases the possibility of avalanches and decreases the arcing current [47].

Drawbacks of SF_6

One large drawback of SF_6 is its large influence on global warming. SF_6 has a global warming potential well over 20,000 [47]. This means that SF_6 is more than 20,000 times worse than carbon dioxide when it comes to its influence on global warming. Consequently it has to be handled with care and contained very well, which makes it expensive.

B.3 Operating mechanisms

The circuit breaker contacts can be separated by several different mechanisms. This section gives an overview of the most commonly used high voltage circuit breaker operating mechanisms.

B.3.1 Pneumatic operating mechanism

A pneumatic operating mechanism uses compressed air to move the contacts of the circuit breaker. Next to the circuit breaker is a tank with dehumidified air at a pressure of about 20 bar [47]. The tank is connected to the circuit breaker and valves and tubes are used to direct the flow of air. By opening a valve the compressed air is released and moves a contact up or down. This is visualized in Figure B.3. Figure B.3 also shows a compressor which represents a central installation which dehumidifies and compresses the air. The pump transports the dehumidified air to the tank which is filled for operation.

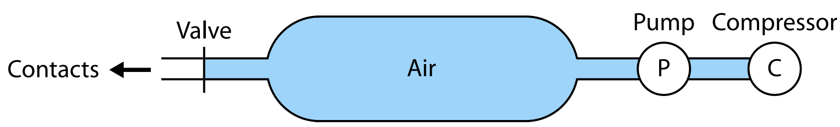

Figure B.3: Schematic representation of a pneumatic operating mechanism

Driving the contacts by a pneumatic mechanism is often done in air-blast circuit breakers. An air-blast circuit breaker needs compressed air as an insulating medium, which gives a need for a tank with compressed air [32, 47]. Since the compressed air is already available, it can also be used for the operating mechanism.

Because the system with the compressed air is rather complex and costly it is implemented less and less.

B.3.2 Hydraulic operating mechanism

The name ’hydraulic operating mechanism’ suggests that the contacts are moved by flows of oil. This is however only partly true. In most cases the energy to drive the contacts apart comes from pressurized nitrogen [32]. A hydraulic fluid is merely used to transfer the energy from the pressurized nitrogen to the contacts [47]. A schematic representation of the hydraulic operating mechanism is shown in Figure B.4. The nitrogen is compressed to about 300 bar [47] by pumping oil into the tank until the membrane has moved far enough to the right. Compressing the nitrogen to such a high pressure will result in a large energy transfer when the valve is opened. Therefore, hydraulic operating mechanisms are most often used in high-energy input circuit breakers.

Instead of the nitrogen the pump could be used push the oil through the valve. However, since a circuit breaker has to operate within milliseconds and the pump cannot build up the required pressure that quickly, the nitrogen has been adopted as a medium of energy storage.

Since the hydraulic operating mechanism is so alike the pneumatic operating mechanism, the hydraulic operating mechanism is also rather expensive and complex.

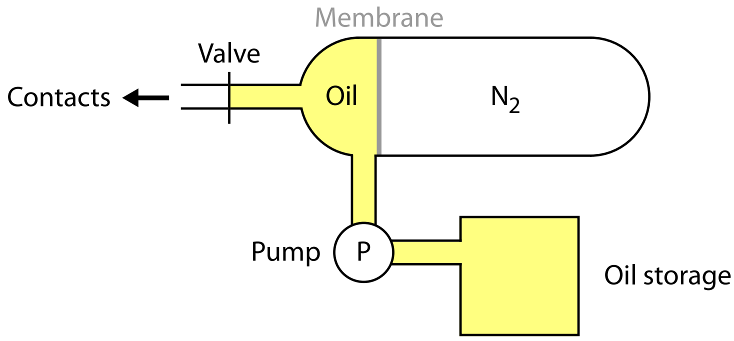

Figure B.4: Schematic representation of a hydraulic operating mechanism

B.3.3 Spring operating mechanism

A great advantage of a spring operating mechanism compared to a hydraulic or pneumatic one is that it has a design which is far less complex [47]. As a result it is cheaper and much more reliable. To move the circuit breaker contact, a latch is opened that stopped the spring from expanding. After the contact is moved a motor starts to charge the spring again to restore the operating energy [32].

A disadvantage of the spring operating mechanism is that it can only be used with a moderate energy demand [47].

APPENDIX C

WEIBULL DISTRIBUTION PARAMETER ESTIMATION

Generally Weibull models are used to model degradation and aging processes [24]. Therefore the Weibull distribution will be used to model the failure rate of the circuit breakers. The probability density function, cumulative density function and failure rate of a Weibull distribution are

$$
\begin{aligned}
f_{\beta,\eta,\gamma}(t) &= \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \exp\left\{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right\} \\
F_{\beta,\eta,\gamma}(t) &= 1-\exp\left\{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right\} \\
h_{\beta,\eta,\gamma}(t) &= \frac{f_{\beta,\eta,\gamma}(t)}{1-F_{\beta,\eta,\gamma}(t)} = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1}
\end{aligned}
$$

The parameters in these distributions are [12, 24]

- t is the measured variable, here the age
- β is the shape parameter, determining a constant, increasing or decreasing failure rate
- η is the scale parameter, influencing the horizontal spread
- γ is the location parameter, moving the distribution such that for $t \leq \gamma$ the probability of failure is zero

Note that the two-parameter Weibull distribution differs from the three-parameter Weibull distribution by having $\gamma = 0$. For estimating the failure rate distribution of the circuit breakers in the database a two-parameter Weibull distribution will be used for the ease of calculation. Although the failure rate distribution $h(t)$ is to be determined, the data from the database will be fitted with the use of the probability density function $f(t)$ and the cumulative density function $F(t)$ for ease of calculation.

C.1 Database properties

The database that is used to calculate the probability density functions includes both failure data and suspension data, the latter being data about circuit breakers that did not fail during the observation period. For the failure data the year of manufacturing and the year of failure were given, so the age at failure could be calculated. The suspension data is grouped in several year of manufacturing categories. These categories are listed in Table C.1.

Commercially available reliability programs, like e.g. Weibull++, are perfect to fit a probability distribution to a combination of failure and suspension data points. However, since the suspension data is grouped in categories rather than known per year these programs generally cannot be used anymore. They do not allow for suspension data that is both left

Table C.1: The age categories of suspension data defined in the database

Category	Class minimum	Class maximum
1	0	4
2	4	9
3	9	14
4	14	19
5	19	24
6	24	29
7	29	

and right censored. An alternative would be to group all the suspension data points in a category at the class minimum. For example, all the circuit breakers in category two were still operational somewhere between four and nine years old. This means that all the circuit breakers were operational and at least four years old. The downside to this strategy is that a lot of information is thrown away. Hence, a custom made likelihood function will be use to estimate the Weibull parameters.

C.2 Likelihood function

The goal is to estimate a probability density function for the age of the circuit breaker. In doing this a likelihood function will be used. A likelihood function is a statistical approach that can be used to estimate the most appropriate model parameters given a set of data. By selecting the parameters which yield the highest likelihood, the parameters that best model the data are calculated. For this application the likelihood function estimates the optimal β and η given the failure and suspension data. Equation C.1 shows the likelihood function that will be used in this case [36].

$$L(p,\beta,\eta) = \left(\prod_{i=1}^{n} p \cdot f_{\beta,\eta}(x_i)\right)\left(\prod_{j=1}^{7}(1-p)^{n_j} \cdot g_j(\beta,\eta)^{n_j}\right) \tag{C.1}$$

In essence the likelihood function consists of two parts. The first part of Equation C.1 concerns the failure data points. First there is a probability p which is the probability that a circuit breaker failed within the observation time. This probability p is thereafter multiplied with the probability, given age x_i. That probability is calculated by the Weibull distribution ($f_{\beta,\eta}$) based on the estimate for the β and η parameters. Multiplying this product for all the failure data points ($1 \leq i \leq n$) in the database gives the likelihood estimator for the failure data points.

The second part of Equation C.1 is the likelihood function for the suspension data. For a suspended data point, the age is only known to belong to a category. Therefore the function cannot calculate the probability for a certain age for a suspension point. It can, however, estimate the probability that the suspension point falls into a certain category. The probability that the age falls in a certain category is calculated by adding the probabilities for all the ages in that category. This can be done by taking the integral from the minimum to the maximum age of the category over the probability density function. However, it is easier to use the cumulative density function. Mathematically this comes down to

$$g_1(\beta,\eta) = F_{\beta,\eta}(4) \tag{C.2}$$
$$g_2(\beta,\eta) = F_{\beta,\eta}(9) - F_{\beta,\eta}(4) \tag{C.3}$$
$$g_3(\beta,\eta) = F_{\beta,\eta}(14) - F_{\beta,\eta}(9) \tag{C.4}$$
$$g_4(\beta,\eta) = F_{\beta,\eta}(19) - F_{\beta,\eta}(14) \tag{C.5}$$
$$g_5(\beta,\eta) = F_{\beta,\eta}(24) - F_{\beta,\eta}(19) \tag{C.6}$$
$$g_6(\beta,\eta) = F_{\beta,\eta}(29) - F_{\beta,\eta}(24) \tag{C.7}$$
$$g_7(\beta,\eta) = 1 - F_{\beta,\eta}(29) \tag{C.8}$$

To cover all the suspension data, the calculation of the likelihood function for the suspension is done for all the categories ($1 \leq j \leq 7$) and for all the data points within those categories (n_j).

C.3 Estimating the parameters

The optimal values for the parameters p, β and η are those for which the likelihood is maximal. The optimal values are indicated by a hat $(\hat{p}, \hat{\beta}, \hat{\eta})$. The maximum of a multi-parameter function is obtained when the partial derivative of the function is taken for that parameter. So, to find the optimal p the following equation has to be solved

$$\frac{\partial L(p,\beta,\eta)}{\partial p} = 0$$

However, the likelihood function contains many products, which makes it difficult to algebraically find $\hat{p}$. Fortunately this is overcome when the $\log$ function of the likelihood is taken. Taking the $\log$ of a function is justified for finding a maximum, as it does not change the position of the maximum. Taking the $\log$ of Equation C.1 yields

$$\begin{aligned} l(p,\beta,\eta) =& \log[L(p,\beta,\eta)] \\ =& n\log p + \sum_{i=1}^{n} \log[f_{\beta,\eta}(x_i)] \\ &+ \sum_{j=1}^{7} n_j \log[1-p] + \sum_{j=1}^{7} n_j \log[g_j(\beta,\eta)] \end{aligned} \tag{C.9}$$

Now, taking the partial derivative to p and setting it to zero results in

$$\frac{\partial l(p,\beta,\eta)}{\partial p} = \frac{n}{p} - \frac{\sum_{j=1}^{7} n_j}{1-p} = 0$$

$$\hat{p} = \frac{n}{n + \sum_{j=1}^{7} n_j}$$

The result is according to what one might expect: the probability that a failure occurs equals fraction of failures in the database.

Calculating $\hat{\beta}$ and $\hat{\eta}$ can be done by iteration in a program like MATLAB. It is advised to use the loglikelihood (Equation C.9) in this case. The regular likelihood equation (Equation C.1) contains many products that multiply probabilities with each other. As probabilities are almost always smaller than one, many multiplications will result in very small numbers. A double precision floating point number, which is commonly used in programs like MATLAB, cannot represent numbers smaller than 10^{-308}. Consequently the likelihood value may always be zero. When the $\log$ of the likelihood function is calculated (Equation C.9) all the products change to sums, which overcomes this problem.

C.4 MATLAB parameter estimation code

In the first part of this section an educative piece of code will show how MATLAB can estimate $\hat{\beta}$ and $\hat{\eta}$ using a loglikelihood function. The second part will show code with the same functionality but a lot faster.

C.4.1 Educational code example

An example of a MATLAB code that could estimate $\hat{\beta}$ and $\hat{\eta}$ is shown in Listing C.1. First the functions, variables and command window are cleared and the opened figures are closed (lines 1-4). Next, the failure and suspension data is provided (line 6-8). The '(..)' in the `fail` vector replaces the vast majority of the failure data points to keep the file readable. The `susp` vector contains the amount of suspension points for each of the categories as defined in Table C.1. Thereafter the β and η ranges are defined that will be iterated along to find $\hat{\beta}$ and $\hat{\eta}$ (lines 10-13). Consecutively the loglikelihood is calculated for all the combinations of β and η (lines 15-20). The calculation is performed by the `likelihood` function that will be introduced later. After all the loglikelihoods are calculated, the `behat` function is used to find the maximum likelihood and the corresponding $\hat{\beta}$ and $\hat{\eta}$ (lines 22-23). This function will also be further introduced later on. At the end, the calculated loglikelihood values and $\hat{\beta}$ and $\hat{\eta}$ are used to plot the loglikelihood (lines 25-30) and the Weibull distribution that best approximates the failure and suspension data (lines 32-40).

Listing C.1: Code of the `main.m` MATLAB file used to find $\hat{\beta}$ and $\hat{\eta}$

```
1  % Clear everything
2  clc
3  close all
4  clear all
5
6  % All failures and suspension data
7  fail = [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 (..) ];
8  susp = [18821 24305 37591 50092 48783 39048 15842 ];
9
10 % Select the beta and eta ranges to test for maximum likelihood
11 beta = 1:0.1:10;
12 eta = 0:1:100;
13 [betamat, etamat] = meshgrid(beta, eta);
14
15 % Calculate the likelihood for all the beta and eta combinations
16 for n = 1:length(beta)
17     for k = 1:length(eta)
18         loglikemat(n, k) = likelihood(beta(n), eta(k), fail, susp);
19     end
20 end
21
22 % Find the optimal beta and eta
23 [beta_hat eta_hat] = behat(beta, eta, loglikemat)
24
```

```
% Plot the loglikelihood
figure()
mesh(betamat, etamat, loglikemat');
xlabel('Shape parameter \beta');
ylabel('Scale parameter \eta');
zlabel('Loglikelihood');

% Set the ages of interest
agevec = 0:50;

% Plot a Weibull PDF based on the derived beta and eta
figure()
plot(agevec, wblpdf(agevec, eta_hat, beta_hat));
title('Probability density function')
xlabel('Age [year]');
ylabel('Probability [-]');
```

The aforementioned `likelihood` function does the actual loglikelihood calculations. The code used in that function is shown in Listing C.2. The code is based on the equations derived in this chapter. First off the parameters n and p as appearing in Equation C.1 are determined (lines 12-15). Next, the probabilities belonging to the age categories, as shown in Equation C.2 through Equation C.8, are calculated (lines 17-24). Consecutively the different parts of Equation C.9 are calculated (lines 26-29). Finally the different parts are added and the loglikelihood is returned (line 31).

Listing C.2: Code of the `likelihood.m` MATLAB file used to calculate the loglikelihood

```
1  function [loglike] = likelihood_old(beta, eta, failure, suspension)
2  % % Calculates the loglikelihood
3  % %
4  % % INPUTS
5  % % beta:       the Weibull shape parameter [float]
6  % % eta:        the Weibull scale parameter [float]
7  % % failure:    the failure data (ages of failure) [array]
8  % % suspension: the suspension data (age categories) [array]
9  % % OUTPUT
10 % % loglike:    the loglikelihood [float]
11 
12 n_fail = length(failure);
13 n_susp = sum(suspension);
14 p_fail = n_fail / (n_fail + n_susp);
15 p_susp = 1 - p_fail;
16 
17 g = zeros(1,7);
18 g(1) = wblcdf(4, eta, beta);
19 g(2) = wblcdf(9, eta, beta) - wblcdf(4, eta, beta);
20 g(3) = wblcdf(14, eta, beta) - wblcdf(9, eta, beta);
21 g(4) = wblcdf(19, eta, beta) - wblcdf(14, eta, beta);
22 g(5) = wblcdf(24, eta, beta) - wblcdf(19, eta, beta);
23 g(6) = wblcdf(29, eta, beta) - wblcdf(24, eta, beta);
24 g(7) = 1 - wblcdf(29, eta, beta);
25 
26 part1 = n_fail*log(p_fail);
27 part2 = sum(log(wblpdf(failure, eta, beta)));
28 part3 = sum(suspension.*log(p_susp));
29 part4 = sum(suspension.*log(g));
30 
31 loglike = part1 + part2 + part3 + part4;
```

The program returns the loglikelihood for all the combinations of β and η. This results in a 3D-plot of the loglikelihood, as shown in Figure C.1.

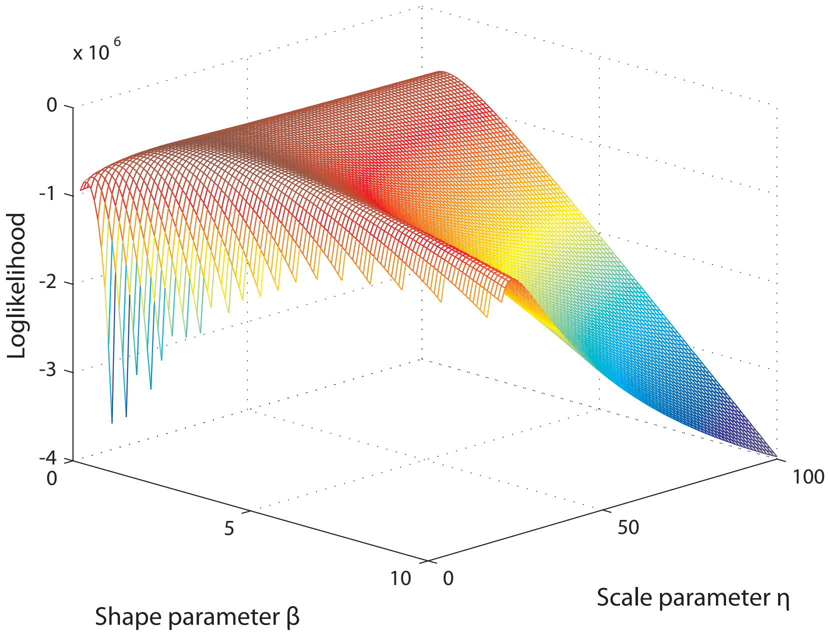

Figure C.1: Loglikelihood for all β and η combinations

Visually a maximum in Figure C.1 can be determined around $0 < \beta < 5$ and $0 < \eta < 50$. This is confirmed by looking for the maximum in the loglikelihood matrix. As stated before, this action is performed by the `behat` function. The implementation of that function in code is listed in Listing C.3.

Listing C.3: Code of the `behat.m` MATLAB file used to find $\hat{\beta}$ and $\hat{\eta}$ in the loglikelihood matrix

```
function [beta_hat, eta_hat] = behat(beta, eta, loglikemat)
% % Calculates the optimal beta and eta
% %
% % INPUTS
% % beta:       the Weibull shape parameter [array]
% % eta:        the Weibull scale parameter [array]
% % loglikemat: the loglikelihood matrix [matrix]
% % OUTPUT
% % beta_hat:   the optimal beta [float]
% % eta_hat:    the optimal eta [float]

[row col] = find(loglikemat == max(loglikemat(:)));
beta_hat  = beta(row);
eta_hat   = eta(col);
```

The `behat` function returns as optimal values

$$\hat{\beta} = 2.1$$
$$\hat{\eta} = 20$$

Since these results are very coarse, the β and η ranges in Listing C.1 (lines 11-12) are refined to the ranges shown in Listing C.4 to calculate $\hat{\beta}$ and $\hat{\eta}$ in more detail.

Listing C.4: Refined β and η ranges for the code of the `behat.m` MATLAB file

```
beta = 2:0.001:2.1;
eta = 19:0.01:21;
```

With the new range settings the program estimates the optimal values for the Weibull distribution at

$$\hat{\beta} = 2.088$$
$$\hat{\eta} = 19.55$$

Using these values to plot the Weibull probability distribution results in Figure C.2. This Weibull density function is the distribution that best fits the failure and suspension data inputted in the model.

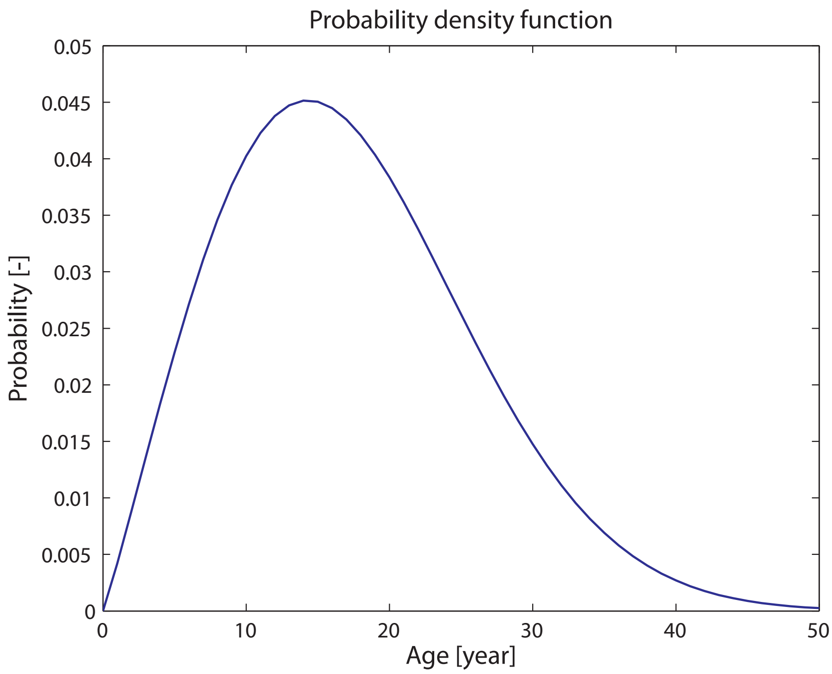

Figure C.2: Probability density function for all the failure and suspension data

The advantage of this way of coding is that it is easily explainable what the steps are to calculate $\hat{\beta}$ and $\hat{\eta}$ and how the MATLAB code implements this. However, the code can be made much faster.

C.4.2 Improved code

MATLAB is a program that is made to calculate results based on vectors and matrices. By using vector calculation large pieces of memory can be addressed at once, decreasing memory accessing time which might be needed when a for loop would be used instead to do the same calculations. For example,

```
x = 0:0.01:5;
y = sin(x);
```

is much faster than

```
x = 0:0.01:5;
for i = 1:length(x)
    y(i) = sin(x);
end
```

To keep the speed up using for loops should be averted as much possible, especially the double for loop in `main.m` (Listing C.1, lines 16-20) which makes the code very slow. In a faster version these loops are removed. The code of that version is shown in Listing C.5. The clearing of old settings (lines 1-4) and plotting of the results (lines 22-30) have not changed with respect to the slower version. The first change is that the failure and suspension arrays are defined as global variables (line 6). This does not improve the speed in itself, but enables parts further on in the code to do so. The declaration of the `failure` and `suspension` arrays do now define the global variables (lines 8-10).

The new code is faster is because it does not calculate the loglikelihood for an entire matrix of combinations of β and η. It starts at initial values for β and η (lines 12-15). These initial values are inserted into the `fminsearch` function, which replaces the double for loop. This function looks for the minimum of a function (`@likelihood`) given initial parameters (`x0`) by changing them until the minimum is found. Using this strategy the majority of β-η combinations will not have to be calculated. As the `likelihood` function has a maximum at $\hat{\beta}$ and $\hat{\eta}$ rather than a minimum it will require some changes, which will be introduced later on. When the minimum is found, the parameters at which the minimum occurs (`x_hat`) are returned. From that vector $\hat{\beta}$ and $\hat{\eta}$ are extracted (lines 19-20).

Listing C.5: Code of the new version of the `main.m` MATLAB file used to find $\hat{\beta}$ and $\hat{\eta}$

```
1  % Clear everything
2  clc
3  close all
4  clear all
5
6  global failure suspension;
7
8  % All failures and suspension data
9  failure = [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 (..) ];
10 suspension = [18821 24305 37591 50092 48783 39048 15842 ];
11
12 % The initial guess for the Weibull parameters
13 beta0 = 2;
14 eta0 = 20;
15 x0 = [beta0 eta0];
16
17 % Use a built-in MATLAB function to find the minimum
18 x_hat = fminsearch(@likelihood, x0);
19 beta_hat = x_hat(1)
20 eta_hat = x_hat(2)
21
22 % Set the ages of interest
23 agevec = 0:50;
24
```

```
% Plot a Weibull PDF based on the derived beta and eta
figure()
plot(agevec, wblpdf(agevec, eta_hat, beta_hat));
title('Probability density function')
xlabel('Age [year]');
ylabel('Probability [-]');
```

As said before, the loglikelihood function has a maximum at $\hat{\beta}$ and $\hat{\eta}$. However, since MATLAB does not offer a `fmaxsearch` function, an alternative is used to find $\hat{\beta}$ and $\hat{\eta}$. The new code of the `likelihood` function is shown in Listing C.6. The first change to the function is in the inputs. The `fminsearch` function keeps on changing the `x` vector (which contains β and η estimates) until the outcome of the `likelihood` function is minimal. To do so, the `likelihood` function may only have one input, `x`. Consequently the inputs containing the failure and suspension data were changed to global variables (line 9). Next, β and η estimates are extracted from the `x` vector (lines 11-12). The main calculations performed by the `likelihood` function were left untouched (lines 14-31). A last important change is in the definition of the output (line 33). Since the `fminsearch` function looks for a minimum and the likelihood function indicates a maximum the output is inversed. Consequently the `likelihood` function will now indicate $\hat{\beta}$ and $\hat{\eta}$ by a minimum.

Listing C.6: Code of the new version of the `likelihood.m` MATLAB file used to calculate the loglikelihood

```
1  function [invloglike] = likelihood(x)
2  % % Calculates the inverse loglikelihood
3  % %
4  % % INPUT
5  % % x:          the beta and eta parameter estimation [array]
6  % % OUTPUT
7  % % invloglike: the inverse likelihood [float]
8
9  global failure suspension;
10
11 beta = x(1);
12 eta = x(2);
13
14 n_fail = length(failure);
15 n_susp = sum(suspension);
16 p_fail = n_fail / (n_fail + n_susp);
17 p_susp = 1 - p_fail;
18
19 g = zeros(1,7);
20 g(1) = wblcdf(4, eta, beta);
21 g(2) = wblcdf(9, eta, beta) - wblcdf(4, eta, beta);
22 g(3) = wblcdf(14, eta, beta) - wblcdf(9, eta, beta);
23 g(4) = wblcdf(19, eta, beta) - wblcdf(14, eta, beta);
24 g(5) = wblcdf(24, eta, beta) - wblcdf(19, eta, beta);
25 g(6) = wblcdf(29, eta, beta) - wblcdf(24, eta, beta);
26 g(7) = 1 - wblcdf(29, eta, beta);
27
28 part1 = n_fail*log(p_fail);
29 part2 = sum(log(wblpdf(failure, eta, beta)));
30 part3 = sum(suspension.*log(p_susp));
31 part4 = sum(suspension.*log(g));
32
33 invloglike = 1/(part1 + part2 + part3 + part4);
```

The increase in speed (or decrease in calculation time) that this change to the files realized is enormous. Comparing the calculation time required by the new version of the code with the old one shows an improvement of a factor 35. Meanwhile, the new code immediately returns $\hat{\beta}$ and $\hat{\eta}$ with four decimals, whereas the first run with the old script yielded one decimal for $\hat{\beta}$ and no decimals for $\hat{\eta}$. So the new code does more in less time. Hence, the new code will be used for the estimation of the Weibull parameters.

APPENDIX D

CIRCUIT BREAKER FAILURE MODES AND INSPECTION PARAMETERS

The goal of the asset failure rate estimation model is to translate inspection results to failure rates. The implementation of the model starts with selecting the relevant failure modes (see Section 2.1). The next step is to select the inputs and link them to the failure modes (see Section 2.2). These three steps, failure mode selection, input selection, and cross-linking of failure modes and inputs are performed in the next three sections.

D.1 Failure mode selection

Lists of failure modes for assets can be obtained from various parties. Amongst them Cigré and IEEE are generally considered the most reliable parties. The failure modes from the IEEE guide are listed in Table D.1. The bold failure modes in Table D.1 are the predominant failure modes and the non-bold failure modes are a subset of the bold failure mode above them.

Table D.1: Circuit breaker failure modes [14]

ID	Failure mode
F10	**Fails to open on command**
F11	Opens but fails to remain open
F12	Opens but fails to interrupt
F13	Opens but fails to maintain open contact insulation
F14	Opens without command
F20	**Fails to close on command**
F21	Closes but fails to conduct current
F22	Closes without command
F30	**Fails to conduct continuous or momentary current (while already closed)**
F40	**Fails to provide insulation**
F41	Fails to provide insulation to ground
F42	Fails to provide insulation between phases
F43	Fails to provide insulation across the interrupter — external
F44	Fails to provide insulation across the interrupter — internal
F50	**Fails to contain insulating medium**
F60	**Fails to indicate condition or position**
F70	**Fails to provide for safety in operation**

Although the failure mode list of Cigré is more detailed, the failure mode list of the IEEE will be used. The main reason therefore is that the IEEE developed a *Guide for the Selection of Monitoring for Circuit Breakers* ([14]) that lists not only failure modes but also failure effects and failure causes. For each failure cause a monitoring option is specified. That last property will be practical when the inputs will be linked to the failure modes.

As stated before, the next step is to select the inputs to the model.

D.2 Input selection

The inputs to the model are taken from the inputs available at TenneT TSO. For every asset type they manage, TenneT TSO has written a *technical maintenance directive*, or TOR (Dutch: technische onderhoudsrichtlijn). A TOR consists of a list of inspection parameters that need to be checked every time an asset needs inspection and/or maintenance. Table D.2 shows the inspection parameters TenneT TSO asks for in their circuit breaker TOR. For completeness Table D.2 includes the units the inspection parameters are measured in. Units shown between square brackets are straightforward units or data formats. An array of units included between curly brackets means that one of the options between them has to be chosen.

Table D.2: Inspection parameters in the circuit breaker TOR of TenneT TSO [52]

ID	Parameter	Unit
L1	Utility	[Name]
L2	Substation	[Name]
L3	Grid link	[ID]
L4	Component identification number	[ID]
L5	Bay	[ID]
G6	Manufacturer	[Name]
G7	Type identification	[ID]
G8	Year of manufacturing	[Year]
G9	Year of installation	[Year]
G10	Insulating medium	{Air, Oil, SF_6}
G11	Rated voltage	[kV]
G12	Rated current	[A]
G13	Rated short circuit current	[kA]
G14	Rated mechanical endurance	[-]
G15	GIS	{Yes, No}
G16	Type of driving mechanism	{Hydraulic, Pneumatic, Spring}
G17	Type of (support/chamber) insulators	{Porcelain, Composite}
G18	Number of interrupting units in series	[-]
G19	Grading capacitors	{Yes, No}
G20	Breaking resistor	{Yes, No}
M21	Last inspection	[Year]
M22	Last maintenance	[Year]
M23	Last overhaul	[Year]
M24	Availability spare parts	{Yes, No}
M25	Maintenance interval	[Year]
M26	Last refill insulating medium	[Date]
M27	Last refill operating fluid	[Date]

Table D.2: Inspection parameters in the circuit breaker TOR of TenneT TSO [52] (continued)

ID	Parameter	Unit
SC28	Switching reactive power	{Yes, No}
SC29	Number of short circuits	[-]
SC30	Relative short circuit current	[%]
SC31	Average load	[A]
SC32	Short circuit current level grid	[kA]
AC33	Location	{Inside, Outside}
AC34	Pollution level	[I, II, III, IV]
C35	Travel characteristic	{Good, Fair, Moderate, Poor}
C36	Number of switching operations	[-]
C37	Resistance measurement	[%]
C38	Breakdown voltage oil arc chamber	[%]
C39	Breakdown voltage oil mechanism	[%]
C40	Quality SF_6	{Good, Fair, Moderate, Poor}
C41	Condition of isolator	{Good, Fair, Moderate, Poor}
C42	Condition of grading capacitors	{Good, Fair, Moderate, Poor}
C43	Condition of breaking resistor	{Good, Fair, Moderate, Poor}
C44	Leakage rate insulating medium	{Good, Fair, Moderate, Poor}
C45	Leakage rate mechanism	{Good, Fair, Moderate, Poor}
C46	Average number of startups hydraulic pump	[1/month]
C47	Average number of pneumatic fills	[1/month]
C48	Condition of accumulator & high pressure circuit	{Good, Fair, Moderate, Poor}
C49	Open time	[%]
C50	Close time	[%]
C51	Contact bounce	[ms]
C52	Simultaneous closing of pools	[%]
C53	Maximum motor current during loading of spring	[%]
C54	Average lead time of oil pump after OCO switching	[%]
C55	Condition of open, close and tripping coils and relays	{Good, Fair, Moderate, Poor}
C56	Condition of secondary circuits	{Good, Fair, Moderate, Poor}
C57	Condition of mechanic drive parts	{Good, Fair, Moderate, Poor}

Legend of parameter IDs:

L##	Location data
G##	General data
M##	Maintenance data
SC##	System condition data
AC##	Ambient condition data
C##	Condition data

As also shown in the footer of Table D.2, the different letters in the parameter IDs specify the type of the parameter. The location data (L##) is information about the identification number, the owner and the physical location of the circuit breaker. This data is primarily gathered for administrative purposes.

The general data (G##) mainly contains the specifications of the circuit breaker. The spec-

ifications can be used to divide all circuit breakers into different subpopulations and to see if the rated values of the circuit breaker are not exceeded.
Maintenance data (M##) is listed for the asset manager to support him in the planning of the next inspections and maintenance events.
To be sure the ratings of the circuit breakers are not exceeded the system condition data (SC##) can be compared to the rated values in the general category group.
The ambient condition data (AC##) indicates how the environment the circuit breaker is placed in may influence its functional behavior.
Last but not least, the condition data (C##) is requested. These parameters represent measurements during inspection and maintenance which indicate the actual technical condition of the circuit breaker. Therefore the condition parameters will be the parameters that will be linked to the failure modes and used as inputs to the asset failure rate estimation model.

D.3 Linking inputs to failure modes

Now both the failure modes and inputs are known, they can be connected to one another. Matching all the parameters from Table D.2 to the full version of Table D.1 from [14] results in Table D.3. For every failure mode is indicated whether and how the underlying failure causes can be monitored. The codes in the *Monitored* column correspond to the IDs from Table D.2.

When the monitoring option field states *No, this is unpredictable* it means that the failure cause is either instantaneous or cannot be prevented by proper monitoring.

One may notice that no monitoring parameters are listed when the failure cause is related to vacuum. This is because TenneT TSO does not manage any vacuum high voltage circuit breakers to manage. However, they are listed in Table D.3 for the sake of completeness.

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34]

Failure mode	Failure effect	Failure cause	Monitored
Fails to open on command	Breaker does not open the circuit to interrupt current	Open or shorted trip coil	Yes, by C55
		Inappropriate or inadequate lubrication of trip latch or trip mechanism	Yes, by C49, C50 and C52
		Loss of stored interrupting energy due to leaks, slippage and breakage	Yes, by C45, C46, C47, C48 and C53
		Control circuit failure	Yes, by C56
		Circuit breaker operation blocked	No, this failure cause is the result of other failure causes
		Mechanism linkage failure between operating mechanism and interrupters	Yes, by C57
		Trip latch surface wear, deteriorated bearings, or deformation of trip latch flat surfaces	Yes, by C57 (and C49, C50 and C52)
		Mechanism cabinet below required temperature	No, is not significant in Dutch conditions
		External circuit failure, including wiring, battery, and protection devices	Yes, by C56
Opens but fails to remain open	Circuit breaker opens and then closes again	Mechanism failure, loss of "hold open" energy (e.g., loss of air pressure on air blast circuit breaker requiring air pressure to hold contacts open)	Yes, by C45, C46, C47 and C48

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34] (continued)

Failure mode	Failure effect	Failure cause	Monitored
	Circuit breaker opens and then repeatedly closes and opens	Failure of anti-pumping scheme	No, this is unpredictable
Opens but fails to interrupt	Fault or load current is not interrupted, and the circuit breaker interrupter has a major failure	Oil contamination	Yes, by C38
		Low gas pressure or density (air or SF_6)	Yes, by C40 and C44
		Loss of vacuum	No, this is not applicable
		Insufficient contact opening	Yes, by C35
		Arc chute failure	No, this is not applicable
		Failure of voltage steering capacitors and resistors[1]	Yes, by C42 and C43
		Puffer failure	No
		Mechanical failure	Yes, by C35 and C49
		Misapplication or other situation beyond circuit breaker capability	No, this is prevented by not exceeding a circuit breaker its ratings
Opens but fails to maintain open contact insulation	Breaker fails to provide required dielectric insulation of contacts immediately after the opening operation	Loss of vacuum	No, this is not applicable
		Mechanism does not travel compete distance	Yes, by C35
		Loss of gas pressure	Yes, by C44 (oil and SF_6) and C47 and C48 (air-blast)
		Too many operations in a time period	No, this is prevented by secondary protection

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34] (continued)

Failure mode	Failure effect	Failure cause	Monitored
		Dielectric stress exceeds the circuit breaker capability	Yes, by C40
		Lightning	No, this is unpredictable
Opens without command	Circuit is unintentionally interrupted with possible safety and economic damage issues	Trip latch not secure	Yes, by C55 and C56
		Stray current in trip circuit (such as from transients, caused by switching surges on adjacent wiring)	Yes, by C55 and C56
		Ground on trip circuit	Yes, by C56
		Self-protective feature of some circuit breakers (some air-blast breakers)	Yes, by C45, C46, C47 and C48
		Loss of voltage on under-voltage trip	No, this protection is not present in TenneT's circuit breakers
Fails to close on command	Breaker does not close the circuit to conduct current	Defective close coil or solenoid	Yes, by C55
		Loss of stored energy	Yes, by C45, C46, C47, C48 and C53
		Inappropriate lubrication	Yes, by C49, C50 and C51
		Control circuit failure	Yes, by C55 and C56
Closes but fails to conduct current	Breaker does not close the circuit to conduct current in one or more poles	Contacts burnt away (electrically eroded)	Yes, by C35 and C51
		Mechanical linkage to contacts broken	Yes, by C52 and C57
		Loss of over-travel preventing full contact closing	Yes, by C35

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34] (continued)

Failure mode	Failure effect	Failure cause	Monitored
Closes without command	Circuit is unintentionally closed with possible safety and economic damage issues	Stray current in close circuit (such as from transients caused by switching surges on adjacent wiring)	Yes, by C55 and C56
		Ground on close circuit	Yes, by C56
		Pilot valve not secure	Yes, by C47 and C54
		Spring release mechanism worn	Yes, by C53
		Vibration of circuit breaker	No
Fails to conduct continuous or momentary current (while already closed)	Breaker does not conduct current with resulting thermal damage to contact assemblies	High-resistance contacts	Yes, by C37
		Ablation of contacts	Yes, by C35 and C37
		Broken or missing contacts; parts in current carrying circuit; bolted joints, sliding, rolling, or moving main contacts; spring failure	Yes, by C35
		Loss of over-travel and contact closing force	Yes, by C35, C49, C50 and C52
Fails to provide insulation	Short circuit on power system or unintentional energization of components	Loss of dielectric medium	Yes, by C38, C40, C44, C45 and C47
		Loss of dielectric integrity of oil	Yes, by C38
		Loss of vacuum	No, this is not applicable
		Moisture in SF_6	Yes, by C40
		Loss of compressed air dielectric	Yes, by C47
		Damaged interrupter from external acts	Yes, by C41, C42 and C43

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34] (continued)

Failure mode	Failure effect	Failure cause	Monitored
		Excessive accumulated interrupted amperes	No, not yet
		Wear-generated particles in interrupter	Yes, by C38, C40 and C51
Fails to provide insulation to ground	Phase-to-ground fault on the power system with possible safety and economic damage; interruption required to power system	Wildlife contact	No, impossible in the Netherlands
		Lightning strike	No, this is unpredictable
		Mechanical damage to insulation	Yes, by C41, C42 and C43
		Water infiltration	Yes, by C39 and C40
		Contaminated bushings	Yes, by C41
		Flash-over caused by system transient event	No, this is prevented by proper specifications
		Excessive temperatures of insulating materials	No
Fails to provide insulation between phases	Phase-to-phase fault on the power system with possible safety and economic damage; interruption required to power system components	Wildlife contact	No, impossible in the Netherlands
		Lightning strike	No, this is unpredictable
		Ionization of surrounding insulating air caused by unusual service conditions	No, this is unpredictable
		Water infiltration	Yes, by C39 and C40
		Foreign material	No, this is unpredictable

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34] (continued)

Failure mode	Failure effect	Failure cause	Monitored
Fails to provide insulation across the interrupter — external	Circuit is unintentionally closed with possible safety and economic damage issues; may result in a major failure of circuit breaker interrupter	Wildlife contact	No, impossible in the Netherlands
		Lightning strike	No, this is unpredictable
		Water infiltration	No, this is not applicable
		Ionization of air during over duty fault	Yes, C41, C42 and C43 (air-blast)
		Excessive voltage applied to circuit breaker	No, this is unpredictable
		Dirt or pollution	Yes, by C41, C42 and C43
		Deterioration of interrupter exterior surfaces caused by partial discharge	Yes, by C41, C42 and C43
		Flash-over of OPEN interrupter caused by system transient event	No, this is unpredictable
		Ionization of surrounding insulating air caused by unusual service conditions	No, this is unpredictable
Fails to provide insulation across the interrupter — internal	Circuit is unintentionally closed with possible safety and economic damage issues; may result in a major failure of circuit breaker interrupter	Loss of dielectric density	Yes, by C40 and C47
		Loss of dielectric integrity of oil	Yes, by C38
		Loss of vacuum	No, this is not applicable
		Excessive voltage applied to circuit breaker	No, this is unpredictable
Fails to contain insulating medium	Loss of insulating medium to environment	Failure of seals, gaskets, corrosion, erosion, and porcelain rupture disk	Yes, by C38, C39, C40, C44 and C45

Table D.3: The link between the IEEE failure modes [14] and TenneT TSO circuit breaker TOR inspection parameters [34] (continued)

Failure mode	Failure effect	Failure cause	Monitored
Fails to indicate condition or position	Operation of power system with a circuit breaker that is incapable or has reduced capacity to perform its functions	Failure of insulating gas density switch	Yes, by C56
	Defective closed, opened, or stored energy indicator causing operator to undertake inappropriate actions	Stuck, broken, or defective indicator	Yes, by C56
		Auxiliary contacts, linkage or wiring	Yes, by C56
Fails to provide for safety in operation	Hazard to personnel	Overpressure of porcelain interrupter. Defects in porcelain.	Yes, by C41, C42 and C43
		Overpressure of pneumatic or hydraulic fluids, spring charging system	Yes, by C48
		Failure of interlocks	Yes, by C56
		Loss of gas and need to isolate	Yes, by C40 and C44
		Improper filling or adding liquid versus gas dielectric medium	Yes, by C40

[1] This was not present in the IEEE publication, but it is a failure mode that must be mentioned here.

Table D.3 gives a complete picture of why certain input parameters can be linked to certain failure modes. However, it is not practical for a quick overview which input parameters can be used for which failure modes. Table D.4 is a short version of Table D.3 which does provide that quick overview. The IDs for the failure modes and input parameters the correspond with the IDs listed in Table D.1 and Table D.2 respectively.

Table D.4: Summary of the link between the inputs and failure modes as described in Table D.3

	Failure modes																
Parameter	F10	F11	F12	F13	F14	F20	F21	F22	F30	F40	F41	F42	F43	F44	F50	F60	F70
C35			X	X			X		X								
C36																	
C37									X								
C38			X							X				X	X		
C39											X	X			X		
C40			X	X						X	X	X		X	X		X
C41										X	X		X				X
C42			X							X	X		X				X
C43			X							X	X		X				X
C44			X	X						X					X		X
C45	X	X			X	X				X					X		
C46	X	X			X	X											
C47	X	X		X	X	X		X		X				X			
C48	X	X		X	X	X											X
C49	X		X			X			X								
C50	X					X			X								
C51						X	X			X							
C52	X						X		X								
C53	X					X		X									
C54								X									
C55	X				X	X		X									
C56	X				X	X		X								X	X
C57	X						X										

APPENDIX E

TRANSITION POINT MODELING

TenneT TSO uses a great variety of inputs to model a circuit breaker. Some of the inputs are not defined by a unit (like volt or ampere), but by a *Good–Fair–Moderate–Poor* scale. This makes it easier for the maintenance crews to summarize the behavior of a subcomponent of a circuit breaker. For the inputs that are defined by a unit the range of values the unit can ascertain is divided into the *Good*, *Fair*, *Moderate* and *Poor* classes. For example, a maximum spring charging motor current between 110% and 135% of the rated maximum motor current is mapped onto the *Fair* class (see Section 6.3.4).

For all the inputs the goal is to find a distribution that connects the input values to failure rates. For the former category (inputs without a unit), the failure rate distribution is defined by the upper and lower bounds of the *Good*, *Fair*, *Moderate* and *Poor* classes (as defined in Section 6.3.1). These bounds are shown in Table E.1.

Table E.1: Failure rate distribution bounds for the *Good–Fair–Moderate–Poor* scale

	Failure rate	
Class	Lower bound	Upper bound
Good	0	0.05
Fair	0.05	0.15
Moderate	0.15	0.25
Poor	0.25	∞

The failure rate distributions for the latter category (inputs with a unit) are defined with help of the upper and lower bounds shown in Table E.1. By linking the input values that correspond to the *Good*, *Fair*, *Moderate* and *Poor* classes to the failure rates they represent, a few data points appear which the failure rate distribution should cross. These data points will be caught in the function $g(i)$ which returns a failure rate on i, the value of the input. This function, however, only contains a few data points. Therefore, $g(i)$ will be modeled by a two-parameter Weibull distribution. This distribution is described by [12, 31]

$$h_{\beta,\eta}(i) = \frac{\beta}{\eta}\left(\frac{i}{\eta}\right)^{\beta-1}$$

where

i is the measured variable, here the input value

β is the shape parameter, determining a constant, increasing or decreasing failure rate

η is the scale parameter, influencing the horizontal spread

The Weibull distribution is compared with the known relationships between input values and failure rates ($g(i)$) to find the β and η parameters that yield the model that fits the data best. To do this, a least squares algorithm is used. The square error is defined as the sum of the squares of the distances between the reference data points and the data points of the model applied to it. Mathematically this comes down to

$$SE = \sum_{j=1}^{n} \left[h_{\beta,\eta}(j) - g(j)\right]^2 \tag{E.1}$$

where n is the number of data points in $g(i)$. The goal is to find the smallest value of the square error SE by changing the β and η. Finding the least square error and bearing in mind that there are four classes with three defined transition points between them, Equation E.1 changes to

$$LSE = \min SE = \min_{\beta,\eta} \sum_{j=1}^{3} \left[h_{\beta,\eta}(j) - g(j)\right]^2 \tag{E.2}$$

The code used to implement Equation E.2 is shown in Listing E.1 and explained below.

First the functions, variables and command window are cleared and the opened figures are closed (lines 1-4). Next, the function that will be used to describe the *Good–Fair–Moderate–Poor* transitions is introduced (lines 6-7). This function is called an anonymous function. Unlike the majority of the MATLAB statements and functions, an anonymous function is not directly evaluated. The function is only defined and can be evaluated later. The parameter `wblfr` is actually a function handle; it has become a evaluable function in itself. The `wblfr` definition shows that

- it is an anonymous function (by the `@`)
- it depends on two inputs (`x` and `xdata`)
- it is a Weibull failure rate distribution with `xdata` as x-axis data, `x(1)` as β and `x(2)` as η

Since the function that calculates the least square error does that iteratively, it requires initial conditions (lines 9-12). Next, the x and y values of the *Good–Fair–Moderate–Poor* transitions are defined (lines 14-16). These are the data points that need to be approximated by the least square error calculator based on the Weibull failure rate distribution given in `wblfr`.

The initial conditions, transition points and Weibull distribution are inserted into the `lsqcurvefit` function (line 19). This function looks for the least square error of the `wblfr` function with respect to the *Good–Fair–Moderate–Poor* transition points (defined by `ydata` and `xdata`). It does this by starting at the initial parameters (contained `x0`) and changing them until the least square error is found (see Equation E.2). When the parameters at which the least square error is detected are found, they are returned via `x_hat`. From that vector $\hat{\beta}$ and $\hat{\eta}$ are extracted (lines 20-21). In the end, the *Good–Fair–Moderate–Poor* transition points and the Weibull failure rate distribution, based on the optimal β and η, are plotted (lines 23-32).

Listing E.1: Code of the `leastsquares.m` MATLAB file used to find the parameters to model the *Good–Fair–Moderate–Poor* transitions

```
% Clear everything
clc
clear all
close all

% The function we want to use to model the inputs is a 2-parameter ...
    Weibull failure rate distribution
wblfr = @(x, xdata) (x(1)/x(2)).*(xdata/x(2)).^(x(1)-1);

% The initial guess for the Weibull parameters
beta0 = 2;
eta0 = 125;
x0 = [beta0 eta0];

% The data points the Weibull distribution needs to approach
ydata = [0.05 0.15 0.25];
xdata = [60 125 250];

% Calculate the beta and eta for which the least square error of ...
    the function is smallest
x_hat = lsqcurvefit(wblfr, x0, xdata, ydata);
beta_hat = x_hat(1)
eta_hat = x_hat(2)

% Plot the input data and the fitted Weibull distribution
figure()
xvec = 0:300;
plot(xdata, ydata, 'b+'); hold on;
plot(xvec, wblfr(x_hat, xvec), 'r');
title('Failure rate distribution for the number of hydraulic pump ...
    starts');
xlabel('Average number of startups hydraulic pump [1/month]');
ylabel('Failure rate [1/year]');
legend('G-F-M-P transitions', 'Best fitted model', 'Location', ...
    'NorthWest');
legend boxoff;
```

APPENDIX F

CIRCUIT BREAKER FAILURE RATE DISTRIBUTIONS

This chapter contains all the failure rate distributions that are being used in the circuit breaker failure rate estimation model. First all the failure modes failure rate distributions are shown. Thereafter follow the asset failure rate distributions. The various graphs denote the different categories that are used within the circuit breaker failure rate estimation model.

F.1 Failure mode failure rate distributions

This section shows all the failure rate distributions used in the failure mode function of the circuit breaker failure rate estimation model. The graphs are made per main kind of service. For each main kind of service the failure rate distributions are shown for the hydraulic, pneumatic and spring operating mechanisms. The cable circuit breaker plot and hydraulic and pneumatic shunt reactor plots are not made due to a lack of data.

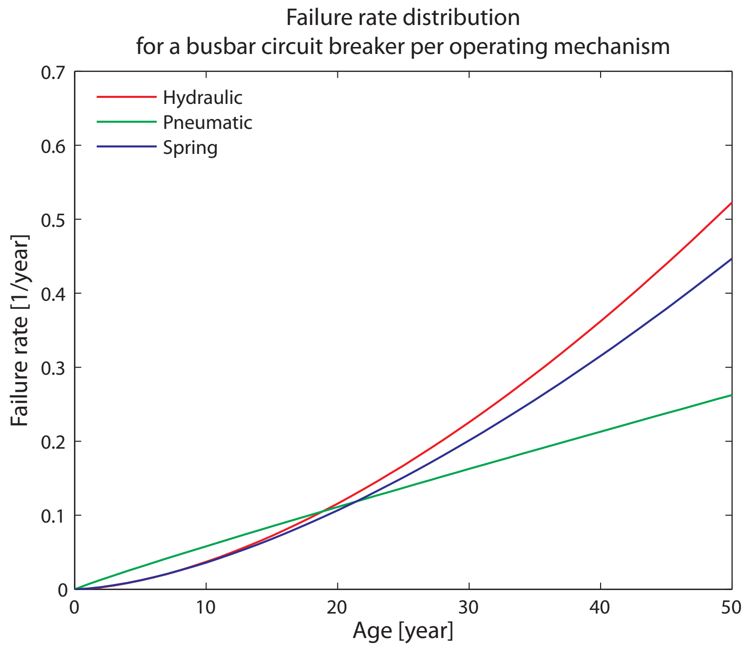

Figure F.1: Failure rate distribution per operating mechanism for a busbar circuit breaker given the *Does not switch* failure mode (H: $\beta = 2.645, \eta = 21.03$, P: $\beta = 1.937, \eta = 18.62$, S: $\beta = 2.564, \eta = 21.49$)

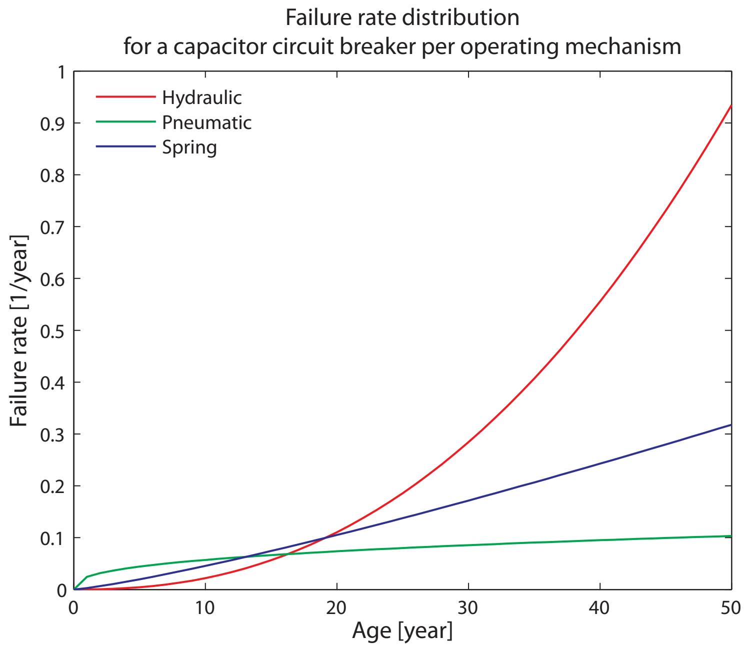

Figure F.2: Failure rate distribution per operating mechanism for a capacitor circuit breaker given the *Does not switch* failure mode (H: $\beta = 3.330, \eta = 22.62$, P: $\beta = 1.368, \eta = 18.94$, S: $\beta = 2.207, \eta = 20.44$)

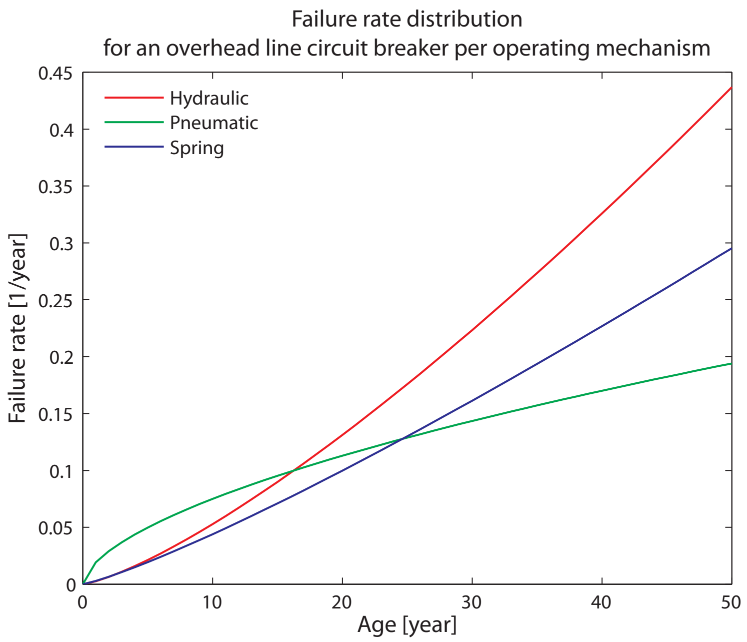

Figure F.3: Failure rate distribution per operating mechanism for an overhead line circuit breaker given the *Does not switch* failure mode (H: $\beta = 2.313, \eta = 18.94$, P: $\beta = 1.591, \eta = 16.05$, S: $\beta = 2.184, \eta = 20.84$)

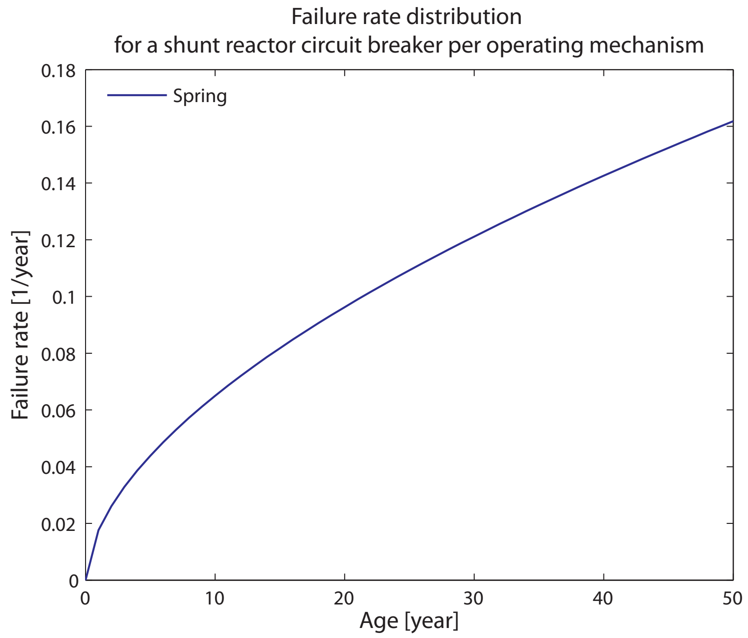

Figure F.4: Failure rate distribution per operating mechanism for a shunt reactor circuit breaker given the *Does not switch* failure mode (S: $\beta = 1.567, \eta = 17.54$)

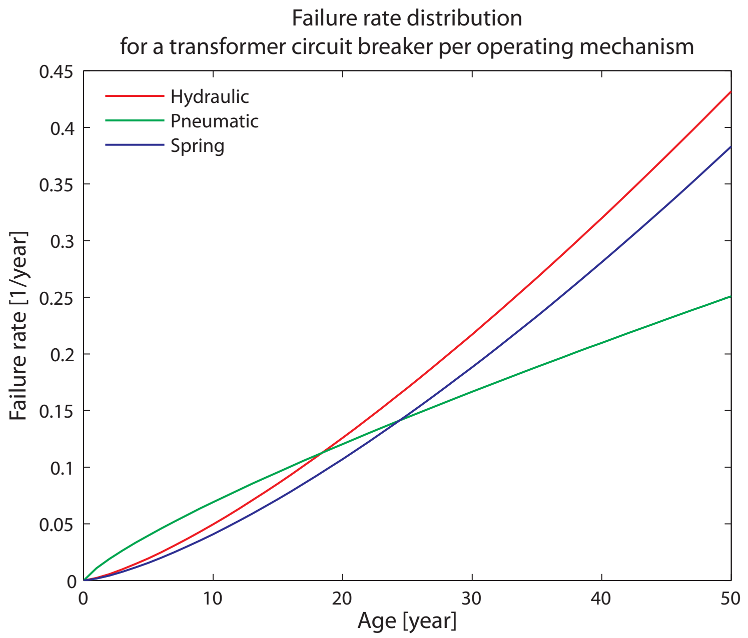

Figure F.5: Failure rate distribution per operating mechanism for a transformer circuit breaker given the *Does not switch* failure mode (H: $\beta = 2.345, \eta = 19.40$, P: $\beta = 1.801, \eta = 17.02$, S: $\beta = 2.391, \eta = 20.94$)

F.2 Asset failure rate distributions

This section shows all the failure rate distributions used in the asset function of the circuit breaker failure rate estimation model. The graphs are made per main kind of service. For each main kind of service the failure rate distributions are shown for the hydraulic, pneumatic and spring operating mechanisms. The cable circuit breaker plot is made based on the average distributions for the operating mechanisms due to a lack of data on cable circuit breaker failures itself.

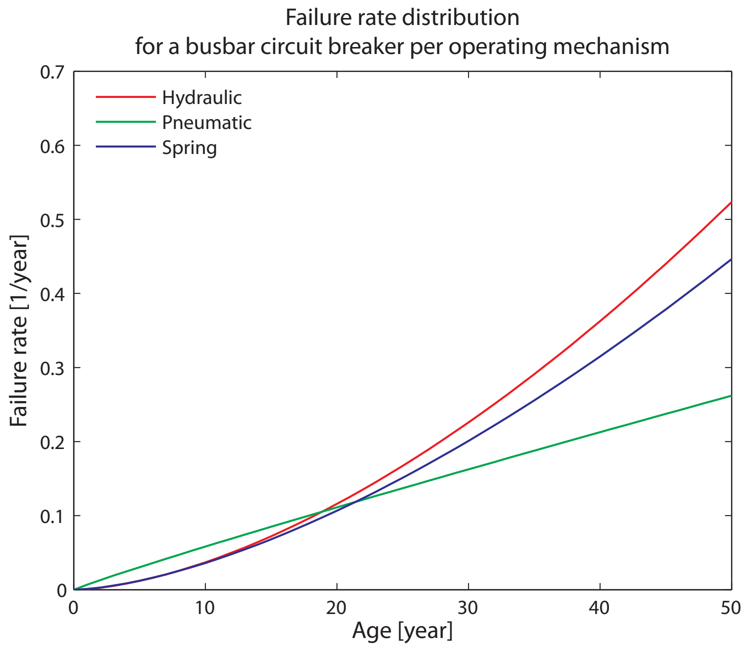

Figure F.6: Failure rate distribution per operating mechanism for a busbar circuit breaker (H: $\beta = 2.646, \eta = 21.03$, P: $\beta = 1.935, \eta = 18.61$, S: $\beta = 2.563, \eta = 21.49$)

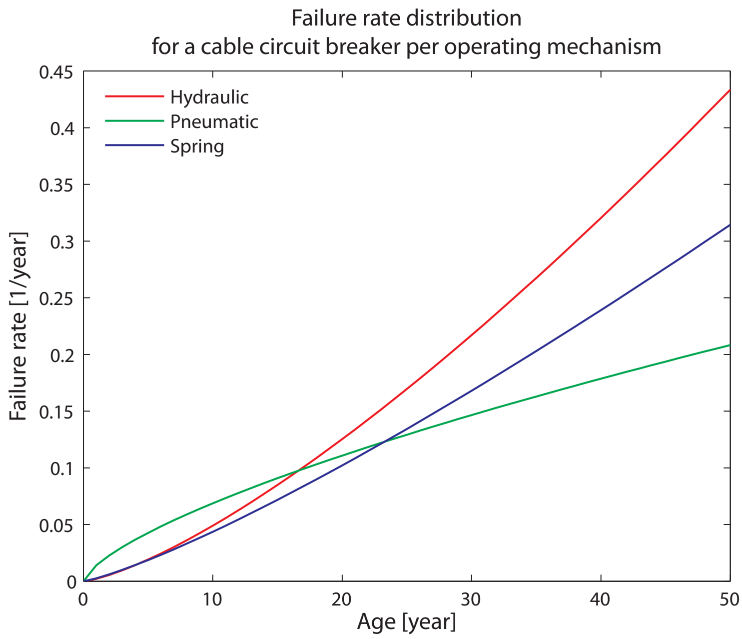

Figure F.7: Failure rate distribution per operating mechanism for a cable circuit breaker (H: $\beta = 2.355, \eta = 19.48$, P: $\beta = 1.689, \eta = 17.03$, S: $\beta = 2.227, \eta = 20.79$)

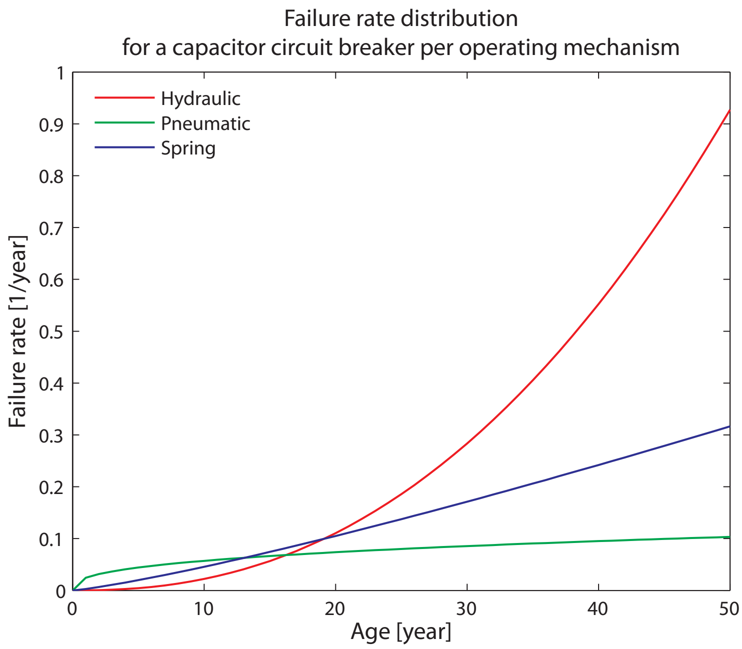

Figure F.8: Failure rate distribution per operating mechanism for a capacitor circuit breaker (H: $\beta = 3.320, \eta = 22.60$, P: $\beta = 1.368, \eta = 18.94$, S: $\beta = 2.203, \eta = 20.43$)

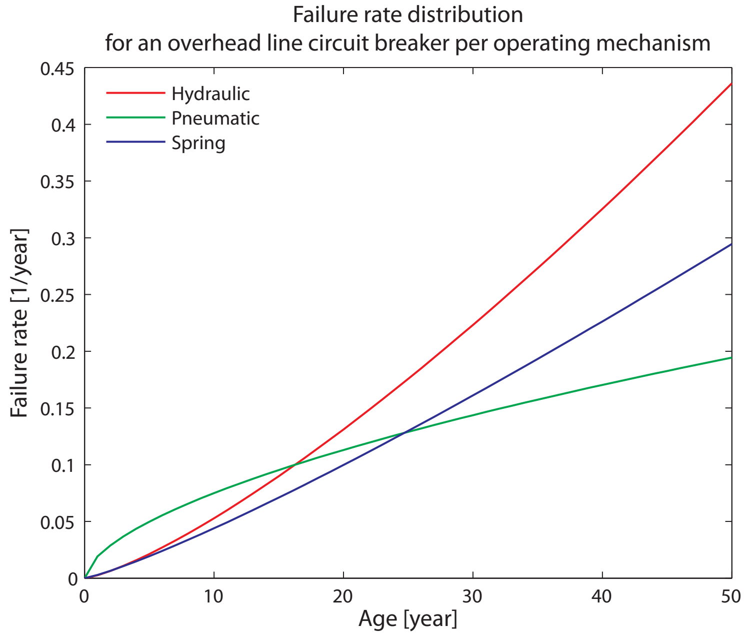

Figure F.9: Failure rate distribution per operating mechanism for an overhead line circuit breaker (H: $\beta = 2.312, \eta = 18.94$, P: $\beta = 1.592, \eta = 16.05$, S: $\beta = 2.182, \eta = 20.84$)

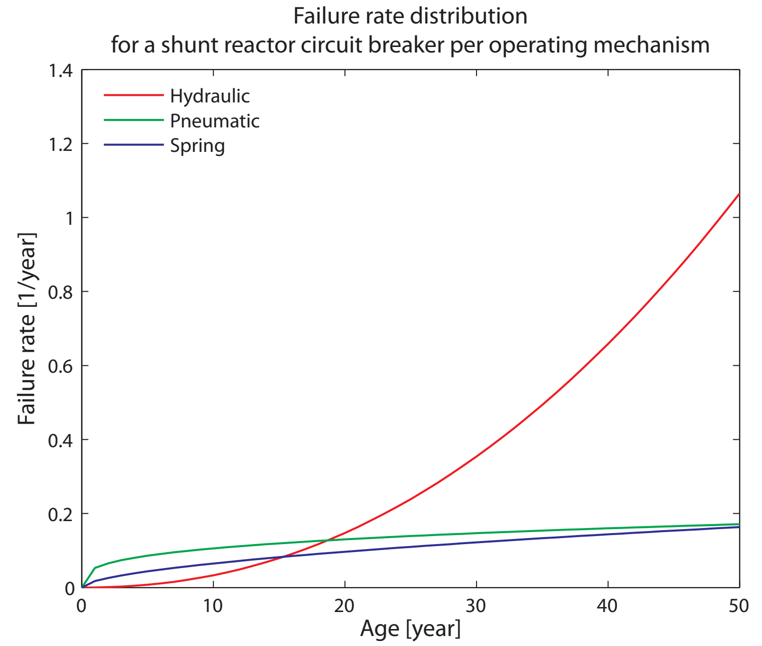

Figure F.10: Failure rate distribution per operating mechanism for a shunt reactor circuit breaker (H: $\beta = 3.157, \eta = 20.43$, P: $\beta = 1.299, \eta = 11.72$, S: $\beta = 1.573, \eta = 17.55$)

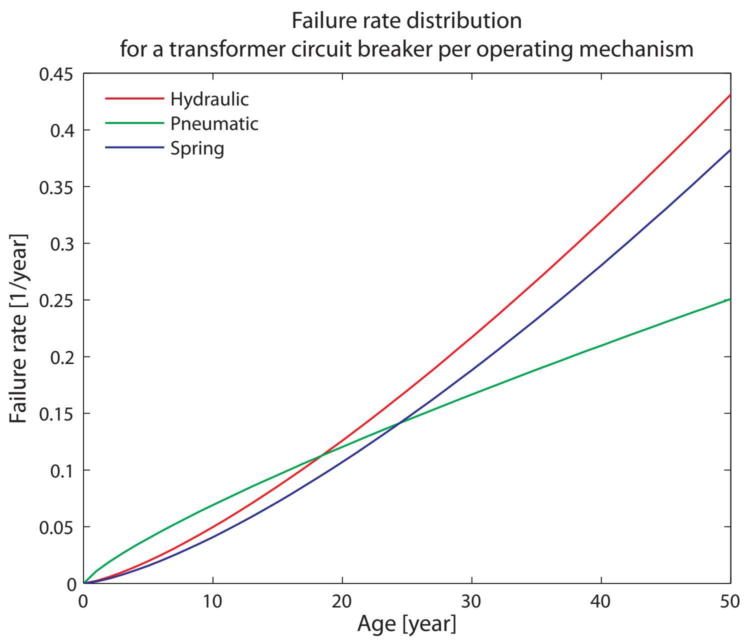

Figure F.11: Failure rate distribution per operating mechanism for a transformer circuit breaker (H: $\beta = 2.343, \eta = 19.39$, P: $\beta = 1.801, \eta = 17.02$, S: $\beta = 2.390, \eta = 20.94$)