Assessing the life cycle costs of an investment strategy

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Preface

This thesis is written as a part of the Master's degree 'Industrial Engineering and Management'. With the completion of my master my time as a student comes to an end. I would like to thank the people who helped make that possible.

First, I would like to thank Bas Peppelman for providing the opportunity and guidance to perform an interesting graduation assignment at the asset management department of Liander. I learned a lot about the Dutch energy network in the past half year. Bas was always easily approachable and ready to help. During my research I was part of the 'Waardegedreven asset management' team. I had great fun working with every member of the team and would like to thank the entire team for their input.

Moreover, I want to thank my university supervisors Reinoud Joosten and Wouter van Heeswijk for their supervision. As a first supervisor, Reinoud was involved from the start of the research and he always provided me with useful feedback and ideas. I would like to thank Wouter for providing feedback at the final stages of my graduation assignment.

Lastly, I would like to thank my girlfriend, family and friends who supported me during my education.

I wish you a pleasant reading.

Niels Voetdijk,
December 2019

Management summary

The electricity network of Liander needs to be reinforced so that the energy transition can be facilitated. Unfortunately, Liander is unable to perform all desired investments due to a lack of technical personnel. Therefore, a prioritisation between projects is required. An investment can be an asset purchase and installation, maintenance, inspection and disposal. We argue that the attractiveness of a single investment depends on the entire investment strategy. For example, the attractiveness of a major maintenance action is meagre if the asset is to be replaced shortly after. Our research objective is to *build a simulation model which can assess the life cycle costs of an investment strategy*. We build the simulation model for a case study on power transformers, with the intent of it being generalisable to other assets.

The idea behind assessing the costs of an asset is central in life cycle costing. The approach allows for making decisions based on a single measure, and relies on monetising the impact of investments. A fair cost measure is essential to a life cycle costing analysis. We measure the life cycle costs in terms of equivalent annuitized costs, which are the annuity equivalent of the net present value. The measure allows for a fair comparison of mutually exclusive alternatives with unequal lives.

In order to simulate an asset's life cycle, we need to know the relationship between failures and maintenance. A maintenance action is aimed at restoring the condition of an asset, such that the probability of failure decreases. The underlying trade-off is the reduction in the risk of failure and the maintenance costs. We model the relationship between the asset's condition and the probability of failure with a degradation model. Our degradation model is based on a Markov chain model, which is a discrete-time stochastic model. The States $1, \dots, N$ correspond to the conditions of ordinally ranked data or ranges of values for continuous data. The degradation transition probabilities of the Markov chain dictate the likelihood of degrading from one state to another in the next period, and maintenance restores the condition to certain states with their own transition probabilities.

A major contribution of our research lies in fitting transition probabilities for our case study on power transformers. Power transformers fulfil the role of transforming a voltage into another voltage. We apply the maximum likelihood approach of Hoskins et al. (1999) to find stationary transition probabilities describing the degradation of power transformers. The approach finds the transition probabilities such that the likelihood of the observations is maximised, and it is applicable to interval-censored data with transitions spanning over different time intervals. Applying this to our case study, where the conditions good, moderate, bad and failed correspond to States 9, 6, 1 and 0 respectively, results in the following probability matrix:

$$\hat{P}_{maximum\ likelihood} = \begin{array}{c} \\ 9 \\ 6 \\ 1 \\ 0 \end{array} \begin{array}{c} \begin{array}{cccc} \quad 9 & \quad\quad 6 & \quad\quad 1 & \quad\quad 0 \end{array} \\ \begin{bmatrix} 0.686 & 0.221 & 0.092 & 0.001 \\ 0.000 & 0.850 & 0.148 & 0.002 \\ 0.000 & 0.000 & 0.979 & 0.021 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{bmatrix} \end{array}$$

However, the assumption that the transition probabilities are constant during the power transformer's life cycle may be too restrictive. We consider the possibility that the probabilities depend on the asset's age and the time spent in a state. We fit transition probabilities for age categories with the maximum likelihood approach of Hoskins et al. (1999), and find large differences between categories. We test whether the transition probabilities depend on the time spent in a state by fitting a semi-Markov model with the method described by Black et al. (2005). Due to a lack of data we are unable to obtain reliable results, but we believe that the method may be interesting for Liander if more data are provided.

We build a simulation model with transition probabilities dependent on the age category to generate random paths for the condition of an asset throughout its life. The purchase, installation, (preventive and corrective) maintenance, inspection, disposal and failure costs are registered and used to calculate the equivalent annuitized costs at the end of the trial. This is repeated one million times in order to generate a distribution of the life cycle costs given an investment strategy. We find that the impact of maintenance is rather small, and argue that the impact of maintenance in our model is too small due to the unrewarded replacement of components. After maintenance is performed on an older asset and certain components have been replaced, these components are unlikely to degrade soon. The transition probabilities of our simulation model depend only on the asset's age, and not the age of the components.

We recommend Liander to expand the model by fitting an asset degradation model on a component level, so that the age of each component is correct after a maintenance action. Furthermore, we also recommend that Liander puts more research into the asset degradation and investment strategy decisions, in order to make the simulation model more realistic. Nevertheless, the main steps required to go from data to an analysis of an asset's life cycle costs for an investment strategy by means of a simulation model are useful for any asset manager who wishes to improve his or her decision making. Therefore, we advise to take the following steps:

1. **Scope the asset category**. The simulation results are only reliable if the assets have similar degradation behaviour. If it is uncertain whether we can assume that certain asset categories have similar behaviour, the transition probabilities can be determined for subsamples in order to compare them.
2. **Gather the condition, failure and cost data**. Extract the data on the condition, failures and costs of the asset. The condition data should be ordinally ranked to be used in a Markov model. Continuous data can be categorised such that condition indices are available.
3. **Classify the failures**. The failures are to be classified based on whether they are preventable through maintenance or not. Preventable failures have a relation to the asset's condition, while the other failures happen irrespective of the condition assigned at an inspection.
4. **Complete condition data**. The conditions of an asset are known throughout different moments in time. Only the preventable failures should be added to the condition data. The failures are assigned to a new state.

5. **Find the transitions**. The transitions between the conditions of an asset are extracted from the condition data. Two subsequent conditions together with the time between the conditions form a transition, as long as no maintenance activities have been performed on the asset between the observations.
6. **Fit the transition probabilities**. The transitions can be used to fit transition probabilities through a maximum likelihood estimation. The transition probabilities can be stationarity or dependent on more than just the current state, but the assumptions underlying the transition probabilities should be appropriate.
7. **Find the probability of unpreventable failure**. The probability of failure resulting from the transition probabilities only covers the probability of a preventable failure. The probability of the other failures should be found as well. The other failures do not depend on the asset's condition, but may depend on other factors.
8. **Find cost parameters**. The cost data should be used to find the parameters of the cost items. The cost items may be influenced by multiple factors, and may be different for every asset.
9. **Define the investment strategy decisions**. The aspects on which to base an investment strategy decision should be defined. These aspects are the factors which influence the decision, such as age.
10. **Complete the simulation model**. The states, parameters, degradation model and investment strategy decisions should be put into a simulation model. The simulation model's logic of our research is available for reference.

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Glossary

DSO	Distribution System Operator
TSO	Transmission System Operator
EACs	Equivalent annuitized costs
LCC	Life cycle costing
LCA	Life cycle assessment
WACC	Weighted average cost of capital
IRR	Internal rate of return
GRP	Generalised Renewal Process
ONAN	Oil natural-air natural
ONAF	Oil natural-air forced
OFAF	Oil forced-air forced
ADP	Approximate Dynamic Programming

Chapter 1 Introduction

In Section 1.1 we introduce Liander and its activities. Next, we identify the core problem of our research in Section 1.2. In Section 1.3 we set out to explain the research objective, and in Section 1.4 we discuss the research questions which will help us achieve the research objective. Section 1.5 covers the methodology we follow in order to answer the research questions. Subsequently, we discuss the scope of this thesis in Section 1.6. Lastly, we explain the outline of this thesis in Section 1.7.

1.1 Liander

Liander N.V. (in short Liander) is a Distribution System Operator (DSO), which means that it is responsible for operating, maintaining and developing its energy network. This network consists of 90,000 km of electricity cables and 42,000 km of gas pipelines used to transport electricity to over 3.1 million customer connections and gas to over 2.5 million customer connections (Alliander, 2018). The catchment area of Liander covers the provinces Gelderland, Noord-Holland, Zuid-Holland, Flevoland and Friesland – as shown in Figure 1.

Liander is part of Alliander, which is a group of companies operating in the Dutch energy sector. Alliander is owned by the provinces Gelderland, Noord-Holland and Friesland, and municipalities in the catchment area of Liander's network. The province Gelderland is the largest shareholder with almost 45% ownership.

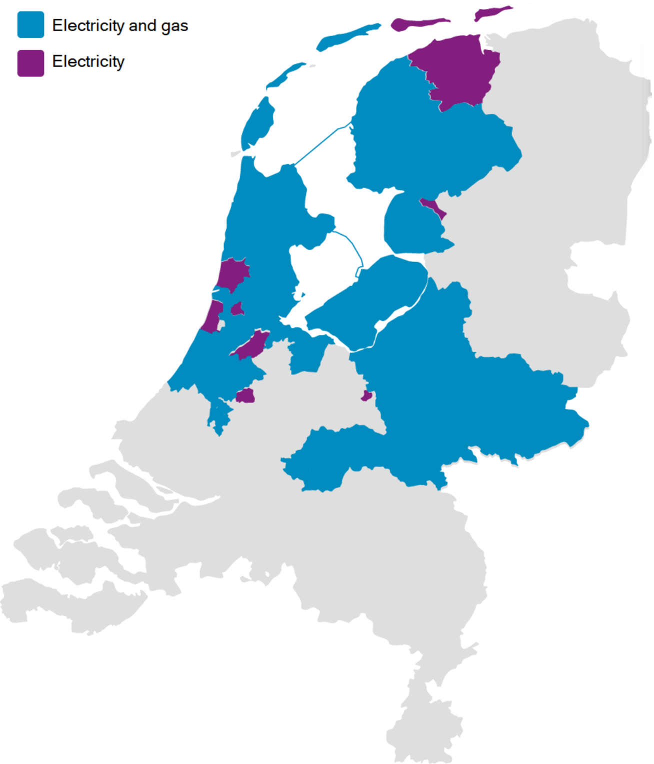

Figure 1: The catchment area of Liander (Alliander, 2019).

Liander, Enexis and Stedin are the largest Dutch regional DSOs. In the Netherlands the electricity network of a regional DSO mainly consists of a medium voltage and a low voltage network. The high voltage electricity network is almost entirely the responsibility of the nationwide Transmission System Operator (TSO) TenneT. Only small parts of it are the responsibility of the regional DSOs. An overview of the Dutch electricity network is given in Figure 2. The Dutch gas network is structured in a similar way as the electricity network. The nationwide TSO for the gas network is Gasunie Transport Services. The regional DSOs are responsible for the networks which connect customers to the network of the nationwide TSO. An overview of the Dutch gas network is given in Figure 3.

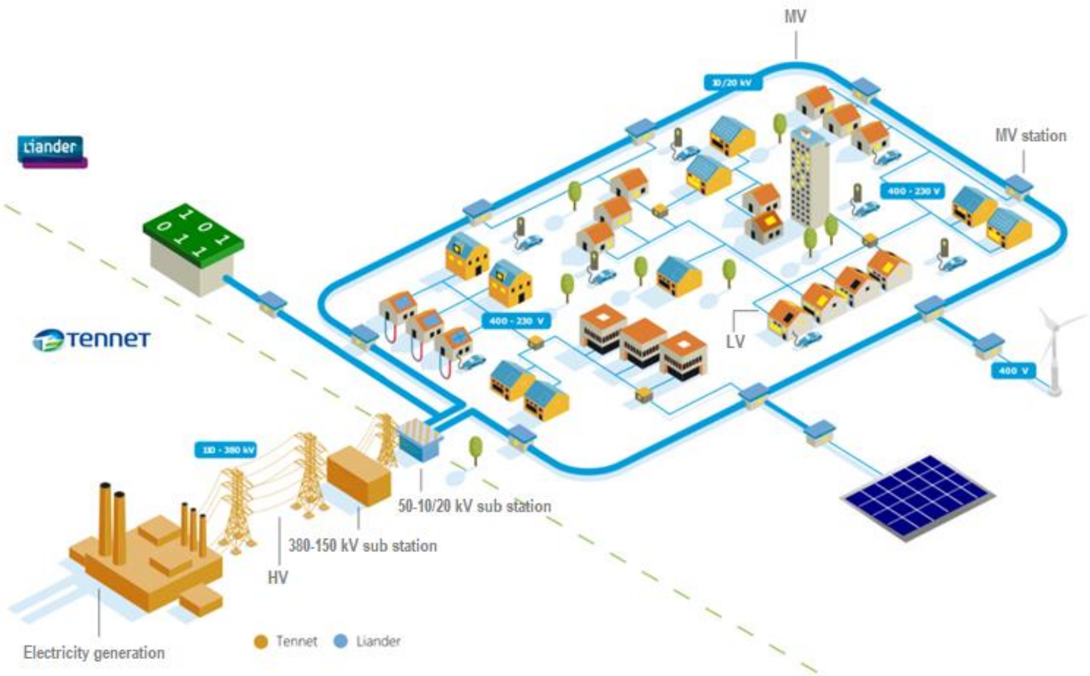

Figure 2: Overview of the electricity network.

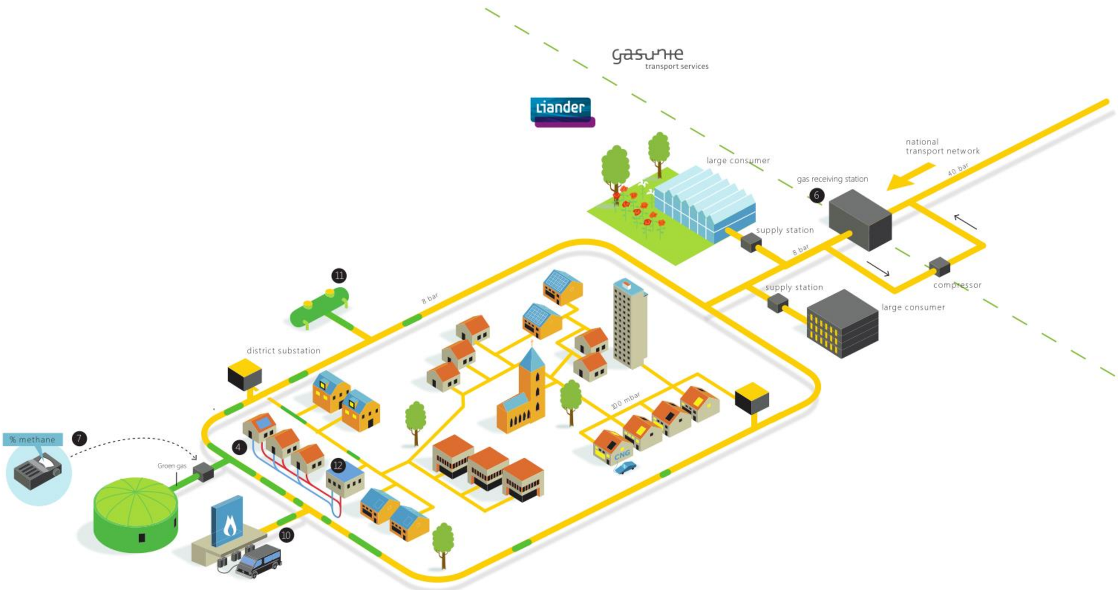

Figure 3: Overview of the gas network.

The figures show that the largest sources of power generation are connected to the customers by first the network of the nationwide TSOs and subsequently the network of a regional DSO. Smaller sources of power generation are directly connected to customers by the network of a regional DSO. The figures also show that the electricity and gas networks have a circular structure. The circular structure allows for rerouting in case a part of the network fails.

Liander’s assets can be categorised in two groups. The first and largest group consists of those which are buried and left unchanged until they are ultimately replaced. The assets are relatively cheap compared to the costs of digging, and consequently no inspections or maintenance actions are performed for them. An energy network consists of so many of them that the purchase and installation costs are important when considering grid expansion. Examples of assets belonging to this group are cables, insulating joints and gas pipelines. The second group consists of assets which are placed above ground. These are typically more expensive and cheaper to reach since digging is not required, and hence inspection and maintenance actions are performed for those assets. Examples of assets which are part of this group are switchgear and power transformers.

1.2 Problem identification

Every year Liander decides where to invest in its networks. An investment is aimed at corrective or preventive replacement, corrective or preventive maintenance, inspection, grid expansion or alterations. Liander manages a vast portfolio of heterogeneous assets and it plans to invest €844 million in their networks in 2019 (Alliander, 2019). Currently, Liander is unable to perform all investments they desire because of two reasons. First, Liander’s ambitions are limited by its available technical personnel. Second, Liander aims to facilitate the energy transition which requires a lot of investments. The energy transition refers to the liberalisation of the energy sector, an increase in decentralised energy production and changes in energy consumption (Verbong and Geels, 2007). The capacity of the electricity network has to be increased rapidly in order to facilitate these changes, though Liander does not have enough technical personnel to perform all of these investments in addition to their regular ones aimed at the conservation of the network. Because of this mismatch between demand and supply, Liander has to prioritise certain investment decisions over others.

The prioritisation process is difficult because Liander is unable to benchmark the attractiveness of an investment strategy. An investment strategy is the entire set of investment decisions for an asset from now until retirement. We argue that we are interested in the attractiveness of an investment strategy rather than a stand-alone investment for an asset, because the attractiveness of an investment decision depends on the other plans Liander has for it. If Liander wishes to replace the asset in the next year, it is probably unwise to perform preventive maintenance in this year. Figure 4 shows two examples of alternative investment strategies that make it possible to consider the impact of a change in the preventive maintenance decision at the start of 2022 given the remainder of the investment strategy. Due to the inability to benchmark an investment strategy, the prioritisation of investments process relies on expert advice. These experts have to conduct research in order to advise Liander in their investment decisions, and consequently the prioritisation process is time consuming and expensive.

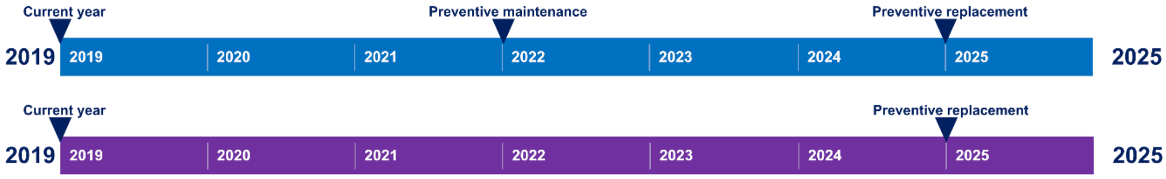

Figure 4: Alternative investment strategies.

The benchmark of investment strategies is possible if a model which is able to quantify their attractiveness exists. Unfortunately, Liander does not have such a model. It is desirable that this model would be generic, so it can be applied to investment strategies for different assets. This would enable asset managers to assess the huge and diverse amount of investment opportunities, instead of having to limit the number of opportunities which can be assessed.

An example of an asset for which it is unclear what investment strategy should be followed is the case of the circuit breakers. Liander has to decide between maintenance and preventively replacing the circuit breakers. The problem here is that Liander is unable to express the attractiveness of each alternative. Ergo, the debate about which alternative is better remains inconclusive and Liander's asset managers have to make their investment strategies based on expert opinions.

Figure 5 shows the problems identified in this section and the causal relation between them.

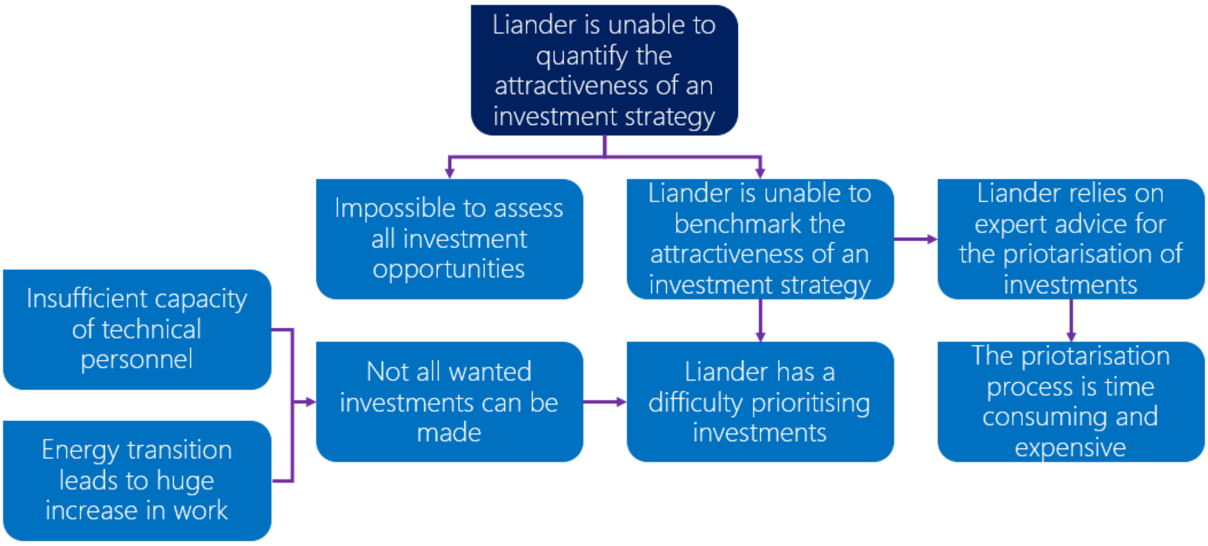

Figure 5: A graphical display of the problem cluster.

The core problem is that *Liander is unable to quantify the attractiveness of an investment strategy*.

1.3 Research objective

The core problem identified in the previous section should be targeted by the research objective. The research objective is to *build a simulation model which can assess the life cycle costs of an investment strategy*. This means that we provide insight in the life cycle costs of an asset given an investment strategy. Follow-up activities such as the optimisation of the life cycle costs by making changes in the investment strategy are neither part of the simulation model, nor our research.

A simulation model is desired because it gives insight in the possible savings of an alternative investment strategy and allows for a validation of the underlying models. The simulation model works on the principle of a Monte Carlo simulation, for which repeated random sampling is used to determine a range of possible outcomes. The advantage of repeated random sampling is that it is practical for modelling the stochastic process of asset degradation for our research. We build the simulation model for a case study on power transformers, but are unable to test whether we can make certain assumptions underlying our degradation model. We refer to our simulation model as a proof of concept, as the degradation model underlying the simulation model requires more research. Changes in the degradation model can be implemented in our simulation model without much trouble, whereas these may not be so easy to implement in an analytical model.

The measure life cycle costs is used in literature to refer to the cumulative cost of a product over its life cycle (International Electrotechnical Commission [IEC], 2014). The idea behind looking at the cumulative cost rather than individual cost items is that cost items interact. The trade-offs that are made in alternatives in the simulation model should therefore be scored on the cumulative cost, as certain individual cost items may decrease while others may increase. The simulation model only considers costs and not benefits, because the benefits are only measureable on a network scale and difficult to distribute fairly among all the assets in the network.

The research objective does not specify for which asset the simulation model should be able to assess the life cycle costs. Section 1.1 explains the difference between the assets which are buried and those which are placed on the surface. Our research focuses on the assets which are placed above ground, and, more specifically, a case study on power transformers. The reason for this is that these are inspected and maintained, and the investment strategy is consequently more complex. If we are able to quantify the costs of a complex investment strategy, the method should also be applicable to a simpler investment strategy for which inspections and maintenance actions are not relevant. The input of the simulation model is flexible, so the model can be reused for other assets. Admittedly, other assets may show other degradation behaviours than power transformers.

1.4 Research questions

As stated in the previous section, our research objective is to *build a simulation model which can assess the life cycle costs of an investment strategy*. We answer the following sub-questions in order to achieve our research objective:

<u>RQ1: How can Liander measure the life cycle costs of an asset?</u>
A method to translate cash flows into a single measure is required in order to compare strategies on life cycle costs. We investigate how Liander can measure their life cycle costs considering the characteristics of our alternatives.

<u>RQ2: Which models in literature explain the degradation behaviour of assets and to what extent are they applicable to our research?</u>
The asset degradation model should explain the changes in the condition over time and the impact of a maintenance intervention. The model should ideally be applicable to all inspection data and assets. We investigate which modelling options are available for our research.

<u>RQ3: How can Liander's data be used to fit the parameters which describe the asset degradation?</u>
The previous research question suggests an asset degradation model which explains its condition throughout its life. We focus on fitting the degradation model's parameters on Liander's data.

<u>RQ4: How well does the simulation model perform on a case study?</u>
We aim at testing whether we can use a simulation model to assess the life cycle costs of an asset. In order to do so, we build a simulation model for our case study on power transformers. The components essential to the simulation model are identified in the first three research questions. As stated earlier, we believe more research into the degradation behaviour is required. Therefore, the simulation model of the fourth research question is merely a proof of concept.

1.5 Methodology

We investigate the first research question by performing literature research. We get acquainted with the concept of life cycle costing and study the cost measures discussed in literature.

With the second research question we aim to gain insights in the modelling of degradation behaviour of an asset and its interaction with maintenance. A literature study has the potential to give new insights which may be applicable to our research. The degradation models of assets are mainly discussed in reliability engineering literature.

For the third research question we investigate methods in literature to find appropriate model parameters. The research question is answered in a hands-on manner, which means that we do not merely describe methods, but also apply them to Liander's data. The intended end results of the third research question are model parameters based on Liander's data fit through methods found in literature. The parameters can be used for our simulation model.

We answer the fourth research question by building a Monte Carlo simulation model in the programming language R, and by performing a case study on power transformers. We test the model for multiple investment strategies.

1.6 Scope

In this section we shortly introduce the investment decisions, and discuss whether they will be taken into account in our research. Besides that, we explain what constitutes an asset for our research.

Preventive and corrective maintenance is carried out to retain a system in or restore it to an operating condition (Do et al., 2015). Preventive maintenance is performed before a failure has occurred and corrective maintenance is performed after a failure has. Maintenance actions are performed on Liander's above ground assets, and for this reason both preventive and corrective maintenance will be part of our research.

Replacement refers to the activity of placing an asset for use in place of an existing one (Institute of Electrical and Electronics Engineers [IEEE], 2000). Corrective replacement is replacement after the asset to replace has failed and preventive replacement is replacement before it has failed. These investment decisions are relevant for Liander's entire asset portfolio and will be taken into account for our research.

Inspection is an examination or measurement to verify whether an item or activity conforms to specified requirements (IEEE, 2000). The asset can be monitored continuously through sensors or in discrete time by personnel. Continuous monitoring is applied to some of Liander's cables and manual inspection is applied to the more expensive assets. Investment decisions are based on the results of an inspection, and we therefore take inspections into account.

Grid expansion increases the capacity of a network. For Liander, a new part of the network can be constructed, or the current network can be replaced or restructured such that its capacity increases. The replacement of an asset is already in the scope of our research, but grid expansion has consequences for a part of the network and not just a standalone asset. Consequently, grid expansion goes beyond the scope of our research and will not be included.

An alteration is any change or addition to the asset other than ordinary repairs or replacements (IEEE, 2000). We see an alteration as an effort aimed at changing the functionality of an asset, for example adding the ability to change the volume of the TV to a remote control. Alteration efforts are not focused on conservation and therefore do not fall under the scope of our research.

The decisions regarding the scope for the investment decisions are summarized in Table 1.

Investment decision	In scope	Not in scope
Preventive maintenance	X	
Corrective maintenance	X	
Preventive replacement	X	
Corrective replacement	X	
Inspection	X	
Grid expansion		X
Alteration		X

Table 1: Investment decisions considered in our research.

We often refer to the term asset, and this term could use some clarification because of its broad definition. Investopedia (2019) defines an asset as a resource with economic value that an individual, corporation or country owns or controls with the expectation that it will provide a future benefit. This definition is quite broad and consequently a wide variety of asset types exists, for example buildings, inventory, bonds, brand names and drilling rights. A more fitting definition for our research is provided in the Netherlands technical agreement 8120, which describes the requirements for a safety, quality and capacity management system for electricity and gas network operations for Dutch DSOs and TSOs. The agreement defines asset as a physical asset necessary in order to achieve the primary objectives of the organisation (NEN, 2014). As the primary objectives of Liander are operating, maintaining and developing its energy network, we refer to the assets in Liander's network when using the term.

1.7 Thesis outline

Each research question described in Section 1.4 is answered in a chapter specifically dedicated to it. In Chapter 2 we answer the first research question by introducing the cost items and researching the procedure for expressing costs into a single measure. We aim at finding a model which is able to simulate the degradation of an asset over time in Chapter 3. This is necessary to answer the second research question. The second research question lays the foundation for the third research question, which is covered in Chapter 4. In this chapter we discuss the methods for fitting parameters of the degradation model. The ability to find model parameters and simulate an asset's life with these model parameters plays a vital role for the simulation model. We explain the simulation model in Section 5.1, and use the remainder of Chapter 5 to discuss a proof of concept of the simulation model by working out a case study. Finally, we discuss our conclusions, recommendations and limitations in Chapter 6.

Chapter 2 Cost engineering

In this chapter we investigate how Liander can measure the life cycle costs of an investment strategy. First, we introduce the concept of life cycle costing in Section 2.1, as this is the basis for the comparison of investment strategies throughout the entire thesis. In Section 2.2 we discuss the relevant cost items and in Section 2.3 we introduce the cost criteria enabling us to express the attractiveness of an investment strategy. Lastly, we provide a conclusion to this chapter by summarising the most important findings in Section 2.4.

2.1 Life cycle costing

The IEC (2014) defines life cycle costing (LCC) as a process of economic analysis to assess the costs of an asset over its life cycle or a part thereof. The purpose of life cycle costing is to support decisions on the acquisition, exploitation, rehabilitation and disposal of assets (van den Boomen et al., 2016). The IEC (2014) describes the following contributions of an LCC analysis:

- Assessment of economic viability of alternatives, for example alternative asset designs, disposal options, asset usages and maintenance policies.
- Identification of cost items and major cost drivers.
- Long-term financial planning.

While the main contribution of LCC is the assessment of alternatives, the identification of major cost items and the timing of these cost items allows organisations to financially prepare for them.

LCC is said to overcome the failures in which the initial costs were emphasised without consideration of subsequent costs (Taylor, 1981; Woodward, 1997). Decisions which are made on the basis of initial costs are unlikely to be optimal, as the commitment to a certain alternative usually leads to unconsidered costs in the future. For example, the acquisition of a machine leads to maintenance and operational costs in the future, but these are not considered if only initial costs of acquisition are taken into account. The trade-off between costs that LCC seeks to assess is shown in Figure 6. The dashed and solid lines represent two alternatives which are considered. Note that the cost categories presented in the figure are not standard for an LCC analysis. LCC focuses on economic sustainability, but it can be integrated with Life Cycle Assessment (LCA) in order to trade off economic as well as environmental impacts (Haanstra et al., 2019).

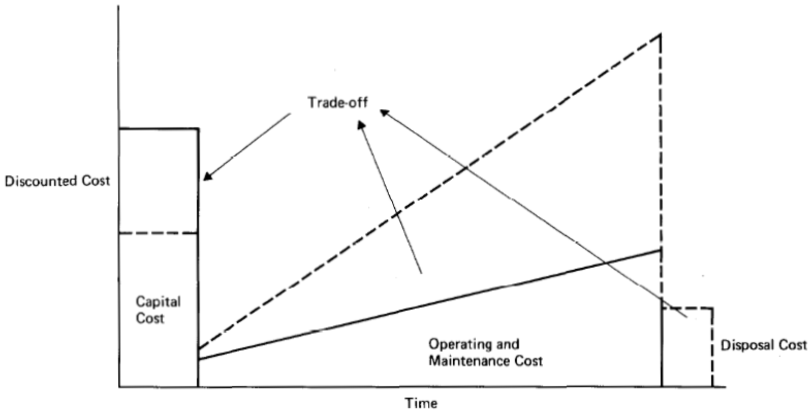

Figure 6: Trade-off of costs (Taylor, 1981).

2.2 Cost items

In this section we introduce and clarify the cost items relevant during an asset's life cycle. The following cost items can be identified: purchase costs, installation costs, (preventive and corrective) maintenance costs, inspection costs, disposal costs, failure costs and other costs.

Purchase and installation costs occur when an asset is bought and placed. These costs should involve the costs for all activities required to install it at the desired location, such as transportation costs, the asset's price, the costs of installation and the costs of testing the installation. When an asset is not new, the investment strategy can still be compared by setting the purchase costs equal to its market value and by neglecting the installation costs.

Preventive and corrective maintenance costs are costs which are incurred when attempting to improve the condition of an asset. Maintenance is only performed on assets which are above ground. Preventive maintenance is generally cheaper than corrective maintenance, because the asset is typically in a better condition and circumstances are less dangerous to the maintenance crew. An asset can be damaged due to a failure in such a way that it poses a danger to the maintenance crew, for example an asset which normally does not conducts electricity but does after a failure. The maintenance crew has to work more carefully, and consequently corrective maintenance is more expensive than preventive maintenance.

Inspections are almost exclusively performed on assets which are above ground. The inspection costs are the costs attributable to assessing their conditions. Inspections can be purely visual or test-based. Visual inspections are based on the asset's physical appearance, and test-based inspections involve tests which are aimed at determining the condition of an asset's attributes. An example of a test is the measurement of the dielectric strength of oil in oil-filled switchgear. The measurement allows for appropriate actions to be performed in case the oil is in a bad condition.

Disposal costs are made whenever the decision is made to replace the asset, whether preventive or corrective. The asset has to be uninstalled and disposed. It may still have residual value, since the material may be sold or the asset may perform another purpose. Hence, the net cash flow at the end of life may be positive.

Failure costs arise in case of a loss of functionality. The exact definition of a failure and the associated costs differ per asset. A cable either fails or not, but other assets may not function entirely as intended while not being seen as a failure.

Other costs are the costs which do not fall under the cost items mentioned above. For example, the costs of the loss of electricity due to the asset's inefficiency. These costs are important when comparing competing assets with different losses.

2.3 Cost criterion

The costs of an investment strategy should be comparable to those of another one. A cost criterion translates multiple cost items into a single measure, and we explore literature to find which cost criteria exist. First, we introduce the concept of financial discounting in Subsection 2.3.1, which is an underlying concept for all cost criteria. Second, we discuss two cost criteria in Subsection 2.3.2.

2.3.1 Financial discounting

The idea behind financial discounting is that money now is worth more than money in the future because of the lost opportunity of doing something with it now and the risk of not receiving it later. For this reason Sullivan et al. (2014) argue that a study which involves the commitment of money for an extended period should incorporate a so-called time value of money. The concept that a time value of money exists is intuitive, since borrowing and lending money usually involves an interest being paid and people thus accept that money now is worth more than money later. Sullivan et al. (2014) describe the following formulas and parameters which are generally used in literature to translate value from one moment in time to another:

$$P = \frac{1}{(1+r)^N} \times F \tag{2.1}$$

$$A = \frac{r(1+r)^N}{(1+r)^N - 1} \times P \tag{2.2}$$

$$F = \frac{(1+r)^N - 1}{r} \times A \tag{2.3}$$

r is the effective discount rate per period, N is the number of periods, A is the annuity equivalent (amount is paid at the end of every period for N periods), F is the future equivalent and P is the present equivalent.

The appropriate discount rate for discounting cash flows is debatable and depends on the context of the project which is valuated. The general view is that riskier projects require a higher discount rate, because investors would want a higher reward for the risk they are taking. However, in studies which only consider costs, it is undesirable to use a higher discount rate for riskier projects. Imagine two projects A and B with an identical negative cash flow (cost) at the same moment in the future and it is believed that project A is riskier than project B. If we apply Eq. (2.1) with a higher discount rate for project A than for project B, the present equivalent of project A is a smaller negative value than the present equivalent of project B. This shows that determining a discount rate for a project should be a careful consideration. Sullivan et al. (2014) recommend quantifying the variability of the estimated cash flows and discounting at a single rate. In other words, by incorporating the stochasticity in outcomes, the discount rate no longer needs to be changed. Most companies use their weighted average cost of capital (WACC) as the discount rate. The following formula shows how the WACC can be calculated (Sullivan et al., 2014):

$$WACC = \lambda(1-t)i_b + (1-\lambda)e_a \tag{2.4}$$

λ is the fraction of total capital obtained from debt, t is the effective income tax rate, i_b is the before-tax interest paid on borrowed capital and e_a is the after-tax cost of equity capital.

The interest rate that a company pays to its bondholders is typically lower than the returns on equity capital. This is caused by the differences in risks that a bondholder and shareholders are bearing in case the company is going through financially difficult times. Instinctively a company would be inclined to increase their debt-to-equity ratio and thus pay a lower WACC. The problem with this logic is that bondholders and shareholders alike will demand a higher return due to an increased risk.

2.3.2 Cost measuring methods

A cost measuring method describes how the cash flows are to be translated into a single criterion used to compare alternatives. Sullivan et al. (2014) describe two methods to calculate a measure to compare alternatives.

The first method is the annual worth method. This method works by calculating the annuity equivalent of all cash flows using Eq. (2.1)-(2.3). When revenues are absent, the result of summing all the annuity equivalents are the equivalent annuitized costs (EACs). In case of mutually exclusive projects, the project with the lowest EACs should be selected. An unconstrained project cannot be evaluated based on EACs, as revenues need to be present in order for the evaluation to make sense. We do not consider two methods proposed by Sullivan et al. (2014), as they only differ with the annual worth method in the moment in time to which the cash flows are translated. These are the present worth method and the future worth method.

The second method is the internal rate of return (IRR) method. The method solves for the discount rate which equates the equivalent worth of cash inflows to the equivalent worth of cash outflows. The criterion on which projects should be selected that follows from solving the aforementioned equation is the internal rate of return. For mutually exclusive projects the project with the highest IRR should be chosen. An unconstrained project should be performed if the IRR is higher than the pre-determined discount rate, which is often the WACC.

We want to evaluate mutually exclusive projects based on costs. In case of mutually exclusive projects the IRR and EACs methods may differ due to the former being an absolute method and the latter a relative method. The internal rate of return method is not suitable for our research because of three drawbacks. First, we are evaluating projects based on costs. The method is only suitable when an evaluation is based on a trade-off between costs and benefits, which is not true in our case. This by itself is enough reason not to use this method. Second, computing the IRR is too computationally extensive considering that the calculation of the IRR needs to happen for every trial. Third, the IRR is not suitable for mutually exclusive alternatives because it is a relative measure. The alternative which performs best on the relative measure may not be the best on an absolute measure, while we are interested in the alternative that performs best in absolute terms. The annual worth method does not have these drawbacks. Therefore, we express the costs in terms of the EACs criterion in our simulation.

2.4 Conclusions

Our research is based around the concept of life cycle costing, which is a method used to support life cycle decisions for asset management. The research objective, a simulation model for life cycle decisions, helps in making life cycle decisions because it assesses the impact on costs of an investment strategy.

The cost items relevant for a simulation model to assess the impact on costs have been identified in this chapter. These cost items are purchase costs, installation costs, (preventive and corrective) maintenance costs, inspection costs, disposal costs and failure costs. A description of the cost items is given in Section 2.2.

Financial discounting and cost measuring methods have been introduced in Section 2.3. Financial discounting should be incorporated in the simulation model in order to take the time value of money into account, since Liander's investment strategies can easily span a period of 60 years. A key step for financial discounting is picking a discount rate. The simulation model will automatically work with the WACC of Liander, but it is possible to change the discount rate. We translate the net present value into the annuity equivalent, so that we have the EACs. We prefer the EACs method over the IRR method for our simulation model.

Chapter 3 Asset degradation

In this chapter we discuss three models which are employed in literature to model the degradation of assets. The models are lifetime distribution, Markov chain and Lévy process models, and we discuss them in Sections 3.1, 3.2 and 3.3 respectively. In Section 3.4 we compare the models and decide which model(s) will form the basis for our simulation study.

3.1 Lifetime distribution models

Lifetime distribution models are models for which an asset can only be in a failed and a not failed condition. The degradation from not failed to failed happens at a random time to failure, and a lifetime distribution model requires finding a density function of the time to failure in order to analyse the failure behaviour of the asset. In Subsection 3.1.1 we introduce lifetime distributions. We discuss literature on how to expand a lifetime distribution model beyond the time to first failure in Subsection 3.1.2.

3.1.1 Introduction to lifetime distributions

A lifetime distribution model works by fitting a distribution for the time to failure. The model only concerns the time to first failure, after which the asset will be replaced. Some common distributions in the domain of reliability engineering are the Exponential distribution and the Weibull distribution. Larsen and Marx (2012) describe how the parameters of a distribution can be estimated by means of maximum likelihood.

$f(t)$ is the probability density function and $F(t)$ is the cumulative distribution function (Larsen and Marx, 2012). In survival analysis studies the reliability $R(t)$ is used to represent the probability of an event not having happened until time t, in our case the probability of an asset not having failed until time t. The reliability can be calculated with $R(t) = 1 - F(t)$.

3.1.2 Expanding beyond the time to first failure

A downside to a model only based on the time to first failure is that it lacks the ability to account for multiple failures per asset. However, Yañez et al. (2002) and Gunckel et al. (2015) explain how the method can be expanded to include multiple failures per asset by modelling the effect of corrective maintenance, also known as a repair. They give an overview of modelling options to model corrective maintenance in Figure 7.

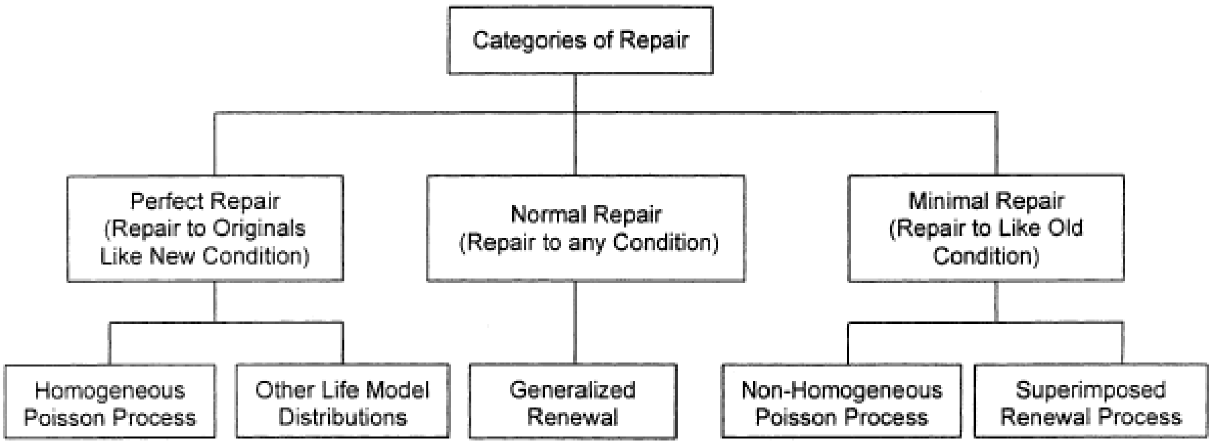

Figure 7: Overview of options for including corrective maintenance (Yañez et al., 2002).

An asset can be restored to any of the five following conditions (Yañez et al., 2002; Gunckel et al., 2015): as good as new, as bad as before, better than before but worse than new, better than new and worse than before. The categories in Figure 7, perfect repair, normal repair and minimal repair, differ in the assumption about what condition the asset is restored to after corrective maintenance.

A perfect repair process is synonymous to a repair to a condition which is as good as new. The process assumes that the different times to failure are independent and identically distributed, so subsequent times to failure for an asset are independent. This assumption seems most reasonable for cases for which the damaged part of an asset is entirely replaced. The processes which fall under the category of the perfect repairs use the same lifetime distribution to draw a new time to failure at the start and each time the asset is repaired. This is similar to saying that the age of it is zero again, even though it clearly is not. The term virtual age refers to the age that the model assumes for the asset, and it is a measure that represents its condition. An asset with a lower virtual age has a longer expected time to failure. The virtual age after a failure is reset to zero under the assumption of perfect repair.

A minimal repair is a repair after which the asset is in the same condition as before the repair. This means that its reliability is the same as it was at the moment it failed. The assumption is most reasonable for assets consisting of a lot of components of which just the one that failed is replaced or restored after a failure. In such cases there is no reason to believe that the asset's reliability has increased, because almost all components are still in the same condition as before. The virtual age assumed by the models is therefore the same as the asset's actual age, so that the reliability remains the same before and after the failure. It should be possible to draw a time to failure conditional on the current age in order to model this. This is identical to acting as if the asset has never failed until the moment of failure and drawing a new time to failure given that information.

A normal repair can restore an asset to any of the five conditions mentioned earlier, and is therefore the most flexible. However, the process in this category is also the most computationally extensive. This process is the Generalised Renewal Process (GRP). The GRP introduces a new variable known as the quality of repair (q), which determines the condition the asset is restored to after corrective maintenance. $q = 0$ corresponds to as good as new, $q = 1$ corresponds to as bad as before, $0 < q < 1$ corresponds to better than before but worse than new, $q < 0$ corresponds to better than new, i.e. an upgrade, and $q > 1$ corresponds to worse than old, i.e. a poorly executed repair. The virtual age is the product of q and the asset's real age. A higher q leads to a higher virtual age and thus a lower reliability. Due to the flexibility of GRP, it can be applied to model the effect of corrective maintenance regardless of the type of repair. Similar to minimal repair, the new time to failure after a repair is drawn conditional on that the asset has survived till the virtual age. The difference is that the virtual age is not the same in those two methods, unless $q = 1$.

Figure 8 shows the real age against the virtual age for perfect repair, minimal repair and normal repair. Perfect repair restores an asset's condition to as good as new, and the virtual age is modelled as if it zero again after each repair. The virtual age is identical to the real age for minimal repair, such that the reliability after a repair is the same as before a repair. The normal repair, also known as GRP, can restore an asset to any condition. The GRP in Figure 8 is modelled such that the asset is restored to a condition which is better than before but worse than new, since the virtual age is lower than the virtual age of the minimal repair and higher than the virtual age of the perfect repair. Note that a different q than the q that corresponds to better than before but worse than new, which is $0 < q < 1$, would lead to a different plot of real against virtual age.

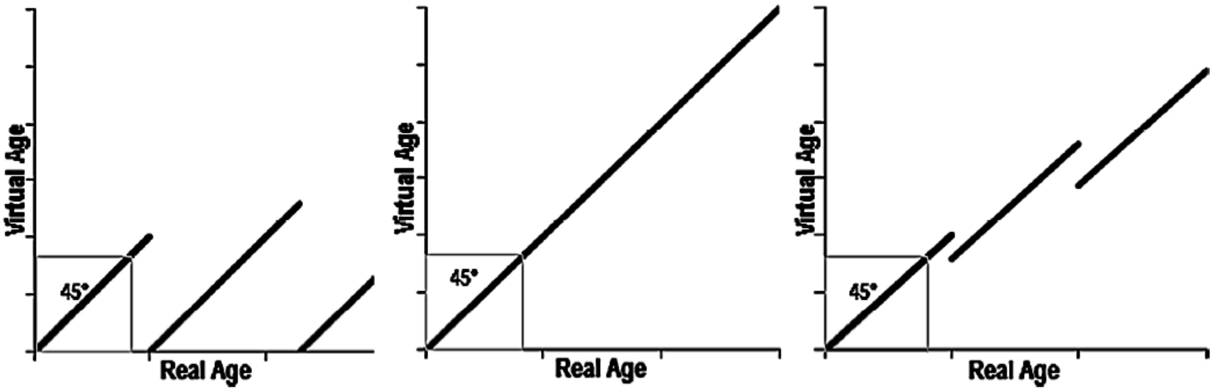

Figure 8: From left to right: perfect repair, minimal repair and normal repair - real against virtual age (Gunckel et al., 2015).

The procedure of fitting a lifetime distribution becomes more cumbersome if corrective maintenance is included. Instead of only data on the time to first failure, data on the time to the second and subsequent failures are also available. As stated earlier, the GRP is the most computationally extensive option to include corrective maintenance. The process introduces a new variable q which also has to be determined by fitting a probability distribution. Yañez et al. (2002) and Gunckel et al. (2015) describe methods which can be used to perform a maximum likelihood estimation of the parameters for a Weibull distribution for the perfect repair, minimal repair and GRP. In case of GRP, this includes an estimation of the quality of repair parameter q.

3.2 Markov chain models

The degradation of assets can be measured or observed. A range of measurements or certain characteristics of observations can be used to assign a state to the asset which indicates its condition. A Markov chain model can subsequently be used to describe the degradation of the asset. In this section we introduce Markov chains.

A Markov chain is a discrete-time stochastic model in which an asset can be in States $1, \ldots, N$. Every discrete time interval, $t = 0,1, \ldots$ the asset can change to another state or remain in its current state. The state at time t is X_t. A stochastic process is said to have the Markovian property if $P(X_{t+1} = j | X_0 = k_0, X_1 = k_1, \ldots, X_{t-1} = k_{t-1}, X_t = i) = P(X_{t+1} = j | X_t = i)$ for $t = 0,1, \ldots$ and every sequence $i, j, k_0, k_1, \ldots, k_{t-1}$ (Häggström, 2002). This means that the probability of going to a certain state in the next period is independent of the states the asset was in prior to the current state. The probabilities of going from one state to another state are stationary if they do not change over time, so if $P(X_{t+1} = j | X_t = i) = P(X_1 = j | X_0 = i)$ for all $t = 1,2, \ldots$. First, we discuss stationary Markov models. Afterwards, we discuss non-stationary Markov models.

A transition matrix with stationary transition probabilities between four states looks as follows:

$$P = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & p_{1,4} \\ p_{2,1} & p_{2,2} & p_{2,3} & p_{2,4} \\ p_{3,1} & p_{3,2} & p_{3,3} & p_{3,4} \\ p_{4,1} & p_{4,2} & p_{4,3} & p_{4,4} \end{bmatrix} \end{array}$$

With $p_{ij} \geq 0$ for all i and j, and $\sum_{j=1}^{4} p_{i,j} = 1$ for all i. $p_{i,j}$ is the probability of going from State i to State j. A state is absorbing if it is impossible to leave the state once entered, so State i is absorbing if $p_{i,i} = 1$. Figure 9 shows a state transition diagram for the transition matrix P. Note that not all probabilities are shown, which indicates that not all transitions are possible. State 4 is absorbing and States 1, 2 and 3 are transient, which means that the system is not able to return to these states from every state. In this case the system cannot return to States 1, 2 and 3 from State 4.

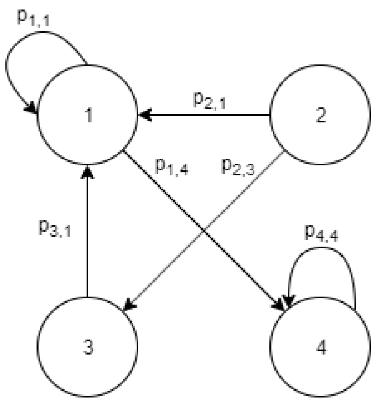

Figure 9: State transition diagram.

P describes the transition probabilities over a single time interval. P^n describes the transition probabilities over n time intervals. A four-state transition matrix over a period of n intervals looks as follows:

$$P^n = \begin{array}{c c} & \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array} & \begin{bmatrix} p_{1,1}^n & p_{1,2}^n & p_{1,3}^n & p_{1,4}^n \\ p_{2,1}^n & p_{2,2}^n & p_{2,3}^n & p_{2,4}^n \\ p_{3,1}^n & p_{3,2}^n & p_{3,3}^n & p_{3,4}^n \\ p_{4,1}^n & p_{4,2}^n & p_{4,3}^n & p_{4,4}^n \end{bmatrix} \end{array}$$

P^n is the nth power of matrix P, which means that its calculation requires matrix multiplication. This means that $(p_{i,j})^n$ is not by definition equal to $p_{i,j}^n$. The following equations shows how P^n can be used to calculate the expected distribution after n intervals E with the initial distribution C (Häggström, 2002):

$$E = CP^n \tag{3.1}$$

E, P and C are matrices, so first P^n can be calculated with matrix multiplication and the result can subsequently be matrix multiplied with C. C has dimensions $1 \times r$ and P has dimensions $r \times r$. P^n then also has dimensions $r \times r$. E consequently has dimensions $1 \times r$. Applying Eq. (3.1) to the four-state Markov chain example looks as follows:

$$\begin{aligned} [e_1 \quad e_2 \quad e_3 \quad e_4] &= [c_1 \quad c_2 \quad c_3 \quad c_4] \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & p_{1,4} \\ p_{2,1} & p_{2,2} & p_{2,3} & p_{2,4} \\ p_{3,1} & p_{3,2} & p_{3,3} & p_{3,4} \\ p_{4,1} & p_{4,2} & p_{4,3} & p_{4,4} \end{bmatrix}^n \\ &= [c_1 \quad c_2 \quad c_3 \quad c_4] \begin{bmatrix} p_{1,1}^n & p_{1,2}^n & p_{1,3}^n & p_{1,4}^n \\ p_{2,1}^n & p_{2,2}^n & p_{2,3}^n & p_{2,4}^n \\ p_{3,1}^n & p_{3,2}^n & p_{3,3}^n & p_{3,4}^n \\ p_{4,1}^n & p_{4,2}^n & p_{4,3}^n & p_{4,4}^n \end{bmatrix} \end{aligned}$$

Markov chain models can be used to assess the performance of an investment strategy. The investment strategy first stipulates when an inspection should be performed and subsequently what action should be chosen knowing the state of the asset. This action can be to do nothing, to perform maintenance or to replace the asset. The state changes depending on the action chosen.

Up till this point only stationary Markov models have been discussed. However, the Markovian property underlying stationary Markov models may not be a realistic assumption for modelling certain stochastic processes, especially when modelling asset degradation. An asset condition is likely to enter a state near the boundary with the preceding state before moving through the interval over time until it crosses the other boundary (Black et al., 2005). This means that the probability of going to another state is likely to increase with the number of time intervals spent in a state. A semi-Markov model relaxes the Markovian property, which means that the transition probabilities depend on the number of time intervals an asset has spent in a state for semi-Markov models.

The model proposed by Black et al. (2005) only allows for a transition to the current and next state. The probability of going from State i to State $i+1$ during the mth time interval after entering State i is $p_{i,i+1}(m)$. This means that the asset has been in State i for $m-1$ consecutive time intervals. The probability of an asset following a certain route is more difficult to calculate than for the stationary Markov model. For example, the probability of an asset starting and staying in State 1 for three time intervals and going to States 2 and 3 in the time intervals after that is $p_{1,1}(1) \times p_{1,1}(2) \times p_{1,1}(3) \times p_{1,2}(4) \times p_{2,3}(1)$.

Black et al. (2005) model the time spent in State i as a stochastic variable with probability density function $f_i(t)$ and cumulative density function $F_i(t)$. The probability that the asset is still in State i after time t is $R_i(t)$, which is defined as $1 - F_i(t)$. The unconditional probability of an asset leaving State 1 during the third time interval is $F_1(3) - F_1(2)$, as it should degrade before the third time interval, but not before the second. The unconditional probability of an asset staying in State 1 during the third interval is $R_1(3)$, as it should not degrade before the third time interval, and thus also not the second time interval. Logically, if an asset does not degrade before the third time interval, it also does not degrade before the second time interval. The probability of going from State i to State $i+1$ in the mth time interval given that it is in State i after $m-1$ time intervals is calculated as follows (Black et al., 2005):

$$p_{i,i+1}(m) = \frac{F_i(m) - F_i(m-1)}{1 - F_i(m-1)} \tag{3.2}$$

Going from State i to State $i+1$ is identical to leaving State i, as it is only possible to go to the current and next state. The advantage of fitting a probability density function to the time spent in a state is that a few parameters can describe the probability of remaining and leaving the state for all m.

The semi-Markov transition probabilities can be used to model the degradation after a replacement or maintenance action. The asset spends the first period in a certain state after a replacement or maintenance action brought it there. For example, a new asset starts in a state which is as good as new. The semi-Markov transition probabilities can be used to model the degradation of the asset to a worse state. A maintenance action restores the condition of the asset, and the same degradation process repeats. The semi-Markov model has time-dependent transition probabilities, but not necessarily age-dependent transition probabilities. As the asset's condition is restored after a maintenance action, the time spent in the state is reset. Consequently, the probability of degradation is not increasing as the age increases. Therefore, the transition probabilities could ideally be expressed as a function of the time spent in a state and the age of the asset:

$$p_{i,i+1}(m, age) = \frac{F_i(m) - F_i(m-1)}{1 - F_i(m-1)} \times G(age) \tag{3.3}$$

This approach has not been investigated by other researchers to the best of our knowledge. The reason for this may be that the model relies on too many parameters which are difficult to estimate.

3.3 Lévy process models

Lévy processes are continuous-time stochastic processes with independent and stationary increments, which means that the probability distribution of the increments $X_{t+h} - X_t$ depends only on h for all t (van Noortwijk, 2009). It is possible to make discrete jumps as well as continuous random walks with Lévy processes. A well-known example of a Lévy process is the Wiener process, which assumes that the increments have a Normal distribution with $\mu = 0$ and $\sigma^2 = h$. The increments of the degradation level are modelled with non-decreasing distributions such as the compound Poisson process and the Gamma processes, as this ensures that the quality level decreases over time (Yang & Klutke, 2000). Compound Poisson processes can be used to model degradation due to discrete shocks and Gamma processes can be used to model fatigue-degradation. A measurement can be performed at an inspection, and this measurement is linked to a degradation level.

Figure 10 shows a random path for the degradation level X_t between the moment the asset starts degrading and the moment of failure. The model assumes that $X_0 = 0$, and that L is the degradation level at which the asset fails. As long as $X_t < L$ the asset is in the working zone, and if at some moment in time $X_t \geq L$ it stops working and has failed. Moments t_1 and t_2 could be moments of inspection with degradation levels X_{t_1} and X_{t_2} respectively. Random paths can be generated starting from X_{t_1} and X_{t_2} in order to approximate a distribution of the time to failure. This distribution should form the basis for the investment decision.

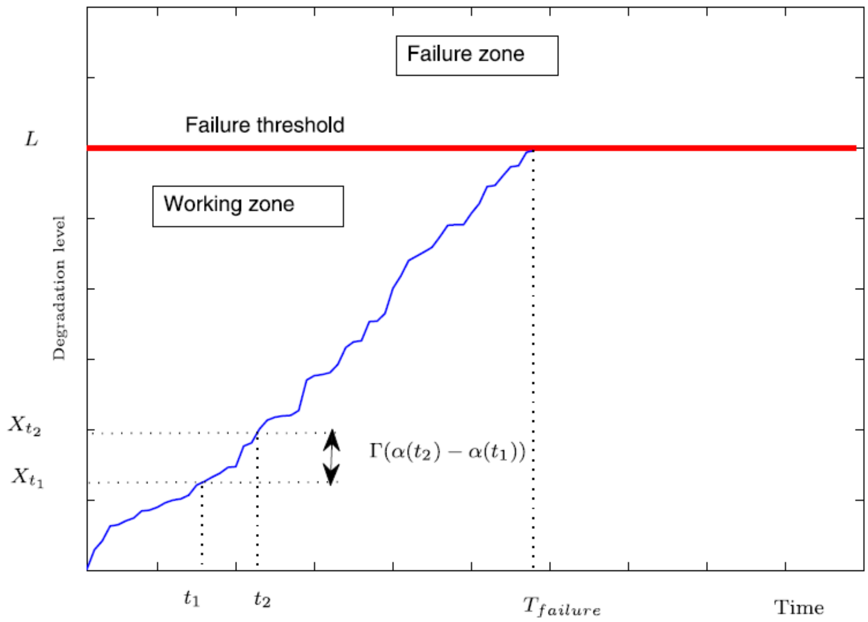

Figure 10: A random path for the asset degradation level X_t (Do et al., 2015).

3.4 Conclusions

The three asset degradation models described in literature can be used in a simulation model. First, we summarise the models presented in this chapter. Afterwards we compare the models and choose the model which is most appropriate.

A lifetime distribution model is built around a probability density function of the time to failure. The impact of corrective maintenance can be included through modelling a virtual age of the asset after a failure.

A Markov chain model is a discrete-time stochastic model in which the condition of an asset is a stochastic variable. Each time interval an asset has certain transition probabilities of remaining in the current state or going to another state. A Markov chain model with stationary transition probabilities follows the Markovian property, which dictates that the probability of going to a certain state depends only on the current state. Semi-Markov models relax the Markovian property and have transition probabilities which depend on the number of time intervals an asset has spent in a state as well as the current state.

Lévy process models are continuous-time stochastic processes with independent and stationary increments. The model can be used in a simulation by generating a random path for a measureable property of an asset for which the increment distribution is fit based on historical data.

The models differ in their approach to the degradation of assets as well as the time. Lifetime distributions describe the degradation between an operating and a failed state in continuous time. A Markov chain can incorporate multiple conditions in discrete time, and it can be used on ordinally ranked and continuous data. The continuous data should be grouped for them to be usable for a Markov chain model. The degradation in Lévy processes is modelled as a continuous process in which the asset condition can take any value higher than the starting level.

The group of assets for which inspection and maintenance is relevant, is placed above ground. Certain inspections of Liander measure a property of an asset in order to get to know the condition, while other inspections are visual and subjective indications of its condition. The measurements may take any variable, while the subjective indications are ordinally ranked. Lifetime distributions are too limited to model the degradation of these assets, as more than two conditions are relevant which these distributions are unable to capture. A Markov model would be able to incorporate the ordinal data as states. Measurements can be split into states by grouping the measurements within certain ranges. Lévy processes can be applied to the measurement data, but not to the ordinally ranked data.

We choose to model the asset degradation with a Markov model, as the Markov model is applicable to the different types of inspection data of Liander. In the next chapter we investigate how we find appropriate transition probabilities.

Chapter 4 Fitting model parameters

We are interested in fitting model parameters which are representative for an asset's degradation. In Section 4.1 we describe the available data to fit transition probabilities. We fit them and test if the they are age-dependent in Section 4.2. The next step is to test whether the transition probabilities are dependent on the time spent in a state, which we discuss in Section 4.3. In Section 4.4 we explain how the probability of failure is determined and in Section 4.5 we test the accuracy of our estimations. We conclude this chapter in Section 4.6. Overall, we use this chapter to describe the road from data to final transition probabilities used for the case study.

4.1 Data description

Liander performs inspections on their above ground assets. The inspections reveal the asset condition, and inspectors assign the condition codes 9, 6 or 1. The Conditions 9, 6 and 1 are interchangeable with the words good, moderate and bad respectively. Unsurprisingly, new assets start in Condition 9 and subsequently degrade to worse conditions. An inspection reveals the condition of an asset, and Liander subsequently decides whether or not to perform maintenance and when to inspect again. A maintenance action is aimed at restoring the asset to a higher condition, from which it degrades to worse conditions again.

The condition codes are registered in Liander's database for inspection data. Inspections and maintenance actions are performed on the asset classes power transformers and switchgear. Inspectors assign condition codes to components as well as the overall condition of the power transformer. We focus on the overall condition code assigned to power transformers, because data on component replacements are lacking. The overall condition code is decided upon by means of the expert opinion of the inspector, and is therefore subjective.

The data set contains information on inspections and maintenance actions of 655 power transformers. The power transformer failures are registered up to 2015 in a different database. The condition codes have been registered actively only in the last few years. Figure 11 shows the number of registered inspections per month. We can observe that only few inspectors assign condition codes before 2014. Inspections prior to January 2012 are disregarded and also not shown in Figure 11, because they are only a fraction of the total number and deemed too far before the broad adoption of assigning condition codes at an inspection.

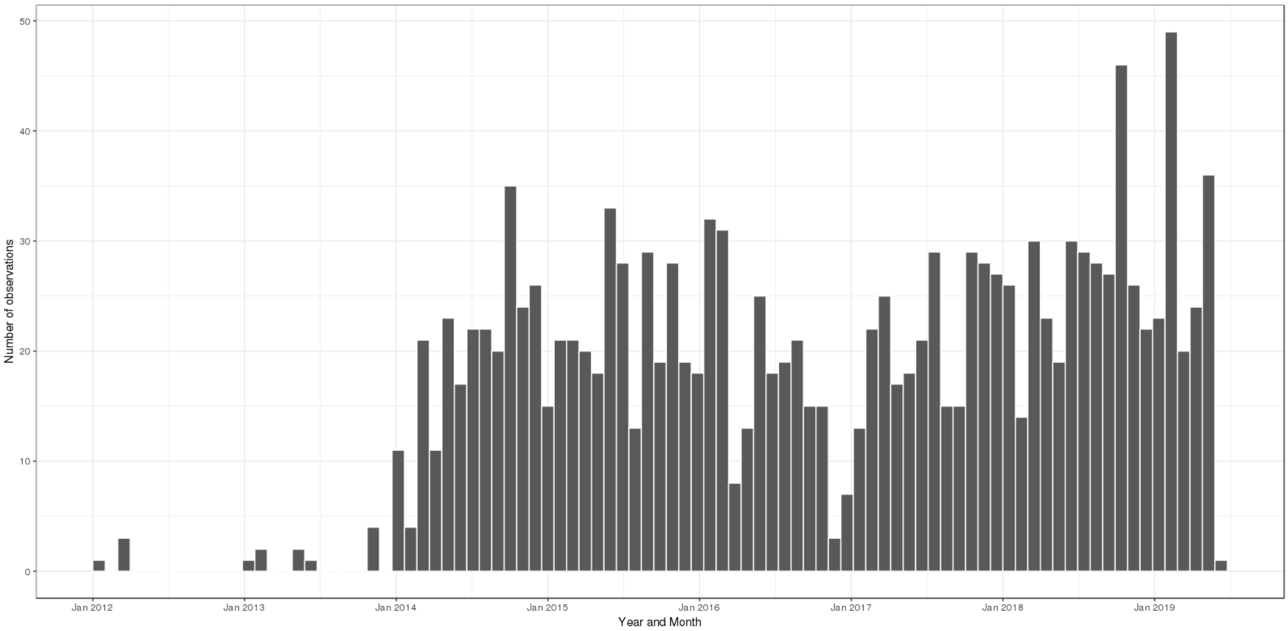

Figure 11: Number of observations per month between 2012-2019.

A transition between condition codes is never observed as soon as it happens, we only know a transition has occurred sometime between two inspections. Failures are an exception to this statement, because Liander can monitor an asset failure without an inspection. For the other conditions the data show the condition has changed or remained the same, but it does not tell us when the condition has changed. This type of data is referred to as interval-censored data, as the data only show in which interval an event has taken place and not exactly when. Figure 12 shows examples of this type of data for three assets. When condition code 9 is assigned to the asset, a blue bar is placed on the timeline. The same holds for condition codes 6 and 1 with the grey and purple bars respectively. Asset 1 is inspected and revealed to be in Condition 1 and in Condition 9 right afterwards. Then, after a period of time a new inspection is performed and the asset is observed to still be in Condition 9. Asset 2 is in Condition 9 at first and in Condition 1 after a while, and Asset 1 is in Condition 9 two inspections in a row and in Condition 6 at the next inspection. The difficulty here is that we do not know exactly when transitions have occurred and even how many. Asset 2 may have jumped from Condition 9 to Condition 1 through Condition 6 or immediately to Condition 1.

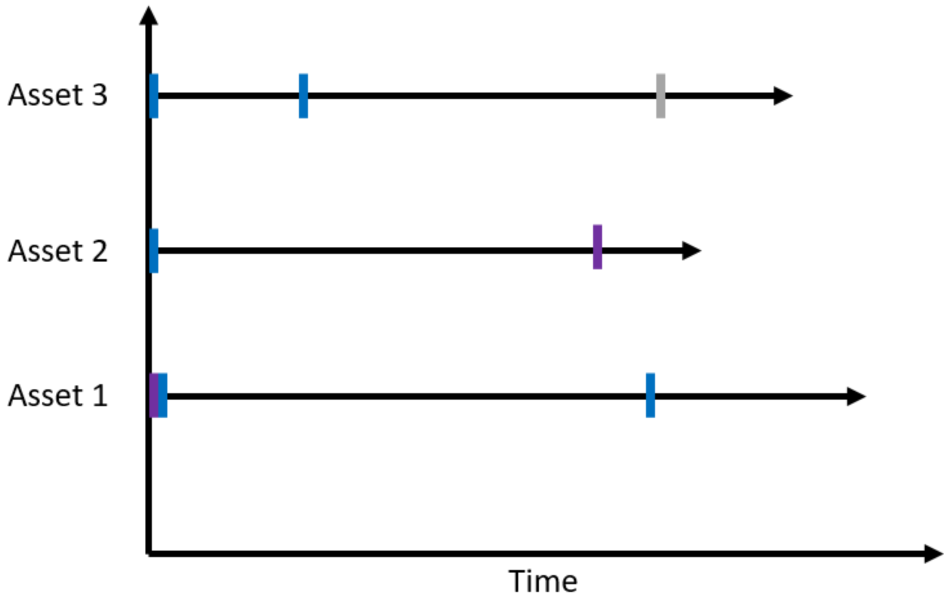

Figure 12: Visual representation of interval-censored data (blue, grey and purple represent Conditions 9, 6 and 1 respectively).

An additional difficulty to the interval-censored data is Liander's inconsistent maintenance registration. Asset managers claim that maintenance activities are not always registered, and consequently it is unclear in which cases the observed data are influenced by maintenance activities. A degradation model is aimed at modelling the degradation of the asset without any interventions. When the data are filled with transitions which are influenced by maintenance actions, the observed transitions are not representative for the degradation. Whenever the maintenance data are available, we remove the transition influenced by maintenance. Furthermore, we remove transitions to a better condition, as the transition is most likely caused by unregistered maintenance. However, we must acknowledge that the transition may in some cases be accredited to the subjectivity of the inspector. This means that the removed transitions may not have always been caused by maintenance. The poor data quality is acceptable, because we can use the data to find a method for fitting model parameters. The method can be applied by Liander once they gathered more reliable data. Having discussed the available data and the data quality, we can now set out to find the transitions and the transition probabilities.

4.2 Stationary transition probabilities

In this section we investigate whether stationary transition probabilities are appropriate for the degradation modelling of Liander's assets. In Subsection 4.2.1 we estimate stationary transition probabilities and in Subsection 4.2.2 we test whether this stationarity may be assumed.

4.2.1 Estimating stationary transition probabilities

In this subsection we discuss how we estimate stationary transition probabilities based on Liander's data described in the previous section. We estimate the probabilities for a one-year period.

As mentioned in the previous section, the conditions assigned to power transformers are 9, 6 and 1. Additionally, a power transformer can completely lose its functionality due to a failure. Conditions 9, 6 and 1 correspond to States 9, 6 and 1 respectively. State 0 corresponds to an asset failure. This results in the following state space, $S = \{9,6,1,0\}$. State 0 is an absorbing state, as an asset cannot escape the state without interference. Table 2 shows the number of power transformer with a certain number of observations.

Number of observations	Number of power transformers
0	56
1	112
2	141
3	129
4	93
5	68
6	37
7	12
8	4
9	2
10	1
Total	655

Table 2: Number of observations per power transformer.

A transition is defined by the observation before, the observation after and the time between the observations. We determine the time between observations by taking the number of days and dividing it by 365. The number resulting from this calculation is rounded to the nearest quarter, e.g. 2.45 years becomes 2.50 years. Power transformers with zero or one observations yield no transitions, because we need two observations for a transition. We find a total of 843 transitions of which 214 transitions are from a worse condition to a better condition. As discussed in the previous section, we remove these transitions and have 629 remaining transitions. Table 3 shows the number of transitions from each state to another.

From \ To	9	6	1	0	Total
9	149	119	45	1	314
6	0	194	73	1	268
1	0	0	45	2	47
0	0	0	0	0	0
Total	149	313	163	4	629

Table 3: Overview of transitions between states.

Only four transitions have the state of failure as the end state, while a total of thirty-one failures have occurred in the period 2012 to 2015. We only consider the period 2012 to 2015 because the inspection data start in 2012 and the failure data stop in 2015. The number of failures which could be linked to a transition is low for two reasons. First, the condition before a failure is not always known, meaning that we do not know the transition between a condition to the state of failure. Second, not all failure causes are considered in the condition code assigned at an inspection. Only the failure causes which are monitored at an inspection should be considered for the transitions, as the start state is not relevant for the failure causes which are not monitored. We can use the transitions to estimate transition probabilities. Hoskins et al. (1999) apply maximum likelihood and least squares approaches to estimate stationary transition probabilities with transitions spanning over different time lengths. It is important that the time length is taken into account for the probability estimation, because the length of a transition influences the probability. The longer a transition takes, the higher the probability of severe degradation. Both approaches of Hoskins et al. estimate a transition matrix $\hat{P}$. Maximum likelihood does this by maximising the probability of the observed transitions. In Chapter 3 the probability of a transition from State i to State j in n time intervals is denoted by $p_{i,j}^{n}$. This probability can be derived from P^n by finding the probability of going from State i to State j. We can calculate the probability of all 629 transitions for a given P, because we can calculate P^n to find $p_{i,j}^{n}$. If we assume independence between transitions, we can calculate the likelihood that a transition matrix P caused the transitions (Hoskins et al., 1999):

$$L(P) = L_1(P) \times L_2(P) \times \ldots \times L_N(P) = \prod_{k=1}^{N} L_k(P)$$

$L_k(P)$ is the probability of the kth transition and N is the total number of transitions. Besides P, $L_k(P)$ depends on the i, j and n of transition k. The likelihood $L(P)$ becomes extremely small for a high number of transitions N, and consequently it makes more sense to take the log-likelihood, $\log L(P)$ (Hoskins et al., 1999):

$$log\ L(P) = \log\ L_1(P) + \log\ L_2(P) + \ldots + \log\ L_N(P) = \sum_{k=1}^{N} \log L_k(P)$$

Note that the same transition matrix $\hat{P}$ maximises both the likelihood and the log likelihood function, so the outcome is the same irrespective of the function that is used. We apply the log likelihood as the objective function and use a non-linear solver algorithm in R.

Least squares chooses $\hat{P}$ such that the squared distance between the transitions and the predictions is minimised. The transitions k are to be aggregated based on the time between inspection n and ordered by State i before and after.

Years	9	6	1	0
0.25	27	25	5	0
0.50	25	26	5	0
0.75	35	19	7	0
1.00	33	16	8	0
1.25	27	20	1	0
1.50	16	22	5	0
1.75	18	26	3	0
2.00	18	24	4	0
2.25	12	20	3	0
2.50	15	8	2	0
2.75	11	13	2	0
3.00	10	12	1	0
3.25	12	9	0	0
3.50	7	9	0	0
3.75	13	8	0	0
4.00	12	4	1	0
4.25	1	2	0	0
4.50	2	2	0	0
4.75	2	1	0	0
5.00	4	1	0	0
5.25	2	1	0	0
5.50	3	0	0	0
5.75	2	0	0	0
6.00	1	0	0	0
6.25	0	0	0	0
6.50	0	0	0	0
6.75	2	0	0	0
7.00	2	0	0	0
7.25	2	0	0	0
Total	314	268	47	0

Table 4: Start state before an n-year transition.

Years	9	6	1	0
0.25	14	30	13	0
0.50	10	30	15	1
0.75	20	23	17	1
1.00	17	23	17	0
1.25	9	28	11	0
1.50	7	25	11	0
1.75	6	23	18	0
2.00	11	21	13	1
2.25	4	22	9	0
2.50	4	16	5	0
2.75	6	11	9	0
3.00	6	8	8	1
3.25	4	12	5	0
3.50	7	7	2	0
3.75	6	11	4	0
4.00	4	10	3	0
4.25	1	2	0	0
4.50	0	3	1	0
4.75	1	2	0	0
5.00	4	1	0	0
5.25	1	2	0	0
5.50	2	0	1	0
5.75	1	1	0	0
6.00	1	0	0	0
6.25	0	0	0	0
6.50	0	0	0	0
6.75	1	1	0	0
7.00	0	1	1	0
7.25	2	0	0	0
Total	149	313	163	4

Table 5: End state after an n-year transition.

Table 4 shows the number of assets in a certain state before the transition and Table 5 shows the number of assets in a state after the transition. For example, of the transitions spanning over a two-year period, eighteen are in State 9 at the start and eleven are still in State 9 after the two years. We can calculate the expected number of assets E per state with Eq. (3.1), knowing the transition matrix P and the start population C. The start populations are ordered per year in Table 4. This allows us to calculate the squared difference between the observed population and the expected population for State i after a transition of n time intervals (Hoskins et al., 1999):

$$S(P) = \sum_t \sum_j \left(e_{t,j} - n_{t,j}\right)^2$$

$e_{t,j}$ is the expected number of observations in State j at time t. $n_{t,j}$ is the actual number of observations in State j at time t. For example, if the expected population in State 9 after three years is ten and the observed population is two, the squared distance for this state and transition time is $(10-2)^2$.

Least squares estimates transition matrix $\hat{P}$ such that the total squared distance is minimised. We apply the total squared distance as the objective function and use a non-linear solver to find the transition matrix which minimises the objective function. Appendix A describes the derivation of a transition probability matrix using a non-linear solver in more detail. We find that the transition probabilities converge to three digits after the decimal point regardless of the starting values. The maximum likelihood and least squares approaches result in the following transition probabilities:

$$\hat{P}_{maximum\ likelihood} = \begin{array}{c} \\ 9 \\ 6 \\ 1 \\ 0 \end{array} \begin{array}{c} \begin{array}{cccc} 9 & 6 & 1 & 0 \end{array} \\ \begin{bmatrix} 0.684 & 0.225 & 0.090 & 0.001 \\ 0.000 & 0.849 & 0.148 & 0.003 \\ 0.000 & 0.000 & 0.981 & 0.019 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{bmatrix} \end{array}$$

$$\hat{P}_{least\ squares} = \begin{array}{c} \\ 9 \\ 6 \\ 1 \\ 0 \end{array} \begin{array}{c} \begin{array}{cccc} 9 & 6 & 1 & 0 \end{array} \\ \begin{bmatrix} 0.506 & 0.256 & 0.228 & 0.009 \\ 0.000 & 0.895 & 0.101 & 0.004 \\ 0.000 & 0.000 & 0.908 & 0.092 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{bmatrix} \end{array}$$

We observe that the transition probabilities per year differ substantially. $p_{1,1}$ and $p_{1,0}$ differ more than five percent, $p_{9,1}$ differs more than ten percent and $p_{9,9}$ differs more than fifteen percent. We believe the maximum likelihood results are superior to the least squares results for two reasons. Firstly, the least squares result gives a high probability to $p_{9,1}$, while this transition is observed less than half as often in the one-year transitions. Secondly, the least squares method does not use the information of each individual transition. It rather uses the aggregated data with the states before and after a transition. The individual transition is disregarded, and this could lead to illogical probabilities. Appendix B confirms this suspicion by comparing the transition probabilities based on non-imputed and imputed data. The transition probabilities estimated with the least squares method differ substantially, while the transition probabilities estimated with the maximum likelihood method do not. Everything considered, we prefer the maximum likelihood approach over the least squares approach, and will use it in the next subsection to test for stationarity of transition probabilities.

A difference between the transitions observed in reality and those assumed possible by the maximum likelihood estimator exists for the transitions to a state of failure. As stated in Section 4.1, the power transformer failures are observed at the moment they happen. The method for estimation is applicable to interval-censored data, which means that we do not know when a transition happens. Therefore, the maximum likelihood estimator assumes that a failure can happen any time between the start and end of the transition, while the transition is certain to happen in the last quarter of the transition period. We adjust the estimator such that a failure can only happen in the final quarter. The distribution E in the quarter prior to the failure can be calculated with Eq. (3.1):

$$E = CP^{n-1}$$

n is the number of quarters in the transition period and C is the starting distribution. For example, if the asset starts in State 9, the starting distribution is $[1 \quad 0 \quad 0 \quad 0]$. We calculate E, which is the distribution in the quarter prior to a failure. We can use this matrix as our starting distribution C to calculate the distribution E after another quarter of degradation. However, we know the asset has not failed yet. Therefore, we calculate the starting distribution conditional on no failure in the first $n-1$ quarters with the following equation:

$$[c_9 \quad c_6 \quad c_1 \quad c_0] = \left[\frac{e_9}{1-e_0} \quad \frac{e_9}{1-e_0} \quad \frac{e_1}{1-e_0} \quad 0\right]$$

The starting distribution C in the quarter prior to a failure is now known and we can use it to calculate the distribution E after another quarter of degradation with the following equation:

$$E = CP$$

E is the distribution after another quarter of degradation. The matrix E is structured as follows: $[e_9 \quad e_6 \quad e_1 \quad e_0]$. e_0 is the probability of our transition to the state of failure, where the failure takes place in the last quarter. If transition k is a transition to the state of failure, we follow the steps described above to calculate e_0. $L_k(P)$ is then set equal to e_0 rather than $p_{i,j}^n$ when estimating $\hat{P}$ with maximum likelihood. The estimation results in the following transition probabilities:

$$\hat{P}_{maximum\ likelihood} = \begin{array}{c} \\ 9 \\ 6 \\ 1 \\ 0 \end{array} \begin{array}{c} \begin{array}{cccc} 9 & 6 & 1 & 0 \end{array} \\ \begin{bmatrix} 0.686 & 0.221 & 0.092 & 0.001 \\ 0.000 & 0.850 & 0.148 & 0.002 \\ 0.000 & 0.000 & 0.979 & 0.021 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{bmatrix} \end{array}$$

The difference between the estimated probabilities using both maximum likelihood approaches is only subtle. We prefer the estimator applied above, as it best matches reality.

On a final note, the probability of failure is underestimated because of two reasons. First, as mentioned earlier in this section, we only consider failures due to causes which are monitored at inspections in order to find the probabilities of going to State 0. Failures due to causes which are not monitored at an inspection are also failures, and should therefore be incorporated in the calculation of the probability of failure. Second, the relative frequency of transitions to a state of failure is lower due the fact that we only have failure data up to 2015, while the other transitions are considered up to the present. A smaller period means fewer failures, which results in a relatively lower number of transitions to the state of failure compared to the number of transitions to another state. We address these issues in Section 4.4.

4.2.2 Testing for stationarity

We have discussed the procedure for estimating stationary transition probabilities in the previous subsection. In this subsection we discuss the appropriateness of assuming stationary transition probabilities.

Assuming stationary transition probabilities would imply that the transitions have the same probability of occurring each year regardless of the age and the time spent in a state. In this subsection we focus on the age and in Section 4.3 we focus on the time spent in a state. To test the assumption of age-independence we split the data in age categories and estimate the transition probabilities for each age category. We exclude transitions to State 0 due to the limited number of observations. The age categories are 15 years and younger, 16 to 30 years, 31 to 45 years and 46 years or older. The asset's age is its age at the start of the transition. Table 6 shows the transition probabilities per age category estimated with maximum likelihood. The number of transitions per age category is shown in the top left corner of each matrix. The number of transitions is 788 instead of the 629 mentioned earlier, because we impute the data as described in Appendix B. With Imputing data we mean that certain transitions spanning over a period longer than two years are split into multiple transitions. The advantage is that these transitions can be distributed over the age categories more accurately.

	≤ 15 years				16-30 years		
n=167	9	6	1	n=141	9	6	1
9	0.881	0.110	0.008	9	0.645	0.266	0.090
6	0.000	0.827	0.173	6	0.000	0.921	0.079
1	0.000	0.000	1.000	1	0.000	0.000	1.000
	31-45 years				≥45 years		
n=260	9	6	1	n=210	9	6	1
9	0.442	0.391	0.167	9	0.482	0.427	0.091
6	0.000	0.837	0.163	6	0.000	0.813	0.187
1	0.000	0.000	1.000	1	0.000	0.000	1.000
	All ages						
n=778	9	6	1				
9	0.685	0.240	0.074				
6	0.000	0.847	0.153				
1	0.000	0.000	1.000				

Table 6: Transition probabilities per age category.

The transition probabilities differ substantially between the age categories. The probability of remaining in the State 9 seems to decrease with age, while the probability of remaining in State 6 seems to be fairly constant. The decline in the probability of remaining in State 9 is also very steep, with a difference of over forty percent between the age categories of assets of 15 years and younger, and assets between ages 31 to 45. We would like to test whether the difference in transition probabilities is statistically significant. Anderson and Goodman (1957) describe a statistical test for exactly this purpose. We test the null hypothesis (H_0) that the transition probabilities are stationary against the alternative (H_1):

$H_0: p_{i,j}(t) = p_{i,j}\ (t = 1,2,3, \dots, T)$
$H_1: p_{i,j}(t) \neq p_{i,j}\ (t = 1,2,3, \dots, T)$

If H_0 is rejected, we may not assume stationarity. Anderson and Goodman (1957) state that the transition probabilities are to be calculated with the following equation:

$$\hat{p}_{i,j}(t) = \frac{n_{i,j}(t)}{n_i(t-1)}$$

Where $n_{i,j}(t)$ is the number of transitions which started in State i at time $t-1$ and are in State j at time t and $n_i(t-1)$ is the number of transitions starting in State i at time $t-1$. $\hat{p}_{i,j}$ is calculated similarly with all transitions rather than only the transitions of a certain period. The probabilities in Table 6 are estimated from multi-year transitions and our age categories are also not per year but rather per fifteen years. We prefer our estimator over the estimator of Anderson and Goodman because it is applicable to our transitions which span different time lengths. Our sample size is too small to find enough transitions starting at a certain age category and ending in the next age category. Therefore, we apply the test with the transition probabilities of Table 6 in order to demonstrate how Liander may use such a test in the future when more transitions are available. We acknowledge that the test is not performed as it should be.

Anderson and Goodman (1957) calculate the following test measure to test H_0:

$$\chi_i^2 = \sum_{t=1}^{T} \sum_{j=1}^{J} n_i(t-1) \frac{\left(\hat{p}_{i,j}(t) - \hat{p}_{i,j}\right)^2}{\hat{p}_{i,j}}$$

$t = 1,2,3, \dots T$ are the age intervals, $j = 1,2, \dots J$ are the states and $n_i(t-1)$ are the number of assets in State i before the transition. Remember that we calculate $\hat{p}_{i,j}(t)$ and $\hat{p}_{i,j}$ differently than should be. Table 7 shows the values for $n_i(t-1)$ for all i and t, i.e. $n_9(0) = 147$ and $n_9(3) = 58$.

State i	≤15 years	16-30 years	31-45 years	≥46 years
9	147	75	105	58
6	15	56	136	132
1	5	10	19	20
Total	167	141	260	210

Table 7: Number of assets starting in each state per age group.

χ_i^2 has a Chi-square distribution with $(J-1)\times(T-1)$ degrees of freedom and a test for all states at once is performed with the test statistic as the sum of all individual test statistics and $J\times(J-1)\times(T-1)$ degrees of freedom (Anderson and Goodman, 1957). We take a significance level of 0.05. Table 8 shows the results of the test and the decision of H_0.

State i	χ^2	$P(X>\chi^2)$	Degrees of freedom	Decision of H_0
9	71.235	0.000%	6	Reject
6	3.674	72.065%	6	Not reject
1	0.000	100.000%	6	Not reject
All states	74.910	1.083%	18	Reject

Table 8: Results of the test for stationarity.

For State 9 and States 9, 6 and 1 combined we find that we reject H_0, which implies that we may not assume stationarity for these transition probabilities. Especially for the transition probabilities of State 9 we find that we may not assume stationarity with a high significance. This result is not surprising, considering that a gap of forty percent exists between the youngest and second oldest age category. As the test is not carried out as supposed to, we cannot rely on the decisions. We assume that the transition probabilities are age-dependent, because the difference between the transition probabilities between age categories is substantial.

4.3 Semi-Markov transition probabilities

In this section we investigate whether the transition probabilities depend on the time spent in a state.

Intuitively, an asset entering a state is likely to have a higher probability of remaining in the state than one which has been in the state for a while. The asset which has just entered the state is among the best in the state, while the one which has already been in the state for a while is among the worst in the state. We would like to test whether the probability of leaving the state is in fact increasing as the time spent in the state is increasing. An asset enters a state after maintenance and subsequently starts degrading to worse states. Therefore, the moment of maintenance is the moment the time spent in a state starts running. Preferably a test similar to the test in Subsection 4.2.2 is performed to see whether the transition probabilities are dependent on the time spent in a state. This would require the transition and the time since the last maintenance to be known in order to estimate transition probabilities. Unfortunately, only few maintenance actions are followed by two inspections in the data set.

Another approach to find evidence for transition probabilities being dependent on the time spent in a state is fitting a semi-Markov model, which is introduced in Section 3.2. If we find a probability distribution that shows a high dependence on the time spent in a state, we can argue that the probabilities are in fact dependent on the time spent in a state. Black et al. (2005) propose a method for fitting a density function to the time till degradation from a state to another state for interval-censored data. The inspection result and the time since maintenance should be determined after a maintenance activity bringing the asset to a predefined state. In our case we look at the maintenance activities bringing the asset to State 9. We exclude State 0 due to a lack of observations. Table 9 shows the number of power transformers in each state a certain number of years after a maintenance action brings the asset to State 9.

The table shows a high number of power transformers degrading to States 6 and 1 within a year. Besides that, we do not observe a real pattern of assets slowly degrading to a lower state as time progresses, possibly due to a lack of observations after three years since maintenance. Therefore, we do not believe that we can use this data to see if the transition probabilities are dependent on the time spent in a state. Instead, we use this data to show how the probabilities of a semi-Markov model can be fit according to Black et al. (2005), so that Liander can use this when they have more data available.

Time since maintenance	9	6	1
1	16	19	12
2	3	10	5
3	9	8	4
4	5	2	2
5	1	0	0
6	2	1	0
7	0	1	1

Table 9: Number of inspections revealing a condition grouped per number of years since maintenance.

The approach described in Black et al. (2005) allows for a one-state transition per time interval. The data in Table 9 suggest that States 9, 6 and 1 can be reached within a year. Therefore, we use a semi-annual time interval, since power transformers can now degrade twice in a year and still reach State 1 from State 9. We use two Weibull distributions to describe the probabilities of degrading from State 9 to State 6 and from State 6 to State 1. $\alpha_{9,6}$ and $\beta_{9,6}$ are the Weibull parameters of degrading from State 9 to State 6, and $\alpha_{6,1}$ and $\beta_{6,1}$ are the Weibull parameters of degrading from State 6 to State 1. Note that the degradation behaviour may be better described with another distribution function than the Weibull distribution. For now, we are only interested in demonstrating the procedure for fitting a distribution to the data for future reference. The key is to find the parameters that best fit the data in Table 9.

For each year since maintenance the power transformers have a certain probability of being in States 9, 6 and 1. The sum of these probabilities is 1. We can calculate the probabilities by determining all possible routes, and then assigning probabilities to these routes. We use the probability of being in State 1 two years after maintenance as an example. We can make four semi-annual one-state jumps in two years. One possible route would be to start and stay in State 9 for the first year, then go from State 9 to State 6 and subsequently go from State 6 to State 1. We denote this route as 9,9,9,6,1. The probability of each transition depends on the state and the time spent in the state. The probability of staying in State 9 during the first half year is denoted by $p_{9,9}(0.5)$. The probability of remaining in State 9 in the second half year is $p_{9,9}(1.0)$. This logic can be applied to all probabilities so that the probability of the route can be calculated. Table 10 shows all routes from State 9 to State 1 for a two-year period along with the probability of the route.

Route	Probability
9,9,9,6,1	$p_{9,9}(0.5) \times p_{9,9}(1.0) \times p_{9,6}(1.5) \times p_{6,1}(0.5)$
9,9,6,6,1	$p_{9,9}(0.5) \times p_{9,6}(1.0) \times p_{6,6}(0.5) \times p_{6,1}(1.0)$
9,9,6,1,1	$p_{9,9}(0.5) \times p_{9,6}(1.0) \times p_{6,1}(0.5) \times 1$
9,6,6,6,1	$p_{9,6}(0.5) \times p_{6,6}(0.5) \times p_{6,6}(1.0) \times p_{6,1}(1.5)$
9,6,6,1,1	$p_{9,6}(0.5) \times p_{6,6}(0.5) \times p_{6,1}(1.0) \times 1$
9,6,1,1,1	$p_{9,6}(0.5) \times p_{6,1}(0.5) \times 1 \times 1$

Table 10: Routes for starting in State 9 and ending in State 1 for a two-year period.

The probability of remaining in State 1 is one, as State 1 is absorbing. Eq. (3.2) describes how $p_{9,6}(m)$ and $p_{6,1}(m)$ are calculated with the Weibull distribution. We also know $p_{9,9}(m) = 1 - p_{9,6}(m)$ and $p_{6,6}(m) = 1 - p_{6,1}(m)$. This allows us to calculate the probability of all routes for a certain $\alpha_{9,6}$, $\beta_{9,6}$, $\alpha_{6,1}$ and $\beta_{6,1}$. The sum of the probabilities of all routes is the probability of being in State 1 two years after maintenance, for example 0.4. The probability of finding four assets in State 1 after two years is now 0.4^4. We can perform this process for all combinations of state and number of years since maintenance. The product of the probabilities resulting from this process is the likelihood of the observations. Similar to finding the stationary transition probabilities in Section 4.2, we use a non-linear solver to find the parameters which maximise the log likelihood.

It should be noted that this process is computationally extensive, as the number of routes explodes as the number of years since maintenance increases. The highest number of routes is 106 for being in State 1 after fourteen semi-annual transitions. We find values of 0.260, 0.017, 0.479 and 0.903 for the parameters $\hat{\alpha}_{9,6}$, $\hat{\beta}_{9,6}$, $\hat{\alpha}_{6,1}$ and $\hat{\beta}_{6,1}$ respectively. It should be noted that the solver finds different parameter values for different starting values, meaning that the result may be a local optimum. Table 11 shows the probabilities corresponding to the obtained parameters.

m	$p_{9,9}(m)$	$p_{9,6}(m)$	$p_{6,6}(m)$	$p_{6,1}(m)$
0.5	0.620	0.380	0.743	0.257
1.0	0.778	0.222	0.828	0.172
1.5	0.836	0.164	0.862	0.138
2.0	0.868	0.132	0.881	0.119
2.5	0.888	0.112	0.894	0.106
3.0	0.902	0.098	0.904	0.096
3.5	0.912	0.088	0.911	0.089
4.0	0.920	0.080	0.917	0.083
4.5	0.927	0.073	0.922	0.078
5.0	0.932	0.068	0.926	0.074
5.5	0.937	0.063	0.930	0.070
6.0	0.941	0.059	0.933	0.067
6.5	0.944	0.056	0.935	0.065
7.0	0.947	0.053	0.938	0.062

Table 11: Probabilities dependent on time spent in a state.

We observe that the estimated probabilities of staying in a state increase as the time spent in a state increases. This pattern also seems observable in our observations. Even though the approach seems applicable for Liander, for now we do not have sufficient data to make any claims on the dependency of the time spent in a state.

4.4 Probability of failure

In the previous section we concluded that a lack of data prevents us from investigating whether the transition probabilities depend on the time spent in a state. Considering that the transition probabilities differ substantially between the age categories, we believe that we should continue with the age-dependent transition probabilities. The problem with the age-dependent transition probabilities in Section 4.2 is that the probability of going to State 0, the state of failure, is not estimated due to a lack of data. In this section we estimate the transition probabilities from States 9, 6 and 1 to State 0.

Eq. (3.1) dictates that the distribution of assets over the states after a year of degradation can be calculated as follows:

$$E = CP$$

Writing out this equation for States 9, 6, 1 and 0 results in the following equation:

$$[e_9 \quad e_6 \quad e_1 \quad e_0] = [c_9 \quad c_6 \quad c_1 \quad c_0] \begin{bmatrix} p_{9,9} & p_{9,6} & p_{9,1} & p_{9,0} \\ p_{6,9} & p_{6,6} & p_{6,1} & p_{6,0} \\ p_{1,9} & p_{1,6} & p_{1,1} & p_{1,0} \\ p_{0,9} & p_{0,6} & p_{0,1} & p_{0,0} \end{bmatrix}$$

Matrix multiplication shows that we can calculate e_0 with the following equation:

$$e_0 = [c_9 \quad c_6 \quad c_1 \quad c_0] \begin{bmatrix} p_{9,0} \\ p_{6,0} \\ p_{1,0} \\ p_{0,0} \end{bmatrix}$$

e_0 is the probability of being in State 0 after a year of degradation, $p_{i,0}$ is the probability of going from State i to State 0 and c_i is the current number of assets in State i. We can use historical data to approximate c_9, c_6, c_1, c_0 and e_0 for all age categories and subsequently estimate the probability of going from States 9, 6 and 1 to State 0. We start with approximating e_0 and subsequently approximate c_9, c_6, c_1 and c_0.

We approximate e_0 by calculating the number of failures per age category per year. From 2012 to 2015 thirty-one failures occurred. The causes of twenty-four failures are preventable with maintenance, while the causes of the remaining seven failures are not. We refer to the first group of failures as preventable failures, and to the latter group as unpreventable failures. We only consider the preventable failures for now. We find the age of the power transformer at the time of failure, and assign the failure to an age category. Next, we sum the number of transformers in each age category for the years 2012, 2013, 2014 and 2015. Now we have the number of failures and the number of possible failures. e_0 is the number of failures divided by the number of possible failures. Table 12 shows e_0, the expected percentage of failing power transformers per year. The general trend seems to be that the expected percentage of failing power transformers increases as the age increases, which is as expected.

Ages	e_0
≤15 years	0.000
16-30 years	0.002
31-45 years	0.013
≥46 years	0.027

Table 12: Percentage of preventable failures per age category per year.

c_9, c_6, c_1 and c_0 can be derived from the inspection data. The asset's age and condition are gathered for all inspections. These inspections are categorised in age groups. The percentage of observations in each state is an approximation of the distribution of assets over the states. For example, if 200 out of a 1000 inspections indicate an asset is in State 9, we assume that the starting distribution in State 9 is 0.2. Table 13 shows the percentage of assets in each state per age category. A failure becomes apparent immediately and is subsequently fixed. Therefore, c_0 is always zero. The table shows that the percentage of assets in State 9 declines as the their age increases. The reverse holds true for States 6 and 1.

Ages	c_9	c_6	c_1	c_0
≤15 years	0.665	0.250	0.085	0.000
16-30 years	0.411	0.495	0.095	0.000
30-45 years	0.295	0.494	0.211	0.000
≥46 years	0.206	0.573	0.221	0.000

Table 13: Percentage of assets in each state.

We now know c_9, c_6, c_1, c_0 and e_0 for all age categories. We can use the following equation derived earlier:

$$e_0 = \begin{bmatrix} c_9 & c_6 & c_1 & c_0 \end{bmatrix} \begin{bmatrix} p_{9,0} \\ p_{6,0} \\ p_{1,0} \\ p_{0,0} \end{bmatrix}$$

We can simplify this equation, because c_0 is always zero. The following equation remains:

$$e_0 = \begin{bmatrix} c_9 & c_6 & c_1 \end{bmatrix} \begin{bmatrix} p_{9,0} \\ p_{6,0} \\ p_{1,0} \end{bmatrix}$$

We have three unknown variables, namely $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$. Therefore, we have to make an assumption for the relative likelihood of the three probabilities. In Subsection 4.2.1 our estimation for all ages resulted in $p_{9,0} = 0.001$, $p_{6,0} = 0.002$ and $p_{1,0} = 0.021$. We assume that the probabilities have the same proportion for all age categories. We can now rewrite our equation such that the relative likelihood between $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$ remains the same:

$$e_0 = \begin{bmatrix} c_9 & c_6 & c_1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{0.002}{0.001} & 0 \\ 0 & 0 & \frac{0.021}{0.001} \end{bmatrix} \begin{bmatrix} p_{9,0} \\ p_{9,0} \\ p_{9,0} \end{bmatrix}$$

We can rewrite this into the following equation:

$$e_0 = \begin{bmatrix} c_9 \times 1 & c_6 \times \frac{0.002}{0.001} & c_1 \times \frac{0.021}{0.001} \end{bmatrix} \begin{bmatrix} p_{9,0} \\ p_{9,0} \\ p_{9,0} \end{bmatrix}$$

Again, we rewrite this equation:

$$e_0 = \begin{bmatrix} c_9 \times 1 & c_6 \times \frac{0.002}{0.001} & c_1 \times \frac{0.021}{0.001} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} p_{9,0}$$

Now, we can calculate $p_{9,0}$ with the following equation:

$$p_{9,0} = \frac{e_0}{\begin{bmatrix} c_9 \times 1 & c_6 \times \frac{0.002}{0.001} & c_1 \times \frac{0.021}{0.001} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}}$$

Then, the probabilities $p_{6,0}$ and $p_{1,0}$ can be calculated with the relative likelihood from earlier:

$$\begin{bmatrix} p_{9,0} \\ p_{6,0} \\ p_{1,0} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{0.002}{0.001} & 0 \\ 0 & 0 & \frac{0.021}{0.001} \end{bmatrix} \begin{bmatrix} p_{9,0} \\ p_{9,0} \\ p_{9,0} \end{bmatrix}$$

We calculate $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$ for each age category. The resulting probabilities are shown in Table 14. Note that the probabilities used to express the relative likelihood of probabilities $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$ are rounded to three digits after the decimal points. We use unrounded numbers to calculate the probabilities shown in Table 14.

Ages	$p_{9,0}$	$p_{6,0}$	$p_{1,0}$
≤15 years	0.000	0.000	0.000
16-30 years	0.000	0.001	0.011
31-45 years	0.002	0.005	0.047
≥46 years	0.004	0.011	0.093

Table 14: Probabilities of preventable failures.

The table shows the probabilities of preventable failures. However, we are also interested in unpreventable failures, because these also impact the assets life cycle. The percentage of unpreventable failures per age category is shown in Table 15. We assume that these probabilities are age-dependent.

Ages	e_0
≤15 years	0.000
16-30 years	0.002
31-45 years	0.007
≥46 years	0.002

Table 15: Percentage of unpreventable failures per age category per year.

These probabilities are added to $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$ in Table 14, as the unpreventable failures have the same probability of occurring irrespective of the current state. The resulting probabilities are shown in Table 22 in Appendix C. Subsequently, the probabilities of failure can be added to the age-dependent transition probability matrices of Subsection 4.2.2. In Appendix C we also explain the procedure to add the probabilities, and show the resulting age-dependent transition probability matrices which include State 0. The age-dependent transition probability matrices allow us to model the complete asset degradation, which brings us a step closer to being able to analyse a trade-off between the costs of an investment strategy.

4.5 Validation

In the previous sections of this chapter we estimated age-dependent transition probability matrices. If these matrices are to be used for decision making purposes, we would like to be certain of them. For this reason we perform a validation. We do this by determining a 95% confidence interval for the age-dependent transition probabilities. The transition probabilities to State 0 are omitted, as these are estimated differently.

For a binomially distributed random variable, the maximum likelihood estimator for p is ${}^{k}/_{n}$ and the $100(1-\alpha)\%$ confidence interval for p when n is large is approximated by the following formula (Larsen and Marx, 2012):

$$\frac{k}{n} \pm z_{\alpha/2}\sqrt{\frac{\left({}^{k}/_{n}\right)\left(1-{}^{k}/_{n}\right)}{n}}$$

k is the number of successes, n is the total number of attempts and $z_{\alpha/2}$ is the value for which $P\left(Z \geq z_{\alpha/2}\right) = \alpha/2$ with Z standard normally distributed. If we were to estimate our transition probabilities by dividing the transitions from State i to State j divided by the transitions from State i, we would be able to use the formula. A transition from State i to State j would count as a success, and a transition starting from State i would count as an attempt. For example, our estimate for $p_{9,9}$ would become the number of transitions from State 9 to State 9 divided by the number of transitions from State 9. The problem is that the transitions in our data cover an unequal number of years, which is why we used a different maximum likelihood estimator to estimate transition probabilities. Therefore, we cannot use the formula presented by Larsen and Marx (2012).

Another method to determine a confidence interval is the bootstrap. The bootstrap method relies on sampling with replacement. For example, the estimation of the transition probabilities for assets of fifteen years or younger is based on 167 observed transitions in this age category. For a single bootstrap sample 167 transitions are sampled with replacement, which means that certain transitions are drawn multiple times while others are not drawn at all. Next, the transition probabilities are estimated based on the bootstrap sample. This is repeated for b bootstrap samples. The 2.5% and

97.5% quantile of the b estimated probabilities are the respective lower and upper bound of the 95% confidence interval. Table 16 shows the confidence interval for the transition probabilities per age category after taking 1,000 bootstrap samples.

Ages	n	$p_{9,9}$		$p_{9,6}$		$p_{9,1}$		$p_{6,6}$		$p_{6,1}$	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
≤15	167	0.841	0.922	0.070	0.148	0.003	0.025	0.705	0.948	0.052	0.295
16-30	141	0.540	0.735	0.190	0.360	0.039	0.149	0.868	0.971	0.029	0.132
31-45	260	0.336	0.544	0.302	0.487	0.100	0.244	0.776	0.887	0.113	0.224
≥46	210	0.340	0.611	0.307	0.568	0.035	0.175	0.753	0.868	0.132	0.247
All	778	0.644	0.726	0.203	0.282	0.049	0.098	0.813	0.876	0.124	0.187

Table 16: 95% confidence interval for transition probabilities per age category.

The confidence intervals of the estimated probabilities are wide. Most of the intervals are wider than 0.100 and some extreme cases are wider than 0.250. Even the age category with the largest sample size, transformers age 31 to 45, has confidence intervals spanning over 0.200. The confidence intervals for the probabilities for all ages is considerably smaller, with a maximum of 0.082. The confidence intervals can therefore be reduced by combining multiple age categories. Adding onto the uncertainty, the estimation of the transition probabilities to State 0 is unreliable, because the data are estimated based on only thirty-one failures. In summary, we should keep the uncertainty in the confidence interval in mind when basing decisions on the estimated parameters.

4.6 Conclusions

In this chapter we have discussed the estimation of transition probabilities for the degradation of power transformers. Section 4.1 introduces the inspection data set covering power transformers. We use the condition codes 9, 6 and 1 together with a failure as the state space. The data covers 655 power transformers in the period 2012 to 2019. Although the data allows for estimating transition probabilities, a few data quality issues arise. The data only covers eight years of inspections and maintenance actions are not always registered.

In Section 4.2 we discuss the estimation of stationary transition probabilities, together with its application to the power transformer data. We explain the estimation approaches which are applicable to transitions covering multiple years found in Hoskins et al. (1999) in Subsection 4.2.1. The maximum likelihood approach is our preferred estimator, and it works by finding the transition probability matrix with maximises the likelihood of the observed transitions. In Subsection 4.2.2 we estimate and compare the maximum likelihood estimates for different age categories. We use the test of Anderson and Goodman (1957) in order to test whether we may assume stationary transition probabilities or not. Unfortunately, we are unable to test the hypothesis as intended. The transition probabilities differ substantially between the age categories, so we assume that the transition probabilities are age-dependent.

In Section 4.3 we attempt to test if the transition probabilities depend on the time spent in a state. The moment of entering a state is known after the registered maintenance activities. The number of assets in each state a certain number of years after a maintenance activity bringing the asset to State 9 can be used to find transition probabilities dependent on the time spent in a state. The procedure for estimating these transition probabilities is mentioned in Black et al. (2005). The results show an increasing probability of remaining in a state as the time spent in a state increases. However, not much data are available for more than three years after maintenance, so the results are unreliable.

We aim to find the missing age-dependent transition probabilities of a power transformer failure in Section 4.4. A lack of data complicates the estimation of the probabilities with maximum likelihood, because we can only find a state before a failure in four out of thirty-one cases. The transition probabilities to the state of failure caused by failure causes which are preventable with maintenance are determined first. We do this by leveraging the fact that the expected number of assets in each state is the result of a matrix multiplication between the current distribution of assets over the states with the transition probability matrix. Subsequently, we use the expected number of failures and the average asset distribution over the states for each age category to find the missing transition probabilities. The probability of failure due to failures causes which are not monitored with inspections are added to the transition probabilities. Although the results are based on only thirty-one failures, we find that the method has logical results.

The transition probability matrices per age category are estimated with a small sample size, with only 141 transitions in the smallest age category of assets. Hence, we perform a validation of our results in Section 4.5. A confidence interval is determined for all transition probabilities per age category by means of bootstrap sampling. The confidence intervals are wide even without the estimation of the transition probabilities to the state of failure, which is based on only thirty-one failures.

All in all, the entire road of data to transition probabilities has been covered in this chapter. Although the resulting transition probabilities are not particularly reliable, our aim of finding a method to estimate the transition probabilities has been achieved. Furthermore, Liander can use the methods in Sections 4.2, 4.3 and 4.5 to fit transition probabilities, test for stationarity, fit transition probabilities dependent on the time spent in a state and assess the confidence interval of the transition probabilities on their own data once the data quality has improved. We use the transition probabilities estimated in this chapter to perform a proof of concept in the next chapter.

Chapter 5 Proof of concept

In this chapter we introduce and apply a simulation model which assesses the life cycle costs of an asset for an investment strategy. We explain the simulation model in Section 5.1. In Section 5.2 we introduce the case study to test our model. Then, in Section 5.3, we compare the current investment strategy to different strategies in order to see whether the impact of the investment decisions is as expected. We assess the sensitivity of the input parameters in Section 5.4, and we conclude this chapter in Section 5.5.

5.1 Simulation model

In this subsection we discuss the model which simulates an asset life cycle. In Subsection 5.1.1 we discuss the cost, degradation and other parameters which are inputs for the simulation model. We explain the simulation model's logic in Subsection 5.1.2. Lastly, we discuss the model's assumptions in Subsection 5.1.3.

5.1.1 Input parameters

The simulation model should assess the impact of an investment strategy on the costs occurring during an asset's life. It relies on modelling the asset degradation and the impact of maintenance to simulate the asset's condition. Besides that, the simulation model requires the costs of the cost items we have introduced in Section 2.2. Lastly, the user's input is needed in the form of an investment strategy together with the number of trials.

The asset degradation can be modelled with a transition probability matrix for each identified age category. The states, the start state and the probability of going from a state to another state are known. Maintenance actions can be used in an attempt to restore an asset's condition to a better condition. Each maintenance action also has a transition probability matrix per age category. Note that the age categories for the transition probability matrices of asset degradation and maintenance are also inputs of the simulation model.

The cost items are purchase and installation costs, preventive and corrective maintenance costs, costs of inspection, disposal costs, failure costs and other costs. The discount rate is used to translate the value of these costs from one moment in time to another. Different types of maintenance actions may be applicable to an asset, for example a minor, medium and major maintenance action. The costs for each maintenance action are required. The additional cost of repairing a failed asset for each maintenance action is required as well.

The user can define an investment strategy which the simulation model follows. The inspection, maintenance and replacement decisions can based on the condition and age. For example, assets found in State 6 at ages ten to twenty are inspected again after five years.

5.1.2 Model structure

The input parameters are used to simulate an asset's life cycle for all trials. The simulation is based on a Monte Carlo simulation for which random sampling is used to generate different paths for the life of an asset. The random sampling takes place to determine the condition of an asset after a period of degradation and after a maintenance action. At the end of the trial, the cash flows and their timing are known. These are used to calculate the EACs. For each trial a new asset life cycle is simulated and the corresponding EACs are calculated, allowing us to assess the spread in life cycle costs of an investment strategy. The logic of simulating a random asset life cycle is shown in Figure 13. The items numbered 1 to 6 are explained in more detail.

1 Draw State j at end of Period i.

The condition of an asset at the end of a period is random. The probability of going to each condition depends on the asset's age and the current condition. For example, the probabilities of a 44-year old asset currently in State 9 going to States 9, 6, 1 and 0 is 0.438, 0.388, 0.166 and 0.008 respectively. These probabilities are dictated by the transition probability matrices. To determine a random condition for our example after a period of degradation, we draw a random number $x \in U[0,1]$. The next condition is determined with the following logic:

$$Next\ state = \begin{cases} 9, & x < 0.438 \\ 6, & x \geq 0.438 \wedge x < 0.826 \\ 1, & x \geq 0.826 \wedge x < 0.992 \\ 0, & x \geq 0.992 \end{cases}$$

This example shows how the transition probability matrices for each age category and the current state can be used to randomly determine the next state.

2 Replacement conditions met?

The replacement conditions are met in three cases. The first case is when an asset has reached the age after which corrective maintenance is applied and it fails. The power transformer is considered to be too old to be worth saving with a reparation and is replaced. The second case is when the asset is retired at a pre-specified age. The asset can be retired after this age if an inspection reveals its condition to be critical. The critical conditions are specified in the model input. Additionally, if all conditions are specified to be critical, the asset is replaced when it hits the pre-specified age without an inspection being needed. The third case is when an asset has failed and cannot be repaired. The asset is damaged too much to be worth repairing, and is replaced instead.

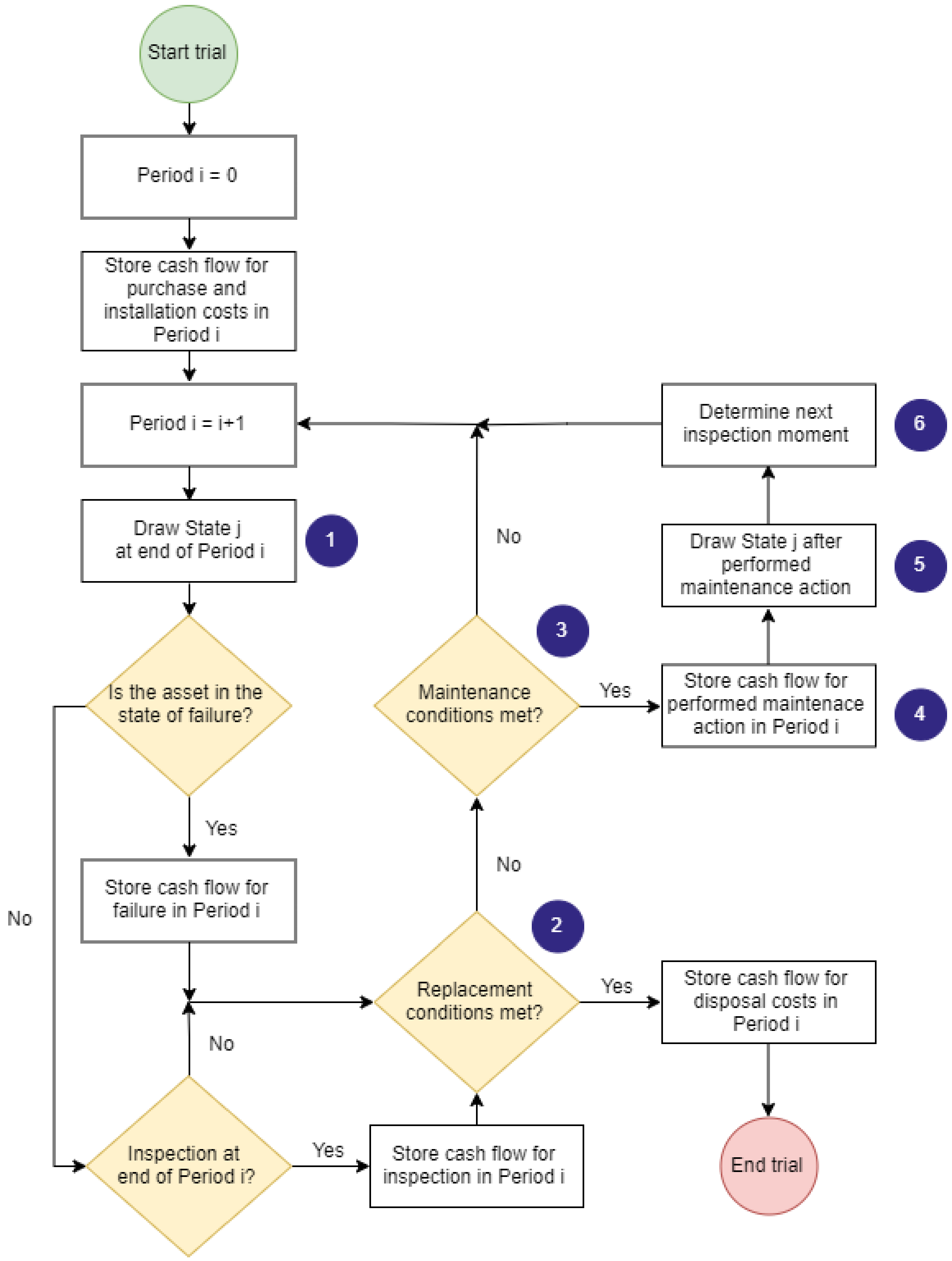

Figure 13: Logic of the simulation model.

3 Maintenance conditions met?

The conditions at which maintenance is performed can differ per age category. The states and age at which maintenance should be applied is given for each maintenance action, as explained in the previous subsection. Maintenance can only be applied after a failure or after the condition of the asset has been revealed by an inspection.

4 Store cash flow for performed maintenance action in Period i.

Each maintenance action has its own cost. Besides that, it is possible to add an additional cost to a maintenance action in case of an asset failure. A failed asset is more expensive to perform a maintenance action on in some cases, for example when additional safety precautions have to be followed.

5 Draw State j after performed maintenance action.

Similar to drawing the state after a period of asset degradation, the state after a maintenance action is also dependent on the current age and state. As opposed to an asset's condition degrading, the maintenance action is aimed at improving its condition. The process of drawing a new state after a maintenance action is similar to the process of drawing a new state after a period of degradation.

6 Determine next inspection moment.

The next inspection moment is dependent on the current age and state. The inspection intervals are determined in the investment strategy. The inspection interval is added to the current asset's age to find the new age at which an inspection will occur. Note that an asset failure may occur before the next inspection interval. When this happens and the asset is repaired, the new state and age are used to determine a new age for inspection.

5.1.3 Assumptions

In this subsection we address four assumptions of the simulation model.

The first assumption is that time is discrete rather than continuous. The implications of this assumption are that an inspection, a maintenance action and asset degradation can occur at the end of a period. Of course, the period length is chosen by the user, so the period length can be chosen such that it is appropriate for the case at hand.

The timing of cash flows is a second assumption. The timing of cash flows impacts the EACs, as a cash flow at a later moment is discounted more heavily and thus results in lower EACs. We assume end-of-period cash flows, as this corresponds to the timing of inspections and maintenance actions.

A third assumption is that costs are constant. For the cost items purchase cost, installation costs, inspection costs and disposal costs this assumption seems reasonable, while the costs of the other cost items may vary. The maintenance costs may be higher than expected due to some unforeseen problems. The failure costs depend on multiple factors. For example, a failure of a power transformer leads to power outage. The longer the power outage lasts, the more Liander has to pay to compensate customers and hence the higher the failure costs. Getting insight in the spread of the cost items is a cumbersome task. Due to time constraints, we assume costs are constant.

The fourth assumption is about the transition probabilities. The transition probabilities of degradation and maintenance impact depend only on the asset's age and current condition. In reality, other factors impacting the transition probabilities may exist. An example would be the time spent in a state discussed in Section 4.3.

The assumptions of constant costs and transition probabilities depending only on the current state and the asset's age may be invalid in certain cases. This may also mean that the investment strategy would allow for investment decisions based on the costs of the decision rather than only the age and the state. For example, an asset would be repaired if the costs of the reparation would be lower than a certain amount. These options are currently not implemented.

5.2 Case study

We have introduced the power transformer inspection data in Chapter 4, and used them to estimate transition probabilities. In this section we start out by introducing the power transformers themselves. We subsequently discuss the input data used for the simulation model.

The simulation model is applied to a case study regarding power transformers. Power transformers are a part of the electricity grid and fulfil the role of transforming a voltage into another voltage. Energy is transmitted at high voltage as much as possible for two reasons. First, energy losses are lower when electricity is transmitted at high voltage. Second, fewer cables are required to transmit electricity at high voltage, leading to lower purchase costs. The voltage is lowered so that the energy can be distributed to customers. This task is performed with power transformers. Power transformers are often categorised by their voltage, cooling system and manufacturer. Liander's power transformers are categorised by the voltages 150 kV, 110 kV, 50 kV, 20-35 kV and 1-20 kV. The most common cooling systems are oil natural-air natural (ONAN), oil natural-air forced (ONAF) and oil forced-air forced (OFAF), which refer to the method for cooling the windings of a power transformer.

The transition probabilities determined in Chapter 4 are based on data from 150 kV, 110 kV and 50 kV substations and 20 kV and 10 kV control stations. At a substation the voltage is transformed from high voltage to a lower one. A 150 kV substation may for example transform the 150 kV to 10 kV. A control station is used to keep the voltage at the desired level. The voltage drops when electricity is being transported over a long distance. The control station has a power transformer which is able to convert the lowered voltage to the initial voltage. The power transformers in this data set have different cooling systems and have been produced by different manufacturers. These three factors, the voltage, cooling system and manufacturer, may influence the transition probabilities.

The costs for the case study of a 80 MW power transformer are based on internal documents, input from experts and assumptions. Table 17 shows the cost items used in the simulation. Note that the residual value is not a cost but a revenue.

Cost item	Cash flow
Purchase	€700,000
Installation	€80,000
Inspection	€1,000
Regular maintenance	€5,000
Revision (after failure)	€250,000
Residual value	−€80,000
Disposal	€20,000
Failure	€100,000
Other	€0
WACC	0.037

Table 17: Cost items.

The costs are debatable for some items. For example, a power transformer loses energy and this loss costs money. The calculation of the money lost depends on the percentage of capacity used, and is case dependent. For now, we do not consider this cost as it would require more research, and it is not required for a proof of concept. In general, the costs are merely indications of the actual cost parameters and are only used for the purpose of testing the simulation model.

For the asset degradation, we use the age-dependent transition probabilities shown in Table 23 of Appendix C. The impact of the maintenance actions, regular maintenance and revision, is estimated using the condition codes before and after the maintenance action. The transition probabilities of a regular maintenance action are calculated as follows:

$$\hat{p}_{i,j} = \frac{n_{i,j}}{n_i}$$

Where $n_{i,j}$ is the number of transitions starting in State i before maintenance and ending in State j after maintenance, and n_i is the number of transitions starting in State i before maintenance. Table 18 shows the transition probabilities after a regular maintenance action per age category. A revision only receives a condition after the maintenance action, and not before. However, the condition code after the revision is almost exclusively Condition 9. The probability of going to State 9 after a revision is therefore one, except when the asset is in the failed state. A failure can only be repaired by a revision and not by regular maintenance, but only for around 50 percent of the failures. Therefore, the following transition probabilities are used to determine the state after a revision:

$$P_{revision} = \begin{array}{c} \\ 9 \\ 6 \\ 1 \\ 0 \end{array} \begin{array}{c} \begin{array}{cccc} \quad 9 & \quad\; 6 & \quad\; 1 & \quad\; 0 \end{array} \\ \begin{bmatrix} 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 0.500 & 0.000 & 0.000 & 0.500 \end{bmatrix} \end{array}$$

n=100	≤ 30 years					n=74	31-40 years			
	9	6	1	0			9	6	1	0
9	1.000	0.000	0.000	0.000		9	1.000	0.000	0.000	0.000
6	0.408	0.592	0.000	0.000		6	0.500	0.500	0.000	0.000
1	0.480	0.400	0.120	0.000		1	0.625	0.292	0.083	0.000
0	0.000	0.000	0.000	1.000		0	0.000	0.000	0.000	1.000
n=112	41-50 years					n=72	≥51 years			
	9	6	1	0			9	6	1	0
9	1.000	0.000	0.000	0.000		9	1.000	0.000	0.000	0.000
6	0.250	0.750	0.000	0.000		6	0.229	0.771	0.000	0.000
1	0.387	0.387	0.226	0.000		1	0.367	0.333	0.300	0.000
0	0.000	0.000	0.000	1.000		0	0.000	0.000	0.000	1.000

Table 18: Transition probabilities after regular maintenance.

We do not test whether the transition probabilities are age-dependent or not, as we merely intend to test the model on a case study. The parameters in this section allow us to simulate an asset's life cycle and assess the life cycle costs over this life cycle.

5.3 Benchmark

In this section we compare the current investment strategy with alternatives to see whether an improvement is possible. In Subsection 5.3.1 we discuss the current investment strategy and run the simulation model to assess the life cycle costs. The logic behind finding the current investment strategy is having a strategy of reference. We compare alternatives to this strategy in Subsection 5.3.2.

5.3.1 Current investment strategy

In this subsection we first describe the investment strategy employed by Liander for power transformers. Then, we use the simulation model to assess the performance of the current investment strategy. We use the current strategy to more easily assess the impact of changes in the investment strategy to the EACs in the next subsection.

The investment strategy currently employed by Liander is discussed with experts. Liander does not follow a pre-defined investment strategy, but follows the advice of experts. This means that the current investment strategy cannot be captured easily and we have to make some assumptions. A strict rule is that no inspections and maintenance actions are performed during the first twelve years, unless an asset fails. Afterwards, regular maintenance is applied every three, five or ten years. The interval for regular maintenance depends on the type of power transformer and is independent of the current asset condition. We use an interval of five years for our analysis. Regular maintenance is always accompanied by an inspection. A revision is assumed to be performed only in case of a failure. The asset's age of replacement is not specified currently, since the moment of replacement is based on expert opinions. Power transformers can reach ages up to 60 years. Therefore, we set the age for corrective replacement to thirty-five and the age for preventive replacement to 60. The asset is replaced at age 60 no matter the condition.

We simulate the life of the power transformer one million times. Afterwards, the EACs are calculated for each life cycle. Figure 14 shows a loss exceedance curve of the EACs under the current investment strategy. The loss exceedance curve shows that the EACs of a power transformer are certain to be higher than €33,071 under the current investment strategy. These costs correspond to having no failures at all and just the regular maintenance and inspections every five years since year twelve. The probability of this scenario is actually quite high, as this best case scenario happens in 34.0% of the trials. We also observe a rapid increase as soon as the EACs rise above €33,544, instead of a smooth line with steadily increasing costs. This small jump is caused by a failure in the final few years before preventive replacement at age 60. The tail is caused by an unrepairable failure happening between ages sixteen to thirty. The purchase and failure costs are now spread over a short period of time, resulting in extremely high EACs.

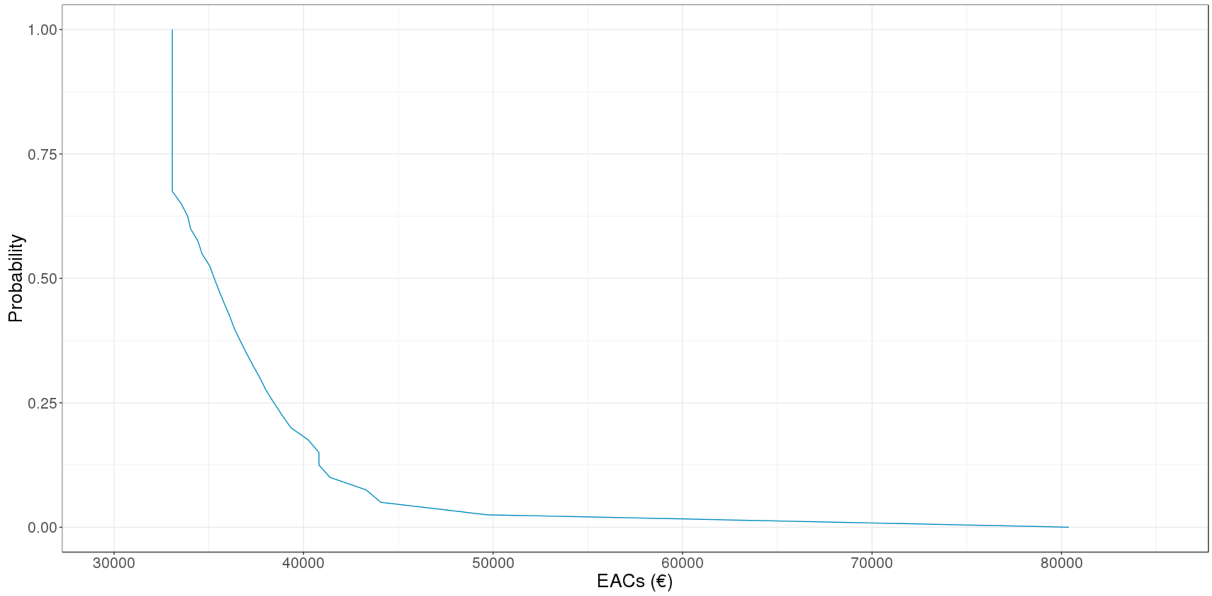

Figure 14: Loss exceedance curve of the current investment strategy.

5.3.2 Alternative investment strategies

Now that we know the performance of the current investment strategy, we set out to compare it to alternatives. In the comparisons we are going to make in this subsection, Alternative 1 refers to the investment strategy currently followed by Liander and Alternative 2 refers to the alternative we wish to investigate.

The first alternative investment strategy we are investigating is having a smaller interval for regular maintenance and inspections. Instead of performing maintenance and an inspection every five years starting from age twelve, we perform maintenance and an inspection four years after finding the power transformer in State 9 and two after finding it in one of the other states. The goal of this alternative strategy is to reduce the tail by having a more conservative maintenance strategy. Figure 15 shows the loss exceedance curves for Alternatives 1 and 2. Overall, we can observe that the curves are not massively different. Alternative 1 performs better on the best scenarios, similar on the tail and worse between the tail and the best scenarios. This can be explained by the more conservative maintenance strategy of Alternative 2. Alternative 1 is cheaper for those scenarios where the asset has no failures, as less maintenance is required. Instead of lowering the tail, the more conservative maintenance strategy lowers the scenarios before the tail. This may be due to the fact that even for the Conditions 9 and 6, there still exists a probability of failure for the age category sixteen to thirty years. And these failures cannot always be repaired. This means that we are unable to eliminate the tail, as a probability of failure will always exist.

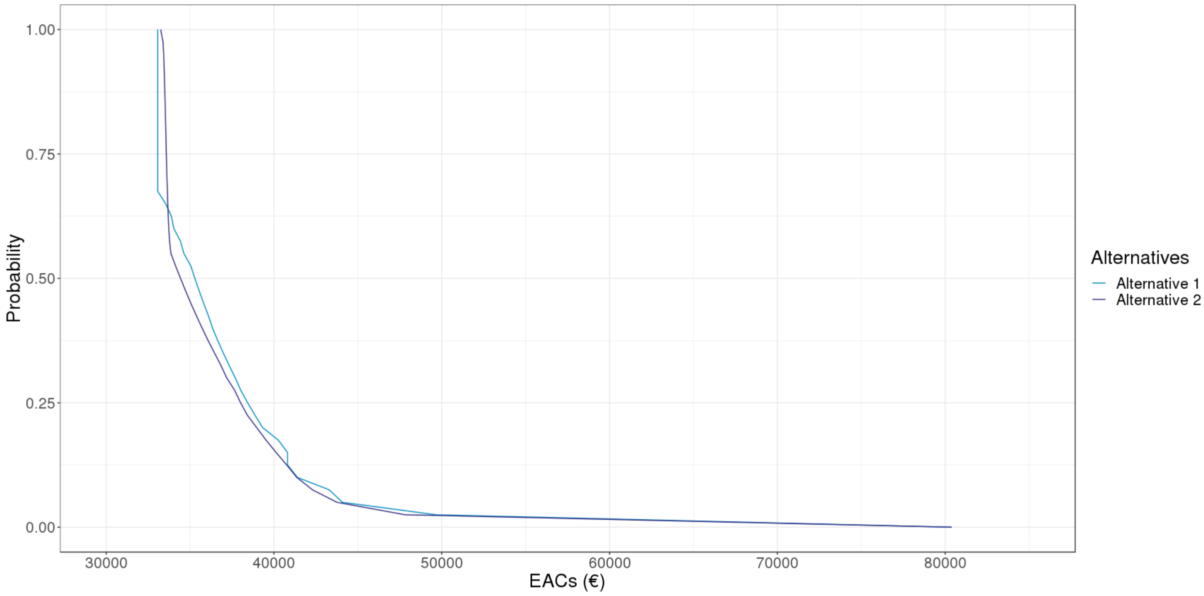

Figure 15: Loss exceedance curves of Alternative 1 (current strategy) and Alternative 2 (more maintenance).

As the tail seems to be difficult to reduce, we switch our focus to the trade-off between the increasing risk of failure as the age increases and the benefit of not having to replace the asset for another year. We compare the current strategy to a strategy where preventive replacement is performed at age 50, so ten years earlier. Figure 16 shows the performance of both investment strategies. We observe that Alternative 1 has lower EACs for the best scenario, while the two alternatives are comparable in all other cases. Intuitively, we may best the current investment strategy by increasing the age of preventive maintenance. However, the probability of failure is the same for assets older than 50 years. This means that the risk of a failure does not increase, but the costs are spread over more years. In reality the risk is likely to increase, so the resulting performance would be unreliable.

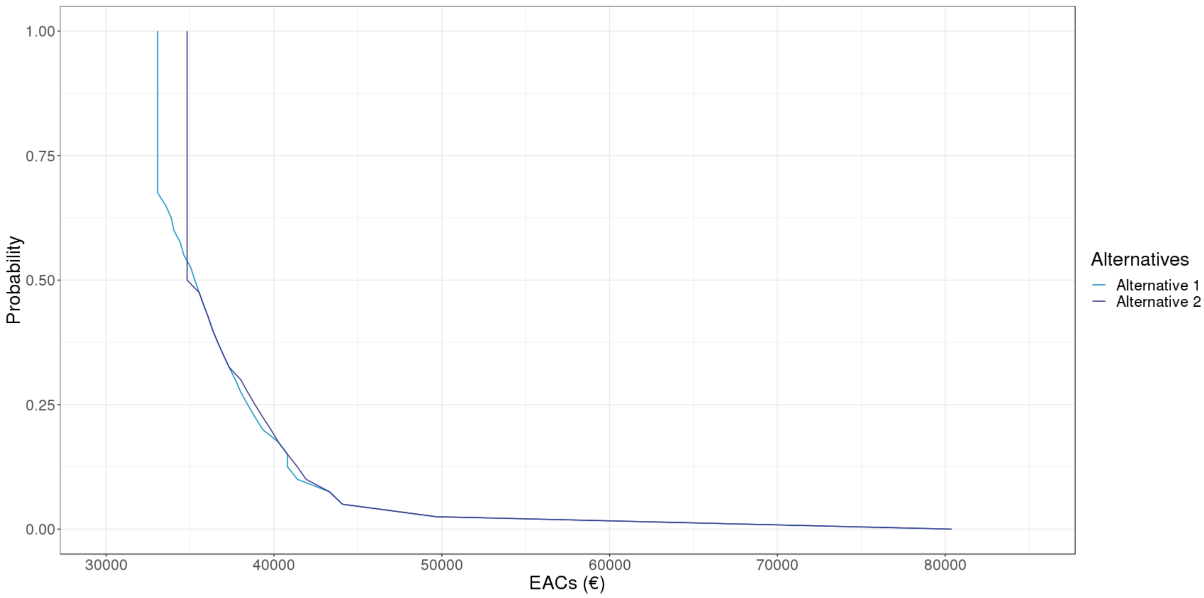

Figure 16: Loss exceedance curves of Alternative 1 (current strategy) and Alternative 2 (earlier preventive replacement).

The third alternative we compare to the current strategy is an alternative with age-dependent maintenance rules. The first inspection is performed at age twelve. Afterwards, an inspection is performed six years after finding the asset in State 9 and four years after finding it in another state until age thirty. From age thirty until replacement the inspection interval is five years in State 9 and three years in another state. A revision is still only performed in case of corrective maintenance. Regular maintenance is performed if the asset is found in State 1 before age thirty and in States 6 and 1 after age thirty. The alternative investment strategy is more age-dependent than the current strategy. Figure 17 shows the performance of the two competing investment strategies. Once again, the difference between the two strategies is only marginal.

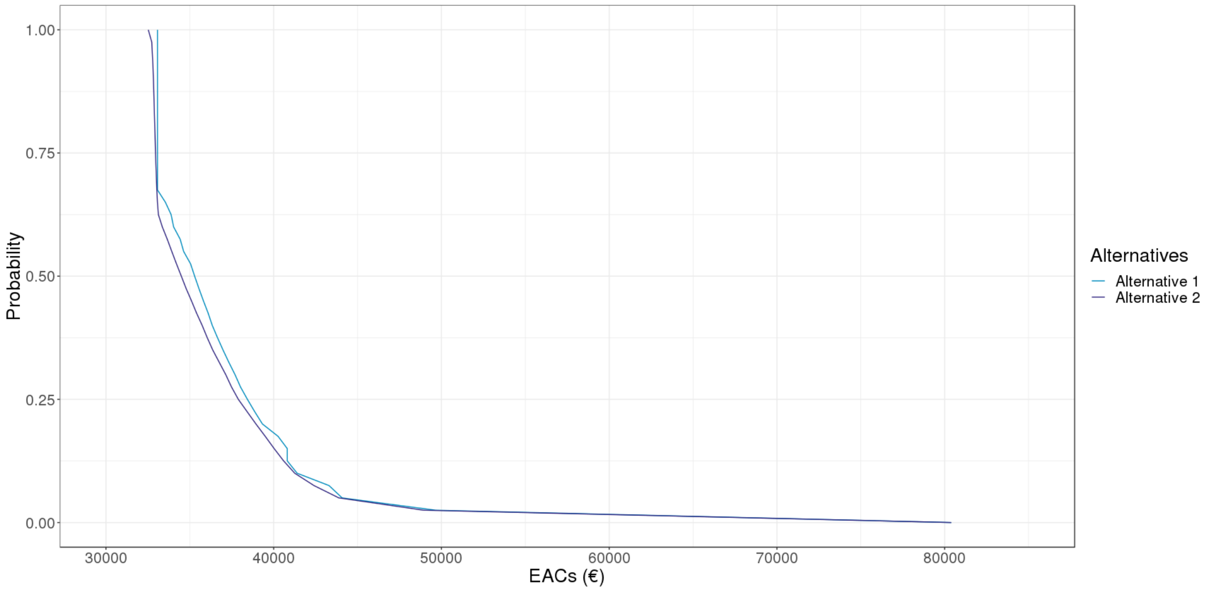

Figure 17: Loss exceedance curves of Alternative 1 (current strategy) and Alternative 2 (age-dependent maintenance).

The last alternative we will investigate is a run to failure investment strategy. This means that we perform no inspections or maintenance actions, and when the asset fails we remove it. Figure 18 shows the performance of the current strategy versus the run to failure strategy. The curve of the run to failure strategy is coarse, because each additional year of survival leads to hugely different EACs than not having survived that year. In the best case scenario the alternative strategy is better than the current strategy. The worst case scenario of the alternative strategy is also better than the worst case scenario of the current strategy. The reason for this is that the asset is not repaired at a young age just to fail again and become unrepairable soon after. Yet, 88.0% of the EACs curve is to the right of the curve of the current investment strategy, suggesting that the run to failure strategy is probably not recommendable.

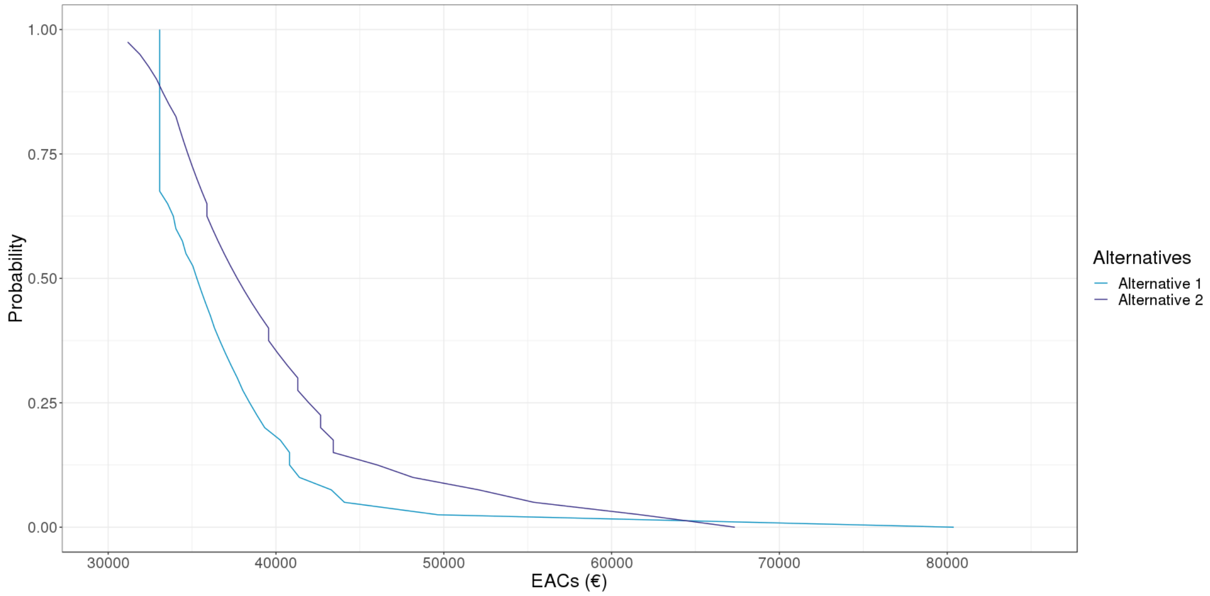

Figure 18: Loss exceedance curves of Alternative 1 (current strategy) and Alternative 2 (run to failure).

5.4 Sensitivity analysis

In the previous section we have observed that the EACs are not too different when comparing two investment strategies. In this section we investigate to what extent the parameters influence the EACs. The sensitivity of the EACs depends on the investment strategy. We use the current investment strategy for this analysis.

First, we evaluate the sensitivity of the EACs regarding the cost parameters. To do this, we run the simulation with different cost parameters and evaluate the effect on the EACs. We evaluate the impact of a five percent increase and decrease of the cost parameters on the 2.5% quantile, the average and the 97.5% quantile of the EACs. Table 19 shows the results of the sensitivity analysis. We make sure that the one million trials which describe the life cycle of a power transformer are identical even if a cost parameter is changed, so that the results are unaffected by randomness.

We observe that the purchase costs have by far the most influence on the EACs. This indicates that the purchase costs dominate the greatest proportion of the EACs. The 2.5% quantile is mainly affected by the purchase and installation costs, because these costs are made for sure even in an extremely fortunate scenario in which the asset experiences no trouble. Similarly, the average EACs are also affected mainly by the purchase and installation costs. The EACs at the 97.5% quantile are most sensitive to the purchase costs, installation costs, failure costs, revision costs and WACC. The life cycles of the assets which have an EACs above the 97.5% quantile are the worst case scenarios, and hence it makes sense that the costs which are made in cases of a failure heavily influence the 97.5% quantile. Surprisingly, the purchase costs still have a bigger impact on the 97.5% quantile.

Parameter	Change	$q_{0.025}$		Average		$q_{0.975}$	
Standard	None	33,071		36,648		49,650	
Purchase costs	+5%	34,532	(+4.42%)	38,232	(+4.32%)	51,449	(+3.62%)
	−5%	31,611	(−4.41%)	35,064	(−4.32%)	47,797	(−3.73%)
Installation costs	+5%	33,238	(+0.50%)	36,829	(+0.49%)	49,856	(+0.41%)
	−5%	32,905	(−0.50%)	36,467	(−0.49%)	49,444	(−0.41%)
Inspection costs	+5%	33,078	(+0.02%)	36,655	(+0.02%)	49,655	(+0.01%)
	−5%	33,065	(−0.02%)	36,642	(−0.02%)	49,645	(−0.01%)
Failure costs	+5%	33,071	(+0.00%)	36,687	(+0.11%)	49,842	(+0.39%)
	−5%	33,071	(+0.00%)	36,610	(−0.10%)	49,458	(−0.39%)
Disposal costs	+5%	33,076	(+0.02%)	36,656	(+0.02%)	49,664	(+0.03%)
	−5%	33,067	(−0.01%)	36,640	(−0.02%)	49,635	(−0.03%)
Regular maint. costs	+5%	33,105	(+0.10%)	36,680	(+0.09%)	49,674	(+0.05%)
	−5%	33,037	(−0.10%)	36,616	(−0.09%)	49,626	(−0.05%)
Revision costs (corrective)	+5%	33,071	(+0.00%)	36,663	(+0.04%)	49,950	(+0.60%)
	−5%	33,071	(+0.00%)	36,633	(−0.04%)	49,350	(−0.60%)
Residual value	+5%	33,053	(−0.05%)	36,615	(−0.09%)	49,592	(−0.12%)
	−5%	33,090	(+0.06%)	36,681	(+0.09%)	49,708	(+0.12%)
WACC	+5%	33,062	(−0.03%)	36,588	(−0.16%)	49,258	(−0.79%)
	−5%	33,081	(+0.03%)	36,711	(+0.17%)	50,031	(+0.77%)

Table 19: Sensitivity analysis of the EACs for the cost parameters.

Next, we evaluate the sensitivity of the EACs to the transition probabilities. The sensitivity of the EACs to the transition probabilities is important, considering that the confidence intervals of the transition probabilities are wide. We investigate the influence of the transition probabilities by adding 0.05 to and subtracting 0.05 from the probabilities whenever the resulting probability would be between zero and one. Note that the change of the cost parameters is relative, while the change of the transition probabilities is absolute. The sum of the probabilities of going from a state to another state should add up to one, so the sum of the unchanged probabilities either decrease or increase by the same 0.05. The decrease or increase is spread over the unchanged probabilities in such a way that the proportion between the other probabilities remains the same. For each transition probability, we analyse the effect on all age categories once and not separately for every age category. The reason for this is that the sensitivity towards the transition probabilities of a certain age category depends on the investment strategy. Furthermore, the analysis of the sensitivity for each combination of age category and transition probability would become quite extensive. Admittedly, the sensitivity of each individual transition probability also depends on the investment strategy, since for example a maintenance focused strategy would have a greater sensitivity to the probability of remaining in State 9 as more time is spent in State 9. Table 20 shows the influence of the changes to the transition probabilities on the 2.5% quantile, average, and 97.5% quantile of the EACs.

Parameter	Change	$q_{0.025}$		Average		$q_{0.975}$	
Standard	None	33,071		36,648		49,650	
$p_{9,9}$	+0.05	33,071	(+0.00%)	36,522	(−0.34%)	48,756	(−1.80%)
	−0.05	33,071	(+0.00%)	36,736	(+0.24%)	49,967	(+0.64%)
$p_{9,6}$	+0.05	33,071	(+0.00%)	36,626	(−0.06%)	49,880	(+0.46%)
	−0.05	33,071	(+0.00%)	36,659	(+0.03%)	49,231	(−0.84%)
$p_{9,1}$	+0.05	33,071	(+0.00%)	36,826	(+0.49%)	49,967	(+0.64%)
$p_{9,0}$	+0.05	33,071	(+0.00%)	86,605	(+136.32%)	609,591	(+1127.78%)
$p_{6,6}$	+0.05	33,071	(+0.00%)	35,958	(−1.88%)	45,821	(−7.71%)
	−0.05	33,071	(+0.00%)	37,180	(+1.45%)	51,873	(+4.48%)
$p_{6,1}$	+0.05	33,071	(+0.00%)	36,878	(+0.63%)	49,967	(+0.64%)
	−0.05	33,071	(+0.00%)	36,353	(−0.80%)	48,756	(−1.80%)
$p_{6,0}$	+0.05	33,071	(+0.00%)	51,415	(+40.29%)	153,420	(+209.00%)
$p_{1,1}$	−0.05	33,071	(+0.00%)	44,763	(+22.14%)	107,302	(+116.12%)
$p_{1,0}$	+0.05	33,071	(+0.00%)	44,763	(+22.14%)	107,302	(+116.12%)

Table 20: Sensitivity analysis of the EACs for the transition probabilities.

The table shows that we find an effect towards the expected positive or negative direction. The EACs decrease when the probability of remaining in a state increases, and they increase when the probability of remaining in a state decreases. The EACs increase when the probability of going to States 0 or 1 increases. Unsurprisingly, an increase of the probability of failure has the biggest effect on the EACs. An absolute increase of 0.05 is quite large for the probabilities of failure, considering that most of them are smaller than 0.05. For example, $p_{9,0}$ is 0.000, 0.002, 0.008 and 0.006 for age categories 15 years and younger, 16 to 30 years, 31 to 45 years and 46 years or older respectively. An increase of 0.05 is a relatively hard increase. The 97.5% quantile of the EACs increases with 1127.78%, because the least fortunate scenarios have shorter lives due to failures and increased failure and revision costs. An increase in $p_{6,0}$ and $p_{1,0}$ also leads to a huge increase in the 97.5% quantile of the EACs for similar reasons. For the other probabilities, an increase and decrease of 0.05 is only a small change relative to the width of the confidence intervals determined in Section 4.5. Even then, we observe an effect of up to 7.71% on the 97.5% quantile and up to 1.88% on the average value of the EACs. This suggests that the confidence interval of the transition probabilities is too wide for the simulation results to be reliable, as the effect of a relatively small change of the transition probabilities already has a significant impact on the EACs.

5.5 Conclusion

In this chapter we propose a simulation model to assess the life cycle costs of an asset and test the simulation model on a case study. We test the model by applying it to our case study of power transformers.

In Section 5.1 we discuss the simulation model which assesses the life cycle costs of an investment strategy by generating random life cycles of an asset. The condition of the asset throughout its life cycle is based on a Markov chain. The model allows for age-dependent transition probabilities between the states and maintenance actions bringing the asset to a higher state with a certain probability. The simulation model uses cost parameters to keep track of the costs made during a life cycle of the asset and calculates the EACs when the it is replaced.

We introduce power transformers and the inputs of the simulation model in Section 5.2. We perform a case study on power transformers, which are able to transform a voltage to another level. Power transformers are maintained through regular maintenance and a revision. The input parameters are based on an 80 MW power transformer.

In Section 5.3 we discuss the current investment strategy and compare it to alternatives. The current investment strategy is difficult to formulate, as it is not followed right now. Consequently, the results of the benchmark should not be interpreted as outperforming the current situation, but rather comparing an investment strategy similar to the current one to alternatives. Overall, we observe that the performance of the different strategies does not deviate by a wide margin.

We investigate the sensitivity of the EACs curve to the model parameters in Section 5.4. Of the cost parameters, the EACs curve is most sensitive to the purchase costs. The transition probabilities have a large impact on the EACs, considering that the change in transition probabilities is relatively small compared to the width of the confidence intervals we have discussed in Section 4.5.

The results in Sections 4.4 and 4.5 indicate that the impact of maintenance in our model may be smaller than the impact of maintenance in reality. In our model, regular maintenance and revisions have a certain probability of improving the condition of the power transformer. After this improvement, the probability of degrading back to a lower state is high for older assets. This means that the benefit of a maintenance action is short-lived. We think this effect is smaller than it should be due to component replacements. When components are replaced, their state is better than would be expected for an asset of a certain age. An unrewarded replacement of components would explain the small difference between the EACs curves of different investment strategies. The limited ability of maintenance to extend the life cycle of the power transformers leads to a difficulty in making a true difference with an investment strategy. In the next section we make suggestions to improve the current assessment of the performance of an investment strategy.

Chapter 6 Conclusions and recommendations

In Section 6.1 we present the most important findings of our research. Then, in Section 6.2, we make recommendations for Liander in order to continue with our findings. Lastly, we discuss the limitations of our research and give suggestions for further research in Section 6.3.

6.1 Conclusions

Our research objective is to *build a simulation model which can assess the life cycle costs of an investment strategy*. The model we propose is a Monte Carlo simulation model which uses a Markov chain model to simulate the condition of the asset throughout its life cycle. The states of the Markov chain model correspond to an asset's conditions and a failure. The assignment of cash flows to specific events, such as purchase, failure and maintenance actions, allows for generating a stream of cash flows for a randomly generated life cycle while following an investment strategy. The equivalent annuitized costs are calculated from this stream of cash flows, which are the annuity equivalent of the net present value. It allows for a fair comparison of mutually exclusive alternatives with unequal lives. Ultimately, the process of generating a random life cycle can be repeated to get insight in the spread of the life cycle costs of an investment strategy.

The simulation model only allows for transition probabilities and investment strategy decisions dependent on the asset's age and condition. We are unable to verify whether the transition probabilities should depend on the time spent in a state for our case study. If this is the case, more research needs to be done in order to allow for transition probabilities dependent on an asset's age and the time spent in a state. Therefore, the simulation model is a proof of concept rather than a finalised simulation model. Furthermore, the assumption of constant costs of our simulation model may need further research. We make the assumption to be able to perform a proof of concept, but we are not sure whether this assumption holds true in reality.

The proof of concept shows the spread of equivalent annuitized costs for multiple investment strategies. We observe that a change in the investment strategy leads to substantially different costs. This is supported by the sensitivity analysis, which shows that the equivalent annuitized costs are dominated by the purchase costs. We argue that the impact of maintenance in our model is too small due to the unrewarded replacement of components. After maintenance is performed on an older asset and certain components have been replaced, these components are unlikely to degrade soon. The transition probabilities of our simulation model depend only on the asset's age, and not the age of the components. Therefore, the transition probabilities may not be representative for an actual case. We provide solutions for this issue in the next section.

6.2 Recommendations

We make five recommendations to Liander regarding the application and improvement of a life cycle costing analysis for assets.

First, we advise Liander to expand the simulation model for multiple components. The proof of concept has shown that the impact of maintenance may not be reliable when assessing the life cycle costs of an asset consisting of components which are replaced during its life. A degradation model for each component would allow for an improved accuracy. These transition probabilities per component would have to be included in the simulation model. In order to estimate these probabilities, Liander needs to track more data on its assets. An asset breakdown structure defines which components belong to an asset, and would allow for tracking events on a component level. The inspection data are already stored on component level, so the main change would be the registration of component replacements and maintenance. Of course, the danger of the simulation model becoming too extensive arises when introducing the degradation on a component level. For example, the investment strategy decisions would depend on multiple conditions rather than one. Therefore, Liander would need to be pragmatic in their approach. The decisions may for example be dominated by certain components, which can be used to simplify the problem.

Second, Liander should gather more data to test whether the transition probabilities depend on the time spent in a state and the asset's age. If Liander were to implement an asset breakdown structure and register data consistently, an analysis of realistic transition probabilities can be performed. The outcomes of a simulation or optimisation model can only be reliable if the inputs are realistic. Moreover, more data would allow for a more reliable estimation of the transition probabilities per age category. The confidence intervals are wide in our current analysis, and we therefore argue that the transition probabilities are too unreliable to use for decision making.

Third, Liander should investigate the cost parameters. In our research we assume constant costs for simplicity. In reality, this assumption may not be true. The decision for corrective maintenance may depend on the costs of repairing the asset, which is not included in our simulation. Liander should research whether costs directly influence the decision, and whether they are constant or not. Furthermore, Liander can opt to include the environmental impact of decisions in its estimation of cost parameters. This requires monetisation of environmental impact. Liander aims to weigh sustainability into its decisions, and letting environmental factors play a role in the decisions would accomplish just that.

Fourth, Liander should analyse the appropriateness of the degradation model for other assets. Even between power transformers differences in the asset degradation may exist. An overview of which assets have similar degradation behaviours is required if the model is to be applied for decision making. For now, the model assumes that the transition probabilities depend only on age. This may not be true for certain assets.

Fifth, we recommend that Liander keeps assets on the same or nearby substations and control stations in mind. Power transformers and other assets are placed together on control stations and substations. Performing actions on multiple assets at the same or nearby substations and control stations results in low travelling times. Deviating from an investment strategy may be worth it if a large reduction in travelling time can be achieved. Liander should consider this trade off when deciding which actions to perform at a certain moment and location.

6.3 Limitations and further research

We discuss five limitations and suggest directions for further research.

First, the application of the Markov model is currently time-based rather than usage based. The asset degradation may depend on the intensity of the usage rather than time for certain cases. The transitions would no longer be defined by the time between the two observations, but by the usage of the asset between the two observations. We did not perform such an analysis. The recommendation for further research is to consider the possibility that the degradation is driven by the intensity of usage rather than time.

The second limitation of our research is that it only shows a method but does not show a reliable case study due to data issues. The case study is not usable to improve the investment strategy. Further research could perform similar research on a case study with a more complete dataset while also modelling the asset on a component level. This would show whether an investment strategy can be outperformed, and by how much.

Third, the test for stationarity of Anderson and Goodman (1957) is based on a different estimator function than the estimator function used in our study. The test is therefore performed differently than intended. An adjusted test which is applicable to our estimator function would be most welcome. Additionally, we would also like to test whether the transition probabilities depend on the time spent in a state. Black et al. (2005) describe how we can fit these transition probabilities based on our data. A test to see whether these differ substantially from the stationary transition probabilities would indicate which transition probabilities are realistic.

The fourth limitation is the absence of an optimisation algorithm which can find the optimal life cycle decisions. The development of this algorithm is premature for Liander, as gathering reliable data has to be their first priority. Other companies may have gathered reliable data already, and can put research effort into optimising an investment strategy. Furthermore, the optimisation of the investment strategy for a single asset is only suboptimal. As stated earlier, the other assets which are nearby also need to be considered in order to perform a more complete optimisation. Two possible directions for an algorithm are Approximate Dynamic Programming (ADP) and enumeration. ADP is a modelling framework that offers several strategies for tackling the curses in large, multi-period, stochastic optimisation problems (Powell as cited in Mes and Rivera, 2017). According to Mes and

Rivera (2017), the common denominator in ADP is that optimisation is used in combination with simulation. The algorithm estimates a value function through simulation, and iteratively attempts several decisions before moving forward in time. This algorithm is interesting, because we already have a simulation model. Enumeration is a brute force method, which calculates an objective function for all solutions. Liander can use business rules to reduce the solution space to a manageable size, e.g. a period of at least three years should remain between consecutive maintenance actions. The objective function would be the expected equivalent annuitized costs, and a method to calculate or approximate them quickly is required to make enumeration possible.

Lastly, the fifth limitation is that the cost reduction of an optimised investment strategy may be disappointing due to technological advancements and changes in legislation. For example, an asset which is new may already be technologically outdated before its end of life. Similarly, an asset may have to be replaced prematurely due to new legislation which forbids certain materials. So, the theoretical cost reduction may not materialise when following an optimised investment strategy.

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Appendix A: Solving for the transition probabilities

We use the non-linear optimisation R package "NLoptR" to estimate the transition probabilities. This package minimises a non-linear objective function. Since the log likelihood objective function should be maximised, we minimise the negative log likelihood function. The least squares objective function should already be minimised.

The NLoptR package allows users to determine which optimisation algorithm should be used. However, only few algorithms are able to handle constraints. The probabilities for each row in the transition matrix have to add up to one. A constraint is able to make sure that this condition is met. We want to be able to use certain optimisation algorithms which are unable to handle constraints as they are faster. Therefore, we have to find another method to make sure the probabilities add up to one. We do this by making use of conditional probabilities. The following matrix shows how the transition probability matrix:

$$P = \begin{bmatrix} ab & a(1-b)c & a(1-b)(1-c) & 1-a \\ 0 & de & d(1-e) & 1-d \\ 0 & 0 & f & 1-f \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$a = Prob(9 \rightarrow 9{,}6{,}1), b = Prob(9 \rightarrow 9|9{,}6{,}1), c = Prob(9 \rightarrow 6|6{,}1), d = Prob(6 \rightarrow 6{,}1),\ e = Prob(6 \rightarrow 6 \mid 6{,}1), f\ = Prob(1 \rightarrow 1)$. $b, c\ and\ e$ are conditional probabilities. For example, b is the probability of remaining in State 9 given that the asset will not go to State 0. The sum of the probabilities in each row adds up to one for all $a, b, c, d, e, f \in U(0{,}1)$. Constraints are no longer required and the number of parameters to estimate is the same as the number of parameters if constraints were used.

Not all probabilities in the transition probability matrix are dependent on parameters. These probabilities are certain because we have removed the transitions for which the state improves. Consequently, we already know that these transitions are never going to happen in the observed data, so estimating them is unnecessary.

Appendix B: Imputing data

The identified transitions span up to 7.25 years. Whenever a transition goes from a state to the same state and it is longer than two years, we split it into multiple transitions. For example, a transition from State 9 to State 9 in 7.25 years is split into three transitions from State 9 to State 9 in two years and one transition from State 9 to State 9 in 1.25 years. This can be done because we know the degradation can only cause a condition to go down, and hence we know the condition would be in State 9 at all moments in time during the 7.25 years. Table 21 shows the transition probabilities estimated by the maximum likelihood and least squares approaches with imputed and non-imputed data.

	Maximum likelihood, non-imputed					Maximum likelihood, imputed			
	9	6	1	0		9	6	1	0
9	0.684	0.225	0.090	0.001	9	0.684	0.225	0.090	0.001
6	0.000	0.849	0.148	0.003	6	0.000	0.849	0.148	0.003
1	0.000	0.000	0.981	0.019	1	0.000	0.000	0.981	0.019
0	0.000	0.000	0.000	1.000	0	0.000	0.000	0.000	1.000
	Least squares, non-imputed					Least squares , imputed			
	9	6	1	0		9	6	1	0
9	0.506	0.256	0.228	0.009	9	0.869	0.023	0.105	0.003
6	0.000	0.895	0.101	0.004	6	0.000	0.986	0.014	0.000
1	0.000	0.000	0.908	0.092	1	0.000	0.000	0.935	0.065
0	0.000	0.000	0.000	1.000	0	0.000	0.000	0.000	1.000

Table 21: Transition probabilities estimated by the maximum likelihood and least squares approaches based on imputed and non-imputed data.

The transition probabilities for the imputed and non-imputed data estimated by maximum likelihood are the same up to three decimal places. The transition probabilities for the imputed and non-imputed data estimated by least squares are substantially different. This shows that the least squares approach can be deceiving, as the data are not different but the estimated transition probabilities are.

Appendix C: Transition probability matrices

In Section 4.4 we have addressed how we find the probability of failure for the age categories. $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$ are estimated for the preventable failures. The unpreventable failures have a probability of occurring which is independent of the current state of the asset. Therefore, these probabilities can be added to $p_{9,0}$, $p_{6,0}$ and $p_{1,0}$ to find the actual probability of failure, both by a preventable and an unpreventable cause.

Ages	$p_{9,0}$	$p_{6,0}$	$p_{1,0}$
≤15 years	0.000	0.000	0.000
16-30 years	0.002	0.003	0.012
31-45 years	0.008	0.012	0.054
≥46 years	0.006	0.013	0.095

Table 22: Probabilities of preventable and unpreventable failures.

The probability matrices from Subsection 4.2.2 Table 6 are transformed to four states with the following rule:

$$P = \begin{array}{c} \\ 9 \\ 6 \\ 1 \\ 0 \end{array} \!\!\begin{array}{c} \begin{array}{cccc} \quad 9 \quad & \quad\quad 6 \quad\quad & \quad\quad 1 \quad\quad & \quad 0 \end{array} \\ \begin{bmatrix} p^*_{9,9}(1-p_{9,0}) & p^*_{9,6}(1-p_{9,0}) & p^*_{9,1}(1-p_{9,0}) & p_{9,0} \\ 0 & p^*_{6,6}(1-p_{6,0}) & p^*_{6,1}(1-p_{6,0}) & p_{6,0} \\ 0 & 0 & 1-p_{1,0} & p_{1,0} \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

Where $p^*_{i,j}$ is the probability of going from State i to State j before adding State 0, so the probability as presented in Table 6. Table 23 shows the transition probability matrices per age category after adding State 0.

	≤15 years					16-30 years			
	9	6	1	0		9	6	1	0
9	0.881	0.110	0.008	0.000	9	0.643	0.265	0.089	0.002
6	0.000	0.827	0.173	0.000	6	0.000	0.918	0.079	0.003
1	0.000	0.000	1.000	0.000	1	0.000	0.000	0.988	0.012
0	0.000	0.000	0.000	1.000	0	0.000	0.000	0.000	1.000
	31-45 years					≥46 years			
	9	6	1	0		9	6	1	0
9	0.438	0.388	0.166	0.008	9	0.479	0.425	0.090	0.006
6	0.000	0.827	0.161	0.012	6	0.000	0.803	0.184	0.013
1	0.000	0.000	0.946	0.054	1	0.000	0.000	0.905	0.095
0	0.000	0.000	0.000	1.000	0	0.000	0.000	0.000	1.000

Table 23: Transition probabilities per age category, including State 0.