



**KTH Electrical Engineering**

# **Risk-based methods for reliability investments in electric power distribution systems**

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Doctoral Thesis  
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Electric Power Systems  
Stockholm, Sweden 2011

TRITA-EE 2011:040  
ISSN 1653-5146  
ISBN 978-91-7501-003-8

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Akademisk avhandling som med tillstånd av Kungl Tekniska Högskolan framlägges till offentlig granskning för avläggande av teknologie doktorsexamen onsdagen den 15 juni 2011 kl 14.00 i sal D3, Lindstedtsvägen 5, Kungl Tekniska Högskolan, Stockholm.

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Tryck: Universitetsservice US AB

# Abstract

Society relies more and more on a continuous supply of electricity. However, while underinvestments in reliability lead to an unacceptable number of power interruptions, overinvestments result in too high costs for society. To give incentives for a socioeconomically optimal level of reliability, quality regulations have been adopted in many European countries. These quality regulations imply new financial risks for the distribution system operator (DSO) since poor reliability can reduce the allowed revenue for the DSO and compensation may have to be paid to affected customers.

This thesis develops a method for evaluating the incentives for reliability investments implied by different quality regulation designs. The method can be used to investigate whether socioeconomically beneficial projects are also beneficial for a profit-maximizing DSO subject to a particular quality regulation design. To investigate which reinvestment projects are preferable for society and a DSO, risk-based methods are developed. With these methods, the probability of power interruptions and the consequences of these can be simulated. The consequences of interruptions for the DSO will to a large extent depend on the quality regulation. The consequences for the customers, and hence also society, will depend on factors such as the interruption duration and time of occurrence. The proposed risk-based methods consider extreme outage events in the risk assessments by incorporating the impact of severe weather, estimating the full probability distribution of the total reliability cost, and formulating a risk-averse strategy.

Results from case studies performed show that quality regulation design has a significant impact on reinvestment project profitability for a DSO. In order to adequately capture the financial risk that the DSO is exposed to, detailed risk-based methods, such as the ones developed in this thesis, are needed. Furthermore, when making investment decisions, a risk-averse strategy may clarify the benefits or drawbacks of a project that are hard to discover by looking only at the expected net present value.

**Key words:** Distribution system reliability, risk management, quality regulation design, customer interruption costs, weather modeling, Monte Carlo simulations.



# Acknowledgment

This thesis summarizes my PhD project carried out at the Division of Electric Power Systems. The project is within the Risk Analysis programme (Riskanalysprogrammet 06-10) financed by Elforsk AB. The financial contributions to the research programme come from many distribution companies, organizations and authorities. The financial support is gratefully acknowledged and I wish to thank all members in the steering committee.

I would like to thank my supervisor Professor Lennart Söder for his encouragement and support throughout this work. I am indebted to my colleagues for providing a stimulating and fun environment. And last but not least, I wish to thank my family for all their support.

*Karin Alvehag*  
Stockholm, 2011



# Dissertation

The appended publications to this doctoral thesis are:

## Publication I

K. Alvehag and L. Söder, “An activity-based interruption cost model for households to be used in cost-benefit analysis”, *Proceedings of Power Tech 2007*, Lausanne, Switzerland, July 2007.

## Publication II

K. Alvehag and L. Söder, “Considering extreme outage events in cost-benefit analysis of distribution systems”, *Proceedings of Australasian Universities Power Engineering Conference (AUPEC)*, Sydney, Australia, December 2008.

## Publication III

M. Jakobsson Ueda, O. Engblom, and K. Alvehag, “Representative test systems for Swedish distribution networks”, *Proceedings of CIRED2009*, Prague, Czech Republic, June 2009.

## Publication IV

K. Alvehag and L. Söder, “Financial risk assessment for distribution system operators regulated by quality regulation”, *Proceedings of Probabilistic Methods Applied to Power Systems (PMAPS)*, Singapore, June 2010.

## Publication V

K. Alvehag and L. Söder, “A reliability model for distribution systems incorporating seasonal variations in severe weather”, *IEEE Transactions on Power Delivery*, Vol. 26, No. 2, April 2011

## Publication VI

K. Alvehag and L. Söder, “The impact of risk modeling accuracy on cost-benefit analysis of distribution system reliability”, *Proceedings of the 17th Power System Computational Conference (PSCC)*, Stockholm, Sweden, August 2011, accepted

**Publication VII**

K. Alvehag and L. Söder, “Risk-based method for distribution system reliability investment decisions under performance-based regulation”, *IET Generation, Transmission & Distribution*, provisionally accepted for publication, 2011.

**Publication VIII**

K. Alvehag and L. Söder, “Evaluation of quality regulation incentives for distribution system reliability investments”, manuscript submitted to *Utilities Policy*, 2011.

In addition to these publications, [1–4] have also been published within the PhD project.

## **Division of work between the authors**

### **Publication I, II, IV, V, VI, VII and VIII**

K. Alvehag drew up the outline, carried out the work and wrote these publications under the supervision of L. Söder.

### **Publication III**

M. Jakobsson Ueda and O. Engblom drew up the outline, carried out the work and wrote this publication under the supervision of K. Alvehag.



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# Chapter 1

## Introduction

*This chapter motivates the interest of research in the topic, defines the objectives and scope, and presents the scientific contributions.*

### 1.1 Background

Reliability of electric power supply is essential in modern society. The devastating consequences of major blackouts are one proof of how heavily dependent society is on a continuous supply of electricity. The electric power system with its generation, as well as its transmission and distribution networks, is one of the most complex technical systems that humanity has created. The reliability demands on this technical infrastructure are high and, despite its complex structure, it is in many cases an extremely reliable system. However, a completely reliable system is impossible to obtain, and a certain level of power interruptions has to be accepted. While underinvestments in reliability lead to an unacceptable number of power interruptions, overinvestments result in too high costs for society. The challenge is to find a socioeconomically adequate level of reliability.

Significant changes in the form of liberalization and privatization have taken place in the electricity business. Many electricity markets in Europe have been re-regulated resulting in the network owners being unbundled from power production [5]. In Sweden, network owners are unbundled both from power production and retail. After the re-regulation, retail and production are conducted on a competitive market. However, the network ownership of transmission and distribution networks constitutes natural monopolies since it is not socioeconomically defensible to have parallel networks serving the same customers. These natural monopolies need to be regulated.

The focus in this thesis is on distribution systems. Historically, cost-based regulation was used, allowing the distribution network owners, also called distribution system operators (DSOs), to charge for their actual costs plus a certain profit [6]. To motivate economic efficiency and to simulate competition in the natural monopoly

of network ownership, the concept of performance-based regulation (PBR) was introduced [6]. In PBR, the DSOs are not always allowed to charge their customers for their actual costs. Profits are no longer guaranteed, but can be earned by cost savings. To prevent cost savings in investments and maintenance resulting in a deterioration of reliability, many PBR regimes in Europe have been accompanied by quality regulations [7]. Quality regulations are relatively new; they were introduced in Italy in 2000, in Norway and Ireland in 2001, in the UK in 2002, in Hungary and Portugal in 2003, in Sweden in 2004, in Estonia in 2005, and in Finland and Lithuania in 2008 [7]. Many other countries have also expressed interest in introducing a quality regulation for reliability [7].

Quality regulations aim to provide incentives for an adequate level of reliability under a performance-based regulation by offering direct financial incentives to the DSOs [8]. By financial incentives such as increased or decreased revenues and an obligation to pay compensation to customers that have suffered long power interruptions, the regulator tries to mimic the outcome of market-like conditions [8]. To find an adequate level of reliability, the benefits for society of power system reliability need to be translated into monetary terms. This is commonly assessed by approximating the consequences of unreliability, i.e. the costs due to power interruptions for customers. To assess these costs, referred to as customer interruption costs, customer surveys are commonly used. A quality regulation transfers some of the customer interruption costs to the DSO. Whether the regulator succeeds in formulating a quality regulation that leads to an adequate reliability level or not will depend on the regulator's ability to properly measure and reconstruct customer interruption costs. Different regulators use different levels of detail in the reconstruction. Accurate customer interruption cost estimations have to be weighted against the drawbacks of a complex regulation. A complex regulation demands more data to be recorded and reported by the DSO to the regulator. To record all the required data, the DSOs may have to upgrade their equipment [9].

Before the re-regulation of the electricity market, retail and distribution were integrated into one company. These companies or DSOs were often publicly owned by, for example, municipalities or cooperatives. In the aftermath of the re-regulation of the electricity market, many DSOs are now investor-owned, and the overall goal is to maximize profit rather than to maximize social welfare [10]. A profit-maximizing DSO will choose the reinvestment project that maximizes profit, taking into account the financial risks due to the quality regulation. In this new environment, a quality regulation design that gives "correct" incentives becomes of great importance.

This brings us to the three research questions that this thesis aims to answer:

**Q1:** *What incentives for reliability improvements in distribution systems do different quality regulation designs imply?*

Designing a quality regulation that results in an adequate level of reliability in a distribution system is indeed a challenging task for the regulator. Quality regulation design tends to become more complex with combinations of regulatory controls for improved reliability both on customer and system

level [7]. Both the quality regulations on customer and system level are important since they fulfill different functions. On system level, the quality regulation has the objective of achieving a socioeconomically adequate level of system reliability, while on customer level the quality regulation ensures the customers minimum guaranteed standards for electricity supply. With a complex quality regulation design, more extensive analyses by the regulator are needed in order to investigate the effects of a certain regulation design on the reliability level.

**Q2:** *How can a risk-based method for society be formulated that estimates customer interruption costs as accurately as possible?*

An accurate assessment of customer interruption cost is essential in cost-benefit analysis of distribution system reliability. Customer interruption costs are a function of many different factors such as customer sector (residential, industrial, etc), interruption duration, and time of occurrence of the interruption. A detailed cost model that estimates the customer interruption costs taking into account as many factors as possible demands a large amount of cost data. These cost data are usually collected in customer surveys. In the surveys, the customers are asked to state their customer interruption cost for different outage scenarios with, for example, varying interruption duration and time of occurrence. However, since the amount of effort that respondents are prepared to devote to filling out surveys is limited, the surveys cannot be too extensive.

**Q3:** *How can a risk-based method for a profit-maximizing DSO be formulated that takes into account the financial risks due to quality regulation?*

Quality regulations imply new financial risks for the DSO since poor reliability can reduce the allowed revenue for the DSO and compensation may have to be paid to affected customers. Most DSOs prefer to have deterministic targets in their investment planning [11]. A common approach when optimizing system reliability, given a fixed budget, is to approve the projects with the highest marginal reliability benefit-to-cost ratio until the budget limit is reached [12]. However, in the presence of a quality regulation, it is not always optimal to spend the entire budget on improving reliability. Sometimes only a part of the budget or a larger budget is needed to maximize the profit. For example, this can be the case if a so-called dead band design is used to give incentives for adequate system reliability. Once the DSO has a system reliability level that is in the dead band, investments that increase the system reliability level but still make it stay in the dead band will not increase the profit for the DSO. In this new regulatory environment of quality regulation, network planning and network operation criteria have to change [13], and new methods that take into account the new financial risks due to quality regulation are needed.

## 1.2 Objectives

Ideally, a quality regulation (QR) should influence a profit-maximizing DSO in such a way that it would choose the same network investments as society would. If the regulation is not well designed, a socioeconomically beneficial reinvestment project is not beneficial for the DSO, and hence is not selected [14]. A risk assessment can be used to evaluate different reinvestment projects aimed to improve reliability by considering the probability of power interruptions and their consequences. The consequences of interruptions for the profit-maximizing DSO will depend on the quality regulation design, while the consequences for society will depend on customer interruption costs.

This thesis has three objectives corresponding to the presented research questions Q1, Q2 and Q3. The objectives are presented in Figure 1.1 and described below.

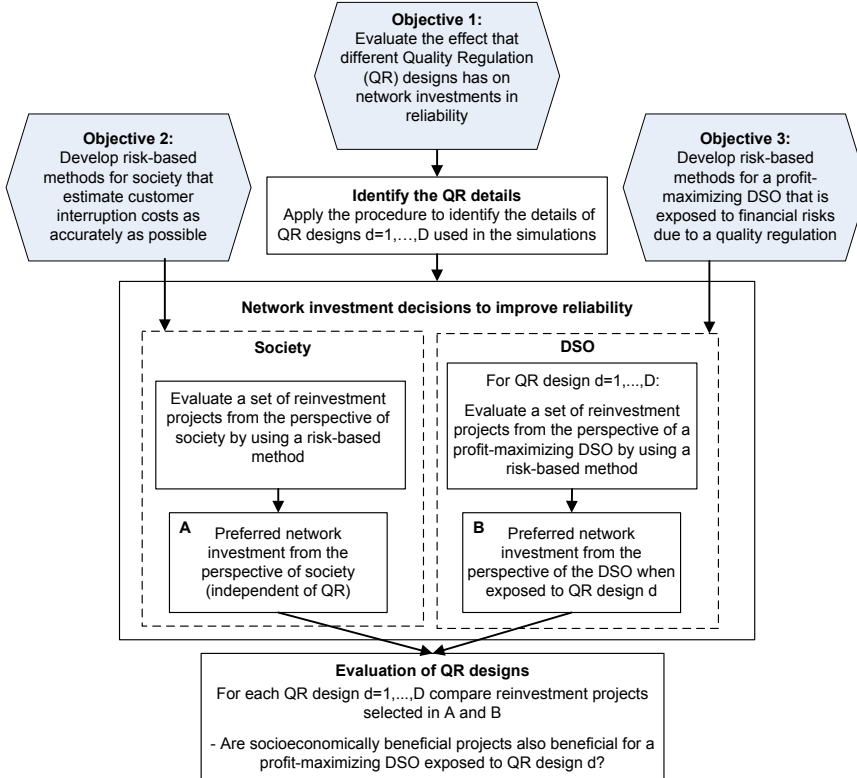


Figure 1.1: Objectives of the thesis.

**Objective 1** is the overall objective of this thesis. The objective is to evaluate the effect that quality regulation designs have on network investments in reliability by comparing the results of risk assessments from the perspective of a profit-maximizing DSO and the perspective of society. Will socioeconomically beneficial reinvestment projects also become beneficial for a profit-maximizing DSO exposed to a quality regulation design? In order to perform risk assessments from the two stakeholders' perspectives, risk-based methods for society and a profit-maximizing DSO need to be developed. This leads us to Objective 2 and Objective 3 of this thesis.

**Objective 2** is to develop risk-based methods for society that estimate customer interruption costs as accurately possible. This method can be applied in value-based reliability planning, which is when cost-benefit analysis constitutes the basis for designing and operating distribution systems [11]. There exist publicly owned DSOs that apply value-based reliability planning [10,11].

**Objective 3** is to develop risk-based methods for distribution system planning for a profit-maximizing DSO that is exposed to financial risks due to a quality regulation.

The developed risk-based methods for society and a DSO will be applied in the risk assessments from the two perspectives when evaluating quality regulation designs as shown in Figure 1.1. Reliability investment decisions are usually not based on annual costs, but rather on net present value calculations using the total reliability cost estimated over a project's lifetime. Besides customer interruption costs (for society) and quality regulation costs (for a profit-maximizing DSO), the total reliability cost also include investment, maintenance and restoration costs.

To capture both the probability and consequences of power interruptions, three risk models – a cost model, a load model, and a reliability model – are needed. The developed risk-based methods for society and a DSO have the same reliability and load models. The cost model is, however, formulated in two different ways depending on whether it is the consequences (costs) for society or for a DSO that are simulated. Quality regulations and customer interruption costs are functions of load-related parameters and therefore a load model that predicts the loss of load due to an interruption is needed. Finally, in order to estimate the probability of power interruptions, a reliability model that describes the failure and restoration process of the components in the power system is also required.

The developed risk-based methods focus on two improvements compared to previous research: inclusion of extreme events and time dependencies based on underlying factors in the risk assessments. Examples of underlying factors are outdoor temperature, weather intensity, and time patterns for electricity dependent activities.

Extreme events are defined as low-probability and high consequences events. The most common approach when making investment decisions is to base them on

the expected values. The expected value is an operation that multiplies the consequence of each event by its probability and sums over all possible events. With this operation, a high frequency event with low consequences has the same weight as a low frequency event with high consequences (if the products are the same). Basing decisions on expected values corresponds to adopting a risk-neutral strategy. A decision-maker may not always be risk-neutral. Instead, low-probability catastrophic events can be of higher concern than more frequently occurring but less severe events. This decision-maker would prefer a risk-averse strategy. The proposed risk-based methods consider extreme outage events in the risk assessments by incorporating the impact of severe weather, estimating the full probability distribution of the total reliability cost, and formulating a risk-averse strategy.

The second improvement is to incorporate time dependencies by using time-varying risk models. A common assumption in risk assessments is that inputs such as customer interruption costs, failure rates, restoration times and loads are uncorrelated. However, all of these inputs are in fact time-dependent, making them correlated. Customer interruption costs depend on the time of occurrence of the interruption. The load demanded by customers varies both on a daily and seasonal basis. Severe weather shows seasonal patterns and since weather affects both failure rates and restoration times for overhead lines, these become time-varying. For example, storms are more frequent in Sweden during the cold period of the year. During this time of the year, demanded load and customer interruption costs are also high. The proposed risk-based methods use time-varying risk models in time-sequential Monte Carlo simulations to capture the time-dependencies.

### 1.3 Scope

This thesis only deals with power reliability regarding system adequacy, which implies that system dynamics and transient disturbances are not considered. The overall power system can be divided into three basic functional zones: generation, transmission and distribution [15]. System adequacy assessment can be carried out at all three of these levels [16]. Besides this division, there is also distributed generation which consists of relatively small-scale generation within the distribution level. In this thesis, generation and transmission are assumed to be fully reliable and the system adequacy analysis is only carried out on distribution level. Furthermore, the effects of distributed generation are not considered in analysis.

Only unplanned power outages that are sustained for more than a few minutes are included in the reliability analysis. This means that costs due to power quality problems, such as voltage sags and short interruptions, are outside the scope of this thesis.

Consequences of power interruptions can relate to many different aspects such as environment and safety concerns. In this thesis, risk-based methods that consider the financial consequences of power interruptions for the DSO and society are developed. The decision-making process in distribution system reliability can also be

formulated as a multi-criteria decision problem. A multi-criteria problem considers not only the financial consequences when making decisions, but also other aspects that are difficult to attach a cost to, such as safety and reputation impact. The methods developed in this thesis can be used to evaluate the financial impact in a multi-criteria problem.

In this thesis, regular maintenance actions are assumed to keep the failure rates constant. How a component's failure rate is affected by maintenance actions is not modeled in detail. Therefore, only reinvestment projects and not maintenance projects have been investigated in the case studies in this thesis. However, the developed reliability model can be further refined to model the failure rate as a function of aging and maintenance.

## 1.4 Scientific contributions

The main contributions of the thesis are the following:

- C1:** A new time-varying reliability model. Failure rates and restoration times for overhead lines during high winds and lightning are modeled as a function of weather intensity. Annual seasonal patterns for severe weather are also incorporated using non-homogeneous Poisson processes.
- C2:** A new time-varying cost model for estimating interruption costs for residential customers. The three main contributors to residential interruption costs are uncomfortable indoor temperature, loss of lighting and interrupted electricity-dependent activities. These three contributors vary with time and hence the consequences of a power interruption will depend on the time of occurrence of the interruption. To formulate a time-varying cost model, information on how the customer interruption costs vary on a monthly, weekly and daily basis is needed. This information is usually collected by extensive customer surveys where households are asked to state their cost for many different outage scenarios. Instead of collecting this information in extensive customer surveys, the proposed model uses already available activity and meteorological data to capture the time variations in the cost. In this way, fewer demands are placed on customer surveys.
- C3:** A new time-varying cost model for estimating the total reliability cost for society or a DSO. For a DSO, the financial risk due to a certain quality regulation design is included. Reliability costs can be calculated using historical data. However, a risk-based method demands a cost model that can calculate the cost of an arbitrary interruption event so it can be applied in a time-sequential Monte Carlo simulation. Therefore, a new cost model is proposed that estimates the total reliability cost as a function of the interruption events that have occurred during the calculation period.
- C4:** A new time-varying load model that captures the effect of extreme temperatures.

**C5:** Two new risk-based methods for reliability investment decisions. The methods can be applied from the perspective of two different stakeholders: society and a DSO. When the stakeholder society is in focus, the goal is to maximize social welfare [10] and customer interruption costs are investigated. By contrast, the overall goal of an investor-owned DSO is to maximize profit [10], and hence quality regulation costs are investigated.

The first method is used for estimating the annual customer interruption cost or the annual total regulation cost. The second method is used for estimating the total reliability cost either for society or for a profit-maximizing DSO during the whole lifetime of a reinvestment project. Both methods consider the fact that the cost (annual cost or total reliability cost) is stochastic since it depends on variables such as the number of interruptions and interruption durations. Time-varying models are combined in time-sequential Monte Carlo simulations to capture the time-dependence in the inputs. The Monte Carlo simulations result in a probability distribution for the cost (annual cost or total reliability cost), and thus different risk strategies can be applied. A new risk-averse strategy based on Conditional Value-at-risk is proposed.

**C6:** Development of two electrical distribution systems, Swedish Urban Reliability Test System (SURTS) and Swedish Rural Reliability Test System (SRRTS). The test systems have been validated and it was confirmed that they are good representatives of actual Swedish distribution networks, and thus suitable for further research on distribution networks and for studies of regulation policies.

**C7:** A proposed method for evaluation of quality regulation incentives for distribution system reliability investments. The evaluation method can be applied to investigate an arbitrary quality regulation design and uses the risk models and risk-based methods proposed in this thesis.

The models and methods proposed have been applied in different case studies. Table 1.1 illustrates the publications and chapters in which the different contributions are presented.

Table 1.1: Where to find the contributions in the publications and in the chapters.

Contribution	Publications								Chapters		
	I	II	III	IV	V	VI	VII	VIII	3	4	5
C1					✓				✓		
C2	✓								✓		
C3						✓	✓		✓		
C4						✓			✓		
C5		✓		✓		✓	✓			✓	
C6			✓								✓
C7								✓			✓

## 1.5 Thesis outline

**Chapter 2** defines risk concepts and describes scope definition for risk analyses, risk estimation and risk evaluation of distribution systems. Terms such as time-sequential Monte Carlo simulations, customer interruption costs, quality regulation and risk tools for handling extreme events are discussed.

**Chapter 3** presents the proposed time-varying risk models. Two proposed cost models that estimate the total reliability cost for society and for a profit-maximizing DSO, respectively, are presented. A new approach for estimating time variations in interruption costs for residential customers is presented. The proposed reliability and load models are also presented. The models have been applied in case studies and the conclusions are summarized in the chapter.

**Chapter 4** develops new risk-based methods for reliability investment decisions. The methods use the proposed risk models and can be applied in cost-benefit analyses or by a profit-maximizing DSO subject to a quality regulation. The decision-maker's attitude toward risk is captured in the applied risk strategy for making investment decisions. By using the proposed risk-based methods, the impact that different risk strategies (risk-neutral/risk-averse) and risk models (non-time-varying /time-varying) have on which reinvestment project is preferred is investigated in case studies. In the chapter, conclusions from the case studies are presented.

**Chapter 5** develops an evaluation method for quality regulation designs. To evaluate quality regulation designs, test systems are needed for the reliability analysis. This chapter presents two developed test systems – a rural and an urban test system – that are representative of Swedish distribution networks. The proposed method is applied in a case study to evaluate what incentives for investments in distribution system reliability two different quality regulation designs give. One design is similar to the Swedish quality regulation that will apply from 2012 and the other design is similar to the current Norwegian quality regulation introduced in 2009. It is investigated whether socioeconomically beneficial reinvestment projects also become beneficial for a profit-maximizing DSO exposed to either of the two quality regulation designs.

**Chapter 6** concludes the thesis and areas for future work are discussed.



## Chapter 2

# Background

*This chapter defines risk concepts and describes scope definition for risk analyses, risk estimation and risk evaluation of distribution systems.*

### 2.1 Definition of risk and its concepts

Firstly, the term “risk” needs to be defined. Risk is defined as a measurable randomness that can be described by a probability distribution, in contrast to uncertainty, which is randomness without a well-defined distribution [17]. Furthermore, the term risk includes both the probability and consequences of a specified event that can do harm [18]. In our case, this event is a power interruption and the financial consequences of the power interruption are investigated. This thesis applies the risk concepts to distribution system reliability with the objective of evaluating different reinvestment projects aimed to enhance reliability. The risk concepts used need to be defined. The definitions presented are mainly based on the international standard IEC 60300-3-9 for risk analysis of technological systems presented in [18]. Risk management is defined as the whole process in Figure 2.1. The different parts of risk management are described more closely here before being applied to distribution system reliability.

**Risk analysis** contains three parts: scope definition, risk identification and risk estimation [18]. The scope definition defines the objective, the considered system, the circumstances, the assumptions, and the analysis decisions. Risk identification identifies the risk by answering the question - What can go wrong? Risk estimation estimates the probability and consequence, thereby answering the questions - How likely is it to go wrong and what are the consequences?

**Risk evaluation** analyzes the options (alternatives) by comparing the risk levels they imply [18].

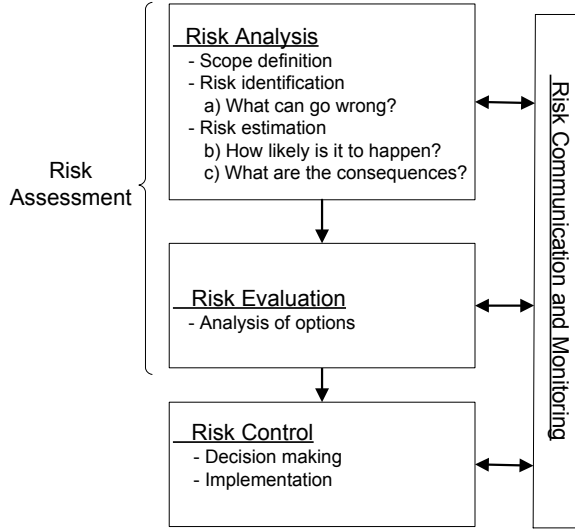


Figure 2.1: The different parts of risk management.

**Risk assessment** is the term for when a risk analysis and a risk evaluation are carried out [18].

**Risk control** is the process of decision-making for managing and/or reducing risk [18]. The risk is reduced by implementing a decision.

**Risk communication and monitoring** are important. Risk communication is exchanging or sharing information between the decision-maker and other stakeholders [19]. Risk assessments should be monitored to make sure that expected results are achieved, assumptions of acceptable risk levels are correct, and that the risk methods are used properly [18].

Of the risk concepts, scope definition for risk analyses, risk estimation and risk evaluation applied on distribution system reliability involve different terms that need to be described. The following sections aim to give the necessary background to these terms for better understanding of the subsequent chapters.

## 2.2 Scope definition for risk analyses of distribution systems

In the scope definition for a risk analysis of distribution systems, the decision-maker needs to define the decision criteria and decision rule.

### 2.2.1 Decision criteria

To select a reinvestment project, the decision-maker must define a decision criterion. The decision criterion is formulated as an optimization problem consisting of reliability and/or cost components. The optimization problem can fall into three general types [10]:

**Type 1** Optimize reliability subject to cost constraints

**Type 2** Optimize cost subject to reliability constraints

**Type 3** Optimize the total reliability cost including the cost to provide reliability and the incurred costs associated with interruptions

A DSO with a fixed budget to spend on reliability improvement projects solves the optimization problem of Type 1. A DSO solving an optimization problem of Type 2 does not have a set budget. Instead, it minimizes the total cost of approved projects until the set reliability targets are fulfilled. In both Type 1 and Type 2, the projects with the highest marginal cost-to-benefit ratio are approved until the budget limit or reliability constraints are reached [10]. This method makes sure that the reliability benefit gained for every coin spent is maximized. The reliability benefit of a project is measured in the reduction of reliability indices. Reliability indices are described in Section 2.3.1.

An optimization problem of Type 3 chooses the set of projects that minimizes the total reliability cost. The total reliability cost is not only the costs of providing reliability but also the incurred costs associated with interruptions. Hence, in contrast to Type 1 and Type 2, which only incorporate the cost due to the specific projects, Type 3 also includes the costs implied by power interruptions. The total reliability cost is in this thesis defined in two ways:

$$C_{Tot}^{DSO} = C_I + C_M + C_R + C_{TotReg} \quad (2.1)$$

$$C_{Tot}^{SOC} = C_I + C_M + C_R + CIC \quad (2.2)$$

where

$$\begin{aligned} C_I &= \text{Investment cost} \\ C_M &= \text{Maintenance cost} \\ C_R &= \text{Restoration cost} \\ C_{TotReg} &= \text{Total regulation cost} \\ CIC &= \text{Customer interruption cost} \end{aligned}$$

The total reliability cost experienced by a DSO subject to a quality regulation is  $C_{Tot}^{DSO}$ . The total reliability cost experienced by society is  $C_{Tot}^{SOC}$ . Before the re-regulation of the electricity market the DSOs were publicly owned by, for example, municipalities or cooperatives. Some publicly owned DSOs apply value-based reliability planning [10], which is equal to minimizing  $C_{Tot}^{SOC}$ . Only the actual costs of reliability for society are included. Quality regulation costs are excluded since they are only a transaction between customers and the DSO. In the aftermath of the re-regulation of the electricity market, many DSOs are now investor-owned, and the overall goal is to maximize profit rather than to maximize social welfare [10]. A profit-maximizing DSO will choose the reinvestment project that maximizes profit, taking into account the financial risks due to the quality regulation. In other words, they will minimize  $C_{Tot}^{DSO}$ .

Traditionally, DSOs prefer to have deterministic targets for system reliability indices to strive for in their investment planning [11], and thereby solve optimization problem of Type 1 and Type 2. The set deterministic targets do not correspond to finding a reliability level where the total reliability cost of interruptions is minimized. In the presence of a quality regulation, it is not always optimal to spend the entire budget or a larger budget on improving reliability. Sometimes, only a part of the budget is needed to maximize the profit. In this new regulatory environment, network planning and network operation criteria have to change [13]. New methods for decision-making on reliability investments are needed that are based on the optimization problem of Type 3. From society's perspective, the deterministic targets may be set higher than customers are prepared to pay for reliability, since they are chosen without considering customer interruption costs. In this thesis, risk-based methods when solving an optimization problem of Type 3 are proposed. Risk-based methods are formulated for both society and a profit-maximizing DSO subject to a quality regulation. By comparing whether the preferred reinvestment projects will be the same for the two perspectives, quality regulation designs can be evaluated.

## 2.2.2 Decision rule

The decision rule is to define how reliability and cost are to be measured. The two optimization problems of Type 1 and Type 2 have a reliability component that can be set to any of the system reliability indices. Multiple reliability indices can also be considered in both Type 1 and Type 2. In Type 1, multiple indices are included in the objective function by a weighted sum of the considered indices. In Type 2, multiple indices can be considered by formulating a reliability constraint for each index.

Apart from a reliability component, all optimization problem types include a cost component. When deciding whether to undertake an investment project or not, economic evaluations assessing the project's future economic performance are carried out. Reinvestment projects in distribution reliability have an impact far into the future and the cash flows for different projects may be distributed differently over their lifetime. Different methods can be used in the economic assessment such

as net present value, internal rate of return, annualized cost and initial cost [10]. In this thesis, net present value (NPV) is applied. NPV is defined as the sum of discounted flows of costs and benefits over a presumed time period [20]:

$$NPV = \sum_{\tau=1}^T PB(\tau, r) - PC(\tau, r) \quad (2.3)$$

where

$$\begin{aligned} PB &= \text{Present value of benefits due to the project} \\ PC &= \text{Present value of costs due to the project} \\ r &= \text{Discount rate} \\ T &= \text{Calculation period} \\ \tau &= \text{The year in which the benefits and costs} \\ &\quad \text{occur, } \tau = 1, \dots, T \end{aligned}$$

The evaluated reinvestment projects  $n = 1, \dots, N$  are compared to a status-quo alternative (project P0). When using an optimization problem of Type 3 as a decision rule, the benefits of a reinvestment project are measured in lowered total reliability cost compared to project P0. This means that the project that maximizes NPV is the same project that minimizes the total reliability cost:

$$\arg \max_n NPV_n = \arg \max_n C_{Tot}^{P0} - C_{Tot}^n \iff \arg \min_n C_{Tot}^n \quad (2.4)$$

## 2.3 Risk estimation of distribution systems

To estimate the risk of power interruptions, both the probability of a power interruption and the severity of its consequences have to be estimated. Customers in the distribution system are connected to load points. To obtain a prediction of load point reliability, a model for the component failure and restoration process is needed. The next step is to map how a component failure affects the reliability in the different load points in the system. This mapping can be carried out by a Failure Mode and Effect Analysis (FMEA). To estimate the load point or system reliability, the results from the FMEA are used in Monte Carlo simulations or analytical calculations. In this thesis, a time-sequential Monte Carlo simulation technique is used to estimate the reliability indices both on load point and system level.

Consequences of power interruptions are faced by both affected customers and the DSO. The consequences of power interruptions for the customers are usually measured in customer interruption costs. The consequences for the DSO are restoration costs and costs due to the quality regulation.

To summarize, risk estimation of distribution systems involves:

- Reliability indices
- Failure and restoration process of a component
- FMEA
- Monte Carlo simulation techniques to estimate reliability indices
- Customer interruption costs
- Quality regulations

The listed terms are described in this section.

### 2.3.1 Reliability indices

Distribution system reliability can be described by load point and system indices, which are often both annual averages of reliability [15]. Commonly used load point indices include the average outage time, the average annual outage frequency, and the average annual unavailability or average annual outage time [16]. The system indices can be calculated by using weighted averages of the individual load point indices. Among the system indices, the customer-based reliability indices are the ones most commonly used [10]. These indices weight each customer equally. For example, a household is given as much importance as an industrial customer. Popular customer-based reliability indices are: System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), Customer Average Interruption Duration Index (CAIDI), Average Service Availability Index (ASAI) and Average Service Unavailability Index (ASUI) [15]. A common load-based index is Energy Not Supplied (ENS) or Expected Energy Not Supplied (EENS). The indices are defined in Appendix A.

### 2.3.2 Failure and restoration process of a component

This section describes the up/down states, the modeling of failure rates, and the different interruption durations for the customers. More details on component reliability analysis can be found in [21].

#### Up/down states

The components in a distribution system, such as lines, cables, transformers, and breakers, are usually modeled as either operating or not operating due to failure. This is modeled using the two states “up” and “down”. The Time To Failure (TTF) for a component is the time until a failure occurs, and the component is no longer operable, i.e. the time spent in the up state. The time until a broken component is available again is the Time To Restore (TTR), i.e. the time spent in the down

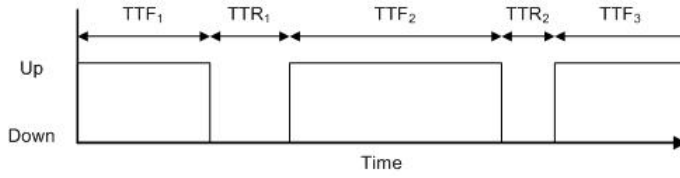


Figure 2.2: The failure and restoration process of a component.

state. The failure and restoration process is illustrated in Figure 2.2.

### Failure rates of components

The time to failure for a component (TTF) is important in the analysis, and this time is strongly related to the failure rate of the component. A component with a high failure rate will probably fail sooner than a component with a low failure rate. The failure rate during the whole lifetime of a component is often referred to as the bathtub curve [10]. The bathtub curve begins with a high failure rate (infant mortality due to manufacturing effects), followed by a constant low failure rate (useful life), and ends with an increase again (wear-out). Regular maintenance actions are assumed in order to prevent an increasing failure rate due to aging in the bottom of the bathtub. One common simplification when modeling power system reliability is to assume constant failure rates [16]. In this thesis, regular maintenance actions are assumed, and hence failure rates are modeled to be constant with respect to aging.

### Interruption durations for load points

The time to restore a component (TTR) can either be a short reclosing time (RcT) or a longer replacement/repair time (RpT/RT) depending on the kind of fault. Two different kinds of faults are generally considered in reliability analysis: active and passive faults [16]. Active faults, such as ground faults and short circuits, trigger the protection system. When a passive fault occurs, the protection system does not have to react. An example of a passive fault is a breaker that spontaneously opens. In order to detect whether a fault is temporary or permanent, the breakers reclose. If the fault is cleared after the reclosing sequence, lasting only a couple of minutes, the fault is temporary and the interruption duration for the affected load points is the short RcT. If the fault remains after the reclosing sequence, the fault is permanent, and repair crew need to be dispatched to repair or replace the broken component. The interruption duration for the affected load points will then be the longer RpT/RT. However, not all load points will necessarily have an interruption during the whole RpT/RT. Every power system has a protection system, consisting

of breakers, fuses and disconnectors, the purpose of which is to protect components in the system, sectionalize the feeders and isolate faults. If an automatic switch device is used, the failure is cleared right away, and can be regarded as a nonfailure event for the load points that have multiple feeding options [22]. The switching time (SwT) is defined as the time it takes for the operator to locate and isolate a fault by using disconnecting components. Depending on the protection system, network configuration and maintenance philosophy, some load points will be affected only by the SwT for a certain failure event while others will be unsupplied during the whole RpT/RT. In this thesis, RpT or RT is referred to as restoration time.

### 2.3.3 Failure mode and effect analysis (FMEA)

To translate the impact of a component failure into load point reliability, an FMEA needs to be carried out. FMEA identifies for each possible failure event, caused by a failed component, affected load points and the interruption duration (RcT, SwT or RpT/RT) for each load point [21]. The different possible types of component failures are included in the FMEA method as separate failure events. For example, a transformer can experience either a temporary or a permanent fault. These are two separate events in the FMEA method. Therefore, it is important that if the first event has occurred, the second cannot occur until the first one is cleared. Note, however, that events affecting different components may overlap. This mapping of an entire distribution system is the most difficult part of the reliability analysis [23].

### 2.3.4 Monte Carlo simulation techniques to estimate reliability indices

To calculate the load point and system reliability indices, two techniques can be applied: an analytical or a Monte Carlo simulation technique. Both approaches need an FMEA as a preparatory step to map up how a component failure affects the load points. Analytical techniques have been used for many years for risk assessments of radial distribution systems to calculate the average load point reliability indices [22]. The average load point reliability indices are estimated using a mathematical model that uses average values of TTF, RpT/RT, SwT, etc.

With the increased availability of high speed computers, Monte Carlo simulation techniques have won more interest for power system reliability analysis [15]. Monte Carlo simulation techniques have the advantage of being able to assess the reliability of more complex distribution systems than analytical techniques can assess. The technique reproduces the random behavior of power systems by treating the problem as a series of real experiments. Instead of using only averages for the inputs, the technique treats the inputs as random variables and allows them to take values according to probability distributions. Assuming a constant failure rate implies that the TTF is exponentially distributed. The distributions for load point interruption durations (RpT/RT, SwT and RcT) are commonly exponential, normal or lognormal [23].

By repeating the procedure many times, the probability distributions for the load point indices are obtained. Having the distributions for the load point indices, the distributions for the system indices can be obtained. The average value of an index distribution corresponds to the average value of the index calculated by an analytical technique.

The more samples in the simulation, the better the estimate of the average index will become. But simulation times increase with the number of samples. To decide the number of samples that are needed, two methods can be applied. The first one is to use a predetermined number of samples in combination with convergence plots to make sure that the considered average index has converged. The second method is to use a stopping criterion. A common stopping criterion uses the coefficient of variation  $\beta$ , and is defined as [15]:

$$\begin{aligned} \text{if } \beta < \epsilon & \Rightarrow \text{Stop simulation} \\ \text{else} & \Rightarrow \text{Take another sample and re-estimate } \beta \end{aligned}$$

Before simulations start, the maximum tolerance error  $\epsilon$  is set. Simulations will carry on taking another sample until the stopping criterion is fulfilled. The coefficient of variation is based on relative standard deviation of the estimated index  $X$ :

$$\beta = \frac{\sigma_X}{m_X \cdot \sqrt{N}} \quad (2.5)$$

where

$$\begin{aligned} \sigma_X &= \text{Sample standard deviation of the estimated index} \\ m_X &= \text{Sample mean of the estimated index} \\ N &= \text{Number of samples taken} \end{aligned}$$

Power distribution systems are typically duogenous systems; therefore the additional requirement  $\sigma_X > 0$  needs to be added [24]. A duogeneous system has two states where one of the states is very dominating. For power distribution systems, this is translated into power interruptions being rare events and for the load points the state “connected” dominating the state “disconnected”. Monte Carlo simulation techniques can be divided into two different types: non-sequential and sequential methods. For the sequential method, the time intervals are picked in chronological order, while for the non-sequential method, this is not the case. Since the time intervals are chosen in chronological order, the time-sequential approach allows for the inclusion of the time dimension in the reliability analysis. The time-sequential Monte Carlo simulation technique thereby allows modeling of the system to be past-dependent which means that the current state depends on the history. There are drawbacks with the sequential simulation method, as it requires more computation time and data storage compared to non-sequential simulation method. However, with faster computers, it is possible to use time-sequential Monte Carlo simulations

on large distribution systems. In [25], for example, time-sequential Monte Carlo simulations were applied on an 11 kV distribution system of one of the largest DSOs in the UK. The simulation type chosen in this thesis is a time-sequential Monte Carlo simulation where the state duration sampling technique [15] is used to simulate component operating histories. With this technique, it is possible to capture the time dependencies in inputs.

### 2.3.5 Customer interruption costs

This section describes four steps on how to use customer interruption costs in reliability planning. Firstly, the factors affecting customer interruption costs need to be identified. Secondly, there are different “kinds” of customer interruption costs. Thirdly, depending on the “kinds” of cost, different survey designs are used to collect customer interruption cost data. Finally, the customer interruption cost data are used to form customer damage functions that are needed in risk assessments to estimate reliability worth indices that can be applied in reliability planning.

#### Factors affecting customer interruption costs

To estimate the consequences of power interruption for customers, customer interruption costs collected in customer surveys are commonly used [15]. Customer interruption costs are challenging to estimate since they are functions of many different factors. As illustrated in Figure 2.3, the factors affecting customer interruption costs can be divided into three groups: customer attributes, outage attributes and geographical attributes.

Customer attributes	Outage attributes	Geographical attributes
<ul style="list-style-type: none"> <li>- Customer sector</li> <li>- Level of preparedness</li> </ul>	<ul style="list-style-type: none"> <li>- Duration</li> <li>- Frequency</li> <li>- Timing</li> <li>- Magnitude</li> </ul>	<ul style="list-style-type: none"> <li>- Outdoor temperature</li> </ul>

Figure 2.3: Examples of factors affecting customer interruption costs.

The impact of a power interruption will be defined by the interrupted activities due to the interruption. Different types of customers perform different types of activities. Therefore, customer interruption costs are assessed by surveys for different customer sectors [26]. For example, customers can be divided into: residential, industrial, governmental & public, agricultural, and commercial customers.

The level of preparedness of the customers also influences how much they will be affected by an interruption [27]. Note that this level most likely depends on the experience customers have of power outages. After a major blackout, many unprepared customers have probably purchased back-up equipment or in other ways elevated their level of preparedness. Of course, characteristics of the outage

itself, such as duration, frequency and time of occurrence, have an impact on the interruption costs [28]. The geographical magnitude of a blackout also affects the interruption costs and inconvenience [27]. Furthermore, geographic attributes such as outdoor temperature may affect the consequences for residential customers [29].

### **Different kinds of customer interruption costs**

Customer interruption costs can be divided into direct and indirect costs, which in turn can be divided into having an economic or a social impact [26]. Direct costs are costs directly caused by electricity not being supplied. Most of the direct interruption costs for industrial and commercial customers such as lost production, and paid staff being unable to work, have an economic impact [26]. Most of the direct interruption costs for residential customers, such as uncomfortable indoor temperature and loss of leisure time, have a social impact.

Indirect costs are not caused by the interruption itself but by an indirect consequence of the outage. An example of an indirect cost that has a social impact is an elevated crime rate during a blackout and an example of an indirect cost with an economic impact is a change in business plan due to a blackout [26].

### **Customer surveys**

There are many different methods to assess customer interruption cost data. No method is universally adopted, but DSOs appear to favor customer surveys for interruption cost information in their planning activities [28]. The customer survey methods focus on the customer valuations of the interruption cost. The strength of the method is that customers are in the best position to know their own costs. With a customer survey, only the direct costs and not indirect costs are collected.

Depending on whether social or economic costs are collected, different survey methods are used. For all customer sectors, except for the residential sector, the direct costs mostly have an economic impact. Therefore, a direct costing method is recommended for these customer sectors [30]. In direct costing methods, customers are asked to identify the impact of a particular hypothetical outage scenario and the associated costs. Residential surveys use contingent valuation methods that are designed to capture more intangible costs such as inconveniences. In the contingent valuation methods, customers are asked to state how much they are Willing To Pay (WTP) to avoid an outage or how much they are Willing To Accept (WTA) in compensation for an outage. A direct costing method can also be applied to the residential sector. In [30] it is recommended to use several different methods for the residential sector.

In customer surveys, customers are faced with different hypothetical outage events. For example, the duration of the interruption may differ between events. Interruption cost data derived from surveys can, however, only cover a fraction of the possible outage events. Commonly, only the interruption costs for the worst

case scenario, i.e. an interruption occurring at the worst time, is surveyed for a few outage durations [27].

Performing a customer survey is a time-consuming and expensive task that requires a large effort to collect a sufficient data sample. The main drawback with survey methods is that the results are quite sensitive to the survey design and implementation [31]. Customer surveys will always generate some “bad” data, such as unrealistically high costs. Therefore statistical analyses of the raw data should be conducted before the data are used [15]. In [32] and [33] procedures for identifying outliers are presented.

### Reliability worth index

To estimate consequences for the customers, the reliability worth index Expected Customer Interruption Cost (ECOST) is often used. The index ECOST, like most of the reliability indices, is an annual index and can be evaluated on either load point or system level depending on the purpose of the study [15]. Since the annual customer interruption cost depends on the attributes shown in Figure 2.3, it will vary from year to year. As the name says, ECOST is the expected value of the annual customer interruption cost,  $cic$ :

$$ECOST = E(cic) \quad (2.6)$$

The annual customer interruption cost,  $cic$ , depend on several factors, one of which is customer damage functions.

Customer damage functions are usually based on customer interruption cost data for the worst case scenario and are commonly estimated for each customer sector as shown in Figure 2.4. Two different procedures for how to calculate the customer damage functions exist: the average process and the aggregating process [27]. In the average process, the customer interruption cost data from the survey is first normalized. After the normalization, an average value of the normalized cost for each customer sector and surveyed duration is calculated. The second procedure, the aggregating process, is to first summarize the customer interruption cost data for each customer sector and duration. The result is then normalized by division by the summation of the normalizing factors. Common normalization factors are total annual electricity consumption, peak load or energy not supplied.

In Figure 2.4, the normalization factor is peak load and the unit of the customer damage function is therefore €/kW. The normalization process will give the values of the customer damage function marked with different symbols in Figure 2.4. To estimate the customer interruption cost for any duration, linear interpolation is used between these values. Since the customer interruption cost data is only obtained for the worst case scenario, i.e. an interruption occurring at the worst time for each sector, the customer damage function shows how the worst case cost varies with interruption duration. To accentuate the fact that the customer damage function for each sector  $S$  is estimated for a reference time, it is denoted  $c_{ref}^S$ .

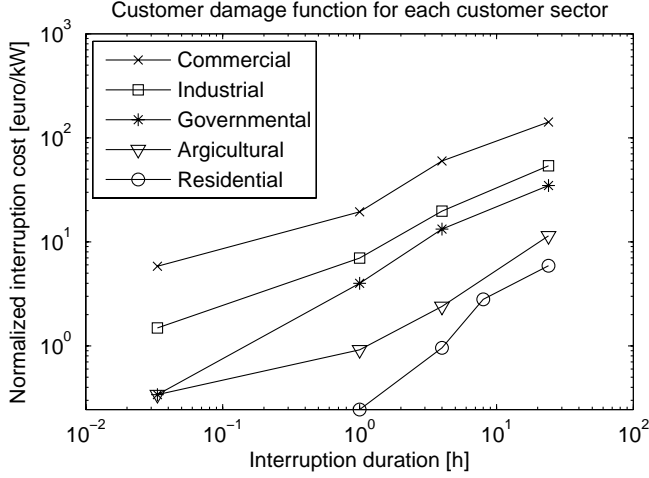


Figure 2.4: Customer damage functions for the worst case scenario for all customer sectors normalized by peak load. The surveyed durations are marked with different symbols. Note the log scale on both the x-axis and the y-axis.

The annual customer interruption cost  $cic$  for year  $\tau$  can be estimated with different levels of detail. Five approaches with increasing level of detail are described in eqns (2.7) - (2.13). In the five approaches, it is assumed that the customer damage function has been normalized by peak load. When regulators reconstruct customer interruption costs in quality regulations, they commonly apply simple approaches such as approaches 1 and 2. For example, the new Swedish quality regulation from 2012 applies Approach 1 [34]. Approach 2 was adopted in the previous Norwegian quality regulation [35]. The current quality regulation in Norway applies a more detailed estimation of  $cic$  described by Approach 4 [9]. In socioeconomic cost-benefit analyses, detailed estimations of  $cic$  are performed using approaches 3-5 [36, 37]. Note that in regulations, the actual outcome of the annual reliability is used when estimating  $cic$ , while in socioeconomic cost-benefit analyses, Monte Carlo simulation techniques are used to predict the annual reliability in order to estimate  $cic$ .

#### Approach 1:

$$cic(\tau) = P_{av} SAIFI c_{ref}^C(0^+) + P_{av} SAIDI \left. \frac{dc_{ref}^C}{dr} \right|_{r=r_a} \quad (2.7)$$

where

$$c_{ref}^C(r) = \text{Composite customer damage function on national level [€/kW]}$$

$$\begin{aligned}
\frac{dc_{ref}^C}{dr} &= \text{Slope of the composite customer damage} \\
&\quad \text{function on national level [€/kWh]} \\
r_a &= \text{Average interruption duration [h]} \\
&= CAIDI = \frac{SAIDI}{SAIFI} \\
P_{av} &= \text{Average hourly load estimated on annual} \\
&\quad \text{energy consumption of network [kW]}
\end{aligned}$$

**Approach 2:**

$$cic(\tau) = \sum_{S=1}^{nr_S} ENS^S \left. \frac{dc_{ref}^S}{dr} \right|_{r=r_a} \quad (2.8)$$

where

$$\begin{aligned}
nr_S &= \text{Number of customer sectors} \\
\frac{dc_{ref}^S}{dr} &= \text{Slope of the customer damage function for} \\
&\quad \text{sector } S \text{ [€/kWh]}
\end{aligned}$$

**Approach 3:**

$$cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{lp}(\tau)} \sum_{S=1}^{nr_S^{lp}} c_{ref}^S(r_i^{lp}) E(P_i^S) nr_C^S \quad (2.9)$$

where

$$\begin{aligned}
nr_{LP} &= \text{Number of load points in the network} \\
nr_I^{lp}(\tau) &= \text{Number of interruptions in year } \tau \text{ for load point } lp \\
nr_S^{lp} &= \text{Number of customer sectors at load point } lp \\
nr_C^S &= \text{Number of customers of sector } S \text{ in load point } lp \\
c_{ref}^S &= \text{Customer damage function for sector } S \text{ [€/kW]} \\
r_i^{lp} &= \text{Interruption duration for load point } lp \text{ due to} \\
&\quad \text{interruption } i \text{ [h]} \\
E(P_i^S) &= \text{Expected loss of load for sector } S \text{ due to} \\
&\quad \text{interruption } i \text{ [kW]}
\end{aligned}$$

**Approach 4:**

$$cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{lp}(\tau)} \sum_{S=1}^{nr_S^{lp}} E(f_h^S) E(f_d^S) E(f_m^S) \cdot c_{ref}^S(r_i^{lp}) E(P^S(t_i)) nr_C^S \quad (2.10)$$

$$= \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{lp}(\tau)} \sum_{S=1}^{nr_S^{lp}} E(\tilde{f}_h^S) E(\tilde{f}_d^S) E(\tilde{f}_m^S) \cdot c_{ref}^S(r_i^{lp}) P_{ref}^S nr_C^S \quad (2.11)$$

where

$f_h^S, \tilde{f}_h^S$  = Time-varying factor for hourly deviation from the reference time for sector  $S$

$f_d^S, \tilde{f}_d^S$  = Time-varying factor for day of week deviation from the reference time for sector  $S$

$f_m^S, \tilde{f}_m^S$  = Time-varying factor for monthly deviation from the reference time for sector  $S$

$E(\tilde{f}_j^S) = [\tilde{f}_j^S(t_i^1) + \tilde{f}_j^S(t_i^2) + \dots + \tilde{f}_j^S(t_i^K)]/K$   
 $j = \{h, d, m\}$ , average time-varying factor

$t_i^k$  = Hour  $k$  of interruption  $i$  occurring at time  $t$

$K$  = Closest whole hour to interruption duration  $r_i^{lp}$

$P_{ref}^S$  = Load at reference scenario for customer sector  $S$  [kW]

$E(P^S(t_i))$  = Expected loss of load for sector  $S$  due to interruption  $i$  starting at time  $t$  [kW]

**Approach 5:**

$$\begin{aligned} cic(\tau) = & \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{lp}(\tau)} \sum_{S=1}^{nr_S^{lp}} [f_h^S(t_i^1) f_d^S(t_i^1) f_m^S(t_i^1) E(P^S(t_i^1)) c_{ref}^S(t_i^1) \\ & + f_h^S(t_i^2) f_d^S(t_i^2) f_m^S(t_i^2) E(P^S(t_i^2)) (c_{ref}^S(t_i^2) - c_{ref}^S(t_i^1)) + \dots + \\ & + f_h^S(t_i^K) f_d^S(t_i^K) f_m^S(t_i^K) E(P^S(t_i^K)) \cdot \\ & (c_{ref}^S(t_i^K) - c_{ref}^S(t_i^{K-1}))] \cdot nr_C^S \end{aligned} \quad (2.12)$$

$$\begin{aligned}
&= \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{lp}(\tau)} \sum_{S=1}^{nr_S^{lp}} [\tilde{f}_h^S(t_i^1) \tilde{f}_d^S(t_i^1) \tilde{f}_m^S(t_i^1) c_{ref}^S(t_i^1) \\
&\quad + \tilde{f}_h^S(t_i^2) \tilde{f}_d^S(t_i^2) \tilde{f}_m^S(t_i^2) (c_{ref}^S(t_i^2) - c_{ref}^S(t_i^1)) + \dots + \\
&\quad + \tilde{f}_h^S(t_i^K) \tilde{f}_d^S(t_i^K) \tilde{f}_m^S(t_i^K) (c_{ref}^S(t_i^K) - c_{ref}^S(t_i^{K-1}))].
\end{aligned}$$

$$P_{ref}^S \quad nr_C^S \quad (2.13)$$

In Approach 1, the customer interruption costs are aggregated to national level using a composite customer damage function for the country together with system indices SAIDI and SAIFI. A composite customer damage function is defined as the aggregated interruption cost for a mixture of customer sectors in a region and is obtained by weighting the customer damage function for the different sectors [38]. There exist different procedures for how the cost functions are weighted. For example, the weight for the customer damage function for sector  $S$  could be determined by the sector's fraction of the total annual electricity consumption for the region considered. The customer composition in a specific distribution system is not captured by this approach. In Approach 2, the customer composition in the system is captured by using the customer damage function and ENS for each sector. However, neither of approaches 1 or 2 considers the impact that interruption duration on load point level has on the customer interruption cost.

Approach 3 includes customer sector and interruption duration on load point level when estimating  $cic$  by using the customer damage function. Approaches 4 and 5 expand Approach 3 by also considering the timing of the interruption. The timing of the interruption is included by unitless scaling factors, referred to as time-varying factors  $f$  or  $\tilde{f}$ . Either  $f$  or  $\tilde{f}$  can be estimated using data from a customer survey. The factor  $f$  is estimated using normalized cost in €/kW, while  $\tilde{f}$  is estimated using cost in €. In Section 3.3 a new approach to estimate  $f$  or  $\tilde{f}$  for residential customers is proposed. The new approach builds on the time variations in the underlying factors that cause the interruption costs. The difference between approaches 4 and 5 is that instead of taking the average of the time-varying factors for an interruption, the factor value for every hour during the interruption is used in Approach 5. The factor value for a specific hour  $k$  of the interruption is then multiplied by the slope of the customer damage function for hour  $k$ . In Approach 4, the customer damage function is evaluated only once for the interruption duration.

### 2.3.6 Quality regulations

Quality regulation can be looked upon as a toolbox of quality controls that the regulator can use to obtain adequate quality levels under a performance-based regulation (PBR). The quality controls can be divided into direct and indirect controls [39].

The purpose of the indirect control is to provide the customers with information on the DSO's quality performance. With direct controls, the regulator directly gives the DSO financial incentives in the form of rewards, penalties and/or obligations to pay compensations to affected customers due to bad quality.

For distribution networks, the quality controls are applied in three areas: commercial quality, continuity of supply (reliability), and voltage quality [8]. Of these three dimensions of power quality, continuity of supply is by far the most important one [39]. Voltage and commercial quality is of little interest if the continuity of supply cannot be ensured.

This thesis only considers direct controls in quality regulation on continuity of supply. In this section, the need for a quality regulation in different regulatory regimes, quality regulation design and ways to implement the financial impact for the DSO are described.

### **2.3.7 The need for quality regulation in different regulatory regimes**

Two types of regulatory regimes exist: cost-based and performance-based [40]. In Figure 2.5, the general difference between a cost-based and a performance-based regulation is shown. With a cost-based regulation, the DSOs are allowed to charge for their actual costs plus a certain profit, which is a reasonable return on their investments. The most common cost-based regulation is rate-of-return regulation. To avoid deviation between the DSO's actual cost and the allowed revenue in cost-based regulation, regulatory reviews are performed frequently (often every year).

The two main groups of PBR are cap regulation (either on price or revenue) and yardstick competition [40]. A third group also exists: the sliding scale regulation [40]. With PBR, the revenues or prices are no longer set related to the DSO's costs but to their performance. PBR, therefore, weakens the link between a DSO's regulated prices or revenues and its costs. The general purpose of applying PBR is to motivate economic efficiency and to put the network owners in a situation that resembles a competitive market [8]. Efficiency is achieved by letting the DSO keep gains, at least a proportion, from efficiency improvements, in accordance with the efficiency regulation. With a PBR, the regulatory reviews are less frequent, usually three to five years [7]. During the regulatory period, the regulator let the DSO run their business without interfering.

The choice of regulatory regime will have an impact on the incentives for cost efficiency. The stronger the cost efficiency incentives are, the greater are the incentives to cut down on investments and maintenance. Therefore, regulatory regimes with strong efficiency incentives are accompanied by a quality regulation. This is illustrated in Figure 2.5. With cost-based regulation there is a low incentive for the DSO to increase efficiency [40]. As the return is fixed, they will receive no benefits for cost reductions. Costs can be transferred to the customers and so are the gains from cost savings.

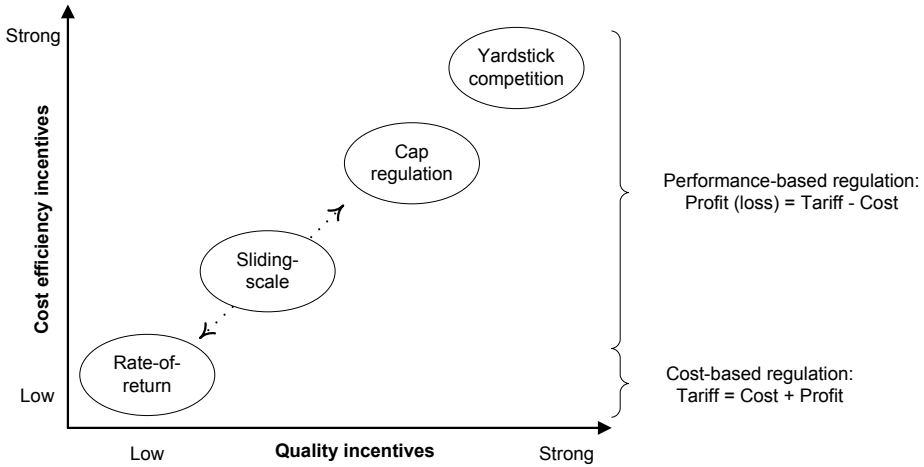


Figure 2.5: The different regimes’ cost efficiency incentives and need for a quality regulation.

Many countries have experienced that a PBR leads to a lower power quality [41, 42]. The reason is as shown in Figure 2.5 that cost savings will increase profit. For example, in Argentina a PBR was introduced in 1991 without a quality regulation, with the result that quality of supply was strongly degraded [41]. The three groups of PBR have different strength in the cost efficiency incentives, and thus they have a different need for a quality regulation. This is illustrated in Figure 2.5.

### 2.3.8 Quality regulation design

Quality regulation can focus on either the process of obtaining adequate quality or the output of quality measured by quality indicators. This section will describe the most commonly used output regulation, and the three direct controls within this kind of regulation.

#### Output regulation based on quality indicators

A quality regulation that is built on quality indicators is the one most used today [7]. This kind of regulation is referred to as “output quality regulation” in Figure 2.6. The quality indicators must be possible to observe and quantify. Central in “output quality regulation” is to have clear instructions and guidance on how these indicators should be measured. If the DSOs measured the indicators differently, the regulation would not be fair. A recent suggestion is to instead turn the attention to the process behind the quality performance: the decisions on investments, network planning and operation, etc [8]. This is the type of quality regulation that is referred

to as “process quality regulation” in Figure 2.6. In Sweden, all DSOs have to submit a risk and vulnerability analysis to the regulator from the beginning of 2006 [43]. This action may be looked upon as a first step towards adopting the “new thinking” of quality regulation where the process, rather than the output, is regulated.

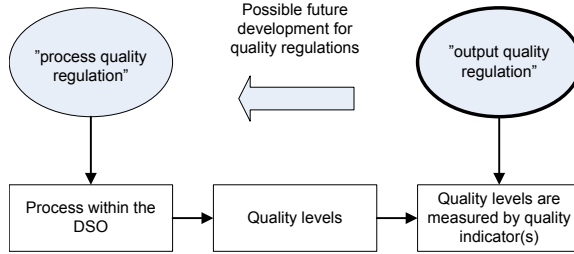


Figure 2.6: Quality regulations can have different focuses.

### 2.3.9 Quality indicators and direct controls

The disturbance of interruptions for a customer is reasonably well described by the number and the duration of interruptions [8]. This is why the quality indicators measure the frequency and duration of interruptions. Quality indicators can be defined on system and/or customer level. The reason for defining quality indicators on different levels is that the regulator wants to control both the average reliability level of the system as well as the reliability level for certain customers. Three direct controls exist: reward and penalty schemes (RPS), guaranteed standard for worst-served customers (GS) and premium quality contracts (PQC) [8]. These three controls are functions of quality indicators. RPS is used to control the average reliability on system level, while GS and PQC are used to control reliability on customer level. The quality indicators and controls on system and customer level are illustrated in Figure 2.7.

SYSTEM LEVEL		CUSTOMER LEVEL	
Quality indicator	Direct control	Quality indicator	Direct control
SAIDI SAIFI ENS	Reward and penalty scheme (RPS)	Duration of interruption Number of interruptions	Guaranteed standard (GS) Premium quality contracts (PQC)

Figure 2.7: Quality indicators mostly used in quality regulations [7] and the three direct controls.

RPS aims to establish a socioeconomically optimal level of system reliability that minimizes the total reliability cost for society and is by far the most difficult

regulatory control to use [8]. In RPS, the regulator specifies performance standards for system quality indicators and implements rewards and penalties for achieving and failing to achieve these standards. Higher quality levels give higher revenues, and in this way the regulator tries to mimic the outcomes of market-like conditions.

GS and PQC focus on reliability on customer level by setting standards for quality indicators such as maximum duration per interruption. The DSO is penalized when it does not fulfill these standards; commonly they have to pay compensation to the affected customers [8]. Often the compensation levels are different for different customer sector and increase as the quality indicator exceeds the standard [7]. While a GS is formulated by the regulator, a PQC is a contract between the DSO and an individual customer. These contracts define the customer compensation if the performance standards agreed upon are not fulfilled. Usually, these contracts are signed with large users that have a need for high quality [8].

As discussed in [44], both GS and RPS are necessary. Only RPS may lead to some areas still having very poor reliability, even though a DSO receives rewards for excellent system reliability. However, since the DSO minimizes its own total reliability cost, a strong GS or PQC may lead to the socioeconomically optimal reliability level not being achieved, despite the fact that the RPS is well designed.

RPSs have been applied since the year 2000 in many European countries [7]. Generally, the GSs have been employed after the introduction of an RPS [8]. The reason is that it is much easier to measure the quality indicators on system level than on customer level. The experience of PQC is quite limited [8]. The design of the direct controls differs significantly between the different countries and is undergoing periodic reviews. In the next section, RPS is described in more detail.

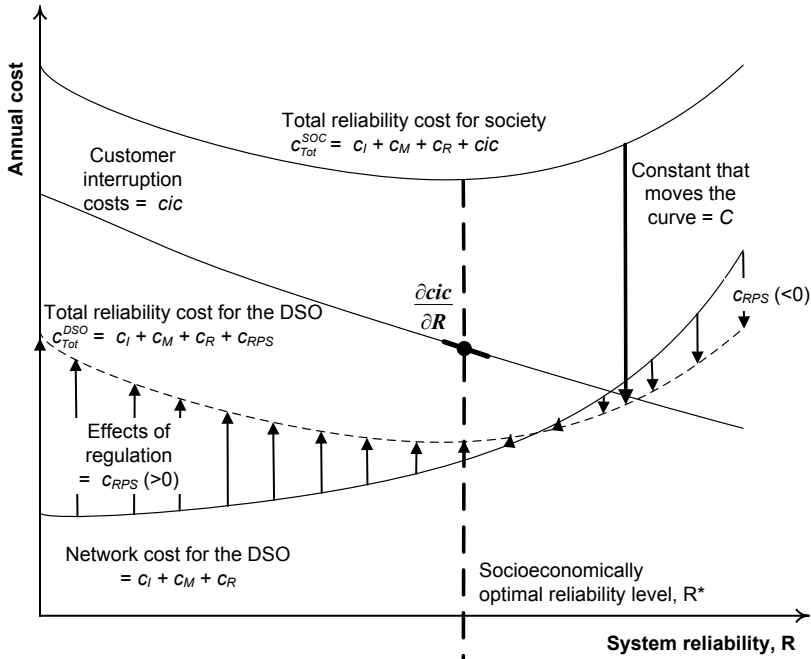
### 2.3.10 Reward and penalty schemes (RPS)

As illustrated in Figure 2.8(a), customer interruption costs decrease as the system becomes more reliable, while the network cost for the DSO increases with the reliability level. Somewhere in between is the socioeconomically optimal level of reliability, which minimizes the total reliability cost for society, i.e. the sum of these two costs [15]. Optimal reliability is achieved when the additional costs of providing higher reliability are equal to the resulting decrease in customer interruption costs. An optimal RPS gives incentives to obtain the socioeconomically optimal level of reliability by forcing a regulated DSO to include customer interruption costs in their own cost function [45].

Assume a quality regulation that only consists of an RPS. Then the DSO's total reliability cost is the sum of costs due to investment, maintenance, restoration and RPS; the curve  $c_{Tot}^{DSO} = c_I + c_M + c_R + c_{RPS}$  in Figure 2.8(a). A profit-maximizing DSO would try to keep the reliability level at a point where its cost is minimized. If  $c_{RPS}$  is designed optimally, this would result in the DSO striving for the reliability level  $R^*$  that also minimizes the total reliability cost for society. See Figure 2.8(a).

In an RPS, a performance standard for system reliability  $\bar{q}_s$  is usually set [8]. Only the customer interruption costs due to the deviation in reliability from this

(a) Cost curves



(b) Cost due to RPS

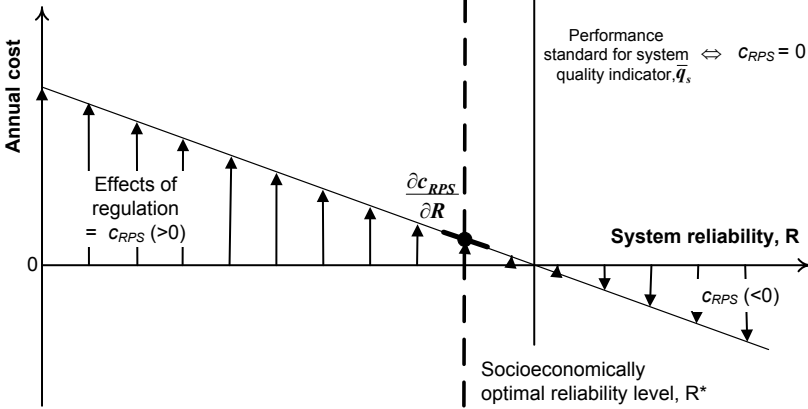


Figure 2.8: The effects of an optimal RPS design when having a profit-maximizing DSO and a quality regulation that only consists of a RPS. (a) shows the different cost curves and (b) shows the cost due to the RPS.

standard are transferred to the DSO. If a DSO has a reliability level that is equal to, below or above the performance standard, the incentive will be zero, a penalty ( $c_{RPS} > 0$ ) or a reward ( $c_{RPS} < 0$ ), respectively [8]. The practical solution is to construct an RPS as shown in Figure 2.9. Different types of RPS exist [39], such as minimum standard, continuous, capped, and dead band. The types can also be combined as, for example, a capped dead band scheme. The slope of the scheme is the monetary value per unit quality indicator and is referred to as incentive rate. The performance standard is also shown in Figure 2.8(b) for a continuous RPS. The allowed revenue for the DSO should cover the costs of providing the reliability level defined by the performance standard [39].

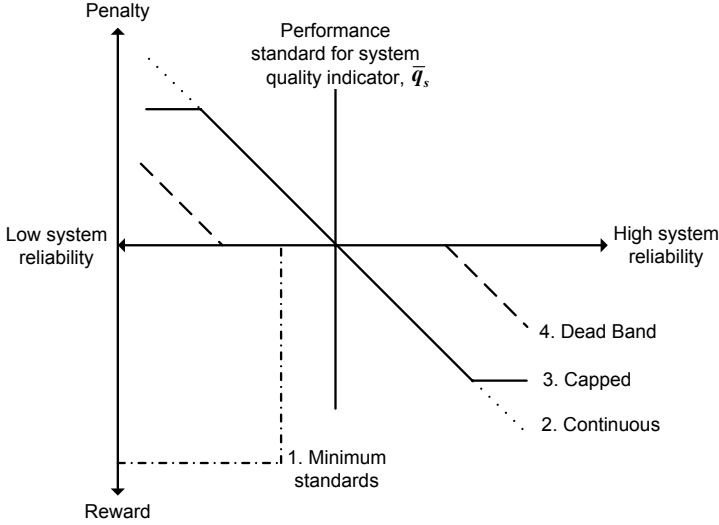


Figure 2.9: Four different types of RPS. The x-axis represents the actual reliability level measured by the system quality indicator and the y-axis represents the financial incentives.

At the socioeconomically optimal reliability level  $R^*$ , the total reliability cost for society is minimized, which is equal to:

$$\left. \frac{\partial c_{Tot}^{SOC}}{\partial R} \right|_{R=R^*} = \left. \frac{\partial (c_I + c_M + c_R + c_{ic})}{\partial R} \right|_{R=R^*} = 0 \quad (2.14)$$

For an optimal RPS the following must also hold:

$$\left. \frac{\partial c_{Tot}^{DSO}}{\partial R} \right|_{R=R^*} = \left. \frac{\partial (c_I + c_M + c_R + c_{RPS})}{\partial R} \right|_{R=R^*} = 0 \quad (2.15)$$

Setting eqn (2.14) equal to (2.15) an optimal RPS must fulfill:

$$\left. \frac{\partial c_{RPS}}{\partial R} \right|_{R=R^*} = \left. \frac{\partial cic}{\partial R} \right|_{R=R^*} \quad (2.16)$$

where

$$\begin{aligned} R &= \text{System reliability level} \\ cic &= \text{Customer interruption cost} \end{aligned}$$

A more rigorous derivation of eqn (2.16) together with assumptions that must be fulfilled can be found in [39]. In [39] it is shown that eqn (2.16) must not only hold at  $R = R^*$ , thus

$$\frac{\partial c_{RPS}}{\partial R} = \frac{\partial cic}{\partial R} \quad (2.17)$$

$$\Rightarrow c_{RPS} = cic - C \quad (2.18)$$

where

$$C = \text{Arbitrary constant}$$

must hold for all values of  $R$  for an optimal RPS. For  $c_{RPS}$  in Figure 2.8, the two derivatives in eqn (2.17) are marked. As can be seen in Figure 2.8, these derivatives are the same; hence,  $c_{RPS}$  is defined to be optimal according to eqn (2.17). The derivative  $\frac{\partial c_{RPS}}{\partial R}$  in eqn (2.17) corresponds to the incentive rate of the scheme. In practice, however, it is not a simple task to design an optimal RPS. Whether the regulator succeeds in setting an optimal  $c_{RPS}$  or not will clearly depend on the regulator's ability to properly measure and reconstruct customer interruption costs [39]. The annual customer interruption cost  $cic$  for year  $\tau$  can be estimated with different levels of detail. Five different approaches to reconstructing customer interruption costs with different detail level were presented in Section 2.3.5.

Note that as long as the incentive fulfills eqn (2.17), all values of  $C$  will lead to the socioeconomically optimal reliability level being achieved. The value of  $C$  only affects the transactions between the DSO and the customers. If the constant  $C$  is set to zero, all customer interruption costs have been transferred to the DSO. The profit-maximizing DSO would then experience the total reliability cost for society. However, if all customer interruption cost were transferred to the DSO, the DSO would likely incur a loss because the allowed revenues generally only cover the DSO's total reliability cost at the performance standard [39]. In Figure 2.8(a) this is illustrated by the constant  $C$ , which moves the total reliability cost curve for society down to the total reliability cost curve experienced by the DSO.

Setting the value for  $C$  corresponds to setting the performance standard since:

$$C = cic(R = \bar{q}_s) \quad (2.19)$$

must hold for eqn (2.18) to be zero at  $R = \bar{q}_s$ . To conclude, irrespective of the level at which the performance standard is set, the optimal reliability level will be achieved by a profit-maximizing DSO as long as the incentive rate is set on the basis of customer interruption costs [39].

### 2.3.11 Implementation of financial impact

Poor quality will imply a financial impact for a DSO regulated by the three direct controls. There are different approaches for how this is carried out:

1. Customer compensation. This is the common way for financial impact of GS [7].
2. Quality aspect incorporated as an explicit term in the formula used to calculate the allowed revenue, linking the allowed revenue or price to the DSO's performance. This is the common way for the financial impact of RPS [7].
3. Quality aspect integrated in the efficiency regulation.

The most common way to implement the quality regulation is to let the quality controls work alongside the PBR [39]. This is the case in approaches 1 and 2. However, in [39], methods for approach 3 that fully integrate the quality dimension into the PBR are suggested. The quality regulation designs that are studied in this thesis use approaches 1 and 2.

Some quality regulations allow a part of the cost of customer compensations and/or the cost due to RPS to be included in the DSO's future revenue (transferred to the customers by increased tariffs). In the Swedish quality regulation from 2006, neither the cost for customer compensations nor rewards and penalties due to RPS are included in the future allowed revenues [46]. In the Norwegian quality regulation from 2007, a DSO is permitted to include a part of the costs due to GS and RPS as increased future allowed revenues [47].

While PBR could either be applied ex-post or ex-ante, the quality regulation is always based on actual performance, and hence applied ex-post. With ex-ante regulation, the tariffs are reviewed by the regulator before the regulatory period. The DSO will then know how much they can charge customers, conditional on the assumptions which form the basis of determining the revenue/price framework being fulfilled. Ex-post regulation is conducted on actual accounts available after the regulation period.

## 2.4 Risk evaluation of distribution systems

To evaluate different reinvestment projects aimed to enhance reliability, risk estimations are carried out for the projects and a status-quo alternative (base case). The impact of each project on decreasing the risk of power interruptions is analyzed. It is the difference in the simulation results with and without implementation of a

reinvestment project that is analyzed. Since estimation errors are likely to affect both of the compared cases in a similar manner, the risk evaluation is less vulnerable to estimation errors compared to if each case was compared to fix values. In the risk evaluation, the decision-maker can try different risk strategies.

### 2.4.1 Risk strategies

A risk strategy describes the decision-maker's attitude towards "risk". In this thesis, two risk strategies are discussed - one for a risk neutral and one for a risk-averse decision-maker.

#### Risk-neutral

A common approach when making investment decisions is to base them on the expected values. Either the expected reliability index or the expected cost is used in the objective function of the optimization problem. The expected value (average) is an operation that multiplies the consequence of each event by its probability and sums over all possible events. Using the expected value, a high frequency event with low consequences will have the same weight as a low frequency event with high consequences (if the products are the same). Basing decisions on average values of the simulation results corresponds to adopting a risk-neutral strategy.

#### Risk-averse

Power systems are in most cases extremely reliable and power interruptions are rare events. Using expected values may, therefore, be misleading since the "average year" never occurs. In the majority of years, a small number of power interruptions occur, and during extreme years with, for example, a major storm, many interruptions can occur. The expected indices/costs are based on all years, but a year that produces these expected values may never have occurred. Instead, the low-probability catastrophic events can be of higher concern for the decision-maker than the more frequently occurring but less severe events. This decision-maker would prefer a risk-averse strategy.

Extreme events are defined as low-probability and high consequences events. To put more weight on the extreme events in the decision-making process, risk tools that focus on these events are needed. To measure the risk of extreme events this thesis adopts two risk tools used in the financial industry. The two applied tools are Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR).

Both of the risk tools are applied to a loss function to estimate the potential loss. The loss function in distribution system reliability applications is the total reliability cost (either  $C_{Tot}^{SOC}$  or  $C_{Tot}^{DSO}$ ). VaR, CVaR and the expected value are illustrated in Figure 2.10. If a probability distribution is heavy-tailed, the VaR is considerably higher than the expected value. Examining the values of VaR and CVaR is interesting since they provide an additional dimension to the risk assessment. Regardless

of whether a system is operating well on average, they are measures of the risk of extreme events.

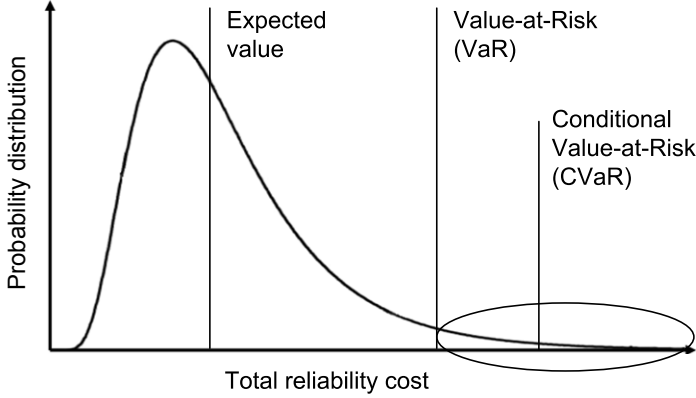


Figure 2.10: The expected value, VaR and CVaR.

$\text{VaR}_{0.95}$  is defined as the total reliability cost that will not be exceeded during 95 percent of all the investigated time periods. Except for the limit 95 percent, which is defined as  $\text{VaR}_\alpha$  with  $\alpha = 0.95$ , the limit 99 percent is also commonly used [48]. The decision-maker can choose to estimate the total reliability cost for any time period. If the major concern is how the total reliability cost varies on an annual basis, the time period is set to one year. VaR can also be applied in investment decisions using NPV where the costs and benefits of a project should be estimated for the project's whole lifetime. In this case, the time period is set to approximately 30 years.

A drawback of VaR is that it give no indication of how great the costs are that occur with a probability of  $1-\alpha$  [48]. To estimate these costs, the average of the costs in the tail of the distribution can be calculated using Conditional Value-at-Risk (CVaR). CVaR is thus the expected total reliability cost during, for example, the 5 percent of the calculation periods with the highest costs.

VaR and CVaR are defined as [48]:

$$\begin{aligned} \text{VaR}_\alpha &= \inf\{x \in \mathbb{R} : P(X > x) \leq 1 - \alpha\} \\ &= \inf\{x \in \mathbb{R} : F_X(x) \geq \alpha\} \end{aligned} \quad (2.20)$$

$$\text{CVaR}_\alpha = E(X|X \geq \text{VaR}_\alpha) \quad (2.21)$$

where  $F_X(x)$  is the cumulative distribution function for the potential loss.

In [49], VaR is introduced for the application to transmission system planning in order to minimize the customer interruption costs. An application of VaR to distribution systems is found in [50], where it is concluded that implementation of VaR in risk assessments of power systems is only in its infancy.



## Chapter 3

# Risk models

*This chapter presents the proposed risk models that are used in the risk-based methods in Chapter 4. The chapter begins with a motivation of the chosen modeling approach. Conclusions from case studies are also presented. Contributions from publications I, V, VI, and VII are presented in this chapter.*

### 3.1 Motivation for chosen modeling approach

This thesis develops time-varying models to capture the time dependencies in inputs: failure rates and restoration times for overhead lines, customer interruption costs and load. The time dependencies are captured in order to estimate the annual customer interruption cost and the total reliability cost for society more accurately. Depending on how the regulator chooses to reconstruct the customer interruption cost, the annual total regulation cost and the total reliability cost for the DSO may also be time-dependent. The developed models also aim to capture extreme events. The overall modeling approach is to build the models on the underlying factors causing the time dependencies and extreme events.

#### Capturing time dependencies in inputs

The three risk models needed in risk assessments of distribution systems are shown in Figure 3.1. The cost model can be formulated in two different ways depending on whether it is the consequences for society or the DSO that are modeled. The load and the reliability models are the same for society as for the DSO.

When formulating the risk models, it is important to consider dependencies. Firstly, the cost model for society, the load model and the reliability model are time-dependent, as illustrated in Figure 3.1. Customer interruption costs are dependent on the time of occurrence of the interruption. Depending on which approach the regulator chooses when reconstructing customer interruption costs, the cost model for the DSO may also be time-dependent. Therefore, this model is dashed in Figure 3.1. For example, in Norway the total regulation cost is time-dependent since

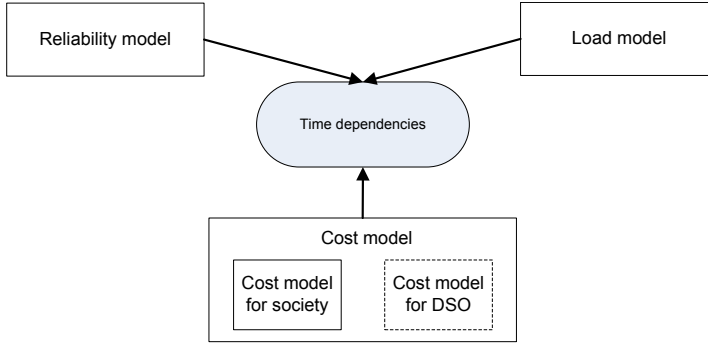


Figure 3.1: The cost model for society, the load model and the reliability model are formulated to capture time dependencies.

Approach 4, eqn (2.10), is used to reconstruct the customer interruption costs. The load varies on a daily and seasonal basis. Regarding the reliability model, some failure causes such as severe weather are more likely to occur during certain periods of the year, resulting in failure rates and restoration times for overhead lines becoming time-varying. Other dependencies are also possible. How prepared a customer is to cope with an interruption is dynamic and dependent on the customer's experience of interruptions; hence, customer interruption costs become dependent on the past reliability level. At high loads, there is a lower level of redundancy in the system, and the probability for interruptions may be increased.

Studies show that the time dependencies in inputs are important when estimating the annual customer interruption cost, and ignoring them may lead to different planning and operational decisions [51, 52]. Therefore, this thesis focuses on incorporating the time dependencies by formulating time-varying risk models.

### Capturing extreme events

A common assumption in power system reliability is that component failures are uncorrelated [16]. In [49], it is emphasized that value-at-risk and conditional value-at-risk under this assumption can be expected to underestimate the probability of great costs since failures are correlated during the extreme outage events that cause the extreme costs. During severe weather, for example, components such as overhead lines become dependent on the same common factor: the weather intensity. Failure rates and restoration times can increase dramatically due to severe weather and multiple failures are relatively common. The increased probability of component failures during extreme conditions must be included in the analysis in order to avoid the underestimation.

### Underlying factors

The time-dependent inputs included in this thesis are failure rates and restoration times for overhead lines, load and customer interruption costs. To capture these time dependencies and their effect on outputs, time-varying models can be formulated using different approaches. Two different approaches are described here: the black box approach and the approach based on underlying factors. As seen in Figure 3.2, models based on both of these approaches have the same outputs: reliability indices, and annual or total reliability costs. The difference is which inputs the models use. Models based on the black box approach use historical data for the inputs. This means that these models do not require any knowledge about how the underlying factors affect the failure rate and restoration times for overhead lines, load and customer interruption costs. Black box models are relatively common in distribution system reliability modeling, and examples can be found in [16, 37, 53]. Models based on underlying factors model the failure rates and restoration times for overhead lines, load and customer interruption costs as a function of the underlying factors. Examples of underlying factors are severe weather, interrupted activities, and outdoor temperature.

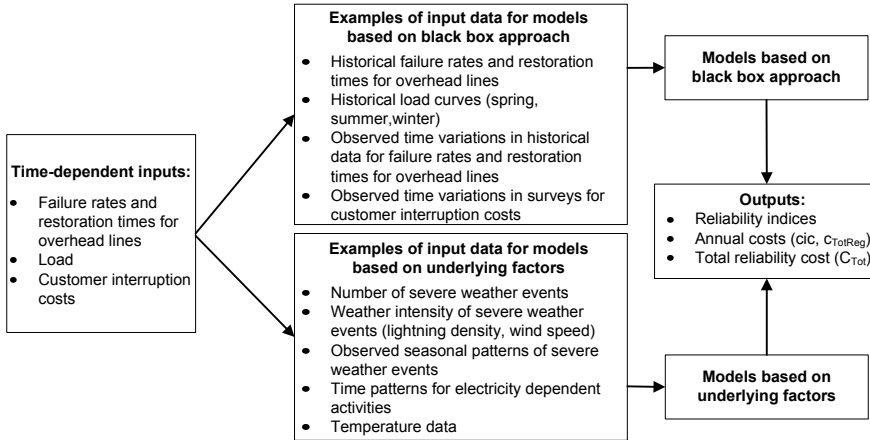


Figure 3.2: Different inputs to models based on the black box approach or based on the underlying factors.

A benefit of models based on the black box approach is that they are less complex than those based on underlying factors. How the underlying factors affect failure rates, restoration times, loads and customer interruption costs does not have to be investigated. The benefit of the models based on underlying factors is that they can be used not only to describe the current risk situation, but also the uncertainties that the future brings. As defined in Chapter 2, risk is a measurable randomness, which can be described by a probability distribution, in contrast

to uncertainty, which is randomness without a well-defined distribution [17]. By collecting historical data, the probability distributions of different inputs can be estimated. However, the underlying factors giving these historical data might change in the future. For example, climate changes may affect the number and intensity of severe weather events. By using models based on underlying factors, scenarios for how the underlying factors may change can be formulated and the effect of uncertainties in the future can be investigated. Since reinvestment in distribution system reliability has a long time horizon these models have benefits over the black box approach. This thesis develops risk models based on underlying factors such as number of lightning and high wind events per year, weather intensity, activity patterns for households, and outdoor temperature.

## 3.2 Proposed reliability model

This section describes the identified areas of improvements for current reliability models, and presents a new reliability model that incorporates the stochasticity of severe weather. The new reliability model was applied in a case study to estimate the probability distributions for reliability indices. Conclusions from the case study are also presented in this section.

### 3.2.1 Identified areas of improvements

Six areas of improvements are presented here. In the development of the new reliability model, these six areas were considered.

- **Failure rates and restoration times for overhead lines should be modeled as functions of weather intensity and not as discrete states**  
The two-state weather model is commonly used to incorporate the effect of severe weather on power system reliability [16]. Using this method, the weather conditions are divided into two states: normal and adverse. The method results in two sets of reliability indices that can be weighted by the probabilities of the two weather states. Overhead line failure rates are, however, functions of weather conditions and increase with the weather intensity level. The weather intensity level is highly stochastic due to the stochasticity in wind speed, snow load and lightning intensity, for example. This makes the use of multiple weather states, each with its specific failure rate and restoration time, somewhat inflexible for power system reliability assessments.
- **Available reliability models need to be tested against empirical outage data for different geographical locations**  
For many DSOs, wind and lightning are the two major failure causes of sustained interruptions due to weather [54–56]. Two different approaches for modeling the overhead line failure rate as a function of wind speed are presented in [57] and [58]. In [57], the failure rate during high wind events is

modeled as a quadratic function of the wind speed. This modeling approach is explained by the fact that the pressure exerted on trees and poles is proportional to the square of the wind speed [59]. However, no verification of the model against failure statistics is made in [57]. In [58], failure statistics have been connected to weather statistics for one geographical location. The obtained data indicated that the number of outages as a function of wind speed was best described by an exponential relationship. In [60], the number of sustained interruptions as a function of lightning flashes during a storm is found to be linear based on data from one utility.

The reliability models in [57, 58, 60] are not tested against empirical outage data for different geographical locations. This must be done in order to find a general reliability model that can be applied in various climates.

- **Investigations are needed to establish how the restoration times for overhead lines are affected by the weather intensity**

In particular for the estimation of SAIDI, the restoration times during severe weather have shown to have a significant effect [61]. The reliability models presented in [57], [58], and [60] only investigated how the failure rates for overhead lines are affected by weather intensity. There is a lack of investigations on how the restoration times for overhead lines are affected by weather intensity.

- **No modeling approach exists for how to consider the seasonal variations in severe weather and the number of severe weather events per year**

A two-state weather model that incorporates a time-varying factor to be multiplied by the failure rate during normal weather conditions was applied in a time-sequential Monte Carlo simulation in [62]. However, [62] did not describe how this factor should be implemented to give an accurate seasonal variation for severe weather and whether it changes from year to year.

- **Previous work lacks the consideration of the combined impact of the seasonal patterns in severe weather and the stochasticity in weather intensity on the probability distributions of reliability indices**

To the best of the author's knowledge, none of the previous works have investigated the combined impact of the seasonal patterns in severe weather and the stochasticity in weather intensity on the probability distributions of reliability indices.

- **No modeling approach that enables the investigations of the effect on reliability due to future climate changes exists**

Future climate changes might imply that severe weather occurs more often, at different times of the year than now and/or that the weather intensity increases. To model the effect on distribution system reliability, an approach

that combines the impact of seasonal pattern in severe weather and the stochasticity in weather intensity must be used. To the best of the author's knowledge, none of the previous works use such an approach.

### 3.2.2 Reliability model that incorporates the stochasticity of severe weather

The new reliability model proposed in this thesis considers both failure rates and restoration times for overhead lines as direct functions of weather intensity. Since the model structure employs the underlying weather factors, the model can easily be used in different climates. The different kinds of weather considered are high winds and lightning, and the developed model can capture the effects when both of these weather conditions are present. The new model combines and extends the approaches presented in [57], [58] and [60] by investigating how the variances in the reliability indices are affected by the stochasticity in severe weather. Weather and outage statistics from different geographical locations in Sweden were connected in a database. Using the database, the current weather conditions for each failure event were identified. In contrast to previous work, model parameters were estimated and validated using data from different locations in order to find a general reliability model.

The new reliability model is described by the following three main steps:

1) Modeling severe weather:

Weather intensity, duration and number of severe weather events per year as well as when during the year these events occur are considered. Since distribution systems cover a limited geographical area, it is assumed that the entire distribution system experiences the same weather conditions at all times. The novelty is the incorporation of the seasonal patterns of severe weather and the stochasticity of the number of events per year by using non-homogeneous Poisson processes.

2) Reliability model formulation:

The new reliability model models how severe weather affects overhead line failure rate and restoration time. Variations in restoration time for all system components due to the availability of crew are also taken into account. The novelty lies in the consideration of the combined effect of high winds and lightning on overhead line reliability as well as in modeling the restoration time for overhead lines as a function of the weather intensity.

The weather intensity levels during high winds and lightning are modeled through the wind speed,  $w$ , and the ground flash density,  $N_g$ , respectively. The time-varying failure rate for overhead lines is modeled as:

$$\begin{aligned} \lambda(w(t), N_g(t)) = & \lambda_{hw}(w(t)) + \lambda_l(N_g(t)) + \\ & \lambda_n(w(t), N_g(t)) \end{aligned} \quad (3.1)$$

where

$$\begin{aligned}
 \lambda_{hw}(w(t)) &= \text{Failure rate during high winds} \\
 \lambda_l(N_g(t)) &= \text{Failure rate during lightning} \\
 \lambda_n(w(t), N_g(t)) &= \text{Constant failure rate during} \\
 &\quad \text{normal weather, equal to } \lambda_{norm}
 \end{aligned}$$

Two different modeling approaches employing, a quadratic and an exponential relationship between the failure rate of overhead lines and wind speed presented in [57] and [58], were tested. Based on the findings in [60], the failure rate of overhead lines during lightning conditions is modeled to be linearly dependent on the ground flash density.

The restoration times due to severe weather depend on the magnitude of damage and the available resources. A new model is proposed for how the restoration time for overhead lines depends on weather intensity. The magnitude of the damage is included by modeling the restoration time as a function of weather intensity through a weight factor,  $f_w$ . The restoration time for overhead lines is defined as:

$$r(t) = f_w(w(t), N_g(t)) f_d(t) f_h(t) r_{norm} \quad (3.2)$$

and for other components as:

$$r(t) = f_d(t) f_h(t) r_c \quad (3.3)$$

where

$$\begin{aligned}
 f_w(w(t), N_g(t)) &= \text{Time-varying factor due to} \\
 &\quad \text{severe weather} \\
 f_h(t) &= \text{Time-varying factor for hourly variations} \\
 &\quad \text{due to the availability of crew} \\
 f_d(t) &= \text{Time-varying factor for daily variations} \\
 &\quad \text{due to the availability of crew} \\
 r_c &= \text{Reference restoration time} \\
 r_{norm} &= \text{Reference restoration time during} \\
 &\quad \text{normal weather conditions}
 \end{aligned}$$

For replacement/repair time (RpT/RT) for overhead lines, the full expression in eqn (3.2) is used. It is assumed that the crew will try to isolate a fault as soon as it occurs regardless of the weather condition; hence, for switching time (SwT) for overhead lines  $f_w = 1$ .

3) Reliability model estimation and validation:

Model parameters were estimated and validated. The novelty is that the reliability model is estimated for one geographical location and validated for another, using empirical data.

Findings show that the failure rate of overhead lines during high winds is best described by an exponential model. The failure rate is approximately constant up to a critical wind speed of 8 m/s. Above this limit, the failure rate increases dramatically. The restoration time for overhead lines was not found to be affected by lightning; however, during high wind events, there is a high probability of multiple failures which result in each failure taking longer to restore. The findings show that the restoration time is approximately constant up to a critical wind speed of 8 m/s. Above this limit, the restoration time appeared to have a linear relationship with the wind speed.

Having a model structure that employs the underlying weather factors makes it possible to investigate the reliability in a power system exposed to different weather conditions, including the effects of future climate changes. For a more thorough description of the different steps, see appended publication V.

### 3.2.3 Application of the proposed reliability model

The model was applied to a test system exposed to weather conditions valid for midland Sweden in publication V using the proposed time-sequential Monte Carlo simulation technique described in Section 4.3. The calculation period  $T$  was set to one year. The novelty with the application analysis is the investigation of the combined impact that the seasonal patterns in severe weather and the stochasticity in weather intensity have on the average and variance of the reliability indices SAIDI, SAIFI and ENS. The findings from the case study are:

- **Seasonal patterns in severe weather may have an effect on the average value of ENS**

SAIDI and SAIFI are not time-dependent indices. Irrespectively, if seasonal patterns in severe weather are modeled or ignored, these indices will have the same average values. However, ENS depends on the load, which makes it time-dependent. Many long interruptions when the load is high might affect the average index value. Results show that there was a slight change in the average ENS when seasonal patterns were modeled rather than ignored. In different climate zones where long interruptions coincide with very high loads, the effect might be more pronounced.

- **Weather stochasticity has a significant impact on the index variance for SAIDI and ENS**

Results show that the weather stochasticity has a significant impact on the variance in the reliability indices SAIDI and ENS. When the weather stochasticity was considered, the variance of these indices increased by 75-100 %.

Accurate assessments of reliability indices are essential for making informed decisions regarding reliability improvements as well as for quantifying differences in reliability performance between networks in quality regulations. For the DSO, it is important to have accurate assessments of the probability distributions of reliability indices in order to model the financial consequences of reward and penalty schemes in quality regulations. If the variances of the indices are underestimated, the DSO is exposed to a higher financial risk than appears to be the case. Severe weather is an uncontrollable factor for the DSO that affects the system reliability performance. If the regulator is to compare the performance of DSOs, exposed to different weather conditions, it is important that the regulator can quantify the effects of severe weather on reliability performance.

### 3.3 Proposed interruption cost model for residential customers

This section describes the identified area of improvement for current customer interruption cost models, and presents a new activity-based interruption cost model for residential customers. The model was applied in a case study, and conclusions from the case study are also presented in this section.

#### 3.3.1 Identified area of improvement

Even though residential customers have the lowest customer interruption costs, it is an important sector since they are many in number. Residential customers are often also located in rural networks where reliability in many cases can be poor due to overhead line networks. Severe weather can lead to this sector being affected by long interruptions.

The reason for choosing residential customers for developing a new cost model lies in the different nature of residential interruption costs compared to interruption costs for other customer sectors. In most customer surveys, residential customers are asked to rank different negative effects of an interruption. Many of the higher ranked negative effects are non-monetary in nature [63–66]. From these rankings, it can be concluded that for households the interruption costs usually measure the inconvenience that an interruption causes. The inconvenience experienced by households is associated with disrupted activities, uncomfortable indoor temperature and loss of lighting [63–66]. This causes residential interruption costs to have a more intangible nature than other sector’s customer interruption costs.

The identified area of improvement leading to the development of a new cost model for estimating residential customer interruption costs is presented here.

- **No approach to estimating time-varying cost factors exists other than asking the customers to state how their interruption cost varies with time in extensive customer surveys**

Households' activities follow a daily pattern and the indoor temperature during longer outages is to a great extent determined by the outdoor temperature, which generally varies with season. Therefore, there are both daily and seasonal variations in residential interruption costs. These daily and seasonal variations in interruption costs for the residential sector are presented, for example, in [64–66].

Detailed approaches that include the time of occurrence when modeling the annual customer interruption costs are preferably used in socioeconomic cost-benefit analyses [51,52]. The two approaches that incorporate the time variations are described by eqns (2.10) and (2.12) in Chapter 2. These approaches require data on how the customer interruption costs vary with day of the week, hour of the day, and month of the year. To collect data, several hypothetical outage scenarios occurring at different times must be included in the customer surveys. This implies that customers need to be asked to estimate how their interruption cost varies on a monthly, daily and hourly basis. For most customer sectors, this is reasonably a moderate task since their interruption costs to a large extent are tangible and monetary. For example, a retail store suffers interruptions costs due to loss of sales which can be estimated with good accuracy from experience. However, for residential customers the non-monetary characteristics of interruption costs can make the estimation difficult. Furthermore, the amount of effort that respondents are prepared to put into filling out surveys is limited. This is particularly relevant for the residential sector [28]. This creates an opening for a new approach to estimate the temporal variations of residential customer interruption costs.

### 3.3.2 Activity-based interruption cost model for residential customers

In contrast to letting residential customers specify how their interruption cost varies on a hourly, daily and monthly basis in extensive customer surveys, the model proposed in this thesis uses data for the underlying factors causing the temporal variations in residential interruption costs: activity patterns, daylight and outdoor temperature. Both approaches for modeling residential interruption costs need customer damage functions for a reference scenario.

Statistics for the underlying factors are often available. Activity patterns are often already available in time-use diary data; see for example [67]. Weather and daylight statistics are also relatively easy to obtain.

To be able to quantify how disrupted activities, loss of lighting and uncomfortable indoor temperature affect the interruption cost, customer valuations of how these effects of an outage influence the inconvenience experienced are also needed. In customer surveys, these valuations are often included and made on an inconvenience scale. The values on the inconvenience scale are not used in absolute terms but rather to identify how households value a certain effect of an outage compared to the other effects. Thus, the proposed model uses “hard” statistical data for the underlying factors while still maintaining the important connection to the customer valuations of the inconvenience experienced during an outage. Because of the non-monetary characteristics of residential interruption costs, it might in many cases be considerably easier for a household to identify and rank these effects than to estimate how their interruption cost varies on an hourly, daily and monthly basis.

The interruption cost for a household for an interruption of duration  $d$  occurring at time  $t$  is modeled as<sup>1</sup>:

$$cost(t, d) = f_{season}(t) \cdot f_{activity}(t) \cdot c_{ref}^R(d) \cdot P_{ref} \quad (3.4)$$

where

$$\begin{aligned} f_{season}(t) &= \text{Time-varying factor for seasonal deviation from} \\ &\quad \text{the reference time} \\ f_{activity}(t) &= \text{Time-varying factor for deviation in activity pattern} \\ &\quad \text{from the reference time} \\ c_{ref}^R(d) &= \text{Customer damage function for the residential sector [€/kW]} \\ P_{ref} &= \text{Load at reference time [kW]} \end{aligned}$$

The influence due to outdoor temperature and daylight is modeled through the season factor,  $f_{season}$ , and the influence due to activity patterns is modeled through the activity factor,  $f_{activity}$ . The activity and season factors model the deviation in activity patterns, daylight and temperature from the surveyed reference outage scenario. For a more thorough description of the two factors, see appended publication I. The concept of using underlying factors to model time variations in customer interruption costs can be applied to other customer sectors than the residential sector.

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<sup>1</sup>Time-varying factors can be estimated on cost data in € or €/kW. In publication I,  $f_{season}$  and  $f_{activity}$  were assumed to be estimated on normalized data (€/kW). Since these factors capture how households value different negative effects of an interruption, it is more reasonable to assume that they are estimated on non-normalized cost data (€). Therefore,  $P_{ref}$  is added to eqn (3.4) compared to eqn (1) in publication I.

### 3.3.3 Application of the proposed activity-based interruption cost model for residential customers

The proposed activity-based interruption cost model was applied in a case study in publication I. The season factor is a function of daylight and outdoor temperature. Weather statistics were used to estimate probability distributions for the daily mean temperature for every month. Statistics are also available for the period of daylight. Often both when the sun rises and when it is daybreak, i.e. daylight, are given. For the evening, both when it is dusk and when the sun has gone down are given. Here, the shorter time interval has been chosen (between daybreak and dusk) to define the period of daylight. To derive the activity patterns, time-use diary data were used. In [67], time-use diary statistics for different European countries are presented. From these statistics, activity patterns as shown in Figure 3.3 were derived. Figure 3.3 shows the share of the population performing each activity during each hour on a weekday. In [3], the proposed model was adopted with a stochastic approach to determine the seasonal and activity factors.

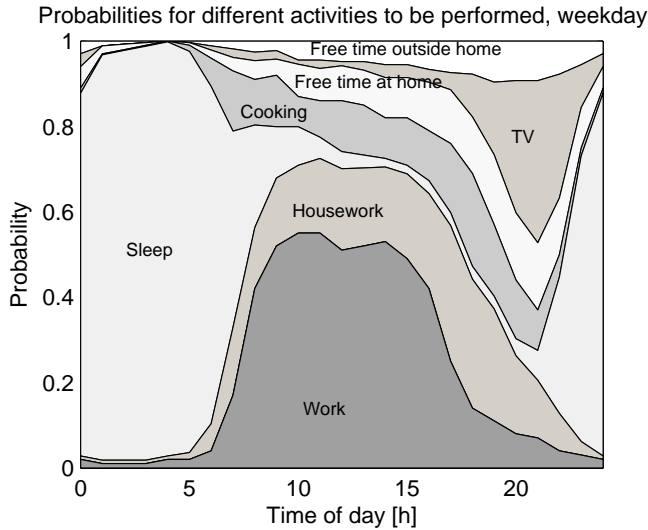


Figure 3.3: The share of the population performing the seven different activities each hour during a weekday. Based on the time-use diary data study [67].

No evaluation of the new approach was made in publication I. To evaluate the new approach to estimating the time-varying factors, the factors are compared to factors estimated using data from customer surveys in Norway and Canada. Norway and Canada are chosen in the absence of Swedish studies on time-varying weight factors. Since 2009, the Norwegian quality regulation has taken the time of occurrence of the interruption into account when reconstructing customer in-

interruption cost using Approach 4 in eqn (2.10). The time-varying factors  $f_h$ ,  $f_d$  and  $f_m$  used in the Norwegian quality regulation are presented in [9]. Using data from the Canadian survey, time-varying factors for hourly and daily variations were estimated in [68].

The monthly average seasonal factor is shown together with the monthly time-varying factor  $f_m$  estimated using the Norwegian customer survey in Figure 3.4. As can be seen in Figure 3.4, the two estimated time-varying factors follow a similar pattern during the year.

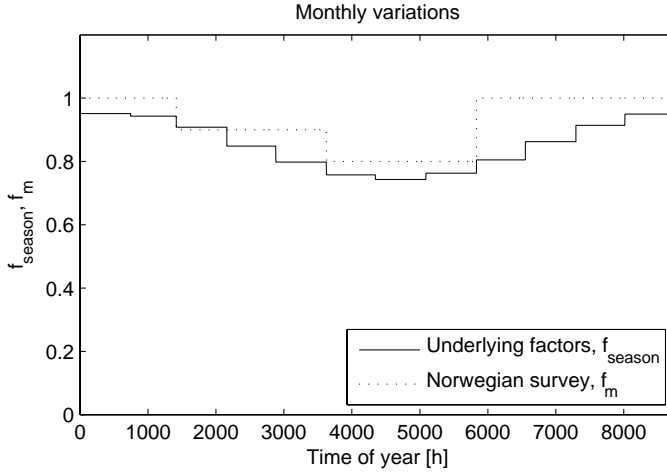


Figure 3.4: Monthly average season factor estimated on meteorological data compared to the monthly time-varying factor estimated on Norwegian customer survey data.

The activity factor together with two hourly time-varying factors  $f_h$  for a week-day are shown in Figure 3.5. To compare the factors, the reference time, for which the factor equals one, needs to be the same. The activity factor was rescaled to match the reference time 4 pm used in the Norwegian survey. This is why the activity factor is on a different level in Figure 3.5 compared to the one given in publication I. All three factors show a similar pattern: a three-step staircase. However, the activity factor is estimated on an hourly basis using activity patterns, which is why it is not a stepwise function as the other two. The estimated activity factor agrees well with the other two factors estimated using customer surveys.

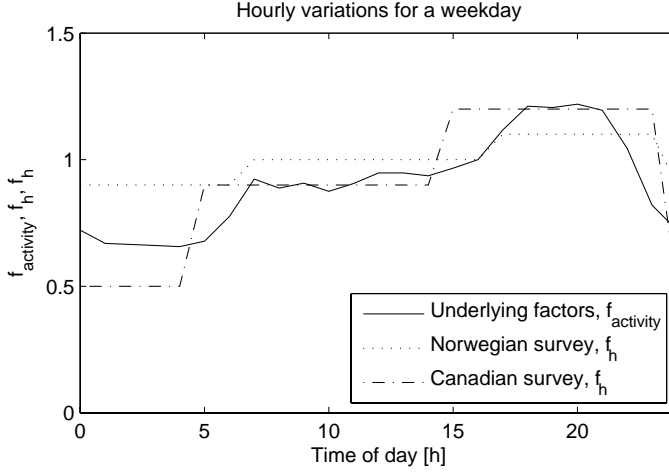


Figure 3.5: Activity factor estimated on activity patterns compared to the two hourly time-varying factors estimated on Norwegian and Canadian customer survey data, respectively.

To conclude:

- **Time-varying factors based on underlying factors need less extensive customer surveys and can be updated easily over time**

The new approach of using underlying factors for estimating time variations agrees well with time-varying factors estimated by surveys. The benefit of using underlying factors is that customer surveys can be less extensive. Shorter surveys probably have a positive effect on the reply rate. Time-use diary studies are conducted regularly and weather statistics are always available, the time-varying factors can therefore be updated easily over time without necessitating an extensive and expensive customer survey.

### 3.4 Proposed cost model for a DSO or society

This section describes the identified area of improvement for current cost models, and presents a new cost model that calculates the total reliability cost for a calculation period with arbitrary outage scenarios. The model has been applied in publications II, VI, VII and VIII.

#### 3.4.1 Identified area of improvement

The identified area of improvement leading to the development of a new cost model is presented here.

- **No cost model exists that estimates the total reliability cost for a calculation period with arbitrary outage scenarios**

When an analytical technique is used to estimate the expected NPV of a project, every year is assumed to be an “average year”. Reliability costs such as average annual restoration cost or average annual total regulation cost can be calculated by using historical cost data. These average cost estimates represent the costs of an average year and are used as input cost data to the analytical technique. However, annual restoration cost and annual total regulation costs are in fact stochastic since they depend on the number and durations of power interruptions. The same is true for the annual customer interruption cost. If a risk-based method is applied, different outage scenarios are simulated, and a cost model that can estimate the total reliability cost for a calculation period with arbitrary outage scenarios is required.

### 3.4.2 Cost model for a DSO or society that calculates the total reliability cost

The new cost model estimates the total reliability cost ( $C_{Tot}^{DSO}$ ,  $C_{Tot}^{SOC}$ ) as a function of the interruption events that have occurred during the calculation period. The total reliability cost for the DSO is defined as:

$$\begin{aligned}
 C_{Tot}^{DSO} &= C_I + C_M + C_R + C_{TotReg} = \\
 &\sum_{\tau=1}^T \frac{c_I(\tau)}{(1+r_{dso})^\tau} + \sum_{\tau=1}^T \frac{c_M(\tau)}{(1+r_{dso})^\tau} \\
 &+ \sum_{\tau=1}^T \frac{c_R(\tau)}{(1+r_{dso})^\tau} + \sum_{\tau=1}^T \frac{c_{TotReg}(\tau)}{(1+r_{dso})^\tau}
 \end{aligned} \tag{3.5}$$

and the total reliability cost for society is defined as:

$$\begin{aligned}
 C_{Tot}^{SOC} &= C_I + C_M + C_R + C_{IC} = \\
 &\sum_{\tau=1}^T \frac{c_I(\tau)}{(1+r_{soc})^\tau} + \sum_{\tau=1}^T \frac{c_M(\tau)}{(1+r_{soc})^\tau} \\
 &+ \sum_{\tau=1}^T \frac{c_R(\tau)}{(1+r_{soc})^\tau} + \sum_{\tau=1}^T \frac{c_{ic}(\tau)}{(1+r_{soc})^\tau}
 \end{aligned} \tag{3.6}$$

where

$$\begin{aligned}
c_I(\tau) &= \text{Investment cost for year } \tau \\
c_M(\tau) &= \text{Maintenance cost for year } \tau \\
c_R(\tau) &= \text{Restoration cost for year } \tau \\
c_{TotReg}(\tau) &= c_{RPS}(\tau) + c_{GS}(\tau) + c_{PQC}(\tau) \\
&\quad \text{Total regulation cost for year } \tau \\
c_{RPS}(\tau) &= \text{Regulation cost due to RPS for year } \tau \\
c_{GS}(\tau) &= \text{Regulation cost due to GS for year } \tau \\
c_{PQS}(\tau) &= \text{Regulation cost due to PQC for year } \tau \\
cic(\tau) &= \text{Customer interruption cost for year } \tau \\
T &= \text{Calculation period} \\
r_{dso} &= \text{Discount rate for the DSO} \\
r_{soc} &= \text{Discount rate for society}
\end{aligned}$$

The total regulation cost in eqn (3.5) is defined as the sum of the costs due to the three regulatory tools: reward and penalty schemes (RPS), guaranteed standard for worst-served customers (GS), and premium quality contracts (PQC). If the stakeholder is society, customer interruption costs are considered instead of the total regulation cost. The reliability in a distribution system may vary a lot between different years. Hence, the annual restoration cost  $c_R(\tau)$ , total regulation  $c_{TotReg}(\tau)$ , and customer interruption cost  $cic(\tau)$  are stochastic, since they depend on the number and duration of power interruptions. The annual investment and maintenance costs are in contrast deterministic.

This section defines the parts that constitute the total reliability cost; investment, maintenance, restoration, total regulation cost and the customer interruption cost are defined. Only the additional maintenance and restoration costs (or savings) due to a considered reinvestment project are considered. In this thesis, the projects investigated are investments in lines or cables; therefore, these costs are given per invested kilometer (km).

The investment cost for year  $\tau$  is modeled as:

$$c_I(\tau) = c_I^{km} nr_{km}^{inv}(\tau) \quad (3.7)$$

where

$$\begin{aligned}
c_I^{km} &= \text{Investment cost [€/km]} \\
nr_{km}^{inv}(\tau) &= \text{Line length invested in year } \tau \text{ [km]}
\end{aligned}$$

The maintenance cost for year  $\tau$  is modeled as:

$$c_M(\tau) = c_M^{yr} nr_{km} + ins(\tau) nr_{km} (c_M^{ins} + c_M^{act}) \quad (3.8)$$

where

$$\begin{aligned}
 c_M^{yr} &= \text{Cost for annual maintenance [€/km]} \\
 c_M^{ins} &= \text{Cost for inspection [€/km]} \\
 c_M^{act} &= \text{Cost for maintenance actions} \\
 &\quad \text{decided upon after inspection [€/km]} \\
 nr_{km} &= \text{Line length in the project [km]} \\
 ins(\tau) &= 1 \text{ if inspection in year } \tau, 0 \text{ otherwise}
 \end{aligned}$$

The restoration cost is split into a fixed cost (material cost) and a variable cost depending on the restoration time and number of persons repairing. The restoration cost for year  $\tau$  is modeled as:

$$c_R(\tau) = \sum_{j=1}^{nrF(\tau)} c_R^{fix} + nr_p c_{hour} r_j(t_j) \quad (3.9)$$

where

$$\begin{aligned}
 nrF(\tau) &= \text{Number of failures in year } \tau \\
 c_R^{fix} &= \text{Fixed restoration cost per failure [€]} \\
 nr_p &= \text{Number of persons repairing} \\
 c_{hour} &= \text{Cost of one working hour [€/h]} \\
 r_j &= \text{Restoration time of failure } j \\
 &\quad \text{described by the reliability model [h]} \\
 t_j &= \text{The timing of failure } j
 \end{aligned}$$

For a DSO subject to a quality regulation, the annual total regulation cost  $c_{TotReg}(\tau)$  is of interest. The total regulation cost for year  $\tau$  is defined as:

$$c_{TotReg}(\tau) = c_{RPS}(\tau) + c_{GS}(\tau) + c_{PQC}(\tau) \quad (3.10)$$

where

$$\begin{aligned}
 c_{RPS} &= \text{Regulation cost due to RPS in year } \tau \text{ [€]} \\
 c_{GS} &= \text{Regulation cost due to GS in year } \tau \text{ [€]} \\
 c_{PQC} &= \text{Regulation cost due to PQC in year } \tau \text{ [€]}
 \end{aligned}$$

Note that  $c_{RPS}$  is the sum of the net penalty costs after the rewards have been subtracted. The cost model for a DSO is applied in publication VII using risk-based method 2 presented in Chapter 4. For society, on the other hand, the annual customer interruption cost  $cic(\tau)$  is of interest. The annual customer interruption cost is calculated using Approach 5 described by eqn (2.13). The cost model for

society was applied in publication VI using risk-based method 2. In publication II  $cic(\tau)$  was estimated using Approach 4, described by eqn (2.10).

The cost model can also be used in risk-based method 1, described in Chapter 4, to estimate the annual customer interruption cost and annual total regulation cost by setting  $c_I(\tau) = c_M(\tau) = c_R(\tau) = 0$ . This was done in publications II and IV, respectively. Both the model for a DSO and the model for society are used when evaluating the effects of quality regulation design in publication VIII. See Chapter 4 and Chapter 5 for conclusions from the performed case studies.

### 3.5 Proposed load model

This section describes the identified area of improvement for current load models, and presents a new temperature dependent load model. The proposed load model has been applied in all appended publications, except publications I-III. In publications I-III load curves are used but the load at extreme temperatures is not captured.

#### 3.5.1 Identified area of improvement

Load demands in distribution systems vary with time, and each customer sector has a different load pattern. It is obvious that the applicability of a risk assessment is limited if only a constant load is considered. The identified improvement leading to the development of a new load model is presented here.

- **Stochastic chronological variations in load are usually not modeled in reliability analyses**

In reliability analysis of power distribution systems, the chronological variations in load are often modeled to be deterministic [51] by using a set of load curves. Different load curves are used to model the load demand during weekdays and weekends, as well as during different seasons. By combining the load curves, the load pattern during the whole year is obtained. This pattern will be the same for every year. In reality, however, the load demand is affected by stochastic factors such as outdoor temperature, making the load pattern different from year to year. Using a deterministic load pattern, extreme loads cannot be captured.

#### 3.5.2 Temperature dependent load model

In this thesis, the outdoor temperature is modeled to be stochastic, which means that extreme temperature conditions and variations in load patterns from year to year can be captured. Reported load curves are often valid in certain temperature intervals and it is possible that the modeled outdoor temperature is below the lowest temperature interval or above the highest.

In [69], it was established that there is a linear relationship between energy consumption and temperature in Sweden that also holds at low temperatures. Since the model in this thesis will be applied to the Swedish climate, only the case of low temperature is considered. However, it is possible that a similar dependency exists in the case of high temperature in warm countries where air conditioning is common. In line with the finding in [69], the temperature dependency in the case of very low temperatures can be incorporated through a coefficient that moves the load curve vertically. The time-varying load for customer sector  $S$  at hour  $h$ , day  $d$ , and temperature  $temp$ , is modeled as:

$$P^S(t) = P_{curve}^S(h, d, temp) \quad (3.11)$$

The new load model incorporates the linear relationship between load and temperature during very low temperature conditions, and thereby captures the loss of load and energy not supplied due to outages occurring on an exceptionally cold winter day.



## Chapter 4

# Risk-based methods for reliability investment decisions

*This chapter presents two proposed risk-based methods that can be applied by society and by a DSO subject to a quality regulation. The first method is used for estimating the annual customer interruption cost or annual total regulation cost. The second method extends the first and is used for estimating the total reliability cost during a reinvestment project's whole lifetime and can be used for net present value calculations. The chapter also summarizes the conclusions from case studies where the proposed risk-based methods have been applied. Contributions from publications II, IV, VI and VII are presented in this chapter.*

### 4.1 Proposed risk-based method 1 - Annual cost

This section identifies areas of improvements for the current methods and presents a new risk-based method for estimating the probability distribution of the annual customer interruption cost or the annual total regulation cost. The method was applied in case studies and conclusions are presented.

#### 4.1.1 Identified areas of improvements

The identified areas of improvements leading to the development of the new risk-based method are presented here.

- **In previous work, there is no method that considers all parts of the total regulation cost**

In quality regulation of continuity of supply the three controls: reward and penalty schemes (RPS), guaranteed standard for worst-served customers (GS), and premium quality contracts (PQC) imply financial risks for the DSO [8]. In [25] and [70], time-sequential Monte Carlo simulations are used to model the effect of GS and RPS, respectively. Neither [25] nor [70] studied the total

financial impact of a certain quality regulation i.e. due to RPS, GS and PQC, nor the variation in this cost.

- **A method that accurately captures the annual variation of the total regulation cost and customer interruption cost is needed**

Most quality regulations are corrected ex-post for each year [71]; therefore, variations in yearly reliability can cause large variations in the annual total regulation cost for a DSO. In cost-benefit analysis, customer interruption costs are considered instead of quality regulation costs. Commonly, the index Expected customer interruption cost (ECOST) is used when evaluating different reinvestment projects in cost-benefit analyses [16]. The way in which different projects affect the variation of the annual customer interruption costs is usually not included in the analysis. It is desirable to have a method that can estimate the probability distribution of the annual customer interruption cost or annual total regulation cost. To accurately describe this cost during more extreme years, models that can capture the effects of extreme events, such as severe weather, are needed.

#### 4.1.2 Risk-based method 1 - Annual cost

This thesis proposes a new risk-based method that models the annual total regulation cost for the DSO, which is defined as the sum of all costs due to the three controls that can be used in a quality regulation. The method can also be used to estimate the annual customer interruption cost. Instead of only considering the average annual total regulation cost or the average annual customer interruption cost, the developed method estimates the probability distribution of the cost and uses risk tools from the financial industry to also measure the costs of more extreme years. The proposed method also incorporates time dependencies in inputs: customer interruption costs, failure rates, restoration times and loads, to gain an accurate estimate of the annual customer interruption cost. Risk models that capture the effect of severe weather are used. The proposed risk-based method 1 is presented in Figure 4.1.

- A:** The first step is to acquire input data, including network configuration, reliability, load, and customer data.
- B:** To capture both the probability and consequences of power interruptions, three risk models: a cost, a load and a reliability model, are needed. The method can be applied from the perspective of two different stakeholders: society and the DSO. If the stakeholder is society, the annual customer interruption cost is investigated. If the stakeholder is the DSO, the total regulation cost is investigated. Therefore, the cost model will have two different formulations depending on the stakeholder. In order to simulate the reliability, a reliability model that describes the failure and restoration process of the components in a power system is required. Customer damage functions

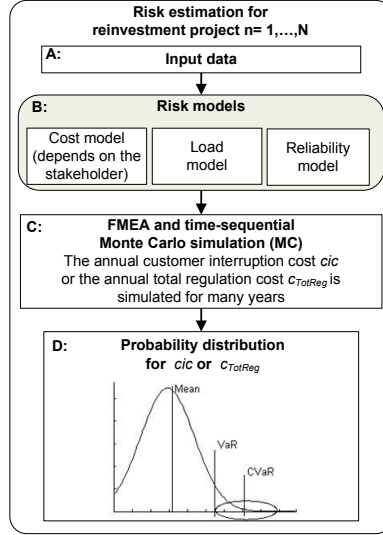


Figure 4.1: Proposed risk-based method 1.

used to estimate customer interruption costs are normalized costs in €/kW or €/kWh. Estimating customer interruption costs in € requires a load model. Estimating the total regulation cost also demands a load model, since quality regulations commonly consist of load related parameters. The load model predicts the loss of load due to an interruption. The risk models proposed in this thesis are presented in Chapter 3.

- C:** A Failure Mode and Effect Analysis (FMEA), described in Section 2.3.3, is carried out. FMEA is a systematic technique for failure analysis that aims to list the different possible failures for each component and what effect the failures have on the load points. Based on the FMEA results, the three risk models are used in time-sequential Monte Carlo simulations to simulate the annual customer interruption cost  $cic$  or the annual total regulation cost  $c_{TotReg}$ . The Monte Carlo simulations result in the probability distribution of the cost. The proposed time-sequential Monte Carlo simulation procedure is described in Section 4.3.
- D:** Instead of only considering the average cost, the developed risk-based method uses the risk tools Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) from the financial industry to also measure the costs of more extreme years. VaR and CVaR are defined in Section 2.4.1.

The risk estimation, step A to D, is performed for each of the different considered reinvestment projects to investigate their effect on  $cic$  or  $c_{TotReg}$ .

For a DSO with one small distribution system in a limited geographical area, the yearly variations in the total regulation cost may be more important than for a DSO owning many distribution systems in different geographical locations. A storm may affect the whole small distribution system and have devastating consequences on the DSO's income. For a DSO with many distribution systems in different locations, a storm will only affect a part of their business.

The proposed risk-based method may be used in NPV calculations when making investment decisions. Then the expected customer interruption cost  $cic$  (ECOST) or expected total regulation cost is used and every year during the project's lifetime is assumed to be an "average" year. With proposed risk-based method 1, only the expected NPV can be estimated.

### 4.1.3 Application of risk-based method 1

Proposed risk-based method 1 was applied to test systems in case studies to estimate the annual customer interruption cost  $cic$  and the total regulation cost  $c_{TotReg}$  in publication II and IV, respectively. The risk-based method was used to evaluate different reinvestment projects and the findings are:

- **The annual customer interruption cost and the annual total regulation cost due to quality regulation have large variances**

The results from the case studies show that both  $cic$  and  $c_{TotReg}$  have large variances. Therefore, it may be interesting for the decision-maker not only to estimate the average, but also to consider the cost of more extreme years with the help of VaR and CVaR in the decision-making process.

Note that at the time the case studies were made, the reliability model presented in Section 3.2 was not finally developed. In publication II, a predecessor of the reliability model was used. The predecessor only modeled the effect of high wind events. It used a quadratic approach to model the relationship between wind speed and failure rate for overhead lines, see [2] for details. In publication IV the effect of severe weather was not considered. Therefore, the variance in this case study can be seen as a lower limit.

## 4.2 Proposed risk-based method 2 - Total reliability cost

This section identifies areas of improvement for current methods and presents a new risk-based method for estimating the probability distribution of the total reliability cost for the whole lifetime of a reinvestment project. This method extends proposed risk-based method 1 and is a risk management method in accordance with the definitions in Section 2.1. The method was applied in case studies and conclusions are presented.

### 4.2.1 Identified areas of improvements

Many other costs than quality regulation costs and customer interruption cost can differ between reinvestment projects such as maintenance, investment and restoration costs. Hence, in order to perform an adequate comparison of projects, the decision criterion should be to minimize the total reliability cost estimated over the projects' whole lifetime [10]. As shown in eqn (2.4) in Chapter 2, the project that minimizes the total reliability cost is the same project that maximizes NPV. The total reliability cost may either be the cost experienced by society  $C_{Tot}^{SOC}$ , which includes customer interruption costs  $C_{Tot}^{SOC}$ , or the cost experienced by a DSO  $C_{Tot}^{DSO}$ , which includes quality regulation costs. The total reliability costs  $C_{Tot}^{DSO}$  and  $C_{Tot}^{SOC}$  are defined by eqns (3.5) and (3.6) in Chapter 3.

The identified areas of improvement leading to the development of the new risk-based method are presented here.

- **Time dependencies are not considered when estimating the NPV of a reinvestment project**

Commonly, analytical methods are used to estimate the expected NPV, assuming that the inputs – customer interruption costs, failure rates, restoration times and loads – are uncorrelated [36, 72, 73]. However, research shows that the inputs are time-dependent, making them correlated, and that this fact is important to consider for accurate assessments of customer interruption costs [51]. Customer interruption cost is an important part of the total reliability cost for society  $C_{Tot}^{SOC}$ , and ignoring the time dependencies can have an impact on the estimated expected  $C_{Tot}^{SOC}$ . Incorporating time dependencies in inputs can also be important for the estimation of the total regulation cost  $C_{Tot}^{DSO}$ . Some quality regulations use a detailed cost model that considers the timing of the interruption when reconstructing the customer interruption cost. In such a case, time dependencies must be considered in order to adequately estimate the financial risks for a DSO.

- **Extreme outage events are not considered when estimating NPV and risk-averse strategies are not formulated**

Commonly, investment decisions are based on the expected NPV. Basing reliability investment decisions on expected values, either calculated by analytical or Monte Carlo methods, corresponds to assuming that the decision-maker is risk-neutral. A different approach is to assume a risk-averse strategy and thereby choose the reinvestment project that maximizes the NPV during the worst possible outcomes. To be able to apply different risk strategies, the whole probability distribution of the total reliability cost is needed. Also, detailed risk models that can capture the extreme years are required. The detailed risk models will be time-varying, accounting for the fact that during short periods of the year, severe weather will increase the components' failure rates and restoration times dramatically.

### 4.2.2 Risk-based method 2 - Total reliability cost

Proposed risk-based method 2 incorporates time dependencies using time-sequential Monte Carlo simulations together with detailed risk models to acquire accurate estimations of  $C_{Tot}^{SOC}$  and  $C_{Tot}^{DSO}$ . The method includes extreme outage events in the risk assessments by incorporating the impact of severe weather, estimating the full probability distribution of the total reliability cost and formulating different risk strategies.

Proposed risk-based method 2 is illustrated in Figure 4.2. The methods involve all the steps of a risk management method as identified in Section 2.1. Risk-based method 1 corresponds to part III) Risk Estimation in Figure 4.2 with the exception that the annual costs are considered.

As can be seen in Figure 4.2, risk-based method 2 can be applied from the perspective of two different stakeholders: society and the DSO. In cost-benefit analysis, the stakeholder society is in focus and the goal is to maximize social welfare. Using cost-benefit analysis when designing and operating distribution systems is referred to as value-based reliability planning [11]. Value-based reliability planning may be used by a publicly owned DSO [10]. By contrast, the overall goal of an investor-owned DSO is to maximize profit [10]. Thus, an investor-owned DSO considers the quality regulation costs when making investment decisions. The only difference in the method for the two perspectives is the cost model in part III); see Figure 4.2.

A profit-maximizing DSO might choose to adopt value-based reliability planning. The reason for this is that investment decisions in NPV calculations are evaluated during the project's whole lifetime. For distribution system investments, the lifetime of a project is very long. The quality regulation design will probably change several times during this period. Therefore, a profit-maximizing DSO may choose to adopt value-based reliability planning (with a high discount rate) assuming that the quality regulation is or will be designed to favor this investment planning philosophy. However, in this thesis a profit-maximizing DSO is assumed to consider a particular quality regulation design when making investment decisions.

With the new risk-based method, it is possible to investigate how different risk models (non-time-varying/time-varying) and risk strategies (risk-neutral/risk-averse) affect network investment decisions.

The method consists of six parts: risk analysis, risk assessment and risk management correspond to performing the parts I)-III), I)-IV) and I)-VI), respectively [18]. The different parts of the method are described in this section.

- I) **Scope definition** defines the study motivation, system boundaries, time horizon, stakeholder, decision criterion, and decision rule. The motivation of this risk study is to evaluate different reinvestment projects, aimed to enhance the distribution system reliability, from the perspective of the stakeholder (society or the DSO). System boundaries are defined by the distribution system under consideration. The time horizon (calculation period) for asset management is between 15-30 years [14] and should be the same for all reinvestment projects considered.

## 4.2. PROPOSED RISK-BASED METHOD 2 - TOTAL RELIABILITY COST<sup>65</sup>

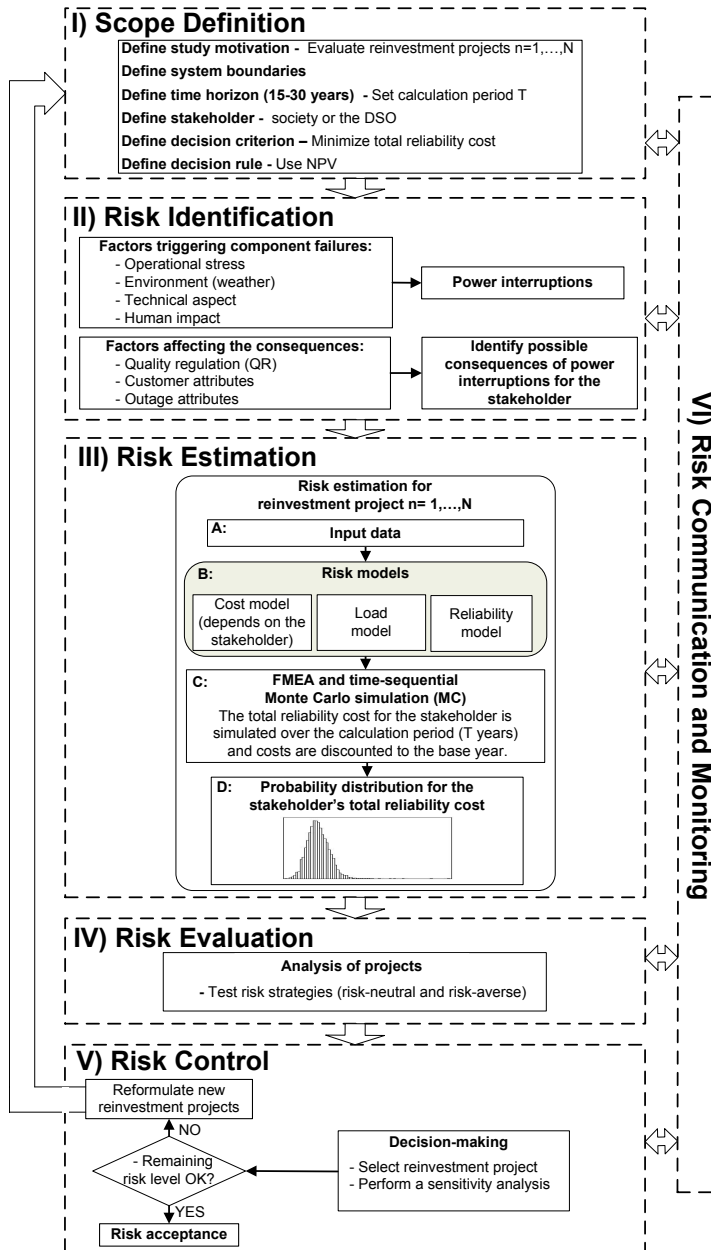


Figure 4.2: Proposed risk-based method 2 for reliability investment decisions.

This thesis develops a risk-based method for reliability investment decisions based on the decision criterion that the total reliability cost should be minimized. The decision criterion has the objective function of Type 3 described in Section 2.2.1. In this thesis, mutually exclusive reinvestment projects are investigated. When choosing between mutually exclusive projects, NPV should be used as the decision rule [20] to assess the economic evaluation of a project's performance.

- II) **Risk identification** identifies the factors that both trigger power interruptions and affect the consequences for the stakeholder. Historical reliability data are reviewed, such as the dominating failure causes.
- III) **Risk estimation** estimates the probability of power interruptions and the resulting consequences.
- A: Network configuration and probability distributions for inputs such as restoration time and time to failure are needed. If time dependencies in restoration times and failure rates are modeled, additional information on weather conditions at the geographical location of the distribution system is required. Also, technical lifetimes of the projects, discount rate, and maintenance, investment and restoration costs need to be specified.
- B: As in risk-based method 1, three risk models are needed for the risk estimation. The proposed risk models adopted are presented in Chapter 3. Instead of estimating the annual cost, the cost model in risk-based method 2 estimates the stakeholder's total reliability cost. The total reliability cost for the DSO is defined by eqn (3.5) as:

$$C_{Tot}^{DSO} = C_I + C_M + C_R + C_{TotReg} \quad (4.1)$$

and the total reliability cost for society is defined by eqn (3.6) as:

$$C_{Tot}^{SOC} = C_I + C_M + C_R + CIC \quad (4.2)$$

In this thesis, both time-varying and non-time-varying risk models are formulated to see how the model formulation affects the investment decisions. The two cases (non-time-varying/time-varying) are described in Section 4.3.

- C: As for risk-based method 1, an FMEA is carried out. The time to failure of the different failure events identified in FMEA are then randomized in a time-sequential Monte Carlo simulation. In the Monte Carlo simulation, the time dimension is included and time dependencies can be modeled. For each simulated calculation period, variables such as severe weather events, number of interruptions and interruption durations will be different, affecting the outcomes of  $C_R$ ,  $C_{TotReg}$ , and  $CIC$ . Note, however, that  $C_M$  and  $C_I$  will be the same for each simulated period. The Monte Carlo simulation procedure is presented in Section 4.3.

**D:** The Monte Carlo simulation simulates  $C_{Tot}^{DSO}$  or  $C_{Tot}^{SOC}$  for many periods of  $T$  years each, which results in a probability distribution. The tail of the distribution on the right side consists of more extreme periods with many interruptions, which resulted in high costs for the stakeholder.

**IV) Risk evaluation** analyzes the different reinvestment projects after a risk estimation has been performed for each project. The decision-maker can use different risk strategies to see how the results vary. When stochastic variables are included in the analysis, the expected net present value,  $E(NPV)$ , can be used, which corresponds to assuming that the stakeholder is risk-neutral according to risk strategy S1.

- **Risk strategy S1: Risk-neutral**

When mutually exclusive projects are considered, a risk-neutral strategy is to choose the project  $n$  that maximizes the expected NPV compared to the status-quo alternative (P0):

$$\arg \max_n E(NPV_n) = \arg \max_n \left\{ E(C_{Tot}^{P0}) - E(C_{Tot}^n) \right\} \quad (4.3)$$

The total reliability cost denoted  $C_{Tot}$  can either be  $C_{Tot}^{DSO}$  or  $C_{Tot}^{SOC}$  depending on the stakeholder. Different risk-averse strategies exist and the maximin criterion is one of these [74]. According to the maximin criterion, the worst possible period (the one with the highest cost) is studied and the project that maximizes NPV for this period is chosen. In this thesis a similar risk-averse strategy is proposed that makes decisions based on the expected value during the worst periods with the highest costs. This is done by using the financial risk tool Conditional Value-at-Risk (CVaR) also called Expected Shortfall [48].  $CVaR_{0.95}(C_{Tot})$  equals the expected total reliability cost during the five percent of periods with highest costs. The proposed risk-averse strategy is referred to as S2

- **Risk strategy S2: Risk-averse**

When mutually exclusive projects are considered, a risk-averse strategy is to choose the project  $n$  that maximizes the decrease in the costs during the 5 % of periods with highest costs:

$$\arg \max_n \left\{ CVaR_{0.95}(C_{Tot}^{P0}) - CVaR_{0.95}(C_{Tot}^n) \right\} \quad (4.4)$$

Even though a decision-maker may choose to make decisions based on the total reliability cost, the improvements in frequency and duration of interruptions that the reinvestment projects imply can still be of interest.

**V) Risk control** is decision-making. Based on the results from the risk evaluation and the risk attitude of the decision-maker a reinvestment project is

chosen and implemented. The investment cost and the discount rate used in the calculations may affect which project is preferred. It is therefore recommended to perform a sensitivity analysis that investigates how the result is affected by changes in investment cost and discount rate. If the estimated risk level after implementation is not accepted other reinvestment projects need to be formulated and investigated.

**VI) Risk communication and monitoring** is a parallel activity that exchanges information about risk between the parts I)-V), as can be seen in Figure 4.2. Risk assessments cover different areas of expertise such as system analysis, component analysis, failure statistics, and economics.

For a successful risk assessment, the parties involved must communicate. Risk communication is also about sharing information about risk between the decision-maker and other stakeholders such as service providers (the restoration work might be outsourced), regulator, and customers [19]. In order for this communication to work, all parties and stakeholders involved must use the same framework where the applied terms are defined.

Within the DSO, an overall approach is needed to ensure that the whole chain of the risk assessment carried out in different parts of the company is optimized. For example, reliability failure statistics should be collected so that all data required by the reliability model is gathered and easy to use as inputs. To be able to optimize the whole process, the process needs to be monitored. Information from all parts I)-V) is required for the monitoring of the process. To facilitate this, an integrated information system in the company may be required. Monitoring and review should be carried out on a regular basis to make sure that acceptable risk levels are correct, and that the applied risk-method and the inputs are properly applied [18].

### 4.2.3 Application of risk-based method 2

Proposed risk-based method 2 was applied in case studies to see if the same reinvestment project is selected if the decision-maker is assumed to be risk-averse instead of risk-neutral and if time dependencies in inputs are considered instead of ignored. The total reliability cost for society  $C_{Tot}^{SOC}$  and for a DSO  $C_{Tot}^{DSO}$  was investigated in publications VI and VII, respectively. The two perspectives are compared in Chapter 5 and publication VIII, where an evaluation method for quality regulation designs is developed. The findings from the case studies are:

- **Time correlations in inputs are important for accurate cost-benefit analysis and estimation of the total regulation cost**

Results for the total reliability cost for society  $C_{Tot}^{SOC}$  show that a different project was selected in the case study when time dependencies were considered, compared to if they were ignored, regardless of whether decisions were made based on a risk-averse or a risk-neutral strategy. This emphasizes the

fact that time dependencies in inputs are important for an accurate estimation of the annual customer interruption cost.

Incorporating time dependencies will affect the total reliability cost for the DSO, sometimes to such an extent that the selected project changes.

- **Quality regulation design has a significant impact on reinvestment project profitability**

The total reliability cost  $C_{Tot}^{DSO}$  was investigated for two different quality regulation designs. One design is similar to the Swedish quality regulation that will apply from 2012 and the other design is similar to the current Norwegian quality regulation introduced in 2009. The results show that different reinvestment projects are selected depending on which of the two investigated quality regulation designs the DSO is exposed to.

- **Complex quality regulation designs demand detailed risk-based methods**

As quality regulation design becomes more complex, more detailed risk-based methods are needed in order to adequately capture the financial risk the DSO is exposed to. For example, in Sweden a new law came into force in 2011 that prohibits interruptions from being longer than 24 hours. With the proposed risk-based method, it is possible to calculate the probability of interruptions exceeding this duration. It is also possible to identify the load points that are at risk when planning for mobile generators. In the case study, it is shown that a DSO using the non-time-varying models concludes that the risk level is negligible, while a DSO using time-varying models concludes that on average one interruption every three years will be longer than 24 hours.

- **A risk-averse strategy shows benefits or drawbacks of a project that cannot be discovered by the expected value**

When making decisions based on either  $C_{Tot}^{DSO}$  or  $C_{Tot}^{SOC}$ , using a risk-averse strategy may clarify benefits or drawbacks of a project that are hard to discover by only looking at the expected NPV. Results in the case studies indicate that time-varying models are needed to describe these benefits or drawbacks accurately. For example, when using non-time-varying models, the benefits of investment in cables for the worst outcomes are underestimated since the effect of severe weather is not captured.

### 4.3 Proposed time-sequential Monte Carlo simulation procedure

The time-sequential Monte Carlo simulation procedure developed in this thesis is described in Figure 4.3. The procedure corresponds to steps C and D in part III) Risk Estimation in Figure 4.2. With a time-sequential approach the actual chronological patterns and random behavior of the system during a year can be

simulated, which makes it possible to incorporate time-dependent costs, failure rates, restoration times, and loads. For each simulated calculation period of  $T$  years, the number of interruptions and interruption characteristics such as duration and time of occurrence will vary.

Two cases of the Monte Carlo simulation procedure have been developed:

**Case 1: No time dependencies** - In this case, constant failure rates and loads together with non-time-varying restoration times and customer interruption costs are applied:

- Average load,  $P(t) = P_{av}$ ,
- Time-varying factors  $f = 1$  in the reliability model and when calculating *cic*,
- Constant failure rate for overhead lines, i.e.  $\lambda(w(t), N_g(t)) = \lambda_{tot}$ .

**Case 2: Time dependencies** - In this case, time-varying failure rates, restoration times, customer interruption costs, and loads are applied. Failure rates and restoration times for overhead lines are modeled to be functions of weather intensity. High wind and lightning events are generated. The number, the timing, and the duration of weather events will vary between years.

The dashed boxes in Figure 4.3 represent the considerations of time-varying failure rates (TVFR), restoration times (TVRT), load (TVLD), and customer interruption cost (TVCIC). In these dashed boxes, the algorithm is different depending on if non-time-varying (Case 1) or time-varying (Case 2) models are used.

The proposed simulation procedure is constructed in a way that makes it possible for underlying factors such as quality regulation design, demanded load or climate to change during a calculation period. If the underlying factors are fixed during the calculation period, simulation time can be reduced. This can be done by estimating the cost probability distribution for one year. Then  $T$  samples are drawn from this distribution to create a calculation period. By redrawing  $T$  samples of the annual cost many times, the probability distribution of the total reliability cost can be produced.

The following remarks can be made on the different steps in Figure 4.3:

- Step 1:** Define the calculation period  $T \geq 1$ . Assume that all components are working and normal weather conditions. Simulation starts with year one; set  $n = 1$ .
- Step 2:** Start year by setting current simulation time equal to zero ( $t = 0$ ).
- Step 3:** Generate a standard uniform random number for each event identified by FMEA and convert to time to failure using each component's failure probability distribution.

- Step 4a:** If time-varying failure rates are considered, generate high wind and lightning events.
- Step 4b:** Identify if a normal failure or a high wind/lightning event occurs first. If a normal failure event occurs first go to Step 5, else go to Step 4c.
- Step 4c:** If a high wind or lightning event occurs first, generate failures during the considered high wind or lightning event. The first failure occurs at time  $t_j$ . Determine if the first failure generated occurs before the high wind or lightning event ends. If no, consider the next high wind or lightning event, and go to Step 4b. If yes go to Step 5'.
- Step 5:** Determine the failure event that will occur first, i.e. the one with the smallest time to failure. Set this time as  $t_i$  and adjust the current simulation time  $t = t + t_i$ .
- Step 5':** Set the time to next failure  $t_j$  and adjust the current simulation time  $t = t + t_j$ .
- Step 6:** If the current simulation time  $t$  is larger than one year (8760 h), go to Step 11. Otherwise, proceed to Step 7.
- Step 7:** Determine the restoration and switching times for the affected component.
- Step 8:** The affected load points are identified for the failure event, and interruption duration (RpT/RT or SwT) for each affected load point is determined. This is done using the results of the FMEA.
- Step 9:** If time-varying restoration times, time-varying load demand and time-varying customer interruption cost are considered, go to Step 9a, else go to Step 9b.
- Step 9a:** Adjust restoration time for availability of crew (failures during non-working hours tend to take longer to repair) and the restoration time for overhead lines due to weather impact (if applicable). Use time-varying factors when calculating  $cic$ . Randomize the temperature at the time of the interruption and calculate the loss of load using the temperature dependent load model. Go to Step 10.
- Step 9b:** Set time-varying factors  $f$  to one (except for when calculating  $c_{TotReg}$ ) and use average load. When calculating  $cic$ , Approach 3 described by eqn (2.9) is used instead of Approach 5.
- Step 10:** For each affected load point, the outage time, energy not supplied, customer interruption cost, and total regulation cost are recorded. Also, the number of interruption for the affected load points is updated. Adjust for overlapping failures. If a load point is affected by a new failure event before it has regained supply, the overlapping time is deducted from the new outage

time and the overlapping failure is only counted as one failure for the considered load points. Assign a new time to failure for the failure event under normal weather conditions. Go to Step 4b.

**Step 11:** For every load point in the system, data that are of interest for the simulated year are saved.

**Step 12:** Check if a whole calculation period has been simulated. If yes go to Step 13; else go to Step 2.

**Step 13:** Save data for the calculation period of  $T$  years. Calculate the outputs: reliability indices, annual costs and the total reliability cost for the calculation period. The deterministic cash flows due to investment and maintenance costs for a calculation period are discounted to the base year. At the end of each calculation period, the stochastic costs due to restoration and total regulation cost or customer interruption cost during the period are discounted to the base year. Since the stochastic costs in the total reliability cost depend on the power interruptions during the calculation period, the total reliability cost will be different for each period. In risk-based method 1, investment, maintenance and restoration costs are not considered, and the variations in the annual cost are investigated, i.e.  $T = 1$ .

**Step 14:** Check if the stopping criterion is fulfilled. The stopping criterion can either be that a fixed number of  $N_{max}$  calculation periods have been simulated or based on the coefficient of variation  $\beta$  described in Section 2.3.4.

**Step 15:** Based on the simulated calculation periods, probability distributions for the outputs are produced.

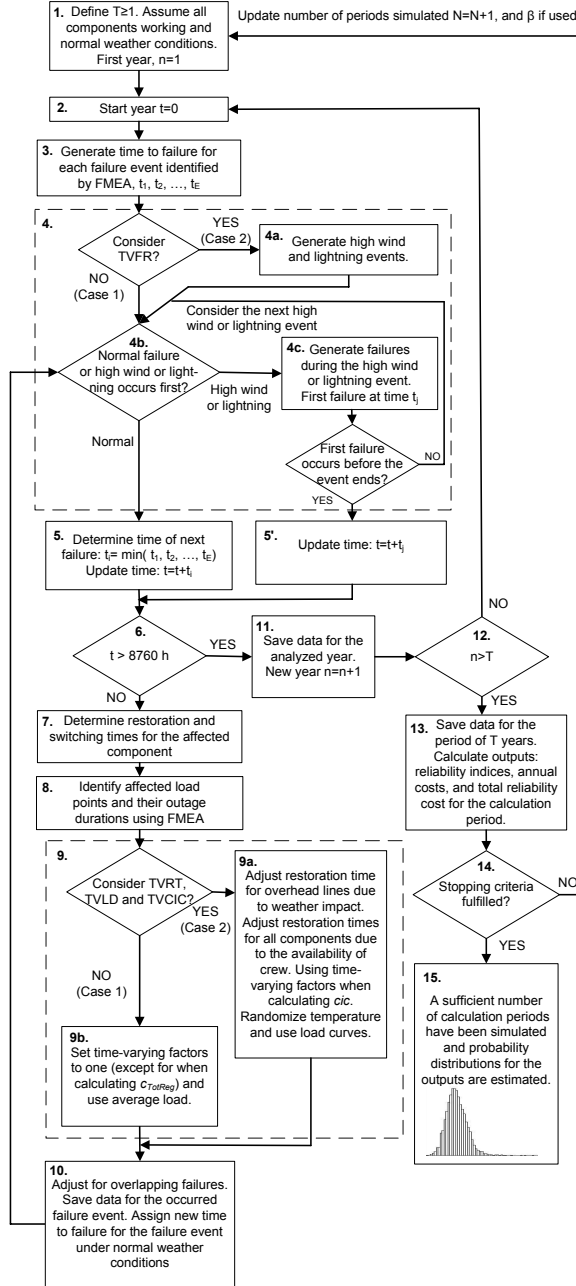


Figure 4.3: Flowchart for the proposed time-sequential Monte Carlo algorithm which corresponds to steps C and D in part III) Risk Estimation in Figure 4.2. The dashed boxes represent the considerations of time-varying failure rates (TVFR), restoration times (TVRT), load (TVLD) and customer interruption cost (TVCIC).



## Chapter 5

# Evaluation method for quality regulation designs

*This chapter presents the proposed evaluation method for quality regulation designs. To evaluate quality regulation designs a test system is needed for the reliability analysis and the customer interruption cost assessments. This chapter, therefore, also presents two developed test systems - a rural and an urban test system - that are representative of Swedish distribution networks. The chapter also summarizes conclusions from a case study where the proposed evaluation method has been applied. Contributions from publications III and VIII are presented in this chapter.*

### 5.1 Developed test systems

Two electrical medium voltage test distribution systems: the Swedish Urban Reliability Test System (SURTS) and the Swedish Rural Reliability Test System (SRRTS), have been developed. The two test systems have been developed in a project within a research program run by the Swedish electricity industry research association - Elforsk [75]. The project was carried out as a master's thesis at KTH under the supervision of the author.

Each test system provides a consistent set of data which enables reliability analysis and customer interruption cost assessments. To ensure the similarity of the test systems to Swedish networks in terms of load, component and customer data as well as network topology, industry representatives of major Swedish power distribution companies were an integral part of the development process.

A validation was performed for the reliability indices SAIDI and SAIFI by using reliability data compiled by the Swedish Energy Markets Inspectorate. From the validation, it was concluded that the developed test systems are good representatives of actual Swedish distribution networks, and thus suitable for further research on regulation policies. For example, the network tariff regulation of Swedish DSOs can be studied by using the developed test systems. In particular, the incentives

that quality regulation gives for investments in reliability can be investigated. In this thesis, the rural network - SRRTS - is used in case studies. The urban network - SURTS - has been used by others in [76] for reliability worth assessments.

SURTS and SRRTS are shown in Figure 5.1 and Figure 5.2, respectively. SURTS has 96 load points, and ten identical loops with approximately 1100 customers and 10 km feeder cable each. SRRTS consists of two modules: Module A and Module B. SRRTS has 44 load points, around 900 customers and consists of both overhead lines and cables. Five different customer sectors are represented in the test systems: residential, commercial, industrial, agricultural (only in SRRTS), and governmental. Each customer category has a set of different load curves to represent seasonal, daily, and hourly variations in load demand. To further capture the variations in load, there are different load curves in different temperature intervals. The proposed time-varying load model presented in Section 3.5.2 extends this approach by also predicting the load during extreme temperatures outside the specified temperature interval.

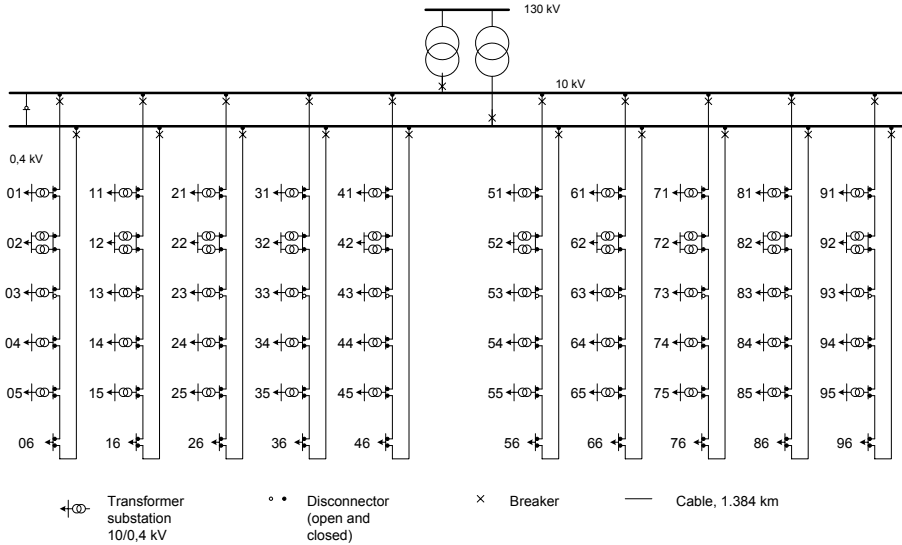


Figure 5.1: The Swedish Urban Reliability Test System (SURTS).

The test systems are implemented in Matlab, where time-sequential Monte Carlo simulations are used in the reliability analysis and customer interruption cost assessments. The time-sequential Monte Carlo simulation procedure in [75] has been developed further in publications IV-VIII to consider the effect of time-variations in inputs, severe weather, overlapping failures and quality regulations. The final simulation procedure was described in publications VI and VII and in more detail in Section 4.3. The test systems are available for download at [77].

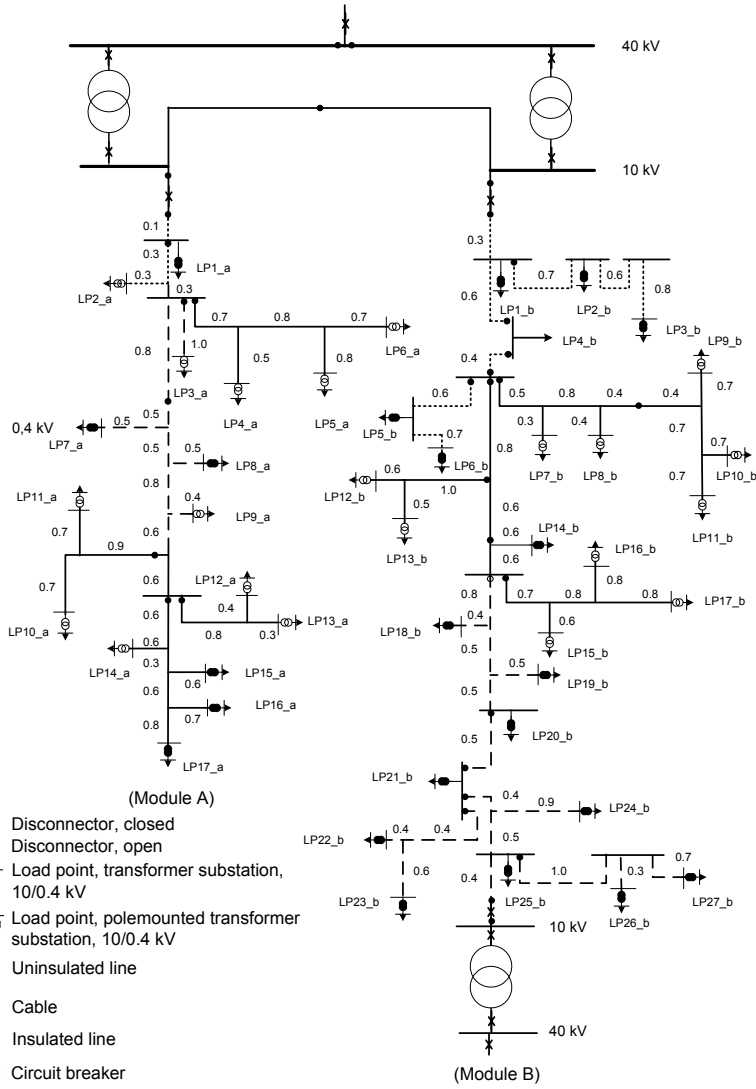


Figure 5.2: Swedish Rural Reliability Test System (SRRTS).

A simplification made when implementing the test systems in order to limit the number of failure events was not to model the reclosing time. This simplification implies that only sustained interruptions that are longer than three minutes are simulated in the Monte Carlo simulations.

### 5.1.1 Modification of the restoration time

The test systems have an average restoration time for overhead lines of five hours, a value obtained from [78]. However, in publication V, the restoration time for overhead lines during different weather conditions was analyzed in more detail. For all investigated service areas, the restoration time for overhead lines during normal weather conditions was found to be three to five hours. However, the average restoration time for overhead lines during all kinds of weather conditions was derived to 10 hours. Hence, in the case studies, an average restoration time for overhead lines of 10 hours was used. The change in restoration time will only affect SRRTS since this is the only network with overhead lines. The Swedish Energy Markets Inspectorate has published a report where the SAIDI values for Swedish rural networks is summarized [79]. According to [79] rural networks have SAIDI values in the interval 100 - 400 min. The SAIDI values for SRRTS and its two modules are all within this interval also when the average restoration time for overhead lines is changed to 10 h.

## 5.2 Proposed evaluation method

Many studies evaluate different reinvestment projects in distribution system reliability from the perspective of either the DSO or society [36, 72, 73, 80–83]. However, to the best of the author’s knowledge, none have compared the results of these studies in order to evaluate different quality regulation designs. The main contribution in publication VIII is an evaluation method for quality regulation designs.

If the regulation is not well designed, a socioeconomically beneficial reinvestment project is not beneficial for the DSO, and hence is not selected [14]. By using the proposed evaluation method, the question “Will socioeconomically beneficial reinvestment projects also become beneficial for a profit-maximizing DSO exposed to a certain quality regulation design?” can be studied. The proposed evaluation method can thus be used by a regulator when investigating the impact of different possible future quality regulation designs. The proposed evaluation method for quality regulation designs is presented in Figure 5.3.

The method consists of three parts:

- I) describes a proposed procedure for identifying the details of a quality regulation. The identified procedure is presented in Section 5.2.1 and can be used to compare different quality regulation designs.
- II) concerns the network decisions to improve reliability. Risk-based method 2 presented in Section 4.2 is used to investigate if reinvestment projects are socioeconomic and/or beneficial for a DSO subject to a certain quality regulation design  $d$ . With the risk-based method, it is possible to predict which reinvestment project is preferred by a regulated DSO and by society. For each outage event during a simulated calculation period, the consequences

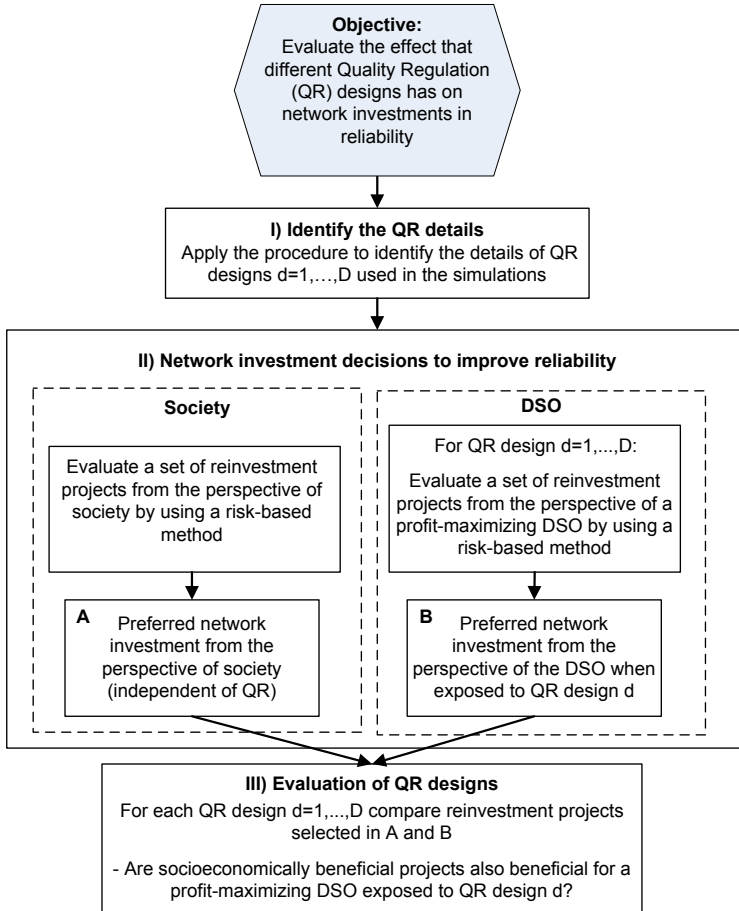


Figure 5.3: Evaluation method for quality regulation (QR) designs.

for society and a DSO subject to the investigated designs  $d = 1, \dots, D$  are estimated.

**III)** evaluates the effect of quality regulation designs on network investments in reliability by comparing the reinvestment projects preferred by a DSO and by society. The evaluation method can be applied to an arbitrary quality regulation design. In publication VIII, the proposed evaluation method is applied to designs similar to the Swedish and Norwegian quality regulations in a case study. Conclusions from the case study are presented in Section 5.2.2.

### 5.2.1 Proposed procedure for identifying quality regulation details

To be able to simulate the financial consequences of a quality regulation, the details of the design must be identified. The procedure consists of seven steps, is general, and can be applied to identify the details of an arbitrary quality regulation design.

The formulation of the quality regulation will define minimum requirements on the Monte Carlo simulation procedure that are needed to adequately describe the financial consequences of the quality regulation design. Note, though, that the minimum requirements to capture the customer interruption cost considered by society might be higher.

#### 1) Define the used data set of interruptions by identifying:

- a) type of interruption (planned/unplanned) included in system quality indicators for RPS
- b) type of interruption (planned/unplanned) included in customer quality indicators for GS
- c) interruption durations included for RPS
- d) interruption durations included for GS
- e) number of years included in system quality indicators (often annual failure statistics are used [84], but longer time periods, for example three years, are employed by some quality regulations [7])
- f) exclusion rules (force majeure, adverse weather, failures in transmission system etc) for RPS
- g) exclusion rules (force majeure, adverse weather, failures in transmission system etc) for GS.

#### 2) Define $c_{RPS}$ by identifying:

- a) quality indicators on system level
- b) performance standards
- c) how often the performance standards is updated
- d) the approach used to reconstruct customer interruption costs, which includes defining incentive rates
- e) type of RPS (capped, continuous, dead band, etc).

#### 3) Define $c_{GS}$ by identifying:

- a) quality indicators on customer level

- b) what factors customer compensation levels depend on
  - c) customer compensation levels.
- 4) **Define the percentage of the costs due to RPS and GS that the DSO is allowed to include as increased future allowed revenues (transferred to customers by increased tariffs).**

5) **Define  $c_{PQC}$  by identifying:**

- a) for which customers PQCs are allowed. Some countries only allow PQCs for customers with a large energy consumption
- b) contract agreements including quality indicator on customer level and compensation levels (decided between DSO and customer, does not involve the regulator).

6) **Define quality standards that do not give any financial incentives but are mandatory by law.**

For example, in Sweden a new law came into force in 2011 that prohibits power interruptions from being longer than 24 hours. There is no financial penalty for this mandatory law. It can, however, be formulated as a criterion for risk acceptance in the risk control step in risk-based method 2. If there are load points that, after a reinvestment project has been implemented, still have a significant probability of suffering interruptions longer than 24 hours, further measures have to be taken to reduce the probability.

7) **Results**

The quality regulation results in financial consequences for the DSO - a total regulation cost for year  $\tau$  - implied by the three direct controls:

$$c_{TotReg}(\tau) = c_{RPS}(\tau) + c_{GS}(\tau) + c_{PQC}(\tau) \quad (5.1)$$

where

$$\begin{aligned} c_{RPS} &= \text{Regulation cost due to RPS in year } \tau \\ c_{GS} &= \text{Regulation cost due to GS in year } \tau \\ c_{PQC} &= \text{Regulation cost due to PQC in year } \tau \end{aligned}$$

Ideally,  $c_{TotReg}$  is designed so that the DSO acts in order to change the quality levels to fulfill the aim in the quality regulation. The aim can, for example, be to ensure that socioeconomically beneficial reinvestment projects also become beneficial for the DSO.

### 5.2.2 Application of evaluation method

The proposed evaluation method for quality regulation designs was applied in a case study in publication VIII. Two different quality regulation designs are chosen for the case study. The first design (D1) is similar to the new Swedish quality regulation that will apply from 2012 presented in [34, 46, 85]. The second design (D2) is similar to the current Norwegian quality regulation introduced in 2009, presented in [9, 47].

The proposed evaluation method was used to investigate the incentives for network investment to improve reliability offered by the two chosen designs. The effect on network investment decisions when the two designs are modified to give optimal incentives for reliability on system level according to eqn (2.17) was also investigated in the case study.

The findings in the case study are:

- **Neither of the quality regulation designs D1 or D2 have an optimal RPS according to eqn (2.17)**

Neither D1 nor D2 let the DSO carry the whole cost of RPS and thereby they do not fulfill the definition of an optimal design of  $c_{RPS}$  according to eqn (2.17). In D1,  $c_{RPS}$  is shared equally between the customers and the DSO. In D2, a percentage of  $c_{RPS}$  is allowed to be included as increased future allowed revenue.

- **A cap on the cost due to RPS that is too low distorts optimality**

The results show that an optimal incentive rate for RPS according to eqn (2.17) may not be enough to give incentives for socioeconomic investments. If  $c_{RPS}$  is capped too low a DSO may not benefit from implementing a socioeconomically beneficial reinvestment project.

# Chapter 6

## Closure

*In this final chapter, conclusions of this thesis are drawn and ideas for future work are discussed.*

### 6.1 Conclusions

This thesis develops:

- **Three time-varying risk models: a cost model, a reliability model, and a load model**

The three models capture time dependencies in inputs: customer interruption costs, failure rates, restoration times and loads. Extreme events due to severe weather are also captured by the proposed reliability model. The models are based on underlying factors, which gives the benefit that they can be used not only to describe the current risk situation, but also the uncertainties that the future brings. For example, it is possible to investigate the effect of climate changes on distribution system reliability. The models are used in the proposed risk-based methods.

- **Two risk-based methods for reliability investments in electric power distribution systems**

The first method estimates the annual customer interruption cost for society or the annual total regulation cost for a DSO exposed to a quality regulation. The method enables calculations of the consequences for an average year as well as the probability for and consequences of more extreme years. The second method extends the first and estimates the total reliability cost during the whole lifetime of a reinvestment project and can be used for net present value calculations. Financial consequences as well as reliability indices are obtained by both methods.

The methods can be used by two different stakeholders: society and a DSO. In cost-benefit analysis, the stakeholder society is in focus and the goal is

to maximize social welfare. Since quality regulation costs are a transaction between the DSO and the customers, they are not included. When value-based reliability planning is performed, as may be the case for a publicly owned DSO, investment decisions are based on a cost-benefit analysis. The overall goal of an investor-owned DSO is, by contrast, to maximize profit. Thus, an investor-owned DSO considers the quality regulation costs when making investment decisions.

- **An evaluation method for investigating the incentives for reliability investments that different quality regulation designs imply**

The method can be used to investigate whether socioeconomically beneficial projects are also beneficial for a profit-maximizing DSO subject to a particular quality regulation design. Firstly, the method defines the quality regulation design. Secondly, one of the proposed risk-based methods is applied to evaluate reinvestment projects from the perspective of the two stakeholders, society and a profit-maximizing DSO subject to the quality regulation in question. Finally, the preferred reinvestment projects for the two stakeholders are compared.

- **Two test systems representative of Swedish distribution networks that can be used to evaluate different quality regulation designs**

One test system for rural networks and one for urban networks have been developed. The test systems contain the data needed for reliability analysis and customer interruption cost assessments.

The developed risk-based methods have been shown in case studies to be applicable to relatively large test systems. Systems with up to 100 load points have been used in time-sequential Monte Carlo simulations. Eight main conclusions drawn from the case studies are summarized below.

- 1) **Weather stochasticity has a significant impact on the index variance for SAIDI and ENS**

Accurate assessments of reliability indices are essential for making informed decisions on reliability improvements as well as for quantifying differences in reliability performance between networks in quality regulations. For the DSO, it is important to have accurate assessments of the probability distributions of reliability indices in order to model the financial consequences of reward and penalty schemes in quality regulations. If the variances of the indices are underestimated, the DSO is exposed to a higher financial risk than appears to be the case. Severe weather is an uncontrollable factor for the DSO that affects the system reliability performance. If the regulator is to compare the performance of DSOs exposed to different weather conditions, it is important that the regulator can quantify the effects of severe weather on reliability performance. In order to model the variance in reliability indices more realistically,

the stochasticity in severe weather should be included. In the developed reliability model, the effect on overhead lines due to the stochasticity in high winds and lightning is considered.

**2) Time-varying cost factors based on underlying factors need less extensive customer surveys and can be updated easily over time**

The new approach of using underlying factors for estimating time variations in residential customer interruption costs agrees well with time-varying factors estimated by surveys. The benefit of using underlying factors is that customer surveys may be less extensive. Shorter surveys probably have a positive effect on the reply rate. The proposed approach uses activity patterns and weather statistics to describe hourly and seasonal variations in residential customer interruption costs. Time-use diary studies are conducted regularly and weather statistics are always available. The time-varying factors can, therefore, be updated easily over time without extensive and expensive customer surveys on interruption costs having to be conducted.

**3) The annual customer interruption cost and the annual total regulation cost due to quality regulation have large variances**

Due to the large variances, it may be interesting for the decision-maker not only to estimate the average, but also to consider the cost of more extreme years in the decision-making process. This can be done with the help of risk tools used in the financial industry such as Value-at-Risk and Conditional Value-at-Risk.

**4) Time correlations in inputs are important for accurate cost-benefit analysis and estimation of the total regulation cost**

A different reinvestment project was selected in a case study when time dependencies were considered, compared to if they were ignored. This was the case for both stakeholders: society and the DSO. The result emphasizes the fact that time dependencies in inputs are important for an accurate cost-benefit analysis and network planning for the DSO.

**5) Quality regulation design has a significant impact on reinvestment project profitability**

Results from a case study show that the quality regulation design has a significant impact on which reinvestment projects are profitable.

**6) Complex quality regulation designs demand detailed risk-based methods**

As quality regulation design becomes more complex, more detailed risk-based methods are needed in order to adequately capture the financial risk the DSO is exposed to. For example, in Sweden a new law came into force in 2011 that prohibits interruptions from being longer than 24 hours. With the proposed risk-based methods, it is possible to calculate the probability of interruptions exceeding this duration. It is also possible to identify the load points that are

at risk when planning for mobile generators. In a case study, it was shown that a DSO operating the rural test system and using non-time-varying models would conclude that the risk level is negligible. On the other hand, a DSO using time-varying models would conclude that on average one interruption every three years will be longer than 24 hours.

**7) A risk-averse strategy shows benefits or drawbacks of a project that cannot be discovered by the average value**

When making investment decisions, a risk-averse strategy may clarify benefits or drawbacks of a project that are hard to discover by only looking at the expected net present value. Results in the case studies indicate that time-varying models are needed to describe these benefits or drawbacks accurately. For example, when using non-time-varying models, the benefits of investment in cables, instead of overhead lines, for the worst outcomes are underestimated since the effect of severe weather is not captured.

**8) A cap on the cost due to reward and penalty scheme that is too low distorts optimality**

The results show that an optimal incentive rate for reward and penalty scheme according to eqn (2.17) may not be enough to give incentives for socioeconomic investments. If the cost due to reward and penalty scheme is capped too low a DSO may not benefit from implementing a socioeconomically beneficial reinvestment project.

## 6.2 Future work

Suggestions for improvements in the developed models and methods are:

- Develop the proposed risk-based methods further so that they account for both risks and uncertainties. Risk is defined as a measurable randomness that can be described by a probability distribution, in contrast to uncertainty, which is randomness without a well-defined distribution. The reliability of a component is stochastic and can vary. However, by using failure statistics, the probability distributions of the time to failure and restoration time can be estimated and the probability of power interruptions can be simulated. Conversely, we have uncertainties where the probabilities are unknown, such as how the quality regulation will be designed in the future. For example, the new quality regulation in Sweden from 2012 will probably change in 2016 [34]. Since both risks and uncertainties will affect the outcome of different investment decisions, it is important to consider them both when evaluating reinvestment projects.
- Make the developed risk-based methods more efficient by cutting simulations times using variance reduction techniques. Advanced risk-based methods are time consuming. To make methods applicable in industry, the simulation

times need to be short. There are different variance reduction techniques that can reduce the simulation times and make the methods more efficient.

- Investigate additional risk strategies. The DSO's attitude towards risk and uncertainties will be summarized in the risk strategy that the DSO uses when taking investment decisions.
- Is there an optimal regulation design that gives the desired outcome for all different risk strategies that the DSO can apply? To analyze this question, more extensive case studies are required. More investigations on how the relationship in strength between the quality regulation on customer level and on system level affects the incentives for investments are needed. Furthermore, analyses of the whole effect of the network regulation, not only studies on the effects of the quality regulation, are needed.
- More research is needed on customer interruption costs during extreme events when a large geographical area is affected by an interruption. Most interruptions typically have rather short durations and only affect a local geographic area (a few city blocks). For these interruptions, it is common to estimate the total costs of the outage by adding up the costs for the individual customers. However, for long-lasting and widespread outages, simply adding up the costs of the individual customers may lead to an underestimation of the total customer interruption costs [86]. One reason for the underestimation is that intangible costs due to lack of public services, for example, are ignored. An example of these types of costs is not being able to use the subway. Underestimating the total costs of extreme outage events in value-based reliability planning or in the quality regulation can, according to [86], result in inadequate catastrophic event reliability.
- Customer interruption costs for short interruptions, with a duration of less than three minutes, have been shown to be large [9]. Voltage disturbances, such as voltage dips, also result in costs for customers [87]. The next step in the evolution of quality regulations may be to include short interruptions and voltage disturbances. Therefore, to adequately estimate the total reliability cost for society and possible future financial risks for a DSO subject to a quality regulation, short interruptions and voltage disturbances should be considered. Norway has already included short interruptions in the quality regulation, and Norway and Italy have started to investigate costs due to voltage disturbances [30].



## Appendix A

### Reliability indices

This appendix defines the customer-based and load-based reliability indices that are calculated on system level. The notations used in the definitions are:

- $\lambda_i$  : Interruption frequency at load point  $i$
- $N_i$  : Number of customers at load point  $i$
- $U_i$  : Annual unavailability or outage time at load point  $i$
- $P_i$  : Average load demand at load point  $i$
- $S$  : Set of load points in the considered system

The reliability indices [15] are defined as:

$$\text{SAIFI - System Average Interruption Frequency Index} = \frac{\sum_{i \in S} \lambda_i N_i}{\sum_{i \in S} N_i}$$

$$\text{SAIDI - System Average Interruption Duration Index} = \frac{\sum_{i \in S} U_i N_i}{\sum_{i \in S} N_i}$$

$$\text{CAIDI - Customer Average Interruption Duration Index} = \frac{\sum_{i \in S} U_i N_i}{\sum_{i \in S} \lambda_i N_i}$$

$$\text{ASAI - Average Service Availability Index} = \frac{\sum_{i \in S} 8760 N_i - \sum_{i \in S} U_i N_i}{\sum_{i \in S} 8760 N_i}$$

$$\text{ASUI - Average Service Unavailability Index} = \frac{\sum_{i \in S} U_i N_i}{\sum_{i \in S} 8760 N_i}$$

$$\text{EENS- Expected Energy Not Supplied} = \sum_{i \in S} P_i U_i$$



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