Masteroppgave

NTNU
Norges teknisk-naturvitenskapelige universitet
Fakultet for informasjonsteknologi og elektroteknikk
Institutt for elkraftteknikk

Trygve Vesseltun Berg

Combining analytical power system reliability assessment methods with Monte Carlo simulation

Masteroppgave i MTENERG
Veileder: Gerd H. Kjølle
Juni 2019

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Combining analytical power system reliability assessment methods with Monte Carlo simulation

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Master's Thesis
Master of Energy and Environmental Engineering
30 ECTS
Department of Electric Power Engineering
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Abstract

This master thesis examines the field of power system reliability assessment through two parts, a literature study on the state of the art within power system reliability analysis methods, and an implementation of two hybrid power system reliability analysis approaches tested on two reliability test systems.

The reliability analysis methods can be divided into two groups, analytical methods and Monte Carlo simulation. The advantages and disadvantages of both types of methods are evaluated. After the characteristics of each method has been established, a discussion regarding combination of reliability methods into hybrid approaches ensues. The idea is to create hybrid methods that enhance the advantages of both methods while minimizing the disadvantages of both methods. Two possible hybrid reliability method configurations are proposed: 1) A combination of the OPAL methodology based on contingency enumeration and state sampling Monte Carlo simulation, 2) A combination of the OPAL methodology based on contingency enumeration and pseudo-sequential Monte Carlo simulation. Both methods are tested on two test systems, RBTS and The Four-Area Test Network.

Simulation results are obtained for both the delivery points of the system, as well as the system as a whole. The hybrid methods are able to calculate the reliability indices, which measures the reliability of a power system. As a benchmark for comparison of the simulation results from the hybrid methods, the OPAL method is used. The total system index for Expected Energy Not Supplied (EENS) is calculated to be at a maximum difference of 2.8% between the hybrid methods and the OPAL Benchmark test. Both test systems have over 95% of the contribution to the EENS index from one single branch outage, due to the islanding of a bus. The reliability indices calculated for the two hybrid methods and the benchmark on the RBTS network differs more than for The Four-Area Network, which is likely due to the fact that The Four-Area Network is much more reliable than RBTS.

The hybrid methods have higher computational cost compared to the OPAL method. Many improvements can be made on both hybrid implementations to reduce computational cost, including: optimizing of code, combine with intelligent techniques (variance reduction, particle swarm optimization, genetic algorithms, machine learning algorithms etc.). Both proposed hybrid methods can be used for reliability assessment of power systems, but further testing and improvement is required in order possibly be established as a more accurate method than the analytical reliability analysis method OPAL, or faster, and sufficiently accurate, than the Monte Carlo simulation methods.

Sammendrag

Denne masteroppgaven undersøker fagfeltet pålitelighetsanalyse av kraftsystemer gjennom to deler, et litteraturstudie om det nye innen metoder for pålitelighetsanalyse av kraftsystemer, og en implementasjon av to hybridmetoder for kraftsystemanalyse testet på to testsystemer for pålitelighet.

Metoder for pålitelighetsanalyse kan deles inn i to grupper, analytiske metoder og Monte Carlo simulering. Begge metodetypene blir evaluert i forhold til deres fordeler og ulemper. Etter at karakteristikkene for alle presenterte metodene har blitt undersøkt, så diskuteres det rundt det å kombinere ulike metoder til hybridmetoder. Ideen er å lage hybridmetoder som forsterker fordelene og minimerer ulempene fra begge de kombinerte metodene. To mulige hybridmetoder blir foreslått: 1) en kombinasjon av OPAL-metoden med state sampling Monte Carlo simulering, 2) en kombinasjon av OPAL-metoden med pseudo-sekvensiell Monte Carlo simulering. Begge metodene blir testet på to testsystemer, RBTS og Fire-Område Testnettverket.

Simuleringsresultater blir funnet for både leveringspunkter i systemet, og for det totale systemet. Resultatene viser at hybridmetodene klarer å regne på pålitelighetsindeksene, som måler påliteligheten til et kraftsystem. OPAL-metoden blir brukt som referansemåling for sammenlikning med resultatene fra simulering av hybridmetodene. Pålitelighetsindeksen for det totale systemets forventet ikke-levert energi (ENG: EENS) blir beregnet til å ha en maksimum differense på 2.8% mellom hybridmetodene og OPAL-referansemålingen. Begge testsystemene har over 95% av bidragene til EENS-indeksen fra utfall av en enkelt gren. Pålitelighetsindeksene beregnet for hybridmetodene og referansemålingen, varierer mer for RBTS enn for fire-område testnettverket, mest sannsynlig på grunn av at fire-område testnettverket er mye mer pålitelig enn RBTS.

Sammenlignet med OPAL-metoden, så kommer begge hybridmetodene med en økt beregningskostnad. Mange forbedringer kan gjøres for begge hybridimplementasjonene for å redusere denne beregningskostnaden, inkludert: optimere/omstrukturere koden, inkludere teknikker for varianseredukjson, kombinering med intelligente metoder (som partikkelsverm-optimering, genetiske algoritmer, maskinlærings-algoritmer osv.). Begge de foreslåtte hybridmetodene kan bli brukt for å evaluere pålitelighet av kraftsystemer, men mer testing, og forbedring, behøves for at metodene muligens skal kunne etablere seg som mer treffsikre enn den analytiske pålitelighetsanalysemetoden OPAL, eller raskere, og like treffsikker, som Monte Carlo simuleringsmetodene.

Acknowledgment

I would like to thank my supervisor Professor Gerd Hovin Kjølle for excellent motivation during the last year. I would also like to extend my greatest appreciation to my co-supervisor Iver Bakken Sperstad, who have been dedicated to giving me valuable guidance since the beginning of the master thesis work.

Trondheim, 24 June 2019
Trygve Vesseltun Berg

Contents

List of Figures

List of Tables

Abbreviations

LG - Local Generation
SAC - System Available Capacity
APC - Available Power Capacity
MCS - Monte Carlo Simulation
PLC - Probability of Load Curtailments
ENLC - Expected Number of Load Curtailments
EDLC - Expected Duration of Load Curtailments
ADLC - Average Duration of Load Curtailments
ELC - Expected Load Curtailed
EENS - Expected Energy Not Supplied
EIC - Expected Interruption Cost
HILP - High Impact Low Probability (Event)
OS - Operating state
HL - Hierarchichal level
OPF - Optimal Power Flow
RBTS - Roy Billinton Test System

1 Introduction

1.1 Background

The global demand for energy, and especially electrical power, is increasing. In 2018 electricity demand rose by 4% [5]. More and more people are relying on being supplied electricity, and with the expectation that it is continuously available. This fact, together with the introduction of new technologies, such as renewable energy sources, electric vehicles and charging, large-scale battery storage, distributed generation, etc., gives an expectation of a more complex power system for the future.

Any component in a power system is always at risk of possible failure, which in turn can lead to partial or total system failure. The quantification of this possibility of failure is found through a reliability analysis of the system and its components. The objective of a reliability analysis is to be used in either a planning or operation context. For planning purposes The wanted level of reliability of a system can be seen from a benefit point of view (i.e. the best possible improvement to system reliability), or a cost-benefit point of view. The trade off cost versus reliability is depicted in figure 1, where one seeks to find the optimum point (minimizing the cost while simultaneously maximizing the reliability). A reliability analysis can be deterministic, such as the N-1 criterion or percentage reserve capacity, or probabilistic in nature. Historically, mostly deterministic approaches have been used. A questionnaire sent to 9 different transmission system operators in the Nordic countries and continental Europe, show that there is a gap between what exists in the research literature and what is being used in practice regarding probabilistic reliability methods [6].

For increasingly complex systems it has been experienced from other areas (such as gas supply, water supply and nuclear power, among others) that probabilistic methods for determining reliability is superior to deterministic methods [7]. A thorough discussion on the benefits of using probabilistic in stead of deterministic methods for power system reliability assessment is presented in [1]. Probabilistic methods have been studied for over half a century, but still deterministic methods, such as the N-1 criterion are used by power utility companies, mostly for operational purposes [6]. In [1], a thorough discussion on the benefits of using a probabilistic method in stead of a deterministic method is presented.

Probabilistic methods for power system reliability are separated into two groups; analytical approaches, and Monte Carlo simulation. Each of these groups contain several methods, each with their advantages and disadvantages, that can calculate the reliability indices for a power system, which is the ultimate goal of a reliability analysis. These probabilistic methods and their character-

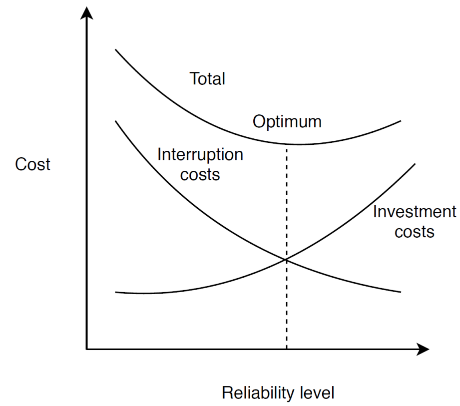

Figure 1: Trade off between cost and reliability

istics will be thoroughly explored.

1.2 Thesis problem

This master thesis seeks to explain the differences between the probabilistic reliability methods, by evaluating the advantages and disadvantages of each method. After exploring these characteristics, the question becomes: can a combination of an analytical method and a Monte Carlo simulation be implemented to reduce computational cost, while keeping a satisfactory accuracy of the reliability indices, and what other benefits does the hybrid method give?

1.3 Scope of thesis

This thesis can be split into two main parts: a literature study on reliability assessment methods, and an implementation of two proposed hybrid reliability assessment methods.

The first part covers the necessary theory for reliability assessment methods of power systems, which includes theory from statistics, system reliability and power systems. The focus of the literature study lies in compiling the state of the art within the power system reliability assessment field, in terms of which methods are being used, and what advantages and disadvantages they present. Certain aspects will only be briefly mentioned, as they are not of particular interest for part two of the thesis.

The second part of the thesis aims to propose two hybrid methods for composite power system reliability assessment, which will be implemented in MATLAB, and tested on two power system networks (RBTS, and the 4-area network). Certain assumptions and simplifications have been made to feasibly implement and test the methods, which will be covered in chapters 5 and 6. An evaluation of the methods and their results on the test system will be done in order to ascertain the usefulness of the proposed methods.

1.4 Structure of thesis

Chapter 1 - Introduction to the thesis background and the problem description.

Chapter 2 - The fundamentals of reliability analysis.

Chapter 3 - Presentation of the different analytical power system reliability methods.

Chapter 4 - Exploring the different Monte Carlo Simulation methods for power system reliability.

Chapter 5 - Combining analytical methods and Monte Carlo simulation to hybrid methods. State of the art of hybrid methods. Two proposed implementations of hybrid methods are presented.

Chapter 6 - A case study is done on two test systems, RBTS and the four area-network, with the two proposed implementation. The methods are tested against a benchmark test of pure analytical and pure Monte Carlo simulation.

Chapter 7 - Analyzes and discusses the results from the case studies.

Chapter 8 - Concludes the master thesis. Discusses possible future work.

Appendix - Contains all the self-written MATLAB code that was created for the implementation of the two hybrid methods. Contains the full results of the simulations of both the hybrid methods and the benchmarks.

2 Reliability analysis of power systems

The concept of reliability was briefly mentioned in the introduction. This chapter will explain the fundamentals of reliability in general, and extend to power system reliability in particular.

2.1 Reliability in general

2.1.1 The concept of reliability

Reliability is "the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time" [7].

Item - a unit of interest, which can be a component, subsystem, or system.

Required function - could be a single function or a combination of functions that is needed for providing a specified service. The required function have to be specified in order to assess reliability.

Some concepts in relation to reliability are (from [7]):

Quality - "The totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs.

Availability - "The ability of an item (under combined aspects of its reliability, maintainability and maintenance support) to perform its required function at a stated instant of time or over a stated period of time.

Maintainability - "The ability of an item, under stated conditions of use, to be retained in, or restored to, a state in which it can perform its required functions, when maintenance is performed under stated conditions and using prescribed procedures and resources.

Safety - "Freedom from those conditions that can cause death, injury, occupational illness, or damage to or loss of equipment or property.
Security - "Dependability with respect to prevention of deliberate hostile actions".

Dependability - "The collective term used to describe the availability performance and its influencing factors: reliability performance, maintainability performance and maintenance support performance.

The goal of a reliability assessment is to provide information as a basis for decision making [7]. There are many areas of application for reliability studies, such as in risk analysis, environmental protection, quality management, optimization of maintenance and operation, engineering design, verification of quality/reliability, etc.

2.1.2 Exponential distribution

To assess the reliability of an item, it has to be modelled in a sufficiently realistic manner, i.e. the results are of practical relevance, while also being sufficiently simple (can be mathematically or statistically handled by available methods) [7].

Probability distributions are often used to model the lifetime of items. There are many of them, but the exponential distribution is the most relevant for this master thesis. A presentation of the most important aspects of the exponential distribution will follow, inspired by [7],[8] and [9].

An item is put into operation at time t = 0. The time to failure, T, of the item has probability density function:

$$f(t) = \begin{cases} \lambda e^{-\lambda t} & \text{for } t > 0, \lambda > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

Where λ is a rate parameter. The cumulative distribution function, CDF, can be found by integrating the probability density function over a time period:

$$F(t) = \int_0^t \lambda e^{-\lambda u} du = 1 - e^{-\lambda t} \tag{2.2}$$

The reliability function, or survivor function, is:

$$R(t) = Pr(T > t) = 1 - F(t) = \int_t^\infty f(u) du = e^{-\lambda t} \text{ for } t > 0 \tag{2.3}$$

The mean time to failure, MTTF, is:

$$MTTF = \int_0^\infty R(t) dt = \int_0^\infty e^{-\lambda t} dt = \frac{1}{\lambda} \tag{2.4}$$

The failure rate function is:

$$z(t) = \frac{f(t)}{R(t)} = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda \tag{2.5}$$

So the failure rate of an item with exponential life distribution is constant, i.e independent of time.

The mean residual life, MRL, can be found by considering the conditional survivor function, where an item that has been functioning for t time units is equal to the survivor function of a new item:

$$MRL(t) = \int_0^\infty R(x|t)dx = \int_0^\infty \frac{e^{-\lambda(t+x)}}{e^{-\lambda t}}dx = \int_0^\infty e^{-\lambda x}dx = \int_0^\infty R(x)dx = MTTF \tag{2.6}$$

MRL is equal to MTTF independent of the age t of the item, and thus the item is as good as new while functioning. This is the memoryless property of the exponential distribution.

2.1.3 Markov models

This subsection contains a brief introduction to Markov models. For further information, see [7], or for a more theoretical approach, see any book on stochastic processes.

So far only the failure models of items have been investigated, but in reality items will fail, and then be restored, repaired or replaced. A typical way of modeling the function of an item is to either be in functioning state (up) or failed state (down). Considering a system with several components, there exists a set of possible states that the system can be in. A stochastic process to model a system with several states and the transitions between them is called a Markov model, or Markov chain. The set of possible states is called the state space.

A state transition diagram of a two-state Markov model is shown in figure 2. The functioning state is denoted 1, and the failed state is denoted 0. The transition between the states is exponentially distributed with failure rate λ and repair rate μ as the exponential distribution rate parameter. The functioning time is m, and the repair time is r. Following the notation used in figure 2, the fault rate is defined as:

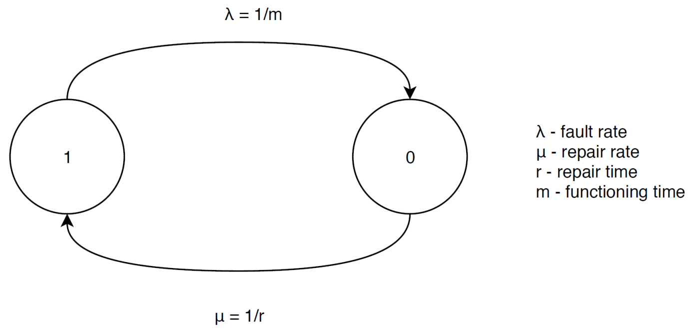

Figure 2: Two state Markov model

$$\lambda = \frac{\text{Number of faults in a given time interval for a component}}{\text{Total time in operation of the time interval}} \tag{2.7}$$

The probability of an item to be down (state 0) and up (state 1), is given as:

$$P_0 = \frac{r}{m+r} = \frac{\lambda}{\lambda+\mu} \tag{2.8}$$

$$P_1 = \frac{m}{m+r} = \frac{\mu}{\lambda+\mu} \tag{2.9}$$

And frequency of encountering a state, f, is defined as the inverse of the cycle time, i.e. the probability of being in the state times the rate of departure from the state:

$$f = \frac{1}{T} = \frac{\mu\lambda}{\mu+\lambda} = P_1 \cdot \lambda = P_0 \cdot \mu \tag{2.10}$$

Markov models can be expanded to include more states, e.g. a degraded state between the up and down states. This increases the complexity and will not be treated in this thesis.

2.1.4 State Space

As mentioned in the last section, the state space is all the possible states a system can take. For a system with one component, there are two system states (as long as the components are based on a simple two-state Markov model). However, if a system connects two or more components, the number of possible system states increases rapidly. For a system of n components, the system has 2^n possible states. Figure 3 shows the state space and transitions between states for a system with two components. This subsection is based on [2] and [7].

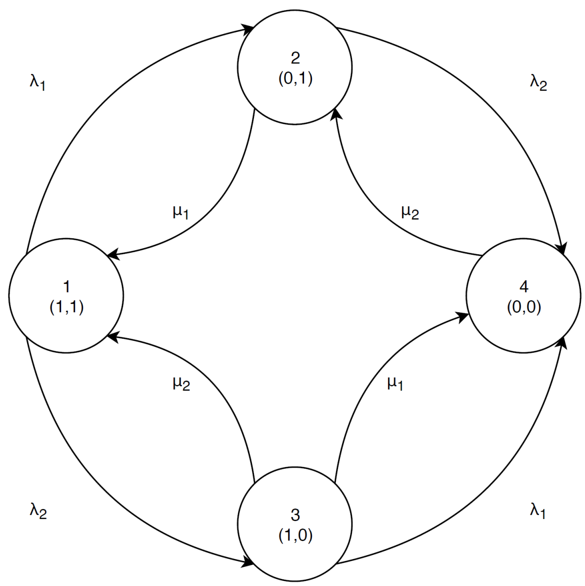

Figure 3: State transition diagram for a system of two components

This system obviously has four possible system states: $1 = \{0, 0\}$, $2 = \{0, 1\}$, $3 = \{1, 0\}$ and $4 = \{1, 1\}$. The probabilities of being in each state is given as:

State 1: Both components up

$$P_1 = \frac{\mu_1}{\lambda_1 + \mu_1}\frac{\mu_2}{\lambda_2 + \mu_2}$$

State 2: Component 1 down, component 2 up

$$P_2 = \frac{\lambda_1}{\lambda_1 + \mu_1}\frac{\mu_2}{\lambda_2 + \mu_2}$$

State 3: Component 1 up, component 2 down

$$P_3 = \frac{\mu_1}{\lambda_1 + \mu_1} \frac{\lambda_2}{\lambda_2 + \mu_2}$$

State 4: Both components down

$$P_4 = \frac{\lambda_1}{\lambda_1 + \mu_1} \frac{\lambda_2}{\lambda_2 + \mu_2}$$

The mean time spent in each state, called mean sojourn time, is found using the departure rate of the states:

$$m_1 = \frac{1}{\lambda_1 + \lambda_2}$$

$$m_2 = \frac{1}{\lambda_2 + \mu_1}$$

$$m_3 = \frac{1}{\lambda_1 + \mu_2}$$

$$m_4 = \frac{1}{\mu_1 + \mu_2}$$

This can further be used to calculate the basic reliability indices of the system (failure probability, failure frequency and mean failure duration). Reliability indices will be discussed later in this chapter. Considering the system structure, i.e. if the components are connected in a series or parallel structure, simplifications can be made.

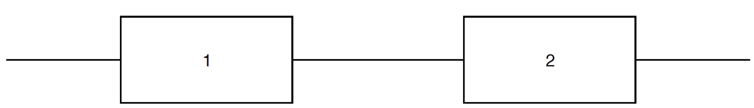

Figure 4: Series structure of two components

For a series structure of two components, as in figure 4, the up state is state 1 (both components are required to be up), and state 2, 3, 4 are thus all down states. The simplified probabilities are then:

$$P_{up} = P_1 = \frac{\mu_1}{\lambda_1 + \mu_1} \frac{\mu_2}{\lambda_2 + \mu_2} \tag{2.11}$$

$$P_{down} = P_2 + P_3 + P_4 = 1 - P_{up} \tag{2.12}$$

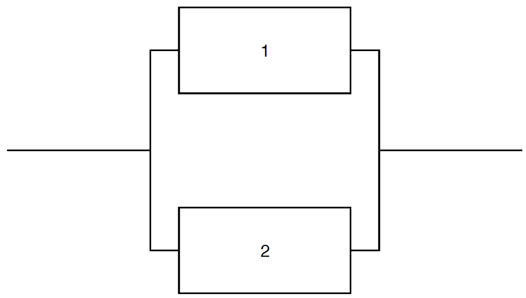

Figure 5: Parallel structure of two components

For a parallel structure of two components, as in figure 5, the up states are state 1, 2 and 3 (only one component is required to be up at a time), and state 4 is a down state. The simplified probabilities are then:

$$P_{up} = P_1 + P_2 + P_3 = 1 - P_{down} \tag{2.13}$$

$$P_{down} = P_4 = \frac{\lambda_1}{\lambda_1 + \mu_1} \frac{\lambda_2}{\lambda_2 + \mu_2} \tag{2.14}$$

For both series structure and parallel structure, the frequency can be calculated with the general eq. (2.10), and taking the relations between the states. The interruption duration can be calculated with the general equation, eq. (2.15):

$$r = \frac{P_{down}}{f_{down}} \tag{2.15}$$

2.1.5 Minimal cut sets

A cut set is a set of components that when fails, causes system failure. A system then contains a chain of cut sets in series (similar to series of components described earlier), and if one cut set fails (i.e. all components within that cut set fails), the system fails. A cut set is minimal when it has the fewest possible components within it and still expresses the cut set (i.e. when you no longer can remove any components and still express the cut set). A series of minimal cut sets are demonstrated in figure 7. In figure 6 there is a system with three components, named 1, 2 and 3. Component 1 is in series with 2 and 3, where 2 and 3 is in a parallel. The cut sets can be simplified in a conceptually similar manner to what was done with the series and parallel components for a state space system calculation (see figures 4 and 5). In essence, component 1 will be the cut set $\{1\}$, and components 2 and 3 will be the cut set $\{2\&3\}$, so the chain retains a series connection of cut sets that is required for the system to function, i.e. either component 1 must fail, or both 2 and 3 must fail for the system to fail.

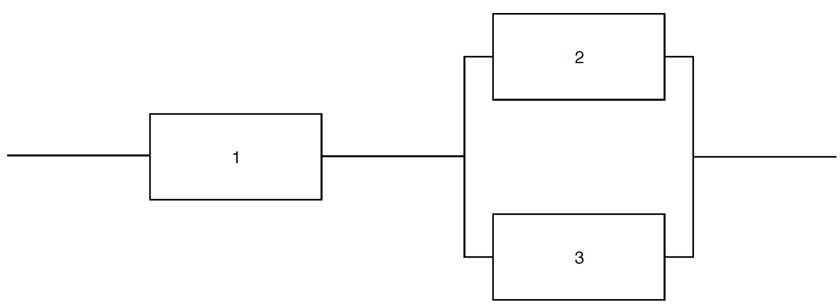

Figure 6: System of three components

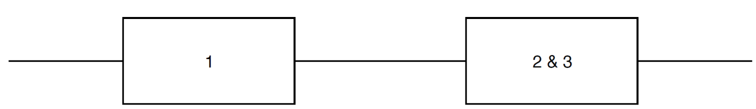

Figure 7: System of three components in terms of its minimal cut sets

2.2 Reliability analysis of power systems - fundamentals

This section contains the theory and concepts that are needed in order to extend the general reliability analysis to treat power systems in particular.

2.2.1 Power system reliability

Power system reliability is defined as "the probability that an electric power system can perform a required function under given conditions for a given time interval" [10], i.e. the quantification of an electric power system's ability to supply adequate electric energy on a continuous basis over an extended period of time. Power system reliability is comprised of two domains; adequacy and security (e.g. [2], [9]). Adequacy means the ability of a power system to deliver sufficient power to the customers in steady state and under normal operating conditions. Security studies assess the dynamics of the power system, and whether or not it will remain within stability and security limits (i.e. for voltage, current, power etc.), [1]. For the purpose of this thesis, reliability is used interchangeably with adequacy.

Important concepts in reliability of power systems, extracted from:

Event - occurrence of a particular set of circumstances. Different events can occur, e.g. failure events, extraordinary events, related to power systems. [6]
Contingency - unexpected failure or outage of one, or multiple, system component(s), such as generators, transmission lines, circuit breakers, switches, or other electrical equipment. [6]
Failure/fault - an item's lack of ability to perform its required function. After failure, the item has a fault. [10]
Outage - state of an item when it is not available to perform its function due to some event directly affecting it. [6]
Interruption - a condition in which the voltage at the supply terminals is lower than 5% of he reference voltage as a consequence of an event. Interruption duration is defined as short for up to and including 3 minutes, and long for a duration longer than 3 minutes. [11]

2.2.2 Reliability assessment framework

Power system reliability have been studied for a long time (several decades), and thus a generic framework for power system reliability assessment has been established (presented in figure 8. The framework contains the main aspects of reliability assessment, e.g. choosing the objectives of the reliability assessment, modelling level, which simulation approach to use etc. The generic framework must be adapted, in terms of simulation technique, theory and models used, to fit the purpose and method of the reliability assessment. The most important aspects from figure 8 will be further explored in this section. For a thorough discussion regarding all these aspects, see [1]

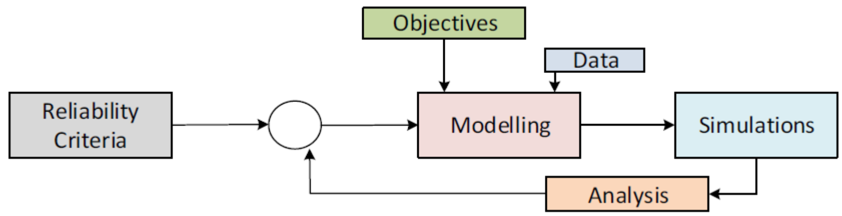

Figure 8: Generic reliability assessment framework, from [1]

2.2.3 Objectives of the reliability assessment

The broader objective of a reliability assessment is to be used for either planning purposes (short, medium or long term), or for operation purposes [6],[1]. In reality, stochastic reliability assessment methods are underused for operation of a power system, but will likely see an increased usage in the future ([6]). For this thesis, the focus is on planning purposes, i.e. choosing the best solution from a suite of candidate alternatives [1]. The decision is made from a cost-benefit standpoint (see figure 1 and the trade off between cost and reliability level). For operation purposes, the decision can be made from a benefit, or security, point of view (remaining within power system operational limits).

The tripartite reliability evaluation complexity [1] is a way to select the best candidate based on three criteria: 1) the required speed of selection, 2) which selection criteria to be used and 3) the selection model (the minimum level of system modelling complexity). Figure 9 shows the different possible categories of assessment approaches (A-D) for different levels of the tripartite reliability evaluation complexity. The categories A-D will be further explored, and methods within these categories are named and evaluated in the two next chapters. An important effect of this relationship (or trade off), is that there cannot be one assessment approach that trumps all, i.e. the approach has to be chosen for its purpose.

2.2.4 Data

Data, together with the objectives, are used to guide the modelling of a reliability assessment 8. Historical reliability data, and technical power system data for the generators, lines, load points, transformers, substations etc. are both required for assessing the reliability of power systems. The reliability data are used for reliability assessment, and the power system data is used for the security violation limits, load flow analysis etc.

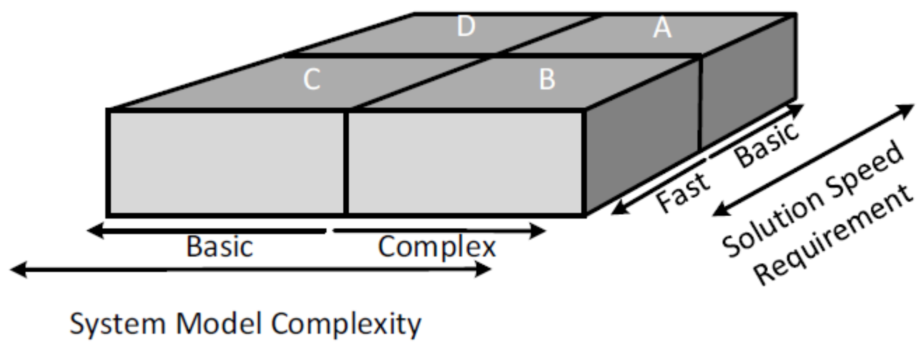

Figure 9: Relationship between the reliability assessment process speed and the system model complexity, from [1]

Reliability data

High quality reliability data is required for predicting the reliability of power systems. In Norway, disturbance and fault statistics have been gathered for over 20 years, using the FASIT standard [12]. Typical reliability data that is used in probabilistic reliability analysis, is fault and repair frequencies of components (lines, cables, transformers, protection systems, generators etc.).

Power system data

For a generator plant, there are a number of data of interest. Security wise, there are certain limits to power injection to the system by the generators to avoid overheating and other destructive outcomes (see [1] for a model with more details). For power system adequacy, the available power capacity, APC, is needed to see if the load demand is met [2]. The injected power from the generator plant is described as in eq. (2.16)

$$S_k^{injected} = P_k^{injected} + jQ_k^{injected} \tag{2.16}$$

where S is the apparent power, P real power, and Q reactive power injections into an arbitrary bus k.

For lines, or branches, data is required for multiple purposes. Their ability to transfer power is determined by their electrical parameters, such as: the impedance Z, admittance Y, reactance X and resistance R (see eq. (2.17)). Using a PI-line model (shunt model), the lines can easily be modeled in terms of its "end-line" susceptance B (see eq. (2.18). Thermal safety limits can be found by using data on wind speed, ambient temperature, solar radiation etc. [1].

$$Z = R + jX \tag{2.17}$$

$$B = \frac{Y}{2} \tag{2.18}$$

where $Y = 1/X_c$ is the total lines capacitive susceptance.

Load data, or load demand, are aggregated at certain load points in the system and follow a chronological pattern. A vector of load demand can then be obtained:

$$\boldsymbol{L_{Load}} = [\boldsymbol{L_1(t)}...L_N(t)] \tag{2.19}$$

where $\boldsymbol{L_1(t)}$ is the load demand at load point 1 for time t.

2.2.5 Reliability Modelling

The modelling process of the reliability assessment uses mathematical expressions to represent the system's behaviour. The level of modelling detail comes at a price of increased computational cost (see figure 9. This balance is something one must consider when choosing the modelling level of the reliability assessment method.

Modelling is an integral part of the reliability assessment. The power system network is modelled, the data are modelled, the level of power system detail (hierarchical level) is modelled, the security aspects are modelled, weather effects, as well as other dependencies, can be modelled, maintenance is modelled etc. It should not be a surprise that the reliability assessment approach is only as good as its models.

Delivery point interruptions

Using data modelling, interruptions on the delivery points can be examined. This subsection is based on [2]. Interruptions occur if the APC at the supply terminals is not sufficient to supply the load demand P. APC is the sum of the System Available Capacity (SAC), the available capacity in the supply system, and the Local Generation (LG) at the delivery point. Mathematically, an interruption occurs when eq. (2.20) is true.

$$P > SAC + LG \tag{2.20}$$

and the amount of interrupted power in the delivery point, P_{interr} is:

$$P_{interr} = P - APC = P - SAC - LG \tag{2.21}$$

The equations (2.20) and (2.21) are true for the adequacy part of reliability. In figure 10, a chronological example is used to show the relationship between APC and a superimposed load curve, to obtain typical reliability indices (interrupted power, duration of interruption and energy not supplied).

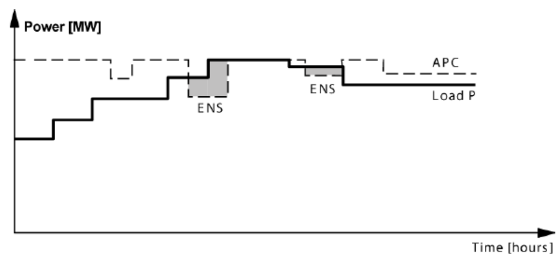

Figure 10: APC-curve with a superimposition of an hourly load curve for a general delivery point, from [2]

Hierarchical levels

For power system adequacy assessment, a hierarchical structure has been developed in order to differentiate the system modelling level based on different functional zones. Figure 11 presents the hierarchical levels, and their functional zones.

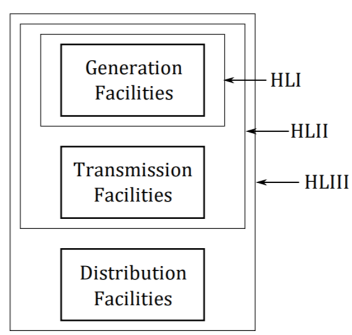

Figure 11: Division of functional zones and Hierarchical levels

HL1 studies evaluates if the total system generation is sufficient for supplying the total system load demand. A depiction of this can be seen in figure 10. An HL1 study is as such, a generating capacity reliability evaluation. These studies are normally used for estimating needed generation capacity, in order to meet the load demand. A Markov model with degraded states (multi-states) can be used here to evaluate reliability with amputated generation [1], [9].

HL2 is an extension of HL1 to also include transmission lines. HL2 systems are often called bulk transmission systems or composite systems. HL2 studies are on a significantly higher modelling level compared to HL1. It is no longer sufficient to look at APC and load demand alone, because load flowing in the transmission lines are necessary to include (as it is a part of the functional zone for a HL2 study). In addition to calculations and considerations of the system, load points (buses) must be evaluated [2]. HL2 includes more detailed failure modes by introducing voltage instability, transient instability and plant thermal overloads [1].

HL3 includes all the functional zones: generation, transmission and distribution. This further complicates the evaluation process into a near impossible task. A solution to solving HL3 is to simplify the evaluation process to first perform an HL2 study, and use the results from that evaluation as an input to the distribution assessment [8].

Security modelling

This section presents security considerations in composite system adequacy evaluation (static), and must not be confused with the security domain within reliability (dynamic). However, it is possible to include transient or dynamic conditions for the adequacy security. The entire section is based on [8] and [1].

To be able to plan and utilise the reliability assessment methods, a set of optimal system actions must be designed in order to keep the system within, or steer it towards, a secure and sufficiently adequate state. A set of system operating states are presented in order to separate the degree to which adequacy and security considerations are satisfied. Figure 12 shows the security operating states and the relations between them.

> The Normal State: All equipment and operation constraints are within limits. Sufficient margin to withstand loss of some element. System is both adequate and secure.
>
> The Alert State: System has loss of some element that results in a current or voltage violation. All constraints are within limits, but no margin to withstand an outage. System is adequate, but not secure.
>
> The Emergency State: Occurrence of contingency, or generation and load changes before corrective action is taken. No load is curtailed, but equipment/operating constraints have been violated. Action must be taken to prevent transfer to Extreme Emergency State. System is neither adequate, nor secure.

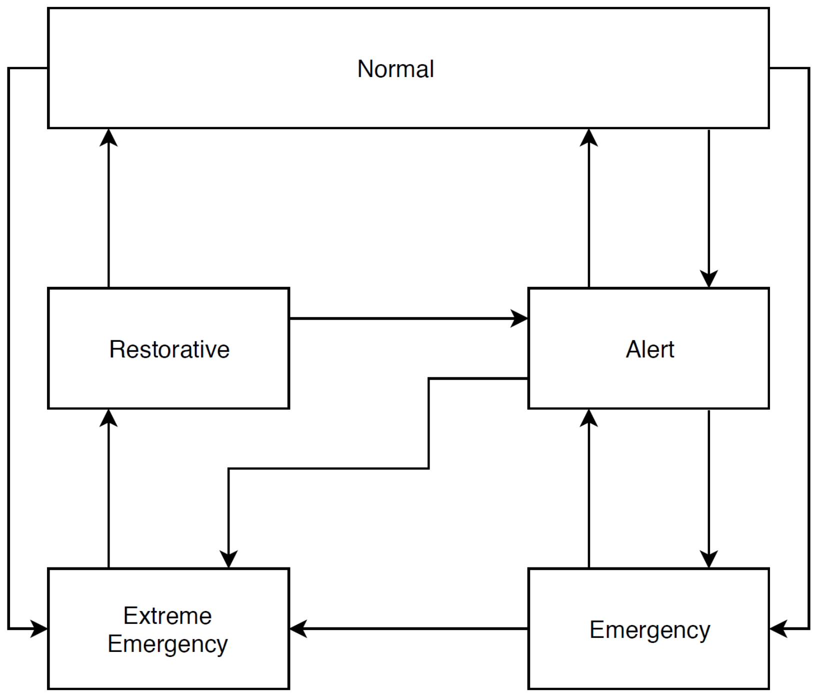

Figure 12: Classification of system adequacy security operating states

The Extreme Emergency State: Equipment and operating constraints are violated, and load demand is not met. Load curtailment (load shedding) must follow in order to return to a former state. System is neither adequate, nor secure, and will experience blackouts.

The Restorative State: To return from extreme emergency, the system operator must perform restorative actions, such as the black starting of generators, and slowly reconnecting the load, until system is restored to a secure state.

Appropriate models and algorithms are required to correct and restore system from the extreme emergency state. A contingency analysis, based on load flow solution, is necessary for assessing the situation as it is, for all load points (buses). Then a set of corrective actions is taken in order to restore security. Corrective actions seeks to alleviate security violations, and is normally conducted by an Optimal Power Flow (OPF) solution. A linear OPF is normally used, as it saves computational time, and is usually accurate enough, since other uncertainties offset the accuracy gained by using a non-linear OPF [8]. Depending on the problem, several corrective actions can be taken, such as: generation rescheduling to reduce load curtailment, or adjustment of generator bus voltages to correct voltage violations and reduce reactive load curtailments. More details on security modelling can be found in [8] and [1].

2.2.6 Contingency analysis

As previously mentioned, an HL2 study requires a mathematical load flow analysis in order to ascertain the severity of a contingency. Contingency analysis for HL1 and HL3 will not be treated in this thesis. The load flow analysis can be studied as a DC problem or as an AC problem. This section is based on [13],[8],[1] and [9].

2.2.7 DC load flow

Generation facilities inject power into the grid. A matrix representation of the power injected is shown in eq. (2.22).

$$\boldsymbol{P} = \boldsymbol{B}'\delta \tag{2.22}$$

where $\boldsymbol{B}'$ is a vector of system susceptance values, and δ is a matrix containing the voltage angle difference between the buses. The power flowing through a line can then be expressed as in eq. (2.23).

$$P = \frac{\delta_i - \delta_j}{x_{ij}} \tag{2.23}$$

where i and j are the nodes at each ends of the line, and x_{ij} is the reactance of the line.

DC load flow is capable of uncovering overloading conditions due to system contingencies, but cannot evaluate the voltage or reactive power constraints. Furthermore it cannot include transmission losses, but DC load flow is still used by many due to its simplicity, speed and ability to always converge [1]. Further details on the DC load flow can be found in any book on load flow analysis, e.g. [13], and [8].

2.2.8 AC load flow - fast decoupled model

A simplified version of AC load flow (see e.g. [13] or [8]), called AC fast decoupled load flow is presented here. The idea is to address the issues related the DC load flow, while retaining a reasonable computational speed.

Using an iteration method, such as the Newton-Raphson method, to solve the basic power flow equations yields eq. (2.24).

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} H & N \\ J & L \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V/V \end{bmatrix} \tag{2.24}$$

This equation can be decoupled by assuming $N = 0$ and $J = 0$, and further simplified by considering $|G_{ij} \sin \delta_{ij}| << |B_{ij} \cos \delta_{ij}|$ and $|Q_i| << |B_{ii} V_i^2|$ to eq. (2.25) and eq. (2.26).

$$\boldsymbol{\Delta P / V = B' \Delta \delta} \tag{2.25}$$

$$\boldsymbol{\Delta Q / V = B'' \Delta V} \tag{2.26}$$

where $\boldsymbol{B'}$ and $\boldsymbol{B''}$ are the constant bus admittance matrices for real and reactive power iteration. The voltage and voltage angle updates using linearized equations. The solution to the AC fast decoupled load flow, can now be obtained for a given system state. A set of equations for system violation can now be formulated, see eq. (2.27) to (2.30) [1], [8]:

$$\boldsymbol{V_m in < V < V_m ax} \tag{2.27}$$

$$\boldsymbol{P_m in < P < P_m ax} \tag{2.28}$$

$$\boldsymbol{Q_m in < Q < Q_m ax} \tag{2.29}$$

$$\boldsymbol{|T| < T_m ax} \tag{2.30}$$

2.2.9 Corrective actions with OPF

Any violations of the equations (2.27) to (2.30) transitions the system into an emergency or extreme emergency state, and thus corrective actions must be taken. OPF is used to reschedule generation to hopefully avoid blackouts. If generation rescheduling doesn't alleviate the violation, load curtailment is necessary. Optimization algorithms are designed to search for the optimal economic solution, for which end users to shed the load for.

An example of an optimization algorithm, is a model of a linear quadratic programming algorithm whose objective function is to minimise generator dispatch cost C for generator i in a system of N generating systems as in eq. (2.31) [1]:

$$min \sum_{i=1}^{N} C_i \tag{2.31}$$

where this optimization problem must be constrained by the limits in equations (2.27) to (2.30), as well as equations (2.32) and (2.33).

$$\boldsymbol{P} + \boldsymbol{D_c} = \boldsymbol{D} \tag{2.32}$$

where $\boldsymbol{P}$ is total real power produced, $\boldsymbol{D_c}$ is the total demand curtailed, and $\boldsymbol{D}$ is the total system demand.

$$\boldsymbol{Q} = \boldsymbol{D_q} \tag{2.33}$$

where $\boldsymbol{Q}$ is the total reactive power produced and $\boldsymbol{D_q}$ is the total system reactive power demand.

The equations and models for the contingency analysis have now been set, and optimisation solvers can now be used to solve the problem.

2.2.10 Dependencies

There are many other factors, than those already mentioned, that influence the power system reliability assessment. Dependencies such as: geography, function, human factors, time dependencies and weather influence, to mention some. An example of dependency based on geography, is two cables lying next to each other, and having common cause failure. Functional dependencies can be related to the protection systems, e.g. spurious (unwanted) tripping of a protection or control system. Human factors are not really tangible in the same way as other dependencies, but can e.g. be related to inadequate operators. Time dependencies can be related to different impactful things that vary with time, such as the varying load demand in terms of the time of day, week or month of the year. Extreme weather has a huge impact on the the number of contingencies, as well as the severity and duration of these on a power system [14]. Quantifying the risk introduced from weather, is incredibly tough to do, due to its stochastic nature and multi-dimensional impact. Including dependencies, and their models, in the power system reliability assessment, will increase the level of complexity of the system, and thus the necessity of the inclusion should be evaluated beforehand.

2.3 Introduction to analysis methods

2.3.1 Analysis methods

There are two main types of methods for power system reliability analysis, the analytical methods and the (Monte Carlo) simulation methods. The following two chapters will take a look at the general aspects of each type of analysis method, and deep dive into some of the actual reliability methods that are being used. All reliability methods have its advantages and disadvantages, and these will be thoroughly examined for the treated approaches.

For both analysis methods, the main goal is to calculate the reliability indices, which will be explained later. Analytical methods uses mathematical models and simplifications in order to calculate these indices, while MCS uses random sampling techniques and a great number of samples in order to establish a distribution of the reliability indices. The analytical methods are usually quite fast, but can lack accuracy in their calculations. MCS can be both fast and slow (usually slower than analytical methods nonetheless), and can normally provide a greater accuracy. MCS can more naturally capture the effects of High Impact Low Probability (HILP) events, and is preferred for systems with a large level of complexity and a high frequency of severe events [8].

2.3.2 Reliability indices

The reliability indices are a way of quantifying the reliability aspects of a power system. There are many variations of reliability indices, and they should be chosen according to what parts of the reliability assessment are of interest. The three basic reliability indices, failure probability, failure frequency and failure duration, have already been mentioned. For power systems there are several additional reliability indices of interest, in regards to lost power, energy not supplied, and the cost of energy not supplied. An overview of the most common reliability indices for HL2 studies, are presented in table 1, based on [15] and [8]. These reliability indices has many different names in use, depending on the hierarchical level, and the author of the text, but essentially they portray the same things.

Table 1: Examples of commonly used reliability indices for HL2 studies

Title	Acronym	Mathematical expression	Unit
Probability of Load Curtailments	PLC	$\sum_{i=1}^{S} p_i$	
Expected Number of Load Curtailments	ENLC	$\sum_{i=1}^{S} F_i$	occurences/year
Expected Duration of Load Curtailments	EDLC	$PLC * 8760$	hours/year
Average Duration of Load Curtailments	ADLC	$EDLC/EFLC$	hours/disturbance
Expected Load Curtailed	ELC	$\sum_{i=1}^{S} L_i F_i$	MW/year
Expected Energy Not Supplied	EENS	$\sum_{i=1}^{S} L_i F_i D_i$	MWh/year
Expected Interruption Cost	EIC	$\sum_{i=1}^{S} L_i F_i W(D_i)$	NOK/year

An explanation to the parameters in table 1: p_i is the probability of system state i, S is the set of all system states associated with load curtailment, $F_i = p_i \sum_{k \in N} \lambda_k$, λ_k is the departure rate of the component corresponding to system state i, N is the set of all possible departure rates for state i, L_i is the load curtailment in state i, D_i is the duration of state i and $W(D_i)$ is a unit interruption cost function.

For the various reliability analysis methods, the indices may be calculated differently, so each of the reliability index calculations will be presented for each of the analysis methods in the following chapters.

2.3.3 Operating states

As mentioned earlier, load demand (and generation) can vary with time. A way of capturing all time-varying information is using operating states (not to be confused with security operating states previously explained). A number of operating states (with constant load and generation within the operating state) can be created to represent the system variations over a time period, such as a year. An example could be to use two operating states, a heavy load operating state (to represent winter months with high load demand), and a light load operating state (to represent the rest of the year) as in [2]. These operating states can then be weighted for the appropriate amount of time (e.g. 3 months for the heavy load, and 9 months for the light load), so time dependencies can be included. It is possible to create as many operating states as you want, but as mentioned in the subsection about dependencies, the complexity, and thus computational costs increases rapidly. More on operating states can be found in [2] and [16].

3 Analytical power system reliability assessment methods

In this chapter, some analytical reliability analysis approaches will be examined. The structure of presentation for the analysis methods are done in four stages: 1) Concept of the method, 2) A summary of the implementation of the method, 3) Calculation of reliability indices, and 4) Evaluation of the methods usefulness, i.e. its advantages and disadvantages. An overview of the most commonly used analytical methods for power system reliability assessment can be found in [3].

3.1 State Space Method

3.1.1 Concept

The State Space Method is based on the Markov model subsection (2.1.3), and the State Space subsection (2.1.4) presented in the previous chapter. As most of the method has already been explored, only a brief continuation is examined in this section. This section is based on [3] and [2].

3.1.2 Implementation

Recalling state transition diagram for a system of two components in figure 3, this is essentially how the implementation of the method is. For a system with more components, there is a huge increase in the number of states and thus the state transition diagram, and the state transition matrix will grow (recall that for a system of n components, there are 2^n possible states), so for large systems, this method is going to be a cumbersome reliability method.

3.1.3 Calculation of reliability indices

The probability of load curtailments (PLC) for two components are calculated as in eq. (2.12) for a series structure, and as in eq. (2.14) for a parallel structure. For more than two components, an iterative process must be used to summarize the total system probability of load curtailments. This is a cumbersome for large systems.

The expected frequency of load curtailments (EFLC) can be calculated as in eq. (2.15).

The expected duration of load curtailments (EDLC) can be calculated as in eq. (3.1)

$$EDLC = d_{down} = \frac{P_{down}}{f_{down}} \tag{3.1}$$

For computing the severity reliability indices (ELC,EENS,EIC etc.) a contingency analysis must be done. This will not be treated in this thesis, but see earlier sections to get a general idea regarding the implementation of a contingency analysis.

3.1.4 Method evaluation

The State Space Method can evaluate the systems entire state space accurately, but cannot (at least not straightforward) be used to evaluate reliability of load points, and thus is not suited for most HL2 studies. The method is fairly simple, but as mentioned, struggles when the number of components in the system increases. In order to be able to use this method effectively, approximations and network reduction techniques are necessary [3].

3.2 Markov cut set method

3.2.1 Concept

This section combines the theory from the sections on Markov models (2.1.3) to Minimal cut sets (2.1.5). The method is based on [17].

This method was proposed as a solution to tackle the problems related to incorporating dependencies into the reliability assessment approach, and to be able to compute the reliability indices for both the system and the load points. In [17] weather effects are incorporated utilizing a two-state weather model.

3.2.2 Implementation

For a full break down of the method implementation, the reader is advised to study [17]. A summary of the implementation steps is provided here:

1. A DC-OPF approach is used to determine the system and load point minimal cut sets (up to a certain order) considering the minimal cut sets as a constrained nonlinear optimization problem. An AC-OPF could be used when voltage is considered, but will reduce speed significantly.

2. An improved algorithm is proposed to compute the bounds of the reliability indices, automatically creating transitional rate matrix for the minimal cut sets. This is done by applying Markov processes to only the components related to the minimal cut sets, and not the entire system.

3. System and load point reliability indices are calculated.

4. The results are analyzed, and for [17] compared against next-event sequential simulation

(NESS) results to verify its effectiveness and accuracy.

3.2.3 Calculation of reliability indices

As mentioned in step 2), an improved algorithm computes the bounds of the reliability indices as an approximation of the actual reliability indices. The bounds are presented in equations (3.2) to (3.5).

$$p_f^u = \sum_i p(\overline{C_i}) \tag{3.2}$$

$$p_f^l = \sum_i p(\overline{C_i}) - \sum_{i<j} p(\overline{C_i} \cap \overline{C_j}) \tag{3.3}$$

$$f_f^u = \sum_i p(\overline{C_i}) * \overline{\mu_i} \tag{3.4}$$

$$f_f^l = \sum_i p(\overline{C_i}) * \overline{\mu_i} - \sum_{i<j} p(\overline{C_i} \cap \overline{C_j}) \cdot \overline{\mu_{i+j}} \tag{3.5}$$

where p_f^u, p_f^l are the first upper and lower bounds for failure probability, f_f^u, f_f^l are the first upper and lower bounds for failure frequency, C_i is the minimal cut set i, $\overline{C_i}$ is the event that all members of C_i fail, $\overline{C_i} \cap \overline{C_j}$ is the joint event that all members of C_i and C_j fail, μ_i is the repair rate of component i, $\overline{\mu_i} = \sum_{i \in C_i} \mu_i$ and $\overline{\mu_{i+j}} = \sum_{i \in C_i \cup C_j} \mu_i$.

Using the inclusion-exclusion principle (from e.g. [7]), increasingly closer bounds of the reliability indices can be obtained.

The Markov cut set method, same as the state space method, also requires a contingency analysis to be able to calculate the severity reliability indices. This will not be further treated in this thesis.

3.2.4 Method evaluation

The Markov cut set method, tested on the modified IEEE RTS, shows its proficiency in determining reliability both for independent faults, and for incorporating dependencies (here: weather fluctuations). The main conclusions are that the Markov cut set method is an effective and efficient reliability assessment method, which can approximate mean values for bounds of the reliability indices comparable to that of the NESS in terms of accuracy. Other advantages include: easy implementation, and the convenience of incorporating more system dependencies, simple interpretation of results, confidence intervals can used as a stopping rule, and the increase of computational cost for calculating load point indices and storing them is insignificant.

3.3 Contingency enumeration method

3.3.1 Concept

The contingency enumeration method evaluates reliability through an analysis process of a selected number of contingencies [3], [15]. One contingency enumeration method is the RELRAD method [18], which is a reliability assessment method utilized on radial power system networks, e.g. the distribution system. Another method is the OPAL method [2], which can be used on meshed networks, such as the transmission system. The OPAL method will be further explored in the next section, and the OPAL prototype (the MATLAB implementation of the OPAL method) defined by [19] and [20] will be used as a starting point for the implementation of hybrid methods.

3.3.2 Implementation

The contingency enumeration method is divided into four steps [3], depicted in figure 13.

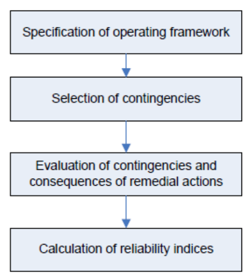

Figure 13: Structure of the contingency enumeration method, from [3]

where the four steps are:

1. Selection of framework for the analysis, i.e. boundaries, operating scenarios, contingency analysis technique, modelling level etc.
2. Selection of contingencies. Only the most important contingencies are selected for evaluation, unless it is feasible to evaluate all contingencies. Every ignored contingency reduces computational speed, as well as the accuracy of the computed reliability indices. As such, the importance of contingencies are often based on their probability of occurrence and their severity. Normally an upper order of contingencies are defined, e.g. only outage combinations of up to two components are selected. Specific critical higher order contingencies may also be added to the contingency list.
3. Selection of contingency analysis, i.e. AC or DC load flow calculations is chosen to solve the load flow problems and ascertain the severity of the contingencies. As mentioned earlier in this thesis, DC calculation is faster, but cannot cover all aspects of the problem (such as voltage problems), and AC calculation is slow and unrealistic for large systems. An efficient

workaround regarding this issue, can be to first utilize DC calculations on all selected contingencies, and then AC calculations on the contingencies that are identified to be of critical importance. Corrective actions and load shedding strategies could have a huge impact on the reliability indices, especially for the load points.

4. Calculation of reliability indices for both load points and the entire system. Annualized values are summed up from all the studied operational states and contingencies.

3.3.3 Calculation of reliability indices

This subsection is based on [15]. The annualized load-point indices are given below for a bus k (assuming a two-state Markov model for component outage):

$$p_k^f = p_j \cdot p_{kj} \tag{3.6}$$

$$F_k^f = F_j \cdot p_{kj}[occurrences/year] \tag{3.7}$$

where p_k^f is the probability of failure at bus k, p_j is the probability of a network outage condition j, $p_k j$ is the probability that the load at bus k exceeds the maximum that can be supplied during j, F_k^f is the frequency of failure at bus k and F_j is the frequency of the occurrence of j. The expected number of load curtailments is then given as eq. (3.8):

$$ENLC = \sum_{j \in x,y} F_j[occurrences/year] \tag{3.8}$$

where $j \in x$ includes all contingencies resulting in line overloads alleviated by load curtailment at bus k, and $j \in y$ includes all contingencies resulting in isolation of bus k. Expected load curtailed can then be obtained as in eq. (3.9):

$$ELC = \sum_{j \in x,y} L_{kj}F_j[MW/year] \tag{3.9}$$

where L_{kj} is the load curtailment at bus k due to contingency j. The expected energy not supplied can then be obtained as in eq. (3.10):

$$EENS = \sum_{j \in x,y} L_{kj}D_{kj}F_j = \sum_{j \in x,y} L_{kj}p_j \cdot 8760[MWh/year] \tag{3.10}$$

where D_{kj} is the duration in hours of the load curtailment. Summing up all the load point indices over all operating states, gives the system total indices.

3.3.4 Method evaluation

The contingency enumeration method is the essence of what an analytical reliability analysis method is. It is powerful for large systems, as it can efficiently remove insignificant contingencies and in turn reduce computational time, but as mentioned, the contingencies must be carefully chosen, as every removed contingency increases the inaccuracy of the reliability assessment.

3.4 The OPAL methodology for reliability of power systems

3.4.1 Concept

A brief summary of the OPAL method [2] is presented here. OPAL was designed to evaluate reliability indices for delivery points, in addition to the system indices, for meshed power system networks utilized for long term planning purposes. OPAL can consider interruptions due to primary faults (power system component faults), and secondary faults (protection system faults).

3.4.2 Implementation

The OPAL methodology is based on an extended version of the contingency enumeration approach. The approach is divided into seven steps which are presented below:

1. Definition of analysis: Defining the power system network, analysis depth (contingency order), operating states, if any additional, manually selected, contingencies should be included and whether to include dependencies (e.g. for protection systems).

2. Generation of contingency lists: In this step an outage list is created, containing potentially critical contingencies for the chosen analysis depth and operating state. The number of possible combinations for each outage order is possible to obtain using simple combinatorics, and thus it is simple to choose a suitable upper contingency order limit. Any critical contingencies over the contingency order limit, can be manually selected and added to the contingency list.

3. Consequence analysis: Contingencies are evaluated by the means of a contingency analysis utilizing DC or AC load flow techniques. Different adequacy problems can arise: voltage violations for PQ-buses (load buses), real or reactive power generation violations for PV-buses (generator buses) or swing-bus (reference bus), thermal overloading, network islanding, load flow does not converge etc. Occurrence of these problems can give four possible outcomes:

    - System is within its operating limits. No action needed. No interruption.
    - System is outside its operating limits. Corrective action needed. No interruption.
    - System is outside its operating limits. Corrective action not sufficient. Load shedding required. Interruption or partial interruption.

- System failure - total interruption (blackout).

The consequence analysis determines: If any interruption of a delivery point occurs, where it occurs, and how much of the load in that delivery point can be served for the given contingency and operating state (given through SAC).

4. Reliability assessment and calculation of reliability indices: the indices are calculated for each delivery point based on minimal cuts and operating state.

5. Inclusion of protection system faults: Contingency lists including neighbouring components must be generated, due to a protection system fault (secondary fault) usually leads to outage of neighbouring components. Different fault types must be investigated, and the consequences of them. In turn it is possible to quantify the these consequences in the same manner as for the primary faults, and add them to the total reliability evaluation.

6. Calculation of time-dependent variation and correlation between parameters: the load varies on a daily, weekly, and yearly basis. SAC will also vary depending on the total loading of the network and topology of the network. A model based on patterns from fault statistics is utilized. Conditional probability of having faults within a certain month, day, or hour can be expressed, which makes it possible to predict and time-tag the faults.

7. Accumulation of reliability indices: In step 4 the contributions to the reliability indices were calculated for each delivery point. With these delivery point indices, the total system indices can be computed.

3.4.3 Calculation of reliability indices

In step 4 of the OPAL method the reliability indices for each delivery point are calculated as follows:

$$\lambda = \sum_{j=1}^{J} \lambda_j [interruptions/year] \tag{3.11}$$

$$U = \sum_{j=1}^{J} \lambda_j r_j [hours/year] \tag{3.12}$$

$$r = \frac{\sum_{j=1}^{J} \lambda_j r_j}{\sum_{j=1}^{J} \lambda_j} [hours/interruption] \tag{3.13}$$

where J is the total number of minimal cuts, λ is the number of interruptions per year, U is the annual interruption duration and r the average interruption duration. Severity of the contingencies can be calculated as follows for a minimal cut j, and a given operating state:

$$P_{interr,j} = P - SAC_j - LG[MW/interruption] \tag{3.14}$$

$$ENS_j = r_j P_{interr,j}[MWh/interruption] \tag{3.15}$$

$$IC_j = c(r_j)ENS_j[NOK/interruption] \tag{3.16}$$

where $c(r_j)$ is a cost function based on the customer damage. Annualized values can be calculated by multiplying equations (3.14) to (3.16) with the number of interruptions per year for minimal cut j, λ_j. For total annualized values on the delivery point for a given operating state, summarize over all minimal cuts j.

The last step of the OPAL method is to aggregate all the reliability indices. Annualized reliability indices for each delivery point DP are found by summing up all contributions over all minimal cuts j and operating states OS:

$$\lambda_{DP,a} = \sum_{j,OS} \lambda_{DP,j,OS,a}[interruptions/year] \tag{3.17}$$

$$UDP, a = \sum_{j,OS} U_{DP,j,OS,a}[hours/year] \tag{3.18}$$

$$Pinterr, DP, a = \sum_{j,OS} P_{interr,DP,j,OS,a}[kW/year] \tag{3.19}$$

$$ENSDP, a = \sum_{j,OS} ENS_{DP,j,OS,a}[kWh/year] \tag{3.20}$$

$$ICDP, a = \sum_{j,OS} IC_{DP,j,OS,a}[NOK/year] \tag{3.21}$$

Annualized aggregate system indices, summarized for all operating states, minimal cut sets, or delivery points (the latter is chosen here):

$$Pinterr, S, a = \sum_{DP} P_{interr,DP,a} = [kW/year] \tag{3.22}$$

$$ENSS, a = \sum_{DP} ENS_{DP,a}[kWh/year] \tag{3.23}$$

$$ICS, a = \sum_{DP} IC_{DP,a}[NOK/year] \tag{3.24}$$

3.4.4 Method evaluation

OPAL is a versatile reliability assessment method. It can calculate indices for load points, minimal cuts, operating states, and the system as a whole. In addition it can include dependencies such as protection system faults or time-dependent variations and parameter correlation. The contingency enumeration part of OPAL makes it a fast method for larger systems, as it only evaluates the most important contingencies, but defining the important contingencies can be difficult. Calculations are done using minimal cut sets, which are approximations that increases computational speed, but reduces the accuracy of the reliability indices. Despite the reduction in accuracy due to approximations, the OPAL method has proven itself to be comparable (or better) to other currently available reliability assessment methods in terms of accuracy of reliability indices [2]. The approximation error tends to overestimate the unreliability. Disadvantages with the OPAL method is the inability to handle extraordinary events, and accurately incorporate weather influences. The OPAL method is continuously improved and expanded upon, so in the future it may be able to handle all its current inabilities.

4 Monte Carlo simulation methods for power system reliability assessment

4.1 Monte Carlo simulation

This chapter serves as an introduction to the different MCS methods with same approach for method evaluation as for the analytic methods in the previous chapter (the four steps). Further details regarding MCS can be found in e.g. [9], [1] and [8].

Monte Carlo methods use random numbers for stochastic sampling. There are several simulation methods that can be utilized, which are divided into non-sequential methods (randomly sampled system states independent of the previous system states), sequential methods (next system state is dependent upon previous system state), and semi-sequential methods (a mix between the two). The system state is given by the state of the components. A state vector can be expressed as in eq. (4.1), where there are m components [9].

$$\boldsymbol{S} = S_1\ S_2\ ...\ S_m \tag{4.1}$$

4.2 Aspects of Monte Carlo simulation

4.2.1 The law of large numbers and the central limit theorem

The MCS methods are fundamentally based on statistical concepts, which are the law of large numbers, and the central limit theorem [8]. A MCS is a converging process, and as the sample size increases, the variance of a reliability index's estimated mean distribution decreases, i.e. the index approaches its true arithmetic mean value with an increasing number of samples (the law of large numbers), see eq. (4.2). If N independent random variables X_1, X_2, ... , X_N follow the same distribution and $E(X_i) = \mu$, then for a small positive number ϵ:

$$\lim_{N\to\infty} P\left[\left|\frac{1}{N}\sum_{i=1}^{N} X_i - \mu\right| < \epsilon\right] = 1.0 \tag{4.2}$$

The central limit theorem states that the distribution of the estimated mean can be approximated by a normal distribution if the number of samples is sufficiently large, as shown in eq. (4.3). Following the same notation as for eq. (4.2), and in addition the variance is $Var(X_i) = \sigma^2$, then:

$$\lim_{N\to\infty} P\left[\frac{|1/N\sum_{i=1}^{N} X_i - \mu|}{\sigma/\sqrt{N}} \leq x\right] = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} e^{-t^2/2}dt \tag{4.3}$$

4.2.2 Coefficient of variation

A measurement of the ratio between the sample's standard deviation (SD) to the sample's mean is called the coefficient of variation (CV), and is a unitless quantity often used for measuring convergence in MCS. For the MCS to fully converge, the CV should approach zero, but in practice a sufficiently small CV could be different for different analyses. In the following equations, eq. (4.4), (4.5), (4.6), and (4.7), the expectation, variance, variance of a mean value, and coefficient of variation (β) is given for an observation value X_i, which is the value of a reliability index for a simulation year i, and N is the total number of simulation years.

$$E(X) = \bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{4.4}$$

$$Var(X) = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})^2 \tag{4.5}$$

$$Var(\bar{X}) = \frac{1}{N}Var(X) = \frac{1}{N}(\frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})^2) \tag{4.6}$$

$$\beta = \frac{S(X)}{\sqrt{N}\cdot E(X)} \tag{4.7}$$

where eq. (4.7) can be re-written to:

$$N = \frac{Var(X)}{\beta^2 E(X)^2} \tag{4.8}$$

where the required N for a desired accuracy level depends on Var(X), which explains why variance reduction techniques are so important for reducing the computational cost.

4.2.3 Random Numbers

As MCS is based on drawing random numbers from a distribution, it is an important part to address. Computers cannot fully create random numbers, only pseudo-random numbers, due to their inherent deterministic characteristic. This thesis uses the "rand" function in MATLAB, which has been through various statistical tests of randomness and independence, and as such is a "good enough" random number generator for most purposes. For more on random number generators, see [8].

A random number, U, sampled from the uniform distribution [0,1] can be utilized together with an equation for the inverse transform of the exponential CDF (remember eq. 2.2), as in eq. (4.9) below, to find the corresponding value of the random variate X on the CDF. A graphical explanation of the process is shown in [9]:

$$X = F^{-1}(U) = -\frac{1}{\lambda} * ln(1 - U) = -\frac{1}{\lambda} * ln(U) \tag{4.9}$$

4.3 State Sampling

4.3.1 Concept

The state sampling method is a non-sequential MCS, i.e. independent of previous system states. Each component in a system has a probability of being available or unavailable (Markov two-state model). The probability of being unavailable is called forced outage rate (FOR). The state sampling method samples a random uniform number, U between [0,1] for all components. U is compared with the FOR values to determine if the component is up or down, see table 2. Doing this for all components gives random states for the total system, which can then be evaluated.

Table 2: Component state probability

Unit State	Probability Table
Up	U $\geq$ FOR
Down	U $<$ FOR

4.3.2 Implementation

A step-by-step guide on how to implement a state sampling method is provided in [9], while an excerpt is provided here. The state sampling method is split into two major steps, that contain sub-steps:

1. Loop through the hours of a year [1,8736].
   (a) Loop through all the components of the system (generators, lines etc.) and for each draw a random number U, which is compared against the FOR value of the component to determine if it is available at the hourly increment.
   (b) Run a contingency analysis on the randomly sampled system state. Count the "failure" (1 hour) and interrupted power.
2. At the end of each simulation year, sum up reliability indices and store them.

This is the process for one simulation year. The process should be repeated until all simulation years have been simulated. Then, the expectation values of the indices can be calculated (average annualized values). The coefficient of variation can be calculated to verify that the indices have converged.

4.3.3 Calculation of reliability indices

The number of failures and failure duration are counted in the simulation process (and are of the same value since 1 failure lasts for 1 hour). They are summed up for each year, and then averaged over the N total simulation years, as in eq. (4.10), i.e the annualized expected number of load curtailments:

$$ENLC = \frac{1}{N}\sum_{i=1}^{N} ENLC_i[occurrences/year] \tag{4.10}$$

Similarly, the lost power computed by contingency analysis (essentially based on eq. (2.21)) was stored and summed up for each year, and can be averaged in the same way (4.11):

$$ELC = \frac{1}{N}\sum_{i=1}^{N} ELC_i = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{8736} P_{interr,i,j}[MW/year] \tag{4.11}$$

Where j is the specific hour in the year i. The energy not supplied can then be calculated by eq. (4.12):

$$EENS = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{8736} P_{interr,i,j} \cdot \Delta t_{i,j}[MWh/year] \tag{4.12}$$

where $\Delta t_{i,j}$ is the duration of the power interruption in hour j in year i. For the state space method, $\Delta t_{i,j} = 1$ (usually), so ELC = EENS.

4.3.4 Evaluation

The state sampling method is the fastest of all the MCS methods, as it does not really on dependent state selection, and thus requires less computation and less storage than other methods. As the strengths lies in the methods speed, the weaknesses lies in its inability to obtain true distributions of the reliability indices [9], and that it cannot, at least not on its own, calculate the frequency index due to not following the chronology of a power system [8]. The frequency of load curtailment would be overestimated, as exemplified in [1].

4.4 State Duration

4.4.1 Concept

This section is based on [8], [9] and [1]. The state duration method is a sequential method where every component in the system has a chronological state history. Drawing random variates from the TTF (time to failure) and TTR (time to repair) distributions in sequence, depending on failure or repair of the component, creates the state histories. The system state history is created by combining all the individual state histories of the components. As a starting point, all components are being assumed available (up).

4.4.2 Implementation

Input data for the state duration method includes a matrix for component transition data. The system states (cycles) are recorded in a matrix. Another matrix is used for "remaining time", i.e. to keep track of the time to next event, current state and next state for each component at the end of a year. The reliability indices are stored in a record matrix (same as for the state sampling method).

A step-by-step guide on the implementation of the state duration method is provided in [9], while an excerpt is provided here. The state sampling method is split into four major steps, that contain substeps:

1. Loop through the components (generators, lines, etc.) of the system.
   (a) Check number of possible states for the components, denoted v
   (b) Loop through the hours of a year [1,8736]. Check the state of the component at the hourly time increment. Generate v-1 random numbers from the uniform distribution. Calculate the possible transition times (TTF or TTR) based on the random numbers. Find the smallest transition time, t. The next state is then the corresponding state to time t. Update the corresponding elements of the state matrix's current state with next state. Increment the current time of the year, k, with k + t.
   (c) When k exceeds the number of hours in a year, subtract the hours in a year from k, and that is the remaining time to next event.
   (d) Remaining time to next event, current component state and arriving state of the component is stored in the component's row in the remaining time matrix.
2. Looping through the hours of a year [1,8736], use the status matrix together with contingency analysis to obtain the reliability indices. When there is interrupted power, count the failure (1 hour), and then the energy not supplied can be calculated.
3. At the end of each simulation year, calculate all the reliability indices, by using the respective counters.
4. For the next year in the simulation, start with a continuation of the previous year.

The simulation procedure is repeated for all simulation years.

4.4.3 Calculation of reliability indices

The reliability indices are counted and calculated in the same manner as for the state sampling method (estimated by their long-term averages). A big difference from the state sampling, however, is that the counted frequency index is accurate.

4.4.4 Evaluation

This method requires a certain length of simulation, i.e. a large sample size, in order to properly converge. Short simulation times can lead to an overestimation of the reliability (due to all components are being assumed available at start). The state duration method is simple (easy to calculate frequency index), flexible (any distribution for the state duration can be used, and degraded states for components can be incorporated) and versatile (proper probability distributions can be obtained in addition to the expectation values for reliability indices). The disadvantages with this method is mostly related to the large computational cost compared to other reliability assessment methods. Another issue is the need for large storage of values. The state duration method is relying on transition data for all components, which could be difficult to provide in a real setting, unless there exists good historic or manufacturing data for the components.

4.5 State Transition

4.5.1 Concept

The state transition method is another sequential MCS, that transitions the system as a whole, instead of individual components. The sum of the components transition rates out of the system state is the total system transition rate out of the state, as in eq. (4.13), where n is the number of transition rates out of a state.

$$\lambda = \sum_{i=1}^{n} \lambda_i \tag{4.13}$$

A random variate T, which is the duration of the current system state, is drawn. T is exponentially distributed with the λ obtained from eq. (4.13) as shape parameter. The probability that the next system state is a specific state, state j, is expressed as in eq. (4.14) [9].

$$P_j = \frac{\lambda_j}{\sum_{i=1}^{n} \lambda_i} \tag{4.14}$$

Eventually, a system transition to the next state has to be made, so the sum of all system state probabilities are equal to one.

$$\sum_{j=1}^{n} P_j = 1 \tag{4.15}$$

Another uniform random number must be drawn to calculate the time to next transition by using eq. (4.9). The method can then continue by iterating the next state, and the next after that, etc. until the simulation is finished.

4.5.2 Implementation

Input data for the state transition method is a list of components with information about: , and additionally two columns are added to keep the track of current and next state of each component. As in the other MCS methods, a record matrix is used to store the reliability indices.

A step-by-step guide on the implementation of the state transition method is provided in [9], while an excerpt is provided here. The state sampling method is split into four major steps, that contain substeps:

1. Loop through the hours of a year [1,8736]
   (a) Current time increment is denoted k
   (b) A while loop is executed while t is too small to increment the time to the next hour. Update current states with the next state. Create a vector with transition rates out of current state. Calculate sum of transition rates eq.(4.13). Create a vector with the probabilities of each possible new state as in eq. (4.14). Construct a cumulative probability vector of the probabilities by adding the next state probability to the sum of previous entries. Draw a random uniform number U that will fall into an interval on the cumulative vector, which gives the next state. Update the next state column in the component list. Another random uniform number is drawn, and used with eq. (4.9) and the transition rate sum to find the time to next event. Next event will occur at k + t.
   (c) The state at k is evaluated with contingency analysis, the failure is counted (1 hour), and reliability indices calculated. Frequency index is only updated if the preceding state was a success.
2. At the end of a simulation year, subtract the the number of hours in a year from the time of occurrence of the next event.
3. At the end of each simulation year, calculate all the reliability indices, by using the respective counters.
4. Repeat the process for all simulation years.

4.5.3 Calculation of reliability indices

Reliability indices are counted and calculated similarly to the state space and state duration methods. As mentioned, the frequency index is only updated if the previous state was a success state.

4.5.4 Evaluation

A requirement for the state transition method, is that the transition rates of the components are exponentially distributed, and data for them are available. State transition has less need for storage, compared to the state duration method, and is able to calculate the frequency index. The state transition method is faster than the state duration method, but is more restricted in terms of its considerations.

4.6 Pseudo-sequential MCS

4.6.1 Concept

This section is based on [1], [21], [22] and [23].

The pseudo-sequential MCS aims to be a compromise between the non-sequential and sequential methods. The idea is to be able to consider chronological sampling, without sampling it chronologically, thus saving computational time.

4.6.2 Implementation

The pseudo-sequential MCS uses a state sampling procedure to randomly sample states. Contingency analysis is used on the sampled states to check for loss of load. If there is a power interruption (loss of load) the state is then used as a starting point for a sequential MCS. State transitions from the starting point is used to extend backward and forward in time for the state. The backward and forward extensions continues until a success state is reached. For the forward time-sequential simulation, the probability for the state transition from X_s (starting loss of load state) to X_t (a specific next state) is shown in (4.16) [21]:

$$P_{st} = \frac{f_{st}}{f_s^{out}} = \frac{P(X_s)}{\lambda}{}_{st} P(X_s) \sum_{i=1}^{M_s} \lambda_{si} \tag{4.16}$$

where f_{st} is the frequency of system state X_s transferring to X_t, f_s^{out} is the frequency of departure from state X_s, $P(X_s)$ is the probability of being in state X_s, λ_{st} is the transition rate of the component whose state changes during the transferring process from X_s to X_t, M_s is the number of possible states that X_s can transfer to.

For the backward time-sequential simulation, the process is similar, but in reverse, i.e. the probability of state transition from X_r to X_s is as in eq. (4.17) [21]:

$$P_{rs} = \frac{f_{rs}}{f_s^{in}} = \frac{P(X_r)}{\lambda}{}_{rs}\sum_{i=1}^{M_r} P(X_i)\lambda_{is} \tag{4.17}$$

where f_{rs} is the frequency that system state X_r transfers to X_s, f_s^{in} is the frequency of entering state X_s, $P(X_i)$ is the probability of being in state X_r, λ_{is} is the transition rate of the component whose state changes during the transferring process from X_i to X_s, M_r is the number of possible states that can transfer to X_s.

The next step of the pseudo-sequential MCS is to calculate reliability indices.

4.6.3 Calculation of reliability indices

Total expectation of the failure duration is the sum of the forward and backward simulations as in eq. (4.18):

$$E(D_s) = \sum_{i \in S} E(D_i) = \sum_{i \in S} \frac{8760}{\sum_j \lambda_j} \tag{4.18}$$

where $E(D_i)$ is the expectation of the failure duration in system state i within the failure subsequence, and λ_j is the transition rate.

The expected energy not supplied can be calculated as follows from eq.(4.19) :

$$EENS = E(H_{EENS}) = \frac{1}{N}\sum_{i=1}^{N} H_{EENS}(X_i) \tag{4.19}$$

where N is the overall times of non-sequential sampling, $H_{EENS}(X_i)$ is the test results of sampled state X_i corresponding to the reliability indices found from eq. (4.20):

$$H_{EENS}(X_i) = \begin{cases} \frac{\sum_{S_j \in M_i} P_s(S_j)D(S_j)}{\sum_{S_j \in M_i} D(S_j)} \; X_i \in X_f \\ 0 \; X_i \notin X_f \end{cases} \tag{4.20}$$

where M_i is the subsequence generated from loss of load states, $P_s(\cdot)$ is the load curtailment of a state, $D(\cdot)$ is the duration of a certain state S_j, and X_f is the set of loss of load states.

4.6.4 Evaluation

The main advantages of the pseudo-sequential method are that it can achieve accurate frequency and duration indices much faster than the sequential MCS methods. The main disadvantage is the mathematically complicated structure of the method, which increases in complexity as more chronological considerations and dependencies are included. The reason for the increase in complexity is because the number of possible state transitions increases with each added component that is characterised by chronological behaviour [1].

4.7 Variance reduction techniques

The idea of variance reduction techniques is to reduce the statistical variance of the reliability index calculations by utilising prior known information about the power system simulation model. Reduction in variance will essentially reduce the time to convergence for the estimation of the reliability indices, thus increasing computational speed, see eq. (4.8). There are many techniques for variance reduction, but these techniques will not be treated in this thesis. The reader is advised to see e.g. [8] for more on variance reduction techniques.

5 Combining analytical and MCS methods for power system reliability assessment

5.1 Overview of power system reliability assessment methods

A lot of different power system reliability assessment methods were explored in the two previous chapters. A summary of those methods with their advantages (+) and disadvantages (-) is presented below:

Analytical methods

- **State space method**
  - \+ Mathematically simple, fast for small systems, accurate indices.
  - – Not at all suited for large systems.
- **Minimal cut set method**
  - \+ Can analyze specific load points, fast since it only considers relevant contingencies.
  - – Approximates answers which introduces accuracy error.
- **Contingency enumeration**
  - \+ Fast since it only evaluates the most important contingencies. Powerful for large systems.
  - – Limited order of contingencies, cannot capture extraordinary events naturally.

Monte Carlo simulation

- **State sampling**
  - \+ Simple concept, fastest MCS method.
  - – Cannot compute true frequency index (overcounting), cannot provide true distributions.
- **State duration**
  - \+ Can use any probability distribution to represent component life, easy to calculate frequency index, can provide distributions of all indices.
  - – Slowest form of MCS, requires storage of a lot of values, requires transition data for all components, overestimates reliability for small sample sizes.
- **State transition**
  - \+ Faster than state duration, can compute frequency index.
  - – Requires exponentially distributed transition rates for components.
- **Pseudo-sequential**

+ Faster than the sequential MCS, can capture frequency index.
– Mathematically complex, which increases with the number of chronological considerations.

Remember that the reliability assessment approach should be selected for it's intended purpose. A conceptualized model to aid the decision of the appropriate reliability assessment method, shown in figure 14, is presented in [1]:

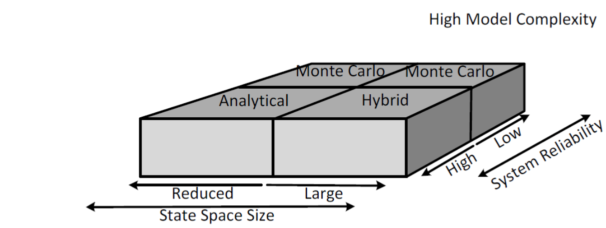

Figure 14: Model for aiding the decision of appropriate system sampling technique, from [1]

Exactly when a system is of low or high complexity order, has to be a subjectively considered by the analyser. The decision is also based on the state space size (system size) and the system reliability (which one could have prior knowledge of, or at least make an educated guess about, based on the configuration of components and their reliability data). An example could be a HL2 study on a large system including dependencies, which is high on the complexity scale. Depending on the system reliability a MCS or hybrid method could be chosen as the reliability assessment approach.

5.2 The concept of hybrid methods

The literature study on reliability assessment methods has uncovered a rather loose utilization of the term "hybrid" within the field. In many cases it is used imprecisely, confusingly, or related to something else entirely. For this thesis, a hybrid reliability assessment method relates to a combination of an analytical reliability method and a Monte Carlo simulation method.

The idea of a hybrid reliability analysis method is essentially to emphasize the advantages of both methods, while minimizing the disadvantages they have. The hybrid methods can be viewed from two sides: you are improving an analytical reliability method by combining it with a MCS that perhaps gives more accurate results, or you are reducing the calculation cost of a MCS when combining it with an analytical method.

There are multiple circumstances where hybrid methods could provide extra benefits, compared to utilizing the methods individually. Consider a contingency enumeration method, which is a fast and effective analytical reliability method (see earlier chapters). The main problems when using a contingency enumeration method are the inaccuracy of the reliability indices, and the inability to capture extraordinary events (HILP events). Seemingly, this is a perfect candidate for combining it with a MCS method, who's advantages are accurate calculation of indices (though sequential- or pseudo-sequential MCS are required for the accurate calculation of the frequency index), and the ability to naturally capture HILP events. A disadvantage, depending on the type of MCS, is the computational cost (long simulation times), which can be reduced with a combination with the contingency enumeration method.

5.3 Hybrid methods in literature

There are various mentions of hybrid reliability methods for power systems in the literature, but a general lack of in-depth explanation of the methods makes it difficult to assess their actual usability. This section presents the most interesting articles regarding hybrid methods.

A general framework for combining analytical models and MCS is described in [24]. The idea is to use a simpler analytical approximation to a more detailed MCS. The MCS then deals with the residual, i.e. the difference between the detailed model and the approximation. Though this article focuses on two variance reduction techniques, the general idea remains the same without them. The results from testing show that a lot of computational cost can be saved by following this framework.

The hybrid methods presented in [8], [25] and [26], are all based on using the state sampling MCS together with some kind of analytical enumeration approach. Perhaps one could argue that they are not "true" hybrid methods after the definition of hybrid methods presented in this thesis. If so, they are in essence MCS methods with simplifications/improvements, similar to what MCS methods with variance reduction would be. The methods from [8] and [25] do however present some interesting concepts regarding the security operating state inclusion in reliability analysis of power systems.

In [27] different possible hybrid schemes based on enumeration and MCS is discussed. One possible hybrid technique is to use enumeration to select transmission contingencies, and MCS to sample the generation contingencies. This can be seen as a stratified sampling scheme (a variance reduction technique). Test results revealed this technique to be unattractive, due to the fact that contributions from the transmission contingencies, when combined with generation contingencies, are too uniformly spread out. An argument is made for variance reduction schemes to be hybrid methods, but for the definition proposed in this thesis, that is not true.

5.3.1 Intelligent "hybrid" methods

In the last few years, intelligent "hybrid" reliability assessment methods have been developed. They promise faster and more efficient system state sampling. These methods are not truly hybrid methods, as they are not combinations of two stand-alone methods, but rather an improvement of MCS methods (similar to variance-reduction schemes). These methods are still fairly new, and somewhat complicated compared to well-established analytical or MCS methods. Some of the methods include:

- Particle swarm optimization [28]: Using state sampling MCS and particle swarm optimization, which is modelled after a population of swarms as they move in packs led by a swarm leader in search of food sources. Particle swarms are useful for finding those elusive states (e.g. related to HILP events), and are good at pruning the non-failed states, which lowers search time.
- Genetic algorithm (mentioned in [1]): was designed to reduce the probability of repeatedly sampling the same state in an MCS, as well as to simultaneously identify the likely state to sample. The idea is based on genetic functions from biology that predict the fitness of the offspring of a sampled population species, thus; if the offspring survives, there is a failed state.
- Support vector machine learning algorithm (mentioned in [1]): this method uses past system state history in order to ascertain factors which led to a failed state. Based on this, it learns how to predict future states.

5.4 Proposed hybrid methods

5.4.1 General concept

The proposed hybrid methods are based on combining the contingency enumeration method with MCS. For the contingency enumeration, the OPAL methodology [2] is chosen. The OPAL prototype [20] is implemented in MATLAB, and includes the opalcons module (contanalysis repository at code.sintef.no, commit 8c55dfc6112) and the reliabilitycalc module (opal repository at code.sintef.no, commit 19340abf1f5). For the MCS methods, two approaches have been studied: a state sampling technique, and a pseudo-sequential MCS. All self-developed MATLAB scripts are found in the appendix.

The general implementation of the hybrid propositions are shown in figure 15.

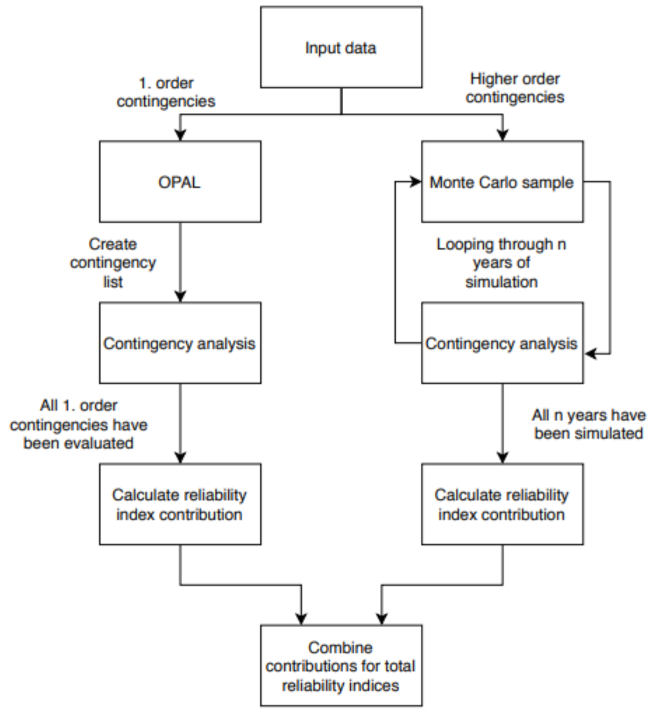

Figure 15: General flow of the proposed hybrid methods

5.4.2 Assumptions and design choices

Certain design choices and assumptions have been made in order to practically implement the proposed hybrid methods:

- All the life-times and repair times (transitional rates) of the components are exponentially distributed.
- The methods are created for the composite power system (HL2 study), but only line outages are considered (generation and transformer outages are not included).
- The OPAL method handles the first order contingencies, and the MCS methods sample the second and higher order contingencies. This is mainly to reduce computational time, and be able to naturally capture HILP events.
- Two operating states have been chosen to represent the variation in load demand during the year in Norway. The first operating state, heavy load, is representing the winter months (i.e. similar to peak load over 3 months time), and the second, light load, is representing the rest of the year (somewhere around 40-60% of peak load demand over 9 months time). In the implementation for the MCS, the heavy load represent the first 2184 hours of the simulation,

and the light load the remaining 6552 hours of the simulation on a per year basis (for a simulation year with 8736 hours).

- Combining the contributions of indices from OPAL and MCS methods is assumed possible. The contributions from both methods are annualized expectation values, and according to [15] should pose no problem being combined.
- Indices that are considered: duration, frequency, interrupted power, and energy not supplied (with focus on the latter). Cost of energy not supplied is not considered.
- Other dependencies, such as protection faults, common faults, or weather related faults are not considered.
- For the contingency analysis, the OPAL prototype's incorporated contingency analysis, based on Matpower, is used [29]. The AC load flow is evaluated, and OPF is used for generation rescheduling / load shedding.

5.4.3 Hybrid proposition 1: OPAL combined with state sampling MCS

This method is based on the OPAL prototype in combination with a state sampling MCS. The idea is to use the OPAL method for assessing only the first order outages, and then the state sampling procedure for assessing all higher (second and above) order outages, as in figure 15. The point of this method is to be fast (faster than full MCS) and to be able to capture HILP events, while improving the accuracy of the indices (compared to full analytical evaluation). This method should be a good (fast) method for evaluating large systems. This method is being used as an indicator of the usefulness of hybrid methods, before a second proposition with pseudo-sequential MCS is implemented.

5.4.4 Hybrid proposition 2: OPAL combined with pseudo-sequential MCS

This method is based on the OPAL prototype in combination with a pseudo-sequential MCS. The idea is pretty similar to the first hybrid proposition. One major difference, is the pseudo-sequential method's ability to accurately calculate the frequency index (which state sampling cannot do), but it comes at a cost of increased computational time. The pseudo-sequential method uses state sampling to sample contingencies which are then simulated chronologically with forward and backward simulation to obtain accurate duration and frequency indices. The forward and backward simulation have been simplified to be equal, since within each operating state, the load is constant. This poses a small inaccuracy in the transit between the operating states, which will have a minimal impact for two operating states. If more operating states are included, then this simplification may not be valid.

In essence, this method should be superior to the first hybrid method in most regards except in terms of computational speed.

6 Hybrid power system reliability analysis - simulation

6.1 Simulation case 1: RBTS

6.1.1 System specifications

The Roy Billinton Test System is a 6-bus test system utilized for reliability assessment. The system has 2 PV-buses, 4 PQ-buses, 9 transmission lines and 11 generating units. The annual peak load is 185 MW for the system. RBTS is depicted in figure 16, where the arrows show the delivery points. For further details about the test system, see [30] or the data-file in the appendix.

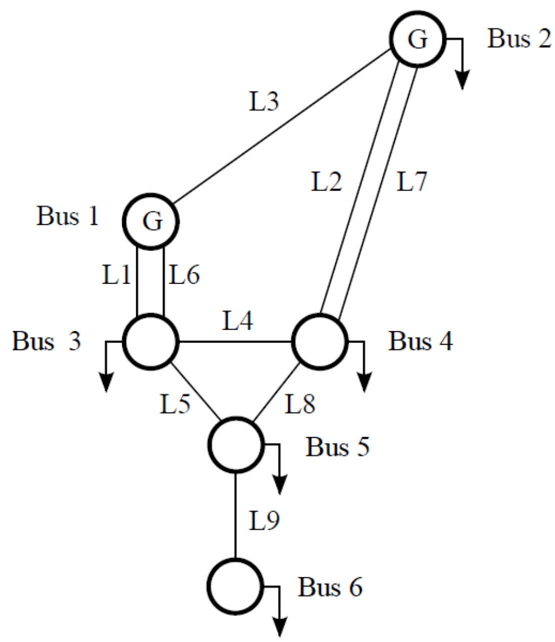

Figure 16: The RBTS network

The chosen operating states (load demand) for the RBTS are presented in table 3. Generation is assumed constant throughout the year.

Benchmark tests on RBTS are done with a full state sampling MCS, as well as with the full OPAL prototype. The results of the benchmark tests can be found in the appendix.

Table 3: Operating states for RBTS

Delivery point	Heavy load [MW]	Light load [MW]
1	20	10
2	85	45
3	40	20
4	20	10
5	20	10

6.1.2 Hybrid 1 simulation

The simulation results, for each delivery point, from Hybrid 1 on RBTS are presented in table 4. The simulation was done for $N = 15000[years]$, which took $t = 520[s]$ and the coefficient of variation for the system energy not supplied was $CV_{sys,EENS} = 0.0138$ which shows a fairly good convergence of the EENS. All system indices will be compared and discussed in the next chapter.

Table 4: Hybrid 1 simulation results for delivery points on RBTS

Delivery point	EENS_dp [MWh/year]	ENLC_dp [occ./year]	EDLC_dp [hours/year]
1	1.39E-06	3.91E-05	0.3412
2	3.565	3.91E-05	0.3416
3	0.00197	3.91E-05	0.3415
4	0.13547	4.03E-05	0.3521
5	220.41	2.00	20.584

The results show that delivery point 5 (bus 6) contributes to about 98,3% of the energy not supplied for the system. This makes sense looking at the topology of RBTS, as delivery point 5 only has one connected line to it, so if that line fails, bus 6 is islanded. Otherwise the results for EENS seem okay, slightly higher than the OPAL benchmark. The frequency and duration indices, especially for delivery points 1, 3 and 4, seems inaccurate.

6.1.3 Hybrid 2 simulation

The simulation results, for each delivery point, from Hybrid 2 on RBTS are presented in table 5.The simulation was done for $N = 15000[years]$, which took $t = 1430[s]$ and the coefficient of variation for the system energy not supplied was $CV_{sys,EENS} = 0.090$ which shows a fairly good convergence of the EENS. All system indices will be compared and discussed in the next chapter.

The results show that delivery point 5 (bus 6) contributes to about 99,98% of the energy not supplied for the system. This makes sense looking at the topology of RBTS, as delivery point 5 only has one connected line to it, so if that line fails, bus 6 is islanded. Otherwise the results for EENS seem okay, slightly below the OPAL benchmark. The frequency and duration indices seem more

Table 5: Hybrid 2 simulation results for delivery points on RBTS

Delivery point	EENS_dp [MWh/year]	ENLC_dp [occ./year]	EDLC_dp [hours/year]
1	2.13E-08	7.85E-05	0.005735
2	0.0400	7.86E-05	0.005736
3	1.17E-05	7.86E-05	0.005736
4	0.0008	8.15E-05	0.005808
5	213.60	2.00	20.01

realistic than for hybrid 1.

6.2 Simulation case 2: The Four-Area Test Network

6.2.1 System specifications

The Four-Area Test Network is a small power system designed for testing and benchmarking of EMPS-NC. The system has 25 buses; 16 PQ-buses and 8 PV-buses, 30 branches (transmission lines/-transformers) and 34 generating units. The annual peak load is 2,5 GW, and the voltage levels are between 132 kV and 300 kV. The Four-Area Test Network is depicted in figure 17, where the arrows represent the delivery points, area 1-3 are hydro power dominated and area 4 has a mix of thermal and wind power. More information about the test system can be found in [4], and data for the network can be found in the appendix.

The chosen operating states (load demand) for The Four-Area Test Network are presented in table 6. Generation is assumed constant throughout the year.

Table 6: Operating states for The Four-Area Test Network

Delivery point	Heavy load [MW]	Light load [MW]
1	222.6812	153.5535
2	0	0
3	278.3565	191.9454
4	122.6449	70.1769
5	0	0
6	318.8415	182.4397
7	0	0
8	355.9062	203.8285
9	315.6149	180.7536
10	50.00001	50

Benchmark tests on The Four-Area Test Network are done with a full state sampling MCS, as well

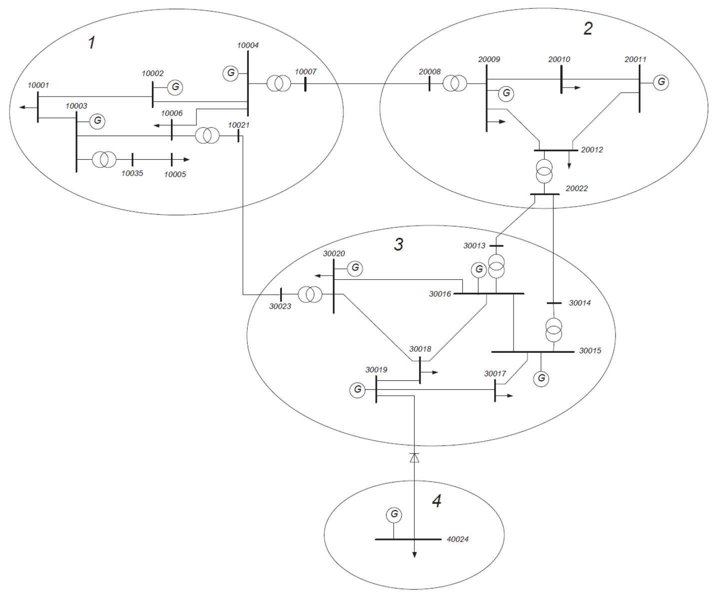

Figure 17: The Four-Area Test Network, from [4]

as with the full OPAL prototype. The results of the benchmark tests, can be found in the appendix.

6.2.2 Hybrid 1 simulation

The simulation results, for each delivery point, from Hybrid 1 on The Four-Area Test Network are presented in table 7. The simulation was done for $N = 150000[years]$, which took $t = 1727[s]$ and the coefficient of variation for the system energy not supplied was $CV_{sys,EENS} = 0.132$ which is not that great of a convergence for EENS, but will suffice for the testing purposes in this thesis.

The results show that delivery point 10 (bus 40024) contributes to about 99,95% of the energy not supplied for the system. This makes sense looking at the topology of The Four-Area Test Network, as delivery point 10 only has one connected line to it, so if that line fails, the bus is islanded. Otherwise the results for EENS seem okay, fairly close to the OPAL benchmark. The frequency and duration indices seems somewhat inaccurate. Something interesting to note, is the frequency and duration for the delivery points 2, 5 and 7 are only influenced by the OPAL calculation. Overall it is easy to conclude, based on the values of the reliability indices, that The Four-Area Test Network is a very solid power system with a high level of reliability.

Table 7: Hybrid 1 simulation results for delivery points on Four-Area Network

Delivery point	EENS_dp [MWh/year]	ENLC_dp [occ./year]	EDLC_dp [hours/year]
1	0.0048	7.99E-06	0.06977
2	0	0.7318	49.2946
3	0.0014	7.99E-06	0.06979
4	3.31E-10	8.43E-06	0.07363
5	0	0.7318	49.2946
6	0.00015	8.43E-06	0.07363
7	0	0.7318	49.2946
8	3.62E-10	8.56E-06	0.0748
9	3.62E-10	8.56E-06	0.0748
10	3.7758	0.0045	0.15

6.2.3 Hybrid 2 simulation

The simulation results, for each delivery point, from Hybrid 2 on The Four-Area Test Network are presented in table 8. The simulation was done for $N = 150000[years]$, which took $t = 4881[s]$ and the coefficient of variation for the system energy not supplied was $CV_{sys,EENS} = 0.1449$ which is not that great of a convergence for EENS, but will suffice for the testing purposes in this thesis.

Table 8: Hybrid 2 simulation results for delivery points on Four-Area Network

Delivery point	EENS_dp [MWh/year]	ENLC_dp [occ./year]	EDLC_dp [hours/year]
1	4.89E-10	1.63E-05	0.1352
2	0	0.7318	49.2946
3	4.11E-07	1.63E-05	0.1352
4	4.79E-10	1.72E-05	0.1360
5	0	0.7318	49.2946
6	5.85E-07	1.72E-05	0.1360
7	0	0.7318	49.2946
8	7.73E-07	1.75E-05	0.1376
9	5.06E-10	1.75E-05	0.1376
10	3.7576	0.00452	0.2128

The results show that delivery point 10 (bus 40024) contributes to about 99,99% of the energy not supplied for the system. This makes sense looking at the topology of The Four-Area Test Network, as delivery point 10 only has one connected line to it, so if that line fails, the bus is islanded. Otherwise the results for EENS seem okay, fairly close to the OPAL benchmark. The frequency and duration indices seem fairly accurate. Something interesting to note, is the frequency and duration for the delivery points 2, 5 and 7 are only influenced by the OPAL calculation. The same conclusions can be reached as for the hybrid 1 simulation, i.e. The Four-Area Test Network is a sturdy power system.

7 Discussion

7.1 System indices comparison

In this section, all the system indices have been gathered and presented together, for easy comparison.

7.1.1 RBTS

System indices are presented in table 9. For RBTS it is clear that the hybrid methods are mainly influenced by the OPAL calculation of the first order contingencies. The state sampling benchmark is not optimized for calculating 1. order contingencies (hence why the computation time is so long). An interesting note is that the EENS for OPAL benchmark is 2,3 times higher than the EENS calculated for the state sampling benchmark. Without further testing, it is impossible to say if the OPAL overestimates, or the state sampling underestimates the indices, or both. When it comes to the frequency and duration indices, the state sampling benchmark clearly overestimates the duration and underestimates the frequency, but with the hybrid methods, the results are fairly similar to that of the OPAL benchmark. Overall, both hybrid methods seem to perform well on RBTS.

Table 9: System reliability indices for RBTS

	OPAL Benchmark	**State Sampling Benchmark**	**Hybrid 1**	**Hybrid 2**
Computation time [s]	4.64	4479	520	1430
CV_EENS	-	0.0093	0.0138	0.0902
ELC_sys [MW/year]	22.26	93.42	31.97	47.60
EENS_sys [MWh/year]	218.07	93.42	224.11	213.64
ENLC_sys [occ./year]	2.07	0.0058	2.0002	2.0005
EDLC_sys [hours/year]	20.36	50.58	21.96	20.03

7.1.2 The Four-Area Test Network

System indices are presented in table 10. For The Four-Area Test Network one can follow the same pattern of correlations between the different methods and indices, as for the RBTS, with one distinct difference; the state sampling benchmark indices are a lot closer to the the OPAL benchmark indices than for RBTS. In fact, reliability indices for all the methods are more similar then for RBTS. The Four-Area Test Network is larger than RBTS, and is a very reliable power system, thus it takes a lot more samples to converge for the EENS.

Table 10: System reliability indices for The Four-Area Test Network

	OPAL Benchmark	State Sampling Benchmark	Hybrid 1	Hybrid 2
Computation time [s]	11.8	3046.5	1727.3	4881.4
CV_EENS	-	0.098	0.132	0.145
ELC_sys [MW/year]	0.225	3.43	0.2453	0.28
EENS_sys [MWh/year]	3.76	3.43	3.78	3.76
ENLC_sys [occ./year]	2.2	0.03	2.2	2.2
EDLC_sys [hours/year]	147.96	260.14	148.45	148.91

7.2 Reliability indices

Frequency and duration indices are required for calculating the EENS and IEC (Interrupted energy cost) indices, which are of great value for power system planners in terms of cost-benefit analyses. If this is important, then steer away from using only the state sampling MCS. However, a hybrid method of contingency enumeration and state sampling has shown that it is fairly close to an analytical approach in terms of frequency and duration indices. A hybrid method using pseudo-sequential MCS comes even closer to the analytical results, but at a cost of increasing the computational cost.

One additional reason for over-counting the duration indices for state sampling (and other methods) is related to how the contingency analysis (opf) calculates lost power. There are events where lost power is so small, something similar to $aE-9$ [MW], where a is an arbitrary number, but still it counts as a loss of load event (thus being counted as 1 hour for the state sampling). One can argue that it would be beneficial to set a minimum limit for the lost power in order to register as a loss of load event.

8 Conclusions and further work

8.1 Conclusions

A thorough literature study on power system reliability assessment has been completed. The most interesting parts related to the different reliability analysis methods, their advantages and disadvantages, are presented in this master thesis. The theory basis for reliability analysis of power system has been gradually explored. The state of the art within analytical and Monte Carlo simulation methods, and combinations of these methods have been explored. Hybrid reliability analysis methods have been defined to be a combination of an analytical method and a Monte Carlo simulation method. Implementations of such methods was discussed, culminating in two proposed hybrid method implementations.

The two proposed hybrid reliability analysis approaches are: 1) The combination of the OPAL methodology using contingency enumeration and a state sampling Monte Carlo simulation, and 2) The combination of the OPAL methodology using contingency enumeration and a pseudo-sequential Monte Carlo simulation. Both methods uses the OPAL part to analyze the first order contingencies, and then uses the MCS to sample the second and higher order contingencies. The contingencies from the MCS are analyzed utilizing AC load flow and OPF for generation rescheduling / load shedding. Reliability indices are aggregated for the OPAL part and MCS part separately, and then combined into the total annualized expectation values.

Both hybrid approaches are tested on two test systems, RBTS and The Four-Area Test Network, and the reliability indices are analyzed. Both test systems have over 95% of the contribution to the EENS index from one single branch outage, due to the islanding of a bus. The results from the hybrid methods show that they compare to the results from the OPAL method (benchmark). For RBTS: hybrid 1 has a 2.8% higher EENS index value than OPAL, and hybrid 2 has a 2% lower EENS index value than OPAL. For The Four-Area Test Network: hybrid 1 has 0.5% higher EENS index value than OPAL, and hybrid 2 has the same EENS index value as OPAL. Even though the state sampling approach cannot calculate proper frequency and duration indices, this is not reflected in the results of the hybrid 1 method. Both hybrid methods track the duration and frequency indices of the OPAL benchmark pretty good (less than 1% difference). This is due to the fact that the contribution from the OPAL reliability index calculation is greater than the contribution from the MCS reliability index calculation. Another noteworthy discovery is that the indices vary more between methods for RBTS than The Four-Area Network, probably because RBTS has a lower reliability level than The Four-Area Network (which is very reliable, all things considered).

Compared to the OPAL methodology, both hybrid methods come at an increased computational cost. This computational cost can be reduced, but never removed completely, with better optimized code, variance reduction techniques, or intelligent improvements (particle swarm, genetic algorithm, machine learning etc.). Hybrid method 1 shows itself as a decent reliability analysis method, but with certain limitations (e.g. one must always pay attention to the calculation of duration and frequency). Hybrid method 2 shows the most promise, and is a potentially useful hybrid method, especially for fast calculation of frequency indices. It falls somewhere in-between the OPAL method and pseudo-sequential MCS in terms of advantages and disadvantages, and usefulness. A possible hindrance for further developing hybrid method 2, is the massively increased complexity due to incorporating more chronological considerations (e.g. more operating states). Further testing is required to examine exactly how useful the hybrid method 2 can be.

8.2 Future work

One of the main conclusions of this thesis is that further testing is required on the hybrid methods to really explore if there are any preference over individual power system reliability analysis methods.

The developed MATLAB code was mainly created for testing purposes, so some generalization is required in order to bring the scripts into an integrated reliability assessment approach. In general, a restructuring for optimization is required. Certain design aspects that has been chosen for the simulations, do not always hold, and thus, requires a different approach, or at least a choice before being utilized as is.

The power system reliability assessment study was done on the composite power system, as an HL2 study, but excluded generation and transformer outages (except for The Four-Area Test System, where the transformers were included as branches). For a full-fledged HL2 study, those components would have to be incorporated. This would obviously change the entire simulation process, and would increase the complexity of the simulation substantially.

The reliability index of interest in this study, was the energy not supplied. As mentioned, for cost-benefit approaches, the expected interruption cost, is important. An incorporation of this index could be done, but then the choice of reliability analysis method plays a huge part. State sampling (and hybrid methods with state sampling) must be used with caution.

There are many intelligent ways to improve Monte Carlo simulation effectiveness, e.g. by using variance reduction techniques, particle swarm optimization, genetic algorithms etc. An example is the approach done in [21], where intelligent state space reduction is used together with the pseudo-sequential Monte Carlo simulation.

Other dependencies could be incorporated as well, such as protection system faults, common faults and weather-influenced faults.

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Appendices

Appendix 1: Data for the test-systems

All the data for RBTS can be found in the attached Excel-file:
"RBTS_benchmark.xls".

All the data for The Four-Area Test Network can be found in the attached Excel-file:
"4-area_network_extra_line.xls".

Appendix 2: MATLAB scripts for the implemented hybrid reliability analysis methods

All MATLAB scripts are found in the attached zip-file.

Appendix 3: Hybrid implementation - simulation results

All the rawdata for the simulation is provided in the attached Excel-file:
"Berg_master_thesis_simulation_results.xls".

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