KU LEUVEN

ARENBERG DOCTORAL SCHOOL
Faculty of Engineering Science

Evaluation of Power System Reliability Management

Towards Socially Acceptable Short-Term Reliability Criteria

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Dissertation presented in partial fulfillment of the requirements for the degree of Doctor of Engineering Science (PhD): Electrical Engineering

January 2018

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January 2018

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Voorwoord

Het elektriciteitssysteem is onderhevig aan tal van onzekerheden en toevalligheden: menselijke fouten, onverwachte en wisselende weersomstandigheden, etc. Het is belangrijk hoe je met deze zaken omgaat, aangezien afschakelingen grote gevolgen kunnen hebben in de moderne maatschappij. Ook het verloop van een doctoraat en het leven daarbuiten worden beïnvloed door toevalligheden: mensen die je ontmoet, kansen die je worden geboden, ingevingen die je krijgt en tegenslagen. Ik ben blij dat ik op mijn doctoraatstraject veel mensen ben tegengekomen die mij mooie kansen hebben geboden, waarmee het aangenaam samenwerken was, die voor het nodige plezier hebben gezorgd en die mij hebben gesteund in voor- en tegenspoed. In dit voorwoord wil ik hen dan ook graag bedanken.

Tijdens het werken aan mijn masterthesis had de onderzoeksmicrobe me te pakken en keek ik er naar uit om een doctoraat te starten. Eerst en vooral wil ik Prof. Dirk Van Hertem en Prof. Geert Deconinck bedanken om mij de kans te geven om dit te doen onder hun begeleiding. Het GARPUR project werd tijdens onze eerste gesprekken voorgesteld als een ambitieus en interessant Europees project rond betrouwbaarheidsbeheer van transmissiesystemen. Gegeven het belang van betrouwbare en betaalbare elektriciteitsvoorziening en de vooruitstrevendheid die men in het project voor ogen had, was ik meteen bereid om hier aan mee te werken. Ook het Fonds voor Wetenschappelijke Onderzoek (FWO) zag de relevantie van het onderwerp in en besloot om mij na een jaar onderzoek een FWO Aspiranten mandaat toe te kennen. Dit gaf me de ruimte om een eigen invulling te geven aan het onderzoekstopic. Dankzij een FWO reisbeurs kon ik me ook verder verdiepen in het onderwerp tijdens een verblijf van 3 maanden aan Durham University. Ik wil het FWO dan ook bedanken voor de financiële steun.

Dirk, als promotor van dit werk heeft u mee richting gegeven aan mijn onderzoek, maar me toch de nodige vrijheid gelaten. Bedankt voor de begeleiding en de mogelijkheden die u me heeft gegeven. De meetings en conferenties waaraan ik kon deelnemen hebben me veel inzicht gegeven en in contact gebracht met mensen met een interessante kijk op de uitdagingen in betrouwbaarheidsbeheer van elektriciteitssystemen en de elektriciteitssector in het algemeen.

Geert, als co-promotor van dit werk nam u regelmatig de tijd om mijn onderzoek te bespreken. Deze meetings lieten me toe om alles op een rijtje te zetten en uw klare kijk gaf me vertrouwen in de weg die ik aan het bewandelen was. Bedankt voor de interessante discussies en de nuttige tips.

I would also like to thank the members of the examination committee. Prof. Hens, bedankt om als voorzitter op te treden van mijn jury. *Prof. Berbers and Prof. Vazquez Sabariego, I am grateful for your useful feedback during the intermediate reporting and the review of my text.* Prof. Proost and Prof. Troffaes, bedankt voor de nuttige feedback op mijn tekst. Ik heb genoten van de aangename samenwerkingen die me toelieten mijn onderzoek te bekijken vanuit een respectievelijk meer sociaal-economisch en wiskundig perspectief. *Prof. Wehenkel, I would like to thank you for the review of my thesis, the feedback during the intermediate reporting and the useful input during the GARPUR meetings.*

Het GARPUR project heeft er mede voor gezorgd dat ik kon samenwerken met zeer bekwame onderzoekers. Eerst en vooral wil ik Marten van harte bedanken voor de aangename samenwerking. Jouw klare kijk op de energieproblematiek, zowel vanuit sociaal-economisch standpunt als vanuit je ingenieursachtergrond, gecombineerd met je enthousiasme en engagement zorgden voor een multidisciplinaire samenwerking die heeft geleid tot technisch en sociaal relevante conclusies. Daarnaast wil ik Wouter, Frederik, Hakan en Tom bedanken voor de samenwerking bij de implementatie van het quantificatie framework.

De vier voorbije jaren heb ik verschillende hoeken van het ESAT gebouw, het land en de wereld gezien. Elk van deze werkomgevingen had zijn eigenheid, maar ik heb van allen even hard genoten. Werken in de ELECTA groep was dan ook meer dan werken alleen. De sportdag, kerstfeestjes, samenkomsten in De Lodge, een uitstap naar Krakau of een spelletje tafelvoetbal, ping pong of voetbal, er waren mogelijkheden genoeg om een optimaal evenwicht tussen inspanning en ontspanning te bewaren. Het was een plezier deel uit te maken van deze hechte groep. *I would like to thank all the colleagues for the pleasant working atmosphere and the nice collaborations during the teaching duties.* Ook de dames van het secretariaat en de IT wil ik bedanken voor het regelen van allerlei praktische en IT gerelateerde zaken.

In juni 2016 kregen we ook een nieuwe werkplaats in EnergyVille te Genk. Speciale dank gaat uit naar Philippe voor de bereidwilligheid om mij op te pikken en de aangename ritten van en naar Genk. Ook bedankt aan de carpoolcollega's die bereid waren om een tussenstop te maken zodat ik kon meerijden naar Genk.

Autumn 2016, I resided three months in the UK for a research visit at Durham University. Prof. Troffaes and Prof. Kazemtabrizi, I would like to thank you to be my hosts. I am grateful for the interesting discussions about my work and the useful feedback. It was a nice experience during which I have learnt a lot. It enabled me to look at my research from a different perspective, which has given me a lot of new insights.

Natuurlijk was er ook een leven naast mijn doctoraat. Bedankt aan mijn voetbalcollega's, trainers en afgevaardigden bij Rapide Wezemaal, KV Mechelen, Familia Academia en the Durham WAFC om een uitlaatklep te bieden voor het onderzoekswerk. Mijn leraressen en klasgenoten in de Academie in Heist op den Berg wil ik bedanken voor de aangename lessen woord en om te helpen bouwen aan de 'yellow brick road' van mijn presentaties. Ook iedereen waarmee ik veel plezier heb gemaakt, lief en leed heb gedeeld en die me de nodige steun heeft geboden wil ik van harte bedanken.

Tot slot wil ik mijn ouders en de Moe en de Va hartelijk danken. Van kleinsaf hebben ze mij alle kansen gegeven en mij op alle vlakken gesteund en gemotiveerd om mijn talenten te ontplooien. Het afgelopen jaar was er één met tal van tegenslagen en veel moeilijke en onzekere periodes. Moe, je had er hard naar uitgekeken om de verdediging van mijn doctoraat mee te maken, maar dat heeft spijtig genoeg niet mogen zijn. Ik zal je positieve ingesteldheid verder meenemen in mijn eigen leven. Deze heeft me alleszins geholpen om ondanks de moeilijke omstandigheden mijn eigen planning aan te houden.

Ik hoop dat u als lezer na het lezen van dit werk beter geïnformeerd zal zijn over de uitdagingen en evoluties in betrouwbaarheidsbeheer van elektriciteitssystemen. Een belangrijke les die ik zelf heb getrokken uit mijn onderzoek en het traject naar dit boekje is de volgende:

Het leven zit vol toevalligheden, maar het belangrijkste is hoe je er mee omgaat.
Life is full of coincidences, but the most important is how you deal with them.

Evelyn Heylen
December 2017

Abstract

An adequate level of reliability in power systems is crucial due to the criticality of reliable, but affordable electricity supply for society. Nowadays, power system reliability is managed based on the deterministic N-1 criterion. This N-1 approach does not aim at cost-optimality and is challenged by the evolutions in power systems. Probabilistic reliability management on the contrary takes into account risks related to power system uncertainties and aims at making decisions based on socio-economic principles. Adequate performance evaluation is required to convince system stakeholders to change their reliability management.

The objective of this work is to contribute to the fundamental understanding of performance evaluation and comparison of short-term reliability management approaches and criteria. A quantification framework is developed, which is modular and generic in design and takes into account the specific characteristics of the evaluation of reliability management. A basic implementation of the quantification framework is applied to test systems to determine characteristics and trends in relative performance, rather than to find the fundamentally optimal reliability management approach and criterion. A performance metric is proposed to verify the technical, economic and social acceptability, practicality and applicability of reliability management. Missing indices to evaluate the inequality between consumers in terms of reliability are developed.

Ideally, reliability management is cost-effective, results in a high reliability level and distributes unreliability equally among consumers. In practice, efficiency, reliability and equality should be balanced, constituting a 'performance trilemma'. Controllable factors of reliability criteria that define intermediate steps between the N-1 approach and fully probabilistic reliability management and the level of detail of the value of lost load data have an intertwined impact on the three aspects of the trilemma. To manage reliability in a way that considers both society's preferences and system operator's capabilities, a transparent dialogue between power system stakeholders is required and transmission system operators should carry out the multi-dimensional analysis proposed in this work for their own systems.

Beknopte samenvatting

Betrouwbare en betaalbare elektriciteitsvoorziening is een belangrijk basisgoed in de moderne maatschappij. Daarom is een geschikt niveau van betrouwbaarheid in het elektriciteitssysteem cruciaal. Vandaag de dag wordt betrouwbaarheid beheerd aan de hand van het deterministisch N-1 criterium. Het N-1 criterium streeft niet naar kostenminimalisatie en evoluties in elektriciteitssystemen leggen de tekortkomingen van dit criterium bloot. Het beheren van betrouwbaarheid op een probabilistische manier laat daarentegen toe socio-economische afwegingen te maken, rekening houdend met de risico's verbonden aan de onzekerheden in het elektriciteitssysteem. Een adequate evaluatie van de prestaties van deze alternatieve methodes in vergelijking met de huidige aanpak is cruciaal om systeemoperatoren en andere belanghebbenden te overtuigen om over te schakelen op een alternatieve aanpak voor betrouwbaarheidsbeheer.

Het doel van dit werk is om bij te dragen tot de fundamentele kennis van de evaluatie en vergelijking van betrouwbaarheidscriteria in kortetermijn-betrouwbaarheidsbeheer. Een modulaire en generische structuur voor een kwantificatieplatform is ontwikkeld, rekening houdend met de specifieke eigenschappen van de evaluatie van betrouwbaarheidsbeheer. Een basisimplementatie van dit platform is toegepast op testsystemen om karakteristieken en trends in relatieve prestaties van betrouwbaarheidscriteria af te leiden, eerder dan om het fundamenteel optimale betrouwbaarheidscriterium te bepalen. De toegepaste prestatie-indicatoren laten toe om de technische, economische en sociale aanvaardbaarheid, de praktische toepasbaarheid en de hanteerbaarheid van betrouwbaarheidsbeheer te evalueren. Ontbrekende indicatoren om de ongelijkheid tussen eindgebruikers in termen van betrouwbaarheid uit te drukken zijn ontwikkeld.

Ideaal gezien is betrouwbaarheidsbeheer kosteneffectief, leidt het tot een hoog niveau van betrouwbaarheid en is onbetrouwbaarheid op een billijke manier verdeeld over de eindgebruikers. Deze drie aspecten leiden echter tot een 'prestatietrilemma' tussen kosteneffectiviteit, betrouwbaarheid en

billijkheid. De drie aspecten van het prestatietrilemma worden beïnvloed door het gebruik van meer gedetailleerde gegevens over de waarde die eindgebruikers hechten aan de niet-geleverde energie en aanpassingen aan het huidige betrouwbaarheidscriterium. Er worden aanpassingen voorgesteld die een geleidelijke overgang naar probabilistisch betrouwbaarheidsbeheer mogelijk maken. Om tot betrouwbaarheidsbeheer te komen dat binnen de praktische mogelijkheden ligt van de systeemoperatoren en voldoet aan de maatschappelijke vereisten, is het belangrijk dat een transparante dialoog gevoerd wordt over de afwegingen tussen betrouwbaarheid, kosteneffectiviteit en billijkheid en dat systeemoperatoren de multi-dimensionele prestatieanalyse voorgesteld in dit werk toepassen op hun eigen systemen.

List of Abbreviations

ACER	Agency for the Cooperation of Energy Regulators
AIT	Average Interruption Time
ASE	Analytical State Enumeration
C&I	Commerce and Industry
CCDF	Composite Customer Damage Function
CENS	Cost of Energy Not Supplied
CIC	Customer Interruption Cost
COC	Customer Outage Cost
CVaR	Conditional Value at Risk
D2CF	D-2 Congestion Forecasts
DACF	Day-Ahead Congestion Forecasts
DS	Demand Share
EENS	Expected Energy Not Supplied
EIR	Energy Index of Reliability
EIU	Energy Index of Unreliability
ENS	Energy Not Supplied
ENTSO-E	European Network of Transmission System Operators for Electricity
ETC	Expected Total Cost
EUE	Expected Unserved Energy
FERC	Federal Energy Regulatory Commissions
GQP	GARPUR Quantification Platform
HILP	High Impact Low Probability

HVDC	High-Voltage Direct Current
IDCF	Intra-Day Congestion Forecasts
IEAR	Interrupted Energy Assessment Rate
IRI	Integrated Reliability Index
LOLE	Loss Of Load Expectation
LOLEV	Loss Of Load Events
LOLH	Loss Of Load Hours
LOLP	Loss Of Load Probability
LPAC	Linear Programming approximation of AC power flows
NRA	National Regulatory Agency
NSS	Non-Sequential Simulation
OPF	Optimal Power Flow
pdf	Probability Density Function
PST	Phase-Shifting Transformer
pu	Per Unit
RES	Renewable Energy Sources
RI	Reliability Indicator
RLC	Relative Load Curtailment
RMAC	Reliability Management Approach and Criterion
SCDF	Sector Customer Damage Function
SCOPF	Security Constrained Optimal Power Flow
SME	Small and Medium Enterprise
SRI	Severity Risk Index
SSBR	State-Space Border Representation
TSO	Transmission System Operator
UCPTE	Union for the Coordination of Production and Transmission of Electricity
UCTE	Union for the Coordination of the Transmission of Electricity
VaR	Value at Risk
VOLL	Value Of Lost Load

WTA	Willingness-To-Accept
WTP	Willingness-To-Pay

List of Symbols

Probability

F	Cumulative distribution function
p	Probability
Π	Multivariate probability density function

Costs and prices

$c^{breaker}$	Price of breaker switching
C^{cons}	Total consumer cost
C^{corr}	Cost of corrective actions
C^{curt}	Cost of load curtailment
c^{marg}	Marginal cost of generating units
C^{prev}	Cost of preventive actions
c^{PST}	Cost of phase-shifting transformer adjustment
$c^{red,-}$	Cost of downward redispatch of generating units
$c^{red,+}$	Cost of upward redispatch of generating units
$C(\rho)$	Reliability costs
C^{tot}	Total cost
γ	Multiplication factor for value of lost load
V^{comp}	Constant weighted average value of lost load used for compensation

V	Constant value of lost load
v	Value of lost load with a particular level of detail
$E[v]$	Average value of lost load

Equality and equity

W	Cumulative demand variable
E	Cumulative unreliability variable
$\mathbf{w}$	Vector of demand ratios
w	Element in the vector of demand ratios
$\mathbf{e}$	Vector of unreliability ratios
e	Element in the vector of unreliability ratios
ξ^{cost}	Inequality ratio in terms of net total cost borne by the consumers
ξ^{ENS}	Inequality ratio in terms of energy not supplied
ξ^{IC}	Inequality ratio in terms of interruption cost
A	Surface area between the Lorenz curve and the line of equality
B	Surface area below the Lorenz curve
U^{cost}	Inequality indicator in terms of net total cost borne by the consumers
U^{ENS}	Inequality indicator in terms of energy not supplied
U^{IC}	Inequality indicator in terms of interruption cost

Functions

f_m	Deterministic function representing the decision-making behaviour of a system operator in short-term reliability management according to reliability management approach and criterion m
$\tilde{f}_m$	Approximate deterministic function representing the decision-making behaviour of a system operator in short-term reliability management according to reliability management approach and criterion m

g_i	Deterministic function representing the evaluation of a performance indicator i
G_0	Equality constraints of security constrained optimal power flow in reference stage
G_s	Equality constraints of security constrained optimal power flow in set S of considered system states
H_0	Inequality constraints of security constrained optimal power flow in reference stage
H_s	Inequality constraints of security constrained optimal power flow in set S of considered system states
h	A set of non-linear algebraic equations in the security assessment
k	A set of non-linear differential equations in the security assessment

General

$\mathbf{B}_{DC}$	Admittance matrix for DC power flow
J	Number of consumers in the set of consumers
σ	Standard deviation
t_α	α-percentile of the t-distribution
$\mathcal{N}$	Sample size
N	Number of components in the system

Indexes

o	Index for a breaker
b	Index for a node
c	Index for a consumer group
k	Index for a component in the system
j	Index for a consumer
da	Index for a day-ahead state
d	Index for the type of day under analysis

h	Index for the time of the day
z	Counting index in calculation of inequality index
i	Index for the indicator under evaluation
l	Index for an interval in the state space of external forcing inputs
m	Index for a reliability management approach and criterion under study
n	Index for an element in a sample
p	Index for a phase-shifting transformer
rt	Index for a real-time system state
s	Index for a considered system state
y	Index for the season
u	Index for a generating unit

Performance indicators and indices

Q	Quantitative performance indicator (random variable)
q	Realization of quantitative performance indicator Q
Q^{period}	Quantitative performance indicator evaluated over a time period (random variable)
q^{period}	Realization of a quantitative performance indicator evaluated over a time period
$\tilde{Q}$	Quantitative performance indicator evaluated based on approximate function $\tilde{f}$ of reliability management

Operational limits

$\bar{P}^{curt}$	Upper limit on load curtailment
Δa_s	Limit on rate of change
$\Delta P^{PST,+,max}$	Upper limit on phase shift of phase-shifting transformer in terms of fictitious power injection
$P^{breaker,max}$	Upper limit on the power flow through the breaker

$P^{breaker,min}$	Lower limit on the power flow through the breaker
P^{max}	Generation capacity of generating units
P^{min}	Minimal active power generation of generating units
$\Delta\theta^{max}$	Upper limit of the phase-shifting angle
$P^{supplied,min}$	Minimum amount of active power that should be supplied
RR	Ramp rate limit of generating units

Parameters

ω^{init}	Initial status of a breaker
ϕ	Constant system parameters
D^{Energy}	Energy demand
DS	Demand share
DS^{ref}	Reference demand share
$\Delta\mathbf{y}$	Size of the interval in the space of external forcing inputs
ζ	Status of the generators
x^{line}	Reactance of the transmission line
κ	Multiplication factor for demand share
P^{load}	Power demand
$P^{PST,+,init}$	Initial setting of the phase-shifting transformer
x^{PST}	Reactance of the phase-shifting transformer
P^{wind}	Realized power output of a wind generation unit
$P^{wind,*}$	Forecast value of a wind generation unit
$P^{wind,*}_{nom}$	Normalized forecast value of a wind generation unit
$\mathbf{x}_0$	Initial state
$\mathbf{Y}$	Random vector of external forcing inputs
$\mathbf{y}$	Realization of the vector of external forcing inputs

Reliability data

λ	Failure rate of a component
ρ^*	Optimal reliability level
ρ	Reliability level
μ	Repair rate of a component

Sets

$\mathcal{B}$	Set of nodes in the system
$\mathcal{O}$	Set of breakers
$\mathcal{C}$	Set of consumer groups
DA	Set of evaluated day-ahead states
$\mathcal{D}$	Set of different types of days under analysis
$\mathcal{J}_g$	Set of consumers belonging to group g
I	Set of indicators under evaluation
$\mathcal{J}$	Set of consumers
K	Set of components in the system
$\mathcal{L}$	Set of intervals in the state space of external forcing inputs
$\mathcal{M}$	Set of reliability management approaches and criteria under study
K^{outage}	Set of components in failure state
$K^{working}$	Set of components in operating state
$\mathcal{P}$	Set of phase-shifting transformers
RT	Set of evaluated real-time system states
S_{N-k}	Set of contingencies that deviates from the set of N-1 contingencies
S_{N-1}	Set of N-1 contingencies
$S_{N-1,generation}$	Set of system states consisting of the N-1 generation contingencies
$S_{N-1,network}$	Set of system states consisting of the N-0 state and N-1 network contingencies

S^{prev}	Set of system states secured with preventive actions only
S	Set of system states considered in reliability management
$\mathcal{U}$	Set of generating units

Time

T	Set of time instants under evaluation
t	Time instant under evaluation

Variables

$\mathbf{a}_{rt}^{corr}$	Corrective actions taken in real-time operation
$\mathbf{a}_{s}^{corr}$	Corrective actions expected to be taken in considered system states
$\mathbf{a}^{prev}$	Preventive actions taken
ΔP	Total redispatch of generating units
ΔP^{-}	Downward redispatch of generating units
ΔP^{+}	Upward redispatch of generating units
L	Branch flow
$P^{breaker}$	Power flow through the breaker
P_{j}^{curt}	Load curtailment of consumer j
$\mathbf{P}^{curt}$	Vector of load curtailment for all consumers
$\mathbf{P}^{inj}$	Vector of net power injections
P^{prev}	Dispatch of generating units after preventive actions
P^{PST}	Fictitious power injection modeling the phase shift in a phase-shifting transformer
$P^{PST,down}$	Fictitious power injection to linearize constraints of phase-shifting transformer (negative phase shift)
$P^{PST,-}$	Fictitious power injection at other side of the phase-shifting transformer
$P^{PST,+}$	Fictitious power injection at one side of the phase-shifting transformer

$P^{PST,up}$	Fictitious power injection to linearize constraints of phase-shifting transformer (positive phase shift)
P	Active power production of generating units
P^{init}	Scheduled active power generation of generating units
$\Delta\theta$	Phase-shifting angle of the phase-shifting transformer
$P^{supplied}$	Amount of active power supplied
Θ	Vector of voltage angles
θ	Voltage angle
$\mathbf{X}$	The random state vector
$\mathbf{x}$	Realization of the state vector
$\tilde{\mathbf{X}}$	Approximate value of the random state vector
$\tilde{\mathbf{x}}$	Approximate value of a realization of the state vector

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Chapter 1

Introduction

1.1 Context of the Research

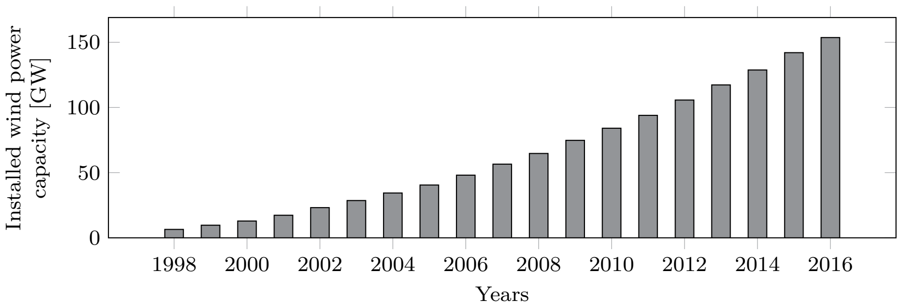
Reliability of electricity supply plays a major role in the economics and social well-being of a modern society and directly influences the quality of life [1]. The cost of a one day blackout is estimated at 0.5% of the gross domestic product of a country, which needs to be complemented with social consequences, such as diseases, deaths and injuries [2]. Also short-term interruptions come at a cost due to loss of production, frozen foods gone bad, traffic accidents,... The Belgian Federal Planning Office has calculated in 2014 that a one hour blackout during working hours would cost €120 million/hour [3]. Moreover, modern society's dependence on electricity is continuously increasing and a lot of critical appliances, such as mobility and heating, rely more and more on electricity. The effect on consumers can be such that the reliability of the local energy provision is key to the selection of a site, particularly for industries such as foundries and large IT providers. The power system can be seen as one of the most critical infrastructures and a correct assessment and adequate level of reliability is of utmost importance.

The power system is also one of the most complex man-made systems in the world and is continuously evolving. Initial power systems mainly connected some generating units with a load centre further away. By interconnecting these small systems in a meshed system, technological and economic advantages were obtained, because the overall load profile is flatter, the unit commitment is more efficient and the conventional generating units operate more optimally. Moreover, less generation reserves are required to handle an (unforeseen) outage and due to the redundancy incorporated in meshed grids, an outage of a transmission component does not necessarily result in a power interruption.

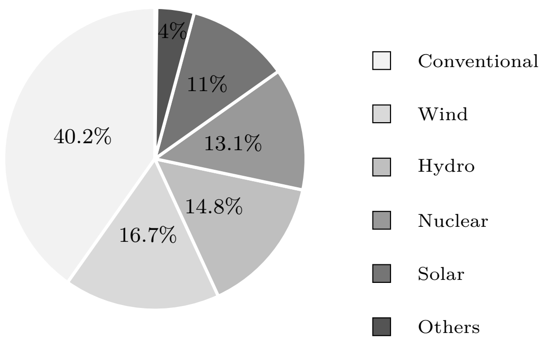
Since 1996, both the US and Europe decided to gradually open electricity markets to competition using unbundling and deregulation or liberalization.[1] Unbundling is the separation of supply and generation of electricity from the operation of transmission networks, whereas deregulation or liberalization is the process of reducing state regulations. Improved competition has consequently resulted in a higher importance of cost-effectiveness and socio-economic aspects, resulting in power systems that are used closer to their limits. Interconnections are currently used to serve the liberalized electricity market by enabling cross-border trade, whereas they were historically mainly built for reliability purposes [7]. For this reason, additional investments are required [7, 8, 9]. However, building new power system infrastructure is a slow process requiring multiple interactions between different stakeholders [10]. A large public opposition exists against the construction of new overhead lines due to visual pollution and concerns about the effect of electromagnetic fields on human health [11]. New technologies emerge that make it possible to incorporate more flexibility and reliability-based choices of electricity consumption in power systems, such as demand-side response [12]. However, it is questioned whether currently-used reliability management approaches can efficiently incorporate these new technologies in power systems [13].

Since 2009, the trend of increasing penetration of Renewable Energy Sources (RES) in power systems, such as wind and solar power generation, was accelerated by European directives aiming at the reduction of greenhouse gas emissions. Directive 2009/28/EC specifies that renewable energy should provide a 20% share in the final European energy demand by 2020. The target for electricity generation is 34.3% of total electricity demand provided by renewable energy sources [14]. Fig. 1.1 shows the evolution of wind penetration in the EU-28 region as well as the electricity production by source in 2016. The installed wind power capacity has increased significantly the last decade resulting in a considerable share in the total electricity production in the EU-28 region. Wind and solar power generation are highly variable and uncertain in nature and result in more distributed, local generation, compared to the traditional system

[1] Liberalization of the European electricity sector was initiated in 1996 with the first electricity liberalisation directive, which should have been transposed in member states' legal systems by 1998. The second liberalization directive adopted in 2003 and directive 2009/72/EC of the Third Energy Package aimed at further strengthening the competition in electricity markets [4]. In the US, electricity deregulation was initiated in 1982 with the implementation of Public Utilities Regulatory Policies Act of 1978. In the late 1990's, electricity liberalization started to gradually spread over the states, with the states in the North-East and California as leads [5]. From 1996 onwards, the Federal Energy Regulatory Commissions (FERC) issued orders that required utilities to provide transmission services on a reasonable and non-discriminatory basis [6].



(a) Evolution of wind penetration in power systems in the EU-28 region



(b) Electricity production in EU-28 by source in 2016

Figure 1.1: Wind penetration in power systems in the EU-28 region and the electricity production by source in EU-28 in 2016 [15].

with large centralized generation plants. This distributed, local generation can lead to power quality problems and increased system stress due to bi-directional flows.

Although unreliability is expensive, maintaining or improving reliability requires actions, which are costly as well. Adequate reliability management tries to make an optimal trade-off between the cost of obtaining a particular reliability level and the cost of interruptions. Since the formation of the Union for the Coordination of Production and Transmission of Electricity (UCPTE) in Europe in 1951, the reliable operation of the interconnected system is ensured by the N-1 reliability criterion. This is still the basis for today's reliability management of Transmission System Operators (TSOs)[2] [16, 17]. Also in the US, the N-1 criterion was introduced after the blackouts of 1965 and 1969. This criterion states that the system should be able to withstand at all times the loss of any of its main elements (lines, transformers, generators, etc.) without significant degradation of service quality. The N-1 criterion is easy to use and transparent and has lead to satisfactory results in the last decades, but it was developed with a traditional system in mind with a centrally planned and operated nature of generation, transmission and distribution [18]. Due to evolutions in the system, shortcomings of the N-1 criterion has become clear [1, 2, 13, 19, 20, 21, 22, 23]:

- Although the N-1 criterion is straightforward, transparent and widely used, it in itself can be interpreted in many ways. In practice, neither the number of elements to be considered (N) nor the type of contingencies considered (-1) is dealt with equally amongst TSOs and even within a single organization.
- The criterion currently does not take into account the probability and severity of contingencies.
- The criterion does not give an incentive based on economic principles, because it does not take post-fault costs into account and mainly favors preventive control, i.e. ahead of real time. This might impose a barrier on the integration of new technologies, which might improve the efficiency of system operation through the use of corrective actions in real time.
- All consumers are assumed equally important.
- The criterion does not consider the stochastic nature of generation and demand.
- The criterion is a binary criterion: the system is either reliable or not reliable. Therefore, an optimal reliability level cannot be obtained or even calculated, which results in over- or under-investments.
- The criterion only takes into account single contingencies. Single contingencies are much more probable than double contingencies if outages are independent events, but hidden failures in the protection system can trigger additional outages cascaded to the original fault. Furthermore, due to significant increase of the rate of outages during bad weather conditions, the probability of two quasi-simultaneous, but independent outages is no longer negligible.

[2] The term 'TSO' is used throughout this thesis, but the core of the analysis does not change with the level of ownership unbundling of the network (full ownership unbundling, independent system operator or independent transmission operator) or with the geographical area of focus (e.g. in North America: independent system operator or regional transmission organization)

Increasing uncertainties, amongst others due to increasing generation of renewable energy sources in the system, challenge currently used reliability management approaches and criteria (e.g., Do we consider no wind in Germany as an N-1 contingency state?, How do we deal with off-shore wind?). Moreover, reports show that major disturbances occur due to combinations of failures not dealt with in the N-1 approach, as it deems them as not probable [24, 25, 26]. Especially the major European events in 2003 [27] and in 2006 [28], which were both disturbances in normal conditions and affected the UCTE system[3], have questioned the use of the N-1 criterion.[4]

Significant research effort has been placed in the development of alternative, probabilistic reliability assessment and control approaches that are able to handle uncertainties more appropriately. First interest in the application of probability methods to generating capacity requirements became evident around 1933, whereas for the first academic attempts in probabilistic reliability evaluation of composite systems, i.e., considering generation and transmission, one needs to go back to the 60's. The history of literature on probability methods in power system reliability evaluation is summarized in [30, 31, 32, 33, 34]. The last decade, several European funded projects, such as TWENTIES [35], PEGASE [36], iTesla[37], Umbrella [38] and GARPUR [39], have contributed to the domain of probabilistic reliability assessment, control or management as a whole. However, system operators are generally not eager to fundamentally change their way of reliability management due to the ease-of-use and the transparency of current approaches and the satisfactory results obtained so far, especially with respect to the overall reliability level achieved. An adequate evaluation and comparison of the performance of different reliability management approaches and criteria is required to quantify potential improvements compared to the currently used N-1 approach. This can help to convince system operators and other system stakeholders to initiate a transition and to guide them towards using an alternative Reliability Management Approach and Criterion (RMAC).

1.2 Scope of the Research

This work focuses on simulation-based assessment of performance of RMACs used in short-term power system operation. Performance evaluation of short-term RMACs is an off-line process and consists of four main steps:

[3]In 1999, the UCPTE re-defined itself as an association of TSOs in the context of the Internal Energy Market, resulting in the Union for the Coordination of the Transmission of Electricity (UCTE).

[4]The event in 2003 resulted in a full blackout of Italy and affected 60 million people and 180 GWh of energy not served. The event in 2006 affected 15 million households spread over the whole of Europe. The resynchronization of the UCTE system was accomplished in 38 minutes and the normal situation was restored in less than two hours [29].

1. Selection and calculation of performance indicators
2. Selection of a performance evaluation technique and appropriate sampling technique
3. Simulation of TSO's decision-making behavior for different short-term RMACs
4. Post-processing of results and comparison of performance of different RMACs

The performance of RMACs covers a spectrum of opposing aspects that determine the applicability and acceptability of an RMAC in practice. Different classes of quantitative indicators can be distinguished from which an appropriate set of indicators should be selected that cover the quantitative aspects determining performance. The applied performance evaluation technique should adequately represent the variabilities and uncertainties present in power systems in the quantitative performance indicators. Some performance aspects are hard to capture in a quantitative indicator, which requires qualitative indicators to be considered as well.

Simulation of short-term decision-making behavior of a TSO according to different RMACs is a multi-faceted task. The TSO decision-making process is largely interlinked with external systems and actors, such as electricity markets, producers and consumers, which are out of the control of the TSO. Moreover, short-term reliability management consists of multiple decision stages, which are interdependent and influenced by the decision-making processes on longer time horizons, such as system development, maintenance and asset management. Reliability management is also subject to a bunch of variabilities and uncertainties due to load, renewable energy sources, component failures, etc., that different RMACs deal with in different ways.

A practical application of alternative RMACs requires a comparison of the performance of RMACs for different external conditions. It is important to identify the sensitivity of the performance of RMACs to exogenous factors that are out of system operators' control. To improve the performance of RMACs for different external conditions, controllable factors to influence each of the performance aspects should be determined.

1.3 State-of-the-Art in Literature

Reliability management based on the N-1 criterion has been frequently questioned during the last decade. Studies argue that a radically different approach may be required to integrate renewable energy sources and smart grid technologies in a cost-effective way [13, 40, 41, 42, 43]. They argue that probabilistic RMACs are better suited to meet the current challenges of the electricity transmission system: uncertain and variable demand and supply, decentralized decision makers, highly interconnected networks, difficulties in building new lines and a general trend towards a more efficient use of the transmission system [13]. A large number of papers is proposing probabilistic approaches for reliability management as alternative for the currently-used deterministic N-1 reliability criterion. Part of them focus on probabilistic reliability assessment, whereas another part focuses on stochastic Security Constrained Optimal Power Flow (SCOPF) formulations to assist TSO decision making.

Probabilistic short-term reliability assessment discussed in literature is typically based on risk-based indices. Risk is defined as the combination of the probability of occurrence of harm and the severity of that harm [44]:

$$\text{Risk} = \text{probability} \cdot \text{severity} \tag{1.1}$$

Risk-based indices can either directly quantify the physical risk [45, 46] or socio-economic risk [22, 47] for end-consumers or indirectly quantify the risk in terms of physical system parameters, such as overload or undervoltage, impacting system security [40, 41, 46, 48, 49, 50, 51, 52]. Each of the approaches differs in terms of how the considered contingencies are selected, i.e., using a predefined set of contingencies [40, 41, 46, 48, 49, 50, 51] or random selection based on failure probabilities [45, 47, 53, 54]. These papers mainly focus on decision support, i.e., how can the operator be assisted in making decisions, taking into account risks. The main decision maker is still the operator. The Icelandic TSO Landsnet has experimented with probabilistic reliability assessment in the context of the GARPUR project and provided real-time risk information to the system operators in the control room [55].

Alternatively, a significant amount of work has already been done on advanced and improved SCOPF formulations to simulate the decision-making behavior of system operators to assist them in their decision making. The actions that should optimally be taken by the system operator are outcomes of these optimizations. Stochastic SCOPF formulations can take into account forecast uncertainty of RES and load and contingency risk [56]. Capitanescu et al. give a concise overview of the state-of-the-art, the challenges and future trends in security constrained optimal power flow [57]. They mainly focus on the theoretical part of the problem, i.e., how to obtain a more detailed simulation of decision-making behavior. However, directly moving from a deterministic N-1 criterion to a fully probabilistic approach based on a stochastic security constrained optimal power flow is challenging in practice. Probabilistic approaches based on optimization are much less transparent for the system operators, as the optimization can be seen as a black box model from his/her perspective. In this case, the operator relies much more on the software rather than on his own experience and analysis. Moreover, detailed modeling of the decision-making process of short-term reliability management covering aspects, such as stability issues, cascading failures [58], different reliability targets in different areas, etc., is challenging [57]. The optimization is also computationally intensive, which challenges the tractability, especially in real, large scale systems. Intermediate steps to bridge the gap between the deterministic N-1 approach and fully probabilistic RMACs should be determined and the change in different performance aspects should be evaluated. Moreover, their sensitivity to various exogenous factors should be assessed to assist power system stakeholders in their move towards improved reliability management.

Although there is a need to appropriately evaluate and compare RMACs to convince power system stakeholders to apply alternative RMACs in practice, the topic is not well covered in literature. Existing studies only focus on specific parts of the problem without integrating them. They propose alternative decision-making tools [59, 60], compare probabilistic and deterministic security assessments [22, 40] or evaluate and compare performance of various reliability management approaches focussing on the interdependence between market performance and system security [61]. SAMREL is an integrated approach for reliability of electricity supply analysis [62]. However, it focuses on long-term planning aspects and considers only deterministic reliability criteria and a limited amount of candidate decisions in the short term. Also literature on specialized techniques to adequately evaluate the performance of short-term RMACs is non-existing, although performance evaluation of RMACs has its own characteristics and differs from traditional reliability assessment in some crucial aspects. A complete and reliable performance evaluation requires that both the real-time system state resulting from reliability management and the decision-making trajectory followed while executing reliability management are evaluated [63, 64]. Reliability assessment on the contrary mainly focuses on the real-time system state. Another important difference is that especially failure states are of interest for reliability assessment. Performance evaluation on the contrary also has to evaluate the performance of reliability management in normal states.

1.4 Objectives of the Research

The main objective of this work is to contribute to the fundamental understanding of performance evaluation and comparison of short-term reliability management approaches and criteria. The main question raised in this respect is: How to evaluate and compare different reliability management approaches and criteria? Several sub-questions can be raised in this context, of which the following subset will be dealt with in this thesis:

1. How should performance of short-term RMACs be defined? Are all necessary indicators available?

2. Which modules are required in a quantification framework to evaluate and compare performance of short-term RMACs? What do they represent and how do they interact?

3. How can techniques that are applied in reliability assessment or other performance evaluation contexts be applied to evaluate performance of short-term RMACs, taking into account the typical characteristics of performance evaluation of short-term RMACs?

4. How to define and assess inequality and inequity in a power system reliability context?

5. What is the impact of the level of detail of value of lost load data on the performance of short-term RMACs?

6. Which controllable factors of RMACs can bridge the gap between a deterministic N-1 criterion and a fully probabilistic RMAC? What are the trends in terms of different performance aspects?

These questions are answered by taking following actions:

1. The study of available quantitative and qualitative performance indicators

2. Design and development of a modular and generic quantification framework for evaluating and comparing performance of power system reliability management approaches and criteria

3. The study of performance evaluation techniques to apply in the developed quantification framework

4. The development of missing performance indicators to quantify inequality and inequity between consumers in terms of reliability

5. An assessment based on an economic model and numerical analysis of reliability management for VOLL data with different levels of detail based on real VOLL data of Norway, Great Britain and the United States

6. The study of controllable factors in short-term reliability management based on a multi-dimensional performance analysis starting from the formulation of the deterministic N-1 approach

The focus in the case studies is on trends in the average performance that can be distinguished if different RMACs are applied, rather than on the exact numbers of the change in performance. For this reason, the analyses are limited to small-scale test systems. The objective of this work is not to develop the optimal RMAC for actual, large-scale systems.

The research focuses on short-term reliability management at the transmission system level. TSO decision-making behavior in the simulations is modeled in an approximate way using a DC SCOPF. Only steady-state security issues are considered, whereas dynamic effects, such as stability issues, are ignored in the analysis. Also the restoration process or cascading failures are not considered in the simulations and cross-border effects due to the application of different reliability targets in different control zones are neglected. Possible failure of corrective actions is not considered.

1.5 Research Context: The GARPUR Project

This research fits within the wider scope of the European FP7 project GARPUR, which stands for Generally Acceptable Reliability Principle with Uncertainty modeling and through probabilistic Risk assessment.[5] The overall objective of this project was to design, develop, assess and evaluate new, probabilistic RMACs that aim at maximizing social welfare.[6]

The main focus of KU Leuven, and specifically the ELECTA research group, in this project was on the development of a quantification platform to evaluate and compare the performance of the newly developed GARPUR RMAC with the deterministic N-1 approach. This thesis work has served as an input to the modular and generic design of the prototype of this quantification platform in the first year of the project.[7]

[5] `http://www.garpur-project.eu`

[6] The project was a collaboration between 7 TSOs, 12 R&D providers and 1 innovation management expert.

[7] Colleagues of the ELECTA research group together with project partners from other universities and industry have worked on a more advanced implementation of the quantification framework. This thesis focuses more specifically on the performance evaluation and comparison of RMACs using a basic implementation of the quantification framework in the case studies.

1.6 Structure of the Text and Contributions

The main contributions of the work are in Chapters 3 to 8, which are based on papers published or submitted for publication in scientific journals or international conferences. Two main parts can be distinguished. The first part, consisting of Chapters 3, 4, 5 and 6, focuses on the assessment of the performance of RMACs from a more methodological point of view. The four main steps, i.e., indicator selection, selection of a performance evaluation technique, simulation of the TSO decision-making process and comparison, are discussed in more detail. The second part, consisting of Chapters 7 and 8, focuses more on the RMACs, and more specifically on their relative performance and how this is impacted by exogenous and controllable factors. A graphical overview of the structure of the text is shown in Fig. 1.2.

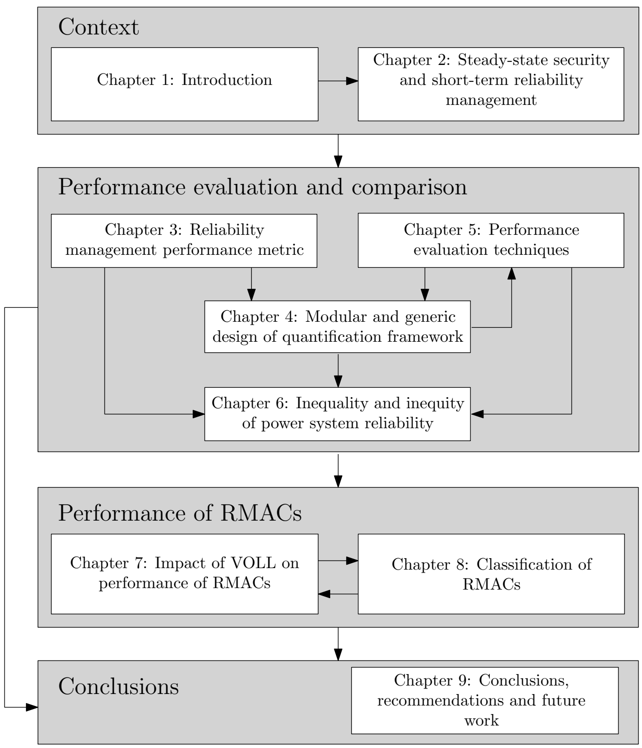


Figure 1.2: Overview of the text.

Chapter 2 is an introductory chapter that provides the theoretical background knowledge about steady-state security and short-term reliability management.

The terminology used in the remainder of the work is introduced.

Chapter 3 elaborates on the indicators to be used in order to obtain a complete picture of the performance of short-term RMACs. Appendix A gives an overview, classification and characterization of indicators presented in literature. Based on the overview of indicators, missing indicators required to obtain a complete performance evaluation are identified. The contributions of this chapter are (i) a classification of power system reliability related indicators available in technical and scientific literature and (ii) a performance metric for reliability management that defines different aspects determining the performance of an RMAC and appropriate indicators to assess them.

Chapter 4 elaborates on the developed quantification framework for evaluating and comparing performance of power system reliability management approaches and criteria. This quantification framework forms the basis for the numerical simulations done in the remainder of this work. The modular design of a framework to quantify the performance of various reliability criteria by evaluating both the real-time system state as well as the decision-making trajectory of the short-term reliability management process is the main contribution in this chapter. The focus in this chapter is on the modular design of the simulation module and its implementation used in the case studies in later chapters.

Chapter 5 focuses on techniques to evaluate performance of short-term RMACs that can be applied in the quantification framework discussed in Chapter 4. Existing evaluation techniques, typically used in a context of power system reliability assessment or other performance evaluation application contexts, are discussed and compared. An overview and comparison of performance evaluation techniques, taking into account the specific characteristics and requirements of performance evaluation of short-term RMACs, are the main contributions of this chapter. Moreover, the problem under evaluation is represented in a condense, analytical way, which facilitates the comparison between techniques.

Chapter 6 elaborates on the importance of considering inequality and inequity in a power system reliability context. The main contributions of this chapter are (i) the application of the concept of inequality and inequity in a power system reliability context and (ii) indices to express the inequality and inequity of the distribution of power system reliability among consumers in the system. The usefulness of the proposed indices is illustrated in three case studies: the analysis of the Belgian load-shedding plan of the winter of 2014-2015, the analysis of real reliability data of Norway and the comparison of short-term RMACs. Measures to reduce inequality and inequity are discussed.

Chapter 7 analyzes the impact of Value Of Lost Load (VOLL) on the performance of short-term RMACs. VOLL should be considered in reliability management based on socio-economic principles that makes a trade-off between preventive, corrective and load curtailment actions. The objective of this chapter is to assess the impact of the level of detail of VOLL data in short-term reliability management. VOLL depends on several exogenous factors and interruption characteristics. The main contributions of this chapter are (i) a literature survey of studies published since 2007 that estimate the effect on VOLL of at least two interruption characteristics and (ii) a theoretical model to show potential efficiency gains if temporal and spatial differentiation in VOLL data are applied in reliability management. The conclusions are supported by numerical analyses of a test system to which VOLL data of three different countries are applied that have different absolute levels of VOLL and different levels of detail. Possible solutions to enable the practical implementation of more detailed VOLL data are suggested.

Chapter 8 focuses on the RMACs themselves: what are their characteristics and how do they differ between each other. A classification framework of reliability criteria based on a limited set of controllable factors that bridge the gap between the deterministic N-1 approach and a fully probabilistic RMAC is the main contribution of this chapter. This classification framework facilitates the understanding of differences between reliability criteria proposed in specialized literature. Six reliability criteria are assessed in a multi-dimensional performance analysis, which illustrates the difficulties to adopt alternative criteria in a practical context. Also possible improvements are revealed in relation to the commonly used N-1 criterion.

Chapter 9 concludes the text. It summarizes the key messages of this work, makes recommendations to power system stakeholders and proposes important topics to further investigate in the context of evaluation and comparison of reliability management approaches and criteria.

Appendices A - D support the main chapters by providing resp. more detailed information about the indicators available in literature, the GARPUR quantification platform, the assumptions made in the modeling and the applied test system.

Chapter 2

Steady-State Security and Short-Term Reliability Management

This chapter elaborates on the theory behind steady-state security and explains its relation to the other aspects determining reliability. The objective of this chapter is to provide the theoretical background required to grasp the concepts in the remainder of this text.

Section 2.1 gives some general definitions of terms frequently used in the remainder of this text. Section 2.2 explains reliability management in more general terms. Section 2.3 dives deeper into the different decision stages in reliability management. Section 2.4 makes the link between reliability and costs, which is crucial to obtain cost-effective and efficient reliability management. Section 2.5 discusses short-term reliability management according to probabilistic and deterministic approaches in more detail. Section 2.6 concludes this chapter.

Parts of this chapter are based on *Steady-state security, Heylen E., De Boeck S., Ovaere M., Ergun H., Van Hertem D., In J. Rueda Torres and F. M. Gonzalez-Longatt editors Dynamic Vulnerability Assessment and Intelligent Control for Sustainable Power Systems, John Wiley & Sons, 2017, ISBN: 978-1-119-21495-3, (In press)* and *Importance and difficulties of comparing reliability criteria and the assessment of reliability, Heylen E., Van Hertem D., Young Researchers Symposium, Ghent, 2014.*

2.1 Definitions

Power system reliability is defined as the ability of an electric power system to perform a required function under given conditions for a given time interval [44]. It quantifies the ability of a power system to provide an adequate supply of electrical energy satisfying the consumer requirements with few interruptions over an extended period of time. Power system reliability consists of *power system security* and *power system adequacy* [65]. An adequate power system has sufficient generation, transmission and distribution facilities in the system to satisfy the aggregate electric power and energy requirements of consumers at all times, taking into account scheduled and unscheduled outages of system components [23]. System security describes the ability of the system to handle disturbances, such as the loss of major generation units or transmission facilities [23].[8] Power system security and adequacy are strongly interdependent, since adequacy is subject to transitions between different states, which are in the strict sense no part of the adequacy analysis, but of the security analysis [18]. Adequacy and security of a power system are interlinked with its coping capacity. The *coping capacity* describes the ability of the operator and the power system itself to cope with an unwanted event, limit negative effects and restore the power system's function to a normal state [67]. The coping capacity of the power system together with its *susceptibility* determine the power system's vulnerability to external threats that can lead to failure modes. If a realized threat leads to an unwanted event in the power system, it is susceptible to this threat. A power system's *vulnerability* is an expression of the problem the system faces to maintain its function if a threat leads to an unwanted event and the difficulties to resume its activities after the event occurred [67]. Vulnerability is an inherent characteristic of the system and depends on the working force of the TSO, its organizational structure and the technical aspects of the system, such as the availability of the components, which is determined by their reliability and maintainability [68].[9] The reliability of the system is determined by its vulnerability, the threats it is facing and the reliability criterion that is applied. The interlinking between different aspects, determining the system's reliability level, are indicated in Fig. 2.1.

[8] The North American Reliability corporation (NERC) denotes security as operational reliability [66]

[9] Maintainability is defined as the probability of performing a successful repair action within a given time [44].

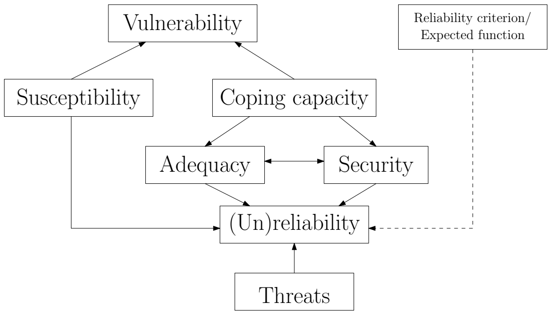


Figure 2.1: Interactions between the aspects determining reliability of power systems.

2.2 Reliability Management: A Combination of Reliability Assessment and Reliability Control

Power system reliability management is defined as taking a sequence of decisions under uncertainty to meet a reliability criterion, while minimizing the socio-economic costs [69]. It aims at serving load with a very high probability and this with the required quality and with a very low frequency of experiencing large system failures, such as blackouts [23]. The power system reliability management process of transmission system operators is illustrated in Fig. 2.2. It consists of two main tasks: i) reliability assessment and ii) reliability control. Reliability assessment aims at identifying and quantifying the actual reliability level. The main objective of reliability control is to keep the system within an acceptable reliability level range or bring it back to a state that has an acceptable reliability level, preferably minimizing the socio-economic costs. To do this, a decision should be selected from the list of candidate decisions taking into account the results of the reliability assessment. This decision can imply a reliability action affecting the system or no action.

2.2.1 Reliability Assessment

Reliability assessment focuses on answering three questions: (1) What can go wrong?, (2) How often will it happen? and (3) What are the consequences if it happens? [70]. Reliability assessment methods calculate indicators to verify whether reliability criteria are satisfied.

Reliability assessment is a combination of security assessment and adequacy assessment. Adequacy assessment verifies whether the system is capable of

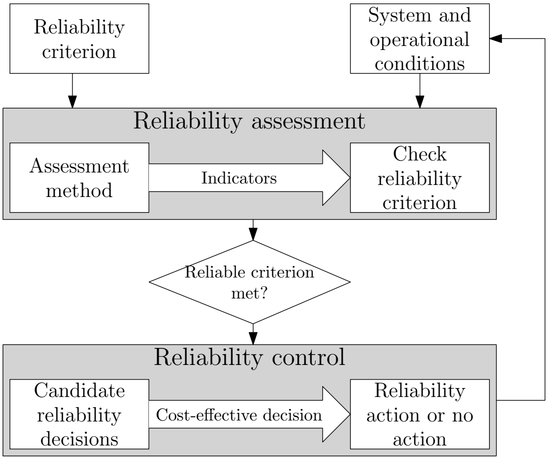


Figure 2.2: Overview of reliability management.

supplying the load under specified contingencies without violating operational constraints. Security assessment on the contrary determines whether immediate response of the system to a disturbance generates potential reliability problems [71]. A distinction is made between dynamic (time-dependent) and static or steady-state (time-independent) security assessment, depending on whether transients after the disturbance are neglected or not. Steady-state security assessment evaluates whether a new equilibrium state exists for the post-contingency system, whereas dynamic security assessment investigates the existence and security level of the transient trajectory in the state space from the original pre-contingency equilibrium point to the post-contingency equilibrium point. The power system in dynamic security assessment can in general be modeled by non-linear differential equations whose boundary conditions are given by the non-linear power flow equations.

$$\frac{d\mathbf{x}}{dt} = k(\mathbf{x}, \mathbf{y}, \mathbf{a}) \tag{2.1}$$

$$0 = h(\mathbf{x}, \mathbf{y}, \mathbf{a}) \tag{2.2}$$

$\mathbf{x}$ is the vector of state variables, $\mathbf{y}$ is the vector of uncontrollable, independent external forcing inputs, $\mathbf{a}$ is the vector of control variables, k is a set of nonlinear differential equations, e.g., generator mechanical equations, and h a set of nonlinear algebraic equations, e.g., load flow [72]. Static security is considered as a first-order approximation of the dynamic power system state, i.e., $\frac{d\mathbf{x}}{dt} = 0$ [73]:

$$0 = k(\mathbf{x}, \mathbf{y}, \mathbf{a}) \tag{2.3}$$

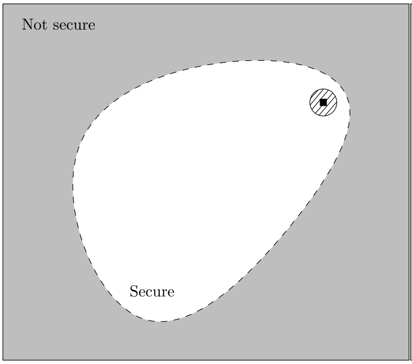
$$0 = h(\mathbf{x}, \mathbf{y}, \mathbf{a}) \tag{2.4}$$

Alternatively, pseudo-dynamic evaluation techniques exist that use sequential steady-state evaluation to assess the impact at several post-contingency stages [74].

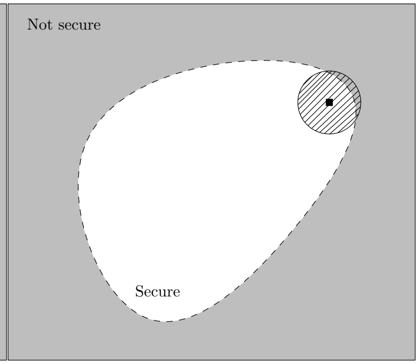
2.2.2 Reliability Control

During the reliability assessment, the state of the power system is determined taking into account the applied reliability criterion. Based on that state, the reliability control mechanism selects a reliability decision from the list of candidate decisions. Decisions imply either a reliability action or no action. Executed reliability actions aim at ending up in a state of the system for which the reliability criterion is satisfied and system security is ensured. This can be graphically illustrated using the State-Space Border Representation (SSBR), as shown in Fig. 2.3. This abstract visualisation depicts the current system operating point relatively to the security border. The location of the operating point, indicated by the black square, is determined by all system variables, such as active power injections, reactive power injections, tap positions of transformers, setpoints of phase-shifting transformers and set points of High-Voltage Direct Current (HVDC) connections. Therefore, the state space can be considered as a multi-dimensional space, with the number of dimensions equal to the number of constrained system variables [29]. The operating point continuously moves around as the system variables are subject to smaller and larger changes, such as load and generated power variations. The uncertainty regarding the system variables has increased during the last decade, which resulted in an increase of the surface area of the uncertainty cloud around the exact operating point, as shown in Fig. 2.3a and 2.3b. Component outages can result in a change of the system limits reducing the secure area, as shown by the dashed area in Fig. 2.3c for a line outage. Alternatively, a generator outage can move the original operating point ('1' in Fig. 2.3d) outside the secure area ('2' in Fig. 2.3d). If the operating point moves out of the secure area, the operator will take actions to restore the system to a secure state as indicated by the arrow in Fig. 2.3c and the arrow between '2' and '3' in Fig. 2.3d. Ideally, reliability control performs these actions at a minimal total system cost.

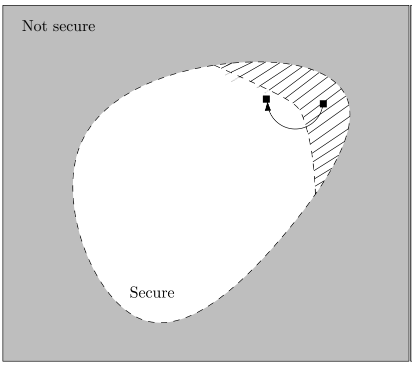
Reliability control actions can be taken on different time horizons and consist of multiple decision stages, with different degrees of available flexibility. Available reliability actions depend on the considered decision stage and time horizon.



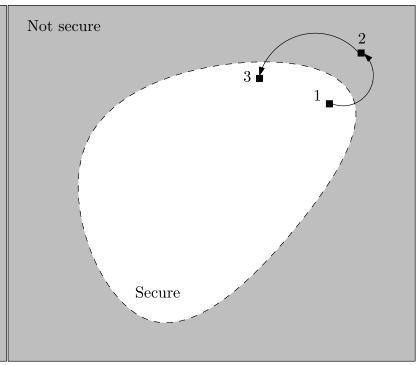
(a) Low uncertainty level.



(b) High uncertainty level.



(c) Line outage reduces secure area and action is required to restore security.



(d) Generator outage moves original operating state (‘1’) outside secure area (‘2’). Action is required to restore security (‘3’).

Figure 2.3: State-space border representations for different cases.

2.3 Main Decision Stages of Reliability Management

Overall power system reliability management is a multi-faceted and multi-dimensional decision-making process, ranging over a time span of years. It can be split in three main decision stages: long-term system planning and development [75], mid-term asset management and maintenance [76], and short-term operational planning and real-time operation [69]. These decision stages are strongly interlinked, consist of multiple processes and range over different time horizons, as shown in Fig. 2.4. Decisions taken on longer time horizons have an impact on shorter time horizons, as they can restrict the actions that are available or require outages to be planned. Moreover, flexibility available in short term should also be considered in long-term decision making.

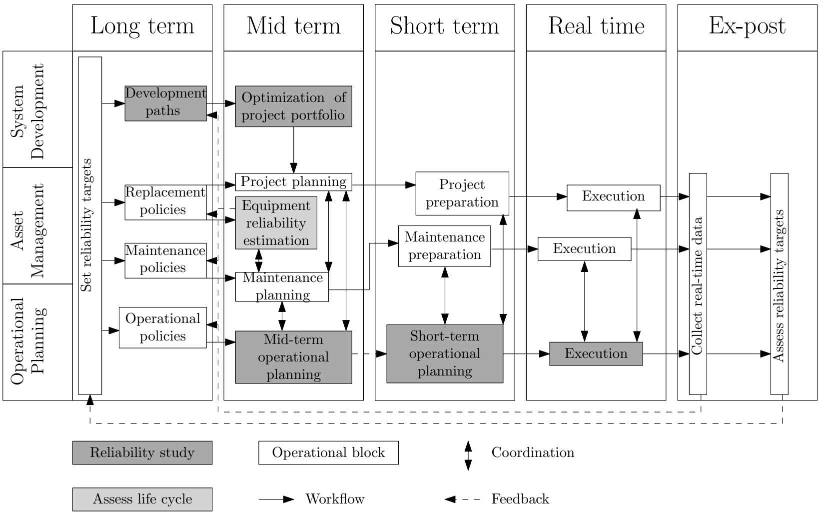


Figure 2.4: Overall power system reliability management split in three main decision stages ranging over multiple time horizons. (Remade after [69, 75, 76])

Uncertainty is higher the larger the time to actual operation, i.e., the system planner faces substantially larger uncertainties than the operator in the control room, as shown in Fig. 2.5. The state of the grid is more certain closer to real time, as well as the generation and load injections in the system. However, the flexibility and possibilities in terms of actions is higher the further from actual operation. The system planner is able to change the system more drastically, e.g., by building new transmission lines or flexible devices, such as a Phase-Shifting Transformer (PST), whereas the operator in the control room only disposes of the equipment available at the moment of real-time operation. Because of these differences, reliability management is performed differently in the different decision stages. This work mainly focuses on short-term operational planning and real-time operation.

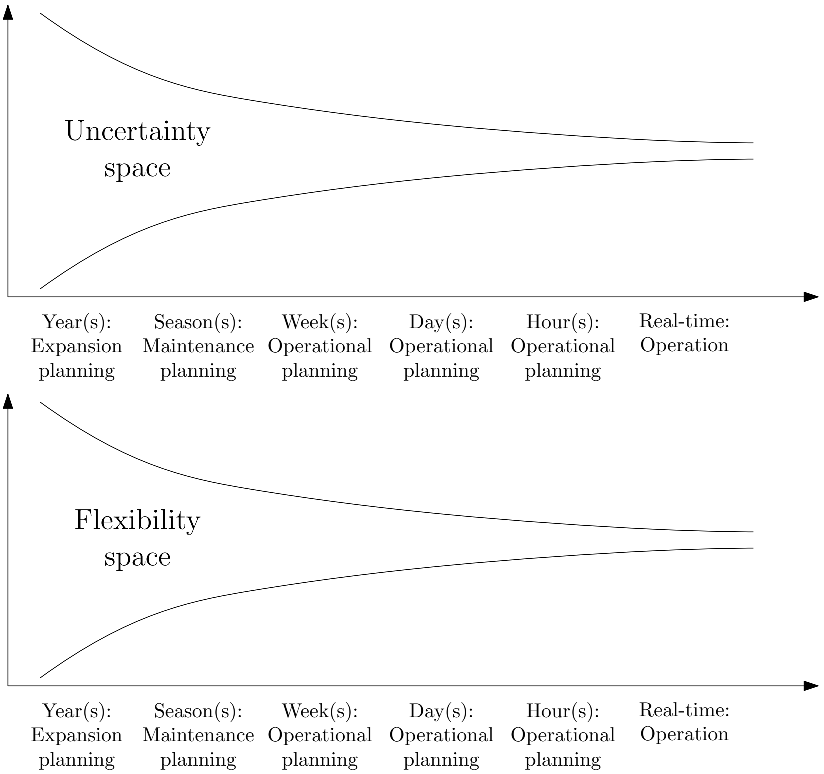


Figure 2.5: The uncertainty and flexibility space in various time frames [77].

2.3.1 Long-term Reliability Management: System Development

Long-term system development is defined to range from more than 10 years up to less than 5 years ahead of real-time [75]. The objective of system development is to install sufficient facilities in the system to enable it to be operated according to the relevant operating standards, taking into account the variation of generation and demand in time and space [75]. The system planner should answer four main questions [10]: (i) Where to invest?, (ii) What type of investment?, (iii) When to invest? and (iv) Who is going to pay for the investment?

Where traditional long-term system planning focused on extreme cases of demand, the number of analyzed generation and demand cases has been gradually increasing with the computational power that has become available. A larger set of cases covers more effectively the volatility in power flows due to renewable generation. These cases are used in a cost-benefit analysis to determine the necessary investments and topological changes in the system. Both cost savings in long-term system design and daily operation are considered.

Besides transmission system development, generation adequacy or security of supply is important to consider in the longer term. No harmonized European or regional standards exist to verify the adequacy, so each TSO adopts its own criterion. The Belgium system operator ELIA uses a probabilistic assessment to calculate the Loss Of Load Expectation (LOLE) and the LOLE95. The LOLE is the anticipated number of hours during which it is not possible for all available generation resources to cover the load in the system for a statistically normal year [78]. The LOLE95 has the same definition, but considers a statistically abnormal year. The thresholds on these indicators differ between countries in Europe, ranging from 3 hours per year in Belgium, France and Great Britain up to 8 hours per year in the Republic of Ireland. Furthermore, some countries, e.g., Sweden and Spain, use different indicators to verify the adequacy [79]. An adequate level of strategic reserves should be contracted to guarantee the security of supply.

2.3.2 Mid-Term Reliability Management: Maintenance and Asset Management

Mid-term reliability management includes both maintenance and asset management and is defined to range from roughly 1-2 years up to 1-2 months ahead of real-time operation [76]. In this time horizon, analyses for maintenance and replacement operations are carried out based on historical data rather than measured data, e.g., for weather forecasts. Although there is still significant uncertainty regarding the operational state, uncertainties are sufficiently reduced to perform a rough assessment of the future power system reliability level and to take preliminary actions to overcome the threats that are detected. Options to construct new transmission infrastructure are no longer available, but replacing conductors, installing reactive power devices or preparing protection schemes are feasible actions. These actions may require that other grid components are put out of service while the action is carried out. These scheduled outages should be planned in such a way that the system and its end-users are minimally affected.

Maintenance actions have a direct cost, but appropriate maintenance actions increase the reliability of the affected system components, resulting in less indirect costs at later decision stages. A good trade-off should be made between direct and indirect costs to avoid that expensive asset management is insufficiently compensated by reliability improvements [76].

2.3.3 Short-Term Reliability Management: Operational Planning and Real-Time Operation

Short-term operational planning and real-time operation is defined to range from the point where forecasts are available up to real-time [69]. Short-term operational planning prepares the system for secure operation and potential contingencies in real-time operation. It is not possible to add new infrastructure to the system at this point in time. Actions are restricted to the existing and available system components [69].

Eight main processes are distinguished in operational planning and real-time operation [69]:

1. Operational policies: Development and revision of operational policies regulating the methods and procedures to be used by system operators.
2. Forecasting: Spatio-temporal prediction of power supply and demand (by the use of mathematical models).
3. Determination of network capacities: Description of the technical congestions limiting the flow of power between nodes and regions.
4. Outage execution: Scheduling of forced outages requested in the asset management and system development decision stage.
5. Reserve management: Contracting long-term reserves, commitment of generators to act as reserves, activation of reserves and settlement of reserves.
6. Voltage control: Planning and execution of voltage control actions to maintain secure voltage levels across the transmission system. Voltage control actions are changing reactive power generation, setting of transformer tap positions, switching of on/off shunt reactors and other reactive compensation devices.
7. Control of component loading: Preventing power flows to violate operational limits of transmission system components taking into account the health of individual components passed from asset management tasks. Available control actions are PST adjustment, topological actions, set-point changing in HVDC converters (back-to-back, embedded connections and combined operation of links), generation redispatch and load curtailment.
8. System protection: Development and execution of system protection schemes, which are automated grid actions that are used in emergency states.

These tasks are also indicated in Fig. 2.6, together with their time span and their sub-tasks.

2.4 Reliability and its Cost

Efficient reliability management in the different decision stages makes a trade-off between the cost to obtain a certain reliability level, i.e., reliability costs, and interruption costs for end-consumers if a certain amount of electricity is not supplied. However, TSO's decision-making behavior is influenced by external actors that are out of TSO's own control, but are affected by the reliability of power systems. Each of these stakeholders experience their own costs and benefits. Fig. 2.7 gives an overview of the interactions between different stakeholders in terms of costs and benefits.

2.4.1 Reliability Costs

Reliability costs are defined as the sum of all the costs to obtain a certain level of reliability. Unreliability is determined by the frequency, duration and the extent of consequences of system malfunctioning. The reliability level can be maintained or improved by working on one or several of these aspects by taking appropriate actions in the different decision stages introduced in Section 2.3. These actions result in reliability costs for system operators. Reliability costs are increasing with the reliability level and reach infinity for a system with 100 % availability on all nodes [77].

2.4.2 Cost of Power Interruptions

Several types of power interruptions can be distinguished, such as a blackout, a brownout, a rolling blackout, load shedding, a local power interruption or load curtailment. A blackout is an unexpected, uncontrolled, complete interruption of power in a particular service area for an undefined period of time. Brownouts are deliberate decreases of system voltage (10%-25%) for a short period of time to prevent the system from failing completely. Most electronic devices do not suffer much from this suboptimal voltage, except for sensitive electronic equipment requiring precise voltage. These sensitive devices might not be able to function and can wear out prematurely due to long-term brownouts. Load shedding corresponds to intentional, controlled power cuts to avoid wider and uncontrolled problems and is applied in rolling blackouts. During a rolling blackout, the electricity supply is intentionally switched off in indicated areas

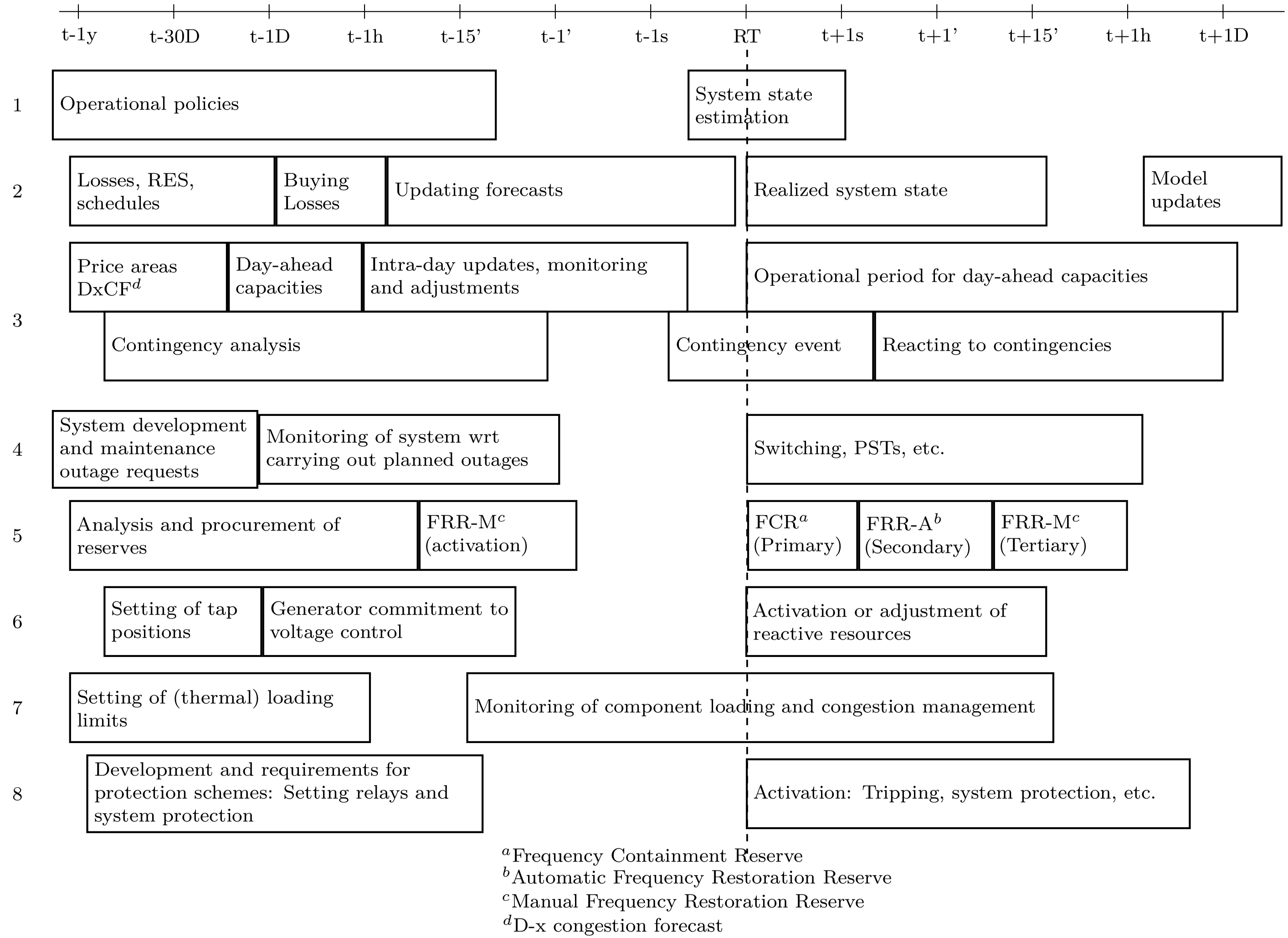


Figure 2.6: Processes in operational planning and real-time operation. (Remade after [69])

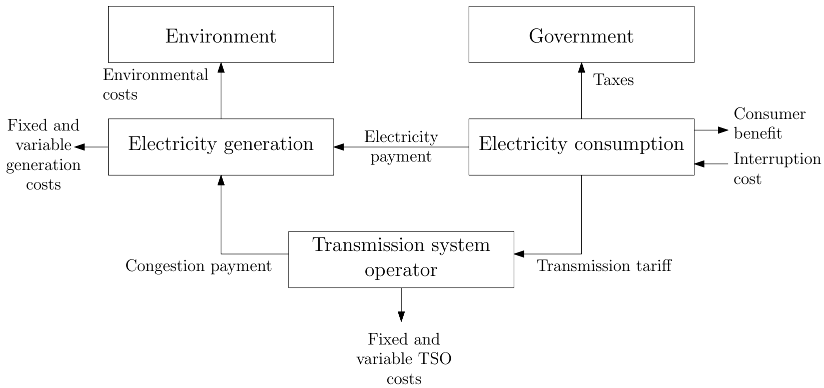


Figure 2.7: High-level interactions of costs and benefits of different stakeholders in power system reliability management. (Remade after [80])

for a fixed period of time.[10] Local power interruptions are unexpected and uncontrolled and are typically the result of an event without system-wide impact that results in a local power outage. Load curtailment entails the voluntarily reduction of load by consumers upon the request of the system operator to avoid load shedding or rolling blackouts or to improve efficiency of operation [81].

However, irrespective of the type of power interruption, consumers will incur a cost as they are not able to use the system for their intended use. This cost depends on the extent of the interruption (both in duration and magnitude) and the consequences of the interruption. The interruption extent is measured as Energy Not Supplied (ENS) [MWh], which is the product of the interrupted load [MW] and the interruption duration [h]. The value assigned to the unserved energy is denoted as the value of lost load. It represents the consequence of the interruption in terms of the average consumer cost, e.g., broken appliances, spoiled food, failed manufacturing, lost utility of electrical heating, etc., of a one-MWh interruption. VOLL is typically difficult and complex to model, as it is dependent on the location (e.g., what is the temperature at the location?), outage attributes (What is the duration, frequency, time, magnitude, ... of the outage?) and consumer attributes.

[10] Rolling blackouts were a hot topic in Belgium in the winter of 2014 - 2015. System adequacy was low at that time due to the retirement and mothballing of conventional power plants, supplemented by the unforeseen closure of three large nuclear units as a result of indication of micro-cracks in two of the reactor vessels and an outage due to sabotage. Eventually, they were not applied.

2.4.3 Optimal Reliability Management

The objective of optimal reliability management from a society perspective is maximization of social surplus. Social or socio-economic surplus is defined as the sum of surplus or utility of all stakeholders, including external costs and benefits, e.g., environmental costs [80].[11] However, social surplus is hard to determine, as not all data are available, especially not while performing short-term reliability management. Under two simplifying assumptions, surplus maximization can be approximated by the minimization of the sum of reliability and interruption costs [80]:

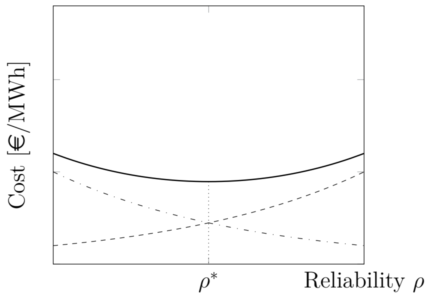
1. Changes in the electricity market should not change the behavior of electricity market actors, such as producers and consumers.
2. Changes in the electricity market should have little effect on other markets.

These two assumptions are never fully met. For example, if electricity becomes more expensive, consumers buy slightly less electricity and have less remaining budget to buy other goods. The sub-optimal reliability level is then the level at which the sum of reliability and interruption costs is minimal.

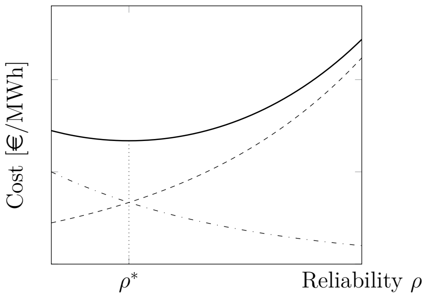
Total costs as a function of the reliability level ρ are represented in Fig. 2.8 by the solid line. Interruption costs, represented by the dashed-dotted line in Fig. 2.8, decrease with increasing reliability level, whereas reliability costs, represented by the dashed line in Fig. 2.8, increase with increasing reliability level. The optimal reliability level ρ^* is obtained at minimal total cost. It corresponds to the reliability level where the marginal reliability costs equals the marginal interruption cost. If the reliability level is above the optimal level, interruption costs are too low, whereas reliability costs are too high. If the reliability level is below the optimal level, interruption costs are too high, whereas reliability costs are too low. To determine if certain actions are increasing or decreasing total costs, the marginal cost and benefit of all possible actions need to be compared, i.e., one has to compare the cost of the action and the resulting decrease of interruption costs.

The optimal reliability level is hard to obtain in practice. Exact values for costs are hard to calculate, because the exact shapes of the functions of interruption cost and reliability cost are hard to determine. Moreover, the optimal reliability level changes over time, depending on external conditions such as e.g., weather. This is shown in Fig. 2.8b for the case with higher reliability cost, e.g., if a

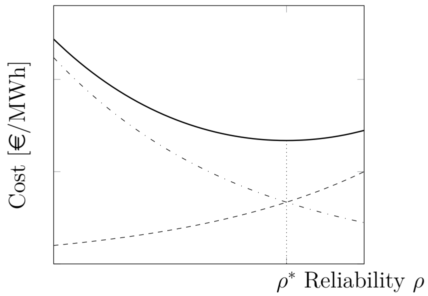
[11] Socio-economic or social welfare has a broader scope as it considers the aggregate utility from all existent markets, whereas surplus is the additional aggregate utility from the existence of one market, e.g., the electricity market [80].



(a) Reference



(b) Higher reliability cost.



(c) Higher interruption cost.

Figure 2.8: Total costs (——), interruption costs (- · - ·) and reliability costs (- - - -) as a function of the reliability level ρ.

sudden drop in RES output is to be expected, and Fig. 2.8c for the case with increased interruption costs, e.g., if harsh weather conditions are expected.

2.5 Deterministic and Probabilistic Short-Term Reliability Management Approaches and Criteria

Optimal reliability management, making a trade-off between reliability cost and interruption cost, is typically probabilistic in nature to take into account the risks related to the uncertainties in power systems. However, probabilistic approaches are seldom used in practical short-term power system reliability management so far. The currently-used N-1 criterion is deterministic. Deterministic and probabilistic approaches differ in several aspects of which one is the set of contingencies considered in the decision making.

2.5.1 Contingencies

A contingency is defined by the European Network of Transmission System Operators for Electricity (ENTSO-E) as the trip of one single or a combination of several network elements that cannot be predicted in advance [82]. High Impact Low Probability (HILP) contingencies are rare contingencies, which have a high impact due to their duration or their extent. They are typically caused by exceptional technical malfunctions, "force majeure" conditions, common mode failures or human errors and are most of the time tackled by the defense plan that is used in an emergency state [29, 83].

The literal meaning of the word contingency is "a future event or circumstance which is possible, but cannot be predicted with certainty". The notion of the word contingency in the context of power system reliability can be extended with state-space uncertainty, e.g., forecast errors in terms of wind and solar power generation and load. A scheduled outage, due to for instance maintenance activities, is not considered as a contingency.

In practice, it is impossible to consider and calculate all possible contingencies in reliability management, because the number of possible combinations of component outages increases as 2^N, with N the number of components in the system, and the state space representing load and generation uncertainty is continuous. For this reason, appropriate rules or state-selection techniques are required [84] or a discarding principle should be used in reliability management [85].

2.5.2 Deterministic Reliability Management

Deterministic RMACs are based on a prescribed set of credible contingencies and do not explicitly consider the probability and severity of these contingencies. Currently-used approaches only consider outages of components as contingencies, whereas uncertainty due to load and renewable power generation is not considered. Nowadays, the N-1 criterion is the most widely used security criterion in operational planning. Although the definition of the N-1 criterion is straightforward, i.e., the system should be able to withstand at all times the loss of any single element without significant degradation of service quality, its implementation differs between TSOs. Each TSO selects a set of credible contingencies, consisting of normal contingencies in its own system and some neighboring systems, as well as some exceptional contingencies. The loss of a single network element, e.g., a single line, a transformer or a generator, is considered as a normal contingency. Exceptional contingencies consist of a single event that affects multiple network components. The system should be secured against this set of credible contingencies, i.e., a credible contingency should not result in an unacceptable disconnection of load, a cascading outage or any other form of instability [86].[12]

Besides N-1, other deterministic reliability criteria exist and are in use. The N-2 criterion is used in parts of the United Kingdom where a higher security is required. It prescribes that the system should be secured against the simultaneous loss of two independent system components during normal operation [88]. In parts of Norway, for instance in very remote regions, the N-0 criterion is applied. This might result in a partial interruption of the power supply to consumers due to the loss of a single element causing violation of operational limits. Some TSOs do not have the strict interpretation that no loss of load is accepted, but have a certain limit to the loss of load that is accepted in the case of a failure [89]. Some TSOs apply the N-1-1 criterion or consecutive N-2 criterion, which considers a sequence of events consisting of the initial loss of a single generator or transmission component, followed by system adjustments, followed by another loss of a single generator or transmission component [90]. The TPL-001-1 standard of NERC specifies a deterministic criterion which is based on four categories of events with different post-fault requirements, as summarized in Table 2.1.

Table 2.1: System performance under normal conditions according to NERC TPL-001-1 standard [91, 92].

Category	System stable	Loss of demand	Cascading outages
N-0	Yes	No	No
N-1	Yes	No	No
N-k	Yes	Planned/controlled	No
N-1-1	Yes	Planned/controlled	No

In the past decades, operational experiences using these deterministic RMACs have been very good due to the predictability and controllability of power system operation. Moreover, N-1 criteria were easily satisfied due to the conservative design of the interconnections at the initial stage, although this could lead to non-optimal operation from a cost-benefit perspective.[13]

Deterministic reliability criteria are straightforward and easy to use, but they have several shortcomings in the light of evolving power systems. An important

[12] According to the system operation guideline of the ENTSO-E, the N-1 criterion means "the rule according to which elements remaining in operation within the TSO's responsibility area after a contingency from the contingency list must be capable of accommodating the new operational situation without violating operational security limits" [87].

[13] Interconnections initially aimed at reducing risks in terms of short-term adequacy, while keeping cross-border flows limited in normal operation.

drawback of a deterministic reliability criterion is that uncertainty is not appropriately considered. The probability and severity of outages of single network components are not explicitly considered. Moreover, uncertainties due to load and renewable power generation are completely ignored. Many stochastic aspects are inherent to power systems due to internal and external events. Firstly, outages are stochastic events, both in terms of their frequency and duration. Events occur stochastically, e.g., uncontrolled vegetation can lead to sudden short-circuits on overhead lines, power system components can fail in an unpredictable manner, etc. Secondly, demand and generation are fluctuating over time, resulting in uncertainties in operating point, both in real time and during forecasting. The variability of (particularly renewable) generation is linked to the weather conditions and influences the market behavior in the system. Furthermore, cross-border interconnections are currently utilized based on the interaction of different markets. The development of the European electricity market has resulted in significantly increased power flows, but also more variable flows.

2.5.3 Probabilistic Reliability Management

Probabilistic RMACs in operational planning take uncertainty into account in a more appropriate way. Considered contingencies due to outages and forecast errors are taken into account with their respective probability of occurrence. They are determined using appropriate state-selection techniques, which can be probability- or risk-based, [84] or based on a discarding principle [85].

Probabilistic RMACs enable the quantification of the reliability level, whereas deterministic criteria are strictly binary, i.e., the system is reliable or not. However, appropriate indicators should be selected to obtain an adequate quantification. A challenge is that the practical meaning of the absolute indicator values might not be very informative, because insufficient experience exists so far. Moreover, different indicators might result in different decisions to be taken [1]. Table 2.2 summarizes the advantages and challenges regarding probabilistic RMACs compared to the shortcomings of the deterministic N-1 criterion.

Probabilistic approaches are already used in reliability calculations for power system planning and development, e.g., to determine the generation reserve in the system development phase. Some countries that use probabilistic reliability criteria for planning are Australia [21], New Zealand [21] and the province of British Columbia in Canada [19]. Surveys have shown that TSOs seldom use probabilities in their short-term reliability management, except for some TSOs that exclude very rare events from the contingency list or treat extreme

Table 2.2: Advantages and challenges of probabilistic RMACs.

Advantages	Challenges
- Uncertainties included - Probability and severity of contingencies considered in decision-making process - Quantified reliability level	- High number of states to consider - Selection of appropriate indicators as different indicators imply different decisions - No practical experience

weather events differently due to higher associated failure probabilities [22, 89]. The Icelandic TSO Landsnet has experimented with probabilistic reliability assessment in the context of the GARPUR project and provided real-time risk information to the system operators in the control room [55]. The need for good reliability data has been identified as one of the barriers towards widespread utilization of probabilistic assessments [21].

2.5.4 Short-term Reliability Management based on the N-1 Criterion

System operation in Continental Europe is based on four operational states that are distinguished in the power system: normal, alert, emergency and blackout [93, 94]. Sometimes a fifth restoration state is added.

Normal In this state, the power system is N-1 secure. For all credible contingencies on the contingency list and taking into account the effect of predefined remedial actions, all operational limits are satisfied.

Alert The power system is in the N secure state. All operational limits are satisfied, but for at least one contingency on the contingency list, the N-1 security is non-compliant. Corrective actions need to be applied to return to the normal, N-1 secure state. If no satisfactory, corrective actions are available, the system will probably enter a less secure state once the operating conditions change, e.g., due to a new contingency or the change of system variables, such as load and generation.

Emergency Operational limits are violated and the system is strongly disturbed. A timely intervention is needed to avoid a full or partial system collapse. The defense plan is executed, consisting of a set of manual and automatic actions, to avoid system collapse and spreading of disturbances to other parts of the own system and neighboring systems. The automatic actions, often described in special and system protection schemes, aim at maintaining the integrity of the backbone of the power system. If part of the system is islanded or disconnected due to the emergency situation, restoration is required.

Blackout A blackout is an involuntary absence of voltage in a certain area of the system or the complete system. This state can result from abnormal variations of voltage or frequency occurring during the emergency state.

Restoration Restoration is the state in which the system is recovering from an alert, emergency or blackout state. If the system is in the blackout state, the objective is to re-energize the backbone of the transmission system as quickly as possible to gradually reconnect generating units and load. Effective restoration is required to minimize the downtime, the costs of the TSO and the interruption costs.

These operational states represent the viability of the system in its current operating modus [95]. The system operator makes decisions and eventually undertakes control actions based on the current and expected state of the system. In the normal state, system operators aim at meeting the standards at a minimal cost, while making provisions for secure, future operation [95]. Control actions can be preventive, i.e., applied prior to the occurrence of a contingency, or corrective, i.e., applied after the occurrence of a contingency. Preventive actions come at a cost, even though no contingency might occur. Corrective actions are predetermined to be activated immediately after the occurrence of a contingency and only infer costs if a contingency actually occurs. However, they imply an additional risk as they might not execute as expected, resulting in insufficient time to take alternative actions. The latter is also denoted as the uncertainty regarding the corrective control behavior. In the alert and emergency state, actions aim at preventing further degeneration. The cost of actions is of less concern in these states and the primary concern is to restore the system in the normal state as quickly as possible.

The impact of contingencies might not be limited to the own control area due to interconnections between systems. Moreover, different TSOs have a different implementation of the N-1 reliability criterion. Therefore, communication and data sharing between TSOs is of utmost importance. Surveys have shown that TSOs are willing to share data among each other, but confidentiality is an important issue for some TSOs [89].

2.6 Conclusion

An adequate reliability level in power systems is crucial due to the criticality of electricity supply for modern societies. Power system reliability is determined by the system's vulnerability, the threats the system is facing and the applied reliability criterion. Reliability management aims at taking a sequence of decisions under uncertainty to meet the applied reliability criterion, while minimizing the socio-economic costs. An appropriate trade-off should be made between actions at different, interlinked decision stages focussing on system development, maintenance and asset management and operational planning and real-time operation. Each of the decision stages is characterized by the available flexibility and uncertainty in the system.

Nowadays, a deterministic N-1 criterion is applied in short-term reliability management. The deterministic N-1 criterion is easy to use and straightforward and has lead to satisfactory results in the past. However, evolutions in power systems challenge currently-used deterministic reliability management approaches and criteria. Deterministic RMACs do not appropriately consider uncertainties in power systems. Their main focus is on providing sufficient redundancy in the system as they favor preventive actions and do not take into account post-contingency costs.

Probabilistic RMACs on the contrary take into account risks related to uncertainties in a more appropriate way. They enable a trade-off between reliability and interruption costs to minimize total system cost. Compared to a few decades ago, system operators have more flexible devices at their disposal to control power flows in short-term operational planning and real-time operation, which enables more efficient operation. Probabilistic RMACs enable system operators to exploit the potential of modern technologies and to re-assess the trade-off between redundancy and flexibility at the different decision stages. To convince power system stakeholders to move towards alternative RMACs, evaluating and comparing different RMACs is crucial.

Chapter 3

Performance Metric for Reliability Management

A large literature consisting of both scientific papers and technical reports exists on quantitative indicators and indices that are used or proposed for use in power system reliability management. However, the literature is not coherent and the terminology is not unified. Moreover, an up-to-date overview and classification of indicators does not exist. More than 15 years ago, Allan and Billinton [18] made a review of existing approaches and measures to evaluate the quality and performance of different power system sectors, such as generation, transmission and distribution. Their discussion of indicators is limited to best practices in the context of probabilistic reliability assessment in systems with more competition and more stakeholders and does not take into account the increasing penetration of RES in the system.

This chapter provides insight in the structure and characteristics of available indicators and indices and how they can be used to represent the performance of a reliability management approach. A classification and characterization of indicators and indices is proposed to serve as a reference for indicator selection and development. Furthermore, a multi-dimensional performance metric to assess the performance of RMACs is proposed.

Section 3.1 clarifies the terminology used in the remainder of the chapter. Section 3.2 discusses characteristics of quantitative indicators and indices. Section 3.3 describes different classes of indicators and their characteristics. This classification is based on a survey of technical reports of system operators and coordinating bodies, such as NERC, ENTSO-E and CEER, as well as scientific literature. Section 3.4 proposes a 'reliability management performance metric' that defines the aspects determining performance of reliability management approaches and criteria and enables the assessment of the multi-dimensional performance. The quantitative and qualitative indicators used in this multi-dimensional metric are described in Sections 3.5, 3.6 and 3.7. Section 3.8 concludes the chapter. An overview of indicators and indices proposed in literature is provided in Appendix A. The described classification and characterization is applied to this set of indicators. Based on this overview, indicators still missing to fully represent performance of reliability management are identified.

This chapter is partly based on the paper *Review and Classification of Reliability Indicators for Power Systems with a High Share of Renewable Energy Sources, Heylen E., Deconinck G. and Van Hertem D.* submitted to Renewable and Sustainable Energy Reviews.[14]

3.1 Definitions

Literature on power system reliability does not make a clear distinction between the terms *measure*, *metric*, *index* and *indicator*. A *measure* is defined as a value quantified against a standard [96], whereas indicators are not related to a standard. Several definitions of the term *indicator* exist. The term *indicator* refers to an observable measure that provides insight into a concept that is difficult to measure directly [97]. According to OECD/DAC[15], an indicator is "a quantitative or qualitative factor or variable that provides a simple and reliable means to measure achievement or to reflect changes connected to an intervention" [98]. According to the definition adopted by USAID[16], an indicator is "a quantitative or qualitative variable that provides reliable means to measure a particular phenomenon or attribute" [99]. However, in the strictest sense, an indicator does not measure. An indicator can be considered as an indication of a measure.

An *index* is defined as a combination of related indicators that intend to provide means for meaningful and systematic comparisons of performance across programs that are similar in content and/or have the same goals and objectives [100]. It can be denoted as a scaled composite variable that can be

[14] The first author is the main author of the paper. The contributions of the first author include the literature survey of reliability-related indicators to identify a characterization and classification of indicators and to make an overview of available indicators.

[15] OECD/DAC: Organisation for Economic Co-operation and Development/Development Assistance Committee

[16] USAID: United States Agency for International Development

considered as a kind of summary measure designed to capture some property in a single number. An index can be considered as a composite statistic that aggregates multiple indicators and makes it possible to rank and summarize observations [101, 102].

Metrics help to put a variable in relation to one or more other dimensions [96]. A *metric* is often used as a general term to describe the method used to measure something, i.e. the resulting values obtained from measuring, as well as a calculated or combined set of indices [103].

Table 3.1 summarizes the definitions.

Table 3.1: Summary of the terminology.

Term	Definition
Measure	Value quantified according to standard
Indicator	Quantitative or qualitative indication of achievement
Index	Composite statistic based on measures and indicators making it possible to rank and summarize observations
Metric	Set of measures, indicators or indices to evaluate a certain property

3.2 Characteristics of Indicators

A multitude of characteristics of indicators and indices (proposed to be) used in reliability management can be distinguished. A unified characterization facilitates the assessment of similarities and differences between indicators. This enables the classification of indicators and indices.

3.2.1 Types of Indicators

Endrenyi distinguished four types of indicators to assess system malfunctioning in a power system reliability context: probabilities, i.e., what is the chance that the system is malfunctioning, frequencies, i.e., how often does the system malfunction, mean durations, i.e., how long lasts the system malfunctioning on average, and expectations of malfunctioning [104]. Replacing *expectations* by *magnitude* results in a more generic characterization. The magnitude of malfunctioning corresponds to the degree of violation of the boundary of acceptable behavior or the magnitude of the consequences of malfunctioning. To determine the proper functioning of a component or system, a definition of satisfactory behavior is required. Based on this definition, the performance of the system can be determined. Risk is an additional type of indicator, which is particularly of interest in the context of increasing uncertainties. Risk indicators take into account the probability and severity, i.e., the magnitude of the consequence, of malfunctioning. These different types of indicators can be further subdivided based on different characteristics.

Hierarchical Levels

Traditionally, three hierarchical levels have been distinguished. In classical power system reliability literature, hierarchical level I (HLI) focuses on the generation facilities, whereas hierarchical level II (HLII) considers both the generation and transmission facilities. Hierarchical level III (HLIII) covers the combination of generation, transmission and distribution facilities [23].[17] Indicators can be specific for a particular level or can be used at multiple levels. Due to the increased penetration of RES and their distributed character, the strict distinction between the three hierarchical levels diminished.

Measures

The main objective of power system reliability management is to obtain a low frequency of inability to serve load with the required quality and a very low frequency of experiencing spectacular system failures, such as blackouts [23]. To achieve this, physical measures, such as voltage, frequency, loading of components, stability and current, should be within limits. Cost-effectiveness of reliability management also comes more to the foreground, which asks for monetary measures to be monitored.

Type of the interruption

A distinction can be made between sustained interruptions and short or momentary interruptions [105]. Especially HLIII indicators make a distinction between types of interruptions based on their duration. Moreover, different indicators can be calculated for planned and unplanned interruptions, which is related to their advance notification [106]. The cost of energy not supplied (CENS) regulation in Norway additionally considers the time of occurrence of the interruption [106].

[17] HLIII studies in practice mainly focus on the distribution level to reduce the problem size.

Scope of the Indicators

Allan and Billinton distinguish between system indicators and load point indicators [18]. They define system indicators as global indicators representing the behavior of the overall system. System indicators are extremely valuable in the context of global observations. Load point indicators on the contrary focus at individual bulk supply points. They evaluate the impact of a certain reliability decision on a particular bulk supply point. Allan and Billinton explicitly mention the complementarity of both types of indicators.

Alternative terms to denote the scope of an indicator are zonal and local indicators. Zonal indicators operate system wide, local indicators by contrast focus on a smaller part of the system, such as a component[18], a node or a supply point. Zonal indicators need to be considered complementary to the local values to provide an overall picture of system behavior [108].

Consumer- and System-Related Indicators

A distinction can be made between indicators that are consumer- and those that are system-related. Consumer-related indicators focus on the impact of an event on one or more consumers. Local consumer-related indicators represent the performance of a particular consumer or consumers of a load point or region, whereas zonal indicators consider all consumers in the system. System-related indicators on the contrary quantify system-related concepts, such as voltage, current and frequency. Local system indicators focus on parts of the system, e.g., a single component or node in the system, whereas zonal system indicators look at the overall system.

Mono-, Bi- and Multi-Parametric Indicators

Indicators can be classified as mono-parametric, bi-parametric and multi-parametric indicators. Mono-parametric indicators employ a single statistical parameter, whereas bi-parametric indicators are expressed by two statistical parameters [109]. A frequency and duration indicator for instance gives information on the average rate a specific state is encountered and the average

[18] A component is a device which performs a major operating function and which is regarded as an entity for purposes of recording and analyzing data on outage occurrences, such as a transformer, series capacitors or reactors etc. Components can consist of multiple sub-components, which are a part or portion of a component which is relevant for quantifying exposure to outage occurrences, or failures, or both, or for identifying the cause of an outage occurrence or failure [107].

residence time in a specific state [109]. Moreover, multi-parametric indicators, i.e., expressed by more than two statistical parameters, can be distinguished.

Leading and Lagging Indicators

Lagging indicators are result-oriented, measure historical events, and tend to be easier to interpret than leading indicators. Leading indicators precede events and are more difficult to obtain. The objective of leading indicators is to recognize and eliminate unreliable actions and at-risk conditions [110]. Leading indicators tend to change before an activity and, as a consequence, can be used as a predictor. They are also denoted as pro-active indicators [97]. Leading indicators gain importance given the increasing uncertainty in power systems. Leading and lagging indicators can also be denoted as ex-ante and ex-post indicators respectively.

Deterministic and Probabilistic Indicators

Indicators can be deterministic or probabilistic in nature. Ex-post or lagging indicators can generally be considered as deterministic. Leading or ex-ante indicators can be deterministic or probabilistic.

Most deterministic indicators are lagging indicators used to measure the historical performance of the power system. Some leading deterministic indicators exist as well, which can be used as an indication for the future performance of the system.

Probabilistic indicators are typically expectations, i.e., the average of a probability distribution [111], which are used ex-ante to estimate the system's performance [112]. They capture uncertainty more adequately than deterministic indicators as both severity and probability of events can be considered. This makes them especially useful in systems with increasing uncertainties.

Activity and Outcome Indicators

A distinction can be made between activity and outcome indicators. Activity indicators give information on the level of targeted activities to improve reliability, whereas outcome indicators measure whether the targeted activity has led to an improved reliability level [97].

3.2.2 Type of Assessment

The reliability assessment to evaluate a particular indicator can be a short- or long-term assessment. Short-term reliability assessment can be dynamic, pseudo-dynamic or static [73, 74] and typically focuses on the composite generation and transmission level (HLII). Long-term reliability assessment is more high level and can focus on the generation level (HLI), the composite generation and transmission level (HLII) or the distribution level (HLIII). The long-term assessment is typically static in nature. Long-term assessments can span years up to decades, whereas short-term assessments typically span seconds up to hours.

3.2.3 Types of Indicator Values

Different types of indicator values can be distinguished, such as maximal or minimal values, average/mean values, expected values, probability density functions, instantaneous values, value at risk, conditional value at risk, etc. Also the period over which the indicator is evaluated can differ. Annual, monthly, daily, hourly or instantaneous indicators can be distinguished or an indicator can focus on a particular period in the year, the worst period for instance [105]. The type of indicator that can be obtained is also related to the type of assessment. Moreover, a distinction can be made between annual and annualized indicators [108].

3.3 Classification of Indicators and Their Characteristics

Literature typically distinguishes adequacy, security and reliability indicators. With the ongoing research on advanced probabilistic reliability management approaches and criteria that aim at cost-effective reliability management, socio-economic indicators gain importance. The focus of this section is to discuss different classes of indicators and attributing characteristics to each of the classes, which facilitates the classification and characterization of indicators.

3.3.1 Adequacy Indicators

Adequacy indicators represent the ability of an electric power system to supply the aggregate electric power and energy required by the consumers, under steady-state conditions, with system component ratings not exceeded, bus voltages and system frequency maintained within tolerances, taking into account planned and unplanned system component outages [44]. The focus is on the consumers rather than the system or individual components. Adequacy indicators are the result of a steady-state assessment and are physical rather than socio-economic in nature. Adequacy indicators exist for the three hierarchical levels as outlined in Section 3.2.1, i.e., generation (HLI), composite generation and transmission (HLII) and composite generation, transmission and distribution (HLIII) [18, 109]. They can be lagging and deterministic or leading and probabilistic outcome indicators. The indicators are of four types, i.e., magnitude, probability, frequency and duration.

3.3.2 Security Indicators

Security indicators show the ability of the system to be operated in such a way that credible events do not give rise to loss of load, operation of system components beyond their ratings, bus voltages or system frequency outside tolerances, instability, voltage collapse, or cascading [44]. Security indicators focus on the composite generation and transmission system (HLII). They are system rather than consumer related. Security indicators are determined based on the results of a dynamic, pseudo-dynamic or steady-state security assessment, depending on whether transients after the disturbance are neglected or not [71]. Steady-state security can be considered as a first-order approximation of the dynamic power system state [73]. Alternatively, pseudo-dynamic evaluation techniques using sequential steady-state evaluation to assess the impact at several post-contingency stages exist [74]. Physical indicators resulting from the security assessment are compared with security limits to determine whether the system operates within security limits and if not, to determine the magnitude of the security limit violation. Security indicators can be deterministic, leading or lagging, or probabilistic, leading outcome indicators. They can be of all five types, i.e., risk, magnitude, probability, frequency and duration. Risk-based security indicators are especially suitable in a context of increasing RES penetration.

3.3.3 Socio-Economic Indicators

Probabilistic RMACs based on socio-economic principles incorporate socio-economic indicators in their decision making [47, 42]. Socio-economic indicators represent different types of costs, benefits or surpluses of individual power system stakeholders or the aggregated system. Actors impacted by power system

Table 3.2: Overview of costs and benefits of and socio-economic interactions between power system stakeholders resulting in an overall system balance [80].

	Stakeholders' balances			System balance
	Consumer balance	Producer balance	System operator (SO) balance	
System costs	+ Consumer benefits			+ Consumer benefits
	- Interruption costs			- Interruption costs
		- Variable costs		- Variable producer costs
		- Fixed costs		- Fixed producer costs
			- Variable costs	- Variable SO costs
			- Fixed costs	- Fixed SO costs
Cost transfers	+ Interruption compensation		- Interruption compensation	
	+ Demand response payment		- Demand response payment	
	- Transmission tariff		+ Transmission tariff	
	- Electricity payment	+ Electricity payment		
		- Capacity fee	+ Capacity fee	
		+ Reserve payment	- Reserve payment	
		+ Congestion payment	- Congestion payment	

reliability are producers, system operators, end-consumers, the government and the environment, all facing different types of costs and benefits. A high-level representation of socio-economic interactions between consumers, producers and system operators is given in Table 3.2. Each of these stakeholders has its own balance, while the interactions between them result in an overall system balance. The upper and lower part of the table make a distinction between respectively system costs and cost transfers. System costs and benefits have resp. a negative and positive effect on socio-economic surplus. Cost transfers appear as costs to a certain stakeholder, while being a payment, and thus benefit, to another stakeholder. Cost transfers do not affect the socio-economic surplus.

Socio-economic indicators can be deterministic or probabilistic. Both socio-economic activity and outcome indicators exist. Socio-economic indicators mainly represent a risk or a magnitude and can focus on the system, the consumer or both at the same time. They can be the result of a long-term or a short-term assessment.

3.3.4 Reliability Indices

The definition of reliability indices differs between different sources. In [44], reliability indices are defined as indications of the probability that an item or system can perform as required, without failure, for a given time interval[19], under given conditions.[20] According to [44], reliability indices are restricted to durations, frequencies and probabilities. By contrast, reliability indices are in some cases also denoted as reliability performance indices. NERC defines reliability as "an electricity service level or the degree of performance of the bulk power system defined by accepted standards and other public criteria" [110]. In this context, reliability indices can be considered as kind of summary measures to represent the system performance with regards to the reliability criterion or reliability standards.

Reliability depends on the one hand on how the system is loaded in comparison to its limits and on the other hand on the reliability of each of its individual components. The calculation of reliability indices is based on adequacy, security and socio-economic indicators and depends on the applied reliability criterion. Up till now, reliability management was mainly based on physical indicators, but the potential of reliability management based on socio-economic principles is recognized in scientific literature [13]. Reliability indices can focus on the consumers and/or the system and can be local or zonal indices. Moreover, all hierarchical levels can be represented in integrated indices, which can combine adequacy, security and socio-economic indicators of different types with appropriate weighing factors, as introduced by NERC in its Integrated Reliability Index (IRI) [110].[21]

3.3.5 Other Types of Indicators

Hofmann et al. [68] formulate high-level indicators for monitoring vulnerability. A distinction needs to be made between indicators for threats, susceptibility, coping capacity and criticality.[22] Indicators for threats and susceptibility are divided in classes: threats due to natural hazard, human threats and threats due to operational conditions [68].

[19]The time interval duration may be expressed in units appropriate to the item concerned, e.g., calendar time, operating cycles, distance run, etc., and the units should always be clearly stated [44].

[20]Given conditions include aspects that affect reliability, such as mode of operation, environmental conditions and maintenance, where applicable [44].

[21]The integrated risk index is discussed in more detail in Appendix A.

[22]The criticality of an infrastructure represents the dependency of the society on that infrastructure [113].

3.3.6 Summary

A summary of the general characteristics of the different classes of indicators is given in Table 3.3. The four classes contain deterministic and probabilistic indicators and incorporate local and zonal indicators.

The distinction between adequacy indicators focusing on the composite generation and transmission system and security indicators resulting from a steady-state analysis and focusing on loss of load is not that clear from their definition. This distinction depends on the type of assessment. Some of the indicators denoted in literature as security indicators can also be classified as HLII adequacy indicators. This is indicated by (x) in Table 3.3. Multiple 'x' in the same section of Table 3.3 indicate that different indicators of that class have different characteristics related to that section. It does not mean that all characteristics need to be present at the same time.

Table 3.3: Characteristics of different classes of indicators.

	Assessment		Measure		System vs consumer		Hierarchical level		
Indicators	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adequacy	o	x	x	o	o	x	x	x	x
Security	x	o	x	o	x	(x)	o	x	o
Socio-economic	x	x	o	x	x	x	o	x	x
Reliability	x	x	x	x	x	x	x	x	x

(1) Short term, (2) Long term, (3) Physical, (4) Socio-economic, (5) System, (6) Consumer, (7) HLI, (8) HLII, (9) HLIII
o = not applicable, x = can be applicable

An overview and classification of indicators and indices proposed in technical and scientific literature is provided in Appendix A. Based on this overview, indicators or indices that are still missing to characterize the different aspects determining the performance of RMACs are identified.

3.4 Reliability Management Performance Metric

The performance of power system reliability criteria is multi-faceted and several opposing objectives need to be considered. To adopt an RMAC, its economic, technical and social acceptability, applicability and practicality are crucial.

Technical acceptability represents the satisfaction of operational limits. These limits are typically verified using physical security indicators. Nowadays, mainly lagging, deterministic indicators are used, which are easy to obtain. NERC and ENTSO-E have defined metrics in terms of lagging deterministic indicators to verify the technical performance [66, 87].[23] However, leading, probabilistic, physical indicators, such as the ones proposed in [41, 45, 114, 115] and the Severity Risk Index (SRI) of NERC [116], are proposed in the literature since the beginning of this century. They enable pro-active behavior in systems with increasing uncertainty as a result of increasing RES penetration.

Economic acceptability evaluates the level of social surplus resulting from the RMAC. Social surplus can be considered as the ideal index for reliability management, but it is not easy to use in practical reliability assessment and TSO decision making. Not all data needed to evaluate socio-economic surplus are available at the moment of decision making and some of the data are difficult to obtain. The value of reliability from the consumer perspective is for instance hard to determine in practice, because the societal value of electric service reliability is very complex and multi-faceted [117]. Total system cost is used as an alternative for social surplus, as it is a good approximation under certain assumptions [80].

Social acceptability is concerned about how the reliability level is perceived by the end-consumers. So far, a formal definition of social acceptability in a power system reliability context does not exist. A definition in an ecosystem management context states: Social acceptability results from a judgmental process by which individuals compare the perceived reality with its known alternatives; and decide whether the 'real' condition is superior, or sufficiently similar, to the most favorable alternative condition. If the existing condition is not judged to be sufficient, the individual will initiate behavior, eventually within a constituency group, that is believed likely to shift conditions toward a more favorable alternative [118]. In a power system reliability context, judgement can be made in terms of the absolute level of unreliability and interruption cost, but also in terms of the distribution of unreliability among consumers. The absolute level of reliability can be represented by adequacy indicators, such as energy not supplied, interruption duration or interruption frequency. The distribution of unreliability among consumers determines the inequality and inequity between consumers and whether consumers perceive to be treated fairly. Indices that quantify the inequality or inequity in terms of the distribution of unreliability among consumers, nodes or consumer groups did not exist so far, but have been developed in the context of this work.

Applicability is determined by the data requirements of the RMAC. It needs to be assessed whether the required data are available or can be collected, whether they are sufficiently accurate and whether they can be used or are protected due to confidentiality issues. Practicality of an RMAC is determined by its ease of use, especially compared to the currently used N-1 approach. Table 3.4

[23] The metrics of NERC and ENTSO-E are discussed in more detail in Appendix A.

gives an overview of the reliability management performance metric. Technical acceptability is ensured by the operational limits considered in the RMAC. Sections 3.5 - 3.7 elaborate on the other aspects of the performance metric.

Table 3.4: Reliability management performance metric.

	Technical	Economic	Social
Acceptability	Operational limits	Total cost/efficiency	Equity Equality Reliability Interruption cost
Applicability	Data integrity and availability e.g., accuracy of measurement devices, time to collect the data	Data availability e.g., Cost of collecting the data	Confidentiality e.g., Data sharing
Practicality/ Ease of use	Objective function Number of states Amount of information and number of reliability indicators		

3.5 Economic and Social Acceptability

Economic and social acceptability of a reliability management approach and criterion are in this work proposed to be verified based on three quantitative indicators: total cost of system operation, the amount of load curtailment in the system and inequality and inequity indices evaluating the distribution of reliability between consumers, nodes or consumer groups.

3.5.1 Total System Cost

Total system cost is the sum of the cost of preventive actions, the cost of corrective actions and interruption costs. Interruption costs equal the amount of load curtailed times the value of lost load (VOLL) and represent the consequences of an interruption for the consumers. The total cost (TC) at a certain time t and real-time state rt is equal to:

$$TC(rt,t) = C^{prev}(\mathbf{a}^{prev}) + C^{corr}(\mathbf{a}^{corr}_{rt}) + \sum_{j \in \mathcal{J}} v_j \cdot P^{curt}_{j,rt} \tag{3.1}$$

where $C^{prev}(\mathbf{a}^{prev})$ and $C^{corr}(\mathbf{a}^{corr}_{rt})$ are resp. the cost of preventive and corrective actions, $\mathbf{a}^{prev}$ and $\mathbf{a}^{corr}_{rt}$ are vectors of resp. preventive and corrective actions, v_j is the value of lost load of consumer j, $P_{j,rt}^{curt}$ is the load curtailment of consumer j in real-time state rt and $\mathcal{J}$ is the set of consumers in the system. Efficiency is defined in this context in terms of potential cost savings of an RMAC compared to the benchmark.

3.5.2 Load Curtailment in the System

The amount of load curtailment in the system, aggregated, per node or per consumer, is here expressed in terms of Relative Load Curtailment (RLC). Relative load curtailment is expressed as the amount of load curtailment rescaled to an equivalent number of minutes in a year:

$$RLC = \left(\frac{P^{curt}}{P^{load}}\right) \cdot 8760 \cdot 60 \qquad [\text{min/year}] \tag{3.2}$$

Where P^{load} is the total demand and P^{curt} is the curtailed load. The indicator RLC is thus an indicator of the absolute level of unreliability in the system.

3.5.3 Inequality in terms of Reliability

Different RMACs imply different reliability decisions [63]. Reliability decisions do not affect all consumers equally. Some are more affected than others, depending on their location and characteristics. If consumers feel that their reliability level is unfairly low compared to other consumers, they could complain and oppose those decisions that lower their reliability level. Therefore, in addition to measuring the change in costs and the change of the overall reliability level, this dissertation argues that power system decision makers should also measure the distribution of unreliability among consumers. Indices to quantify inequality and inequity are developed based on the Gini index, which is used in an economic context to quantify income inequality amongst others. Chapter 6 presents the indices to quantify inequality and inequity in terms of reliability in a single value.

3.6 Data Requirements of RMACs

Appropriate data are important for decent reliability management. Data requirements determine the applicability of RMACs and are a qualitative aspect to be considered in the performance evaluation of an RMAC. The performance of reliability management approaches and criteria can be sensitive to the accuracy of the provided data and required data are not necessarily available or easy to collect. Data requirements of an RMAC are hard to evaluate quantitatively and are assessed by a qualitative indicator based on a scoring system.

3.6.1 Additional Data Requirements in Probabilistic RMACs

Probabilistic reliability management approaches and criteria have additional data requirements compared to their deterministic counterparts. Probabilistic approaches explicitly consider the risk related to power system uncertainties and determine decisions based on a trade-off between reliability and interruption costs. Data are required that appropriately represent uncertainties and costs in the decision-making behavior.

An overview of the data requirements of short-term probabilistic RMACs is given in Table 3.5. Short-term reliability management is influenced by system component and exogenous factors. Technical data are required about system components, such as overhead lines, cables, transformers etc., and exogenous factors, such as demand and generation. These should be complemented in probabilistic approaches with availability data of system components and a quantification of uncertainty regarding exogenous factors, such as demand, generation and weather conditions. Moreover, uncertainty regarding corrective control behavior, i.e., whether the planned corrective control action is executed as expected, can be considered in probabilistic reliability management. The trade-off between reliability and interruption costs made in fully probabilistic RMACs also requires cost data regarding generation, demand and transmission.

Uncertainty

Three types of parametric uncertainty are typically considered in short-term probabilistic RMACs: (i) Related to the availability of system components, (ii) related to load and (RES) generation and (iii) related to the reliability of corrective actions.[24]

i. Availability of system components is determined by their reliability and maintainability. Reliability is defined as the ability to perform as required, without failure, for a given time interval, under given conditions [44]. The reliability of system components is characterized by their failure rate.

[24] Besides the parametric uncertainty, other types of uncertainty are parameter, stochastic, algorithmic, structural, measurement, multi-model and decision uncertainty [119].

Table 3.5: Data requirements for probabilistic RMACs.

	System components	Exogenous	Cost data	
Technical	OHL[a] Cables Transformers SPS[b]	Demand Generation	Generation	Reserves Redispatch Marginal cost ...
Availability	Breakers, Switches Substations VAR compensators		Demand	VOLL Electricity price ...
Uncertainty	Corrective control behavior	Demand Generation Weather	Transmission	Congestion Switching Tap changing Losses ...

[a] Overhead lines
[b] Special protection schemes

Maintainability is defined as the probability of performing a successful repair action within a given time. It measures the ease and speed with which a system can be restored to operational status after a failure occurs [120]. Failure and repair rates are highly impacted by several factors: climate and weather conditions, human behavior, component quality and age, maintenance, replacement and repair policy and quality, loading level, geographical factors and voltage level [121].

ii. Operational planning decisions are based on forecasts of load and RES generation, which are sensitive to forecast errors. Uncertainty regarding load and RES realizations can be represented by a multivariate probability density function incorporating the correlations between these parameters.

The uncertainty of short-term wind power generation P^{wind} for a given forecast $P^{wind,*}$ is given by the probability density function $\Pi_{P^{wind,*}}(P^{wind})$ [122]. This Probability Density Function (pdf) changes with the range of the wind farm power output. Moreover, although wind speed prediction errors can be assumed to be Gaussian, the pdfs of the forecast errors related to the wind power output are not Gaussian. A reasonable assumption for the distribution of the forecast errors of wind power outputs is a beta pdf, due to the bounded nature of the power produced by a wind farm.[25] The mean of the distribution is the forecast value, whereas the standard deviation depends on the level of power injected compared to the rated power of the wind farm. This behavior can

[25] Alternatively, the pdf can be estimated based on historical data using non-parametric approaches.

be approximated using a quadratic curve [122]. The standard deviation is thus a function of the normalized forecast value $P_{nom}^{wind,*}$ as shown in Fig. 3.1.

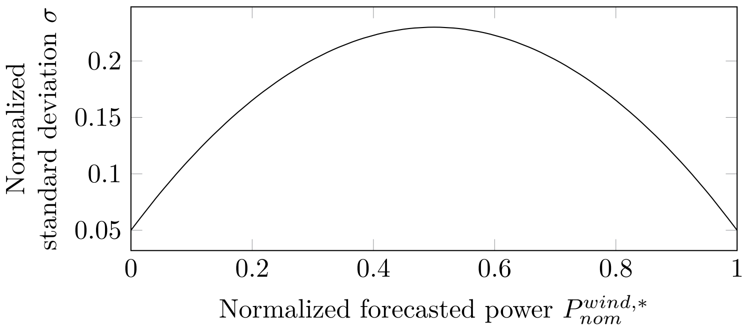


Figure 3.1: Relation between the normalized standard deviation and the normalized forecast value.

Forecast uncertainty of demand can be represented as a multivariate normal distribution with the mean equal to the forecast value and an appropriate coefficient of variation, which is typically smaller than 10% [122]. Correlation between the forecast errors of demand at different nodes in the system and between different wind farms are modeled using a correlation matrix [122], rank correlation or copulas [123].

Uncertainty related to forecast errors is modeled in probabilistic reliability management by considering discrete realizations of forecast errors [57] or using probabilistic constraints [58, 124] in a stochastic programming approach.

iii. Probabilistic reliability management enables a trade-off between preventive and corrective actions, i.e., taking actions to make the system secure ahead of real time with the risk of having unnecessary costs if no contingency occurs versus preparing actions to take at the time a contingency occurs. The latter is risky in the sense that the prepared action might not work as planned, leaving less time and flexibility to come up with an alternative action and possibly more severe consequences. This possible failure of corrective actions can be considered in probabilistic reliability management approaches. However, to do this correctly, probabilities of failure of the different corrective actions that can be prepared are needed. The probabilities of failure of corrective actions depend on several exogenous factors.

Cost

Where deterministic reliability management approaches favor preventive actions, probabilistic RMACs enable a trade-off between preventive, corrective and curtailment actions [57]. The cost of corrective actions is the aggregated cost of all actions that are taken in a certain scenario, consisting for instance of generation redispatch, PST tap changing, branch and busbar switching, VAR compensation, etc. Assigning a cost to each of these actions is crucial to improve the solvability of the optimization problem.

Besides the cost of corrective actions, interruption costs should be modeled, which depend on the value of lost load of the consumers. VOLL is a parameter representing the cost of unserved electricity and depends on several exogenous factors, such as interruption time, type of interrupted consumers, interruption duration, weather conditions, number of consumers affected, current reliability level, advance notification and available mitigating measures.[26]

3.6.2 Potential Issues with Data

Besides the requirement of additional data in probabilistic RMACs, there might be some data related issues in terms of availability, integrity and confidentiality of the data.

Availability

Required data are not necessarily available at the moment of decision making and it might be time consuming or costly to collect them. All these aspects make that data might not be readily available to be used in an alternative probabilistic approach. Some years might pass by before adequate data are collected. An example of data that are not readily available nowadays are probabilities of failure of corrective actions. Collecting failure data is in general time consuming due to the low frequency of failure of system components.

Integrity

Accuracy of the collected data affects the performance of probabilistic RMACs. Due to the low frequency of failure and the dependence of failure probabilities on several exogenous factors (e.g., the failure rate of breakers depends on age,

[26] A more in depth discussion of the impact of VOLL and its level of detail on the performance of RMACs is given in Chapter 7.

number of operations, brand, type, installation, etc.), it is hard to determine exact failure probabilities to use in probabilistic RMACs. Also, the cost of corrective actions is hard to estimate, especially in severe cases, such as in scenarios with cascading and stability issues [57]. The different cost terms are sensitive to several exogenous factors and need to be estimated if they are not known exactly, which typically leaves room for discussion. Applying 'wrong' probabilities and/or costs, will result in suboptimal decisions.

Confidentiality

Confidentiality issues are related to sharing data with other stakeholders. It might be required to share data with market players or with neighboring TSOs to handle cross-border security issues. Confidential data will be treated correspondingly, which might challenge the decision making. Confidentiality issues can also lead to delays in making the data available for decision making.

Moreover, probabilistic RMACs enable the exploitation of demand response and reliability-based choices of electricity consumption. However, this comes at the cost of reduced predictability of the demand profile. Privacy issues come into play when collecting consumer-related data in the context of demand response or to determine more exact values of lost load. Although a broad legal framework on privacy and data security exists at several policy levels, sector specific rules on confidentiality and data handling and security in the context of demand response for residential consumers are still lacking [125].

3.7 Ease-of-use

The ease-of-use and transparency of the currently used N-1 criterion is one of the reasons why TSOs are not eager to change their reliability management. Probabilistic approaches are typically risk-based, taking into account justifiable probabilities and severities of the considered operating states. Deterministic approaches, on the contrary, simplify the situation by not taking into account probabilities and consequences of contingencies. Moreover, ease-of-use is influenced by the number of operating states to consider. Given the increased uncertainty in power systems due to the increased penetration of renewable energy sources and market forces, it might be beneficial to consider additional operating states in the decision-making process. However, this makes the decision-making process more complex. The operator might also need to assess more and different information to make a trade-off between reliability and interruption cost that satisfies the prescribed reliability criterion. This comprises considering more and different indicators, such as socio-economic indicators or leading, risk-based, physical indicators.

Ease-of-use of an RMAC is hard to evaluate quantitatively and is typically assessed by a qualitative indicator based on a scoring system. The different aspects determining ease-of-use, i.e., whether the approach is deterministic or probabilistic, the number of system states to consider and the amount of information to process, can be assessed separately.

3.8 Conclusion

A performance metric of short-term RMACs comprises their economic, technical and social acceptability, applicability and practicality. Applicability and practicality should be represented in terms of qualitative indicators that evaluate the data requirements and ease-of-use of the RMAC. Literature on quantitative indicators that can be used to represent acceptability is not coherent nor unified. Four main classes of indicators can be distinguished each with their own characteristics: adequacy, security, socio-economic and reliability indicators.

Technical acceptability is ensured by constraints in terms of physical security indicators applied in reliability management. So far, coordinating organizations, such as ENTSO-E and NERC, mainly consider security indicators that are deterministic, lagging, physical indicators, which enable an ex-post security assessment of the system. However, leading, probabilistic security indicators become more important. They enable pro-active behavior in systems with increasing uncertainty.

Social and economic acceptability should be verified based on socio-economic indicators, such as total system cost, and reliability indicators, such as the level of load curtailment. Besides the absolute reliability level, equality or equity in terms of power system reliability should be assessed to verify whether consumers perceive to be treated fairly. So far, no index is reported in the existing literature on power system reliability to quantify this aspect.

Chapter 4

Quantification Framework for Evaluating and Comparing Performance of Short-Term RMACs

This chapter presents a generic quantification framework for evaluating and comparing performance of power system reliability management approaches and criteria. The main contribution is the modular design of a framework to quantify the performance of various RMACs by evaluating both the real-time system state as well as the reliability management process. This requires a generic way of combining various aspects of power system operation, including market clearing, determination of operational planning (OP) decisions and taking real-time (RT) actions. The framework is easy to expand and the level of detail can be increased or reduced in a transparent way. The framework is implemented using MATLAB and AMPL for testing purposes [126]. Due to its modular and generic design, modules of the platform can be substituted by existing tools or more advanced implementations with similar functionality.

A large-scale implementation of the quantification framework based on the presented theoretical design can be used to guide the regulator and transmission system operators towards cost-effective reliability criteria. The framework can help them making a trade-off between optimality of social surplus, practicality of reliability management and social acceptance. Possible changes in performance of using alternative reliability criteria can be quantified on stakeholder level and on system level. Another important feature of the framework is the tuning of parameters of reliability criteria.

The main focus of this chapter is on the theoretical background of the quantification framework for evaluating and comparing performance of power system reliability management approaches and criteria. Especially the design of the module to simulate the short-term decision-making process of TSOs is discussed in this chapter. An overview of the framework with its possibilities and its objectives as well as possible applications are described in Section 4.1. Section 4.2 explains the various modules, while the implementation of the different modules used in the case studies discussed in later chapters is given in Section 4.3. Finally, Section 4.4 concludes the chapter.

Parts of this chapter are published in *'Framework for evaluating and comparing performance of power system reliability criteria, Heylen E., Labeeuw W., Deconinck G. and Van Hertem D., IEEE Transactions on Power Systems, Vol. 31 No. 3, pp 5153–5162, Nov 2016.*[27] The link with the design of the GARPUR Quantification Platform (GQP) and the presented framework is explained in Appendix B.

4.1 Overview and Objectives of the Framework

Evaluating and comparing performance of power system reliability management approaches and criteria requires three main tasks:

1. Simulation of the decision-making process according to a particular RMAC, including evaluation of possible candidate decisions,
2. Quantifying performance of various RMACs in terms of reliability and socio-economic indicators, both at system level and stakeholder level,
3. Comparing performance of various RMACs.

The relationships between these three tasks in the quantification framework is shown in Fig. 4.1. Firstly, a RMAC is selected from a list of candidate RMACs. The reliability criterion is satisfied by taking appropriate reliability decisions. Resulting actions lead to a final operational state of the power system, which is evaluated together with the actions taken. To enable benchmarking, this process is repeated with identical load, generator and grid data, but for a known

[27]The first author is the main author of the paper. The contributions of the first author include the development of the quantification framework and the modeling and analysis of the case study described in the paper.

RMAC, e.g,. based on the N-1 criterion. The post-processing stage compares results for various assumptions and RMACs. Results of the comparison can be used to evaluate the relative performance of RMACs and to tune parameters of RMACs, such as risk level for instance.

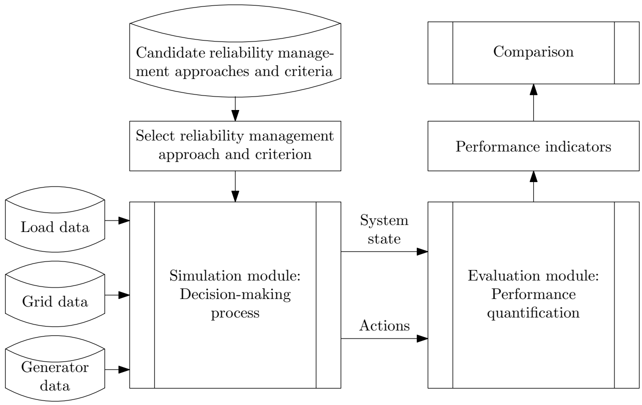


Figure 4.1: Overview of the quantification framework for evaluating and comparing performance of power system reliability management approaches and criteria [127].

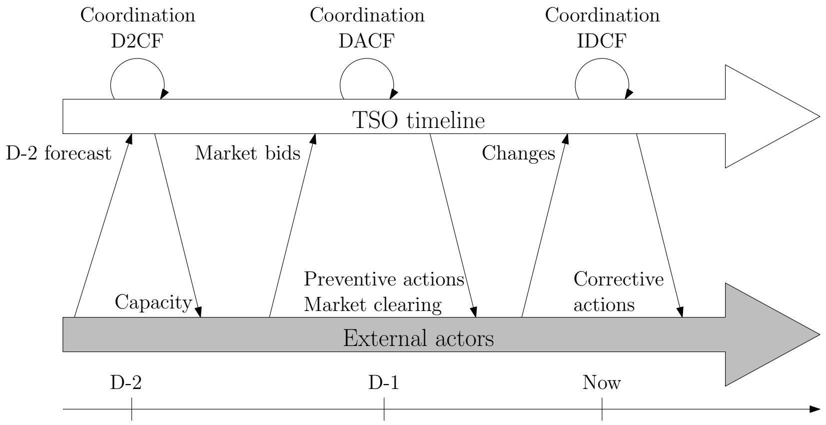
4.2 Simulation of TSO Decision-Making Processes

The framework presented focuses on the short-term decision-making process of the transmission system operator, i.e., day ahead (D-1) up to real time (RT). The decision-making process consists of two stages:

- Operational planning stage or scheduling
- (Near) real-time operation stage

A challenge of the short-term operational planning and real-time operation is that the decision-making process consists of multiple stages that are interlinked with external systems, such as load and generation, as shown in Fig. 4.2 for D-2, D-1 and real-time reliability management. These external systems are controlled by external actors and are out of the control of the system operator.

Scheduled generation commitments at the different nodes in the system are obtained from the day-ahead market clearing. In case of a *copper plate* day-ahead market, security constraints and power system limits are not taken into



D-2 Congestion Forecasts (D2CF)
Day-Ahead Congestion Forecasts (DACF)
Intra-Day Congestion Forecasts (IDCF)

Figure 4.2: TSO's decision-making process of short-term reliability management influenced by decision making of external actors.

account in the market clearing. This might require planning of actions, such as redispatch, phase-shifting transformer tap changing or topological changes, to satisfy the reliability criterion and the system limits. Scheduling of these actions is done in the operational planning stage, considering the unit commitment schedule resulting from the market clearing process based on forecasted load and generation and the reliability criterion. Measures taken during the operational planning stage are called preventive actions, which are taken before real-time to achieve security and improve the ability to withstand the possible effects of potential contingencies [128]. Moreover, corrective actions can be prepared for the set of credible contingencies, which are applied if one of the contingencies occurs in real time.

The operational planning stage is based on expected system states that might differ from the real-time system state. Therefore, a final decision stage based on the real-time realizations of demand, generation capacity and outages needs to be included. Outcomes of this real-time decision stage are called corrective actions, needed in real-time to satisfy the applied reliability criterion and meet operational limits.

Links between the two decision stages and the various modules in the implementation are shown in Fig. 4.3. The 'IN'-block combines modules delivering input for the quantitative simulation module. The 'OUT'-block contains outputs of the quantitative simulation module. Following subsections describe the modules.

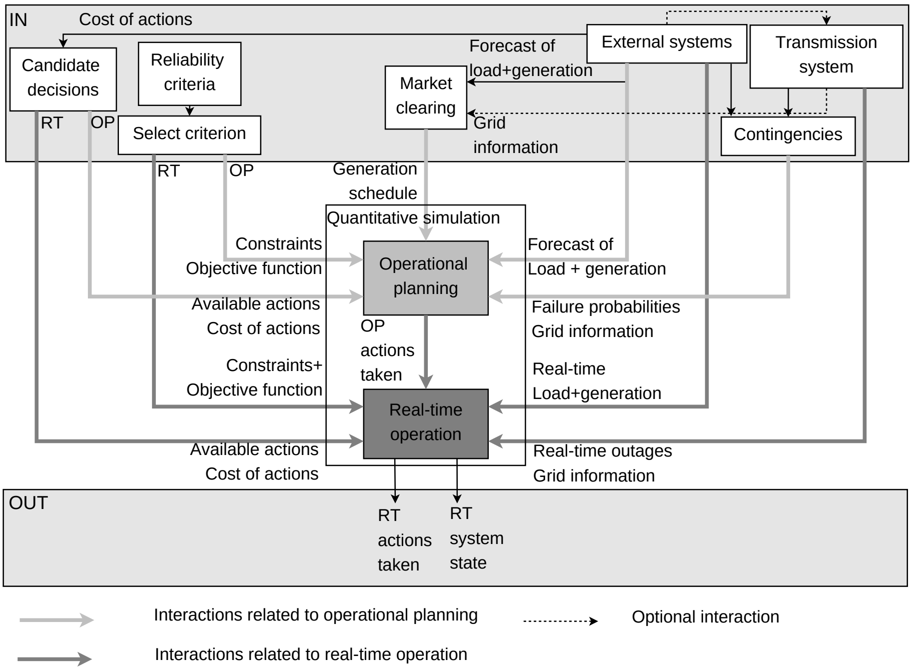


Figure 4.3: Overview of the simulation module together with its outputs and modules serving the inputs. ‘RT’ and ‘OP’ refer to data of a particular module regarding real-time operation and operational planning respectively.

4.2.1 External Systems

The ‘external systems’-module contains systems over which the TSO has limited control:

- Generation, of which the module contains forecast and real-time generation capacity, failure and repair rates, marginal costs of generation, capacity available for reserves, cost of reserve provision and redispatch cost;
- Load, of which the module contains forecast and real-time demand in the system, value of lost load;

- Market, of which the module contains the type of the market, i.e., constrained market or copper plate market;[28]
- Weather, of which the module contains forecast and real-time values of wind speed, wind direction, solar power, temperature at different points in the system, etc.

Spatio-temporal correlation in meteorological data and load data can be included using correlation matrices. Impact factors of weather parameters on operational limits, e.g., dynamic line rating, and reliability data, e.g., failure rates, can also be provided by this module.

All these external systems are interdependent and serve as an input for the TSO decision-making processes of operational planning and real-time operation. The level of detail associated with the external systems module determines to a large extent the data requirements of the framework.

4.2.2 Transmission System

The 'transmission system'-module contains parameters related to the grid and its components:

- Topology of the grid, i.e., connections between the nodes, location of load and generation, location of flexible devices, switchgear, etc.
- Characteristics of system components, i.e., operational limits of lines and flexible devices, settings of flexible devices, impedance of lines, status of components, etc.
- Reliability data of system components, i.e., failure and repair rates of lines and flexible devices, etc.

Reliability data and characteristics of system components are in practice influenced by weather conditions as well as decisions taken in earlier time horizons, such as maintenance actions influencing the failure rate of components.

Grid information coming from the 'transmission system'-module is used to model the base case system. Additional cases of credible system states that might need to be considered simultaneously in the quantitative simulation of the decision-making process according to a particular reliability criterion are added to this model. Furthermore, the 'transmission system'-module provides

[28]This work only takes the day-ahead market explicitly into account.

operational limits of system components that are considered as constraints in the quantitative simulation.

4.2.3 Contingencies

The 'contingencies'-module is related to the unexpected failure of system components. Failure of system components can be caused by internal or external factors such as [129]:

- Internal factors
  - Aging
  - Overloading
  - Switching cycles
  - Maintenance and repair policy
- External factors
  - Extreme weather
  - Vegetation and wildlife
  - Theft and vandalism
  - Damaging cables or touching lines for instance during construction works

The 'contingencies'-module gets failure and repair rates of system components as an input from the 'transmission system'-module and serves three purposes:

1. Determination of the probability of occurrence of various states of a particular system component.
2. Determination of the probability of an outage of a particular (combination of) system component(s)
3. Contingency selection

Reliability over the lifetime of a system component is typically modeled using a 'bathtub curve', consisting of three main stages, as shown in Fig. 4.4. The stage of early failures, sometimes also denoted as the infant mortality or burn-in phase, represents a decreasing failure rate, because defective components are identified and discarded and handling and installation errors are surmounted.

The second stage of random failures has a constant failure rate. The third stage of wear-out failure has an increasing failure rate due to aging and wear.[29]

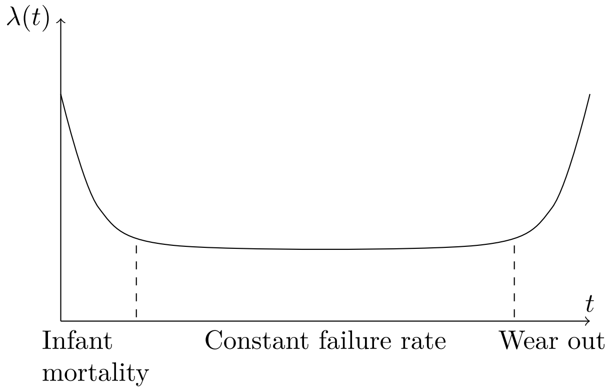


Figure 4.4: Bathtub curve to model reliability over the lifetime of a system component.

The bathtub curve is sometimes simplified by assuming a constant failure rate over the whole lifetime of a component. If also the repair rate is considered to be constant, this results in exponential distributions of time-to-failure and time-to-repair, which satisfy the conditions of a Markov process. However, due to non-exponentially distributed time-to-repair, systems are in general non-Markovian. Moreover, bad weather conditions or bad maintenance might result in non-constant failure rates. This requires methods of supplementary variables, device of stages, semi-Markov processes [132] or simulation techniques to be applied. However, if assumptions of exponentially distributed time-to-failure and time-to-repair do not imply significant differences, approximate methods, such as a Markov process, may be used to determine the probability to find the component in a failure state [104].

The probability of occurrence of an outage of a particular (combination of) system component(s) can be directly used in the objective function specified by the RMAC to weigh outcomes for various expected system states in the decision-making process. Furthermore, probabilities are needed in analytical evaluation techniques to weigh the performance of a particular outcome of the decision-making process in the overall performance of the RMAC. To reduce the computational burden of the analytical evaluation techniques, appropriate contingency selection methods can be applied [132, 133, 134].

[29] Although the bathtub curve is widely mentioned in literature, its application to manufactured products is questioned [130]. Alternatives are presented such as for instance a ‘roller-coaster’ curve [131].

The probabilities can also be used to sample the status of various transmission system components according to their availability, resulting in time series of the status of all components. These samples are useful in Monte Carlo simulations, which can be applied to evaluate the performance of a particular RMAC.

4.2.4 Candidate Decisions

The time horizon determines the candidate reliability decisions of a transmission system operator. In the short-term horizon from D-1 up to real time, candidate decisions differ between the operational planning stage and the real-time operation stage. An overview of possible candidate decisions is given in Table 4.1.[30] Candidate decisions available in real time can also be considered in the decision-making process of operational planning as they serve as additional flexibility that is still available in real time. However, it depends on the applied type of RMAC whether this is allowed.

Table 4.1: Overview of possible candidate decisions in operational planning and real-time operation.

Real-time operation	Operational planning
No action	No action
Generation redispatch	Contracting reserves
Load curtailment	Contracting flexibility
Bus bar and line switching	Generation rescheduling
Transformer tap changing	+ Actions real-time operation

The ‘candidate decisions’-module provides constraints and cost functions in parametric form for the simulation of the decision stages. Values for the parameters in these functions come from the ‘external systems’- and ‘transmission system’-modules.

4.2.5 Reliability Criteria

Outputs of the ‘reliability criteria’-module are constraints that need to be satisfied and the objective function according to which the reliability needs to be managed, both in parametric form. Constraints posed by the reliability criterion consist of limits on reliability indicators, such as expected load curtailment, as well as limits on physical quantities in the system, e.g., branch flow limits

[30] A complete overview of the operational planning and real-time operation process can be found in Fig. 2.6. The focus in this work in on the process denoted as ‘component loading’ in Fig. 2.6.

that cannot be violated in particular credible system states. Depending on the characteristics of the reliability criterion, credible system states can be defined deterministically, e.g., all contingency cases up to N-k system states, or probabilistically, e.g., all likely system states up to a cumulative probability of occurrence of X% or risk based [127, 135]. An alternative way to define the set of considered contingencies is using a discarding principle, which neglects a subset of contingencies based on the residual risk level [85]. Depending on the criterion and the decision stage, credible system states can consider possible outages of transmission system components as well as real-time realizations of demand and generation capacity, which are uncertain intra-day. Power flow constraints for all credible system states are included in the Optimal Power Flow (OPF) formulation and those are coupled by coupling constraints based on ramp rate limits among others. Constraints can also be of a stochastic nature, e.g., chance constraints [136], which need to be satisfied in a particular percentage of the cases. Alternatively, constraints can focus on the α-percentile of worst outcomes to limit consequences of bad outcomes [137].

Social surplus is an appropriate metric to rank performance of various available reliability decisions. It consists of consumer surplus, i.e., the difference between Willingness-To-Pay (WTP) and the price paid for the good, and producer surplus, i.e., all profits in the market. In case of the electricity system, both generators and grid operators are considered as producers [138]. However, not all data to determine social surplus are known by the TSO when reliability decisions must be taken. Therefore, it is not possible in practice to operate the system using the ideal objective function that maximizes social surplus.

To mimic TSOs' decision-making behavior it is important to take into account TSOs' data availability. Artificial rules based on physical or reliability indicators or alternative socio-economic indicators need to be developed and applied in practice. Alternative objective functions aim at minimizing total system cost, possibly taking into account weights for the probability of occurrence of credible system states [59, 139]. Conditional Value at Risk (CVaR) or Value at Risk (VaR) can also be used as objective function to include risk aversion of the decision maker [138, 136].

4.2.6 Quantitative Simulation

The 'quantitative simulation'-module performs the decision-making process at the two decision stages. For the operational planning decision stage, the decision-making process is implemented as a two-stage stochastic security constrained optimal power flow taking into account:

- Constraints posed by the reliability criterion regarding credible real-time system states
- Operational limits in the transmission system
- Available candidate decisions
- Power flow constraints

If multiple (combinations of) decisions satisfy reliability and operational limits, possible (combinations of) decisions are ranked based on the objective function as specified by the RMAC. The outcome of the optimization is a set of operator actions that are optimally taken ahead of real-time to satisfy the reliability criterion and operational limits.

In the real-time decision-making process, similar types of constraints are taken into account, but the uncertainty is reduced. The outcome of the operational planning decision stage is used as an input for the real-time operation stage. A SCOPF formulation is used, which results in corrective actions that need to be taken in real time to obtain an acceptable reliability level in the system as defined by the reliability criterion.

Failure of corrective actions in real-time operation can be considered in the decision-making process by including an additional decision stage, introducing additional states [139]. Furthermore, additional stages in the optimization process can be used to include pseudo-dynamic behavior of the system to guarantee that constraints are satisfied in the post-contingency state before and after corrective actions are fulfilled [74].

The quantitative simulation can use a non-linear AC SCOPF or alternative, approximate, convex implementations. The true distinction between easy-to-solve and hard-to-solve problems mainly aligns with convexity versus non-convexity of the optimization problem, rather than linear versus non-linear problems. Convex problems can be solved with a guaranteed convergence in polynomial time to global optimality, whereas non-convex, smooth optimizations typically solve quickly to a local optimum or slowly to a global optimum [140]. Relaxations by a process of only removing equations from the feasible set of the original problem provides strong quality assurances on the solution of both the relaxed and original problem. This is not the case with linearization [140]. Examples of approximate implementations are linear-programming models that include reactive power and voltage magnitudes in a linear power flow approximation (Linear Programming approximation of AC power flows (LPAC)) [141], convex relaxation approximations [142] or a DC SCOPF with reduced computational burden [143].[31] The outcome of the DC SCOPF can be verified

[31] An overview of recent work on power flow formulations is given in [140]

by using it as an input for an AC power flow to check satisfaction of reactive power limits, branch flow limits and voltage limits. If constraints are not satisfied, actions can be taken based on heuristics in an attempt to find a solution (optimality is not guaranteed) [62]. Alternatively, an iterative approach that complements or substitutes the optimization can be used as well. The outcome of the quantitative simulation is the final grid state and the actions taken by the TSO aiming at a secure and operational system.

4.3 Implementation of the Simulation Module

The simulation module and its input modules can be implemented with different levels of detail, depending on the final purpose of the analysis. The level of detail should be different if the objective is to analyze differences in decisions taken when an alternative RMAC is applied to a real system than if only indicative results or trends should be obtained based on realistic test systems. This work mainly focusses on the latter, which does not require a fully fledged implementation of the different modules.[32]

4.3.1 High-Level Analytical Formulation of the Simulation Module

TSO's short-term reliability management according to a particular RMAC m is a dynamic process that can be written analytically as:

$$\mathbf{X}_m(t) = f_m(\mathbf{X}_m(t-1), \mathbf{Y}(t)) \qquad \text{with } \mathbf{X}_m(0) = \mathbf{X}_0 \tag{4.1}$$

$\mathbf{Y}(t)$ is a time series of vectors of external forcing input variables and $\mathbf{X}_0$ a vector describing the initial state of the system. Both $\mathbf{Y}(t)$ and $\mathbf{X}_0$ are independent of the applied reliability criterion. $\mathbf{X}_m(t)$ is a time series of the vector of state variables obtained if RMAC m is applied. Capital symbols refer to vectors of random variables, whereas non-capital symbols refer to a realization of the corresponding random variable. Some of the input parameters are non-stationary, e.g., due to daily cycles. The function f_m describes the short-term decision-making behavior of a TSO based on a particular RMAC m. f_m is deterministic and differs between RMACs to represent their way of

[32]The implementation of the quantification framework in the GARPUR project mainly focuses on the verification of prescribed decisions if an alternative RMAC is applied in a real system, i.e., a part of the French grid. This requires a more detailed implementation of the quantitative simulation module, which was out of the scope of this work and was executed by colleagues of the research group, as discussed in appendix B and [140].

handling uncertainties in the system. The system itself is described by a vector of constant parameters ϕ. Table 4.2 summarizes the parameters and variables collected in the input and state vectors introduced in Eq. (4.1).

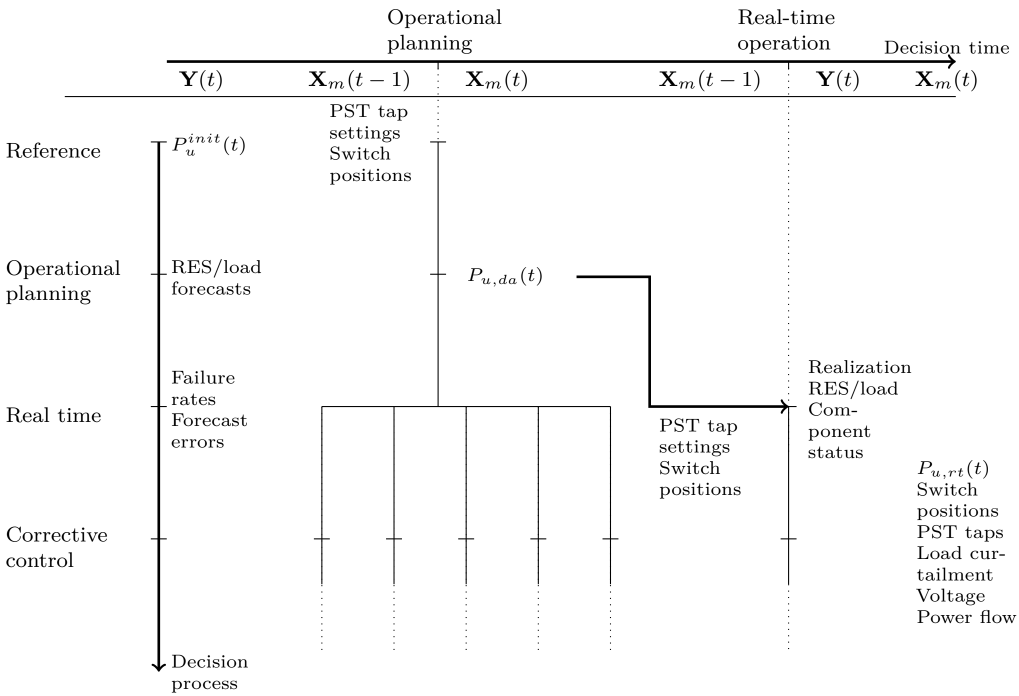
Table 4.2: Examples of state variables and parameters in the simulation module.

External forcing inputs $\mathbf{y}$	Constant parameters ϕ	State vector $\mathbf{x}$	Initial conditions $\mathbf{x}_0$
Load forecast and realization	Line Parameters	Generation dispatch (D-1/RT)	PST tap positions
Wind forecast and realization	Generation capacity	Load supplied	Switch positions
Component status	Parameters reliability criterion	PST tap positions	
		Switch positions	
	Failure probability[a]	Voltage	
	Operational limits[a]	Branch flow	
	Cost terms[a]		

[a] Can be time varying or constant in time

Short-term reliability management ranges from a few days ahead of real time up to real time and consists of multiple decision stages, as was shown in Fig. 4.2. The implementation in this work focuses on the two-stage decision-making process consisting of day-ahead operational planning and real-time operation, which Fig. 4.5 illustrates in more detail. The operational planning decision stage is initiated by the reference stage, which consists of the outputs of the day-ahead market clearing $P_u^{init}(t)$. The operational planning stage determines actions to take ahead of real time to satisfy the operational limits in real time and is based on forecast values of load and RES generation. Besides the forecasts, possible real-time system states are considered in this decision making to take into account the uncertainty related to failures of components and forecast errors. Depending on the applied reliability criterion, different sets of possible real-time system states are considered. The outcomes of the operational planning $P_{u,da}(t)$ are used as an input for real-time operation together with the PST tap settings and switch positions at the previous time instant and the real-time realizations of RES generation, load and component statuses. The real-time operation stage results in corrective actions required to restore the system to a secure state, such as switch positions, PST tap settings, generator output, and the variables determining the real-time system state, such as voltages and power flows.[33]

[33] Additionally, a short-term post-contingency stage and corrective control behavior stage can be considered, but these stages are not considered in the implementation. The short-term post-contingency stage takes into account the impact of automatic generation control actions that are used to relieve operational limit violations shortly after a contingency takes place. However, this state is not necessarily the most cost-effective state and might be not secure for other contingencies, which asks for a corrective control stage. These corrective actions might



$P_u^{init}(t)$:Generator output after D-1 market clearing at time t
$P_{u,da}(t)$:Generator output after preventive redispatch at time t
$P_{u,rt}(t)$:Generator output after corrective redispatch at time t

Figure 4.5: Multi-stage procedure of the decision-making process of short-term reliability management ranging from day-ahead operational planning up to real-time system operation.

This multi-stage decision-making process represented by f_m is typically simulated using consecutive multi-stage optimizations, also denoted as SCOPF. The computational burden of these optimizations is a challenge, due to the large number of binary variables that is introduced in the formulation, especially in real systems with thousands of nodes.

Different reliability criteria imply different security constraints in the optimization formulations, leading to different functions f_m. Differences exist in terms of which and how system states are considered in the decision stages ahead of real-time. Moreover, the way costs at different stages are considered can

fail, which is denoted as the corrective control behavior. This can have a large impact on the security of the system. For this reason, currently used deterministic approaches aim at securing the system mainly using preventive actions.

differ and additional thresholds can be imposed on reliability indicators, such as energy not supplied or power not supplied, either aggregated or separated per contingency, node or consumer.

4.3.2 Quantitative Simulation

Each stage of the two-stage decision-making process considered in this work, i.e., day-ahead operational planning stage and real-time operation stage is modeled by a DC SCOPF. This DC SCOPF is a mixed integer linear program (MILP).[34]

The general formulation of the SCOPF of operational planning is:

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}} C^{tot}(\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}) \tag{4.2}$$

$$\text{subject to: } G_0(\mathbf{x}_{da},\mathbf{a}^{prev},\mathbf{y}_{da}) = 0 \tag{4.3}$$

$$H_0(\mathbf{x}_{da},\mathbf{a}^{prev},\mathbf{y}_{da}) \geq 0 \tag{4.4}$$

$$G_s(\mathbf{x}_s,\mathbf{a}_s^{corr},\mathbf{P}_s^{curt},\mathbf{y}_s) = 0 \qquad \forall s \in S \tag{4.5}$$

$$H_s(\mathbf{x}_s,\mathbf{a}_s^{corr},\mathbf{P}_s^{curt},\mathbf{y}_s) \geq 0 \qquad \forall s \in S \tag{4.6}$$

$$|\mathbf{a}_s^{corr} - \mathbf{a}^{prev}| \leq \Delta\mathbf{a}_s \qquad \forall s \in S \tag{4.7}$$

Where $\mathbf{x}$ are the state variables, $\mathbf{a}^{prev}$, $\mathbf{a}_s^{corr}$ and $\mathbf{P}_s^{curt}$ are the control variables and $\mathbf{y}_{da}$ and $\mathbf{y}_s$ are the external forcing inputs in respectively the day-ahead stage and the states s in the set of credible system states S. G_0 and G_s represent the set of equality constraints in resp. the reference state and the credible states s, whereas H_0 and H_s represent the set of inequality constraints in resp. the reference state and the credible states s. $\Delta\mathbf{a}_s$ limits the rate of change between the reference state and the credible state s, for instance in the case of ramp rate limits.

The difference with the SCOPF for real-time operation is that the system parameters in real time $\mathbf{y}_{rt}$ are less uncertain than $\mathbf{y}_{da}$. Therefore, another set of states S can be considered. The real-time operation stage uses the outcomes of the operational planning stage, the preventive actions $\mathbf{a}^{prev}$, as an input. These are part of the parameter set $\mathbf{y}_{rt}$, together with the real-time realizations of wind generation, load and contingencies. The outcomes of the real-time operation stage are the corrective actions that should be executed in real time $\mathbf{a}_{rt}^{corr}$ and the real-time system state characterized by $\mathbf{x}_{rt}$.

[34]Information about the assumptions made in the DC SCOPF and the validity of the assumptions applied in a DC power flow can be found in Appendix C.

4.3.3 Reliability Criteria

Depending on the applied reliability criterion, the objective function differs in terms of how uncertainty is taken into account. A general formulation of the objective function in operational planning is:

$$C^{tot}(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}, \mathbf{P}_s^{curt}) = C^{prev}(\mathbf{a}^{prev}) + \sum_{s \in S} p_s \cdot [C^{corr}(\mathbf{a}_s^{corr}) + C^{curt}(\mathbf{P}_s^{curt})] \tag{4.8}$$

Each of these cost terms can be subdivided in different terms corresponding to the costs of different reliability actions. Depending on whether a probabilistic or deterministic RMAC is applied, the second term will be treated differently. Also the set of considered system states S differs between RMACs.[35]

4.3.4 Transmission System Modeling

To model the system in the quantitative simulation module, the data representing the power system should be appropriately imported. Data handling is not straightforward in practice: data are missing, data sets contain bad data, different models are used for the same, etc. Consistent data are crucial to obtain adequate results. The transmission system data can be directly provided in MATPOWER format. However, transmission system operators typically have their data in a commercial software format, such as PSSE RAW data format, or CIM format [144]. Converters are implemented to convert the system data in the appropriate MATPOWER format to be used in the quantification framework.[36]

4.3.5 Candidate Decisions

A reduced set of possible candidate decisions is included in the basic implementation of the quantification framework applied in the case studies of this work. Candidate decisions consist of taking appropriate reliability actions or taking no action at all. Each action comes at a cost, which is part of the respective cost functions. The constraints that need to be satisfied for each reliability action are part of the function H_0 and H_s in resp. Eq. 4.4 and 4.6.

[35] The objective of this chapter is to give a general representation of the objective function. Different classes of RMAC are discussed in more detail in Chapter 8, taking into account additional constraints that can be added to the optimization formulation to limit the amount of load curtailment in total or per node.

[36] The converters were developed in the framework of the GARPUR project based on existing implementations [145] that were made consistent and were modified to be used in the quantification framework [146].

Generator Redispatch

Generator redispatch consists of changing the power output of dispatched generators to compensate for generator outages or to relieve congestion. It makes use of the available upward and downward power reserves in the system [147]. The TSO can ask generators to change their power output in a downward or upward fashion.

Depending on the type of redispatch, the involved stakeholders need to be economically compensated in an appropriate way. Therefore, generation redispatch comes at a cost. Generation redispatch can be used ahead of real time or as a real-time corrective action. The redispatch cost terms that are part of C^{prev} and C^{corr} are:

$$C^{prev}(\Delta P_{da}^{+}, \Delta P_{da}^{-}) = \sum_{u \in \mathcal{U}} \left[c_{u,da}^{red,+} \cdot \Delta P_{u,da}^{+} + c_{u,da}^{red,-} \cdot \Delta P_{u,da}^{-} \right] \tag{4.9}$$

$$C^{corr}(\Delta P_{s}^{+}, \Delta P_{s}^{-}) = \sum_{u \in \mathcal{U}} \left[c_{u}^{red,+} \cdot \Delta P_{u,s}^{+} + c_{u}^{red,-} \cdot \Delta P_{u,s}^{-} \right] \tag{4.10}$$

Where $c_{u,da}^{red,+}$ and $c_{u,da}^{red,-}$ are resp. the upward and downward redispatch cost of generating unit u in the day-ahead stage, $c_{u}^{red,+}$ and $c_{u}^{red,-}$ are resp. the upward and downward redispatch cost of generating unit u in the real-time stage, ΔP_u^{+} and ΔP_u^{-} are resp. the upward and downward redispatch of generating unit u in the different decision stages, i.e., the day-ahead stage da and the credible state s, and $\mathcal{U}$ is the set of all generating units.

The constraints that need to be satisfied in the context of generator redispatch are:

$$P_u^{min} \leq P_{u,da} \leq P_u^{max} \qquad \forall u \in \mathcal{U} \tag{4.11}$$

$$\Delta P_{u,da} = P_{u,da} - P_u^{init} \qquad \forall u \in \mathcal{U} \tag{4.12}$$

$$0 \leq |\Delta P_{u,da}| \leq RR_{u,da} \qquad \forall u \in \mathcal{U} \tag{4.13}$$

where P_u^{min} and P_u^{max} are resp. the upper and lower limit of generating unit u, $P_{u,da}$ the scheduling of generating unit u in the day-ahead stage, P_u^{init} the scheduling of generating unit u after the day-ahead market clearing and RR_u the ramp rate limits of generating unit u.

To linearize the problem, following equations are used in which ΔP_u^{+} and ΔP_u^{-} are considered as an upper bound on positive and negative redispatch, respectively:

$$\Delta P_{u,da} = \Delta P_{u,da}^{+} - \Delta P_{u,da}^{-} \qquad \forall u \in \mathcal{U} \tag{4.14}$$

$$P_{u,da} - P_u^{init} \leq \Delta P_{u,da}^{+} \qquad \forall u \in \mathcal{U} \tag{4.15}$$

$$P_u^{init} - P_{u,da} \leq \Delta P_{u,da}^{-} \qquad \forall u \in \mathcal{U} \tag{4.16}$$

$$0 \leq \Delta P_{u,da}^{+} \leq RR_{u,da} \qquad \forall u \in \mathcal{U} \tag{4.17}$$

$$0 \leq \Delta P_{u,da}^{-} \leq RR_{u,da} \qquad \forall u \in \mathcal{U} \tag{4.18}$$

Similar constraints need to be considered for each state s considered as credible state in the operational planning optimization:

$$\zeta_{u,s} \cdot P_u^{min} \leq P_{u,s} \leq \zeta_{u,s} \cdot P_u^{max} \qquad \forall u \in \mathcal{U}, \forall s \in S \tag{4.19}$$

$$\Delta P_{u,s} = \Delta P_{u,s}^{+} - \Delta P_{u,s}^{-} \qquad \forall u \in \mathcal{U}, \forall s \in S \tag{4.20}$$

$$P_{u,s} - P_{u,da} \leq \Delta P_{u,s}^{+} \qquad \forall u \in \mathcal{U}, \forall s \in S \tag{4.21}$$

$$P_{u,da} - P_{u,s} \leq \Delta P_{u,s}^{-} \qquad \forall u \in \mathcal{U}, \forall s \in S \tag{4.22}$$

$$0 \leq \Delta P_{u,s}^{+} \leq RR_u \qquad \forall u \in \mathcal{U}, \forall s \in S \tag{4.23}$$

$$0 \leq \Delta P_{u,s}^{-} \leq RR_u + M(1 - \zeta_{u,s}) \qquad \forall u \in \mathcal{U}, \forall s \in S \tag{4.24}$$

$\zeta_{u,s}$ is a binary variable which disables the dispatch of generating units u that are out of service in system state s.

Phase-Shifting Transformer Tap Changing

A phase-shifting transformer (PST) is able to control the power flow through a certain transmission line and therewith the power flow in the entire grid. The power flow is controlled by changing the phase angle over the line from θ to $\theta + \Delta\theta$. A PST induces a voltage in quadrature of the phase voltage in the transmission line to change the voltage magnitude and phase angle. The induced voltage is controlled by the tap positions. A PST can be represented as a reactance in series with a phase shift as shown in Fig. 4.6 [148].

Two additional active power injections, each at a side of the PST, can be used to model the phase-shifting angle $\Delta\theta$ [148]. These two additional power injections $P^{PST,+}(\Delta\theta)$ and $P^{PST,-}(\Delta\theta)$ change the power flow through the transmission line. These power injections are fictitious as they do not exist in reality, so their sum should be zero. Moreover, the phase shifting should be within the operational limits. The equivalent model of the phase-shifting transformer is shown in Fig. 4.7.

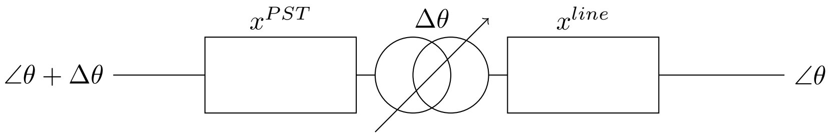


Figure 4.6: Graphical representation of a phase-shifting transformer in series with a transmission line.

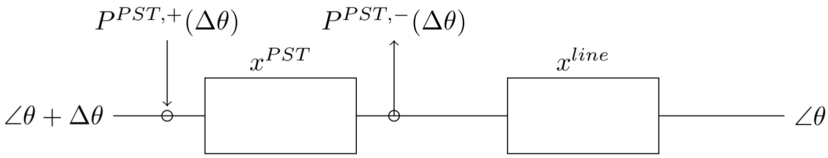


Figure 4.7: Equivalent model of a phase-shifting transformer in series with a transmission line.

The cost of phase-shifting transformer tap changing is much lower than the cost of generation redispatch or load curtailment, but due to the wear out of the device a switching cost should be attributed to it. This also helps the solver in finding an optimum. This cost should be taken into account in the respective cost functions:

$$C^{prev}(\Delta\theta) = \sum_{p \in \mathcal{P}} c_p^{PST} \cdot \Delta P_{p,da}^{PST} \tag{4.25}$$

$$C^{corr}(\Delta\theta_s) = \sum_{p \in \mathcal{P}} c_p^{PST} \cdot \Delta P_{p,s}^{PST} \tag{4.26}$$

with c_p^{PST} the cost of tap changing of PST p and $\Delta P_{p,da}^{PST}$ and $\Delta P_{p,s}^{PST}$ the change in active power injection of the fictitious power source in resp. the reference state da and the credible state s.

Moreover, following constraints should be taken into account in the optimization:

$$P_{p,da}^{PST,+} - P_{p,da}^{PST,-} = 0 \qquad \forall p \in \mathcal{P} \tag{4.27}$$

$$0 \leq \Delta P_{p,da}^{PST} \leq \Delta P_p^{PST,+,max} \qquad \forall p \in \mathcal{P} \tag{4.28}$$

$$|P_p^{PST,+,init} - P_{p,da}^{PST,+}| = \Delta P_{p,da}^{PST} \qquad \forall p \in \mathcal{P} \tag{4.29}$$

where $P_p^{PST,+,init}$ represents the setting of PST p before the operational planning stage is executed and $P_{p,da}^{PST,+}$ represents the PST setting determined in the operational planning stage. $\Delta P_p^{PST,+,max}$ is determined based on the maximum phase-angle shift of the PST $\Delta\theta^{max}$ as:

$$\Delta P_p^{PST,+,max} = \frac{\Delta\theta^{max}}{x_p^{PST}} \qquad \forall p \in \mathcal{P} \tag{4.30}$$

x_p^{PST} is the reactance of the PST for which appropriate values can be found in [149, 150]. $\mathcal{P}$ represents the set of all PSTs in the system.

The absolute value can be linearized by replacing Eq. (4.27) and (4.28) by following equations:

$$\Delta P_{p,da}^{PST} = \Delta P_{p,da}^{PST,up} + \Delta P_{p,da}^{PST,down} \qquad \forall p \in \mathcal{P} \tag{4.31}$$

$$\left.\begin{matrix} 0 \\ P_{p,da}^{PST,+} - P_p^{PST,+,init} \end{matrix}\right\} \leq \Delta P_{p,da}^{PST,up} \leq \Delta P_p^{PST,+,max} \qquad \forall p \in \mathcal{P} \tag{4.32}$$

$$\left.\begin{matrix} 0 \\ P^{PST,+,init} - P_{p,da}^{PST,+} \end{matrix}\right\} \leq \Delta P_{p,da}^{PST,down} \leq \Delta P_p^{PST,+,max} \qquad \forall p \in \mathcal{P} \tag{4.33}$$

To represent the phase-shifting transformer tap changing in the corrective decision stage, the constraints should be repeated $\forall s \in S$, similarly to the case of generation redispatch. PST settings should be determined for each state s. The initial settings $P_p^{PST,+,init}$ should be replaced by the preventive settings $P_{p,da}^{PST,+}$ in Eq. (4.29), resulting in:

$$|P_{p,da}^{PST,+} - P_{p,s}^{PST,+}| = \Delta P_{p,s}^{PST} \qquad \forall p \in \mathcal{P}, \forall s \in S \tag{4.34}$$

Topological Actions

The power flow in the grid can also be controlled by making topological changes, such as for instance connecting or disconnecting a branch or switching a breaker in a substation. This enables system operators to alleviate possible congestion in a cheap way [151]. In this work, only branch switching is considered.

Similar to PST tap changing, a cost should be assigned to breaker switching, which should be considered in the cost function:

$$C^{prev}(\Delta\omega_{da}) = \sum_{o \in \mathcal{O}} c_o^{breaker} \cdot \Delta\omega_{o,da} \tag{4.35}$$

$$C^{corr}(\Delta\omega_s) = \sum_{o \in \mathcal{O}} c_o^{breaker} \cdot \Delta\omega_{o,s} \tag{4.36}$$

with $c_o^{breaker}$ the cost of switching breaker o and $\Delta\omega_{o,da}$ and $\Delta\omega_{o,s}$ the change in breaker status of breaker o in resp. the reference state da and the credible state s.

Breakers are modeled in optimal power flow formulations with on/off constraints. This means that the constrains are enabled if the binary variable of the respective breaker is equal to one and are disabled otherwise. They are considered as lossless elements [152]. The constraints are modeled as:

$$\omega_{o,da} \cdot P_o^{breaker,min} \leq P_{o,da}^{breaker} \leq \omega_{o,da} \cdot P_o^{breaker,max} \qquad \forall o \in \mathcal{O} \tag{4.37}$$

$$-M(1-\omega_{o,da}) \leq \theta_k - \theta_m \leq M(1-\omega_{o,da}) \qquad \forall o \in \mathcal{O} \tag{4.38}$$

$$|\omega_o^{init} - \omega_{o,da}| = \Delta\omega_{o,da} \qquad \forall o \in \mathcal{O} \tag{4.39}$$

$$0 \leq \Delta\omega_{o,da} \leq 1 \qquad \forall o \in \mathcal{O} \tag{4.40}$$

ω_o^{init} and $\omega_{o,da}$ represent resp. the status of the breaker in the initial state and after preventive control and equals one if the breaker is closed and zero if the breaker is open, M is a big number and $P_o^{breaker}$ represents the power flow through the breaker. Eq. (4.38) sets the voltage angles θ_k and θ_m at the end nodes of the breaker equal to each other. The absolute value in Eq. (4.39) can be linearized in a similar way as with the phase-shifting transformer.

In the corrective control stage, the constraints should be repeated for all states s in S. The breaker status $\omega_{o,s}$ of each breaker needs to be determined for each state $s \in S$. The constraint in Eq. (4.39) should be replaced by the constraint in Eq. (4.41) to take the preventive status of the breaker as a reference:

$$|\omega_{o,da} - \omega_{o,s}| = \Delta\omega_{o,s} \qquad \forall o \in \mathcal{O}, \forall s \in S \tag{4.41}$$

Demand Flexibility

Demand flexibility is another measure available to ensure the power balance while satisfying operational limits. A distinction needs to be made between voluntarily and involuntarily demand flexibility. Load shedding refers to involuntarily, intentional power cuts and aims at avoiding wider problems in emergency situations. It is typically considered as a measure of last resort. Consumers are typically not compensated if the TSO has to curtail load in emergency situations. Load curtailment or demand-side management covers the voluntarily reduction of load by consumers upon the request of the system operator to avoid load shedding or rolling blackouts or improve efficiency of operation. The request by the system operator to shift demand over time can be expressed using economic incentives or using a direct request, such as for instance using an app [81].[37]

Although subtle differences exist in the different types of demand flexibility, this work sticks with the term load curtailment to cover different types. Load curtailment is considered to be executed by the system operator in this work and is applied in emergency situations or when this turns out to be more cost-effective if a trade-off between preventive, corrective and load curtailment actions is made. The cost of load curtailment is determined by the interruption cost, which is the product of the amount of load curtailed and the value of lost load.

Load curtailment is typically not allowed in the preventive decision stage and is only considered as an available action in real-time operation. Load that is not supplied has a value for the affected consumers, which should be taken into account in the decision-making process. Therefore, following cost terms should be taken into account:

$$C^{curt}(\mathbf{P}_s^{curt}) = \sum_{j \in \mathcal{J}} P_{j,s}^{curt} \cdot v_j \tag{4.42}$$

where v_j represents the value of lost load for each consumer j and $P_{j,s}^{curt}$ the load curtailment of consumer j in considered state s.

The amount of load curtailment is also limited to the demand in the system. In the case of demand-side management, if flexible load contracts are considered or to safeguard critical appliances, it is also possible to take into account a lower bound on the amount of load that should be supplied.

$$P_{j,s}^{curt} = P_{j,s}^{load} - P_{j,s}^{supplied} \qquad \forall j \in \mathcal{J}, \forall s \in S \tag{4.43}$$

$$P_{j,s}^{supplied,min} \leq P_{j,s}^{supplied} \leq P_{j,s}^{load} \qquad \forall j \in \mathcal{J}, \forall s \in S \tag{4.44}$$

4.3.6 External Systems: Day-Ahead Market

The day-ahead market is the daily market clearing at power exchanges, which creates a plan for the operation of the power system the next day and is the main market for electrical power [129]. The modeling of the power flow, power transmission and trade constraints is key for the modeling of the market clearing.

[37] An example of such an app was applied in Belgium in the winter of 2014-2015 when system adequacy was low.

The day-ahead market uses an auction mechanism to clear the market. A merit order of generation units is created, starting with the cheapest unit available up to more expensive units, until the entire load can be supplied. The price formation in the day-ahead market is typically done based on the principle 'pay-as-cleared'. This means that all units are remunerated at the marginal price of the system given by the intersection of the demand and supply bids. The price is set by the most expensive generator dispatched to clear the market. Market clearing within a single area is typically based on a copper plate system, i.e., the physical network constraints are not taken into account [153].

4.3.7 Contingencies

Branches and generators are considered as two state component models or two state continuous time Markov chains [104]. The state set consists of the 'working' state and the 'outage' state and at each time instant t the component is in either of the two states. The state transitions are determined by the failure rate λ and repair rate μ of the component, as shown in Fig. 4.8.

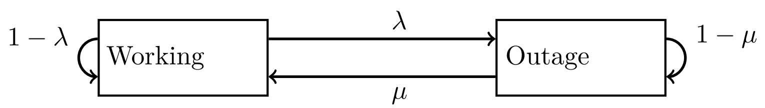


Figure 4.8: State diagram of the two state component model.

The Markov chain only bases itself on the most recent available information and does not take into account earlier history. This is also denoted as the Markov property, i.e., the probability of ending up in a certain state only depends on the state at the previous time step. The Markov chain is time homogeneous, because the transitional behavior does not change over time [154].

A continuous Markov chain can be viewed as a Markov chain where the transitions between states are defined by (constant) transition rates, as opposed to transition probabilities at fixed steps. The probabilities of changing states in an incremental time interval dt are modeled by the following differential equations:

$$\frac{dp^{working}}{dt} = \mu \cdot p^{outage} - \lambda \cdot p^{working} \tag{4.45}$$

$$\frac{dp^{outage}}{dt} = \lambda \cdot p^{working} - \mu \cdot p^{outage} \tag{4.46}$$

If the initial conditions are $p^{working} = 1$ and $p^{outage} = 0$, this results in:

$$p^{working}(t) = \frac{\mu}{\lambda + \mu} + \frac{\lambda}{\lambda + \mu} \cdot e^{-(\lambda+\mu)\cdot t} \tag{4.47}$$

$$p^{outage}(t) = \frac{\lambda}{\lambda + \mu} - \frac{\lambda}{\lambda + \mu} \cdot e^{-(\lambda+\mu)\cdot t} \tag{4.48}$$

For $t \to \infty$, the reliability of being in an outage or working state becomes:

$$p^{working} = \frac{\mu}{\lambda + \mu} \tag{4.49}$$

$$p^{outage} = \frac{\lambda}{\lambda + \mu} \tag{4.50}$$

Combinations of failures of system components k in a system state s are considered to be independent and are calculated as:

$$p_s = \prod_{k \in K^{outage}} p_k^{outage} \prod_{k \in K^{working}} (1 - p_k^{outage}) \tag{4.51}$$

Where K^{outage} is the set of components in failure state and $K^{working}$ is the set of components in working state.

This implementation is a simplification of reality, because memoryless and time homogeneous behavior is not satisfied in practice. Transition probability density functions are generally not exponential and change over time. Moreover, multiple component failures cannot be considered as completely independent. Common mode failures or cascading failures can happen, which do not satisfy the assumption of independence.

4.4 Conclusion

Comparing performance of RMACs is important to convince stakeholders of applying an alternative reliability management approach and criterion. This chapter proposes a quantification framework for evaluating and comparing performance of short-term RMACs. A large scale implementation of the framework based on the presented theoretical design can be used to guide regulators and TSOs towards technically, economically and socially acceptable RMACs. The framework focuses on power system operational planning and real-time operation decision-making processes. The integrated, generic and modular design used in the presented framework goes beyond existing literature, which focuses on selected issues, without analysing the full reliability problem in an integrated manner. Due to the modular structure of the quantification framework, building blocks can easily be replaced by more elaborated or detailed blocks with the same functionality.

This chapter focused on a discussion of the simulation module, its input modules and their interactions. A basic implementation of the simulation module based on a DC SCOPF is used in the case studies in later chapters. This implementation is sufficient to have an indication of relative performance of different RMACs and analyze trends in performance. The presented framework is used as the base for the development of the GARPUR quantification platform, which incorporates a more detailed implementation of the quantitative simulation module and is tested on real systems.

Chapter 5

Performance Evaluation of Short-Term RMACs

The overall decision-making process of selecting an appropriate reliability management approach and criterion is influenced by long-term and short-term uncertainties. To assess the long-term impact of using an alternative reliability management approach and criterion, similar uncertainties need to be considered as in transmission expansion planning [155]. The performance of short-term reliability management is also influenced by several short-term uncertainties, such as contingencies, load and renewable energy sources, behavior of corrective control, behavior of exogenous actors and unforeseeable events. The focus of this chapter is on the performance evaluation of short-term reliability management impacted by short-term uncertainties. The analysis of long-term uncertainties is out of the scope of this thesis.

Performance evaluation of short-term RMACs is an off-line process and consists of four main steps:

1. Selection of a performance evaluation technique and appropriate sampling technique
2. Simulation of TSO's decision-making behavior for different short-term RMACs
3. Selection and calculation of performance indicators
4. Post-processing of results and comparison of performance of different RMACs

The focus of this chapter is on the first point, which needs to be executed before the quantification framework discussed in Chapter 4 can be used, and the fourth point. The simulation of the decision-making process (point 2) and the calculation of performance indicators (point 3) were discussed in more detail in respectively Chapters 4 and 3.

Section 5.1 describes the performance evaluation of short-term RMACs in an analytical way. Section 5.2 describes techniques to evaluate performance of short-term RMACs that enable an efficient use of the quantification framework discussed in the previous chapter in analyses with different objectives. Section 5.3 discusses the advantages and shortcomings of the techniques, generally and in the context of the objectives of this thesis work. Section 5.4 elaborates on the performance evaluation technique used in the case studies in later chapters and discusses its procedure. Conclusions and key take-aways of this chapter are given in Section 5.5.

Parts of this chapter are published in the paper *Qualitative comparison of techniques for evaluating performance of short-term power system reliability management, Heylen E., Troffaes M., Kazemtabrizi B., Deconinck G. and Van Hertem D., Innovative Smart Grid Technologies Conference 2017.*[38]

5.1 Analytical Formulation of Performance Evaluation

The objective of performance evaluation is to translate the decision-making trajectory and real-time system state represented in the vector $\mathbf{X}_m$ resulting from the application of an RMAC m in quantitative performance indicators $Q_{i,m}$:

$$Q_{i,m}(t) = g_i(\mathbf{X}_m(t)) \tag{5.1}$$

where g_i is a deterministic function translating the state space vectors $\mathbf{X}_m(t)$ into a performance indicator $Q_{i,m}(t)$. Performance indicators $Q_{i,m}(t)$ can be system related, such as over- or undervoltage or line overloading, consumer related, such as energy not supplied or outage cost, or can consider aspects of both, such as total system cost.[39] The value of the performance indicator at time t implicitly depends on the previous state and the external forcing inputs at time t. For this reason, the performance indicators follow a trajectory

[38]The first author is the main author of the paper. The contributions of the first author include the review and comparison of the techniques.

[39]Besides the quantitative indicators, qualitative aspects need to be considered in a complete performance evaluation, such as data issues and ease of use, resulting in a multifaceted analysis.

over time that depends on the applied reliability management approach and criterion. Fig. 5.1 gives a schematic overview of the complete procedure using the analytical notation introduced in this chapter and Chapter 4.

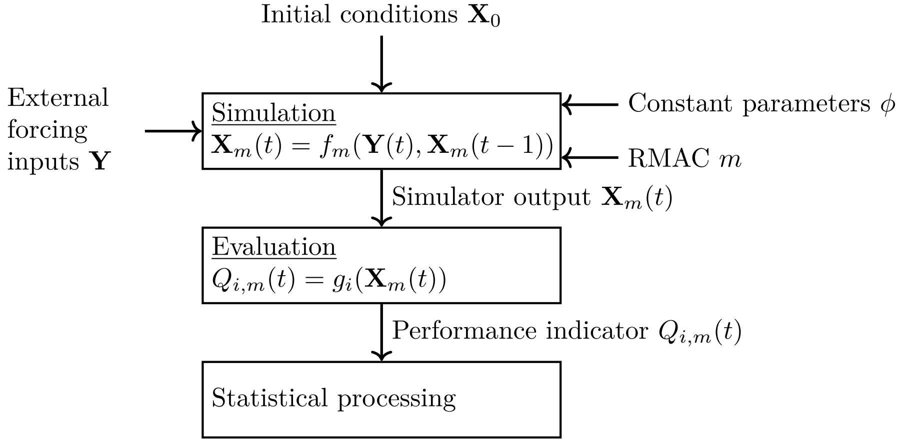


Figure 5.1: Schematic overview of the different steps in quantitative performance evaluation of short-term RMACs.

5.2 Performance Evaluation Techniques

Techniques for evaluating performance of short-term RMACs can be classified in simulation techniques and analytical approaches. Simulation techniques, such as Monte Carlo simulation, simulate the actual process and random behavior of the system. The uncertainty in terms of external forcing inputs Y is included in the sampling process, as values with a higher probability occur more frequently in the sample [18]. Conclusions about the distribution of the output variables can be made based on simulation techniques. Analytical techniques are typically based on a mathematical model resulting in a specific solution for a given input. Uncertainties can be included using stochastic models. A distinction can be made between sequential and non-sequential techniques.

A similar classification exists for reliability assessment techniques. Reliability assessment can be considered as part of the performance evaluation. However, major and important differences between reliability assessment and performance evaluation exist. A complete and reliable performance evaluation requires that both the real-time system state resulting from reliability management and the decision-making trajectory followed while executing reliability management are evaluated [63, 64]. Reliability assessment on the contrary mainly focuses on the real-time system state. Another important difference is that especially failure states are of interest for reliability assessment. Performance evaluation on the contrary also has to evaluate the performance of reliability management in normal states. A better trade-off between preventive and corrective actions has the potential to improve performance in normal states. Complete performance evaluation of reliability management approaches and criteria, considering both the decision-making trajectory and the real-time system states, has not been specifically covered in literature so far. Nevertheless, an efficient and complete performance evaluation of different RMACs is crucial, given the importance for society of an adequate reliability level.

5.2.1 Sequential Simulation

Sequential simulations enable system stakeholders to make conclusions about the distribution of performance indicators for time periods of length T, e.g., a year. A sample of $\mathbf{Y}(0), \ldots, \mathbf{Y}(T)$ with $\mathcal{N}$ realizations is generated. For each realization, $\mathbf{x}_{m,n}(t) = f_m(\mathbf{x}_{m,n}(t-1), \mathbf{y}_n(t))$ is recursively calculated with $\mathbf{x}_{m,n}(0) = \mathbf{x}_0$. Performance indicators $q_{i,m,n}^{period} = \sum_{t=1}^{T} q_{i,m,n}(t)$ can be evaluated using Eq. (5.1) for each realization n of duration T.

A sample should represent the variation between different time periods of length T in terms of uncertainties regarding load and wind forecasts and realizations and availabilities of system components. A sample can be generated based on historical time series of forecasts and realizations of load and wind and system component statuses or based on statistical models of load, wind power and failure and repair of system components [156]. However, the former is challenging due to non-stationarities in the time series, whereas the latter is challenging due to correlations between the parameters in the multi-dimensional input parameter space.

The mean of the performance indicator and its confidence interval can be approximated as:

$$E[Q_{i,m}^{period}] \approx \frac{1}{\mathcal{N}} \sum_{n=1}^{\mathcal{N}} q_{i,m,n}^{period} \pm t_\alpha \cdot \frac{\sigma[q_{i,m}^{period}]}{\sqrt{\mathcal{N}}} \tag{5.2}$$

where $\sigma[q_{i,m}^{period}] = \sqrt{\frac{1}{\mathcal{N}-1} \sum_{n=1}^{\mathcal{N}} (q_{i,m,n}^{period} - \bar{q}_{i,m}^{period})^2}$ is the sample standard deviation, $\bar{q}_{i,m}^{period} = \frac{1}{\mathcal{N}} \sum_{n=1}^{\mathcal{N}} q_{i,m,n}^{period}$, and t_α is the α-percentile of the t-distribution.[40] Moreover, the (joint) marginal distribution of performance indicators $Q_{i,m}(t)$ can be determined based on the simulations, which enables the verification of the relative performance of RMACs at each time instant t in the period T.

5.2.2 Non-Sequential Simulation

Non-Sequential Simulation (NSS) techniques enable system stakeholders to draw conclusions about the (relative) performance of different RMACs at an average point in time and the uncertainty on this value. Evaluations are made for random snapshots. For each snapshot, the different decision stages in short-term reliability management are simulated. Non-sequential simulations of short-term reliability management can be represented as:

$$\mathbf{x}_{m,n} = f_m(\mathbf{x}_0, \mathbf{y}_n) \quad \forall n \in 1..\,\mathcal{N} \tag{5.3}$$

where $\mathbf{y}_n$ is a realization of external forcing inputs in the sample and $\mathbf{x}_0$ the initial conditions. The time dependence is not explicitly considered in non-sequential simulations. Mean and variance of the performance indicators $Q_{i,m}$ can be calculated similarly to Eq. (5.2).

The sample of $\mathcal{N}$ system states should represent the correlation between the input parameters and the distributions of the external forcing inputs. The sample of external forcing inputs can be generated based on stochastic models, but this is challenging due to correlations between the parameters of the input space. Alternatively, samples can be randomly drawn from (historical) time series of the different parameters in the external forcing input space. However, non-stationarities in the time series make this challenging.

The performance of short-term reliability management strategies might be strongly affected by a set of high-impact contingencies that only occur with a low probability. The effect of these contingencies only becomes visible in the result after a large number of simulations. To reduce the number of simulations, importance sampling can be applied. By sampling based on a different distribution than the distribution of interest, highly impacting states of the external forcing input space appear more often in the sample. However, finding such an alternative distribution is typically challenging [158, 159].

[40] Alternatively, non-parametric bootstrapping can be used to obtain asymmetric confidence intervals taking into account the asymmetry of the distribution of the performance indicators. However, uncertainty is typically underestimated with bootstrapping techniques [157].

5.2.3 Emulation

An emulator is a statistical representation of a simulator and is typically developed using a Gaussian process or analogous Bayes linear theory based on a reduced number of simulations [160, 161]. It enables the determination of uncertainties in model outputs arising from numerous sources of uncertainty, e.g., parametric uncertainty, condition uncertainty, functional uncertainty, stochastic uncertainty, etc. [119] Emulation is applied in other application contexts requiring highly complex models that are computationally intensive to simulate, such as transmission expansion planning [162], system generation planning [163], climate models [164] or to predict the behavior of nuclear power reactors [161]. The statistical models are typically based on different hierarchical levels, i.e., less detailed models that are more frequently evaluated and more complex, detailed models that are harder to evaluate and are only evaluated a limited number of times. The error made due to approximation can be estimated from the statistical model [160, 161].

The single step function f_m, representing the simulator of the RMAC m, is a deterministic function, which can be approximated by a function $\tilde{f}_m$, the emulator:

$$\tilde{\mathbf{X}}_m(t) = \tilde{f}_m(\tilde{\mathbf{X}}_m(t-1), \mathbf{Y}(t)) \tag{5.4}$$

The emulator should satisfy two criteria [160]:

1. The emulator should represent the true value $f_m(\mathbf{x})$ at the points of the training set, due to the deterministic characteristics of the function.
2. At other points, the distribution for $f_m(\mathbf{x})$ should have a mean value $\tilde{f}_m(\mathbf{x})$ that represents a plausible interpolation or extrapolation of the training data and the probability distribution around the mean represents the uncertainty about how the simulator might interpolate/extrapolate in a realistic way.

The function $\tilde{f}_m$ is determined based on simulations for a training sample of external forcing inputs and system states $(\mathbf{x}_m(t-1), \mathbf{y})$. The training sample is a subspace of the input region of interest of the single step function f_m. Prior beliefs about the simulator, i.e., before the training data are considered, are taken into account. These prior beliefs are represented by the mean and covariance structures of the Gaussian process [161]. The difference between statistical emulation and traditional regression is that traditional regression does not satisfy the above criteria. Polynomial regression might satisfy the first one, but fails to satisfy the second [160].

Instead of simulating the exact function f_m for different external forcing inputs $\mathbf{y}$ and different previous system states $\mathbf{x}_m$, the function $\tilde{f}_m$ can be evaluated directly in terms of $\mathbf{y}$ and $\mathbf{x}_m(t-1)$. This results in an approximate value of the non-sequential performance indicator $\tilde{Q}_{i,m}$. The expected value of the approximate indicator can be calculated directly if the multivariate distribution $\Pi(\mathbf{x}_m, \mathbf{y})$ is known:

$$E[\tilde{Q}_{i,m}] = \int_{\tilde{\mathbf{X}}_m} \int_{\mathbf{Y}} \Pi(\mathbf{x}_m, \mathbf{y}) \cdot g_i(\tilde{f}_m(\mathbf{x}_m, \mathbf{y})) d\tilde{\mathbf{X}}_m d\mathbf{Y} \tag{5.5}$$

However, this is rarely the case in practice as the multivariate distribution of the system states is hard to determine. Alternatively, direct evaluations of the approximate function $\tilde{f}_m$ for a sample of external forcing inputs and system states that represents the multivariate distribution $\Pi(\mathbf{x}_m, \mathbf{y})$ can be used.

Eq. (5.4) corresponds to the emulation of the single step function $\mathbf{x}_m(t) = f_m(\mathbf{x}_m(t-1), \mathbf{y}(t))$. The emulation of this single step function can be used to construct an emulator for the dynamic simulator of the decision-making process $(\mathbf{x}_m(1), \ldots, \mathbf{x}_m(T)) = f_m(\mathbf{x}_0, \mathbf{y}(1), \ldots, \mathbf{y}(T))$. In this case, the full simulator output $(\mathbf{x}_m(1), \ldots, \mathbf{x}_m(T))$ is approximated by iteratively applying $\tilde{\mathbf{x}}_m(t) = \tilde{f}_m(\tilde{\mathbf{x}}_m(t-1), \mathbf{y}(t))$, with $\tilde{f}_m$ the single step function in Eq. (5.4) for different time series of external forcing inputs and initial system states $(\mathbf{x}_0, \mathbf{y}(1), \ldots, \mathbf{y}(T))$ within the input region of interest of the full simulator. The distribution of the sampled trajectories $(\tilde{\mathbf{x}}_m(1), \ldots, \tilde{\mathbf{x}}_m(T))$ needs to be verified to determine whether the applied training data for the single step emulator are adequate. If not, further runs of the single step function are required and the procedure needs to be repeated [161].

If an emulator of the dynamic simulator can be obtained, the calculation time can be significantly reduced compared to a simulation approach, as time-consuming simulations are replaced by analytical function evaluations. However, a challenge of emulation is the sampling of an appropriate training set. Short-term reliability management is subject to a complex, highly dimensional parameter space of external forcing inputs, which might be hard to process in an emulation technique. A sufficiently high number of simulations is required to obtain a satisfactory approximation $\tilde{f}_m$, if the function f_m is highly variable. This aspect is difficult to verify without knowing the exact behavior of the function. Moreover, high impact low probability events might not be well represented in the emulator if only a small number of system states is simulated. Therefore, it is important that the emulator is also trained on extreme events.

5.2.4 Analytical State Enumeration

Analytical State Enumeration (ASE) considers a prescribed set of combinations of external forcing inputs and initial conditions with probabilities assigned to them. The fact that the probability distribution of the initial state $\mathbf{x}_0$ is not known analytically and is hard to determine in practice leads to a similar challenge as in non-sequential simulation. Therefore, initial conditions are typically assumed to be constant. The state space of external forcing inputs $\mathbf{Y}$ is divided in intervals $\Delta\mathbf{y}_l$ for which the function f_m is simulated at one point $\mathbf{y}_l$ in the interval. The function f_m is approximated by assigning the same function value $f_m(\mathbf{x}_0, \mathbf{y}_l)$ to all $\mathbf{y}$ within the interval $\Delta\mathbf{y}_l$. The accuracy of the results strongly depends on the set of intervals Ł and the sizing of the intervals $\Delta\mathbf{y}_l$, which can be improved using appropriate snapshot selection techniques.

The probability of occurrence of a state in the interval $\Delta\mathbf{y}_l$ is calculated as:

$$\Pi(\mathbf{x}_0, \Delta\mathbf{y}_l) = \int_{\Delta\mathbf{y}_l} \Pi(\mathbf{x}_0, \mathbf{y}) d\mathbf{y} \tag{5.6}$$

The expected value of the performance indicator can be approximated as:

$$E[Q_{i,m}] \approx \sum_{l=1}^{Ł} \Pi(\mathbf{x}_0, \Delta\mathbf{y}_l) \cdot f_m(\mathbf{x}_0, \mathbf{y}_l) \tag{5.7}$$

Applying state enumeration in a sequential context is challenging and would require the simulation of a prescribed set of time series of external forcing inputs. However, the set of all possible time series is hard to approximate with a reduced set of time series due to the many possible combinations of external forcing inputs at different time instants. Also the probability of occurrence of a certain time series is hard to obtain. Alternatively, shortened sequences can be applied, for instance representing characteristic days, which can be selected using heuristics, clustering techniques or optimization-based methods [165].

5.3 Comparison of Performance Evaluation Techniques

The techniques to evaluate performance of short-term RMACs introduced in the previous section are compared in this section. An assessment is made taking into account the objectives of this thesis, which explains the choice of the applied evaluation technique. This incorporates the choice between sequential and non-sequential techniques on the one hand and between simulation and analytical techniques on the other hand.

5.3.1 Sequential versus Non-Sequential Evaluation

Sequential and non-sequential evaluation techniques cover different levels of detail and have a different computation time. The trade-off between these two aspects depends on the objective of the analysis. Alternatively, pseudo-sequential techniques can be considered.

Sequential

Sequential simulations consider the dynamic process of decision making in short-term reliability management. Time correlations and interdependencies between decisions taken at subsequent time instants are taken into account. To consider this high level of detail in the simulations, sequential simulations are done over a longer time period T, which increases the simulation time.[41] Moreover, a sufficiently high number of simulations should be executed for time periods with similar characteristics, e.g., for different years.

Performance of RMACs depends on external conditions, such as weather, demand levels, etc., which vary between time instants t in the period T. Sequential simulations make it possible to determine the marginal distribution of performance indicators for each time instant t in the period T. Based on these results, the performance of reliability management approaches and criteria over the period T under consideration can be fine-tuned. Given the characteristics of sequential evaluation techniques, they can be used to compare the detailed decision-making process according to an alternative RMAC with the state-of-the-art decision making in real systems and to fine-tune the performance of promising RMACs.

Non-Sequential

Non-sequential techniques consider evaluated time instants to be independent and do not consider time correlations of input parameters or interdependencies in decision making between time steps. This is a strong simplification, but significantly reduces computation time compared to sequential techniques. Non-sequential techniques are typically applied in high-level analyses that aim at obtaining indicative results in terms of performance. Due to their lower computation time, non-sequential techniques are better suited to assess a large set of RMACs with different settings of controllable parameters. Also a large

[41] The high simulation time is already an issue in simulations for a single time instant, especially in large systems with a large set of binary variables. This was discussed in more detail in Section 4.3.

set of exogenous factors can be analysed to assess which factors have the highest impact on the different performance dimensions.

Pseudo-Sequential

Studies in the context of power system reliability assessment have shown that similar results can be obtained in terms of energy not supplied and load curtailment if non-sequential simulations are used compared to sequential simulations [166, 167, 168]. However, based on non-sequential simulation techniques, interruption duration and interruption frequency cannot be determined as quantitative performance indicators. Pseudo-sequential approaches are developed that make it possible to determine interruption duration and interruption frequency indicators in a traditional reliability assessment [169, 170, 171]. These approaches only execute sequential simulations for reduced time periods. However, they cannot be directly applied in a performance evaluation context, as they mainly focus on failure states. The performance of RMACs is influenced by the trade-off between preventive and corrective actions, which also has an impact in normal states without component failures. Pseudo-sequential techniques that perform well in the context of overall performance evaluation of RMACs are not yet available in literature.

5.3.2 Comparative Case Study of Non-Sequential Evaluation Techniques

The objective of the case studies in this thesis is to obtain indicative results in terms of performance of different RMACs. The focus is not to quantify the exact change in performance, but to observe trends in the average performance that can be distinguished if different RMACs are applied. This explains the choice of a non-sequential evaluation technique in the case studies. The three non-sequential approaches, i.e., non-sequential simulation, analytical state enumeration and emulation, are illustrated and compared for a basic three-node test system as shown in Fig. 5.2.

In this test system, the expected value of the cost of preventive actions is estimated if the N-1 criterion is applied in the operational planning stage. The input variable is the total demand in the system, which ranges from 40 MW up to 125 MW. Fig. 5.3a shows the probability density function of the total demand in the system. This is clearly multi-modal and does not follow a standard parametric distribution. The distribution of demand over the nodes is assumed to be constant. The system only relies on conventional generation. The analysis is done for a system in which all components are available in the

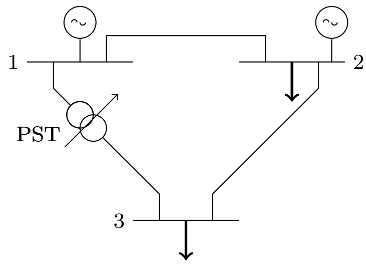


Figure 5.2: Three-node test system.

operational planning stage. The described assumptions result in an analysis with one input, i.e., total system load, and one output variable, i.e., expected preventive costs.

Fig. 5.3b shows the approximation of the function f_m using supervised learning based on Gaussian processes.[42] Besides the estimate of the function, the 99% confidence interval around the estimate is given. The main uncertainty on the estimate is found at the beginning and the end of the range of total system load. Fig. 5.3c shows the approximation of the function f_m in the analytical state enumeration approach. The range of total system load is divided in several intervals and an evaluation is made in each interval. Fig. 5.3d shows the sample of output variables resulting from the non-sequential simulation technique and how this resembles the function f_m and the probability density function of total system demand.[43] The density of the data points in the sample corresponds to the probability of occurrence of a certain total demand in the system.

Table 5.1 compares the non-sequential simulation, emulation and analytical state enumeration techniques in terms of the obtained expected preventive cost and the number of simulations. Non-sequential simulation is a computationally intensive approach, even in small, low-dimensional systems, because a representative sample of the whole range of total system demand should be simulated. Monte Carlo simulation converges very slowly, i.e., as $\sqrt{\mathcal{N}}$, which means that a tenfold increase in accuracy requires a hundredfold increase in the sample size. An advantage of Monte Carlo is that the speed of convergence does not depend on the dimensionality of the problem, which is normally the problem with analytical integration, such as quadrature methods [174]. Random sampling

[42] The emulation is executed using the Scikit-learn python package for machine learning [172]. The covariance structure or function, which specifies the covariance between pairs of random variables, is modeled using a radial basis function kernel. This covariance function has the property that it is almost unity between variables whose inputs are very close and decreases as their distance in the input space increases [173].

[43] Only a randomly selected subset of the total sample is plotted for clarity reasons.

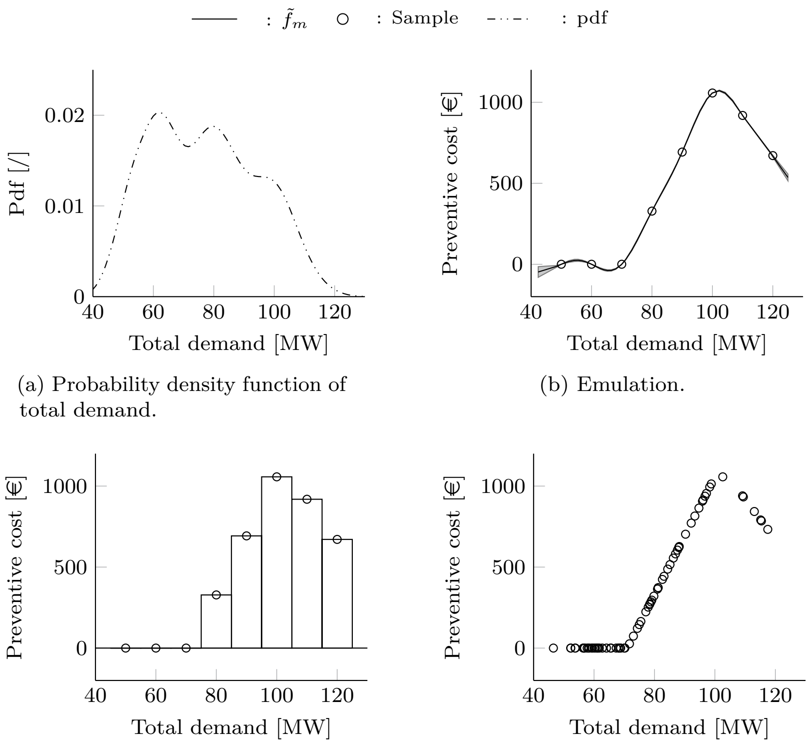
is applied in this case study. This implies a large number of simulations as shown in the second and third row of Table 5.1. On the contrary, the method is easy to understand and apply and makes it possible to verify the uncertainty on the expected value in terms of a confidence interval and the significance of differences in performance between different RMACs based on paired hypothesis tests. Moreover, the distribution of the quantitative performance indicators can be assessed. The emulation technique gives similar results as non-sequential simulation. The emulation technique is based on a reduced set of simulations and a high number of function evaluations of the approximate function $\tilde{f}_m$ with a very low computational cost. The result of analytical state enumeration lies within the confidence intervals of the simulation and emulation techniques. Confidence intervals cannot be estimated based on analytical state enumeration, as this technique focuses on expected values [18]. However, the approach is particularly useful to obtain indicative results in terms of the average change in performance.

Table 5.1: Results of the three-node case study.

	$E[C^{prev}]^1$[€]	Number of simulations ${f_m}^2$	Number of evaluations $\tilde{f}_m$
ASE	353.21	8	/
NSS	348.55 [338.52;358.58]	10000	/
	349.19 [343.89;354.50]	36000	/
Emulation	347.66 [337.48;357.83]	8	10000
	353.60 [348.17;359.03]	8	36000

[1] The results between brackets represent the 99% confidence interval
[2] The computation time per simulation is the same for the three techniques

Emulation has an advantage compared to analytical state enumeration, namely that it enables the quantification of uncertainty for all points which have not been evaluated [162]. Emulation is more difficult to apply with multi-dimensional input and output spaces, which might contain discrete variables. ASE is easy to use on the contrary. A drawback of analytical techniques is that simplifying assumptions and approximations need to be made due to the complex nature of short-term reliability management [18]. This makes them hard to apply in highly-dimensional systems with a lot of uncertain parameters. The performance of analytical techniques can be improved using principal component analysis in a preprocessing step. This analyzes the importance of different parameters in the parameter space and makes it possible to reduce the dimensions of the parameter space by focussing on the most influential parameters.



(a) Probability density function of total demand.

(b) Emulation.

(c) Analytical state enumeration.

(d) Non-sequential simulation.

Figure 5.3: The application of non-sequential performance evaluation techniques to a three-node test system with total system demand as input variable and preventive costs as output variable.

5.4 Implementation of the Evaluation Module

The case studies in this work use time-collapsed models in non-sequential techniques. These types of models ignore correlations across time, but are suitable to determine trends in performance between different RMACs. One hour time steps are considered. A non-sequential, analytical state enumeration technique that evaluates performance of RMACs for a characteristic set of system states is applied in the case studies.

5.4.1 Evaluation Procedure

An important part of the evaluation procedure is the selection of system states to evaluate. The set of system states under evaluation should theoretically consist of all possible operating states, considering component outages and operating states representing uncertainties regarding forecast errors of load and RES generation. However, this is not possible in practice. System states should be selected that are used as input for the operational planning stage and real-time operation stage. Operational planning states are characterized by the forecast of load and RES and possible system outages. Real-time system states are conditional upon the day-ahead, operational planning state and represent the realization of load and power generation from RES, as well as contingencies.[44]

It is important that the selection of real-time system states under evaluation is not biased towards a certain RMAC. For instance, if only the N-1 contingency states are considered in the evaluation procedure, it might be that the performance obtained for the N-1 criterion is better than its effective performance. To avoid bias towards a certain criterion, the contingency set in ASE used for the evaluation consists of the union of the contingency sets of each of the RMACs under evaluation complemented with some additional contingencies. This is graphically illustrated in Fig. 5.4. The additional contingencies are selected based on their probability of occurrence, i.e., the most probable contingencies up to a prescribed cumulative probability are considered.

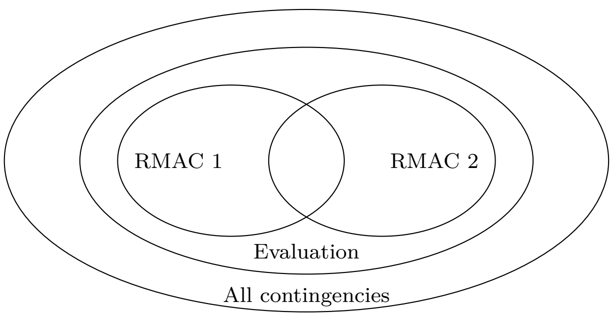


Figure 5.4: Relation between the set of contingencies under evaluation and the set of contingencies considered in the RMACs.

Day-ahead market clearing and operational planning are simulated for the parameters related to each of the states in the set of operational planning

[44]The selection of system states in the case studies is discussed in more detail in the respective case studies in later chapters.

states, after which the real-time system states are simulated. If all real-time system states related to the operational planning state are simulated, the next operational planning state is selected and the procedure is repeated. Finally, if all states are treated, the results are used as an input for the quantitative evaluation of the performance in which the performance indicators $Q_{i,m}$ are calculated. ASE explicitly takes into account the probability structure in the calculation of the expected values of the performance indicators. The evaluation procedure is shown in Fig. 5.5.

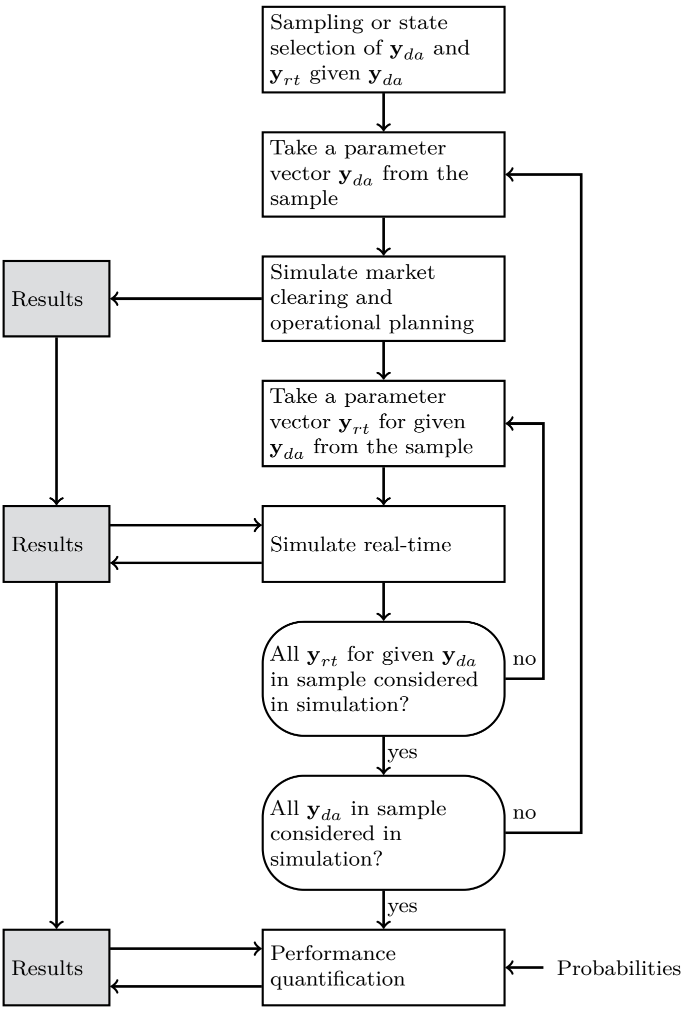


Figure 5.5: Evaluation procedure.

5.4.2 Comparing Performance of RMACs

Different RMACs will lead to different decisions implying a different performance. If the same process with equal input data is repeated for various RMACs, performances can be compared. Comparing the performance of RMACs is preferably done on a relative scale. Therefore, benchmarking against a well-known RMAC is a useful approach. Quantification of performance of RMACs using the performance metric and quantification framework proposed in resp. Chapters 3 and 4 makes it possible to obtain a numerical indication of change in performance if an alternative RMAC is used in specific circumstances. However, the performance of reliability criteria strongly depends on various system parameters, such as value of lost load, system robustness, etc. [127]. Therefore, RMACs with changing parameters, e.g., the considered contingency set, reliability targets, etc., as a function of system characteristics and conditions might be more effective.

5.5 Conclusion

Two types of techniques to evaluate performance of reliability management approaches and criteria can typically be distinguished: analytical techniques and simulation techniques, which can be sequential or non-sequential in nature. Although the same classes of techniques are applied in reliability assessment, the characteristics of performance evaluation differ from reliability assessment. Firstly, performance evaluation requires that the complete decision-making trajectory according to a certain RMAC is evaluated besides the real-time system state that results from it. Secondly, performance evaluation should consider both normal and failure states, whereas reliability assessment mainly focuses on failure states. These differences should be taken into account in the evaluation procedure.

Sequential and non-sequential simulation and analytical techniques each have their advantages and shortcomings. Their applicability and suitability in a certain context depend on the objectives of the analysis. The objective of this work is to give indications of possible changes in performance if alternative RMACs are applied rather than to make a detailed analysis of using an alternative RMAC in a real system. For this reason, non-sequential techniques are applied. They enable system stakeholders to evaluate the performance and verify its sensitivity to exogenous factors for a large set of RMACs with different settings of the controllable parameters, given the long computation time of the SCOPF to simulate TSO's decision-making behavior.

Chapter 6

Inequality and Inequity of Power System Reliability

Many decisions of network operators and regulators have an effect on the reliability level of power systems: building new lines, the installation of power flow control equipment, increased penetration of intermittent generation [175], generation adequacy load-shedding plans [78], the application of new reliability criteria [63], asset management and maintenance [176], cross-border cooperation on balancing [177], etc. However, these decisions do not affect all consumers equally. Different types of consumers exist and some are more affected than others, depending on their characteristics and location. If consumers feel that their reliability level is unfairly low compared to other consumers, they could complain and oppose those decisions that lower their reliability level. Therefore, in addition to measuring the change in costs and the change of the overall reliability level, it is important that power system decision makers also assess the relative distribution of unreliability among consumers. Assessing inequality and inequity between consumers in terms of reliability levels makes it possible to take appropriate measures to reduce inequality and inequity, either directly or indirectly. This can suppress public opposition against decisions that are crucial to improve the performance of power systems and has a positive effect on their social acceptability.

No indices that express the distribution of unreliability among consumers in a single number and are therefore easy to interpret have been presented before. Nowadays, the assessment of equality and equity, if performed, is done based on graphs, tables or operator assessment based on judgement calls or questionnaires. These are hard to assess and compare in a unified way, resulting in less effective decision making. To measure the inequality and inequity of power system reliability, this chapter reformulates the Gini index in terms of reliability. The proposed index is generic in the sense that different reliability indicators can be applied. The index can also be used to evaluate generator connectivity, e.g., to assess inequality in terms of RES curtailment. This work formulates the Gini index in terms of energy not supplied, total cost for consumers and interruption costs. In this way, the adapted Gini index, which is normally used to measure income inequality [178, 179, 180, 181], can be used in a power system reliability context. The inequality assessment can be applied by regulating bodies and system operators in the assessment of reliability decisions in different contexts, e.g., adequacy, security, investment decisions, etc.

Section 6.1 formulates the definition of equality and equity in a power system reliability context. Section 6.2 describes the design of the indices and discusses their strengths and weaknesses. The usefulness of the indices is illustrated in three case studies, each with a different background: (i) adequacy, (ii) security and (iii) real reliability data. The first case study, in Section 6.3, evaluates the inequality resulting from the 2014-2015 load-shedding plan in Belgium.[45] The second case study, in Section 6.4, focuses on the comparison of the inequality resulting from short-term reliability management based on different reliability management approaches and criteria. The third case study, in Section 6.5, investigates inequality and inequity between different consumer groups based on real reliability data of Norway. Section 6.6 discusses the practical use of the inequality index and introduces possible measures to reduce inequality and inequity of power system reliability. Finally, Section 6.7 concludes.

This chapter is partly based on the paper *Inequality of Power System Reliability: A Summarizing Index, Heylen E., Ovaere M., Proost S., Deconinck G. and Van Hertem D.*, submitted to IET Generation, Transmission and Distribution.[46]

[45]Because of generation adequacy concerns in the winter of 2014-2015, the Belgian load-shedding plan came into the picture. This plan enables the Belgian TSO ELIA to temporally shed load in different regions in case of emergency. Public opposition to this plan was large, because people felt that the burden of the load shedding was placed on a small group of (rural) consumers and that the plan affected some industrial areas and some regions more than others.

[46]The first author is the main author of the paper. The contributions of the first author include the idea of using an inequality index for reliability and the modeling and analysis of the case studies about the load-shedding plan and the comparison of RMACs. The design of the inequality indices based on the Gini index are the result of a collaboration between the first two authors. The paper includes an additional case study to illustrate the usefulness of the indices in the assessment of investment decisions.

6.1 Definition of Inequality and Inequity of Power System Reliability

Economists make a distinction between equality and equity. Equity is defined as giving everyone what they need or deserve, whereas equality is defined as treating everyone the same, regardless of differences in needs or desert. This section translates the economic definition to the power system reliability context. A generic inequality ratio is defined, in which different reliability indicators can be applied. Depending on the indicator that is applied, the definition of the inequality ratio will be closer to equality or to equity.[47]

6.1.1 Generic Inequality Ratio

The inequality ratio expresses whether a certain entity, i.e., node, consumer group or individual consumer, is treated equally or equitably and depends on the consumer's share in total demand and its share in total unreliability expressed in terms of a reliability indicator.

The vector $\mathbf{w}$ contains the share of demand of each consumer[48] j in the total electrical energy demand in the set $\mathcal{J}$ of all consumers:

$$w_j = \frac{D_j^{Energy}}{\sum_{j' \in \mathcal{J}} D_{j'}^{Energy}} \tag{6.1}$$

with D_j^{Energy} the electrical energy demand of consumer j.

The vector $\mathbf{e}$ contains the share of unreliability in the total unreliability for each consumer j in terms of a Reliability Indicator (RI):[49]

$$e_j = \frac{RI_j}{\sum_{j' \in \mathcal{J}} RI_{j'}} \tag{6.2}$$

with RI_j the reliability indicator of consumer j expressing its reliability level.

The following conditions need to be satisfied for vectors $\mathbf{w}$ and $\mathbf{e}$:

$$\sum_{j' \in \mathcal{J}} w_j = \sum_{j' \in \mathcal{J}} e_j = 100\% \tag{6.3}$$

[47] In this work the term 'inequality ratio' is used for all specifications.

[48] In this definition, the inequality amongst consumers is used, but similar formulations can be used on substation or regional levels.

[49] The set of reliability indicators that is applicable in the inequality ratio is not limited to the ones proposed in this work.

$$w_j = 0 \Longrightarrow e_j = 0 \tag{6.4}$$

The first condition (6.3) guarantees that all demand and all unreliability is distributed over all consumers, while the second condition (6.4) states that consumers without electricity demand cannot suffer interruptions that cause unreliability.

A distribution of reliability is considered to be fair if all consumers contribute to the unreliability according to their share in total demand:

$$\xi_j = 1, \forall j \in \mathcal{J} \text{ with } \xi_j = \frac{e_j}{w_j} = \text{ inequality ratio} \tag{6.5}$$

If the distribution is not perfectly equal, some consumers j are more ($\xi_j > 1$) or less affected ($\xi_j < 1$).

6.1.2 Equality versus Equity

Different reliability indicators can be applied in the inequality ratio. Depending on the applied reliability indicator, the definition of the ratio inclines more towards equality or equity.

Firstly, inequality can be defined in terms of energy not supplied. The inequality ratio in this case equals:

$$\xi_j^{ENS} = \frac{ENS_j}{\sum_{j' \in \mathcal{J}} ENS_{j'}} \cdot \frac{\sum_{j' \in \mathcal{J}} D_{j'}^{Energy}}{D_j^{Energy}} \tag{6.6}$$

This implies that a set of consumers is considered to be treated equally if their share in total energy not supplied equals their share in total demand, irrespective of their characteristics. Depending on whether the index is used in an ex-ante or ex-post evaluation, resp. Expected Energy Not Supplied (EENS) for a set of events or Energy Not Served (ENS) for a single event or a sequence of events is used.

Inequality can also be defined in terms of total cost borne by consumers C_j^{cons}, i.e., the interruption cost due to load curtailment, received compensations and payments made in the context of a compensation scheme:

$$\xi_j^{cost} = \frac{C_j^{cons}}{\sum_{j' \in \mathcal{J}} C_{j'}^{cons}} \cdot \frac{\sum_{j' \in \mathcal{J}} D_j^{Energy}}{D_j^{Energy}} \tag{6.7}$$

This definition of equality implies that a consumer is treated fairly, if its share in the total cost borne by all consumers equals its share in total demand, i.e., consumers with a higher demand have more costs. This definition can be usefully applied to verify the effectiveness of a compensation scheme.

Alternatively, equality can be formulated in terms of interruption cost. Interruption costs are the product of a consumer's energy not supplied ENS_j and his/her value of lost load v_j. This formulation states that interruption costs are distributed fairly if the share of each consumer in the interruption cost equals its share in total demand. The inequality ratio in this case equals:

$$\xi_j^{IC} = \frac{ENS_j \cdot v_j}{\sum_{j' \in \mathcal{J}} ENS_{j'} \cdot v_{j'}} \cdot \frac{\sum_{j' \in \mathcal{J}} D_{j'}^{Energy}}{D_j^{Energy}} \tag{6.8}$$

This definition of equality is closer to equity of reliability, because VOLL is correlated with need and desert. However, VOLL is not fully correlated with need and desert. For example, poor households may be more in need of reliable electricity supply, but will typically have a lower VOLL than rich households. On the contrary, it makes sense to provide a higher reliability level to hospitals or high VOLL industry. Fairness is a combination of equity and equality, so that the specifications of the inequality ratio are complementary [182].

An interpretation of the difference between equality and equity in terms of power system reliability for a set of consumers with equal demand, but different values of lost load is illustrated in Fig. 6.1. A set of consumers with equal demand is considered to be treated equally if all consumers have the same amount of load curtailment. The equity amongst consumers in terms of unreliability is ensured if the interruption cost is equal for all consumers, i.e., $P_j^{curt} \cdot v_j =$ Constant. This means that consumers with a higher value of lost load will have a lower level of load curtailment. If consumers have different demand levels, their relative amount of interruption cost should be proportional to their demand share, whereas the amount of load curtailment will be inversely proportional to their value of lost load in a more equitable case.

6.2 An Inequality Index for Power System Reliability

Many different inequality indices have been proposed in the economic literature. These indices are used to compare income distributions between countries or to verify the impact of certain decisions, such as the introduction of a tax on the distribution of income within a certain country. These indices have been applied to insurance [183], education [184] and biodiversity [185]. Based on the definition of equality provided in the previous section, this section develops an

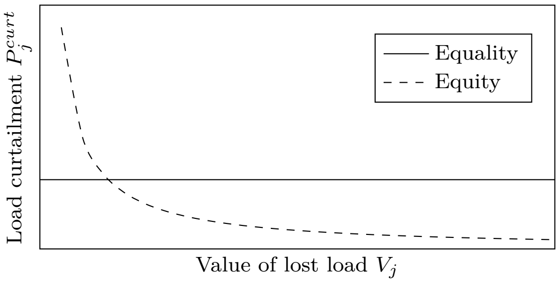


Figure 6.1: Difference between equality and equity in a power system reliability context for consumers with different VOLL but equal demand D_j^{Energy}.

inequality index, which enables the quantification of inequality and inequity of power system reliability in a single value.

6.2.1 Inequality Indices

Various inequality indices are reported in the literature: the variance, the coefficient of variation, the relative mean deviation [178], the standard deviation of logarithms, the 20:20 ratio, the Palma ratio, Theil's index [186], the Atkinson index [179], the Schutz or Hoover index [187] and the Gini index [188]. The strengths and weaknesses of each of these indices have been studied extensively in the economic literature. For example, the variance is not scale invariant[50] and the relative mean deviation fails to satisfy the principle of transfers.[51] In addition, the inequality indices differ in their sensitivity to transfers: the Palma ratio and the 20:20 ratio particularly focus on the extremes of the distribution, whereas the Gini index focuses on the middle of the distribution [188, 189].

A perfect inequality index does not exist, but the Gini index is the most widely used. One of the reasons for its popularity is that it is easy to understand how to compute the Gini index based on Lorenz curves.

[50]Scale invariance ensures that if everyone's reliability level or demand is multiplied by a constant value, the degree of inequality remains unchanged [188].

[51]The principle of transfers states that a transfer in the share of reliability Δe from a consumer j to a consumer j' should decrease the value of the inequality index if $\xi_j > \xi_{j'}$ and $\frac{e_j - \Delta e}{w_j} \geq \frac{e_{j'} + \Delta e}{w_{j'}}$ [178].

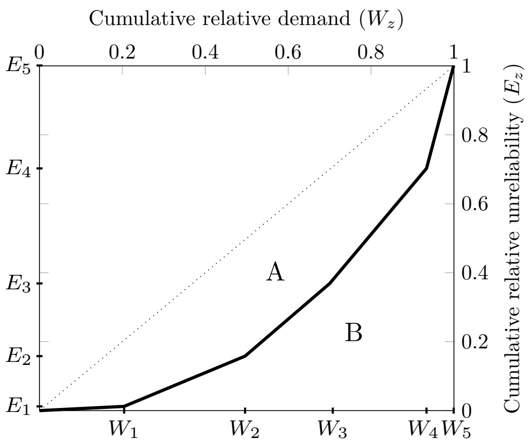


Figure 6.2: Lorenz curve in terms of power system reliability. The line of equality is dotted.

6.2.2 Lorenz Curves

The distribution of reliability between consumers can be represented in a Lorenz curve. A Lorenz curve plots the cumulative share of demand W_z with respect to the cumulative share of unreliability E_z, with all consumers ranked according to an increasing inequality ratio ξ_j. The inequality ratio represents the slope of the different pieces of the piecewise-linear Lorenz curve. This is shown in Fig. 6.2.

If the distribution of reliability is completely fair (i.e., when $\xi_j = 1 \; \forall j \in \mathcal{J}$), the Lorenz curve is a straight line with coefficient of direction equal to 1, as illustrated by the dotted line in Fig. 6.2. If the distribution of reliability is not completely fair, the Lorenz curve will be below the equality line, as illustrated by the bold line in Fig. 6.2. The closer the Lorenz curve is to the equality line, the more equal the distribution of reliability.

6.2.3 The Gini-based Inequality Index of Power System Reliability

The proposed Gini-based inequality index of power system reliability U is defined as the ratio of the surface area between the line of equality and the

Lorenz curve (A) over the total surface area under the line of equality (A+B):

$$U = \frac{A}{A+B} \tag{6.9}$$

Surface area B can be calculated using the surface areas of the trapezoids under each of the pieces of the piecewise-linear Lorenz curve. This leads to the following formula for U:

$$U = |1 - \sum_{z=1}^{J} (W_z - W_{z-1})(E_z + E_{z-1})| \tag{6.10}$$

with W_z the cumulative proportion of relative demand ($W_z = \sum_{j=1}^{z} w_j \; \forall z = 1..J$, $W_0 = 0$ and $W_J = 1$) and E_z the cumulative proportion of relative unreliability ($E_z = \sum_{j=1}^{z} e_j \; \forall z = 1..J$, $E_0 = 0$ and $E_J = 1$). The consumers j are ranked such that $\xi_j \leq \xi_{j+1}$.

The proposed index summarizes inequality as a value between zero and one. A value of zero means that unreliability is distributed equally among all consumers. The closer the inequality index is to one, the more unreliability is limited to a few consumers.

6.2.4 Characteristics of the Proposed Inequality Index

The main strength of an inequality index is that the extent of inequality is summarized as a single value between zero and one. This enables a simple assessment of the perceived fairness of power system decisions. The index is particularly useful in comparison with a well-known reference case or to compare the performance of different power system decisions, because it is difficult to attribute a practical meaning to a particular value of the index due to lack of practical experience. Aggregating the distribution of reliability into a single value reduces the informational content. Two very different distributions of unreliability can have the same index value and the index does not capture where the inequality actually occurs in the distribution. However, complemented with the inequality ratios ξ_j calculated per consumer j, a lot of information can be obtained more easily than based on the original data. Although the position of each consumer with respect to the equality situation cannot be directly derived from the inequality index, it can be obtained based on the inequality ratios ξ_j calculated per consumer j.

6.3 Case Study I: Controlled Load-Shedding Plans

TSOs with insufficient generation or transmission capacity have the capability and authority to carry out controlled load shedding to prevent uncontrolled failures and blackouts. For example, NERC requires American balancing authorities and transmission operators to have automatic under-frequency load-shedding plans [190] and manual load-shedding plans [191], whereas ENTSO-E requires European TSOs to have automatic under-frequency control schemes [192]. TSOs are free to choose which loads to shed in case of emergency, except for high priority significant grid users who should never be shed. However, TSOs generally choose a subset of consumers, which creates public concerns, because people might feel unequally treated.

This case study examines the load-shedding plan that was proposed by the Belgian TSO for the winter 2014-2015.[52] Public opposition to this plan was large, because people felt that the burden of the load-shedding fell on a subset of consumers, while at the same time the benefits accrued to all consumers. This section calculates the inequality index of the load-shedding plan. Moreover, it is illustrated for a basic compensation scheme how to assess the effectiveness of compensation schemes to reduce inequality in terms of the consequences of unreliability.

6.3.1 Data and Assumptions

The Belgian load-shedding plan for the winter of 2014-2015 divided Belgium in 5 zones and each zone was further divided into 6 slices.[53] Each slice corresponded to 520 MW of sheddable power, resulting in a total foreseen sheddable load of 3120 MW, as summarized in Fig. 6.3. During load shedding, one of these slices of 520 MW is disconnected for around 3 hours according to a rotation system. Slices within a particular zone are determined based on their geographical location to guarantee geographical spreading, and on their value of lost load (VOLL), as rural areas with lower population density and less critical electrical equipment are preferred above urban areas.

Total system load is assumed to be 13120 MW, which means that 10 GW of load is never affected. These consumers are considered to be in slices 7' and 7".

[52] At that time, Belgian system adequacy was low due to retirement and mothballing of conventional power plants, supplemented by the unforeseen closure of three large nuclear units as a result of indications of micro-cracks in the reactor vessels.

[53] A recent update of the load-shedding plan uses 8 slices each corresponding to 500 MW up to 750 MW instead of 6 slices of 520 MW [78].

Slices	NW	NE	CE	SW	SE	TOTAL
1	130	130	130	65	65	520 MW
2	130	130	130	65	65	520 MW
3	130	130	130	65	65	520 MW
4	130	130	130	65	65	520 MW
5	130	130	130	65	65	520 MW
6	130	130	130	65	65	520 MW
7'			8000 MW			
7"			2000 MW			
TOTAL						13120 MW

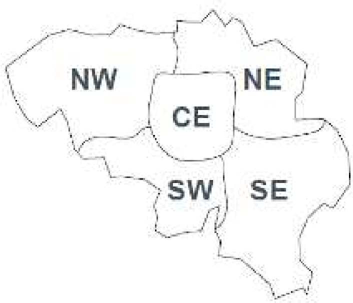


Figure 6.3: The division of Belgium into zones and slices for the load-shedding plan in the winter of 2014-2015 (Data: ELIA).

Slice 7' represents densely populated areas with 8 GW of low-VOLL consumers, whereas slice 7" represents 2 GW of critical high-VOLL consumers.[54]

6.3.2 Results

Table 6.1 gives demand share and ENS share per slice, resp. $\mathbf{w}$ and $\mathbf{e}$, and the inequality indicator U^{ENS} between the slices of the controlled load-shedding plan after 1 up to 6 geographical rotations. That is, $\mathbf{e}_6$ is calculated based on the aggregated ENS after 6 rotations, assuming that each time a different slice is affected. Power demand and load curtailment are assumed to last for a fixed time period Δt, i.e., $D_j^{Energy} = P_j^{load} \cdot \Delta t$ with P_j^{load} the power demand of consumer j [MW] and $ENS_j = P_j^{curt} \cdot \Delta t$ with P_j^{curt} the load curtailment of consumer j [MW]. Only consumers with similar characteristics are considered in the calculation of U^{ENS}, i.e. slice 7" is omitted. From Table 6.1, it is clear that, under the given assumptions, inequality decreases if load shedding is applied more often. Rotation between the different slices implies that those consumers who have been treated very unfairly with the first action receive a favorable treatment in the next one. However, because a large share of demand remains unaffected (slice 7'), inequality is still high, i.e., U^{ENS} close to 1, even after shedding each of the 6 slices once.[55]

[54]These assumptions are a simplification of the real situation to obtain an illustrative case study. In reality, consumers in different slices are more diversified and more subgroups can be considered in the different slices, especially in the unaffected slice 7.

[55]It should be noted that the effect on the inequality in the case studies can be considered as a marginal effect. Depending on the initial distribution of reliability, some decisions might make the overall distribution of reliability more equal. In a practical setting, the effect of decisions on the existing distribution of unreliability should be assessed. The initial

Table 6.1: U^{ENS} after 1 up to 6 rotations of the controlled load-shedding plan proposed in Fig. 6.3, only considering consumers with similar characteristics.

Slice j	$\mathbf{w}$	$\mathbf{e}_1$	$\mathbf{e}_2$	$\mathbf{e}_3$	$\mathbf{e}_4$	$\mathbf{e}_5$	$\mathbf{e}_6$
1	0.047	1	0.5	0.333	0.25	0.2	0.167
2	0.047	0	0.5	0.333	0.25	0.2	0.167
3	0.047	0	0	0.333	0.25	0.2	0.167
4	0.047	0	0	0	0.25	0.2	0.167
5	0.047	0	0	0	0	0.2	0.167
6	0.047	0	0	0	0	0	0.167
7'	0.719	0	0	0	0	0	0
U^{ENS}		0.95	0.91	0.86	0.81	0.77	0.72

Although it is difficult to obtain equality of reliability between consumers in the practical application of load-shedding plans, it is possible to distribute the economic consequences of the activation of load-shedding plans more equally over all consumers in the system. A practical measure is to compensate affected consumers. If (part of) the economic burden is shared by all consumers, consequences of an interruption will be distributed more equally. However, the exact interruption cost per consumer is hard to determine and the use of a fixed price might result in over- or undercompensation, depending on the consumer and the level of compensation.

Table 6.2 shows the impact of compensating affected consumers based on the amount of energy not supplied. The compensation per MWh equals a percentage of the weighted average VOLL of the affected consumers, ranging from no compensation up to a compensation equal to 100% of the weighted average VOLL. The weighted average is equal to $V^{comp} = \sum_{j \in \mathcal{J}} e_j \cdot V_j$. The economic burden of the compensation is shared between all consumers and is divided according to their demand share, for example through energy-based transmission tariffs. In this illustrative case, the VOLL of the affected consumers is assumed to be equal. The inequality index is calculated using Eq. (6.7). Inequality can be significantly reduced if a compensation scheme is put in place, even in the case of partial compensation. 100% compensation results in complete equality under these assumptions. However, if VOLL differs between consumers in the affected slices and interruptions are compensated at average VOLL, some consumers will be over-compensated, whereas others will be under-compensated, resulting in a remaining level of inequality between the consumers.

distribution of reliability among consumers in the case studies in this dissertation is assumed to be equal.

Table 6.2: Evolution of inequality in terms of net total cost borne by the consumers U^{cost} as a function of the number of rotations and the relative amount of compensation.

	Rotations					
Compensation	1	2	3	4	5	6
0%	0.95	0.91	0.86	0.81	0.77	0.72
30%	0.70	0.66	0.63	0.60	0.56	0.53
50%	0.52	0.49	0.47	0.44	0.41	0.39
80%	0.22	0.21	0.20	0.19	0.17	0.16
100%	0	0	0	0	0	0

6.4 Case Study II: Comparison of Short-Term Reliability Management Approaches and Criteria

TSOs and policy makers are typically interested in potential overall efficiency gains or total system cost savings when changing their reliability management approach and criterion. However, social acceptance is crucial to practically deploy an alternative RMAC. One of the aspects on which the social acceptability of an RMAC can be judged is the inequality between consumers in terms of reliability. This case study illustrates the assessment of the inequality between consumers in terms of reliability based on the inequality indices U^{ENS} and U^{IC} in a comparative study of two short-term RMACs: (a) the deterministic N-1 criterion and (b) a probabilistic approach aiming at the minimization of expected total system cost.

6.4.1 Data and Assumptions

Two decision stages are considered in short-term reliability management: day-ahead operational planning and real-time operation. The N-1 criterion aims at securing all single branch and generator outages and the N-0 state given the forecast of net demand. All states are considered as equally probable and equally severe. The probabilistic approach on the contrary aims at minimizing the expected total system cost taking into account the most probable contingencies up to a cumulative probability of 99% and 7 possible realizations of net total demand. The probabilistic approach takes into account that VOLL differs between consumer groups and over time [193].

Performance evaluation of the two RMACs is executed using an analytical non-sequential state enumeration technique. Operational planning is simulated for a set of time instances for which forecast values of net total demand are given. For simplification, the set of time instances consists of $6 \times 3 \times 4 = 72$ time instances, representing 6 periods in the year (winter, early spring, late spring, summer, early autumn and late autumn), 3 types of days (weekday, Saturday and Sunday) and 4 times of the day (night, morning, noon and evening). The outcomes of the different time instances are weighted by their probability of occurrence [193]. In a second step, corrective control is simulated for a set of real-time realizations that are conditional upon the operational planning state. This set is the Cartesian product of the most probable contingencies up to a cumulative probability of 99.6% and 11 possible real-time realizations of net total demand.[56] The realizations are derived from a normal distribution with mean equal to the forecast value of net total demand at the corresponding time instance and a coefficient of variation of 4%.[57]

The simulation of preventive and corrective control is executed using a DC security constrained optimal power flow (SCOPF) in which generation redispatch, branch switching, phase-shifting transformer tap changing and load curtailment are considered as available actions [194]. The simulations are executed using a MATLAB implementation [63] interfacing with the DC SCOPF, which is implemented in AMPL [126].

A five-node network, based on the Roy Billinton Reliability test system [195], is used.[58] VOLL data for Norway are applied [196] and two consumer groups (residential and non-residential) are distinguished. Detailed data about the test system and the VOLL data can be found in resp. Appendix D and Chapter 7.

6.4.2 Results

Evaluating the inequality between consumers is not straightforward if no clear definition and summary measure of inequality exist. Nowadays, equality is typically assessed based on the distribution of energy not supplied among different nodes or consumers [13]. Fig. 6.4 shows the share of ENS per node if an N-1 criterion and probabilistic RMAC are applied. Based on these data,

[56] The numbers of realizations considered in the probabilistic decision making and the performance evaluation are not optimized. The number of realizations considered in the evaluation is larger than in the decision making, because the performance evaluation should favorably use a more detailed representation of the forecast uncertainty to verify the impact of the assumptions made in decision making. The realizations in probabilistic decision making and performance evaluation are symmetrically and equidistantly chosen around the forecast value, with a maximal deviation of $+/-3\sigma$.

[57] Forecast uncertainty of demand can be represented as a multivariate normal distribution with the mean equal to the forecast value and an appropriate coefficient of variation, as indicated in [122].

[58] To serve the illustrative purpose of this case study, a five-node test system is used. The index can similarly be applied to larger systems.

it is difficult to decide which of the two RMACs results in the highest level of inequality and to quantify the difference, even for this small five-node test system. This type of analysis does not take into account the share of demand at each node, which should be naturally related to the share of ENS in an inequality assessment. Fig. 6.4 illustrates the need for an adequate definition of inequality as well as a summarizing measure that facilitates the comparison between different reliability decisions and reliability management approaches.

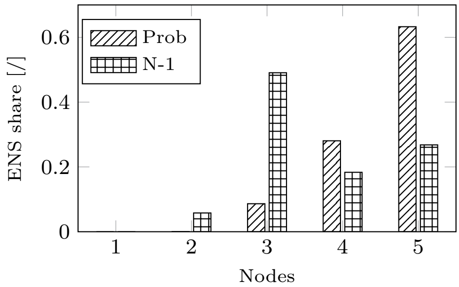


Figure 6.4: The share of energy not supplied per node if the N-1 and probabilistic reliability management approach are applied.

Fig. 6.5 shows the Lorenz curves of inequality between consumers at different nodes (U^{ENS}_{node}) for both RMACs. This figure clearly shows that inequality is higher with the probabilistic RMAC ($U^{ENS}_{prob,node} = 0.57$) than with the deterministic N-1 reliability criterion ($U^{ENS}_{N-1,node} = 0.11$). The probabilistic approach exploits the differences in VOLL between consumer groups and over time, whereas the N-1 approach does not. As a result, the probabilistic approach leads not only to a higher level of inequality of reliability, but also to lower socio-economic costs (64% lower in this case study).

Part of the efficiency gains can be used to decrease public opposition to the higher inequality of reliability. Fig. 6.6 identifies the most unfairly treated nodes by plotting the inequality ratios ξ^{ENS}_j. This figure shows that consumers from nodes 4 and 5 have a disproportionately low reliability level with the probabilistic RMAC, which means that they should be remunerated or safeguarded against other reliability-decreasing decisions. Based on Fig. 6.4, it might be concluded that node 3 is unfairly treated if the N-1 approach is applied. However, Fig. 6.6 indicates that node 3 has a fair level of ENS taking into account its higher demand share. The proposed methodology to evaluate inequality assesses this information in a transparent way.

On top of the inequality between nodes (U^{ENS}_{node}), the index can also be calculated for inequality between different consumer groups (U^{ENS}_{cg}) or between individual

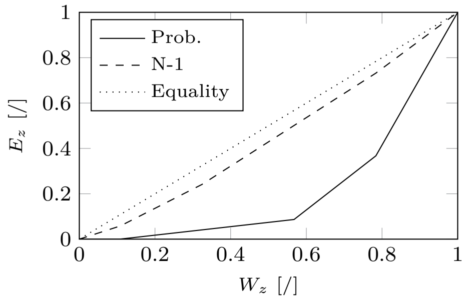


Figure 6.5: Lorenz curves for inequality between nodes in terms of expected energy not supplied for the two reliability management approaches compared to the line of equality.

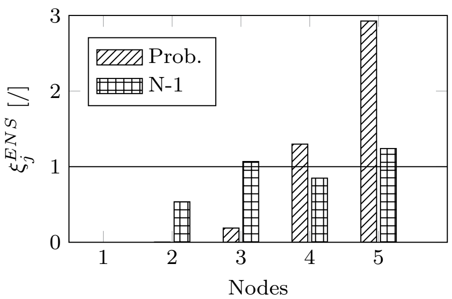


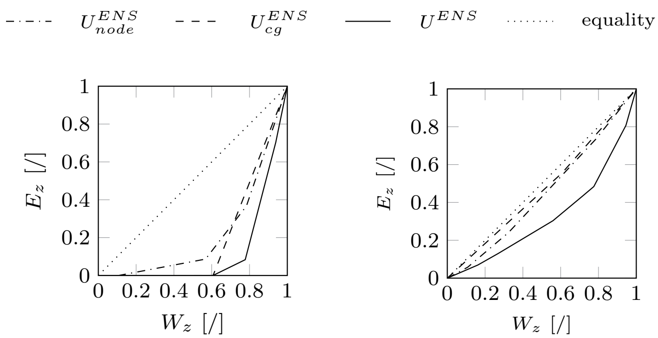
Figure 6.6: Inequality ratios per node for probabilistic reliability management and reliability management based on the N-1 criterion.

consumers (U^{ENS}). Inequality ratios ξ_g^{ENS} per group g, i.e., per node for U^{ENS}_{node} or per consumer group for U^{ENS}_{cg}, equal:

$$\xi_g^{ENS} = \frac{\sum_{j' \in \mathcal{J}_g} ENS_{j'}}{\sum_{j \in \mathcal{J}} ENS_j} \cdot \frac{\sum_{j \in \mathcal{J}} D_j^{Energy}}{\sum_{j' \in \mathcal{J}_g} D_{j'}^{Energy}} \tag{6.11}$$

with $\mathcal{J}_g$ the subset of consumers belonging to group g. Calculating inequality between individual consumers is hard in practice, because exact energy not supplied and demand per consumer are not available to TSOs. They only have estimations or nodal values. However, by grouping consumers per node (U^{ENS}_{node}) or per consumer group (U^{ENS}_{cg}), the Lorenz curve is an approximation of the Lorenz curve that considers all consumers individually. This is graphically illustrated in Fig. 6.7. Table 6.3 shows that this approximation of the

Lorenz curve results in lower values of the inequality indices U_{node}^{ENS} and U_{cg}^{ENS}, quantifying the inequality between nodes and between consumer groups respectively, compared to U^{ENS}, which considers different consumer groups at different nodes. Individual inequality is always understated if aggregation is used. Nevertheless, the conclusion remains unaffected that the probabilistic RMAC leads to higher inequality than the deterministic approach in this case study, whatever the compared groups.



(a) Probabilistic (b) N-1

Figure 6.7: Impact of grouping consumers per node (U_{node}^{ENS}) or per consumer group (U_{cg}^{ENS}) on the Lorenz curves.

Table 6.3: Inequality between nodes U_{node}^{ENS}, between consumer groups U_{cg}^{ENS} and between individual consumers U^{ENS} for the two types of reliability management.

	Probabilistic	N-1
U_{node}^{ENS}	0.57	0.11
U_{cg}^{ENS}	0.61	0.05
U^{ENS}	0.75	0.35

Lastly, even if data is available at the level of individual consumers, it makes sense to calculate the inequality between nodes or between consumer groups. Consumers' perception of their peers influences which groups need to be considered in the calculation of the inequality index. If consumers are concerned about equality between consumer groups (e.g., residential and non-residential), the inequality index U_{cg}^{ENS} should be used. If they are more concerned about equality between individuals, irrespective of their consumer group, the inequality index U^{ENS} should be used. Similarly, the inequality index can also be calculated within groups, such as the inequality between residential consumers or between non-residential consumers, as shown in Table 6.4. This table shows that for the presented case study the inequality between residential consumers does not increase much when moving from the N-1 criterion to the probabilistic RMAC, while it increases more between non-residential consumers. These conclusions show where to put the focus if actions should be taken, but they are hard to make without the use of an inequality index as the one proposed in this dissertation.

Table 6.4: Inequality U^{ENS} between consumers in the two considered consumer groups for the two reliability management strategies.

	Consumer groups	
	Residential	Non-residential
Prob.	0.38	0.66
N-1	0.32	0.30

Besides the inequality, the inequity of the two RMACs can be assessed. The probabilistic RMAC results in an index $U^{IC} = 0.73$, whereas for the deterministic N-1 criterion $U^{IC} = 0.54$. The difference in inequity between the probabilistic and deterministic RMAC is smaller than the difference in inequality. However, inequity is still higher for the probabilistic RMAC than for the deterministic N-1 criterion. This is the case, because the probabilistic RMAC will always try to curtail the consumers with the lowest VOLL rather than aiming at equitable load curtailment. This means that the interruption cost is borne by a reduced set of consumers.

6.5 Case Study III: Electricity Reliability in Norway

The Norwegian Water Resources and Energy Directorate (NVE) has been collecting detailed reliability data since 1995 using the FASIT tool [197]. All Norwegian transmission and distribution network operators are required to report the consequences of each outage. Based on the reported interruption time period of each affected consumer type, the tool calculates the interruption duration, interrupted power, ENS and interruption cost for each consumer type at each location. The resulting reliability data are published every year for six voltage levels, 19 counties, 117 network operators and 36 consumer groups [198]. The remainder of this section takes a closer look at the distribution of reliability in different counties and among consumer groups in Norway.

6.5.1 Distribution of Reliability between Counties

The distribution of unreliability among different counties is hard to evaluate by decision makers based on detailed reliability data. Fig. 6.8 shows the share in total ENS of each of the counties for the 11 years. Based on this figure, one might conclude that unreliability is distributed quite equally among countries in the different years, except for some years in counties 12, 14 and 17. However, this analysis does not take into account the relative electricity consumption of each of the counties, which is an important factor to determine the equality of the distribution of unreliability.

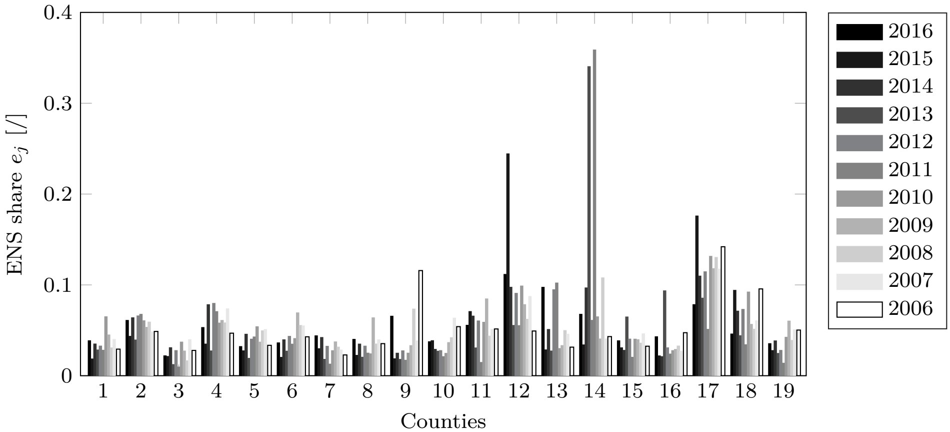


Figure 6.8: Detailed reliability data for the 19 Norwegian counties in 2006-2016 in terms of share in total ENS (Original data: [198]).

Fig. 6.9 shows the inequality ratio ξ_j^{ENS} for each county j for 2006 to 2016. This figure shows that some rural areas have an inequality ratio above one, meaning that they have a relatively high level of ENS. On the contrary, inequality ratios are below one in the more urban southern counties, notably Oslo (3) and its surroundings. The peaks in this figure are more pronounced and the inequality of the distribution of unreliability in terms of ENS is illustrated more clearly.

The reliability level differs between counties and its distribution differs over time. Evaluating the evolution of inequality in terms of reliability is only possible by aggregating the information into a single value. Fig. 6.10 shows the evolution of the inequality index U^{ENS} of the distribution of reliability between counties. This figure shows that inequality was high in 2011, 2013 and 2015. The inequality does not show a particular upward or downward trend, which makes sense as inequality is not a policy objective at the moment.

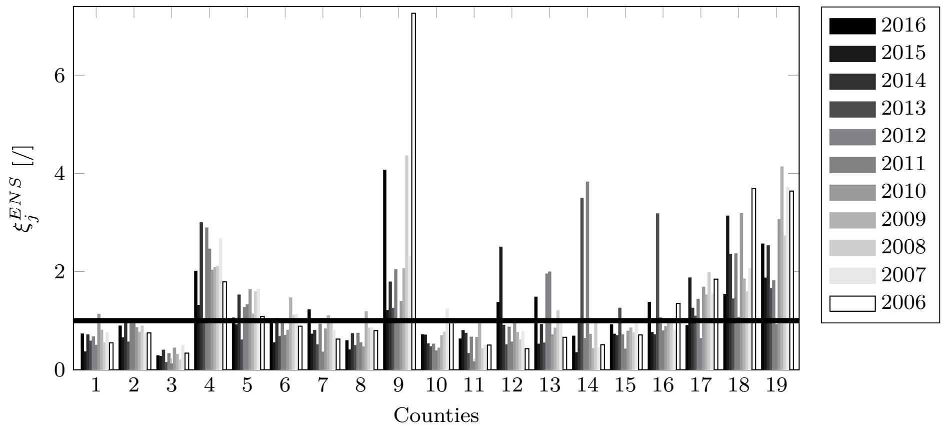


Figure 6.9: Inequality ratios ξ_j^{ENS} for the 19 Norwegian counties in 2006-2016 (Original data: [198]).

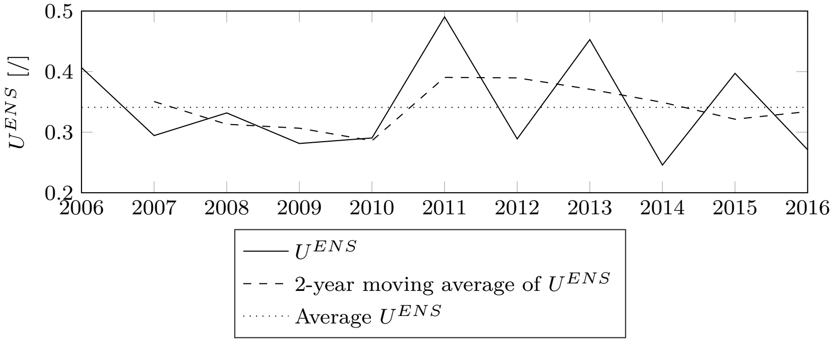


Figure 6.10: Inequality index U^{ENS} between Norwegian Counties in 2006-2016 (Original data: [198]).

6.5.2 Distribution of Reliability between Consumer Groups

The Norwegian data also enable the assessment of the inequality of the distribution of reliability between consumer groups. Fig. 6.11 shows the inequality ratio ξ_c^{ENS} for each consumer group c for 2012 to 2016. This figure shows that agricultural and residential consumers have an inequality ratio above one, meaning that they have a relatively high level of ENS. Industry and large industry have the lowest inequality ratio.

Similarly, Fig. 6.12 shows the inequality ratio ξ_c^{IC}, based on interruption

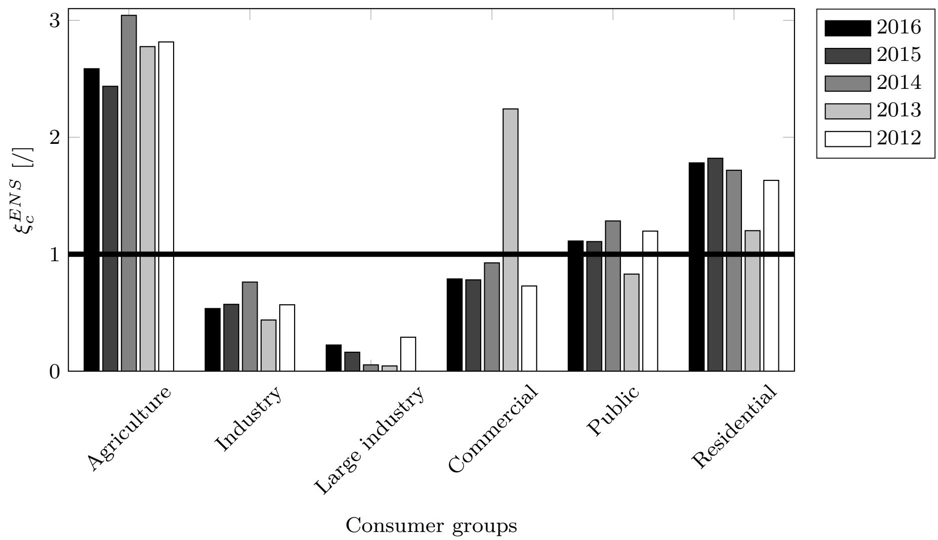


Figure 6.11: Inequality ratios ξ_c^{ENS} for the six consumer groups in 2012-2016, based on energy not supplied (Original data: [198]).

costs, for each consumer group c for 2012 to 2016. This figure shows that the interruption cost of large industry is relatively low, whereas the interruption cost of commercial consumers is relatively high.

The analysis of both figures shows that large industry receives a favorable treatment, both in terms of energy not supplied and interruption cost. Although agriculture has a relatively high level of ENS, its low VOLL makes that it is on average fairly treated in terms of interruption cost. Commercial consumers are on average fairly treated in terms of ENS, but are on average highly unfairly treated in terms of interruption cost.

Fig. 6.13 shows that in Norway there was no particular trend in the inequality between consumer groups in 2012-2016 expressed in terms of U^{ENS} and U^{IC}. Again, this makes sense as inequality is not a policy objective at the moment. Fig. 6.13 also shows that the values of the inequality indices depend on the level of consumer aggregation. The indices increase if the six consumer groups are disaggregated into 36 groups.

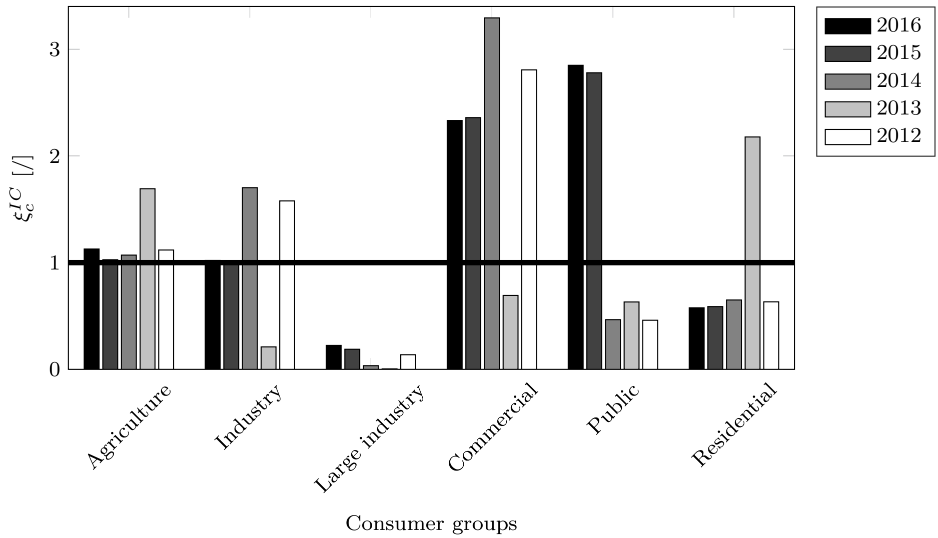
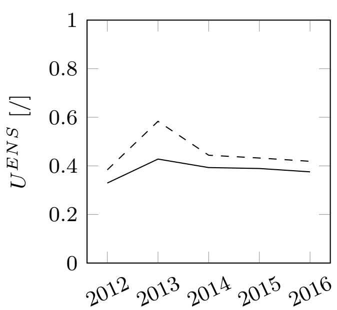
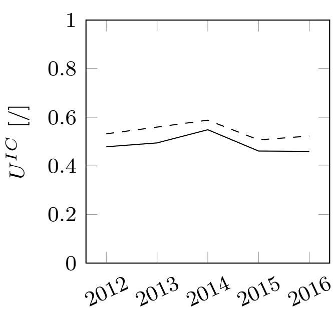


Figure 6.12: Inequality ratios ξ_c^{IC} for the six consumer groups in 2012-2016, based on interruption costs (Original data: [198]).



(a) U^{ENS}



(b) U^{IC}

Figure 6.13: The evolution of inequality indices U^{ENS} and U^{IC} for different levels of aggregation of consumers, i.e., 6 groups (——) and 36 groups (- - - -) (Original data: [198]).

6.6 Discussion

The proposed inequality indices enable system stakeholders to quantify the inequality between consumers in terms of reliability and to take action if the inequality is unacceptable from a social perspective. Modern technologies and contractual evolutions provide measures to influence the inequality between consumers, but society's preferences in terms of fairness should be clearly stated to make effective decisions.

6.6.1 Towards a Practical Inequality Assessment

An effective application of the inequality assessment requires that the authorities and regulatory agencies determine society's preferences regarding certain aspects. First, the definition of fairness should be clearly expressed: Equality, i.e., everyone gets the same level of reliability, deservedness, i.e., everyone gets what he/she merits, or need, i.e., those that have more to give should give a greater percentage of what they have to help others who are unable to contribute much. Different definitions are typically complementary. Second, it is important to determine consumers' perception of their peers as this determines the aggregation applied in the inequality assessment. Third, society's preferences in terms of the acceptable level of inequality should be clearly stated to obtain thresholds that define socially acceptable decisions.

6.6.2 Reducing Inequality

If the inequality index shows that the distribution of unreliability among consumers is highly unequal, measures can be taken to reduce this inequality. This is possible based on the principle of transfers [178]. This principle states that a transfer Δe of the share of unreliability from a consumer j to a consumer j' decreases the value of the inequality index if $\xi_j^{ENS} > \xi_{j'}^{ENS}$ and $\frac{e_j - \Delta e}{w_j} \geq \frac{e_{j'} + \Delta e}{w_{j'}}$. This requires a more detailed study to see which consumers are mostly affected in a positive and negative way. Based on this study, the TSO can decide to safeguard the most affected consumers if load curtailment is required in the future.

From a socio-economic perspective it might be better to have a certain level of inequality, e.g., in systems with remote and sparsely populated load points. In this case, it is not economically viable to have the same level of redundancy for these remote load points as for a densely populated area. This decision might result in a higher share of energy not supplied in these remote load points. A cost-effective way to reduce the level of inequality in this case might be to invest in small, local generation or storage units, possibly (partly) subsidized. Other options are a market for reliability or end-consumer contracts where the price depends on the reliability level. Bi-lateral interruptible load contracts between TSOs and large industrial consumers with flexible processes are already in place nowadays, but they might be extended to include smaller consumers as well. These kinds of economic compensations result in a more equal distribution of the cost of unreliability, whereas the inequality in terms of energy not supplied is not changed. Also the equity between consumers will improve, as consumers can indicate what they need with these reliability-based electricity consumption choices. Smart grids with smart metering and demand-side management can help in this respect.

To obtain satisfactory results, the design of these measures should be done with care. This requires a multi-faceted analysis. Moreover, the exact determination of interruption costs is challenging, which makes it hard to determine an adequate compensation for affected consumers. Not only are energy not served and demand per consumer hard to obtain, also exact values of lost load per node or per consumer are rarely available in practice. However, the Fourth Energy Package of the European Commission prescribes that all member states have to establish at least a single estimate of VOLL for their territory and can establish a VOLL per bidding zone, if they have several ones. In many other regions such obligation does not yet exist, but more and more studies are estimating VOLL with a higher level of detail, taking into account differentiation in terms of type of consumers, time and duration. An overview of these studies can be found in Chapter 7.

6.7 Conclusion

A fair distribution of power system unreliability is crucial to reduce public opposition against adequacy and security measures, such as the introduction of an alternative reliability management approach and criterion. It is one of the aspects to ensure their social acceptability. The proposed inequality indices evaluate the distribution of reliability among different entities, such as nodes, consumer groups or individual consumers, but can also be used to evaluate equality in terms of generator connectivity. They quantify inequality of power system reliability resulting from network operators' and regulators' decisions in a single value. This enables stakeholders to assess the level of inequality and inequity between different entities in a more transparent way. Regulating bodies and transmission system operators can usefully apply the indices to assess decisions in the context of system adequacy, security, investment, etc.

This work has illustrated the application in three case studies, focusing on load-shedding plans, the evaluation of short-term reliability management approaches and criteria and the analysis of Norwegian reliability data.

Modern technologies, such as smart meters, and contractual evolutions provide measures to influence the inequality between consumers, either directly or indirectly by redistributing the consequences of unreliability. The effectiveness of these measures can be verified using the proposed inequality indices.

Chapter 7

Impact of Value of Lost Load on the Performance of Short-Term RMACs

Short-term reliability management based on socio-economic principles, which makes a trade-off between preventive, corrective and load curtailment actions, should take into account the cost of interruptions for end-consumers. The cost of electricity interruptions is determined by the amount of energy not supplied and the value of lost load (VOLL). VOLL is a parameter representing the cost of unserved electricity and is generally expressed in monetary units per kWh or MWh. It is an essential parameter to determine the optimal reliability level of a power system.

Various studies have estimated VOLL for different countries and for different interruption characteristics, such as interruption duration, time of interruption, interrupted consumer, location and advance notification. Better-informed reliability decisions are possible by using these detailed VOLL data. The impact of using different degrees of VOLL detail in short-term reliability management is assessed. A theoretical model that shows the efficiency gains – defined as the (relative) cost decrease – of using a VOLL that differs over time and between consumers is developed. Realizing the full efficiency potential of consumer-differentiated VOLL depends on the technological curtailment possibilities. A distinction is made in this study between perfect curtailment, random curtailment and spatial curtailment – an intermediate option where a network operator curtails load in regions depending on their VOLL. The theoretical model is illustrated using the quantification framework discussed in the previous chapters focusing on expected total system cost of TSOs' operational planning and system operation using different levels of VOLL detail. In addition, it is studied how VOLL differentiation impacts the distribution of unreliability between different consumers.

Section 7.1 discusses the current use of value of lost load data. Section 7.2 surveys the growing literature that estimates VOLL as a function of different interruption characteristics for different countries. VOLL data of Norway, Great Britain and the United States are discussed in more detail. Section 7.3 studies analytically the efficiency gains of using a VOLL that differs over time and between consumers. Section 7.4 expands this analysis to a five-node illustrative network and analyzes the trade-off between efficiency and equality in terms of reliability if different levels of VOLL detail are used. Section 7.5 discusses the findings of the analyses. Section 7.6 concludes.

This chapter is based on the discussion paper *How detailed value of lost load data impact power system reliability decisions: a trade-off between efficiency and equity, Ovaere M., Heylen E., Proost S., Deconinck G. and Van Hertem D., Discussion paper series, DPS16.26 KU Leuven, Department of Economics.*[59]

7.1 Current Use of Value of Lost Load

VOLL is used in many applications such as load curtailment contracts [199], network investment decisions [200], cost-benefit analyses, quality incentive schemes of transmission and distribution networks [201], energy legislation and reliability standards[60] [203]. Most of these applications simplify the VOLL to a single, constant value.

The most advanced use of detailed VOLL data to date is the Norwegian Cost of Energy Not Supplied (CENS) regulation. In the CENS regulation, TSO and DSO revenue caps depend on the interruption costs in their area. Interruption costs are calculated for different consumer groups and both the time and duration of interruptions have an effect on interruption costs [204]. The CENS regulation is expected to give network operators better incentives to achieve an optimal reliability level, for example, by providing a higher level of reliability

[59]The first two authors are the main authors of this paper and contributed equally to this study. The contributions of the second author include the modeling and simulation of the case study and the post-processing of the results of the case study. The discussion of the impact of the level of detail of VOLL is the result of a collaboration between the first two authors.

[60]In Great Britain, a loss of load expectation (LOLE) of 3 hours per year corresponds to a VOLL of £17 000 /MWh [202].

to high-VOLL consumers or at high-VOLL moments – e.g., by taking more conservative operating decisions or speeding up restoration times. In the Italian quality regulation of distribution networks, VOLL of residential consumers is set at €10800 /MWh, whereas VOLL of non-residential consumers is set at €21600 /MWh [205]. Interruptions of non-domestic consumers are thus more costly and therefore network operators have an incentive to provide them a higher level of reliability. However, apart from being used in reliability incentive schemes, available detailed VOLL data are not widely used in reliability decision making.

7.2 Literature Review of Detailed VOLL Data

VOLL depends on many factors [206]:

- Interruption time: season, day of the week, time of the day;
- Interrupted consumers: residential, commercial, industrial, public;
- Interruption duration;
- Weather at the time of interruption;
- Number of consumers affected;
- Current reliability level;
- Advance notification of the interruption;
- Mitigating measures.

Various empirical studies have estimated VOLL as a function of these different factors. Table 7.1 lists 13 studies and shows the level of VOLL detail for each study.[61] The table shows that almost all studies estimate VOLL for different consumer types. Some consider as much as 15 consumer types [207, 208, 209, 210], while others consider only two or three [200, 211, 212]. Many studies also include the influence of the interruption time on VOLL. Most of them distinguish between time of the day, type of day in the week and season. In addition, some studies estimate the influence of interruption duration, advance notification and location.

[61] The survey is restricted to studies published since 2007 that estimate the effect on VOLL of at least two interruption characteristics.

Table 7.1: Studies that estimate VOLL as a function of different interruption characteristics.

Country	Consumer type	Time	Duration	Advance notification	Location	Source
Australia	x		x			[213]
Austria	x	x	x			[208]
Cyprus	x	x				[210]
Germany	x				x	[207]
Great Britain	x	x				[212]
Ireland	x	x			x	[214]
Netherlands	x	x			x	[215]
New Zealand	x	x	x		x	[200]
Norway	x	x	x	x		[196]
Portugal	x	x				[216]
Spain	x				x	[209]
Sweden		x	x			[217]
United States	x	x	x	x	x	[211]

As an illustration, Table 7.2 to Table 7.4 present detailed VOLL data of Great Britain [212], Norway [196] and the United States [211]. These data show VOLL for different consumer groups as a function of season, type of day, and time of the day. The Norwegian data consider four consumer types (residential, industry, commercial, and public) and 36 interruption times (three times of interruption, three days and four seasons). The British data consider two consumer types, i.e., residential consumers and Small and Medium Enterprises (SMEs), and eight interruption times. Finally, the United States' data consider three consumer types, i.e., residential consumers, small Commerce and Industry (C&I) and large C&I, and 16 interruption times. All data are expressed in both the home currency and in €$_{2015}$/MWh.[62] All three studies use stated-preference methods to determine the VOLL data.[63] Comparison of VOLL between countries should be done with care [222] since all stated-preference methods differ to some extent in terms of formulation of questions, cost normalization factors, scenario designs and data formats and since countries differ culturally.

The British and United States data show VOLL as a single value for each time of interruption. The Norwegian data are displayed differently. Table 7.3 shows multipliers for the time of the day, type of day and season. Norwegian VOLL for a particular time is found by multiplying the standard VOLL with the

[62] Purchasing power parities [218] are used for conversion.

[63] Stated-preference methods involve asking consumers their Willingness-To-Accept (WTA) payment for an outage and Willingness-To-Pay (WTP) to avoid an outage (contingent valuation or choice experiments), or asking the cost of specific interruptions (direct worth). Several cost estimation methods exist, each of them having its advantages and disadvantages [215]. Best-practice guidelines provide recommendations for correct VOLL estimation [219, 220, 221].

corresponding multipliers:[64]

$$v_c(t(h,d,y)) = v_c \cdot \gamma_{h,c} \cdot \gamma_{d,c} \cdot \gamma_{y,c} \tag{7.1}$$

v_c corresponds to the base VOLL per consumer group c and $\gamma_{h,c}$, $\gamma_{d,c}$ and $\gamma_{y,c}$ are the multipliers to incorporate the effect of respectively the time of the day (e.g., day vs. night), the type of day (e.g., week vs. weekend) and the season.[65]

Comparison of the three datasets shows that residential consumers have a lower VOLL than industrial consumers. On weekdays, VOLL of industrial consumers is between 5 (GB, not winter, not peak weekday) and 300 (US, winter weekday afternoon) times higher than for residential consumers. During weekends, their VOLL is more similar. Residential VOLL in Great Britain is higher and closer to industrial VOLL than in the United States and in Norway. Industrial VOLL is the same order of magnitude in all three countries, except for small commercial and industrial consumers in the United States, which have a substantially higher VOLL.[66]

The detailed VOLL data of Great Britain, Norway and the United States are used in the numerical illustration of Section 7.4, but the level of detail is restricted to consumer type and time of interruption.

Table 7.2: Great Britain VOLL as a function of time characteristics and consumer groups [212, Table 1 and Table 2]. The upper part of the table is expressed in [£$_{2011}$/MWh], whereas the lower part of the table is expressed in [€$_{2015}$/MWh].

	Not winter				Winter			
	Weekday		Weekend		Weekday		Weekend	
	Peak	Not peak	Peak	Not peak	Peak	Not peak	Peak	Not peak
Res.	9 550	6 957	9 257	11 145	10 982	9 100	10 289	11 820
SMEs	37 944	36 887	33 358	34 195	44 149	39 213	35 488	39 863
Res.	11 093	8 081	10 753	12 946	12 757	10 571	11 952	13 730
SMEs	44 077	42 849	38 749	39 722	51 284	45 551	41 224	46 306

[64]This assumes that the effect of time, day and season on VOLL is independent. For example, the relative decrease of VOLL in summer for residential consumers is the same irrespective of the time or day.

[65]The Norwegian data also include the effect of interruption duration on VOLL. In the remainder of this chapter, VOLL is assumed to be linear in duration, while in general VOLL is concave in duration.

[66]Note that VOLL of a consumer type is an average of individual consumers of this type, in between which large differences are possible.

Table 7.3: Norwegian VOLL as a function of time characteristics and consumer groups [196, Table A and Table B].

		Residential	Industry	Commercial	Public
VOLL [NOK_{2010}/MWh]		5 000	116 000	192 000	170 000
VOLL [€$_{2015}$/MWh]		469	10 926	17 984	15 888
Season $\gamma_{y,c}$	Winter	1	1	1	1
	Spring	0.57	0.87	1	0.67
	Summer	0.44	0.86	1.02	0.51
	Autumn	0.75	0.88	1.06	0.58
Day $\gamma_{d,c}$	Weekday	1	1	1	1
	Saturday	1.07	0.13	0.45	0.3
	Sunday	1.07	0.14	0.11	0.29
Time $\gamma_{h,c}$	2 AM	0.4	0.12	0.11	0.43
	8 AM	0.69	1	1	1
	6 PM	1	0.14	0.29	0.31

7.3 Theoretical Analysis

Probabilistic reliability management enables a trade-off between preventive and corrective actions and load curtailment. Total cost of reliability management decreases if detailed VOLL data are used in short-term probabilistic reliability management instead of one constant VOLL at all times and in all regions. This efficiency gain is shown using an economic model.

Suppose a cost $C(\rho)$ is needed to supply 1 MWh of electricity at reliability level ρ. This reliability cost is assumed to be constant throughout the year. It is increasing convex in the reliability level and approaches infinity at $\rho = 1$. The reliability level is here represented by the relative amount of demand supplied $\rho \in [0, 1]$:

$$\rho = \frac{\sum_{c\in\mathcal{C}}(P_c^{load} - P_c^{curt})}{\sum_{c\in\mathcal{C}} P_c^{load}} \tag{7.2}$$

That is, ρ is the fraction of total power demand that is supplied to consumers in a certain period.

The optimal reliability level ρ^* is found by minimizing the sum of reliability cost $C(\rho)$ and interruption cost $(1 - \rho)V$:[67]

$$\min_{\rho} \{C(\rho) + (1 - \rho)V\} \tag{7.3}$$

[67] If the reliability cost $C(\rho)$ includes all social costs of reaching a reliability level ρ, the optimal reliability level is also the welfare optimum. If only private TSO costs are included, the optimal TSO value differs from the welfare-optimal reliability level.

Table 7.4: United States VOLL as a function of time characteristics and consumer groups ([211, Table 3-10, Table 4-10 and Table 5-11]). (a) is expressed in [$\$_{2009}$/MWh], (b) in [$€_{2015}$/MWh].

		Summer							
		Weekday				Weekend			
		Morning	Afternoon	Evening	Night	Morning	Afternoon	Evening	Night
(a)	Residential	3 412	2 559	2 428	2 428	4 002	3 018	2 887	2 887
	Small C&I	306 833	372 941	196 500	196 045	188 750	236 621	112 156	110 332
	Large C&I	17 774	24 978	21 054	15 688	12 771	18 191	14 857	11 088
(b)	Residential	2 947	2 210	2 097	2 097	3 457	2 607	2 493	2 493
	Small C&I	265 004	322 100	169 713	169 319	163 019	204 364	96 866	95 291
	Large C&I	15 351	21 573	18 184	13 550	11 030	15 711	12 831	9 576
		Winter							
		Weekday				Weekend			
		Morning	Afternoon	Evening	Night	Morning	Afternoon	Evening	Night
(a)	Residential	2 428	1 706	1 378	1 378	2 821	2 034	1 640	1 640
	Small C&I	423 091	530 688	248 931	244 828	250 299	32 370	135 863	131 760
	Large C&I	14 539	21 360	16 232	12 161	10 035	14 992	10 963	8 231
(b)	Residential	2 097	1 473	1 190	1 190	2 437	1 757	1 417	1 417
	Small C&I	365 415	458 343	214 996	211 452	216 177	279 967	117 342	113 798
	Large C&I	12 557	18 448	14 019	10 503	8 667	12 948	9 468	7 109

This is at the point where marginal reliability cost equals marginal interruption cost:

$$C'(\rho^*) = V \tag{7.4}$$

This first-order condition shows that VOLL influences the optimal reliability level. Since the reliability cost increases in ρ, a high VOLL calls for a high reliability level and a low VOLL for a low reliability level. For example, if VOLL is higher in winter than in summer ($V_{winter} > V_{summer}$), the reliability level should also be higher in winter than in summer. If a TSO, however, bases its reliability level on the yearly-average VOLL $\bar{V}$, it will aim at a constant reliability level $\bar{\rho}$ throughout the year.[68] As a result, its network is too reliable in summer and not sufficiently reliable in winter. This is shown in Fig. 7.1, where the reliability levels are found at the intersection of the VOLL and the marginal reliability cost, which is increasing in ρ. In this figure, the reliability cost is the area below the marginal reliability cost $C'(\rho)$, up to the reliability level ρ, while the interruption cost is the area below the VOLL up to $1 - \rho$.

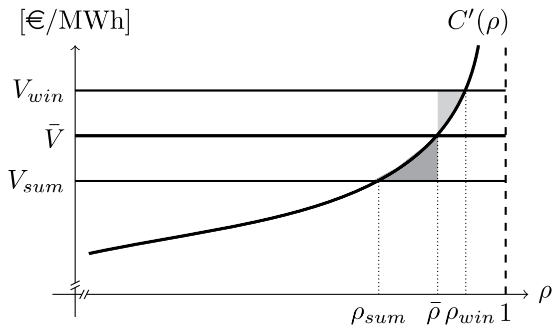


Figure 7.1: Efficiency gains if VOLL differs over time.

If the TSO modifies the reliability level with changing VOLL ($\rho_{sum} < \bar{\rho} < \rho_{win}$), instead of aiming at a constant reliability level $\bar{\rho}$, the sum of reliability costs and interruption costs will be lower. This efficiency gain is defined as:

$$[C(\rho) + (1-\rho)V] - [C(\rho^*) + (1-\rho^*)V] \;\; [€] \tag{7.5}$$

or

$$1 - \frac{C(\rho^*) + (1-\rho^*)V}{C(\rho) + (1-\rho)V} \;\; [\%] \tag{7.6}$$

[68] Obviously, in reality the reliability cost is not constant throughout the year. For example, if $C(\rho)$ is higher in winter and VOLL is constant, it is optimal to have a lower reliability level in winter than in summer. But for the sake of our argument we restrict our focus here to the change of VOLL over time.

Fig. 7.1 shows these efficiency gains as the dark grey triangle in summer ($\rho = \bar{\rho}$, $\rho^* = \rho_{sum}$) and the light grey triangle in winter ($\rho = \bar{\rho}$, $\rho^* = \rho_{win}$). In summer, reliability costs are too high and interruption costs are too low; in winter, reliability costs are too low and interruption costs are too high.

Next, suppose that VOLL is constant throughout the year, but differs between consumers. In this case, efficiency gains are achievable by providing low-VOLL consumers with a lower reliability level than high-VOLL consumers. The highest efficiency gain is achieved if demand is curtailed from lowest to highest VOLL [223]. This can be denoted as perfect curtailment. Perfect curtailment is only possible when the TSO has the technical capabilities to curtail individual consumers. When this is not possible, efficiency gains are still achievable when curtailment is performed first in low-VOLL regions, in this work denoted as spatial curtailment. Spatial curtailment leads to lower interruption costs than random curtailment.

Fig. 7.2 illustrates the efficiency gains of perfect, spatial, and random curtailment. VOLL is assumed to be uniformly-distributed between V_{min} and V_{max}. This is the downward-sloping line. Moving from random curtailment (with average VOLL $\bar{V}$) to spatial curtailment (with regional VOLLs V_1 and V_2) leads to an efficiency gain equal to the light grey area. This is the sum of lower reliability costs (A) and lower interruption costs (B). The dark grey area is the additional efficiency gain of moving from spatial to perfect curtailment. This is the sum of additional lower reliability costs (C) and additional lower interruption costs (D). Interruption costs are lower because low-VOLL consumers are curtailed first. For spatial curtailment these are consumers in the low-VOLL area 1; for perfect curtailment these are the consumers with the lowest VOLL, in both region 1 and 2. Moving from random curtailment to perfect curtailment, the decrease of reliability costs is thus A+C+E and the net decrease of interruption costs is B+D-E.

The regional VOLLs, represented by V_1 and V_2 in Fig. 7.2, depend on the correlation of VOLL between regions. They differ more if low-VOLL consumers are all concentrated in one region. In that case, the reliability level ρ^{sp} is closer to the optimal reliability level ρ^* and interruption costs of spatial curtailment are lower.

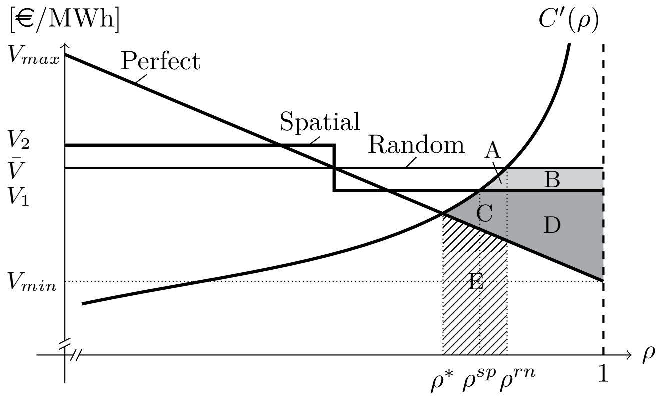


Figure 7.2: Efficiency gains and reliability level of random ρ^{rn}, spatial ρ^{sp}, and perfect curtailment ρ^*, if VOLL differs between regions.

7.4 Numerical Illustration of the Impact of VOLL Detail in Short-Term Reliability Management

The theoretical concepts of the previous section are verified in a numerical five-node case study. During operation of the electricity system TSOs face many challenges: line outages and generation outages occur, unscheduled loop flows pass through the network and demand and intermittent supply differ from forecasts. As a result, the TSO takes preventive and corrective actions or curtails load to ensure that demand and supply are always balanced without violating any operational limit. Short-term, probabilistic reliability management makes a trade-off between preventive, corrective and interruption costs by taking into account the risks related to power system uncertainties. This trade-off is influenced by the level of detail of the VOLL data considered in decision making.

7.4.1 Evaluation of Short-Term Reliability Management

Short-term reliability management consists of two parts: real-time operation and operational planning. Both aim at minimizing expected total system cost.

Real-Time Operation

When disturbances occur in the power system, the TSO takes corrective actions or curtails load to keep the system in balance. Possible corrective actions $\mathbf{a}_{rt}^{corr}$ during real-time (RT) operation are generation redispatch, phase-shifting transformer tap changing and branch switching. The TSO takes at each time instant t those actions that minimize the cost of corrective actions and the cost of load curtailment, subject to operational constraints [194].

$$\min_{\mathbf{a}_{rt}^{corr}, P_{c,rt}^{curt}} \left[C^{corr}(\mathbf{a}_{rt}^{corr}) + \sum_{c \in \mathcal{C}} P_{c,rt}^{curt} \cdot v \right] \tag{7.7}$$

$$\text{s.t. operational limits}$$

Interruption costs are the product of curtailed load $P_{c,rt}^{curt}$ and VOLL v for all consumers. The specification of v depends on the level of VOLL detail:

$$v \in \{V, v_t, v_b, v_c\} \tag{7.8}$$

That is, VOLL is constant (V); VOLL differs over time t ($v_t = V(t)$); VOLL is aggregated per node b and differs for all time instants t ($v_b = V(b,t)$); or VOLL differs between consumer groups c and over time t ($v_c = V(c,t)$). Eq. (7.7) shows that different levels of detail in VOLL data change the trade-off between corrective actions and load curtailment and affect which consumers and which regions to curtail. The level of detail has an effect on the choice of corrective actions $\mathbf{a}_{rt}^{corr}$ and load curtailment $P_{c,rt}^{curt}$, which, in turn, affects total system cost.

Operational Planning

Real-time operation is preceded by the operational planning stage. Operational planning (OP) is executed some time before real-time operation, for example, in day-ahead for the 24 hours of the next day. During operational planning, the TSO determines the optimal dispatch of electricity generation, taking into account uncertainties about future real-time states s of the system. The difference between the unconstrained day-ahead market dispatch and the dispatch after operational planning is the cost of preventive redispatch. The TSO determines the preventive actions $\mathbf{a}^{prev}$ that minimize the sum of preventive costs $C^{prev}(\mathbf{a}^{prev})$ and expected real-time costs, consisting of the cost of corrective actions $C^{corr}(\mathbf{a}_{s}^{corr})$ and load curtailment $P_{c,s}^{curt} \cdot v$, subject to operational constraints for all states s in the set of considered system states S:

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr},P_{c,s}^{curt}} \left[C^{prev}(\mathbf{a}^{prev}) + \sum_{s\in S} p_s \cdot \left(C^{corr}(\mathbf{a}_s^{corr}) + \sum_{c\in\mathcal{C}} P_{c,s}^{curt} \cdot v \right) \right] \quad (7.9)$$

$$\text{s.t. operational limits } \forall s \in S$$

where p_s is the probability of occurrence of a possible future real-time state s. The TSO takes into account a set of possible future real-time states S when deciding on its preventive actions $\mathbf{a}^{prev}$. The set S is in this case study the Cartesian product of the most probable contingencies up to a cumulative probability of 99% and 7 possible real-time realizations of net total demand derived from a normal distribution with mean equal to the forecast value of net total demand at time instant t and a coefficient of variation of 4%.[69] As a result, VOLL does not only affect corrective actions and load curtailment, but also preventive actions of forward-looking TSOs.

Eq. (7.3) of our theoretical analysis is a simplified version of Eq. (7.9). While in the theoretical analysis the TSO chooses the reliability level ρ directly, he/she takes a number of preventive ($\mathbf{a}^{prev}$) and corrective ($\mathbf{a}_{rt}^{corr}$) actions in the case study, which lead to a certain reliability level. The reliability cost $C(\rho)$ of the theoretical analysis includes both the cost of preventive and corrective actions.

Evaluation

Performance of short-term reliability management for various levels of VOLL detail is evaluated in terms of Expected Total Cost (ETC). ETC consists of costs of preventive actions, costs of corrective actions and cost of load curtailment.

$$\begin{aligned} ETC(v) = \sum_{t\in T} p_t \cdot [C^{prev}(\mathbf{a}^{prev}(v,t)) + \dots \\ \sum_{rt\in RT} p_{rt|t} \cdot \left(C^{corr}(\mathbf{a}_{rt}^{corr}(v,t)) + \sum_{c\in\mathcal{C}} P_{rt,c}^{curt}(v,t) \cdot v_c \right) \Bigg] \end{aligned} \quad (7.10)$$

Preventive, corrective and curtailment actions

$$[\mathbf{a}^{prev}(v,t), \mathbf{a}_{rt}^{corr}(v,t), P_{rt,c}^{curt}(v,t)] \quad \forall c \in \mathcal{C} \quad (7.11)$$

[69] The number of realizations is not optimized. The realizations are symmetrically and equidistantly chosen around the forecast value, with a maximal deviation of +/-3σ. The coefficient of variation is based on [122].

are taken by a TSO based on the available VOLL information, i.e., the level of detail in the VOLL data, $v \in \{V, v_t, v_b, v_c\}$. Load curtailment costs are evaluated at the true VOLL of a consumer v_c.[70]

Evaluating all possible future real-time system states rt is not feasible in practice. Therefore the set RT is the Cartesian product of the most probable contingencies up to a cumulative probability of occurrence of 99.6 % and 11 possible real-time realizations of net total demand derived from a normal distribution with mean equal to the forecast value of net total demand at time instant t and a coefficient of variation of 4%. This set of system states is larger than the set S considered in decision making to evaluate reliability management also in system states that are not considered in advance.[71]

In addition to ETC, two other important indicators are the overall reliability level and equality between consumers. The reliability level is expressed in terms of relative load curtailment RLC represented in an equivalent number of minutes per year as given in Chapter 3, Eq. (3.2). Equality of the reliability level between consumers is evaluated using the index proposed in Chapter 6, Eq. (6.10), using the inequality ratio in Eq. (6.6).

7.4.2 Data

The numerical illustration uses a five-node test system and considers VOLL data of three different countries (Great Britain, Norway and the United States). The same analysis is repeated for each of the countries to determine a range of potential improvements in performance of short-term power system reliability management if more detailed VOLL data are used. The three datasets consider a different number of consumer types and temporal cases, resulting in different levels of detail. A year is represented by 72 typical time instances, constituting all temporal cases considered in the VOLL data. To unify the data with respect to consumer types, consumers are split into only two categories: residential and non-residential consumers. The share of residential and non-residential demand in total system demand changes throughout the year. Non-residential consumers correspond to the aggregated share of all consumers except the residential ones, i.e., large and small C&I combined in the United States and industry, public and commercial combined in Norway. By unifying the test set, the results for the data of Norway, GB and the US can be compared, although their VOLL

[70] Eq. (3.1) defines the ideal evaluation of total system cost in terms of the value of lost load per individual consumer v_j. However, this level of detail is not available in the considered data. Therefore, we have used the highest level of detail available, i.e., VOLL per consumer group v_c.

[71] The number of realizations is not optimized. The realizations are symmetrically and equidistantly chosen around the forecast value, with a maximal deviation of +/-3σ.

data have different levels of detail. Detailed data about the test system can be found in Appendix D.

If more detailed VOLL data are used, three cases are distinguished. In the first case, different consumer groups are considered each with their respective VOLL $v_c(b,t)$ and are considered to be curtailable at their respective VOLL. In the second case, VOLL is aggregated per node using a weighted average of the VOLL of the different consumer types $v_b(t) = \sum_{c\in\mathcal{C}} DS(c,b,t) \cdot v_c(b,t)$, with $DS(c,b,t)$ the share of consumer group c in total demand at node b at time t. In the third case, VOLL is aggregated per time instant using a weighted average of the VOLL at different nodes and the share of total load at that node: $v_t = \sum_{b\in\mathcal{B}} DS^{ref}(b) \cdot v_b(t)$, with $DS^{ref}(b)$ the demand share of a node b in total demand.

7.4.3 Results

Probabilistic reliability management is simulated using a probabilistic security constrained DC optimal power flow [194] implemented in AMPL [126]. This DC SCOPF is interfacing with the other modules of the quantification framework modeled in Matlab to provide the necessary input data [63, 129].

Table 7.5 gives summary statistics of the detailed VOLL data. First, the average VOLL ($E[v]$) is significantly lower in Norway than in GB and US. Second, when VOLL is constant throughout the country, but differing over time (v_t), temporal variation, represented by the coefficient of variation $\frac{\sigma}{\mu}$, is high for Norway, average for US and low for GB. The higher temporal variability in Norway is likely due to the larger relative difference between cold winters and temperate summers. In Norway, the minimum country-wide VOLL is only €255 /MWh, whereas it is a hundredfold in both GB and US. The country-wide maximum is between €9423 /MWh and €116560 /MWh. This means that optimal reliability will differ substantially over time if the Norwegian data are applied, will differ a bit with the US data and will not change much with the GB data. Third, when VOLL is allowed to change over time and is differentiated between nodes (v_b), the minimum and maximum VOLL diverge in all three countries. Fourth, when in addition VOLL is differentiated between consumers (v_c), minimum and maximum VOLL diverge even more in all three countries. As a result, the lower the minimum VOLL, the less preventive actions will be taken, as a loss of load is not costly.

Table 7.5: Summary statistics of detailed VOLL data in Norway, Great Britain and United States in [€/MWh].

		Norway	GB	US
Average VOLL	$E[v]$	2 095	31 632	57 312
v_t	$\frac{\sigma[v]}{E[v]}$	1.1898	0.088	0.4367
	min	255	28 251	27 277
	max	9 423	36 836	116 560
v_b	min	108	15 035	4 832
	max	12 338	51 284	370 364
v_c	min	83	8 081	1 190
	max	19 063	51 284	458 343

Table 7.6 shows the relative change of expected total system costs ΔETC for the five-node test system, which is defined as

$$\Delta ETC = \frac{ETC(v) - ETC(V)}{ETC(V)} \cdot 100\% \tag{7.12}$$

where v equals VOLL differentiated per consumer group (v_c), VOLL differentiated per node (v_b), or VOLL differentiated per time instant (v_t), depending on the case under investigation. V represents a constant VOLL for all nodes and consumer groups in all temporal cases.

Table 7.6: Relative expected total system cost savings using VOLL data of three countries with different levels of detail.

ΔETC [%]	v_t	v_b	v_c
Norway	-10.68	-20.27	-43.28
GB	-0.01	-3.03	-9.37
US	-0.95	-11.14	-29.52

Table 7.6 shows that potential cost savings differ between the cases with the data from Norway, Great Britain and the United States. They strongly depend on the absolute value of lost load. First, as expected from the theoretical analysis, cost savings increase with a higher degree of VOLL differentiation. The lower the minimum VOLL that can be curtailed in case of contingencies, the less costly preventive actions are needed. As the minimum and maximum VOLL diverge with a higher degree of differentiation, cost savings increase accordingly. Secondly, cost savings are large with the Norwegian data, because the minimum VOLL is close to the cost of preventive and corrective actions. For temporal differentiation (v_t), cost savings are substantial with the Norwegian data, low

with the US data and negligible with the GB data. Cost savings are the result of an interplay between temporal variation, characterized by the coefficient of variation in Table 7.5, and the absolute level of the minimum VOLL. The lower the absolute level of minimum VOLL and the higher the temporal variation, the larger the cost savings.

Fig. 7.3 takes a closer look at how the cost savings of Table 7.6 depend on preventive, corrective and curtailment actions. The Norwegian data lead to decreased costs primarily because less preventive actions are taken, as its cost of curtailing residential consumers is low. With the GB and US data, cost of preventive actions and curtailment cost decrease when shifting to spatial (v_b) and perfect curtailment (v_c).

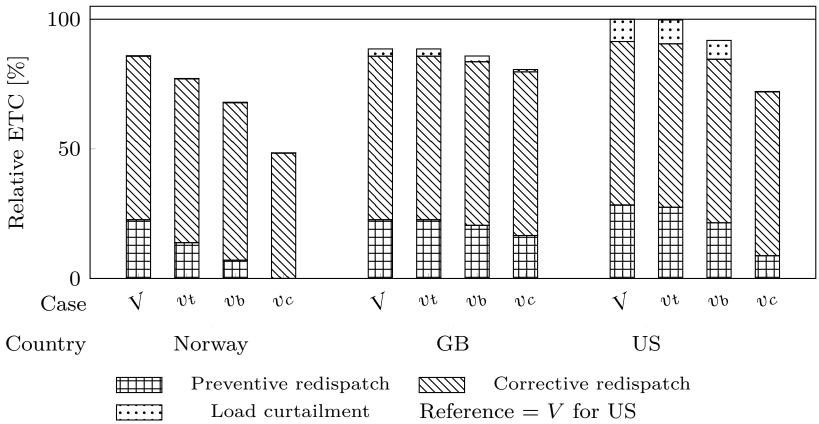


Figure 7.3: Evolution of cost terms in expected total system cost for different levels of detail of VOLL.

Another important aspect to consider in the discussion is equality of the reliability level between different consumers. If more detailed VOLL data are used and TSOs are able to curtail load based on VOLL, particular consumer groups might experience lower reliability levels. Table 7.7 shows the relative load curtailment per node and consumer group. The last column shows the inequality index U^{ENS}, evaluating the distribution of reliability among consumers, as defined in Eq. (6.10). Table 7.7 shows first that spatial curtailment (v_b) considerably increases inequality. In all three countries, curtailment is almost completely limited to node 5, where low-VOLL residential consumers are located. Second, perfect curtailment (v_c) also increases inequality, but less than spatial curtailment. Curtailment is almost completely limited to residential consumers, as they have the lowest VOLL most of the time. Third, changing VOLL over

Table 7.7: Relative load curtailment [min/year] (per node and consumer group), consumption weighted average RLC and inequality index (U^{ENS}) for different levels of VOLL detail and VOLL data of three different countries.

		Nodes									
	VOLL	2		3		4		5		RLC_{avg}	
Country	Detail	Res	Non res	Res	Non res	Res	Non res	Res	Non res	[min/year]	U^{ENS}
Norway	V	-	1.12	0.31	0.49	1.1	0.37	3.48	16.59	1.91	0.66
Norway	v_t	-	1.04	0.42	0.76	0.66	0.57	3.91	13.59	1.91	0.58
Norway	v_b	-	0.05	0	0	0.16	0.09	23.09	45.54	6.25	0.81
Norway	v_c	-	0.06	14.16	0	127.8	0.03	109.16	0	27.86	0.75
GB	V	-	0.8	0.31	0.31	1.01	0.39	3.5	18.11	1.91	0.7
GB	v_t	-	0.8	0.31	0.31	1.02	0.39	3.5	18.11	1.91	0.7
GB	v_b	-	0	0.05	0.05	0	0	6.52	15.2	1.91	0.82
GB	v_c	-	0.02	1.9	0.01	2.51	0	8.81	0.07	1.91	0.74
US	V	-	1.19	0.92	0.1	0.37	0.72	3.71	15.74	1.91	0.68
US	v_t	-	1.19	0.3	0.49	1.06	0.51	3.94	14.78	1.91	0.64
US	v_b	-	0.11	0.02	0.02	0.02	0.01	4.91	19.95	1.91	0.85
US	v_c	-	0.02	2.45	0	1.87	0	8.48	0.13	1.91	0.73

time (v_t) does not increase inequality. Using Norwegian and US data, inequality slightly decreases, whereas with GB data, it is constant.

Relative load curtailment does not change if more detailed VOLL data are used, except when spatial and perfect curtailment, respectively based on v_b and v_c, are exploited in the Norwegian data. In that case RLC increases, because curtailing consumers is cheaper than expensive preventive and corrective actions. This is because the absolute level of VOLL is lower in the Norwegian data than in the GB and US data.

7.5 Discussion

The trade-off between efficiency and equality of reliability is an important aspect to consider when introducing more detailed VOLL data. Table 7.8 summarizes the reduction of expected total cost (ΔETC) and the inequality index (U^{ENS}) for the VOLL data of the three countries with different levels of VOLL detail. If VOLL is equal for all nodes, but differs over time, total cost decreases, without a significant effect on equality. With the Norwegian and US data, inequality decreases, but this seems to be by chance, as the TSO curtails nodes more randomly.[72] Detailed VOLL data per node v_b or per consumer group v_c, however, have a larger potential for cost savings, but at the expense of increasing inequality. Inequality is higher for spatial curtailment than for perfect curtailment. This is because spatial curtailment focuses mostly on the same node (node 5). Perfect curtailment, by contrast, focuses on those consumers with the lowest VOLL. Because they are different groups over time, curtailment is more diversified and inequality is lower. This means that if VOLL data is available, but perfect curtailment is technologically infeasible, a country should carefully assess if the efficiency gains of spatial curtailment make up for the increased inequality.[73]

Two issues merit more discussion. First, currently most TSOs do not use even a constant VOLL in their short-term reliability management. Especially not one that is based on extensive VOLL studies. TSOs' reliability decisions are guided by the N-1 criterion. This criterion states that an unexpected outage of a single system component may not result in a loss of load. That is, when a single system component fails, the transmission system should still be able to accommodate all flows without load curtailment. The detailed data required for probabilistic reliability management (failure rates, forecast errors,

[72] Although not completely randomly, because the network topology and the cost of preventive and corrective actions also affect curtailment decisions.

[73] Options to reduce inequality are discussed in more detail in Chapter 6.

Table 7.8: Summary table presenting the trade-off between efficiency and equality for the VOLL data of the three countries.

	Norway				GB				US			
	V	v_t	v_b	v_c	V	v_t	v_b	v_c	V	v_t	v_b	v_c
ΔETC [%]	0	-10.68	-20.27	-43.28	0	-0.01	-3.03	-9.37	0	-0.95	-11.14	-29.52
U^{ENS} [/]	0.66	0.58	0.81	0.75	0.7	0.7	0.82	0.74	0.68	0.64	0.85	0.73

wind and solar data, detailed demand and generation data, and, of course, VOLL) are not yet widely available. However, advances in communication and information technologies facilitate gathering this data. With more data available, TSOs can gradually introduce probabilistic methods and interruption costs into reliability management. Moreover, the Fourth Energy Package of the European Commission prescribes that all member states have to establish at least a single estimate of VOLL for their territory and can establish a VOLL per bidding zone, if they have several ones.

Second, actual VOLL strongly depends on the currently perceived reliability level, which is high with currently used reliability management [224]. Therefore, VOLL values are in fact not absolute, but conditional upon the perceived reliability level at the moment of the survey. If the reliability level is high, people do not take many actions to prepare for an interruption. A low reliability level on the contrary encourages local investments, e.g., in storage or local generation, to prepare for interruptions. If spatial or perfect curtailment is implemented, the reliability level would change for different consumer groups, which in turn changes their VOLL. Due to its low VOLL values, Norway might be mostly impacted by this effect, as people will experience lower reliability levels if exact VOLL data are taken into account in reliability management.[74] Taking into account behavioral feedback effects of VOLL is important, but a lengthy learning process.

This chapter focused on the efficiency gains in short-term reliability management. However, considerable gains are also possible in the mid term and long term. A better understanding of interruption costs will lead to better maintenance and system expansion decisions.

Lastly, the increase of intermittent generation will require significant expansions in transmission infrastructure [225]. However, the high costs of transmission

[74]The analysis is done for a small-scale test system to which the VOLL data the three countries are applied to obtain comparable results. The networks of the respective countries are not considered in the analysis.

investments and the difficulties to build new lines in both rural and urban areas could hinder this development [226]. This will push power system operation closer to its limits. In such a stressed power system, the use of detailed VOLL data will yield even higher benefits.

7.6 Conclusions

Many empirical studies have estimated how VOLL depends on interruption characteristics – especially consumer type and time of interruption. However, few applications actually use detailed VOLL data to improve power system reliability. A theoretical analysis and a numerical illustration of short-term reliability management both show that incorporating detailed VOLL data leads to considerable efficiency gains. The numerical illustration leads to potential gains between 3% and 20% when spatial curtailment is used, and between 9% and 43% when perfect curtailment is used.

The analysis showed that this efficiency gain has a downside. Equality of reliability decreases when more cost-effective spatial and perfect curtailment are used in the case study. Striking the balance between these opposing objectives is the role of a regulator, based on society's preferences. When only temporal aspects of VOLL are incorporated, efficiency gains are lower, but the case study shows no significant effect on equality. This is shown by the Norwegian VOLL data that have much temporal variability

To reap the benefits of detailed VOLL data in short-term reliability management, two conditions need to be met. First, TSOs need to move away from the currently-used N-1 reliability criterion and move towards probabilistic reliability management that facilitates a trade-off between preventive, corrective and interruption costs. Second, more VOLL studies are needed to improve detailed VOLL data. A widespread roll-out of smart meters have the potential to facilitate the determination of VOLL for different consumer types and different interruption times and can help to achieve perfect curtailment.

Chapter 8

Short-Term Reliability Management Approaches and Criteria

The strict dichotomy between the deterministic N-1 criterion and a fully probabilistic reliability criterion is a simplification. Several reliability criteria exist between these two extremes. The objective of this chapter is to distinguish intermediate steps to bridge the gap between the deterministic N-1 approach and an advanced, fully probabilistic RMAC to facilitate the practical application of probabilistic RMACs. This chapter proposes a classification of reliability criteria based on four controllable factors: (i) the set of considered system states, (ii) the objective function, (iii) the allowed real-time actions and (iv) optional non-technical constraints. This classification improves the understanding of the differences between reliability criteria for short-term reliability management proposed in specialized literature.

The multi-dimensional performance assessment of six proposed reliability criteria is illustrated in a five-node test system. This illustration, however, does not intend to identify the fundamentally optimal reliability criterion for actual large-scale systems, but intends to indicate general characteristics and relative performance of different reliability criteria. Based on this analysis, the difficulties to adopt alternative criteria in a practical context as well as possible improvements in terms of different performance aspects are revealed in relation to the currently applied N-1 criterion.

Section 8.1 presents the classification of reliability criteria and describes six reliability criteria that range from the deterministic, strict N-1 reliability criterion to a fully probabilistic reliability criterion based on socio-economic principles. The six reliability criteria are evaluated along five performance indicators: (i) expected total cost, (ii) unreliability, (iii) inequality between consumers in terms of reliability, (iv) data requirements and (v) ease of use, in a case study in Section 8.2. Section 8.3 discusses the results, while in Section 8.4 the classification framework is applied to the reliability management approach and criterion developed in the GARPUR project. Section 8.5 concludes the chapter.

This chapter is based on the paper *A multi-dimensional analysis of reliability criteria: from deterministic N-1 to a probabilistic approach, Heylen E., Ovaere M., Proost S., Deconinck G. and Van Hertem D.* submitted for publication in IEEE Transactions on Power Systems.[75]

8.1 Classification of Short-Term Reliability Management Approaches and Criteria

Reliability criteria guide reliability management of TSOs, from long-term system development to short-term operational planning and real-time operation [227]. In each of these planning horizons, the TSO continuously takes actions to minimize the cost of satisfying the reliability criterion. Reliability management in this dissertation focuses on the cost minimization problem of the TSO in operational planning and real-time operation:

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}} \left[\sum_{s\in S} C^{tot}(\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt})\right] \tag{8.1}$$

$$\text{s.t. } G_0(\mathbf{a}^{prev}) = 0 \tag{8.2}$$

$$H_0(\mathbf{a}^{prev}) \leq 0 \tag{8.3}$$

$$G_s(\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}) = 0 \qquad \forall s \in S \tag{8.4}$$

$$H_s(\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}) \leq 0 \qquad \forall s \in S \tag{8.5}$$

$$|\mathbf{a}_s^{corr} - \mathbf{a}^{prev}| < \Delta\mathbf{a}_s \qquad \forall s \in S \tag{8.6}$$

[75] The first two authors are the main authors of the paper and contributed equally to the study. The contributions of the first author include the modeling and analysis of the reliability management approaches and criteria, as well as the development of the multi-dimensional analysis. The development of the classification framework and the interpretation and discussion of the results are the result of a collaboration between the first two authors.

In operational planning and real-time operation, the TSO's objective is to minimize total cost $\sum_{s \in S} C^{tot}(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}, \mathbf{P}_s^{curt})$, while satisfying the power flow equations (equality constraints G_0 and G_s) and operational limits (inequality constraints H_0 and H_s) [57]. During operational planning, the TSO takes the most cost-effective preventive actions $\mathbf{a}^{prev}$ to ensure that these constraints are met in all considered system states $s \in S$.[76] The set of considered system states depends on the applied reliability criterion.

If contingencies happen in real-time and preventive actions turn out to be insufficient, the TSO can take corrective actions $\mathbf{a}_s^{corr}$ or resort to load curtailment $\mathbf{P}_s^{curt}$.[77] They choose the cheapest actions that are within the constraints of the applied reliability criterion to make sure operational limits are still met. Unconsidered system states could lead to uncontrolled brownouts or blackouts, if corrective actions are not able to deal with the realized real-time system state.

The remainder of this section formulates and discusses the six considered reliability criteria.[78] Table 8.1 summarizes the analyzed reliability criteria along the four proposed characteristics.[79]

8.1.1 N-1 Reliability Criterion

Currently, all TSOs use the N-1 reliability criterion or some variant in short-term reliability management. This straightforward criterion states that networks should be able to withstand a loss of one circuit without causing overloads of any other circuit and such outages must not threaten the integrity of system operation [230]. A direct link between the preventive and corrective stage is not made if not required and the system is secured ahead of real-time, if possible. The TSO's objective function is deterministic and limited to minimizing the cost of preventive actions. The expected costs of corrective and curtailment actions in real-time are not explicitly considered. The set of considered system states consists of all N-1 contingencies and is usually called the N-1 contingency set. In

[76] Examples of available actions in the operational planning stage are generation redispatch, branch switching, phase-shifting transformer tap changing, and ensuring the availability of upward and downward reserves [228].

[77] Possible corrective actions are branch switching, secondary voltage control, capacitor and reactor bank switching, the use of upward and downward reserves, phase-shifting transformer tap changing and load curtailment [57].

[78] To simplify the notation, $G_s()$ represents the set of all constraints, i.e., the equality and inequality constraints in the reference state and each system state s and the constraint of the rate of change.

[79] The discussed reliability criteria mainly focus on risk-neutral reliability management. Alternatively, risk averse objective functions can be considered that are typically implemented using robust optimization techniques [229].

case of N-1 network contingencies, the network should be able to accommodate all resulting flows. The mathematical formulation of the N-1 reliability criterion is:

$$\min_{\mathbf{a}^{prev}} [C^{prev}(\mathbf{a}^{prev})] \tag{8.7}$$

$$\text{s.t. } G_s(\mathbf{a}^{prev}) = 0 \qquad \forall s \in S_{N-1,network} \tag{8.8}$$

In case of N-1 generation contingencies, real-time corrective actions $\mathbf{a}_s^{corr}$, like upward and downward use of reserves, are needed to restore the balance between demand and supply.

$$G_s(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}) = 0 \qquad \forall s \in S_{N-1,generation} \tag{8.9}$$

In any case, load curtailment is not allowed in N-1 system states (i.e., in both network and generation N-1 contingencies). The N-1 reliability criterion does not explicitly prepare for multiple contingencies. In these cases, load curtailment could turn out to be required to prevent a blackout in real-time operation. In many countries, the exact definition of the N-1 reliability criterion differs from the above strict formulation.

8.1.2 Deterministic Reliability Criterion with a Different Set of Considered System States

The mathematical formulation of this reliability criterion is similar to that of the N-1 reliability criterion. The primary difference is the set of considered system states, which is allowed to differ from the N-1 contingency set.

$$\min_{\mathbf{a}^{prev}} [C^{prev}(\mathbf{a}^{prev})] \tag{8.10}$$

$$\text{s.t. } G_s(\mathbf{a}^{prev}) = 0 \qquad \forall s \in S^{prev} \tag{8.11}$$

$$G_s(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}) = 0 \qquad \forall s \in S \setminus S^{prev} \tag{8.12}$$

This reliability criterion requires a TSO to minimize its cost of preventive actions C^{prev} while meeting the constraints for a subset of all considered system states S^{prev} with preventive actions only and for the remaining considered system states $S \setminus S^{prev}$ with both preventive and corrective actions to balance demand and supply. The set of considered system states S could be defined in different ways. It could, for example, include N-1 network contingencies, but exclude generator and busbar failures from the N-1 contingency set [89, p.25]; increase the contingency set to include multiple dependent failures with a high probability of occurrence; change the contingency set over time (e.g., including double-circuit failures only during adverse weather) or between regions (e.g., including more contingencies for urban areas or business districts); etc. In addition to contingencies, the set of considered system states could also include deviations from the expected operating condition, like forecast errors of demand and intermittent supply. In its most general form, the set of considered system states S is the Cartesian product of credible contingencies and considered operating conditions. S is always a subset of the infinite set of all possible future real-time states and contingencies (RT). Fig. 8.1 illustrates different sets of considered system states in the Cartesian plane of contingencies and operating conditions: the set of N-1 network contingencies $S_{N-1,network}$, the set of N-1 contingencies S_{N-1}, a set of N-k contingencies S_{N-k}, a general set S of contingencies and operating conditions and the set of all possible real-time operating states and contingencies RT.

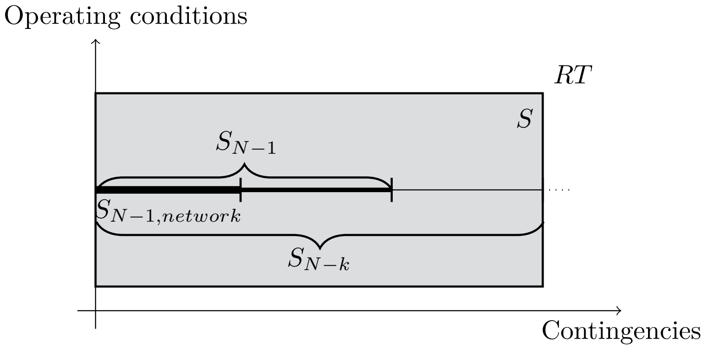


Figure 8.1: Different sets of considered system states in the Cartesian plane of contingencies and operating conditions.

It is also possible that (well-informed) state selection leads to a set of considered system states in which not all of the N-1 contingencies are included. This might be, for instance, because the probability of occurrence or the impact of the excluded states is too low. The impact on the performance indicators of such sets is hard to predict, as this is an interaction between the impact of the additional and removed operating states.

8.1.3 Probabilistic Reliability Criterion without Load Curtailment in Considered States S

If the TSO takes the expected cost of corrective actions in considered system states $s \in S$ into account in operational planning, its objective function becomes probabilistic. The TSO simulates which actions it will take in each of the considered system states and the expected cost is calculated as the product of the cost of actions in each state and its associated probability of occurrence. First, suppose that load curtailment is not allowed in considered system states. The mathematical formulation becomes:

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr}} \left[C^{prev}(\mathbf{a}^{prev}) + \sum_{s \in S} p_s \cdot \left(C^{corr}(\mathbf{a}_s^{corr}) \right) \right] \tag{8.13}$$

$$\text{s.t. } G_s(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}) = 0 \quad \forall s \in S \tag{8.14}$$

The difference between this criterion and the previous criterion is that a TSO now incorporates the effect of its preventive actions on the cost of its corrective actions, instead of just checking if the constraints are met. This enables an explicit trade off between preventive and corrective actions.

8.1.4 Probabilistic Reliability Criterion

If, in addition, load curtailment is allowed in considered system states and the TSO also takes the expected cost of load curtailment into account in its operational planning minimization, this results in a fully probabilistic reliability criterion [22, 40, 59]. The mathematical formulation is:

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}} \left[C^{prev}(\mathbf{a}^{prev}) + \sum_{s \in S} p_s \cdot \left(C^{corr}(\mathbf{a}_s^{corr}) + C^{curt}(\mathbf{P}_s^{curt}) \right) \right] \tag{8.15}$$

$$\text{s.t. } G_s(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}, \mathbf{P}_s^{curt}) = 0 \quad \forall s \in S \tag{8.16}$$

With $\mathbf{P}_s^{curt}$ the vector of load curtailment [MW] of all consumers in state s. The difference between this criterion and the previous criterion is that the effect of preventive actions on the cost of corrective actions and load curtailment is incorporated. This enables an explicit trade off between preventive, corrective and curtailment actions.

8.1.5 Probabilistic Reliability Criterion with a Constraint on the Aggregate Reliability Level

Where the fully probabilistic reliability criterion aims at minimizing the expected total cost (ETC), it can also reduce the reliability level considerably [193]. Therefore, social and political concerns could lead to the addition of a constraint on the value of the expected aggregate reliability level $\bar{P}^{curt}$. Such a constraint is one way to limit the decrease of the reliability level. If the constraint is binding, ETC will be higher. The mathematical formulation becomes:

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}} \left[C^{prev}(\mathbf{a}^{prev}) + \sum_{s\in S} p_s \cdot \left(C^{corr}(\mathbf{a}_s^{corr}) + C^{curt}(\mathbf{P}_s^{curt}) \right) \right] \quad (8.17)$$

$$\text{s.t. } G_s(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}, \mathbf{P}_s^{curt}) = 0 \quad \forall s \in S \quad (8.18)$$

$$\sum_{j\in\mathcal{J}} \sum_{s\in S} p_s \cdot P_{j,s}^{curt} \leq \bar{P}^{curt} \quad (8.19)$$

with $\mathcal{J}$ the set of all consumers.

8.1.6 Probabilistic Reliability Criterion with Constraints on Individual Reliability Levels

The reliability constraint can also be imposed at the level of the individual instead of the aggregate. In that case, the constraint provides a minimal expected reliability level $\bar{P}_j^{curt}$ for each consumer j.

$$\min_{\mathbf{a}^{prev},\mathbf{a}_s^{corr},\mathbf{P}_s^{curt}} \left[C^{prev}(\mathbf{a}^{prev}) + \sum_{s\in S} p_s \cdot \left(C^{corr}(\mathbf{a}_s^{corr}) + C^{curt}(\mathbf{P}_s^{curt}) \right) \right] \quad (8.20)$$

$$\text{s.t. } G_s(\mathbf{a}^{prev}, \mathbf{a}_s^{corr}, \mathbf{P}_s^{curt}) = 0 \quad \forall s \in S \quad (8.21)$$

$$\sum_{s\in S} p_s \cdot P_{j,s}^{curt} \leq \bar{P}_j^{curt} \quad \forall j \in \mathcal{J} \quad (8.22)$$

8.2 Case Study

A case study applies the six reliability criteria introduced in Section 8.1 to a five-node test system. The performance of the reliability criteria is evaluated based on the reliability management performance metric proposed in Chapter 3, which uses 5 performance indicators. The results are summarized in Table 8.3.

Table 8.1: Summary of the six reliability criteria.

	(a)	(b)	(c)	(d)	(e)	(f)
1. Set of considered states	S_{N-1}	S_{N-k}	S	S	S	S
2. Curtailment allowed in S	no	no	no	yes	yes	yes
3. Objective function	Det.[1]	Det.	Prob.[2]	Prob.	Prob.	Prob.
4. Non-technical constraints	/	/	/	/	$\bar{P}^{curt}$	$\bar{P}_j^{curt}$

[1] Deterministic [2] Probabilistic
(a) Deterministic with N-1 contingency set
(b) Deterministic with different set of considered states
(c) Probabilistic without curtailment
(d) Probabilistic
(e) Probabilistic with aggregated constraint
(f) Probabilistic with individual constraint

8.2.1 Data

The illustrative five-node test system is based on the Roy Billinton reliability test system [195]. Detailed data about the test system can be found in Appendix D. The simulation is repeated for a more stressed and a less stressed case as defined in Table 8.2 to verify the sensitivity of the results. This numerical illustration uses VOLL data from Norway [196]. Two consumer types are considered: residential and non-residential customers. The share of residential and non-residential demand in total system demand changes throughout the year, as discussed in Appendix D.

Table 8.2: Summary of the three cases for the sensitivity analysis.

	More stressed	Base case	Less stressed
Load	105%	100%	95%
Failure rates	150%	100%	75%
Repair times	150%	100%	75%
Line rating	91%	100%	136%

8.2.2 Evaluation

An analytical non-sequential state enumeration technique is applied. The quantitative performance indicators are evaluated for a set T of time instances for which forecast values for load and renewable power generation are given.

Corrective reliability management is simulated for a set RT' of real-time realizations for each time instance in the set T. This set is the Cartesian product of possible contingencies and real-time operating states.[80] The latter are conditional upon the forecast values. Preventive and corrective reliability management are modeled using a DC security constrained optimal power flow in AMPL [126]. In each simulation, the specifics per criterion as discussed in the next section are taken into account. Available actions are generation redispatch, branch switching, phase-shifting transformer tap changing and load curtailment, depending on the applied criterion [194]. The simulations are done in Matlab using an interface with AMPL. The optimization problem is solved using the CPLEX solver [231].

Performance of the RMACs is evaluated based on the performance metric introduced in Chapter 3. Five indicators, three quantitative and two qualitative indicators, are used: expected total cost[81], relative load curtailment, inequality, data requirements and ease-of-use.[82]

Expected values of the quantitative performance indicators $Q_{i,m}$ over all time instances t and real-time states rt are obtained in the analytical state enumeration approach using:

$$E[Q_{i,m}] = \sum_{t \in T} p_t \sum_{rt \in RT} p_{rt|t} \cdot Q_{i,m}(rt, t) \tag{8.23}$$

The time instances t in the set T are characteristic time instances representing a year. A weight p_t is assigned to each of the characteristic time instances in the set T. These weights represent the proportion of all hours in a year belonging to a certain class represented by a certain characteristic time instance. $p_{rt|t}$ is the probability of being in real-time state rt at time t. Since the set RT is the infinite set of all possible contingencies and all possible operating conditions, Eq. (8.23) is in practice evaluated for a finite subset $RT' \subseteq RT$, where the set of system states considered in the RMAC $S \subseteq RT'$ [64].

Qualitative aspects, such as ease of use and data requirements, are hard to quantify. A scoring system from +++ to - is used, representing resp. the best and worst case.

[80] For this case study, the following assumptions are made: Most probable contingencies up to a cumulative probability of 99.73% and 11 realizations of net total demand based on a normal distribution of which the mean equals the forecast value and the coefficient of variation is 4%.

[81] The evaluation of interruption cost in the total cost is based on the VOLL data per consumer group, as discussed in Chapter 7 (Eq. (7.10)).

[82] These indicators were discussed in more detail in Chapters 3 and 6.

8.2.3 Implementation of the Reliability Criteria

Criterion (a) in Table 8.1 considers all N-1 branch and generator outages in the preventive decision stage. All these operating states are considered to be equally probable. Load curtailment is avoided for this contingency set and all consumers are treated equally. The objective is to secure the system preventively as much as possible and corrective actions are considered as a last resort. The above also holds for criterion (b), but the set of considered contingencies is different.

Criteria (b) - (f) consider a larger set of contingencies than criterion (a): The most probable contingencies up to a cumulative probability of 99.7%. The failure of some large generator units is not considered in the contingency set of criteria (b) - (f) in this case study, due to their low probability of failure. The set S_{N-k} consists of 28 contingencies compared to 19 contingencies in the set S_{N-1}.

The set of considered system states S for reliability criteria (c) - (f) consists of the Cartesian product of the elements of the contingency set S_{N-k} and 7 possible real-time realizations of net total demand. These realizations are determined based on a normal distribution with the forecast value of net total demand as mean and a coefficient of variation of 4%. Probabilistic criteria (c) - (f) take into account exact probabilities.

Whereas probabilistic criterion (c) tries to avoid load curtailment, criteria (d) - (f) allow load curtailment if this tends to be more cost effective. However, criteria (e) - (f) have upper limits on the amount of load curtailment, i.e., on aggregated load curtailment for criterion (e) and individual limits for criterion (f). In the latter case, the limit on aggregated load curtailment is distributed over the consumer groups according to their demand share.[83]

The set of operating states used in criterion (b), S_{N-k}, and criteria (c) - (f), S, is graphically illustrated in Fig. 8.2. Some system states included in the N-1 contingency set S_{N-1} are not included in the alternative sets S_{N-k} and S, due to their low probability of occurrence, but some higher order contingencies are added to these sets.

8.2.4 Results

Table 8.3 summarizes the performance of the six reliability criteria in the base case of the considered five-node test system, as indicated in Table 8.2. The results of the more and less stressed case are summarized in Table 8.4.

[83] The limit on aggregated load curtailment equals 0.2% of the maximal total demand in the base case of the five-node system.

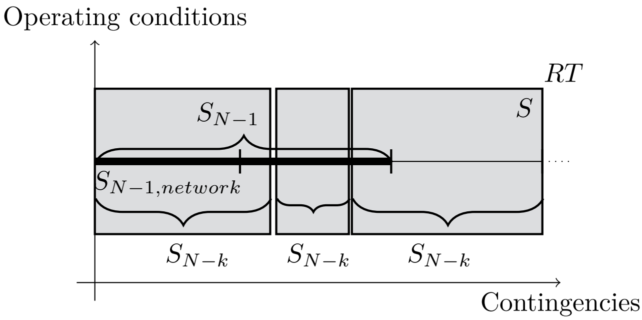


Figure 8.2: Graphical representation of the sets of operating states S_{N-1}, S_{N-k} and S (indicated by the gray area) used in resp. criterion (a), criterion (b) and criteria (c) - (f) as indicated in Table 8.1. The state-space RT represents the space of all possible real-time operating states determined by contingencies and operating conditions.

Expected Total Cost

The first row of Table 8.3 shows that expected total cost decreases when moving from criterion (a) to criterion (d) and increases again when imposing restrictions on the aggregate (crit. (e)) and individual (crit. (f)) reliability level. Criterion (b) results in a lower ETC than criterion (a), because in our case study the set of considered system states S excludes low-probability contingencies that require costly preventive actions. Generally, the change of ETC from (a) to (b) depends on the current performance of the N-1 criterion. If the N-1 criterion is too stringent, enlarging the set of considered system states leads to even higher total costs. If the N-1 criterion is too loose, enlarging the set of considered system states could lead to lower total costs. Next, ETC decreases by moving from deterministic criteria (a) and (b) to probabilistic criterion (c), because more information is included in the operational planning decision. Criterion (c) makes an explicit trade-off between preventive and expected corrective actions [42]. By additionally allowing load curtailment, if this is less costly than alternative corrective actions, criterion (d) leads to even lower ETC. In this case study, most of the decreased ETC is due to a better trade-off between preventive and expected corrective actions (crit. (c)). A smaller part is due to allowing load curtailment in considered system states (crit (d)). The higher VOLL is compared to the costs of other corrective actions, the larger this effect [193]. The ETC of criteria (e) and (f) can be anywhere between the ETC of criteria (c) and (d). The more stringent the imposed reliability constraint is, the higher the ETC. Individual constraints on the reliability level (crit. (f)) always lead to an equal or higher ETC than an aggregate constraint (crit. (e)), as load curtailment of low-VOLL consumers is now substituted for corrective or preventive actions, or load curtailment of consumers with a higher VOLL. To summarize:

$$ETC_d \leq ETC_e \leq ETC_f \leq ETC_c \leq ETC_b \text{ and } ETC_a \tag{8.24}$$

Unreliability

The second row of Table 8.3 shows the unreliability for each of the six criteria. The effect of a particular reliability criterion on the reliability level is closely related to its effect on ETC. Criterion (b) has a slightly higher unreliability, because in our case study not all elements in the N-1 contingency set S_{N-1} are part of the set S_{N-k}. Moving from deterministic to probabilistic criteria has a mixed effect on reliability, depending on the exact formulation of the criterion. Disallowing load curtailment in considered states in a probabilistic approach (crit. (c)) does not imply that unreliability is zero, because load curtailment could still be necessary in non-considered states. Allowing load curtailment in considered states (crit. (d)) decreases ETC even more, but at the expense of a highly increased unreliability. Evidently, constraints on the reliability level (crit. (e) - (f)) decrease the unreliability, but at the expense of a higher ETC. To summarize:

$$RLC_c \leq RLC_f \leq RLC_e \leq RLC_d \tag{8.25}$$

Inequality

U_{ENS} in Tables 8.3 and 8.4 summarizes the inequality between consumers in terms of reliability. Inequality between consumers depends on the relative amount of load curtailment. The results of the more stressed case in Table 8.4 indicate that deterministic criteria lead to higher ETC and lower inequality, whereas probabilistic criteria that allow load curtailment lead to lower ETC and higher inequality. The reason is that deterministic criteria treat all consumers equally, because they make no use of the differentiation to optimize cost-wise, whereas these probabilistic criteria differentiate between consumers or nodes in terms of VOLL. Inequality is lower if individual constraints on load curtailment are applied (crit. f) than for criteria (d) and (e), but at the expense of higher ETC. This is the case, because the inequality resulting from the differentiation in VOLL is reduced by these individual limits, which are based on consumers' demand share. If systems are less stressed, such as the base case in Table 8.3 and the less stressed case in Table 8.4, RLC is lower for criteria (a) - (c) and possibly concentrated in a reduced number of consumers. This increases the inequality between consumers resulting from criteria (a) - (c) and reduces the difference with criteria (d) - (f).

Data Availability

The fourth row of Table 8.3 shows that more data are needed as we move from left to right. Probabilistic approaches (c) - (f) typically require more information than deterministic approaches. Firstly, probabilities of failures should be known. Moreover, forecast errors can be considered and for criteria (e) and (f) appropriate limits on load curtailment should be determined. Some of these data are currently not available for TSOs and might be hard to obtain in practice. Failure probabilities might be imprecise, as well as forecast errors, which might lead to inappropriate reliability management. Moreover, value of lost load and the cost of corrective actions are hard to determine exactly.

Ease-of-use

The last four rows of Table 8.3 show that the ease of using the considered criteria decreases from left to right, because more operating states need to be considered, more information needs to be taken into account and the probabilistic nature of criteria (c) - (f) adds a layer of complexity to reliability management.

Table 8.3: Performance evaluation of the six considered reliability criteria in the base case: The first three indicators give a numerical value and the last two indicators are expressed qualitatively as (-/+/++/+++), resp. from worst to best (relative).

Base case	Criteria of Table 8.1					
	(a)	(b)	(c)	(d)	(e)	(f)
1. ETC^{rel} [%]	100	87.34	34.62	26.63	33.83	34.50
2. RLC [min]	0.0046	0.0077	0.0046	18.87	1.83	0.19
3. U^{ENS} [/]	0.741	0.6128	0.569	0.811	0.794	0.604
4. Data requirements	+++	++	+	+	-	-
5. Ease of use	+++	++	+	+	-	-
5a. Type	Det.	Det.	Prob.	Prob.	Prob.	Prob.
5b. # of states[1]	19	28	196	196	196	196
5c. # output info	+++	++	+	+	-	-

[1] Dependent on the state selection algorithm
The numerical values cannot be generalized to real systems, but the trends between reliability criteria can.

Sensitivity Analysis

Table 8.4 summarizes the results of the sensitivity analysis for the more stressed and less stressed cases defined in Table 8.2. In the more stressed case, the relative difference in total system cost between the deterministic and probabilistic approaches is slightly decreased. Both in the more stressed and the less stressed case, the trends in differences between the criteria in terms of relative ETC and RLC are the same as in the base case.

Table 8.4: Sensitivity of the six considered reliability criteria in a more stressed case and a less stressed case.

More stressed	Criteria of Table 8.1					
case	(a)	(b)	(c)	(d)	(e)	(f)
ETC^{rel} [%]	100	84.34	37.93	27.89	37.04	37.42
RLC [min]	0.0796	0.0862	0.0632	20.3	1.92	1
U^{ENS} [/]	0.353	0.473	0.3569	0.815	0.693	0.581
Less stressed	**Criteria of Table 8.1**					
case	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
ETC^{rel} [%]	100	88.36	32.42	25.00	31.66	32.33
RLC [min]	0.0002	0.0016	0.0001	17.7	1.82	0.189
U^{ENS} [/]	0.718	0.476	0.694	0.814	0.829	0.629

8.3 Discussion

Despite the advantage of probabilistic criteria to decrease the cost of reliability management, the N-1 criterion, or a variation of this, is still used by all network operators. Barriers against implementing probabilistic approaches are mainly due to data, complexity and transparency issues. The proposed intermediate steps can help to gradually move towards probabilistic approaches. However, some assumptions are made in the modeling approach, which should be placed in the right perspective.

8.3.1 Barriers against Implementing Fully Probabilistic RMACs

The main barriers for probabilistic criteria are the lack of available and accurate data, as well as the difficulty to understand and use the approach. These are the factors summarized by the two qualitative indicators. To advance towards probabilistic reliability criteria, both the data and the ease-of-use should be improved.

Data can be gathered at a decreasing cost due to advances in communication and information technologies. Devices to measure climatic data, real-time voltage and current data, and regional demand and generation data are being installed in many countries. In an initial stage, aggregate data can be used, such as location-independent forecast errors of load and renewable generation, a time-independent VOLL, and constant failure probabilities of lines and generation. More detailed data can be included in the decision-making process once they are available, such as spatially-dependent forecast errors, time-dependent VOLL, and failure probabilities that depend on component lifetime and external conditions. However, the accuracy of these data influences the decision-making behavior. Therefore, it is important to check the sensitivity of the performance of reliability criteria with respect to the exactness of the values of the provided data. If both the sensitivity of the results to the accuracy of the data and the uncertainty on the accuracy of the data is high, accounting for imprecise probability in the decision making might be favorable [232].

Probabilistic criteria are inherently more complex than their deterministic counterparts, as probabilistic approaches make decisions based on trade-offs instead of on a binary criterion. They have a steep learning curve and the ease-of-use is low nowadays due to the lack of practical experience. However, the transition from deterministic to probabilistic approaches can be facilitated by taking intermediate steps between the currently used N-1 criterion and a fully probabilistic criterion. The amount of data and complexity can be gradually increased, in line with experience gained. A first step is to define an adequate set of system states to consider. This set can be probability-based or can be a time-dependent set of considered contingencies or system states based on an implicit trade-off between the cost of preventive and corrective actions and the implied security risk.[84] This requires appropriate state selection techniques [233]. Only changing the set of considered system states retains the simplicity of deterministic criteria, while employing the cost-reducing trade-offs of probabilistic criteria. A well-selected set of considered system states can for instance reduce conservatism regarding low-probability N-1 states, which may be costly to secure preventively. In a next step, expected interruption costs can be added to this trade-off. In later steps, explicit probabilistic trade-offs can be introduced in practical short-term reliability management.

Another barrier for probabilistic criteria is their alleged lack of transparency. Comparing transparency of probabilistic and deterministic approaches is not straightforward, because they are both transparent about different aspects.

[84]For example, a different set for high and low demand or normal and adverse weather.

Deterministic criteria are transparent about when and why reliability actions are undertaken and about which contingencies do not lead to interruptions. However, they are less transparent about the risk level and the incentive used in contingency selection. Transparency of probabilistic criteria depends on their practical implementation. Probabilistic criteria can be transparent about objectives, constraints, trade-offs or the risk level, while balancing reliability, equality and efficiency. However, fully probabilistic RMACs are in general less transparent about the set of contingencies that is preventively secured and the selected reliability actions are much more dependent on the system state.

8.3.2 Assumptions in the Modeling Approach

The modeling approach of the case study incorporates a number of assumptions TSOs might be concerned about in a practical analysis. These assumptions might impact reliability management decisions, but do so for both deterministic and probabilistic approaches. Moreover, the objective of this study is not to formulate the optimal reliability criterion to be used in a practical TSO context or to develop a SCOPF formulation that can be used in on-line system operation. The study aims at providing insight in the impact of controllable factors of reliability criteria that can facilitate the transition from deterministic N-1 to probabilistic approaches.

First, in addition to the two considered decision stages (i.e. day-ahead operational planning and real-time operation), TSO's reliability management consists of several additional stages, e.g. the D-2 decision stage, the intraday market and the short-term preventive stage. All these decision stages could be considered in probabilistic modeling [85, 234, 235]. Each of these decision stages is also influenced by external factors that are out of the control of the TSO, such as markets, balance responsible parties, generators and loads.[85]

Second, the decision-making process influences all aspects of power system reliability and stability. The formulation used for this paper, DC (optimal) power flow, is a simplified representation that does not consider particular aspects, such as voltage or transient stability issues. Stability issues due to topological actions are an important concern of certain system operators and should be integrated in SCOPF formulations to support TSO's decision making. Topological actions can conceptually be integrated in the approach presented in this dissertation. However, the considerable amount of binary variables involved

[85] In turn, market actors can also be affected by changing reliability management practices. For example, if the amount of preventive actions decreases, generators receive less revenue from preventive redispatch after day-ahead clearing (in single-price zones) or from security-constrained day-ahead clearing (in multi-price zones or nodal pricing).

in this decision making increases the computation time and the (numerical) stability of the different cases is not verified. Therefore, system operators take these aspects indirectly into account, by harvesting the operator's knowledge in SCOPF algorithms. They only focus on a predefined list of topological actions for which the stability is verified.

Third, the effect of short-term probabilistic reliability management on the mid and long term also needs to be studied [227]. For example, more stressed systems could need higher maintenance expenditures and have higher losses. A more efficient use of current transmission capacity also leads to fewer additional investments.

8.3.3 Handling the Trade-Off between Efficiency, Reliability and Equality

From an economic perspective, the optimal RMAC minimizes total system cost resulting in the most efficient reliability and inequality level.[86] Deviations from this economically optimal RMAC to reduce load curtailment or inequality in terms of reliability lead to inefficiencies and additional costs. However, with the current mindset regarding power system reliability, TSOs are concerned about their reputation in terms of providing continuity of power supply and end-consumers are not used to low reliability levels and large differences between consumer in terms of reliability. Intermediate steps are required to initiate the transition to probabilistic reliability management based on economic incentives and a trade-off needs to be made between efficiency, reliability and equality, constituting a performance trilemma.

The results in this analysis have shown that an adequate set of considered system states and a trade-off between preventive and corrective actions have the potential to improve efficiency while having a similar performance in terms of equality and reliability. Further efficiency improvements are possible if load curtailment is considered in the trade-off. However, this comes at the cost of reduced reliability and may have a negative impact on equality, depending on the level of system stress.

To obtain an adequate RMAC considering TSO's capabilities and society's preferences, a transparent dialogue between power system stakeholders is important to clearly state society's preferences in terms of the performance trilemma between efficiency, reliability and equality. This defines social acceptability in each of the three performance dimensions and determines how

[86] Minimization of total system cost can be considered as an approximation for social surplus maximization under certain assumptions [80].

far one can go in realizing efficiency improvements at the cost of inequality and unreliability. Measures, such as new, smart technologies and flexibility devices, as well as new types of contracts enabling consumers to make reliability-based choices of electricity consumption, should be further investigated to realize a prescribed trade-off between equality, efficiency and reliability. Moreover, TSOs should carry out the proposed multi-dimensional analysis for their systems to ensure practicality and applicability of the RMAC.

8.4 Application of the Classification Framework

Probabilistic reliability criteria are not yet used in practice in short-term reliability management, but the EU FP7 project GARPUR has proposed and analyzed an advanced, probabilistic, short-term reliability management approach and criterion [80, 85]. The GARPUR approach can be analyzed by our proposed classification framework along the four characteristics of Table 8.1:

1. The set of considered system states is determined using a discarding principle, which neglects a subset of contingencies for which the expected interruption cost is lower than a specified maximal, residual risk level. This set differs for different time instants.
2. Load curtailment is allowed in considered system states.
3. The objective function is probabilistic and aims at minimizing total socio-economic system cost.
4. A reliability target ensures that the probability of reaching unacceptable system states is lower than a fixed tolerance.

In light of these four characteristics, the reliability approach proposed in the GARPUR project resembles criterion (e) of the proposed classification framework.[87] As analyzed in Section 8.2.4, this category of criteria leads to a lower ETC than deterministic criteria, without overly decreasing reliability.

[87]Where this paper focuses on four high-level characteristics of different reliability criteria, the GARPUR project has focused more on the equally-important topic of the exact implementation of probabilistic criteria and the tuning of decision parameters, such as the set of considered system states [80, 85].

8.5 Conclusion

This chapter has proposed a classification of short-term reliability management approaches and criteria according to four characteristics. A case study has illustrated how different RMACs can be compared in a multi-dimensional analysis using three quantitative and two qualitative performance indicators. This case study shows that the largest savings of expected total cost are due to a trade-off between preventive and corrective actions. A smaller portion is due to additionally including curtailment actions in the trade-off. Limits on individual or aggregate unreliability levels decrease unreliability, but increase expected total costs when compared to a fully probabilistic approach. Inequality between consumers in terms of reliability for different RMACs depends on the level of system stress.

In practice, equality, reliability and efficiency should be balanced, constituting a 'performance trilemma'. A transparent dialogue between power system stakeholders is required about the trade-offs between efficiency, equality and reliability to optimally handle the performance trilemma. Moreover, it is up to TSOs to carry out the proposed multi-dimensional analysis for their systems, which will facilitate the move towards an adequate reliability management approach and criterion that considers both TSO's capabilities and society's preferences.

Chapter 9

Conclusion

Reliability management approaches and criteria should be revised in the context of evolving power systems. The currently used, deterministic N-1 criterion is frequently questioned the last decade and a paradigm shift towards probabilistic approaches might be needed to efficiently integrate renewable energy sources and new technologies in power systems. To convince system stakeholders to move towards alternative RMACs, performance of RMACs should be defined, changes in performance when using an alternative RMAC should be adequately evaluated and intermediate approaches that bridge the gap between the currently used N-1 criterion and a fully probabilistic approach should be provided. Although there is a need to appropriately evaluate and compare performance of RMACs to convince power system stakeholders to apply an alternative RMAC in practice, the topic is not well covered in literature.

The main objective of this work is to contribute to the fundamental understanding of evaluating and comparing performance of short-term reliability management approaches and criteria, which can be formulated in the main question: how to evaluate and compare different power system reliability management approaches and criteria? Evaluation and comparison of performance of RMACs consists of multiple aspects of which a subset are addressed in this work by answering following questions:

1. How should performance of short-term RMACs be defined? Are all necessary indicators available?
2. Which modules are required in a quantification framework to evaluate and compare performance of short-term RMACs? What do they represent and how do they interact?

3. How can techniques that are applied in reliability assessment or other performance evaluation contexts be applied to evaluate performance of short-term RMACs, taking into account the typical characteristics of performance evaluation of short-term RMACs?
4. How to define and assess inequality and inequity in a power system reliability context?
5. What is the impact of the level of detail of value of lost load data on the performance of short-term RMACs?
6. Which controllable factors of RMACs can bridge the gap between a deterministic N-1 criterion and a fully probabilistic RMAC? What are the trends in terms of different performance aspects?

Conclusions of the work are summarized in Section 9.1. Section 9.2 formulates recommendations to the power system stakeholders. The research also brought forward interesting topics for future research, which are discussed in Section 9.3.

9.1 General Conclusions

Conclusions of the work can be divided in three domains: (i) the performance of RMACs, (ii) evaluation of the performance and (iii) dealing with the performance trilemma between efficiency, reliability and equality.

9.1.1 Performance of RMACs

Performance of reliability management approaches and criteria is multifaceted and consists of qualitative and quantitative aspects. A selection of appropriate quantitative indicators is based on the provided classification and characterization of indicators and indices (proposed to be) used in power system reliability management.

A complete picture of performance should firstly consider the socio-economic performance of RMACs, which can be quantified by socio-economic indicators and indices. The ideal indicator of socio-economic performance is social surplus. Due to data issues, this indicator is hard to apply in practice. It can be approximated well by total system cost under some assumptions.

Secondly, technical performance of RMACs should be considered, which can be verified in terms of adequacy and security indicators. Probabilistic, security indicators become more important in reliability management of systems with increasing uncertainties. So far, coordinating organizations, such as ENTSO-E and NERC, typically use a probabilistic assessment for generation adequacy, but the proposed security indicators are mainly deterministic, lagging, physical indicators to assess security of the system ex-post.

Thirdly, social acceptability of an RMAC is important. Besides the evaluation of the absolute levels of reliability and interruption cost, it is important to assess whether reliability is equally distributed among consumers. This work has defined equality and equity in terms of power system reliability and proposed summarizing indices to quantify the equality and equity of the distribution of reliability between entities, e.g., nodes, consumer groups or individual consumers.

Fourthly, applicability of an RMAC should be assessed. Applicability is influenced by data requirements. Probabilistic RMACs rely on additional data, such as reliability and cost data, that are not readily available and sometimes time consuming and/or costly to collect. Moreover, it might be hard to ensure the accuracy of the data and confidentiality issues might come into play.

Fifthly, practicality or ease-of-use of the RMAC is also important, especially from the perspective of the system operator. Alternative RMACs might require the handling of a larger set of operating states, additional information and indicators and a more complex trade-off between different cost terms.

9.1.2 Evaluation and Comparison of Performance

Evaluation of performance of RMACs has specific characteristics. Firstly, performance evaluation requires that the complete decision-making trajectory of a TSO according to a certain RMAC is evaluated besides the real-time system state. The TSO decision-making process consists of multiple stages and is affected by exogenous factors that are out of TSO's control. Secondly, performance evaluation should consider both normal and failure states to assess the efficiency of the trade-off between preventive and corrective actions, whereas reliability assessment mainly focuses on failure states.

A quantification framework that incorporates these characteristics has been presented. The integrated, generic and modular design used in the presented quantification framework goes beyond existing literature, which focuses on selected issues, without analysing the full reliability problem in an integrated manner. Due to the modular structure of the quantification framework, building blocks can easily be replaced by more elaborated or detailed blocks with the same functionality. A more extensive implementation of the quantification framework, developed in the GARPUR project, is used by the French TSO to evaluate and compare its current decision-making behavior with the decisions taken with an alternative RMAC.

The quantification framework consists of three main modules: (i) the simulation module, (ii) the evaluation module and (iii) the comparison module. The simulation module is fed by several sub-modules that model the contingencies, external systems, such as demand, generation and the market, the transmission system and the applied RMAC. The core of the simulation module is the security constrained optimal power flow that simulates TSO's decision-making behavior for different RMACs.

Techniques for performance evaluation that can be applied in the evaluation module are divided in analytical and simulation techniques and can be sequential or non-sequential in nature. The applicability of each of the techniques depends on the objective of the analysis. Performance evaluation is mainly challenged by the long computation time of the mixed integer program of the SCOPF that models TSO's reliability management.

The comparison module provides a relative indication of the change in performance if different RMACs are applied and benchmarks the RMACs against an existing, well-known approach based on an N-1 criterion.

9.1.3 The Performance Trilemma

The ideal RMAC is cost-effective, results in a high reliability level and distributes unreliability equally among consumers. However, a trade-off should be made between efficiency, reliability and equality in practice, constituting a performance trilemma.

Moving from the N-1 approach to a fully, probabilistic RMAC benefits from intermediate steps to facilitate the practical implementation. These intermediate steps can be realized by changing controllable factors of the RMAC that have an impact on each of the performance aspects. A characterization of RMACs is proposed based on four controllable factors: (i) the set of considered system states, (ii) the objective function, (iii) the allowed real-time actions and (iv) optional non-technical constraints.

Reliability management can be made more efficient by considering an adequate set of operating states and applying a probabilistic objective function that enables system operators to make a trade-off between preventive, corrective and load curtailment actions. Efficiency gains are defined as reductions in total system cost. A trade-off between preventive and corrective actions result in significant efficiency gains, without implying a loss in terms of reliability or equality. The impact of considering curtailment actions in the trade-off on the performance depends on the magnitude of value of lost load and the degree of differentiation in the applied VOLL data. A theoretical analysis and a numerical illustration of short-term reliability management both show that incorporating detailed VOLL data that enable spatial and perfect curtailment, leads to considerable efficiency gains. Equality between consumers in terms of power system reliability reduces in the analysed test system. Efficiency gains with no significant effect on equality can be obtained with VOLL data with much temporal variability if temporal differentiation in VOLL is used. However, VOLL data and their level of detail should be improved to fully reap the potential.

Equality and equity in the system can be improved in a direct or indirect way. Direct measures to reduce inequality focus on safeguarding consumers that are unfairly treated at a certain point in time if load curtailment is required in the future. Indirect measures focus more on redistributing the consequences of unreliability. This reduces inequality in terms of net total consumer costs, while inequality in terms of energy not supplied remains. Examples of indirect measures are reliability-based transmission tariffs, a market for reliability, end-consumer contracts where the price depends on the reliability level and bi-lateral interruptible load contracts for small-scale consumers. Smart grids with smart metering and demand-side management can also enable reliability-based consumption choices of consumers. These choices represent the need or desire of the consumer, which improves the equity, as consumers can indicate what they need or desire.

A large set of possible measures exists to play on each of the three sides of the triangle. However, a transparent dialogue between power system stakeholders is required about the trade-offs between efficiency, equality and reliability to optimally handle the performance trilemma shown in Fig. 9.1.

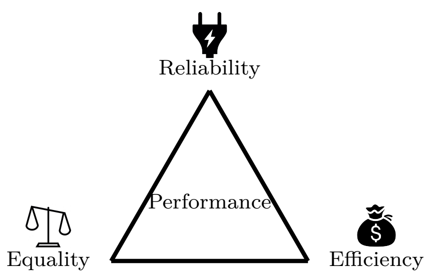


Figure 9.1: The performance trilemma of short-term reliability management approaches and criteria.

9.2 Moving towards Probabilistic Reliability Management in Practice

Based on the outcomes of a discussion between system stakeholders about the trade-offs that should be made in the performance trilemma of RMACs and promising results obtained in a simulation context and pilot projects [55], regulatory incentives should be put in place to stimulate the reassessment of currently-used RMACs. This will facilitate the move towards an adequate reliability management approach and criterion that considers both TSO's capabilities and society's preferences.

If benefits are proven for different stakeholders and objectives are set, a gradual implementation of alternative RMACs in practice can be initiated. Recommendations for different power system stakeholders are formulated based on the findings in this work. However, moving towards alternative reliability management approaches and criteria is not straightforward, as this requires changes in regulation, security standards and network codes. The procedure to change regulation, security standards and network codes consists of multiple stages and interactions between different stakeholders.

9.2.1 The Process of Changing Reliability Management Approaches and Criteria

Several stakeholders are involved in the move towards applying alternative reliability management approaches and criteria in practice. In the end, transmission system operators should apply the RMAC. They are by law obliged to provide a minimal quality level for electricity.

European TSOs should comply with the European network codes developed by ENTSO-E. These European codes are developed taking into account the non-binding opinion and recommendations in framework guidelines of the Agency for the Cooperation of Energy Regulators (ACER).[88] The European network codes developed by ENTSO-E are not intended to replace the necessary national network codes for non-cross-border issues [236]. These national codes, standards and regulations can be initiated by the TSOs themselves. The national codes should be approved by the National Regulatory Agency (NRA). Alternatively,

[88]According to Regulation (EC) N°714/2009, the network codes have to facilitate the harmonization, integration and efficiency of the European electricity market.

national regulations can be enforced by the authorities in a law, e.g., the national law regarding the organization of the electricity market in Belgium.[89]

Fig. 9.2 gives an overview of the interactions between the stakeholders involved in developing and modifying operational security standards and regulations.

9.2.2 Recommendations to Power System Stakeholders

This work serves as a base to initiate a transition towards alternative reliability management approaches and criteria. Recommendations for different stakeholders to initiate this transition are formulated. Moreover, the conclusions of the work are assessed in the context of the current Belgian Electricity law to verify whether foundations already exist in practice to support the transition.

Conclusions of this Work in the Context of the Belgian Electricity Law

The Belgian electricity law states that regulation should contribute to the development, in the most cost-effective way, of secure, reliable and efficient, non-discriminating power systems, which are consumer oriented (Art. 23 §1.4). Moreover, regulation should aim at a high level of universal and public service in the context of electricity supply and should contribute to the protection of critical/vulnerable consumers (Art. 23 §1.8) [237]. Article 23 §1.4 of the Belgian electricity law is challenged by the performance trilemma introduced in this work, as power systems should be cost-effective and efficient, reliable and non-discriminating, implying equity or equality. This work has shown that appropriate trade-offs should be made between efficiency, reliability and equality to determine an acceptable reliability management approach and criterion. Article 23 §1.8, on the contrary, puts constraints on the cost-effectiveness of reliability management, as it implies a universal reliability level with special protection for critical consumers. This implies in terms of VOLL differentiation that temporal differentiation would be allowed, but that differentiation between different consumers is limited to two consumer groups: critical and non-critical consumers.

Authorities and Regulatory Agencies

The first step in the transition towards alternative RMACs is to clearly state society's preferences in terms of the performance trilemma. Sufficient

[89] National codes, standards and regulations can only be applied if they are more stringent than the European network codes.

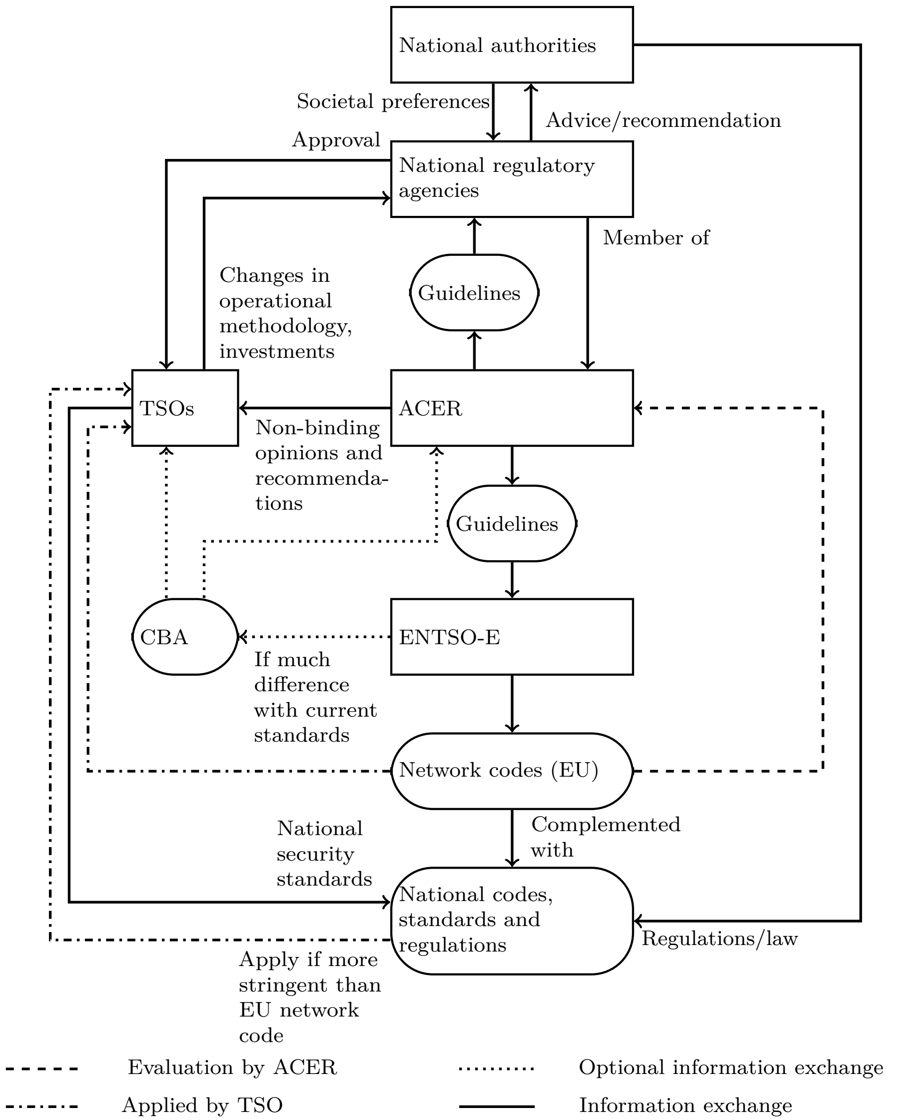


Figure 9.2: Interactions between the stakeholders involved in changing operational security standards, network codes and regulations.

possibilities exist to make an adequate trade-off between equality, efficiency and reliability, given the potential of new, smart technologies and flexibility devices, as well as new types of contracts enabling consumers to make reliability-based choices of electricity consumption. Reliability management approaches and criteria that are able to handle these measures adequately might require a paradigm shift compared to the traditional picture of reliable electricity supply.

A choice should be made between unconditional or individual reliability levels. Is the objective to supply every consumer with a similar level of reliability, irrespective of its transmission tariff, electricity price or location, or should the price be explicitly linked with the reliability level, to enable consumers to choose a different reliability level depending on the price. The technical evolutions of smart meters and interruptible appliances, combined with contractual evolutions such as priority and reliability contracts, make it possible to supply every consumer with its preferred reliability level. This could range from receiving a rebate in exchange for the possibility of some brief interruptions, as done in the 20/20 rebate program in California [238], to offering complete reliability-dependent retail contracts. These possibilities will open up the debate of the unconditional provision of a basic and necessary good, such as electricity.

Transmission System Operators

The paradigm shift might take a long period, but transmission system operators can already take actions in the short term to gradually move towards probabilistic reliability management approaches and criteria. TSOs can verify the applicability and practicability of probabilistic reliability management approaches. It is important to make an assessment of additional data that are required and whether these data are available or if certain issues might arise in terms of availability, integrity or confidentiality. Moreover, they should carry out the proposed multi-dimensional analysis of alternative RMACs in their own systems to verify the impact of different controllable factors in practice. A first controllable factor that requires attention is the set of system states considered in reliability management. Adequate state selection, eventually resulting in sets of system states that differ over time, can lead to quick wins in terms of cost-effectiveness compared to the currently used N-1 criterion without having a large impact on reliability and equality. A second aspect to focus on is the trade-off between preventive and corrective actions. N-1 favors preventive actions resulting in overly conservative decision making at certain time instants. Technologies, such as phase-shifting transformers and switching actions, which are already available, and demand-side response and storage, which might become more mature in the future, increase the short-term flexibility in power systems, which reduces the need for redundancy.

An important choice to be made in this context on the long term is about an appropriate trade-off between redundancy and flexibility: Do we invest in more cables and transmission lines to make our power system more reliable or do we focus on using our current infrastructure more efficiently by investing in flexibility devices, such as phase-shifting transformers, demand response, batteries, series compensation and other flexible alternating current transmission system (FACTS) devices. The optimal choice will probably involve both investment in redundancy and flexibility. Probabilistic approaches for reliability management have the advantage of making this choice more explicit compared to the currently used N-1 criterion. A related choice is the decision between repair and replace: Do we invest in new assets or do we repair, refurbish or retrofit the assets. Again, probabilistic approaches can help in this decision making by more explicitly considering costs and benefits.

9.3 Future Work

The transition from reliability-centred, deterministic reliability management towards fully probabilistic reliability management based on socio-economic principles requires a paradigm shift. The availability of an unconditional, reliable electricity supply is embedded in culture and society in Europe. However, evolutions in power systems and the possibilities that come with them raise the question whether this is still the way to go or whether a new value system regarding the fairness and appropriateness of the reliability level is required to fully exploit potential efficiency improvements of probabilistic reliability management. The management of the transition towards cost-effective, socially acceptable and practically applicable reliability management is a multi-disciplinary task, involving social science, engineering science and applied mathematics.

This thesis touched upon several research topics in the context of performance evaluation of RMACs. Three main domains on which significant advancements can be made based on the conclusions and findings in this work can be distinguished: (i) performance evaluation of RMACs, (ii) social and economic acceptability of RMACs and (iii) technical acceptability, applicability and practicality of RMACs.

9.3.1 Performance Evaluation

Significant advancements can be made in the context of performance evaluation techniques. Research in this field is limited so far, although performance evaluation of RMACs has its own characteristics. Reductions in computation time are important due to the long simulation time of TSO decision-making behavior, especially in large systems.

Research effort should be placed on the development of more efficient performance evaluation techniques. Emulation is promising in this respect, because it reduces the number of computationally intensive simulations by evaluating an approximate analytical function. Alternatively, the development of pseudo-sequential simulation techniques requires more attention. These techniques can capture the dynamic process of decision making in reliability management, while optimizing the duration of the period under evaluation.

Significant reductions in computation time of simulation techniques can also be obtained if adequate variance reduction techniques are applied, such as importance sampling and the principle of control variates [239]. However, many algorithms available to reduce the computation time in composite reliability assessment, such as importance sampling [240] and state space pruning [132], cannot be directly applied in performance evaluation. They focus on the failure states with load curtailment. In performance evaluation, the importance of a system state is not determined by the fact whether it is a failure state or not, but by the values of the different performance indicators under evaluation.

Performance evaluation is also challenged by the uncertainty on the input data. Failure rates and repair rates of components are, for instance, not exactly known due to the low probability of occurrence of failures, while the results are sensitive to this kind of information. Although the data are not exact, evaluations are typically based on one single value for these parameters. To propagate the uncertainty related to these parameters in the result, imprecise probability methods, such as probability bounding, should be applied [241].

To reduce the simulation time of the decision-making behavior, the potential of proxies determined with machine learning techniques to model shorter-term decision-making stages in the decision-making process should be further exploited [242] and optimization solvers should be further improved in terms of accuracy and speed.

In terms of indicators used in a reliability context, future work should focus on further development of risk-based, leading, probabilistic, security and socio-economic indicators that can be used to guide the decision-making process of reliability management towards cost-effective decisions. However, besides the definitions of the indicators, a guideline to determine appropriate thresholds for the indicators in different systems is as important.

9.3.2 Social and Economic Acceptability of RMACs

Measures, such as reliability-based transmission tariffs, a market for reliability, end-consumer contracts where the price depends on the reliability level, bilateral interruptible load contracts for small-scale consumers and the practical implementation of new technologies, such as smart meters and other smart devices, have the potential to influence the efficiency, reliability and equality of RMACs. Future work in this context has to focus on the one hand on the careful design of these measures. The proposed inequality and inequity indices can be usefully applied to evaluate the impact of such measures on the distribution of unreliability and its consequences among consumers. The trade-off between efficiency, reliability and equality is on the other hand influenced by the controllable factors of RMACs. More theoretical and applied research is needed on the intermediate steps between the deterministic N-1 criterion and probabilistic criteria. This will lead to practical points of reference for TSOs to bridge the gap between them, which improves the practicality of alternative RMACs.

Future work should also look into formal statistical decision theoretic frameworks, such as multi-attribute utility theory, to deal with the three aspects in the performance trilemma.

9.3.3 Technical Acceptability, Applicability and Practicality of RMACs

Technical acceptability of RMACs can be improved by considering concerns of TSOs regarding the application of security constrained optimal power flow formulations. Especially, stability issues due to topological actions are an important concern of system operators. SCOPF formulations in theory search for the most optimal topological action among all possible topological changes. However, the considerable amount of binary variables involved in this decision making increases the computation time and the stability of the different cases is not verified. Therefore, system operators suggest to harvest the operator's knowledge in the SCOPF algorithms, by only focussing on a predefined list of topological actions for which the stability is verified. Moreover, the SCOPF formulations are not 100% reliable as they do not converge in all cases if no approximations are made. The number of cases for which this happens can be reduced by improving the algorithms. Other aspects that can be considered in the modeling of TSO's decision-making behavior are the cross-border effect of reliability targets applied in neighboring control zones.

Applicability of RMACs is mainly determined by their data requirements. Due to the sometimes long and expensive data collection process, it is important to determine which data mostly impact the performance of RMACs. Also the impact of the accuracy of the data on the performance of RMACs should be assessed.

Appropriate decision support tools can improve the practicality of probabilistic RMACs. These tools should clearly visualize the increased amount of information and indicators that should be handled in advanced RMACs. An appropriate trade-off should be made between the level of detail of the information and the clarity of the visualization.

Appendix A

Overview and Classification of Indicators

A multitude of indicators and indices is presented and described in literature, ranging from indicators and indices used in a practical context to more theoretical indicators and indices that are suggested for future reliability management. Traditional reliability management approaches and criteria (RMACs) are deterministic in nature and are mainly based on physical indicators. However, traditional, deterministic RMACs might be overly conservative or too loose and therefore not cost effective. Alternative risk-based RMACs are proposed in literature, which take into account uncertainties in the system more adequately [59, 60, 85, 243, 244, 245, 246]. Moreover, cost minimization measures might be included to improve the cost-effectiveness of reliability management. Each of these RMACs is based on a specific set of indicators and indices.

This section gives an overview of practical indicators and indices that are prescribed by ENTSO-E and NERC or discussed by the CEER, as well as indicators and indices discussed in scientific literature. The indicators and indices are classified in the classes discussed in Section 3.3 and the characteristics discussed in Section 3.2 are assigned to them.

A.1 Adequacy Indicators

NERC prescribes to evaluate resource adequacy probabilistically based upon reserve margin projections and emerging risks that have been identified in a long-term reliability assessment. The long-term reliability assessment is a peak-driven, deterministic approach to gage resource adequacy. NERC defines five probabilistic adequacy indices in their guidelines that are complementary to the deterministic approach [247, 248].

- Expected Unserved Energy (EUE): A measure of the resource availability to continuously serve all loads at all delivery points while satisfying all planning criteria [MWh]. The expected amount of energy not supplied by the generating system during the period of observation, due to capacity deficiency [249].
- Loss Of Load Hours (LOLH): The expected number of hours per year when a system's hourly demand is projected to exceed the generating capacity.
- Loss of load expectation[90] (LOLE): The expected number of days per year for which the available generation capacity is insufficient to serve the daily peak demand.
- Loss Of Load Probability (LOLP): The probability of system daily peak or hourly demand exceeding the available generating capacity during a given period.
- Loss Of Load Events (LOLEV): The number of events in which some system load is not served in a given year.

To verify the HLII adequacy and security, NERC defines an Adequate Level of Reliability (ALR) in terms of reliability standards [66]. The objective is to obtain standards that balance the cost of risk mitigation and the cost of risk itself. System performance metrics are defined to verify the reliability standards and to provide feedback for improving them.[91] Part of NERC's indicators to verify the adequate level of reliability are adequacy oriented:

- ALR1-3: Planning reserve margin
- ALR6-2: Energy emergency alert 3 (firm load interruptions due to capacity and energy deficiencies)

[90] Sometimes also denoted as Loss of Load Expectancy.

[91] A more detailed definition and description of each of the different ALR indices can be found at `http://www.nerc.com/comm/PC/Performance%20Analysis%20Subcommittee%20PAS%20DL/Forms/AllItems.aspx?RootFolder=%2fcomm%2fPC%2fPerformance%20Analysis%20Subcommittee%20PAS%20DL%2fApproved%20Metrics&FolderCTID=0x0120007EFA0B77D434004AA06B4964C0C6F33D`

- ALR6-3: Energy emergency alert 2 (deficient capacity and energy during peak load periods)

The other indicators are mainly system security oriented.

ENTSO-E initially prescribed a deterministic approach for system adequacy assessment, which was based on the point with the highest load. Due to the increasing penetration of RES and the increasing uncertainty that comes with it, a gradual movement towards a probabilistic approach is initiated with ENTSO-E's target methodology for adequacy assessment [250]. This methodology proposes to use a set of 5 indicators in a generation adequacy assessment. Besides LOLE and LOLP, which are also proposed by NERC, these indicators are:

- Full load hours of generation: The time needed to produce the total energy under full load conditions of the generators, which represents the utilization rate of the generation park
- RES curtailment: Amount of energy from renewable energy sources that cannot be produced due to security reasons
- CO_2 emissions: Amount of CO_2 emissions

Loss of load probability (LOLP), loss of load expectancy (LOLE) and expected unserved energy (EUE)[92] are frequently used in a practical context of adequacy assessment. They are suggested by NERC and used e.g., in Belgium, Finland, France, Great Brittain, Hungary, Ireland and the Netherlands in a probabilistic assessment to verify generation adequacy. Also in scientific literature, these indicators are frequently suggested [18, 251]. Newell et al. propose to use normalized expected unserved energy (EUE) for setting the resource adequacy standard, because it is a more robust and meaningful measure of reliability that can be compared across systems of many sizes, load shapes and uncertainty factors [252]. In Spain and Sweden, generation adequacy is verified in terms of the capacity margin, which is a deterministic indicator [79, 105].[93] This is a very simple indicator, but not appropriate in systems with a significant amount of intermittent generation [111].

[92] Sometimes also denoted as loss of energy expectation (LOEE) or expected energy not supplied/served (EENS) in a generation adequacy context, which have the same definition [18]. A slight difference with EENS is that EENS is not only used in a generation adequacy context, but is also applied on the HLII and HLIII level.

[93] Capacity margin is defined as the proportion by which the total expected available generation exceeds the maximum expected level of electricity demand, at the time at which that demand occurs [253].

Adequacy assessment of the transmission system (HLII) is the responsibility of the individual countries in Europe [111]. Indicators used by system operators to assess the adequacy of their composite generation and transmission systems are [111, 251]:

- Expected energy not supplied (EENS): The expected total summated energy not supplied to any of the load buses irrespective of the cause and the location of the deficiency
- Energy Index of Unreliability (EIU): EENS normalized by the total energy demanded
- Energy Index of Reliability (EIR): EIR = 1-EIU
- System minutes: EENS normalized by peak demand representing equivalent minutes of unavailability.
- LOLE_{P95}: The expected number of hours during which load cannot be covered by all available means in a very cold winter, i.e., a critical scenario
- Average Interruption Time (AIT): A measure for the amount of time that the supply is interrupted, expressed as the total number of minutes that the power supply is interrupted during the year [111].

The definition of LOLE differs between sources. NERC defines LOLE as the expected number of days per year with a deficiency calculated based on the peak load per day or a load curve [247]. In Europe, LOLE is defined as the expected number of hours per year during which it will not be possible for all the generation resources available to the system to cover the load, even taking into account the interconnections [111]. The latter is equivalent to the LOLH defined by NERC or can also have the notion of an hourly LOLE. A frequently used LOLE threshold is the industry-accepted reliability standard of 1 day in 10 years or 0.1 days/year [254]. It is important to notice that this does not corresponds to a LOLH of 2.4h/year, because the LOLH corresponding to a LOLE of 0.1 days/year can be significantly higher.

A set of other local and zonal indices that can be used in composite generation and transmission system evaluation (HLII) is proposed in [18] and [251]. EENS can be used as an adequacy indicator at different hierarchical levels. The distinction depends on the primary cause of the interruption, which can be lack of power (HLI), lack of interconnection (HLI and HLII), line overload (HLII) or network splitting or isolated nodes (HLII). A drawback of EENS is that it cannot be used to compare different systems. This requires a normalization [111]. Adequacy indicators that can be used on HLIII are discussed by Allan and

Billinton [18]. Moreover, an IEEE standard is created focussing on distribution adequacy indicators [255]. Although these indicators are referred to as reliability indices in [255], their main focus is on adequacy aspects. Most commonly-used adequacy indicators on the distribution level (HLIII) in Europe are SAIFI and SAIDI[94] [256].

An overview and characterization of the different adequacy indicators is given in Table A.1. Existing literature makes a clear distinction between the different hierarchical levels. However, due to the increasing amount of distributed generation, the distinction becomes much less clear and composite evaluations will become more important.

A.2 Security Indicators

To verify security-related standards of the adequate level of reliability, NERC has defined some security related indicators [66]:[95]

- ALR1-4: Bulk power system transmission related events resulting in loss of load
- ALR1-5: Transmission system voltage profile
- ALR1-12: Interconnection frequency response
- ALR2-3: Activation of underfrequency load shedding
- ALR2-4: Average percent non-recovery disturbance control standard events
- ALR2-5: Disturbance control events greater than most severe single contingency
- ALR3-5: Interconnected reliability operating limit/system operating limit exceedances

[94] SAIFI stands for System Average Interruption Frequency Index, which represents the number of consumer interruptions divided by the number of consumers served, while SAIDI stands for System Average Interruption Duration Index and represents the sum of consumer-sustained outage minutes per year divided by the number of consumers served [111].

[95] A more detailed definition and description of each of the different ALR indices can be found at http://www.nerc.com/comm/PC/Performance%20Analysis%20Subcommittee%20PAS%20DL/Forms/AllItems.aspx?RootFolder=%2fcomm%2fPC%2fPerformance%20Analysis%20Subcommittee%20PAS%20DL%2fApproved%20Metrics&FolderCTID=0x0120007EFA0B77D434004AA06B4964C0C6F33D

Table A.1: Classification of adequacy indicators.

Indicators	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Reference
LOEE										[18]
EENS										[18]
EIR	x	o	o	o	o	x	x	o	o	[18]
EIU										[18]
System minutes										[18]
EUE										NERC, [18, 79, 252]
LOLH	o	o	o	x	o	x	x	o	o	NERC, [18]
Loss of load duration (LOLD)										[257]
Maximum load curtailed										[18]
Maximum energy curtailed										[18]
Average load curtailed/curtailment										[18]
Average energy not supplied/curtailment	x	o	o	o	x	o	o	x	o	[18]
Average load curtailed/load point										[18]
Average energy curtailed/load point										[18]
Maximum system load curtailed under any contingency condition										[18]
Maximum system energy not supplied under any contingency condition										[18]
Expected load curtailed										[18]
Expected demand not supplied										[257]
EENS	x	o	o	o	o	x	o	x	o	[18]
Modified bulk power energy curtailment index										[257]
System minutes										[18]
Bulk power interruption index										[257]
Bulk power supply average MW curtailment/disturbance	x	o	o	o	x	o	o	x	o	[257]
Bulk power energy curtailment index										[257]
ALR1-3										NERC

System average interruption frequency index (SAIFI)										[18, 255, 256, 258]
Customer average interruption duration index (CAIFI)	o	o	x	o	x	o	o	o	x	[18, 255, 256, 258]
Momentary average interruption frequency index (MAIFI)										[255, 256]
Momentary average interruption event frequency index (MAIFI_E)										[255]
Average system interruption frequency index (ASIFI)										[255, 256]
Transformer SAIFI										[256]
Equivalent number of interruptions related to the installed capacity (NIEPI)										[256]
System average interruption duration index (SAIDI)										[18, 255, 256, 258]
Customer average interruption duration index (CAIDI)	o	o	o	x	x	o	o	o	x	[18, 255, 256, 258]
Outage duration at individual load point										[18]
Customer total average interruption duration index (CTAIDI)										[255, 256]
Average system interruption duration index (ASIDI)										[255, 256]
Full load hours of generation										ENTSO-E
RES Curtailment										ENTSO-E
CO_2 Emissions	x	o	o	o	x	o	x	o	o	ENTSO-E
Generation reserve margin										[105]
Percent reserve evaluation										[105]
Loss of the largest generating unit										[105]
Average service availability index (ASAI)										[18, 255, 258]
Customers experiencing multiple interruptions (CEMI_n)	o	x	o	o	x	o	o	o	x	[255]

Customer experiencing longest interruption durations (CELID)										[255]
Customers experiencing multiple sustained interruption and momentary interruption events (CEMSMI_n)										[255]
Customers experiencing multiple momentary interruptions (CEMMI_n)										[111]
AENS	x	o	o	o	x	o	o	o	x	[18]
Energy not distributed (END)										[256]
EENS	x	o	o	o	o	x	o	o	x	[18]
Transformer SAIDI	o	o	o	x	x	o	o	o	x	[256]
Equivalent interruption time related to the installed capacity (TIEPI)										[256]
Customer minutes lost (CML)										[256]
Average interruption time (AIT)	o	o	o	x	x	o	o	x	o	[256]
Average interruption duration (AID)										[256]
Average duration of load curtailed/load point										[18]
System average restoration index (SARI)										[256]
Average number of curtailments/load point	o	o	x	o	x	o	o	x	o	[18]
Average interruption frequency (AIF)										[256]
ALR6-2										NERC
ALR6-3										NERC
Probability of load curtailment	o	x	o	o	o	x	o	x	o	[257]
Expected duration of load curtailment	o	o	o	x	o	x	o	x	o	[18]
Expected duration of load curtailment (local)										[257]
Expected frequency of failure	o	o	x	o	o	x	o	x	o	[18]
Expected number of curtailments (local)										[18]
Maximum duration of load curtailment	o	o	o	x	x	o	o	x	o	[18]
Average duration of curtailment/curtailment										[257]

Failure rate at ind. Load point	o	o	x	o	o	x	o	o	x	[18]
Unavailability at ind. Load point	o	x	o	o	o	x	o	o	x	[18]
LOLEV LOLF LOLE $LOLE_{P95}$	o	o	x	o	o	x	x	o	o	NERC [257] NERC, ENTSO-E, [18, 79] [111]
LOLP	o	x	o	o	o	x	x	o	o	NERC, ENTSO-E, [18, 79, 259]

(1) Magnitude, (2) Probability, (3) Frequency, (4) Duration, (5) Deterministic, (6) Probabilistic, (7) HLI, (8) HLII, (9) HLIII
o = not applicable, x = applicable

- ALR4-1: Automatic transmission outages caused by failed protection system equipment
- ALR6-1: Transmission constraint mitigation
- ALR6-11: Automatic AC transmission outage initiated by failed protection system equipment
- ALR6-12: Automatic AC transmission outages initiated by human error

In 2013, ENTSO-E published the second version of the network code on operational security, which prescribes that European transmission system operators should monitor deterministic security indicators based on a state classification. According to this network code, the TSO shall classify the system state based on 5 well-defined categories: normal, alert, emergency, in-extremis and restoration. Dy Liacco presented the 3 state security-state diagram in 1967 [260] and an extended 5 state version was proposed by Fink and Carlsen in 1978 [261]. Billinton and Khan proposed in 1992 to calculate frequency and probability of being in a particular state as security indicators [262].

In 2015, ENTSO-E started merging the three operational network codes (operational planning and scheduling, operational security and load frequency control and reserve) in a single system operation guideline. This guideline prescribes that in operational planning five indicators should be calculated that count the number of events due to a certain cause that result in a degradation of system operation conditions [87]:

- OPS 1A: The number of events per year that result in a degradation of system operation conditions due to an incident on the contingency list
- OPS 1B: The number of events in OPS 1A caused by an unexpected discrepancy of demand or generation forecasts
- OPS 2A: The number of events per year that result in a degradation of system operation conditions due to Out-of-Range contingencies
- OPS 2B: The number of events in OPS 2A caused by an unexpected discrepancy of demand or generation forecasts
- OPS 3: The number of events per year that result in a degradation of system operation conditions due to lack of active power reserves

OPS 1B and OPS 2B focus on the impact of uncertainty due to RES and load, which becomes more important in modern power systems.

Besides the indicators for operational planning, a multitude of performance indicators should be reported annually in the context of operational security [87]. This set of indicators consists of indicators representing the frequency of an event, as well as indicators representing the duration and/or magnitude of events:

- RT1: Number of tripped transmission system elements per year per TSO;
- RT2: Number of tripped power generation facilities per year per TSO;
- RT3: Energy not supplied per year due to unscheduled disconnection of demand facilities per TSO;
- RT4: Time duration and number of instances of being in the alert and emergency states per TSO;
- RT5: Time duration and number of events within which there was a lack of reserves identified per TSO;
- RT6: Time duration and number of voltage deviations exceeding the voltage ranges specified in [87]
- RT7: Number of minutes outside the standard frequency range and number of minutes outside the 50% of maximum steady-state frequency deviation per synchronous area
- RT8: Number of system-split separations or local blackout states
- RT9: Number of blackouts involving two or more TSOs

RT4, RT5 and RT6 are bi-parametric rather than mono-parametric indices, as they include both the duration and frequency of the event.

Ni et al. [41], Ciapessoni et al. [114] and Dissanayaka et al. [115] proposed some probabilistic security indicators, such as low voltage risk indicator, overload risk indicator, voltage instability risk indicator, cascading risk indicator, overloading risk indicator, high current risk indicator and transient stability risk indicator. These risk indicators combine the magnitude and the probability of a security limit violation. Kirschen et al. have developed a probabilistic indicator of system stress that can be used complementary to the N-1 approach in power system operation. This probabilistic indicator is based on expected energy not served (EENS). It is a probabilistic, leading indicator that enables operators to implement preventive measures and plan corrective measures taking into account probabilities and consequences of contingencies [45].

An overview of the security indicators is given in Table A.2. To evaluate the security indicators, busbar voltages, active power flows, reactive power flows and frequency should be monitored [87].

A.3 Socio-Economic Indicators

The ideal reliability level is obtained at maximal socio-economic surplus.[96] Socio-economic surplus is the sum of surplus or utility of all stakeholders, including external costs and benefits (e.g., environmental costs) over the expected operating range [80]. Total system cost minimization equals socio-economic surplus maximization under two simplifying assumptions: (i) changes in the electricity market should not change the behavior of electricity market actors such as producers and consumers and (ii) changes in the electricity market should have little effect on other markets [80].[97]

He et al. denote total system cost as the social cost consisting of the operating cost, which depends on the generated power and the operating cost function of the generators, and the interruption cost, where the interruption cost depends on the amount of load curtailment and the customer interruption cost function [59]. Besides the generator costs, other costs should be included in the operating cost, such as the cost of line switching, reactive power management, PST tap changing and other reliability actions that can be taken. The cost of these actions is typically lower than the generator costs, but cannot be neglected. Operating cost is an activity indicator rather than an outcome indicator.

Allan and Billinton specify the Customer Interruption Cost (CIC) and Customer Outage Cost (COC) [18]. CICs are interruption costs per interruption and are used to determine the Composite Customer Damage Function (CCDF) and Sector Customer Damage Function (SCDF). CICs are typically determined based on surveys. COCs at a particular bus can be deduced from the CDFs, the energy consumed by consumers at that bus and failure rates and repair times, i.e., the frequency of the outage and the outage duration. The SCDFs can be converted into global indices of value of lost load (VOLL) or Interrupted Energy Assessment Rate (IEAR) [263]. VOLL expresses the value of unserved energy at a particular location, type of consumer and moment in time, for a particular duration and a particular type of interruption. It is the marginal interruption cost with respect to energy not supplied, i.e., the interruption cost

[96] Practical indicators differ from ideal indicators in the sense that practical indicators should be easy to use and all data to calculate the indicator should be available.

[97] These assumptions are never fully met. If, for instance, electricity becomes more expensive and consumers' price elasticity is less than one, consumers will buy less electricity and will have less budget to buy other goods.

Table A.2: Classification of security indicators.

<table>
<tr><th>Indicators</th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th><th>(5)</th><th>(6)</th><th>(7)</th><th>Reference</th></tr>
<tr><td>Low voltage risk indicator</td><td rowspan="8">x</td><td rowspan="8">o</td><td rowspan="8">o</td><td rowspan="8">o</td><td rowspan="8">o</td><td rowspan="8">o</td><td rowspan="8">x</td><td>[41]</td></tr>
<tr><td>Voltage instability risk indicator</td><td>[41]</td></tr>
<tr><td>Cascading risk indicator</td><td>[41]</td></tr>
<tr><td>Overloading risk indicator</td><td>[41]</td></tr>
<tr><td>High current risk indicator</td><td>[114]</td></tr>
<tr><td>Transient stability risk indicator</td><td>[115]</td></tr>
<tr><td>Loss of load risk indicator</td><td>[114]</td></tr>
<tr><td>Expected energy not served</td><td>[45]</td></tr>
<tr><td>ALR1-12</td><td rowspan="3">o</td><td rowspan="3">x</td><td rowspan="3">o</td><td rowspan="3">o</td><td rowspan="3">o</td><td rowspan="3">x</td><td rowspan="3">o</td><td>NERC</td></tr>
<tr><td>ALR6-1</td><td>NERC</td></tr>
<tr><td>RT3</td><td>ENTSO-E</td></tr>
<tr><td>ALR1-4</td><td rowspan="18">o</td><td rowspan="18">o</td><td rowspan="18">o</td><td rowspan="18">x</td><td rowspan="18">o</td><td rowspan="18">x</td><td rowspan="18">o</td><td>NERC</td></tr>
<tr><td>ALR2-3</td><td>NERC</td></tr>
<tr><td>ALR2-4</td><td>NERC</td></tr>
<tr><td>ALR2-5</td><td>NERC</td></tr>
<tr><td>ALR3-5</td><td>NERC</td></tr>
<tr><td>ALR4-1</td><td>NERC</td></tr>
<tr><td>ALR6-11</td><td>NERC</td></tr>
<tr><td>ALR6-12</td><td>NERC</td></tr>
<tr><td>OPS1A</td><td>ENTSO-E</td></tr>
<tr><td>OPS1B</td><td>ENTSO-E</td></tr>
<tr><td>OPS2A</td><td>ENTSO-E</td></tr>
<tr><td>OPS2B</td><td>ENTSO-E</td></tr>
<tr><td>OPS3</td><td>ENTSO-E</td></tr>
<tr><td>RT1</td><td>ENTSO-E</td></tr>
<tr><td>RT2</td><td>ENTSO-E</td></tr>
<tr><td>RT8</td><td>ENTSO-E</td></tr>
<tr><td>RT9</td><td>ENTSO-E</td></tr>
<tr><td>Average number of voltage violations/load point[1]</td><td>[18]</td></tr>
<tr><td>ALR1-5</td><td rowspan="2">o</td><td rowspan="2">o</td><td rowspan="2">o</td><td rowspan="2">o</td><td rowspan="2">x</td><td rowspan="2">x</td><td rowspan="2">o</td><td>NERC</td></tr>
<tr><td>RT7</td><td>ENTSO-E</td></tr>
<tr><td>Expected number of voltage violations[1]</td><td>o</td><td>o</td><td>o</td><td>x</td><td>o</td><td>o</td><td>x</td><td>[18]</td></tr>
<tr><td>RT4</td><td rowspan="3">o</td><td rowspan="3">o</td><td rowspan="3">o</td><td rowspan="3">x</td><td rowspan="3">x</td><td rowspan="3">x</td><td rowspan="3">o</td><td>ENTSO-E</td></tr>
<tr><td>RT5</td><td>ENTSO-E</td></tr>
<tr><td>RT6</td><td>ENTSO-E</td></tr>
</table>

(1) Risk, (2) Magnitude, (3) Probability, (4) Frequency, (5) Duration, (6) Deterministic, (7) Probabilistic
o = not applicable, x = applicable
[1] This indicator was denoted as an adequacy indicator in [18], however, this does not correspond with the definitions of adequacy and security indicators.

of an additional 1 MWh interruption [80]. Another indicator that quantifies the value of reliability is the willingness-to-pay (WTP), which represents the consumers' willingness to pay to improve their continuity of supply [111]. VOLL, IEAR and WTP can be considered as criticality indicators, as they represent how critical reliable electricity supply is for consumers. VOLL is the most widely used indicator and referred to by ENTSO-E [111, 264].

Based on these criticality indicators, the monetary consequences of interruptions for consumers can be estimated. Different indicators to quantify the monetary consequences of interruptions can be distinguished, but no unified terminology exists for the indicators. Allan and Billinton define ECOST as the product of IEAR and LOEE and denotes this as expected outage cost. Zhang and Billinton on the contrary specify ECOST as the annual expected customer damage cost at a specified system service area or load bus. ECOST is in this case based on the expected energy not supplied (EENS) and the composite customer damage function [265].[98] Wang and Billinton use the same formula for ECOST as Zhang and Billinton, but they give ECOST two different meanings: "expected customer interruption cost" and "total system interruption cost" [266]. They can be considered as a local and a zonal indicator respectively. In the GARPUR project, (expected) interruption costs are defined as the product of the (expected) energy not supplied and the value of lost load and represent the negative economic impact on electricity consumers of an electricity interruption [80]. This indicator is sometimes also denoted as social value of EENS [111].

Table A.3: Classification of socio-economic indicators.

Indicators	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Reference
Social welfare/surplus[1] Total system cost[1]	o	x	o	o	o	x	x	x	o	[80] [59]
Customer outage cost Customer interruption cost	o	x	o	o	o	o	x	x	o	[18] [18]
ECOST Expected interruption cost Social value of EENS	x	o	o	o	o	o	x	o	x	[18, 265, 266] [80] [111]
Operating cost	o	x	o	o	o	x	o	x	o	[59]

(1) Risk, (2) Magnitude, (3) Probability, (4) Frequency, (5) Duration,
(6) System, (7) Consumer, (8) Deterministic, (9) Probabilistic
o = not applicable, x = applicable
[1]Both system and consumer related

[98]LOEE, EENS and EUE are essentially the same [18].

A.4 Reliability Indices

NERC's definition of reliability consists of two concepts: adequacy and security.[99] This definition is further refined with the identification of specific characteristics that define an adequate level of reliability (ALR) [66, 267]:

- The system is controlled to stay within acceptable limits during normal conditions
- The system performs acceptably after credible contingencies
- The system limits the impact and scope of instability and cascading outages when they occur
- Facilities are protected from unacceptable damage by operating them within facility ratings
- Integrity can be restored promptly if it is lost
- The system has the ability to supply the aggregate electric power and energy requirements of the electricity consumers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components

In 2007, NERC proposed three major indices, which intend to capture and represent multiple reliability parameters in easy-to-understand reliability performance metrics [110, 268]:

- Reliability performance gap: To measure how far the system is from expected performance under contingencies[100]
- Adequacy gap: To measure the capacity and energy shortage from the expected adequacy level under steady-state conditions[101]
- Violation index: Index based on standardized weights depending on the predefined impact of violating a standard (Violation risk factor (VRF)) and the ex-post assessment of the degree of violation (Violation severity level (VSL)) to measure the reliability improvement from compliance with NERC reliability standards [110]

[99] Security is denoted as operating reliability in a NERC context.
[100] http://www.nerc.com/pa/RAPA/PA/Pages/ReliabilityPerformanceGap.aspx
[101] http://www.nerc.com/pa/RAPA/PA/Pages/AdequacyGapQuarterlyView.aspx

In 2010, NERC proposed a severity risk index (SRI)[102] and an integrated reliability index (IRI). The IRI consists of three risk-based indices: An event driven index (EDI), a condition driven index (CDI) and a standards/statute driven index (SDI). These three indices are combined in the IRI with appropriate weighing factors. The event severity risk index is developed to measure the relative severity ranking of events based on event occurrence rate and their impact to the bulk power system, which can be among multiple dimensions, e.g., load or facilities. Different events are combined in the event driven index (EDI). The CDI is an integrated index that combines the different ALR indicators in a single index with appropriate weighing factors. In order to integrate indices that have different units, five trend ratings are identified to quantify each metric's performance level. The SDI verifies the risk of non-compliance with the standards, taking into account the risk of violating the standards and the impact of this violation [267]. A consultation of power system stakeholders resulted in feedback and comments on the developed indices, such as about the indices' transparency, the practical meaning of the values of the indices and how to react upon them and the values of the weight factors that are used and how to choose them [269].

Perceived reliability is a function of the proximity of the system operation to the operational limits and the individual component reliability. Examples of general component reliability indicators are time to repair, operating time between failures, failure rate, failure intensity, ... [44, 270]. Reliability or performance indicators are defined specifically for certain components. For instance for power plants indicators are defined, such as unit capability factor, unplanned capability loss factor, time availability factor, capacity factor, net electrical energy production, forced outage rate, equivalent forced outage rate, commercial availability, etc. These indicators differ between different types of generating units [105]. A detailed discussion of component reliability indicators is out of the scope of this work.

A.5 Discussion

Security indicators specified by NERC and ENTSO-E are still mainly lagging and deterministic. The lagging, physical, deterministic indicators are especially suitable to evaluate the decision making ex-post, i.e., if the uncertainty is already reduced, in order to verify whether reliability standards are satisfied. Probabilistic, leading security indicators can help in being pro-active to handle uncertainties in power systems. NERC initiated the transition towards more

[102] Updated in 2014 [116]

Table A.4: Classification of reliability indices.

Indicators	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Reference
Probability of failure[1]	o	o	x	o	o	x	o	o	x	[18]
Severity risk index Event driven index	o	x	o	o	x	x	o	x	o	NERC NERC
Standards / statute driven index	x	x	o	o	o	x	o	x	o	NERC
Condition driven index	o	x	o	o	o	x	o	x	o	NERC
Reliability performance gap Adequacy gap Violation index	o	o	o	x	o	x	o	x	o	NERC NERC NERC

(1) Risk, (2) Magnitude, (3) Probability, (4) Frequency, (5) Duration, (6) System, (7) Consumer, (8) Deterministic, (9) Probabilistic
o = not applicable, x = applicable
Indicators with multiple x in the same section of the table combine multiple characteristics
[1] This indicator is denoted as HLII adequacy indicator in [18], but can be better classified as a reliability index.

probabilistic reliability management in both long term and short term, but the major efforts in terms of probabilistic indicators are found in scientific literature.

NERC focuses a lot on system performance indicators. It has developed integrated reliability indices, combining different aspects in one value. The advantage of these integrated indices is that focusing on less, well selected indices reduces the complexity of reliability management. However, integrated indices are perceived as less transparent and the values are hard to interpret and react upon adequately, especially with limited user experience. Their practical applicability and usefulness should be proved [269]. ENTSO-E on the contrary puts less effort in developing overall performance indices. However, in contrast to NERC, ENTSO-E is more actively concerned about the socio-economic aspects. It recognizes the impact of interruption costs on the economic value of reliability [111]. Its adequacy indicators are also more directly related to the issue of increasing RES penetration. CEER recommends to harmonize the adequacy indicators used by TSOs to verify the continuity of supply. It suggests to use SAIDI and SAIFI for long interruptions, MAIFI for short interruptions and ENS for interruptions at the transmission level. The calculation and weighting methods should be harmonized as well [106]. Also the proposal for the Clean Energy Package includes directives to harmonize the risk and reliability assessment. It suggests to monitor the security of electricity supply using EENS [GWh/year] and LOLE [h/year] [271].

Appendix B

GARPUR Quantification Platform

The quantification framework discussed in Chapter 4 is the base for the GARPUR Quantification Platform (GQP) discussed in [129]. The GQP, which can be considered as a more advanced implementation of the quantification framework discussed in this thesis, was implemented in collaboration with colleagues of the ELECTA research group and other academic and industrial project partners.

The prototype of the GQP has been designed to serve as a general-purpose platform for evaluating different RMACs in different contexts using numerical simulations. It is designed to cover day-ahead operational planning and real-time operation. Alternative short-term RMACs are benchmarked against the currently used N-1 approach to assess the socio-economic impact and the impact on reliability.

A more detailed and sophisticated implementation of the GQP is used in a pilot test performed by the French transmission system operator RTE. This pilot test uses the GQP in a near real-life context. The focus of the test is on a part of the French control zone. Advancements are made in the implementation of the SCOPF to simulate TSO's decision-making behavior according to a certain RMAC: A short-term post-contingency system state is added, risk of failure of corrective actions is considered, contingency relaxation is implemented and alternative approximations of the AC SCOPF are applied. Converters to pre-process CIM data and PSS-E raw data are developed to be able to use data formats commonly used by TSOs. Full details of the more detailed implementation of the GARPUR quantification platform can be found in [140]. Also the post-processing of the results, calculation of indicators and modeling of contingencies are part of the scope of the GQP. The performance evaluation techniques, performance metric and inequality index proposed in this dissertation can be used in the evaluation module of the GQP.

Appendix C

DC Power Flow Assumptions

The security constrained optimal power flow used to simulate TSO's decision-making behavior according to a certain RMAC is based on a DC power flow. This appendix elaborates on the assumptions made in a DC power flow formulation and their validity.

C.1 Power Flow Equations

The implementation used in the case studies is based on a DC SCOPF [272]. This problem can be formulated as a linear and convex optimization program. The three basic assumptions underlying a DC SCOPF are:

- The resistance of each branch is negligible compared to its reactance
- The voltage magnitude at each node equals the base voltage
- The voltage angle difference across any branch is sufficiently small, i.e., $\cos(\theta_{b_1} - \theta_{b_2}) \approx 1$ and $\sin(\theta_{b_1} - \theta_{b_2}) \approx \theta_{b_1} - \theta_{b_2}$

with θ_b the voltage angle at node b. To reduce the chance of numerical instability, the DC SCOPF is typically formulated in normalized Per Unit (pu) values.

Taking into account these assumptions in the traditional AC power flow equations results in the simplified DC formulation of power flow. The active power branch flow equation can be expressed as:

$$L_{b_1b_2} = \frac{1}{x^{line}_{b_1b_2}}(\theta_{b_1} - \theta_{b_2}) \quad \forall \text{ branches} \tag{C.1}$$

with $x^{line}_{b_1b_2}$ the reactance of the branch between node b_1 and b_2. Kirchoff's first law can be expressed as:

$$\sum_{u \in \mathcal{U}} P_{u,b_2} + \sum_{j \in \mathcal{J}} P^{load}_{j,b_2} + \sum_{\substack{b_1 \in \mathcal{B} \\ b_1 \neq b_2}} L_{b_1b_2} = 0 \quad \forall b_2 \in \mathcal{B} \tag{C.2}$$

$$\mathbf{P}^{inj} = \mathbf{B}_{DC} \cdot \Theta \tag{C.3}$$

with $P_{u,b}$ the active power generation of generation unit u at node b, $P^{load}_{j,b}$ the active load of consumer j at node b, $\mathbf{B}_{DC}$ the admittance matrix for DC power flow, Θ the vector of voltage angles and $\mathbf{P}^{inj}$ the net active power injections at the different nodes. Eq. (4.3) and (4.5) consist of Eq. (C.1) and (C.3), resp. for the initial state and for all considered states $s \in S$.

C.2 Lossless Transmission Lines

Each network element causes a small energy loss that is dissipated in the resistance of the network element. The R/X ratio is typically used to characterize the impact of the loss on the result of power flow calculations. This R/X ratio is typically between 0.08 and 0.3 for an overhead line, because the reactance is usually many times larger than the resistance. The R/X ratio of a cable system on the other hand equals nearly one. Values of typical reactance and resistance values for different voltage levels in the Belgian transmission system are given in Table C.1. The high-voltage system mainly consists of overhead lines resulting in low R/X ratios, whereas the medium-voltage system has a higher R/X ratio due to the higher amount of cable connections. Also the European transmission system mainly consists of overhead lines, resulting in low R/X ratios.

DC power flow assumes lossless transmission lines, i.e., the resistance is assumed to be much smaller than the reactance of the line. Purchala et al. state that neglecting the resistance can be considered to be valid if R/X is smaller than 0.25 [274].

Table C.1: Resistance and reactance values in the Belgian power system [273, 274].

Voltage [kV]		380	220	150	70
	min	0.025	0.038	0.018	0.034
Resistance [Ω/km]	avg	0.031	0.067	0.090	0.174
	max	0.038	0.088	0.292	0.425
	min	0.278	0.184	0.071	0.034
Reactance [Ω/km]	avg	0.325	0.364	0.374	0.360
	max	0.353	0.429	1.458	0.756
	min	0.080	0.125	0.238	0.111
R/X [/]	avg	0.095	0.182	0.238	0.083
	max	0.119	0.286	1.000	1.250

C.3 Small Angle Difference

The small angle difference assumed in DC power flow introduces an error on the obtained power flows. The error on the active power flow due to the assumption of a small angle difference can be calculated as:

$$\epsilon_P = \frac{|\theta - sin(\theta)|}{sin(\theta)} \tag{C.4}$$

The error on the reactive power flow equals:

$$\epsilon_Q = \frac{|1 - cos(\theta)|}{cos(\theta)} \tag{C.5}$$

The total error on the apparent power equals:

$$\epsilon_{tot} = \epsilon_P + \epsilon_Q \tag{C.6}$$

The total error due to the small angle difference assumption is smaller than 0.5% if the angle difference in normal operation is smaller than 5°, as shown in Fig. C.1. The measured angle difference in the highly meshed, European continental power system is generally low, even when it is heavily loaded. Voltage angle differences in the Belgian power system are generally smaller than 7° and are below 2° in 94% of the lines [274].

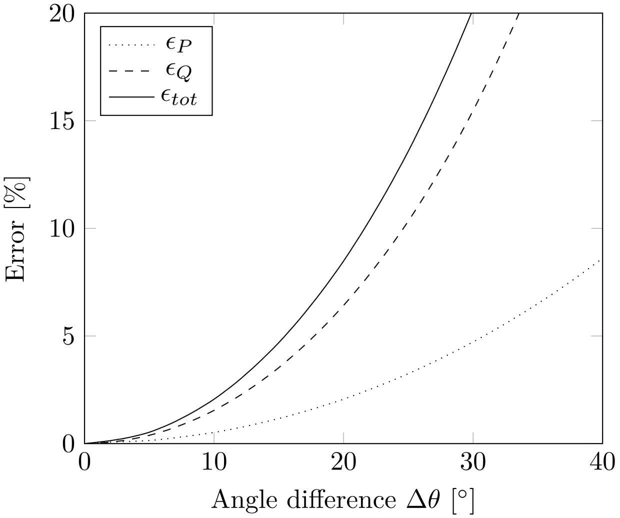


Figure C.1: Error induced due to the assumption of small angle differences.

Appendix D

Five-Node Test System

This appendix summarizes the data of the five-node test system applied in the case studies in Chapters 6, 7 and 8. The illustrative five-node test system is based on the Roy Billinton reliability test system for which grid data, generator data and reliability data are available in literature [195].

D.1 Network

The network is shown in Fig. D.1. Generation is located in node 1 and 2; demand is located in node 2 to 5. Table D.1 shows the reactance x^{line}, capacity and failure probability for the seven transmission lines.

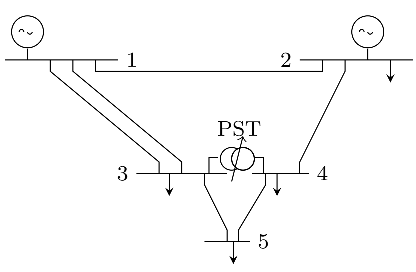


Figure D.1: Circuit diagram of the five-node test system.

Table D.1: Line data.

From node	To node	x^{line} [pu]	Capacity [MVA]	Outage probab.	Phase-shifting transformer
1	3	0.18	85	0.0017	No
2	4	0.6	71	0.0057	No
1	4	0.48	71	0.0046	No
3	4	0.12	71	0.0011	Yes
3	5	0.12	71	0.0011	No
1	3	0.18	85	0.0017	No
4	5	0.12	71	0.0011	No

D.2 Generation

The generation park consists of conventional power plants with a high marginal cost and wind power plants with a marginal cost near zero, but uncertain availability. Table D.2 summarizes generators' marginal costs and outage probability data for the case studies. Outage probability data differ between the case studies in the different chapters.

Table D.2: Generation data.

Node	Capacity [MW]	Type	c^{marg} [€/MWh]	Outage probab. Chapter 6 & 7	Outage probab. Chapter 8
1	40	conventional	13.83	6.2E-3	6.2E-7
1	40	conventional	13.83	6.2E-3	6.2E-7
1	10	conventional	13.83	6.2E-3	6.2E-3
1	20	wind	0.04	6.2E-3	6.2E-3
2	40	conventional	13.83	6.2E-3	6.2E-7
2	20	conventional	13.83	6.2E-3	6.2E-3
2	20	wind	0.01	6.2E-3	6.2E-3
2	20	wind	0.03	6.2E-3	6.2E-3
2	20	wind	0.05	6.2E-3	6.2E-3
2	5	conventional	13.83	6.2E-3	6.2E-3
2	5	conventional	13.83	6.2E-3	6.2E-3

Upward and downward redispatch costs depend on the marginal cost of the generator and differ between the preventive and corrective stage. Wind generators are not available for positive redispatch.

D.3 Demand and VOLL

The forecast of total system demand is based on the hourly load profile defined for the Roy Billinton reliability test system over a whole year [195]. The annual peak load forecast for the considered system is 165 MW. For simplification a year is represented by 6 x 3 x 4 = 72 temporal cases. That is, the set T is the Cartesian product of 6 seasons (early spring, late spring, summer, early autumn, late autumn and winter), 3 days (weekday, Saturday and Sunday), and 4 times of day (morning, noon, evening and night). Each temporal case has its own probability of occurrence determined by the proportion of time instances in a year represented by a certain temporal case. The definitions of the seasons and times of day are summarized in Table D.3. Total system demand for each of the 72 temporal cases is calculated as the mean over all valid hours.

Table D.3: Specifications of the seasons and times of day considered in the demand modelling.

Season	Range dates	Winter period	Time of day	Range hours	Peak period
Early spring	22/3 - 21/4	Yes	Morning	5h - 10h	Yes
Late spring	22/4 - 21/6	No	Noon	11h - 16h	No
Summer	22/6 - 21/9	No	Evening	17h - 22h	Yes
Early autumn	22/9 - 21/10	No	Night	23h - 4h	No
Late autumn	22/10 - 21/12	Yes			
Winter	22/12 - 21/3	Yes			

Table D.4 gives the reference share of total demand per node that is attributed to a particular type of consumer $DS^{ref}(c,b)$ together with the share of the total demand at that node $DS^{ref}(b)$. Table D.4 shows that most demand is located in node 3, consisting mostly of residential and commercial demand. Node 4 contains mostly industrial demand, whereas node 5 contains mostly residential demand.

Table D.4: Demand shares of different nodes in total demand and of different consumer groups at different nodes.

	Node	Residential	Industry	Commercial	Public	Total demand share $DS^{ref}(b)$
$DS^{ref}(c,b)$	2	0	0.8	0.2	0	0.125
	3	0.4	0	0.4	0.2	0.5
	4	0.3	0.5	0.1	0.1	0.25
	5	0.8	0.1	0.1	0	0.125

The case studies executed in this work consider probabilistic approaches based on differentiated VOLL data, i.e., differentiation in time and between nodes or consumer groups. The 72 typical time instants introduced above constitute all temporal cases considered in the VOLL data applied in the case studies. To unify the considered VOLL data with respect to consumer types, consumers are split into only two categories: residential and non-residential consumers. Non-residential consumers correspond to the aggregated share of all consumers except the residential ones. The share of residential and non-residential demand in total system demand changes throughout the year. Table D.5 shows the multiplication factors that take this effect into account. The Demand Share (DS) of consumer group c at node b in total system demand at time t is calculated as:

$$DS(c,b,t) = \frac{DS^{ref}(c,b) \cdot \kappa_h(c) \cdot \kappa_d(c) \cdot \kappa_y(c)}{\sum_{c \in \mathcal{C}} DS^{ref}(c,b) \cdot \kappa_h(c) \cdot \kappa_d(c) \cdot \kappa_y(c)} \tag{D.1}$$

with $c \in \{\text{residential, non-residential}\}$ and t determined by the time of day h, type of day d and season in the year y.

Table D.5: Time dependent multiplication factors for the demand share of different consumer groups.

		Residential	Non-residential
Time $\kappa_h(c)$	2 AM	0.7	1.3
	8 AM	1.3	0.7
	2 PM	0.8	1.2
	6 PM	1.3	0.7
Day $\kappa_d(c)$	Weekday	0.8	1.2
	Saturday	1.15	0.85
	Sunday	1.3	0.7
Season $\kappa_y(c)$	Winter	1	1
	Spring	0.9	1.1
	Summer	1.1	0.9
	Autumn	1	1

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List of publications

Reviewed Journals

Published

1. **Heylen E.**, Labeeuw W., Deconinck G., Van Hertem D. "Framework for Evaluating and Comparing Performance of Power System Reliability Criteria." IEEE Transactions on Power Systems, 31 (6), 5153-5162, 2016

Under review

2. **Heylen E.**, Ovaere M., Proost S., Deconinck G., Van Hertem D. "A Multi-Dimensional Analysis of Reliability Criteria: From Deterministic N-1 to a Probabilistic Approach," submitted to IEEE Transactions on Power Systems

3. **Heylen E.**, Ovaere M., Proost S., Deconinck G., Van Hertem D., "Inequality of Power System Reliability: A Summarizing Index." submitted to IET Generation, Transmission and Distribution.

4. **Heylen E.**, Deconinck G., Van Hertem D, "Review and Classification of Reliability Indicators for Power Systems with a High Share of Renewable Energy Sources." submitted to Renewable & Sustainable Energy Reviews

Book contributions

5. **Heylen E.**, De Boeck S., Ovaere M., Ergun H., Van Hertem D., "Steady state security." Dynamic Vulnerability Assessment and Intelligent Control

for Sustainable Power Systems, John Wiley & Sons, 2017, ISBN: 978-1-119-21495-3 (In press)

International Conferences

Published

6. **Heylen E.**, Troffaes M., Kazemtabrizi B., Deconinck G., Van Hertem D. "Qualitative Comparison of Techniques for Evaluating Performance of Short Term Power System Reliability Management." International Conference on Innovative Smart Grid Technologies. Torino, 26-29 September 2017, 6 pages, IEEE

7. **Heylen E.**, Deconinck G., Van Hertem D. "Impact of Increased Uncertainty in Power Systems on Performance of Short Term Reliability Management." International conference on Probabilistic methods applied to power systems. Beijing, 16-20 October 2016, pp. 343-348, IEEE

8. **Heylen E.**, Deconinck G., Van Hertem D. "Analysis Framework for Performance Evaluation of Reliability Management in Power Systems with Increased Uncertainty." Risk, reliability and safety: Innovating theory and practice. European Safety and Reliability Conference. Glasgow, 25-29 September 2016, pp. 2322-2329. London, UK: Taylor and Francis group

9. **Heylen E.**, Deconinck G., Van Hertem D. "Impact of Value of Lost Load on Performance of Reliability Criteria and Reliability Management.". PowerTech. Eindhoven, 29 June - 2 July 2015, 6 pages, IEEE

10. **Heylen E.**, Jordens R., Patteeuw D., Helsen L. "The Potential of Air-Water Heat Pumps in a Belgian Residential Retrofit Context in relation to Future Electricity Prices." International Conference on System Simulation in Buildings. Liege, 10-12 December 2014, 19 pages

11. **Heylen E.**, Van Hertem D. "Importance and Difficulties of Comparing Reliability Criteria and the Assessment of Reliability." IEEE Young Researchers Symposium. Gent, 24-25 April 2014, 6 pages, EESA

Accepted

12. **Heylen E.**, Ovaere M., Deconinck G., Van Hertem D. "Fair Reliability Management: Comparing Deterministic and Probabilistic Short-Term

Reliability Management." Power and Energy Society General Meeting. Portland, Oregon, USA 5-10 August 2018, 5 pages, IEEE

Under review

13. **Heylen E.**, Ovaere M., Deconinck G., Van Hertem D. "Short-Term Reliability Management in Modern Power Systems: The Way Forward." EnergyCon. Limassol, 3-7 June 2018, 6 pages, IEEE

Reports

14. GARPUR consortium. "D7.1 Functional description of the quantification platform." [Online] Available: http://www.garpur-project.eu/deliverables, 2015.

15. GARPUR consortium. "D7.3 Report on a broader comparison of different reliability criteria including recommendations on how to evolve into an industry grade tool." [Online] Available: http://www.garpur-project.eu/deliverables, 2017.

16. Ovaere M., **Heylen E.**, Proost S., Deconinck G., Van Hertem D, "How detailed value of lost load data impact power system reliability decisions: A trade-off between efficiency and equity." Discussion paper series, DPS16.26 KU Leuven, Department of Economics, 2016