Probabilistic Analysis for Optimal Power System Operation Using Flexible Smart Solutions

A Thesis submitted to The University of Manchester for the degree of

Doctor of Philosophy

In the Faculty of Engineering and Physical Sciences

2017

by

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Nomenclature

List of Symbols

Indices

j	Index of generating units running from 1 to J
i	Index of load points running from 1 to N
S	Index of load types running from 1 to s ₄
t	Index of hours running from 1 to T
У	Index of simulation days running from 1 to Y
l	Index of lines running from 1 to L
Ζ	Index of data points from 1 to n
na	Index of number of poles from 1 to na for ARMA model
пс	Index of number of poles from 1to nc for ARMA model

Parameters

p_c	Probability of component c state
p_l	Probability of the load level l
R_q	Risk measure of system state q
λ	Failure rate
μ	Repair rate
COV	Coefficient of variation
pf	Power Factor
σ_w	Contractual price for wind spillage
$VOLL_i^s$	Value of lost load at load point <i>i</i> and load type <i>s</i>
\hat{BEDI}_i	Normalized value of expected duration interruption index in the base case
$D_i^{s \; BASE}$	Duration of interruption of load type s at load point i under the base case
P_g^{\max}	Maximum power output of a generation unit
P_g^{\min}	Minimum power output of a generation unit
P_d^{\max}	Maximum forecast load
$VL_i^{s,\max}$	Upper limit of the voluntary load reduction for customer type s
В	System matrix including potential contingencies
win	Per unit window for load reduction sampling

rs	Random number between {0,1}
t_{MAX}	Maximum hour limit of load recovery
$f_{\scriptscriptstyle REC}^{s}$	Customer's availability to recover the load
V_{ci}	Cut in wind speed
V_r	Rated wind speed
V_{co}	Cut out wind speed
P_r	Rated power output of wind turbine
$T_{c}(t)$	Conductor temperature at hour <i>t</i>
R(t)	AC conductor resistance at operating temperature T_c at hour t
$P_{c}(t)$	Convection heat loss at hour <i>t</i>
$P_r(t)$	Radiated heat loss at hour t
$P_{s}(t)$	Solar heat gain at hour t
I(t)	Conductor current at hour <i>t</i>
$V_m(t)$	Wind speed at hour t
$K_{angle}(t)$	Wind direction at hour <i>t</i>
$T_a(t)$	Ambient temperature at hour <i>t</i>
a_s	Solar absorptivity of OHL conductor surface
D	External diameter of the conductor
S	Global solar radiation
З	Emissivity of the OHLconductor
K_f	Thermal conductivity
ρ_f	Density air
μ_f	Dynamic viscocity of air
P_{Di}^{min}	Minimum load at node <i>i</i>
pf	Power factor
S_1^{STR}	Seasonal thermal rating of line <i>l</i>
P_{Ci}^{up}	Maximum existing generation at node <i>i</i>
β	Probability having maximum wind generation
v	Percentage of peak demand
$P_{\rm D}^{peak}$	System peak demand
-D BESP. ^{rel}	Expected relative spillage at node <i>i</i>
	Histogram of simulated voltages at node <i>i</i>
rı n	Per unit voltage region
'l	
Δf_{ii}	Change of maximum newer flow
,,,	Change of maximum power flow

β_{br}	Set of specific branches
$IVSP_j^{max}$	Maximum involuntary spillage
VSP_{i}^{max}	Maximum voluntary spillage
NC _X	Network cost that is not exceeded with probability X
m_t	Mean wind speed
sig_t	Standard deviation of wind speed
<i>g</i> ij	Real value of the line admittance
bij	Imaginary value of the line admittance

Variables

$Pg_i(t)$	Active Power output of generation unit <i>j</i> at hour <i>t</i>
I_m	Ampacity of real time thermal rating
θ	Phase angles of nodal voltages
σ	Marginal offer price forvoluntary load reduction
$\mu_{i}\left(t ight)$	Nodal marginal price of load point <i>i</i> at hour <i>t</i>
$\gamma_i^s(t)$	Slope coefficient for load recovery at node <i>i</i> , type <i>s</i> , hour <i>t</i>
P_f^{\max}	Overhead line real-time thermal rating
$P_{di}(t)$	Power supplied to load point <i>i</i> at hour <i>t</i>
$\sigma_i^s(t)$	Marginal offer value for voluntary load reduction, load type s at load point i at hour t
$VI_{s}^{s}(t)$	Amount of voluntary load reduction of load type a st load point i at hour t
$U_i(v)$	Amount of voluntary load reduction of load type's at load point <i>i</i> at hour <i>i</i>
$IVL_i(l)$	Amount of involuntary load reduction of load type s at load point t at nour t
$D_i^{s}(t)$	Duration of interruption of load type <i>s</i> at load point <i>i</i> at hour <i>t</i>
Pc_i^s	Total load shedding of load type s at load point i at hour t
$f_{RED}^s(t)$	Load type <i>s</i> availability to respond to a demand response call at hour <i>t</i>
$CVL_i^s(t)$	Contracted voluntary load reduction of load type s at load point i at hour t
$SP^{y,t}_{i}$	Spillage at node <i>i</i> day <i>y</i> hour <i>t</i>
	Weights showing relative importance of load curtailment as compared to wind
$ au_1$, $ au_2$	spillage
x_{TCSC}	Reactance of TCSC of branch ij
VSP _j	Voluntary spillage at node j
IVSP _j	Involuntary spillage at node <i>j</i>
LC_i	Load Curtailment at node i
$C_g(t)$	Cost of generation unit
$C_{LC}(t)$	Cost of load curtailments

$C_{VSP}(t)$	Cost of voluntary wind spillage
$C_{IVSP}(t)$	Cost of involuntary wind spillage
n _i	Number of intervals for LHS sampling applied for network component <i>i</i>
e(t)	White noice disturbance value for ARMA modelling
\mathcal{E}_{Z}	An error term for a certain observation z
r_z	Residuals of observation z
X_Z	Input variables of ANN model
y_z	Output variables of ANN model

Functions

p_q	Probability of system state q
CI_q	Contribution of the failure state q
$GR_{j}(\cdot)$	Revenue of generator <i>j</i>
$LC_{i}(\cdot)$	Cost of delivered demand at node <i>i</i>
$VLR_{i}(\cdot)$	Revenue for voluntary load type <i>s</i> reduction at node <i>i</i>
$IVLR_i$ (·)	Revenue for involuntary load type s reduction at node i
$\hat{R}^s_i(\cdot)$	Ranking order for load type s at node i
$\left[\Lambda^{-} ight]_{i}^{s}\left(\cdot ight)$	Size of load reduction for load point <i>i</i> type <i>s</i>
$\left[\Lambda^{+} ight]_{i}^{s}\left(\cdot ight)$	Size of load recovery for load point <i>i</i> type <i>s</i>
$Savings_i^s(\cdot)$	Customer savings for load point i type s in the event that demand response materiliazes
$C_{payback \ i}^{s}(\cdot)$	Payback cost due to load recovery at node <i>i</i> type <i>s</i>
$\pi^s_i(\cdot)$	Profit of load customer at load point <i>i</i> type <i>s</i>
$VaR_{_{\psi}}^{^{NR}}(\cdot)$	Value at risk for network rewards at confidence level ψ
$VaR^{NC}_{1-\psi}$	Value at risk for network costs at confidence level $1-\psi$
$P(\cdot)$	Wind turbine power output for wind speed V_m
$ ho_{i}(\cdot)$	Criterion for ranking of nodes for SVC connection
$\Delta BENS \& SP_{i}$	Criterion for ranking of branches for TCSC connection

Acronyms

AAAC	Aluminium alloy conductor
ACSR	Aluminium conductor steel-reinforced
AIC	Akaike information criterion
ANN	Artificial Neural Network
ARMA	Auto Regressive moving average model

BPSO	Binary Particle Swarm optimization
DG	Distributed Generation
DNOs	Distribution Network Operators
DR	Demand Response
DRLR	Demand Reduction and Load Recovery module
DSM	Demand side management
DTR	Dynamic Thermal Rating
ES	Energy Storage
EHPs	Electric Heat Pumps
EV	Electric Vehicles
FACTS	Flexible AC Transmission Systems
ICTs	Information and Communication Technologies
RTTR	Real Time Thermal Ratings
LCTs	Low Carbon Technologies
LHS	Latin Hypercube Sampling
MAE	Mean Absolute Error
MAPE	Mean AbsolutePersentage Errors
MCS	Monte Carlo Simulation
MOPSO	Multi Objective Particle Swarm Optimization
NSMCS	Non Sequential Monte Carlo Simulation
OHLs	Overhead Lines
OPF	Optimal Power Flow
PDFs	Probability Distribution Functions
PSO	Particle Swarm Optimization
PVs	Photovoltaic systems
RTS	Reliability test system
VaR	Value at Risk
SeTR	Seasonal Thermal Rating
SMCS	Sequential Monte Carlo Simulation
SOs	System Operators
STR	Static Thermal Rating
SVC	Static Var Compensator
TCSC	Thyristor Controlled series compensator
TCR	Thyristor Controlled Reactor
TSO	Transmission System Operator
UPFC	Unified Power Flow Controller
VOLL	Value of Lost Load
WTG	Wind Turbine Generation
μCHP	Micro- combined heat and power units

Abstract

Title: Probabilistic Analysis for Optimal Power System Operation using Flexible Smart Solutions Miss Alexandra Kapetanaki, The University of Manchester, 2016

Today's power systems are rapidly changing. The low carbon technologies (e.g. wind and solar generation, electric vehicles and heat pumps) are increasingly being connected to electrical grids allowing zero fuel cost and less polluting network operation; on the other hand, these same technologies cause greater intermittency and lower levels of system reliability. Furthermore, uncertain events such as adverse weather conditions that can cause network component failures lead to greater stress on the power system, as well as tighter security margins and greater operating costs. At present, many power utilities are seeing power system management as a challenge. To this end, smart energy solutions are being tested and applied as these can help mitigate operational and planning issues, while integrating the highest possible level of low carbon technologies.

This thesis investigates how smart energy methodologies can help improve power system operation. Demand response, dynamic thermal ratings of overhead lines and FACTS devices are all considered as smart energy solutions that require further investigation. The modelling of these concepts is investigated and state-of-the-art methods are incorporated into the system reliability analysis. Assessment of power system operation is implemented using both probabilistic and deterministic criteria.

Several contributions are presented in this thesis related to the field of reliability analysis for optimal power system operation. The first contribution of this research is a probabilistic framework for optimal demand response scheduling, which determines optimum ranking lists for both load reduction and load recovery based on reliability and economic risk metrics. The model also quantifies improvements in network performance, as well as customer profits received from participating in the demand response program for day ahead scheduling. The second contribution is the deployment of real time thermal ratings of overhead lines, which is applied in chronological analyses within both deterministic and probabilistic frameworks. The simulation results show that network-operating costs are lower under a probabilistic

analysis than under a deterministic one. The third contribution is a probabilistic methodology to find the optimal deployment of wind energy sources, while minimizing wind curtailment to meet contractual obligations. The model gives the maximised hourly deployable wind capacities, minimised wind spillages, as well as reliability and operational cost indicators. The fourth contribution is a methodology for the optimal ranking of different FACTS devices based on their contribution to reducing both load and wind curtailments. Here, an additional investigation has been done, which determines the impact of FACTS and RTTRs on maximising the utilization of wind resources. Further contributions include improvements of simulation time for probabilistic analysis, implementation of a load-forecasting model for demand response loads, as well as the development of weather forecasting models for real time thermal ratings and wind generation output modelling.

Declaration

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Acknowledgements

First and foremost, I would like to express my deepest gratitude to my supervisor, Dr Victor Levi, for the continuous guidance, advice, support and encouragement throughout this research. I am also extremely grateful to him for providing solutions and being next to me every time a problem arose during my PhD. I am very proud to having been his student. Finally, I really appreciated his fruitful discussions and invaluable comments, which inspired me to pursue a technical career in industry.

I would like to thank my colleagues and friends Shengji Tee, Negar Shams, Papiya Dattaray, Jiashen Teh, Zhao Liu, Peter, Jonathan Gomez, Atia Adrees, Nick Good, Muhammad Buharri, Yutian Zhou, Angelina Sirri, Panagiotis Papadopoulos, Kevin Zhang, Han, Sami Abdelmrahman, Trevor David, Etete Obio, Eduardo Martinez Cesena, Tuba Gozel for their friendly support and for the very enjoyable times we had together.

I gratefully acknowledge the Engineering and Physical Sciences Research council (EPSRC) for sponsoring this project within HubNet.

Finally, I would like to thank my familly, especially my mother and my sisters Nadia, Valentina, Marva and Katerina for their understanding, patience and support during the completion of my PhD. I owe them lots of thanks and love back for being there for me every step of my life.

Last but not least, my sincerest thanks to Dr Jonathan Schachter who fully encouraged me and inspired me for my research. I also really appreciate his help in reviewing my papers and thesis; his comments were very insightful. I am finally extremely grateful to him for having made me enjoy Manchester to the fullest. "To my beloved mother and to Jonathan"

List of Publications

International Journal Publications

- [A1] K. Kopsidas, A. Kapetanaki, V. Levi, "Optimal demand response scheduling with real time thermal ratings of overhead lines for improved network reliability", IEEE Trans. Smart Grid, DOI: 10.1109/TSG.2016.2542922, 2016
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1 Introduction

System operators, driven by increased demand and integration of low carbon technologies (wind, co-generation, electric vehicles), are currently investigating smart energy solutions to relieve network congestions and improve network resilience to future uncertainties. Such technologies include Real Time Thermal Ratings (RTTR), Demand Response (DR), Flexible Alternative Current Transmission Systems (FACTS) and Energy Storage (ES). Having a great deal of flexibility by using these technologies can facilitate both power system operation and power system planning. Improving network performance and reducing operational costs are the two most significant effects of using smart solutions on power system operation. In addition, having the ability to alter decisions as uncertainty unfolds, for instance by implementing a DR scheme or RTTR or other flexible solutions, allows system operators to postpone or even avoid costly investments, while at the same time keeping the system reliable and secure no matter how uncertain the future turns out to be. The benefits of using probabilistic criteria to evaluate power system reliability instead of deterministic techniques are still under research in the literature especially when smart solutions are involved for power system operation. Consequently, the reliability that flexible actions provide in power system operation is investigated in this thesis using probabilistic criteria. This introductory chapter discusses the need for using flexibility in power systems and introduces the concepts and methods used throughout this thesis for quantifying the reliability of the system when flexibility concepts are applied. After reviewing the literature on the application of flexible solutions in power systems, research gaps are identified and the main objectives of this thesis are presented.

1.1.1 Probabilistic analysis

The way electricity is generated and consumed is rapidly changing, requiring the transition towards a new low-carbon electricity system that is led by increasing innovation, efficiency and policy measures. Nonetheless, such a drastic change brings with it a large number of challenges and a very high level of uncertainty and risk. This makes operation as well as investment decisions in power systems very difficult. It is critical to take into account different types of uncertainties and respond by suitable system operation in order to resolve uncertainties. The uncertainties can include: i) electricity demand, which could rise due to the electrification of heating and transport; ii) greater competition in markets exposes customers and investors to more volatile prices, and as a result, makes energy markets increasingly uncertain, strategic decisions difficult and in particular investments in lowcarbon energy systems; iii) integration of distributed generation on the demand side (e.g., generation on demand customer premises combined with, say, electric heat pumps and electric vehicles) as well as on the supply side (e.g., wind, solar and cogeneration) will require projections of net electricity demand, and therefore level of required capacity is becoming even more uncertain; and iv) uncertainty in renewable generation poses a number of challenges in the operational planning given the lack of predictability. Therefore, developing a probabilistic framework and operational tool capable of incorporating uncertainty in the operation and planning of modern power networks is essential. In particular, failing to consider uncertainties in operational and investment decisions can result in irreversible energy network assets to become stranded (not being used efficiently), or overloading of these assets reduces their lifetime and replacement age.

There are two general approaches for assessing system reliability: direct analytical methods and simulation methods [1]. Although, analytical techniques are accurate and provide relationships between inputs and results, they are based on simplified assumptions, which do not capture chronological aspects that might be significant for certain systems. Also, for more complex systems analytical techniques are computationally infeasible. On the other hand, simulation techniques (in particular Monte Carlo methods) based on random sampling can easily model complex systems as well as the frequency and duration features, which are useful to quantify as they give information on the entire system performance value thus helping system operators estimate errors in data and make best decisions. Analytical techniques are helpful for calculating an approximated value of a system's performance, while simulation techniques are able to provide an entire probability distribution for these values highlighting the fact that uncertainty can lead to a wide range of values, not just one. Using probability distributions gives a practical means to planners since they can assess whether differences in indices occur due to real changes in performance or due to statistical variations. For example, Probability Distribution Functions (PDFs) of duration/frequency of a load point interruption can provide significant information for adequacy system planning and can prove useful in estimating the errors resulting from inaccurate data. Some of the most commonly used indices are the Expected Energy Not Supplied (EENS) and Expected Customer Interruption Durations (EDI) for composite power systems, which will be explained in detail in Chapter 2.4. Similarly, to quantify the financial risk of deploying network corrective actions, PDFs of generating costs, load costs, wind curtailment costs can be determined using the Value at Risk (VaR) metric, which will be described in Chapter 6.1.3. Probabilistic assessment methods in power systems are mainly applied to different hierarchal levels [1]. The first level (HL I) addresses the generation subsystem, the second level (HL II) analyses the generation and transmission systems, while the third level (HL III) deals with the system as a whole, including the distribution subsystem. This thesis focuses on the second level, HL II.

1.1.2 Low Carbon Technologies

Reduction of carbon emissions is a challenge today. As a result, many governments are introducing targets to decrease these emissions. For instance, by 2020 the EU has commited to have 20% of their energy demand generated by renewables [2] meaning that 30% of the electricity demand must be met by renewables in the UK [3]. Thus, the adoption of low carbon technologies (LCTs) by power system operators has been encouraged. These are related to distributed generation such as wind farms and photovoltaic systems (PVs), electrothermal technologies, such as electric heat-pumps (EHPs) and micro-combined heat and power units (μ CHP), as well as transport electrification, such as electric vehicles (EV).



Figure 1-1: Renewable sources integration introduces need for greater flexibility[4]

Future smart grids will feature high integration of LCTs, as illustrated in blue and orange (renewables and renewables spillage) in Figure 1-1, to enable efficient and economical grid operations. However as RES integration in the grid is increased, more flexible ways of managing the intermittency and sudden changes in renewables production are necessary. In the case where wind production is higher than the required load (e.g.: 00:00am to 05:00 in Figure 1-1) then some renewables production may need to be curtailed in order to reduce or avoid network congestions. For example, during hours of high wind generation (e.g.: from 00:00 to 07:00 in Figure 1-1), thermal plants have to generate at minimum export load in order to minimise waste and spillage from RES production when demand is low. However, as RES production suddenly drops, (e.g.: from 08:00 to 14:00 in Figure 1-1 and 19:00 to 21:00) thermal plants need to quickly ramp up to supply the higher load levels and high daily peaks. During the evening peak, low renewable levels may not be enough to supply the entire load, thermal plants hence need to produce at maximum export load; if this is not enough, then more expensive, highly flexible units (e.g.: peakers, gas reciprocating engines, OCGTs) are required to come online. As a result, greater flexibility in the energy system is crucial to allow the transition from a traditional fossil-fuel-based generation to one based on LCTs [5]. While for example renewable energy offers a cheaper and cleaner energy supply, it imposes great challenges for modern grids because most renewable resources are unpredictable in nature [6]. In particular, the predictability of renewable resources is still limited by current forecast methodologies. Similarly, with the popularization of EV, the uncertainty of the time space distribution of EV charging will remarkably create more difficulties for power system control, which requires greater investigations in power system operation and planning [7]. For instance, it is critical to determine temporal and spatial distribution of EV charging load. Consequently, LCTs can pose several technical issues to power networks as outlined below:

- LCTs change the current flows and shape of the load cycle where they are connected. This can cause:
 - 1.1. Thermal ratings to be exceeded,
 - 1.2. System voltage to rise beyond the acceptable limits.
- 2. Reverse power flows, i.e. power flows in the opposite direction to which the system has been designed.
- 3. LTCs can contribute to fault levels, which can raise the fault level above the rating of network equipment.
- 4. A number of power quality limits can be affected by LCTs:
 - 4.1. Contributions to harmonics, particularly if a significant number of invertor controllers is present,
 - 4.2. Voltage imbalance which affects power quality,
 - 4.3. Voltage fluctuation or flicker if the output of renewables changes rapidly.

Despite adding greater flexibility to the networks, in the sense that power systems are operated with a number of real time controls, it remains indispensable for smart grid to stay secure and reliable. The increased controllability of renewables can only be utilized if suitable control architecture is established. Several novel control structures can support this idea such as Energy Storage (ES), Real time thermal ratings (RTTR), Demand Response etc., which will be described in the following sections.

1.1.3 Smart Grid and Smart Solutions

Smart grid is a term for a modern power system that integrates existing and new features in order to provide the following [8]:

- To ensure secure and sustainable electrical energy supplies and to combine the primary resources of traditional energy sources, flexible storage, and new and dispersed generation sources,
- To increase the network and generation capacity and to develop technical solutions that can be deployed rapidly and cost effectively, enabling existing grids to accept power injections from distributed energy resources without exceeding operational limits,
- To establish interfacing capabilities that allow new designs of grid equipment and new automation and control arrangements to be successfully interfaced with existing traditional grid equipment.

In response to power system challenges such as increasing demand, infrastructure ageing and high integration of renewable sources, smart grid concept is deployed to accomondate existing and forthcoming changes in power systems. Smart grid has modernized the way electricity is generated, transported, distributed, and consumed by integrating smart transmission and distribution networks, smart control centres, smart substations, smart load scheduling and load balancing. This is achieved using several technologies such as sensing, communications and control for the real-time operation of the grid (ICTs, smart meters, phasor measurement units, data acquisition-SCADA), as well as smart technologies which optimize networks operation, e.g. modifications in distribution network topology using switching, control of power flows using real time thermal rating (RTTR) data, flexible AC transmission systems (FACTS) to control flows and voltages, demand side management and energy storage.

The European Technology Platform formed the Smart Grids program in 2005 and the US Department of Energy a similar initiative in 2007 [9]. The joint vision of the program was to provide affordable, clean, efficient, reliable, secure and economic power supply through efficient energy management on power networks at all times [10][11][12]. The challenges to implement smart grids are summarised as follows:

- Environmental challenges: Traditional electric power production, as the largest CO₂ emission source, must be changed to mitigate the climate change. In addition to that,

a shortage of fossil energy resources has been foreseen in the next few decades. Natural catastrophes, such as huricanes, earthquakes and tornados can destroy the smart grids easily. Finally, the available and suitable space for the future expansion of power networks has decreased considerably.

- Market/customer needs: Future developed system operation technologies and power market policies need to be developed to sustain the transparency and liberty of the competitive market. Customer satisfaction with electricity consumption should be improved by providing high quality/price ratio electricity and customers' freedom to interact with the grid.
- Infrastructure challenges: The existing infrastructure for electricity transmission and distribution has rapidly aging components and insufficient investments for network improvements. With the pressure of the increasing load demands, the network congestion is becoming worse. The fast online analysis tools, wide area monitoring, measurement and control, and fast and accurate protections are needed to improve security and reliability of the networks with minimum investment required.

Development and implementation of active smart grids is not trivial. It is something new and different from the 'fit and forget' approach currently applied so often. Additional investments for control and communication systems are required. Barriers are often financial, not technical. Adding more flexibility into the network and helping avoid high uplift payments and large irreversible capital investments will provide tremendous value for all parties concerned with an efficient, economic and secure network operation. Real time thermal ratings (RTTR) [13][14], demand-side management (DSM) and demand-side response (DSR) [15][16][17], storage devices [18] [19][20], FACTS [21][22], phase-shifters [22][23] and so on, are some of solutions that have been proposed to help provide such flexibility. These can help alleviate congestion, reduce renewables' spillages and minimize demand disruption by either shifting flexible loads from periods of high-energy demand and congestion to off-peak ones, by controlling the flow of power over the network, or act as a post-fault corrective action, thus enhancing the ability of the system to accommodate intermittent renewables [24][25].

Demand Response (DR) is defined as changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high whole-sale market prices or when the reliability is jeopardised [26]. DR activation can be manual, where the load adjustment is manually performed after receiving notification of an upcoming DR event. It can be semi-automated, where a local control system follows prepro- grammed DR strategies following a notification. Finally, DR can be activated remotely using an event initiation signal to control loads directly. This fully automated DR activation is assumed in this thesis. During times of network faults, DR can help mitigate the effect of the fault by redispatching loads in such a way that this reduces congestion and stress on network assets. Using DR as a post-fault corrective action can also help reduce the number of customer interruptions, reduce the lengths of interruptions and increase the number of customers being reconnected following a fault [17]. In the context of planning under uncertainty, these flexible solutions can provide tremendous value in helping defer large irreversible investments until at least some uncertainty is resolved and the need for large capacity reinforcements is fully established [27]. Furthermore, as more DR is deployed, a multitude of other services and benefits become available across the supply-chain, affecting system operators (SOs), transmission and distribution network operators, utilities, retailers and customers. Customers can benefit from reduced electricity prices as DR can help reduce average generation costs, while network operators can rely on DR to increase system reliability.

To understand the effect of DR on supply and demand, we show in Figure 1-2 how demand and supply change for a system under normal condition and one under emergency condition. Let's assume that the demand curve D^N is 75 GW and the merit order curve (or supply curve) S^N intersect D^N at a capacity of 75 GW. At that point, the clearing price (equal to the marginal cost of the most expensive generation unit required to supply this demand) is around 90 £/MWh. In the event of an emergency, when a failure occurs, for instance due to a line tripping or to a generator shutdown, then the loss of this component causes the supply curve S^N to shift to the left, thus causing the electricity price to spike up as very high short run marinal cost plants are required to supply the load. In this case, the price reaches 230 £/MWh (red dot) where the demand D^N and the new supply curve under emergency condition S^E meet. At the same time, the load is shed (LS) by around 7 GW (this value is for illustrative purposes only). To reduce the amount of LS and bring the price back down to a more reasonable level, DR can be used to make the demand curve more elastic, represented by the new demand curve D^{DR} . Once the amount of available DR is determined, a rescheduling of generators after inclusion of DR is done, giving a new supply curve S^{DR} that allows some load to be reconnected as DR customers are disconnected and compensated. This leads to an increase of 3 GW of demand being reconnected and leads to a decrease in the price, from 230 \pounds/MWh to 110 \pounds/MWh (green square), as shown in Figure 1-2. This price decrease is due to plants with lower short run marginal cost being committed instead of high short run marginal cost peaking plants.

In this thesis, particular focus will be put on the quantification of the profits incurred for customers by participating in a DR program as well as the improved network reliability when DR is applied.



Figure 1-2: Merit order effect of RES integration and Demand Response [28]

Real time thermal rating (RTTR) is an upcoming technique used to calculate the rating of electrical conductors based on local, real-time weather conditions, which usually leads to an increased rating as compared to traditional static thermal ratings. RTTR is another part of the

large suite of smart grid technologies, which can eliminate or reduce the need for new conductors, while giving network operators more information about the state of the system. RTTR at the operational stage can be used both for prefault conditions to supply load with cheaper generation or to avoid wind spillage from renewable sources and during post fault conditions to decrease involuntary load reduction and therefore increase network reliability [17]. Another benefit RTTR can provide is at the planning stage allowing additional load to be connected in order to avoid costly network reinforcements [13]. A probabilistic RTTR model is introduced in [14] to capture the uncertainties in the measurement of weather parameters, line rating modelling and also in the failures of network components (generators and circuits). This model thus not only provides a circuit rating value but also assesses how robust this value is to different uncertainties. As a result, system operators can take better operational decisions. In this thesis, quantification of operational network costs (generation cost, customer interruption costs, wind curtailment costs), as well as improved network reliability when RTTR is applied, is reported.

Flexible AC transmission systems, FACTS, can be deployed as an alternative smart grid technology to flexibly reduce voltage limit and thermal capacity violations, contribute to fewer transmission power losses, improve stability and security and ultimately contribute to a more efficient operation of the transmission system [29]. From an operational point of view, FACTS operate by supplying or absorbing reactive power, increasing or reducing voltage and controlling the series impedance of transmission lines or phase angles [30]. This could then bring savings in operating costs without jeopardizing the level of system security. From the planning point of view, FACTS enable the utilization of existing facilities and therefore reduce the demand for new investments [31]. For instance, the transmission network company in England and Wales, National Grid, installed phase shifter transformers specifically to enhance power transfers across system and accommodate new generation in the northern part of the network [32]. However, FACTS are quite expensive in some cases, since they include lots of electronic devices and power converters; consequently, several studies exist in the literature based not only on technical and cost considerations but also on return of investements [33]. The impact of FACTS on networks reliability has been extensively investigated in [34][35][36]. This thesis concetrates on the impact of certain FACTS technologies on the maximum utilization of wind sources within probabilistic analysis.

High interest in integrating energy storage into power systems operation and economy has been recently experienced. The major benefits of energy storage include electric energy shift in time, frequency and voltage regulation and transmission congestion relief. Renewable sources are non-dispatchable and their output is uncertain due to wind speed or solar irradiation, which means that a part of wind or solar power has to be curtailed [37]; transmission congestion or voltage problems are the main reasons of this. At the same time thermal generators cannot operate below their low output limits in order to satisfy load when it is on its minimum. As a result, energy storage system can shift the generation pattern and smooth the variation of wind power over a desired time horizon. It can also be used to mitigate possible price hikes or sags [38][39]. In [38] the required energy storage capacity, charging and discharging power ratings for different wind generation penetration levels are recognized . On the other hand, in [39] energy storage is deployed to determine the maximum wind energy utilization considering minimum wind spillage levels. Energy storage is also used in combination with demand side management at a household level [40]. This study aims to store energy during off-peak demand hours and release back this energy to the system during peak periods, so not only lower wholesale energy prices can be achieved from customers' perspective, but also there is support to lower voltage distribution networks for reducing network investments. However, there is more room for research related to energy storage combined with demand response on a bigger network scale, as well as to consider this combination in reliability analysis. In this thesis, energy storage is mentioned as the future work being combined with the proposed DR and RTTR models in power networks rich in wind generation.

1.1.4 Research Aims and Objectives

From the points highlighted above, current flexible energy concepts and their impact on power systems is a new topic. Also, their so-far implementation using probabilistic analysis is neither clear, nor fully applicable when dealing with probabilistic phenomena. The aim of the project is to optimize the current modelling methods used for operation and planning by including flexible smart solutions in a probabilistic framework. Because probabilistic analysis requires high computational time especially for highly complex systems, the first part of this work focuses on the development of a novel computational tool that leverage computational intelligence as applied to the evaluation of composite power system reliability. Such innovative methodologies and techniques can be applied to future power systems with large penetration of wind power and/or flexible corrective actions. The second part of this work is the application of flexible methodologies to solve energy systems operational problems with the improved network reliability and the minimum operational costs. The third and final part of this work aims at developing a methodology to maximize wind integration considering minimum wind curtailment in the presence of flexible corrective actions. This methodology is both easily implementable and flexible enough to solve large and complex real-world power network operational problems. Hence, the main goal of this thesis is developing innovative algorithms that are used to study modern and flexible electrical networks, which will contribute to environmentally sustainable and economically efficient electrical energy systems.

To achieve these aims, the following objectives have been defined:

• Development of novel probabilistic computation methods to leverage computational intelligence and processing power.

To critically review existing Monte Carlo sampling reduction methods applied in reliability analysis of power systems, to assess the methodologies, assumptions, advantages and limitations of each model and select the most appropriate technique for the problem studied. Such innovative methodologies and techniques will be applied for probabilistic analysis of future power systems with large penetration of wind power and/or FACTS, real time thermal rating, demand side management and energy storage. The main goal of this work is to explore innovative algorithms in order to reduce the CPU time of simulation-based reliability assessment.

• Deployment of load forecasting and wind forecasting methods

To present a mathematical forecasting algorithm for short term load projection, which is used in conjuction with the demand response applications in power system operation. This is exemplified by forecasting of different load types (industrial, commercial, residential, large users) to obtain more accurate results within simulations of power system operation.

To present a stochastic forecasting algorithm for short term wind forecasting, which is used as an input for calculation of real time thermal ratings and wind turbine active power productions in the simulation of power system operation.

• Deployment of Real Time Thermal Rating model to relieve network congestion

The fast rate of integration of renewable energy sources, especially wind farms, into existing networks, while environmentally beneficial, tends to impact the operation of power systems both economically and technically. For this reason, it is an imperative to conduct studies and include novel concepts like RTTR in order to reduce reinforcements of electrical networks and calculate the costs and benefits in transmission planning schemes.

• Deployment of Demand Response to reduce network congestion

To present a probabilistic framework for DR to quantify network performance improvements and maximize customer profits. To give the answers to the problems such as: What is the maximum amount of DR in the transmission system for the different load types? How much the expected energy not supplied (EENS) index and expected duration of customer interruptions (EDI) are reduced, etc?

• Deployment of FACTS to reduce network congestion and alleviate voltage issues

Flexible AC transmission plants, such as phase shifter transformers, thyristor controlled series compensators and static var compensators can be used to divert power flows into the transmission corridors where enough capacity is available so that network overloads can be eliminated. By a coordinated control of FACTS devices the network can be utilized in a more efficient way and the flexibility of the network increases. Using power electronics technologies and fast electronic switching, FACTS are a promising option in the creation of flexible power networks. Reactive power as well as active power flow can be quickly changed following a contingency, so that post contingency constraint violations are swiftly eliminated.

• To quantify the maximum wind deployment level using flexible control actions

To present a rigorous analysis for maximum wind utilization in the presence of flexible controls incorporated into a probabilistic framework. To quantify the financial benefits from deploying such flexible concepts for improving network reliability and operation cost.

1.1.5 Main Contributions of the Thesis

The work within this thesis contributes to a number of areas of power systems research, specifically related to the use of probabilistic – reliability analyses, which include smart energy system solutions. The main outcome of this research is the development of a novel probabilistic framework and tool used to optimize power system operation and improve network planning decisions subject to operational uncertainties. The design of this framework resulted in the ability to make network operation decisions considering multiple uncertainties and to quantify the reliability and financial improvement that each flexible action gives in order to postpone or avoid costly network reinforcements.

References prefixed with the letter 'A' refer to publications, which have arisen from the work completed during this research. A full list of international journal and conference publications is included in the List of Publications at the beginning of the thesis. The contributions achieved in this thesis can be summarised as follows:

- A review of Monte Carlo sampling reduction tecniques applied to power systems is presented. Proposed multi particle swarm optimization (MOPSO) heuristic technique to minimize Monte Carlo Simulation (MCS) is proposed [A5]. The proposed MOPSO filtering technique is developed subject to three objective functions: 1) Probability of a given state, 2) Total load curtailment in a given state, 3) Transmission system capacity considering weight factors, which distinguish the importance of the overhead lines. This helps to search faster the significant network operation system states and make MCS converge faster.
- A new algorithm for short-term load-forecasting of DR under uncertainty is proposed, and the functionality required for developing such a module is described. The module provides high forecasting performance when dealing with nonlinear and multivariate

problems involving large datasets. This makes it particularly suitable for short-term load prediction for disaggregated sites with the aim of optimizing the DR process when the data relating to the operating regime or load characteristics of the individual devices and loads connected are unavailable [A1].

- Extensive reviews of "flexible" methods for optimizing network operation considering both deterministic and probabilistic approaches. A thorough review of the benefits of RTTR, DR and FACTS devices in power network's operation is conducted. The operational conditions (intact network and N-1 operation) and the practicalities associated with each "flexible" device/method are examined [A1, A4, A6, A7, A8]. The extensive literature survey showed that using the above mentioned flexible concepts in stochastic post-contingency analyses did not consider both security and economic criteria. This is a major research gap, which is addressed in this thesis.
- Investigation of the benefits that real time thermal ratings model provides in terms of system reliability and operating costs under probabilistic versus deterministic analysis [A4]. Probabilistic reliability assessments prove to be superior approaches than deterministic ones when thermal ratings based on OHL's properties are accounted for. As a key recommendation arising from this work, there is a need to change the current operational framework based on deterministic analysis and move on towards a probabilistic approach, such as the one presented in this thesis. In fact, the modelling of uncertainty is the only way to explicitly quantify and acknowledge the value of flexible solutions such as RTTR, and thus accrue all the relevant economic benefits mentioned throughtout.
- A probabilistic framework for optimal demand response scheduling in the day-ahead planning of transmission networks is proposed [A1]. The model incorporates load recovery plans by optimizing the customers' position in the joint energy and reserve market. The methodology recognizes several types of uncertainties, and finds optimal demand response scheduling using the network security and customer economics criteria. The model has been extensively tested in the presence of both renewable sources and real
time thermal ratings. It is shown that improvements in reliability indicators are considerable, while customers' revenues are significantly higher, particularly under emergency conditions.

- A probabilistic framework for minimizing wind spillage and maximizing capacity of the deployed wind generation, whilst improving system reliability is proposed [A2, A3]. Wind spillages are classified in voluntary and involuntary and prioritized with probabilistic cost coefficients. The model shows that using multiple reliability indicators can be a good choice for operational decisions on optimal wind management, since this approach results in significant reduction of operating costs especially for high probability confidence intervals.
- Methodologies for best placement of FACTS devices are proposed to further increase wind utilization using the probabilistic analysis [A2]. Installation of static var compensators (SVC) and thyristor-controlled series capacitors (TCSC) is proposed based on load and wind curtailments caused by violation of voltage and thermal constraints. The probabilistic simulation results are then compared with the state enumeration results. It was shown that the proposed methodologies improve economics of network operation as well as its reliability.

1.1.6 Thesis Overview

This thesis consists of nine chapters in total. The eight chapters that follow this introduction are outlined below:

Chapter 2 – Power System Reliability Analysis

This chapter provides information on different aspects of reliability in power systems (section 2.1). The concept of deterministic approach versus probabilistic approach is described in section 2.2, whereas different types of probabilistic approaches are discussed in section 2.3. Afterwards, an insight into both non-sequential and sequential Monte Carlo simulations is described and the formulas for reliability indices are derived in section 2.4. Finally, conclusions are drawn about the most appropriate methods to be applied for the assessment

of considered power system. Finally, power system analysis is done using techniques presented: the algorithms for AC and DC Optimal Power Flow (OPF) make use of, respectively, non-linear and piecewise linear programing.

Chapter 3 – Literature Review on Smart Solutions in Energy Systems

This Chapter presents a review of current smart solutions applied in energy systems. The concept of each solution is first explained and the evolution of the solutions is given. Next, their application within both deterministic and probabilistic analyses is presented. The gaps and inconsistencies in the literature review are discussed and points that need further investigation are summarised.

Chapter 4 – Deployed Models of Low Carbon Technologies and Smart Solutions

Chapter 4 presents the application of low carbon technologies in power systems in section 4.1 as well as the modelling of smart flexible solutions (RTTR, FACTS, DR) in order to accomondate the high level of Low Carbio Technologies integration in power systems. Probabilistic methods are developed for each flexible solution with the aim to improve power system reliability and to either minimize operating costs or to maximize the profits of customers in a day ahead planning. The proposed algorithm is applicable for both system normal and emergency conditions.

Chapter 5 – Components of the Developed Reliability Assessment Methodologies

Section 5.2 presents a thorough review of current Monte Carlo sampling reduction methods in order to improve the computational efficiency of algorithms, especially those that are applied to problems of great complexity and high dimensionality. This section provides information for different reliability reduction methodologies. More specifically, it illustrates reliability assessment techniques such as sequential MC combined with Latin Hypercube Sampling (LHS) and non-sequential MC combined with Particle Swarm Optimization (PSO). Probabilistic modelling of power systems components is given in section 5.1. These are classified as component failure modelling, repairable failure modelling, network modelling in terms of reliability as well as load modelling. Load forecasting and wind modelling are then introduced for real time power system operation. Load sampling is implemented through short-term load forecasting using neural networks technique, while wind sampling is implemented through ARMA stochastic model.

Chapter 6 – Optimal Demand Response Scheduling with Real Time Thermal Ratings for Network Reliability

Chapter 6 presents the network modelling objectives, description of case studies and results of application of real time thermal ratings within the probabilistic methodology for optimal demand response scheduling in the day-ahead planning of transmission networks. Section 6.2 includes case studies design for RTTR and DR modelling, while section 6.3 shows the results on different IEEE test networks extended with wind farms at suitable locations.

Chapter 7 – Optimization of Wind Energy Utilization through Corrective Scheduling and FACTS Deployment

Chapter 7 presents the network modelling objectives, case studies description and results of a probabilistic framework for minimizing wind spillage and maximizing capacity of the deployed wind generation, whilst improving system reliability. Section 7.2 includes case study design for optimal wind deployment. The simulation results in section 7.3 make comparisons between MCS and the state enumeration results. It is shown that optimal wind deployment can have higher impact in terms of reliability and economics in emergency conditions, since the violation of power systems constraints is minimized.

Chapter 8 – Conclusions and Future Work

In this chapter the main conclusions of the research are summarised and suggestions are made for the future development and improvement of the presented methodologies.

2 Power System Reliability Analysis

Summary:

This Chapter presents the application of Monte Carlo methods to power system adequacy assessment. The traditional deterministic techniques are first discussed and compared to Monte Carlo techniques. A secure network is a network that is able to respond to disturbances, whether these are pre-empted (certain) or not (uncertain). Deterministic methods can only provide a secure network operation when the system is exposed to credible and pre-empted risks of failures and outages. However, deterministic analysis cannot solve the network security problem if unexpected failures or outages occur. As a result, probabilistic analyses using simulation methods are developed to capture all possible stochastic uncertainties in power networks. State enumeration and Monte Carlo techniques are elaborated as the main simulation methods. Monte Carlo approach is usually selected for probabilistic network evaluations because it can handle more complex systems and provide system planners with a whole set of probability distribution functions of different quantities. Monte Carlo analysis includes sequential and non-sequential simulation approaches, the differences of which (concept and equations) are thoroughly described in this section. The last section of the chapter presents load flow techniques used within Monte Carlo simulation procedures; these are AC and DC Optimal Power Flow (OPF) models, which are used to evaluate the intact and contingent system states.

2.1 Power system reliability

Power system reliability evaluation is based on probabilistic methods and a wide range of reliability indices can be determined. However, before applying any probability theory, it is necessary to acquire a complete understanding of the power system. Only after this understanding has been achieved, a model can be derived and an appropriate evaluation technique can be chosen. The following steps should be addressed:

- o Understand the way in which the components and system operate,
- Identify the way in which they can fail,
- Deduce the consequences of the failures,
- Derive models to represent these characteristics.

After having resolved the above steps an evaluation technique can be selected, and a probabilistic tool developed which enables the analyst to transform knowledge of the system into a prediction of its likely future behaviour. There are two main categories of evaluation techniques: deterministic and probabilistic. A comprehensive explanation of their applicability and their methodological steps are presented in the following sections.

2.2 Deterministic versus Probabilistic Planning Including Reliability Assessment

The most common deterministic criteria indicate that certain network outages will or will not result in a system failure. The deterministic criterion mainly used for planning of bulk electric power systems, is known as the N-1 criterion [41]. If this criterion is satisfied, the loss of any *single* network component will not result in load curtailment. Subsequently, the system operation in a particular state is considered 'reliable' if the occurrence of any selected credible single contingency (i.e most probable/plausible contigencies) does not violate the operational limits. On the other hand, the system is considered 'unreliable' if the occurrence of a credible contingency causes a violation of operating limits [42]. Unfortunately, the system can still be exposed to risks of failures and outages even though there are no *credible* network outages leading to violations of operating constraints. In other words, even if we

apply deterministic analysis and the system is considered reliable, in reality, there are many more risks that were not considered and can cause violation of operation constraints. As a result, deterministic techniques, which are sometimes referred to as engineering judgement, do not include an assessment of the actual system reliability as they do not incorporate the probabilistic or stochastic nature of system behaviour and component failures. Therefore, these approaches are not adequate, although they are easier to understand. In contrast, probabilictic methods can incorporate many significant factors that affect the reliability of the system. These techniques provide quantitative indices, which can be used to decide if the system performance is acceptable or if changes need to be made. Probabilistic techniques can be based on analytical/ state enumeration techniques or Monte Carlo Simulation techniques. The deterministic approach is presented first and it is followed by a description of the probabilistic techniques for reliability analysis.

Undoutebly, reliability assessment of power networks provides invaluable information to the system managers, designers, planners and operators. Over the past few decades, many attempts have been made with the goal to develop techniques for reliability, economic and operational assessment of power system operation. One of these attempts is the deterministic approach, which was introduced and applied in real-life circumstances. Several deterministic criteria and techniques have been developed; for example, they give information about percentage reserves in generation capacity planning or N-1 contingency criteria (worse case scenarios) in transmission planning, etc. [1].

Nonetheless, performance of deterministic techniques has some limitations, such as:

- They do not reflect the stochastic systems behaviour e.g. customer demands, intermittent generation, certain component failures, etc.,
- The analysis may not consider all relevant system states resulting in unreliable network,
- They can lead to insufficient evaluation of system adequacy and reliability.

These are the determining factors that led to the need to recognize not only the severity of the event but also how it affects the operation and performance of the system. The necessity to evaluate many other aspects of system risk required development of the probabilistic evaluation techniques for power systems; these are discussed in the next section.

2.3 Reliability Analysis of Power Systems

Over the past forty years, many probabilistic evaluation techniques have been developed and there are many current studies that contribute to the integration of probabilistic techniques into the everyday power system analysis. Some of the techniques are reliability worth evaluation, probabilistic load flow, probabilistic fault analysis, probabilistic transient stability and probabilistic transmission line design [1]. The selection of a relevant technique and its validity completely depends on the particular problem and the models used to represent the examined system. The concept of power system reliability is first introduced and then the different techniques are discussed.

Power System Reliability is the probability that a given power system will be able to be adequate under a given set of credible disturbances at any given moment while supplying its electrical demand over a given operational time interval. Therefore, the critical question is "How a power system can be reliable?" It is evident that the answer to this is a combination of solutions that consider the highly probabilistic way of power system operation subjected to external as well as internal factors. The external factors are the environmentally related failures, whilst internal factors consider generation, transmission, protection components related failures. Given the high number of failures that might occur and taking into consideration that a failure can be somewhat network and time specific, it is obvious that the probabilistic problem is of combinatorial nature.

Reliability problems in the domain of power systems can be characterized by two aspects, namely adequacy and security. System adequacy assesses the sufficiency of the existing system facilities to potentially satisfy customer demand in any given instant [43]. System security assesses the ability of the power system to respond to disturbances arising in the system. The research undertaken in this thesis uses reliability adequacy assessment of power systems. The corresponding methods are given after a brief introduction of the system security assessment.

Power system security can be categorised by the following three criteria, as illustrated in Figure 2-1:

- Overload security: circuits and transformers are operated within acceptable limits. A failure may result in overloads, which might cause potential system blackout following cascading failures.
- Voltage security: A failure may cause voltage instability of the system and this might lead to potential system collapse.
- Dynamic security: A requirement that generators have enough reserve in order to maintain system operation at 50 Hz. A failure can lead to loss of generation, which results in overloading in some areas of the system and eventually potential blackout.



Figure 2-1: Security Reliability Assessment

However, the majority of probabilistic techniques that have been reported so far deal with reliability adequacy assessment. In particular, they analyse and discuss appropriate reinforcements for satisfying the load demand and system operational constraints of the system.

There are two general approaches for assessing system reliability: state enumeration techniques and simulation methods. State enumeration techniques make use of system models and evaluate the reliability indices from these models using analysis of the pre-specified set of system states. The exact mathematical equations can become quite complicated and approximations may be required when modelling complex systems and complex operating procedures [1]. On the contrary, simulation techniques such as MCS

estimate the reliability indices by simulating the actual process and random behaviour of the system [2]. Therefore, simulation techniques provide greater flexibility in modelling and they can be performed easier with the use of computers. That is the main reason for increased number of studies using simulation techniques. The principal application of both techniques is summarised below:

- Monte Carlo Simulations have been used in composite system adequacy evaluation and probabilistic voltage and transient stability assessments.
- State enumeration techniques have been used in substation reliability evaluations.

However, Monte Carlo techniques can also be applied to substation reliability evaluation and state enumeration methods can also be utilized in composite system evaluation. The latter is limited by modelling complexity of the power system operation.

2.3.1 State Enumeration

In the State Enumeration method, the system states are generated one by one according to a predetermined level of contingency [43][44][45], for instance a first order independent failure or second order independent failure, and so on. Since all the events in a power system are considered independent, the system state probability is calculated by multiplying the probabilities of the combination of elements, i.e. network components including generators and load levels. This is shown in equation (2-1):

$$p_q = \prod_{c \in C} p_c \times p_l \tag{2-1}$$

In equation (2-2), p_q is the probability of the system state q, p_c is the probability of component c state, C is the set of all components in the system and p_l is the probability of the load level. The probability of the component state is represented by either its availability or unavailability according to the enumerated system state. For instance, if a system contains ten components and the enumerated state has one failed component, the system states probability will equal the unavailability of the failed component times the availability of nine other components times load level probability. Next, the system state is examined to find out whether it is a system success or a failure state. If the latter is the case, the consequence of

the failure state is obtained using failure effects analysis. The consequence can be any of the risk measures such as demand not supplied or energy not supplied. Then the contribution of this system state to reliability indices is computed using (2-2).

$$CI_q = p_q \times R_q \tag{2-2}$$

where CI_q is the contribution of the failure state q to the reliability index, and R_q is the risk measure. The total reliability index (*CI*) is the summation of index contributions from all failure states (set *S*) as given by (2-3).

$$CI = \sum_{q \in S} CI_q \tag{2-3}$$

The main strength of state enumeration method is its simplicity compared to simulation methods, but it is infeasible to deal with large systems due to long computation time. This is specifically true in cases where the level of contingency is higher than the first failure level or N-1. Another drawback of this method is that it can not handle the events that are chronologically time dependent [1].

2.3.2 Monte Carlo Techniques

The traditional simulation technique is Monte Carlo Simulation (MCS) method. The MCS is a stochastic simulation methodology, which can be applied as sequential and non-sequential simulation procedure. Sequential MCS samples system states in time order over different periods while non-sequential MCS generates and samples system states in a random fashion. Sequential MCS requires greater computational power but handles sequentially correlated events. On the other hand, non-sequential MCS substantially improves computational efficiency. For this reason, non-sequential MCS is often preferred over sequential MCS in many applications. However, the physical phenomena modelled in this thesis required chronological modelling and subsequent application of the SMC procedure.

2.3.2.1 Sequential Monte Carlo Simulation

The Sequential Monte Carlo Simulation (SMCS) method is used to simulate power network operation when the chronological physical phenomena are of significant importance. In order

to capture the system states in chronological sequence two basic sampling techniques are used. These are the state duration and system state transition sampling. The most popular is the state duration technique and it is further discussed below [1].

A SMCS procedure is developed to simulate chronological phenomena such as wind generation, load curtailments and real time thermal ratings. Initially, the state duration sequence sampling technique samples the exponential probability density functions of the form $e^{-\lambda t}$ where λ is the failure rate. If the system is composed of ageing plants then Weibull distribution function can be used. The main steps of the state duration sampling technique are as follows:

- All plants are assumed to be initially in the up state.
- The time to failure (TTF) is calculated by sampling it from the cumulative distributuin function (1 e^{-λt}), that is, by equating it to the random number U with uniform distribution in the range [0,1]. This gives TTF as shown in equation (2-4) where λ is the failure rate of the plant:

$$TTF = -\frac{1}{\lambda}\ln(1-U) \tag{2-4}$$

• Similarly, if a plant is a down state, its time to repair (TTR) is determined using (2-5):

$$TTR = -\frac{1}{\mu} \ln(1 - U)$$
 (2-5)

where μ is the repair rate.

• The above steps are repeated over the duration of the system's mission time to create an array of systems states in a chronological manner.

The main steps of the sequential Monte Carlo simulation procedure are illustratively shown in Figure 2-2. They are briefly described below:



Figure 2-2: Sequential Monte Carlo simulation flowchart

- 1. Set the number of MC sample *Y*=1.
- 2. For each component sample system state using state duraion sampling technique.
- 3. Apply power flow analysis to determine power flows and adequacy of the system.
- 4. If there is no violation of constraints, the simulation proceeds to the next chronological step, otherwise this is counted as a failure state. The reliability indices are calculated (e.g. loss of load) and it is proceeded with the simulations.
- 5. Update expected values of reliability indices, if chronological steps have been completed.
- 6. Check the convergence of each index using the coefficient of variation (COV).
- 7. Stop the simulation if COVs of all indices are less than a pre-specified value, typically ranging from 2% to 5%. Otherwise, set Y=Y+1 and go back to step No.2

The main advantage of the SMCS is that it can be used to evaluate frequency and duration indices and it is mathematically simple to implement. The main disadvange is that it needs high computational time to converge especially when all chronological behaviours in a power system are modelled. Convergence criteria are described in section 2.3.2.3.

2.3.2.2 Non-sequential Monte Carlo Simulation

In contrast to the SMCS the non-sequential Monte Carlo simulation (NSMCS) method does not consider the sequence of events and therefore the events are independent (i.e. not following a sequence). In particular, it assumes that a system state depends on the combination of all component states and therefore each component state can be determined by sampling the probability that the component appears to have in that state. The system state sampling technique in the NSMCS method considers each time point or system state independently of another and therefore cannot be used to record and evaluate frequency and duration indices.

In general, a plant can reside in a number of discrete mutually exclusive states. In the case of a two-state representation, the probabilities of residing in the up and down states are the availability and unavailability, respectively. Random sampling in the NSMCS is achieved by generating a uniformly distributed random number U from the range (0, 1). This value is compared with the forced outage rate (FOR) of the component, as specified by (2-6):

$$FOR = \frac{\lambda}{\lambda + \mu} \tag{2-6}$$

If U<FOR, then the unit is deemed to be in the down state; otherwise the unit is deemed to be available. A similar procedure can be applied if the considered unit has one derated state. For instance, assuming that the generating unit has three states (up, down and derated), the probabilities of being in the down and derated states are P_down and P_der respectively. Consequently a random number U_i in the range [0,1] can be used to determine the component state [1]:

- 1. If $U_i < P_down$, then the generating unit is deemed to be in the down state,
- If P_down<Ui<P_down+P_der, then the generating unit is deemed to be in the derated state,
- 3. If $U_i > P_down + P_derated$, then the unit is deemed to be in the up state.

The implementation of the non-sequential technique is simple and is illustrated in Figure 2-3. Additionally, in non-sequential simulation load is represented by load levels, while in

sequential MC it is represented in a chronological order. In this thesis, for the non-sequential implementation the load curve is divided into 20 steps using clustering technique (see chapter 5.1.4). The probability of each level was determined and the cumulative probability is calculated. For the selection of load level a random number in the interval [0, 1] is generated and compared with the cumulative probabilities of the load levels.



Figure 2-3: Non-sequential Monte Carlo simulation flowchart

The non-sequential MCS can be briefly described by the following steps:

- 1. Set the ordinal number of the MC sample (Y).
- For each component generate a random number U in the range [0,1] If U<FOR, then the unit is deemed to be in the down state; otherwise the unit is deemed available.

- 3. Randomly sample the multistep load model based on the probabilities of each load level.
- 4. Apply power flow analysis to determine power flows and adequacy of the system.
- 5. If there is no violation of constraints, the simulation proceeds to the next load level step *ls*, otherwise this is counted as a loss of load state.
- 6. If there are no more load level steps update the calculation of expected values indices and check the convergence of each index using the coefficient of variation (COV) and go to the next Monte Carlo simulation year *Y*.
- Stop the simulation if COV is less than a pre-specified value, typically ranging from 2% to 5%. Otherwise, set Y=Y+1 and go back to step 2.

2.3.2.3 Convergence criteria

Coefficient of Variation (COV) is widely used to measure convergence of indices estimated by means of Monte Carlo simulation [43]. It is defined in (2-7):

$$COV = \frac{\sqrt{Var(E(F(x)))}}{E(F(x))}$$
(2-7)

Var (E(F)) represents the variance of the estimated index and E(F) estimates the expected value of function F(x). Since Var(E(F))=Var(F)/Y where *Y* is the total number of iterations, equation (2-7) can be rewritten as follows

$$COV = \frac{\sqrt{\frac{1}{Y} \left(E(F^2) - \left(E(F) \right)^2 \right)}}{E(F)}$$

$$COV = \frac{\sqrt{\frac{1}{Y} \left(\frac{1}{Y} \sum_{i=1}^{Y} F_i^2 - \left(\frac{1}{N} \sum_{i=1}^{Y} F_i \right)^2 \right)}{\frac{1}{Y} \sum_{i=1}^{Y} F_i}}{\frac{\sqrt{\sum_{i=1}^{Y} F_i^2 - \frac{1}{N} \left(\sum_{i=1}^{Y} F_i \right)^2}}{\sum_{i=1}^{Y} F_i}}$$
(2-8)

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 F_i is the value of the test function at iteration *i*. Typically COV ranges from 2% to 5%. The COV of 3%, for instance, roughly means that the index being estimated carries the error of less than 3%. In other words COV can be interpreted as the upper bound of an index's error.

2.4 Indices for Adequacy Assessment

Reliability indices are the quantitative measures of systems performance from the perspective of system adequacy. These indices are expected statistical values that give a reasonable measure of future system performance. The composite system reliability indices can generally be classified into probability, frequency, duration and expectations indices. The probability indices measure how likely an event will occur. Frequency indices measure the expected rate of ocurrence of an event per unit of time. Duration indices measure the expected time that an event will last for. Expected indices are the averages of expected consequences of an event. Reliability indices are usually calculated for load points and the overall system. The following indices are the most commonly used in composite power system reliability analyses [43].

LOLP-Loss of Load Probability

$$LOLP = \sum_{i \in S} p_i \tag{2-9}$$

where p_i is the probability of system state *i* and *S* is the set of all system states associated with load curtailment.

ENLC-Expected Number of Load Curtailments (occ./yr)

$$ENLC = \sum_{i \in S} F_i \tag{2-10}$$

where F_i is the system state frequency which can be calculated by (2-11).

$$F_i = p_i \sum_{k \in V} \delta_k \tag{2-11}$$

where δ_k is the departure rate of the component corresponding to system state *i* and *V* is the set of all possible departure rates corresponding to state *i*.

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EDLC- Expected Duration of Load Curtailments (hr/yr)

$$EDLC = PLC \times 8760 \tag{2.12}$$

(2-12)

EDNS-Expected Demand not Supplied (MW/year)

$$EDNS = \sum_{i \in S} Pc_i p_i \tag{2-13}$$

where Pc_i is the load curtailment in system state i

EENS-Expected Energy not Supplied

$$EENS = \frac{\sum_{y \in Y} \sum_{t \in T} Pc(t)}{\gamma}$$
(2-14)

where *Y* is the total number of MCS years

The basic reliability indices used in generating system adequacy assessment are Loss of Load Probability (LOLP), Expected Power Not Supplied (EPNS) and Expected Energy Not Supplied (EENS). The most commonly used reliability indices for the second level H2 are the EENS, LOLP and Expected Duration of Load Curtailment (EDLC), as shown in (2-14), (2-9), (2-12) respectively. Finally, for the third level H3, the most important indices are System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Frequency Index (SAIDI) [1, 2].

2.5 Power System Analysis

In power system reliability analysis, one of the main procedures is the identification of violated network constraints resulting in load shedding (failure state). In generation adequacy assessment or single area reliability assessment, this identification can be easily done through simple algebra; that is checking whether total generation capacity is less than load demand or not. On the contrary, composite system reliability evaluation requires an optimization tool called Optimal Power Flow (OPF) to perform this task. The OPF model can be based on AC power flow equations and it is called AC OPF algorithm. If it is based on DC power flow model it is called DC OPF algorithm; both algorithms are explained in the following sections. The main differences between the two algoriths are that AC OPF is able to give the

information about reactive power, voltages and power angles at buses. However, it takes longer time to solve, as AC OPF requires nonlinear programming methods. On the contrary, DC OPF is unable to evaluate voltages and reactive flows as it deals with active powers only. Despite this disadvantage, it is widely employed due to its computational speed and its ability to always converge.

2.5.1 AC OPF Model

The AC power flows in a transmission line which connects buses i-j are given by [46].

$$P_{ij} = V_i^2 g_{ij} - V_i V_j [g_{ij} \cos(\theta_i - \theta_j) + b_{ij} \sin(\theta_i - \theta_j)]$$
(2-15)

$$Q_{ij} = -V_i^2 b_{ij} - V_i V_j [g_{ij} \sin(\theta_i - \theta_j) - b_{ij} \cos(\theta_i - \theta_j)]$$
(2-16)

where P_{ij} and Q_{ij} are, respectively, the real and reactive power flows in line *i*, *j*, V_i and V_j are the voltages at buses *i* and *j* respectively, θ_i and θ_j are the voltage angles at buses *i* and *j* respectively, g_{ij} is the line conductance and b_{ij} the line susceptance.

In the developed studies, AC OPF is applied using a composite objective function that consists of two terms: the first is minimization of the total load curtailment, whilst the second is minimization of the total generating cost. Its mathematical formulation is:

$$min\left\{z = \sum_{j} C_{Gj} \cdot P_{gj} + \sum_{i} VOLL_{i} \cdot Pc_{i}\right\}$$
(2-17)

Subject to

$$P_{gi} - (P_{di} - Pc_i) - \sum_{ij} P_{ij} = 0$$
(2-18)

$$Q_{Gi} - (Q_{Di} - tg(\varphi_i) \cdot Pc_i) - \sum_{ij} Q_{ij} = 0$$
(2-19)

$$-I_{ij}^{max} \le I_{ij} \le I_{ij}^{max} \tag{2-20}$$

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$$P_{gj}^{min} \le P_{Gj} \le P_{gj}^{max} \tag{2-21}$$

$$Q_{gj}^{min} \le Q_{gj} \le Q_{gj}^{max} \tag{2-22}$$

$$V^{\min} \le V_i \le V^{\max} \tag{2-23}$$

$$0 \le Pc_i \le P_{di} \tag{2-24}$$

where C_{gj} is marginal cost of generation P_{gj} at node *j*, *VOLL*_{*i*} is value of the lost load *Pci* at node *i*, P_{Di} , Q_{Di} and φ_i are active load, reactive load and load angle at node *i*, $P_{ij}(\cdot)$, $Q_{ij}(\cdot)$ are active and reactive powers in branch *ij*, Q_{gi} is reactive power production of a generator at node *I* and I_{ij} is current flow in branch *ij*. The lower and upper limit values are denoted by superscripts min and max, respectively.

Equations (2-18) and (2-19) define active and reactive power balances at all nodes. A constant power factor is assumed for each nodal load, giving reactive power curtailment $tg(\varphi_i) \cdot Pc_i$ in (2-19). Active $P_{ij}(\cdot)$, reactive power flows $Q_{ij}(\cdot)$ and current $I_{ij}(\cdot)$ in branch *ij* are functions of terminal voltage magnitudes and angles.

Thermal constraints of all branches are expressed by inequalities (2-20), in which either STR or RTTR is used for OHL. Voltage constraints are given by (2-23), whilst limitations of dispatchable generation are modelled with (2-21) and (2-22). Limits on load curtailments are shown in (2-24).

2.5.2 DC OPF Model

AC power flow algorithms have high calculation precision but does not have fast speed. In system planning or power market analysis, the requirement of calculation precision is not very high, but the requirement of calculation speed is of most concern, especially for a large-scale power system. The DC power flow is a simplification of AC power flow, which is also called MW-only method. DC power flow requires voltage maginitutes to be equal to 1pu,

ignore the resistance of the branch (only branch reactance x_{ij} is considered) and the angle difference between the two ends of the branch is very small so that $cos\theta_{ij}=1$ and $sin\theta_{ij}=\theta_{ij}$.

The general DC OPF used in the developed studies is described by the following equations:

$$min\left\{z = \sum_{j} C_{gj} \cdot P_{gj} + \sum_{i} VOLL_{i} \cdot Pc_{i}\right\}$$
(2-25)

Subject to:

$$P_{Gi} - P_{di} - B_i \theta = 0 \tag{2-26}$$

$$P_f = H\theta \tag{2-27}$$

$$-P_{ij}^{max} \le P_f \le P_{ij}^{max} \tag{2-28}$$

$$-P_g^{min} \le P_f \le P_g^{max} \tag{2-29}$$

Using DC OPF, constraints (2-26) represent nodal power balance equations, which also include potential contingencies within the system matrix *B*. Constraints (2-27) express the branch flows in terms of the nodal phase angles, while constraints (2-28) enforce the corresponding branch flow capacity limits. Finally, constraints (2-29) set the generation limits.

2.6 Conclusions

This chapter described the assessment techniques of power system reliability analysis. Reliability adequacy studies can evaluate better network operation states, since they can consider all the possible uncertainties (load, generation, transmission lines, weather, etc.) and thus can contribute to more objective decisions. Probabilistic studies are classified as state enumeration and simulation techniques. A comparison between the two techniques was given to show the capabilities of both techniques and the limitations of the state enumeration technique are highlighted. Simulation methods include sequential and non-sequential Monte Carlo simulations. A detailed algorithm of both types and how they are modeled was given. There are two important differences between sequential and non sequential approaches. Failure effects are studied in a chronological time order in sequential simulation, whereas in non-sequential the availability or unavailability of a component is not related to the previous or next MC trial. The second difference is associated with the load model. In sequential MC approach the annual load curve is used with the hourly granularity, whilst a multi-step load curve is usually applied in the non-sequential procedure. The chapter also provided a list of the most commonly used indices in composite power system reliability assessment.

3 Literature review on Smart Solutions in Energy Systems

3.1 Demand Response literature review

In order to meet the security criteria, the system operators usually rely on the available transmission and generation capacities, as well as ancillary services provided by generators. In such a system, consumers behave in a passive way as: 1) There is no direct communication between the system operator and consumers; and 2) Consumers are not equipped with smart devices, which can change consumption promptly.

In the future power system, however, consumers will play an important role in improving the security and reliability of the system. The idea is to provide smart home energy management systems to consumers, and on a broader scale, to create a smart grid so that consumers will become more alert to the energy price and power system status. In such a system, consumers are very likely to change their consumption pattern based on the signals, which they receive from system operators. Changes in end-user demand in response to the electricity market signals or network operators' signals are defined as demand response programs.

In [47] demand response programs are categorised into Incentive Based and Price Based programs (IBP & PBP) as shown in Figure 3-1. Under an incentive based program the customer might provide an ancillary service - usually in the form of load curtailment - at a

time when the network experiences a security problem. A contract between the system operator and the customers defines such services, which includes level of load curtailment, service payments and penalties for not responding at the required time. In the case of a long term contract, customers bid for load curtailment in the electricity market and as a result market operators have more flexibility for balancing the system or dealing with possible outages.

In a price based demand response program, consumers receive a dynamic energy price rather than a flat tariff. Being updated on the energy price for any market balancing period, consumers are very likely to shift some loads to the times when the energy price is lower. One of the main objectives of the price-based demand response program is to have a rather flat daily load profile. In this way, some of the investments, which are made to maintain the reliability of supply during peak hours can be deffered or even cancelled. Therefore, as an alternative to transmission expansion, consumers can be encouraged to either change their consumption patterns or participate in other types of demand response.

An incentive based demand response program is investigated in this thesis for a day ahead planning with the aim to improve network reliability and maximize financial incentives for the customers. The whole analysis is applied on the transmission level; demand response applications for different network scales, load types and network conditions are discussed next and developed in Chapter 4.2.



Figure 3-1: Demand Response Programs classified in different categories [47]

The role of Transmission System Operator (TSO) is to maintain the transmission system and to make sure that the system is run within operational standards and limits by balancing demand and supply at all times. Electricity is traded from several years in advance up to 1 month before physical delivery through forward contracts that are bi-lateral or over-thecounter via a broker. From 1 month prior to delivery up to Gate Closure, electricity is traded on the Power Exchange (PEX), ran by APX, or over-the-counter through a broker, where participants can continusously trade their positions before giving their Final Physical Notification to National Grid. The day-ahead planning of generation in the GB is hence done on the PEX, one day prior to real-time delivery. Under the Balancing Settlement Code, participants are required to submit an Initial Physical Notification at 11am at the day-ahead stage and their Final Physical Notification at Gate Closure. After Gate Closure, National Grid is responsible for matching system supply and demand up to the point of delivery through the Balancing Mechanism (BM), which typically accounts for approximately 2% of any given day's electricity volume [48]. In the wholesale market, Elexon in the UK is responsible for calculating the imbalance volume and imbalance price if actual volumes do not match the expected production or consumption, and make sure that any money paid for imbalances are settled [49]. In order to further improve the security of the power system, in this thesis demand reduction strategies are applied during peak hours when network contingencies may occur. This resulted in savings sufficient to compensate the supply cost associated with load recovery at off-peak hours. Therefore, it is necessary to evaluate the impact of both load reduction and load recovery in a probabilistic framework.

DR programs can be applied to various company sectors such as transmission, distribution and retail. Yet DR has been mainly studied for distribution systems (DS) [50], [51] and partly for the transmission systems [52], [53], whereas little research has been conducted in a retail sector [54][55]. The developed DR scheduling focuses on a day-ahead planning of a transmission network considering all customers across the whole power system.

The integration of DSM in the TS operation and planning process has become a topic of interest over the last twenty years. At present, only industrial loads are controlled by TSO in system emergencies. However, if the smart metering is able to report the potential demand response of the domestic customer sector ahead of real-time operation, the TSO could provide various actions, such as central generation rescheduling, full deployment of non-reschedulable generation, etc. [56]. As a result, knowing the demand response on a system level, TSO can minimize the cost of consumer's electricity by optimizing their operating actions. In this regard, TSO can also affect the most economic load recovery for all loads, which participated in demand response. Examining both the impact of load reduction and load recovery is important for demand response scheduling; a literature review of demand response based on load-types, sizes as well as network contingency levels is discussed next.

DR is dependent on load-types, since consumption (and recovery) patterns are different for each customer type. This involves shedding and recovering loads specific to the type of customer (i.e. residential, industrial, large users and commercials), or to specific appliances. Domestic and small commercial loads are studied in [55][57][58] but the research fails to assess how critical each customer type is at specific network load point in terms of number and duration of interruptions.

Load-size DR models put particular focus on the load recovery amount given that the amount of load recovery may not necessarily be equal to the amount of load reduction [59]. No study

has yet assessed the effect of the duration of planned or forced outages on the energy reduction or payback for different consumer types, except in [60]. However, research in [60] only refers to different industrial load recovery shapes following an outage, making the generalization for other load types questionable. Examining different sizes and shapes of both load reduction and recovery is thus essential for a complete and accurate network assessment.

DR can also be applied following a network contingency [61][62]. While customers reduce their consumption in system emergencies, when high nodal prices are expected, the effect of load recovery is ignored [61][62]. DR savings for TSOs are accounted for in [9] using enumeration techniques, as opposed to Monte-Carlo Simulations, and thus fail to include the whole set of contingencies a network might incur [20]. Finally, instead of applying DR every time a contingency occurs, as in [61][62], which may lead to adverse effects for the TSO, DR should be applied only when the reliability is improved and when savings are higher than the expected cost of paybacks.

In this thesis, essential features of the Demand Response scheduling are as follows:

- Optimal nodal load reductions are calculated using the optimum power flow model, and are then dissagregated into voluntary and involuntary components. Voluntary component represents the amount of DR at a particular node, which has been agreed between the customer and the TSO on a contractual basis.
- Different load recovery profiles for customer types are considered within 'payback periods' and they are initiated when the load customer's revenue is highest.
- The whole modelling is implemented from the load customer's perspective to maximise their revenues.
- The analysis is applied in a probabilistic framework and hence the network performance improvements are quantified.
- Financial risk measures are used to determine the economical potential of applying Demand Response.

3.2 Thermal Ratings literature review

The current planning and operational practice considers constant thermal rating under normal conditions for a transmission line assuming pessimistic weather conditions [63]. Based on steady state conductor temperature, CIGRE proposed a widely used method for thermal rating calculation [64]. Nonetheless, it has proven to be almost equivalent to the IEEE method [65]. For most practical transmission line design and operation applications, both methods can be considered equivalent and the difference in ampacity results are generally not significant, especially considering the precision of most environmental input parameters. For some less typical applications such as high wind speed and/or wind speed calculation when wind direction is parallel to the conductor axis, users of these standards should be aware of the variations in the calculated ratings (up to 8.5% in one particular situation examined).

Thermal rating of transmission lines depends on the weather conditions and therefore it changes as these conditions change with time [66]. According to the method proposed in [67], a maximum allowable conductor temperature is selected and thus the corresponding permissible current can be derived. In this calculation, some assumptions about the weather conditions and the position of the sun are required. In most deterministic approaches, the worst case scenario is considered using ambient temperature Ta=40°C, wind speed 0.61-1.53m/sec, solar radiation 890-1100W/m², emissivity 0.1-0.5 and absorptivity 0.1-0.6 [67]. Besides, several deterministic methods assume wind direction perpendicular to the conductor. This assumption overestimates the thermal rating as it does not consider the case of conductor overheating when the wind is blowing parallel to the conductor axis. It is demonstrated in [68] that the conductor cooling due to wind parallel with the conductor axis is approximately 40% of that when the wind is perpendicular to the axis. In addition, although the values of the relevant parameters are chosen in such a way to provide safety margins, there is still a small probability that the real temperatures exceed 40°C. Thus, it can be concluded that even conservative deterministic methods can lead to inappropriate thermal ratings and hence conductor overheating and aging.

Some other factors should also be considered when thermal raings of OHLs are calculated based on OHL physical properties, e.g. conductor sag, loss of strength and fittings. In [69],

the impact of line overloading above thermal rating on the conductor chemical and physical properties is assessed and a composite risk model is derived based on this impact. In [70], the main factors which must be considered when setting the thermal ratings are conductor sag, conductor loss of strength due to annealing and limitations of the conductor fittings. It has been shown that the conductor fittings can be ignored if they are appropriately designed [71]. For that reason, the method proposed in [69] considers only conductors sag and loss of strength. In this model the conductor strength decreases up to the point when it becomes equal to the tension load. After this point, the conductor breaks which identifies the end of its life. Assuming that, initially, the conductor expected lifetime is t_{init}, this time decreases as the conductor operating temperature becomes higher than the thermal rating. The time reduction is caused by the conductor annealing, which increases the rate of conductor loss of strength. However, the method described in [69] does not consider the benefits of increasing the transmission line thermal rating. In other words, although the risk levels associated with such actions increase, the load curtailments decrease and therefore, there are many economic incentives for increasing the thermal capacity of lines. Consequently, a reliability analysis should be performed with higher thermal ratings in order to assess improvement in system reliability indices.

Assuming that mechanical and physical characteristics of OHLs are within limits, weather data models are investigated to precisely calculate thermal ratings. In [72], historical weather condition measurements are used for a statistical analysis and thereby for the calculation of thermal ratings. For instance, when the measurements are obtained by the weather stations or monitoring devices the probability distribution function (PDF) of the ambient temperature and the wind speed can be defined for the particular geographical region. Since the parameters of the PDF are specified, the sampling result can be plugged into the IEEE thermal model and the maximum ampacity of the conductor can be calculated. The probabilistic methods also include some assumptions of other relevant parameters, such as solar irradiation, which are usually selected in a deterministic way. Acquiring data from PDFs can be applicable only to non-chronological studies. Besides, producing weather PDFs on a yearly basis is less accurate than considering smaller chronological intervals unless the data show the same pattern thoughout the entire year.

In [73], a probabilistic method for seasonal thermal rating calculation is proposed. According to this method, the sets of weather condition measurements should be divided into subsets depending on the season in the year. Each subset is analyzed separately and different thermal ratings are calculated for each period of time. As a result, the thermal ratings are closer to the actual ampacity of the lines and higher utilization of the network is achieved. However, these methods make use of static thermal ratings, which are set in advance and are not affected by the operating conditions of the lines.

In [74], the advantages of dynamic thermal ratings over the static thermal ratings are discussed. These ratings are based on real time measurements and therefore they are close to actual ampacity of the lines. This can significantly increase the utilization of the network and enhance system reliability. Moreover, the changing ratings are continuously monitored and reported to the system operator providing warnings about potential network congestions. The biggest disadvantage of dynamic thermal ratings is the expensive monitoring devices, which are required to provide real time measurements.

Conductor temperature measurements are used in [75] to calculate dynamic thermal ratings of OHLs. Conductor's temperature measurements of an 115KVA transmission line demonstrated that 80% of the time in December the dynamic thermal rating is 15% higher than the fixed thermal rating. In [76], it is proposed to use a dynamic cable rating (DCR) system which has been deployed to alleviate the congestion in a cable connected to a power plant in the south of Texas. However, the proposed DCR system is also used to benefit system operator's position in the energy market. In particular, the weather forecast is used to estimate the available ampacity and so the real time market price is analyzed in order to achieve the best bidding strategy in the market.

RTTR applications have also contributed to increase wind energy utilization. In [77], probabilistic analysis for RTTR application is proposed to facilitate wind integration in Humber Estuary region. This study addresses the challenging task for National Grid to accommodate the imminent wind powers. This is the consequence of the lack of transmission capacity, which forces the wind generation to spill excess wind through throttling of the turbines. Probabilistic models of the wind power and dynamic thermal ratings are proposed to calculate system benefits. The models proposed, based on actual meteorological data of

the region and thus the seasonal correlations between wind power and thermal ratings of transmission are also calculated. MCS was used for the analysis taking into consideration the relevant probability distributions functions and the corresponding correlations. After having applied sensitivity analysis, the transmission lines on the top of priority for real-time thermal rating monitoring were tracked and the economic benefits from using RTTR were calculated. However, the whole analysis was conducted without taking into consideration how the conductor temperature affects the thermal ratings, as it was assumed to be fixed. Also, the analysis doesn't consider the impact of RTTR on wind spillage values as well as on the loss of load in the Estuary region. Similarly, in [78], a statistical model is introduced for RTTR of OHL in a wind intensive area. More specifically, laboratory tests were conducted with maximum, medium and minimum wind speed measurements using the various thermal time constants of a particular conductor. The results of these tests were used as a guide for measurement rate of weather parameters. According to that, 5 minutes measurement step was chosen as the best time interval to include the transient behavior of the conductor temperature in the RTTR model. Monitoring system was placed in two 110kV single circuits and the measurements (weather conditions, output conductor temperature and load parameters) plugged into the model, which resulted in an estimated conductor temperature for the particular circuits with an average error of 0.5 degrees. It should be mentioned that the advantage of this model is that it predicts the conductor temperature without taking into account the physical parameters of the conductor. However, the accuracy of the model is valid for low load levels. New measurements should be carried out for high load (high conductor temperature) to validate the accuracy of the model, as well as to find the impact on the reliability of the local network examined.

In [79], a probabilistic technique in conjunction with reliability analysis is proposed to calculate the thermal rating. More specifically, the hourly values of ambient temperature, wind speed and wind direction are measured for a 144hour period. Then the PDF of each ambient condition is identified, whereas the maximum allowable conductor temperature and the solar heat gain are selected deterministically. Using all these values and running sequential MCS, the probability distribution function of the conductor thermal rating can be derived for the next hour. Considering all the previous methods, a maximum allowable conductor temperature is assumed in such a way that the risk of thermal rating violations is

kept at minimum. None of these methods, however, considers the consequences of a thermal rating violation related to the conductor integrity.

To summarise, it is proposed in this thesis to use real themal ratings of OHLs in a probabilistic framework in order to achieve the following goals:

- 1) Calculations of the real conductor temperatures in a sequential analysis and capture the impact of this on real thermal ratings as well as on network reliability.
- 2) Calculations of the real conductor resistances in a sequential analysis and capture the impact of this on real thermal ratings as well as on network reliability.
- 3) Seasonal thermal ratings are produced using weather PDF functions obtained from weather measurement subsets depending of the season of the year.
- 4) Increase network operation flexibility to undertake the most economical actions in a probabilistic analysis by connecting RTTR with cheaper generation units.
- 5) Quantify the true potential of demand response when real time thermal ratings of OHLs' are calculated.

3.3 FACTS literature review

In a flexible network, the deployment of FACT devices can be done for enhancing the reliability of the network and mitigating the post fault violation of network constraints. In this way the flexibility of the system to unforeseen uncertainties can be boosted. Since construction of FACTS devices is an alternative to network reinforcement, it is necessary to compare the cost of network expansion with the cost of deploying these flexible options.

A number of FACTS characteristics are listed below [80]:

- High-gain type controllers based on high-speed switching,
- Improve steady state system performance, that increase transmission capacity and control transmission flows, as well as improve voltage profile across the system,
- Improve system transient and dynamic stability by damping system oscillations,
- Reduce financial costs and environmental impact associated with building new transmission lines,

• They are highly reliable devices and require minimal maintenance.

Three different FACTS can be chosen to control the power flows and voltages in a network. The first device is the Thyristor-Controlled Series capacitor, TCSC [29][81], which directly alters the transmission line reactance. The second is known as the Thyristor-Controlled Voltage regulator, TCVR [82][83] and controls the magnitude of the voltage. The third is Thyristor-Controlled Phase Shifting Transformer, TCPST, which modifies the phase angle and active power flows [84].

Since changes in active power flow lead to a change in the reactive power demand in the entire network, whose variations may prove difficult to handle using the distant generators, a Static Var Compensator, SVC, is added to the three already selected componenets. SVC is mainly used to improve the voltage profile in the network. The influence of FACTS on the power transmitted on a line between two buses i and k, is presented in Figure 3-2. The active power flow P_{ik} is influenced by phase angle difference δ_{ik} and reactance x_{ik} , whilst reactive power flow is related to the difference in nodal voltages (V_i - V_k) and reactance x_{ik} . Consequently, Figure 3-2 shows the active power flow equation between two buses i and k and its variables that can be controlled by each FACTS devices.



Figure 3-2: Impacts of FACTS devices on the variables involved in the active power flow equation

There are many FACTS applications but UPFC are probably the most versatile FACT devices, because they can control and optimize the active and reactive power flows in the transmission systems. UPFC is comprised of the static synchronous compensator (STATCOM) and the static synchronous series compensator (SSSC).

A literature review of different models of FACTS as well as detailed FACTS physical modellings and their impact on the reliability assessment of a power system is given in the following paragraphs.

UPFC is initially employed in [85] for reliability evaluation of composite power systems. In this study the reliability model of UPFC is represented by a two state Markov model and the effect of this is assessed on both IEEE RTS system and Roy Billington Test System (RBTS) system. It is shown that in the IEEE RTS system the FACT device has almost no effect on the system reliability, whereas it slightly improves the reliability of the RBTS system. This is because both systems are strong and reliable transmission systems. However, it is indicated that in the event of load growth the FACTS can significantly improve transmission reliability.

In [34], UPFC is included in the reliability analysis of the power system. A simple two-bus network is utilized as a demonstrative system, and reliability indices are calculated. The UPFC device is modelled as a two state component in the system and its outage would not affect the connected transmission line. The results show that the reliability indices decreased considerably when the UPFC device was applied. This means that the application of UPFC considerably improved the reliability of the system.

At the same time, the impact of UPFC on power system reliability is studied in [34] and it is shown that UPFC is not sufficient due to the simple two bus system studied as well as neglecting the optimal UPFC control mode and settings. In [86] the physical model of the UPFC device is developed. Thus, the optimal mode and settings can be easily selected and so the reliability of the system will be improved to a greater extent. The reliability indices are calculated including the expected unserved energy cost (EUEC) and the expected load curtailment (ELC). The proposed methodology is applied to a nine-bus system (Western System Coordinating Council-WSCC) and the results showed that UPFC control mode has a significant effect on post-contingency conditions. Also, the results of reliability analysis proved that the reliability of the power system significantly increased because of use of the UPFC.

A comprehensive reliability model of a 16-state distributed static series compensators (DSSCs) is discussed in [87]. The best placement scenario of DSSC is determined based on

EENS and EIC reliability indices on the IEEE RTS 24 bus system. In particular, the deployment of DSSCs decreases EENS by 12.32% and EIC by 14.56%. Comparative studies showed that increased value of communication link failure rate and repair time make EENS index higher than without communication link failure.

A comparative study utilizing three types of FACTS devises is done in [88] for reliability evaluation of power systems: SVC, STATCOM and thyristor controlled series compensator (TCSC). More particularly, a modified four state-model is used to model the SVC, a series reliability model is used for STATCOM, both a two state and three state models are used for TCSC. The central control unit of all FACTS is presented by a two state model. Consequently, sequential Monte Carlo simulation is applied for the reliability analysis and the results indicate when the reliability improvement outweighs the increase in investment and O&M costs. The study concludes with the comparison between traditional reinforcement and corrective control with FACTS; the FACT devices are undoubtedly preferable in terms of reliability and economic improvements.

Beside the impact of FACTS on system reliability, the benefits of FACTS on power losses, operational cost and other features have been investigated. There are several approaches for optimal placement and sizing of FACTS reported in the literature. The multiobjective evolutionary algorithm has been applied to optimally locate the UPFC [89] and the thyristor-controlled phase-shifting transformer (TCPST) in order to minimize real power losses [90]. Particle swarm optimization (PSO) technique is used to find the optimal location of TCSC, SVC and UPFC to improve system loadability [91]. Similarly, evolution strategies are used in [92] to optimally locate FACTS in order to determine maximum increase of system loadability while keeping the power network secure. The optimal placement of FACTS, whilst considering total fuel cost is investigated in [33]. The best location of UPFC to minimize the generation cost and the UPFC investment cost was found using steady state injection model of UPFC, continuation power flow technique and OPF technique [93]. Multiple UPFC optimum placement is developed in [94] investigating a centralized optimal control scheme using evolutionary programming algorithm to provide best voltage profile.

In summary, no research was done so far to investigate the impact of FACTS on the following aspects:

- Determine best FACTS locations based on ranking lists of nodes and branches most appropriate for connection using load and wind curtailments as the objectives,
- Optimum FACTS operation using probabilistic indices such as expected energy not supplied (EENS) and expected wind spillage index (ESP).
- Quantify network reliability improvement when optimally located FACTS are involed in system's operation.

3.4 Corrective Scheduling for Renewable Energy Sources literature review

Connection of wind energy sources has continuously grown over the last decade, giving saturated levels and deferral to new wind connections in some countries [95][96]. The size of wind capacity that can be accommodated is usually driven by network thermal and voltage constraints, fault ride-through and stability capabilities, required spinning reserve, etc. [37][97][98][99]. Once wind units are connected, system operator needs to consider both network security and contractual obligations with generators; the latter is usually expressed in terms of maximum allowable wind curtailment or 'spillage' [37][100]. To this end, the operator can apply various controls to keep the wind spillage under the prescribed level and even increase the deployable wind generation.

Different aspects of wind energy integration have been investigated in [97] - [101]. Hydropumped storage is used in [97] to increase deployed wind power during frequency disturbances, whilst studies [100][24][25] use energy storage to consume surplus wind production. Research in [98] determines how increased wind integration affects the system indices, stochastic unit commitment with wind generation is introduced in [99], whilst advanced wind forecasting techniques are applied in [102]. Maximization of connected wind sources to meet deterministic security criteria is done in [103][104]; required wind spillages are determined for different wind connection levels, but they are not optimized. Besides, it was not recognised that maximum wind capacities can be found from the contracted wind spillages using a probabilistic approach only. Reliability studies, which include probabilistic wind modelling, usually do not include wind spillages [105][106][101]. The applied approaches did not consider that load and wind curtailments should be jointly treated. Integration of even higher levels of wind generation can be achieved through network reinforcements [101][39][107]; although the approach in [39] considers wind curtailment cost term, it fails to recognise stochastic nature of network component and unit failures.

The optimal power flow (OPF) analysis can be used to to minimize the levels of wind spillage and thus increase the connections of renewables of different type. The corrective actions used in an OPF can be scheduling of flexible generation units, application of dynamic thermal ratings of overheal lines or cables, application of energy storage, voltage or active and reactive power regulation using FACTS devices and demand response scheduling. A generation scheduling model is used in [108] to maximize wind and solar generation outputs. A Lagrangian relaxation method and particle swarm optimization methods are used to solve the problem of maximum wind integration. Similarly, an N-1 secure day-ahead dispatch of generation units is proposed in [109] to optimally deploy wind generation. However, it has to be pointed out that it is necessary not only to decrease the levels of wind curtailment, but also to reduce the frequency and duration of wind curtailments. For example, Figure 3-3 shows wind spillage probability values for the whole of the UK [110]. It is shown that the highest probability of 0.7 has wind curtailment up to 100 MW, whereas probability less than 0.12 is recorded for highest magnitudes from 200-1500MW. Although information is given about the magnitude of wind curtailments, there is no information about duration and frequency of wind spillages subject to different network outage durations. For this reason, it is essential to carry out a probabilistic - sequential analysis in order to identify the expected values of wind spillage magnitudes, durations and frequency whilst taking into account all possible network uncertainties.


Figure 3-3: Wind Power curtailments in the UK - National Grid [110]

The following operational and control procedures can be used to allow for further wind deployment, while maintaining network operation within satisfactory voltage and thermal limits:

- 1) Demand side management (DSM) and demand side response (DR):
 - a) Apply DSM/DR at the receiving end of (an) overloaded line(s), or at nodes whose voltage is below a lower limit,
 - b) Apply DSM/DR to the loads whose contribution to mitigating an overload or undervoltage is highest,
 - c) Apply optimum power flow (OPF) in the form of the minimum load curtailment (MLC) model, whose objective is minimisation of weighted load curtailments (i.e. DSM/DR loads with different priorities), subject to thermal and voltage limits being satisfied.
- 2) Energy storage:
 - a) Reduce asset overload, particularly during network contingencies (discharging),
 - b) Providing voltage support by reactive current injection (discharging),

- c) Absorb high levels of DG generation and resolve potential overvoltage problems (charging),
- d) Shift load to ensure network security,
- e) Phase balancing.
- 3) Generation constraint management:
 - a) Reduce generation at a node with excessive voltage or at the sending terminal node of an overloaded circuit/transformer,
 - b) Reduce generation at all nodes which contribute most to the mitigatation of the considered thermal or voltage problem,
 - c) Apply OPF model in which 'production cost' of variable DG is minimised. Negative weights are associated with the (linear) term of variable DG 'production costs', so that generation of variable DG is in fact maximised within pre-specified limits. If all variable DG are of equal importance (i.e. there is no priority order in generation constraint management), all weights can be set to -1.
- Dynamic network reconfiguration (refers to moving the Normal Open Points (NOP) across the network to satisfy preselected security or economic based criteria) using the following prioritised objectives,
 - a) Optimise the economic criterion if all loads can be supplied, with no generation curtailment and all operating constraints satisfied.
 - b) If the generation or load curtailment is required, use contracted variable DG or DSM/DR. Minimise variable DG curtailment or amount of DSM/DR if the (rest of) load can be supplied within operating constraints.
 - c) Where operational constraints cannot be satisfied, minimise (squared) violation of network constraints (i.e. voltage and thermal limits) so that the load is supplied and DG is within specified limits; variable DG curtailment and DSM/DR load shedding can be taken into account.
 - d) Where the 'fixed' load or DG cannot be delivered, maximise delivered load or DG production while meeting some of the operational constraints.
- 5) Application of dynamic circuit and transformer ratings will consider,

- a) Thermal overload elimination by increasing network capacity.
- b) Improve the security of the system by keeping the network within dynamic thermal limits.
- c) Facilitate increased connection of wind generation.

Deployed Models of Low Carbon Technologies and Smart Solutions

Summary:

This chapter provides models of smart solutions used to mitigate operational and planning issues incurred by connection of low carbon technologies, as well as to improve performance of the power networks. Models of new low carbon technologies (LCTs), such as renewable sources (wind), are presented in this chapter. Then new "smart" solutions are developed and implemented when there are operational and planning issues (e.g. violation of operational limits, planning standards, etc). The considered "smart" solutions are demand side management (DSM), real time thermal ratings (RTTR), FACTS and corrective scheduling. Each smart technology methodology is developed in the context of the probabilistic approach used for reliability analysis. All assumptions and considerations used for the development of the reliability-based models are presented alongside appropriate justifications.

4.1 Wind Energy Deployment

4.1.1 Overview of the methodology

The objectives of the proposed probabilistic approach for day-ahead planning of systems with large penetration of wind are threefold: a) Maximize deployed wind generation to meet contractual obligations; b) Increase overall system reliability; and c) Reduce system operation cost including costs of non-delivered load and curtailed wind generation. These objectives are achieved by following means: a) Reschedule dispatchable generation; b)

Curtail load and wind generation; c) Deploy SVC and TCSC devices; and d) Deploy RTTR on overhead lines (OHL). The developed models of the last two controls (FACTS (SVC&TCSC) and RTTR) are described in more detail in Chapter 7.

The main building blocks of the optimum wind deployment are:

- 1. Connection of wind generation using industry criteria.
- 2. Prioritization of wind curtailments by allocating the 'cost coefficients' to wind curtailments in order to get the optimum wind energy deployment.

These building blocks are described in the next section, whilst the corresponding simulation results are presented in Chapter 7.

4.1.2 Connection of wind generation

To speed-up connection process, utilities often provide developers with maximum permissible generation capacities that can be connected at system nodes. The calculation can be done using either formula-based approach [111], or more complex iterative load-flow method [112]. The non-firm connection denotes calculations based on the intact network, whilst firm connection implies single circuit outages [103][104].

The formula based approach, also applied by the French transmission system operator RTE [111], makes use of the following assumptions: a) First Kirchhoff's Law is used; b) All lines originating from node *i* are fully loaded; and c) Most onerous operating regime is considered. The maximum connection capacity P_{WGi}^{max} of wind generation at node *i* is:

$$P_{WGi}^{max} = (P_{Di}^{min} + pf \cdot \sum_{l} S_{l}^{STR} - P_{Gi}^{up})/\beta$$

$$(4-1)$$

where P_{Di}^{min} is the minimum load at node *i*, *pf* is the power factor, S_l^{STR} is line *l* seasonal thermal rating, P_{Gi}^{up} is envisaged existing generation at node *i*, and $\beta \in [0, 1]$ is the ratio of the expected wind speed during summer minimum with respect to the maximum speed (typically 0.8 in RTE [113]). Summation in (4-1) goes over all lines *l* connected to node *i* in case of non-firm connection, or over all lines *l* but the one with the highest capacity in case of firm

connection. The total wind generation that can be connected at all nodes in the network is then limited to [105]:

$$\sum_{i} P_{WGi}^{max} \le v \cdot P_D^{peak} / wf \tag{4-2}$$

where v is the percentage of peak demand that can be supplied by wind generation, P_D^{peak} is the system peak demand and $wf \in [0, 1]$ is the wind factor indicating percentage of the total wind capacity utilized to supply the peak demand.

The main idea of the load-flow based approach is to gradually increase 'new' generation at node *i* and run the AC power-flow until one of the thermal or voltage constraints is not reached. In case of wind generation, the maximum connection capacity is further divided by the factor β as in (4-1). In this way, both non-firm and firm connection capacities are found.

4.1.3 Wind Curtailment Prioritization by Using Cost Coefficients

All OPF calculations are initially done with wind spillage coefficients equal to unity. The results so obtained indicated that it would be advantageous to associate different 'cost coefficients' to wind curtailments. To this end, wind spillages are classified as 'voluntary' and 'involuntary'. The first category relates to the quantity limited by the contracted average annual spillage (usually around 5%) and priced at contractual price σ_w (σ_w =55.5 £/MWh is used [104]). Involuntary spillages are limited by the maximum allowed wind curtailment and are priced using the marginal prices at the considered nodes. The cost coefficients are defined as:

$$\xi_{i} = \begin{cases} \overline{BESP_{i}}^{rel} \cdot \sigma_{w} & \text{, voluntary spillage} \\ \overline{BESP_{i}}^{rel} \cdot \mu_{i}^{p} & \text{involuntary spillage} \end{cases}$$

$$(4-3)$$

$$BESP_i^{rel} = \sum_{y=1}^{Y} \sum_{t=1}^{T} \left(\frac{SP_i^{y,t}}{P_{WGi}^{up}} \right) / Y$$
(4-4)

where ξ_i is spillage cost at node *i*, $BESP_i^{rel}$ is expected relative spillage at node *i* in the first SMCS, σ is contracted price, μ_i^p is p-th percentile of base marginal price at node *i*, *Y* is total

number of simulated days, T=24h, and $SP_i^{y,t}$ is spillage at node *i* day *y* hour *t* from the OPF results. \overline{BESP}_i^{rel} in (4-3) is normalized expected spillage at node *i*; normalization is done with $\Sigma_i BESP_i^{rel}$ over all nodes. Note that μ_i^p are hourly marginal prices (or Lagrange multipliers) from the OPF model and the percentile values are obtained when the first simulation stage is completed (see section 7.1.1).

The cost coefficients (4-3) are associated with the linear cost terms in the OPF objective function in the second simulation stage – Chapter 7.1.2. Another option is also examined to define spillage cost coefficients by 24 hourly periods; then equation (4-4) is replaced with:

$$BESP_{i,t}^{rel} = \sum_{y=1}^{Y} \left(\frac{SP_i^{y,t}}{P_{WGi}^{up}} \right) / Y$$
(4-5)

Normalized spillages $\overline{BESP}_{i,t}^{rel}$ are used in equations (4-3) where normalization is again done over all nodes $\Sigma_i BESP_{i,t}^{rel}$.

4.1.4 Wind turbine modelling

The available wind energy production in a forthcoming year is highly uncertain; it is highly dependent upon wind speed, wind direction, location, altitude and terrain. Because of this, aggregated daily profiles do not represent the conditions seen in the reality. For this reason the wind generation output is modelled on the network busbar level rather than using the uniform wind profile across the entire system. Besides, the developed model is considered for periods of high and low wind generation at times when local and system maximum and minimum loading levels occur.

The power output of a wind turbine generator (WTG) is driven by the wind speed and the corresponding relationship is non-linear. It can be described using the operational parameters of the WTG, such as cut-in, rated and cut out wind speeds. The hourly power output is obtained from the simulated hourly wind speed using the relations.

$$P(V_m) = \begin{cases} 0 , 0 \le V_m \le V_{ci} \\ (A + B \times V_m + C \times V_m^2) \times P_r , V_{ci} \le V_m \le V_r \\ P_r , V_r \le V_m \le V_{co} \\ 0 , V_m > V_{co} \end{cases}$$
(4-5)

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where P_r , V_{ci} , V_r , and V_{co} are, respectively, rated power output, cut-in wind speed, rated wind speed and cut-out wind speed of the WTG, whilst V_m is simulated wind speed at hour *t*. The power output constants A, B and C are determined by V_{ci} , V_r , and V_{co} , as shown in [33]. All WTG units used in this study are assumed to have cut-in, rated, and cut-out speeds of 14.4, 36, and 80km/h, respectively.

Three different WTG types whose nominal powers are different are used in simulations; $P_r=10MW$, $P_r=6MW$ and $P_r=2.5MW$. Since weather stations are at different heights, it is necessary to convert the wind speed at the corresponding height of the WTG's altitude. It is shown in [114] that the turbulence theory in the surface boundary layer has demonstrated that for a contant stream flow and neutral atmospheric conditions, the wind speed profile is logarithmic and the method to convert the wind speed to different heights involves the following quantities: the wind speed at different height, *V*; the wind speed at a standard site, V_c ; and *C* being the correction factor. The conversion is described by the following expressions [114]:

$$V_c = \frac{V}{C} \tag{4-6}$$

where *C* is defined as $C = A \times \log \frac{h_{mes}}{Z_o}$, where the parameters *A* and *Z_o* vary for various landscapes. *Z_o* represents the roughness length which corresponds to the height below which the wind speed is zero and *A* is a parameter which transpose the wind measurements to the standard site. Table 4-1 gives the values of different landscape types aiming to adopt the landscape configuration effect on the required wind speed value [114].

Table 4-1: Roughness Length Z_o and parameter A for Various Categories of Ground.

Landscapes	Category	Zo (m)	А
Large areas of water (ocean, sea, lake)	1	0.005	0.166
Flat terrain with grass or very low vegetation, without tree nor construction	2	0.02	0.182
Flat expanses with possibly some insulated obstacles (trees in order dispersed) - Open area -Airport	3	0.07	0.202
Campaign with high cultures (but, vine, small fruit trees), loose bocage, dispersed habitat	4	0.25	0.229
Slightly urbanized zones	5	0.3	0.232
Dense bocage, orchards, kindling, residential suburb	6	0.4	0.240
Urban or industrial zones, forests, etc.	7	1	0.266
Centre of large cities	8	2.5	0.292

The hourly wind output profile per season (winter, spring and summer) is illustrated in Figure 4-1 considering equations (4-5) and (4-6) as well as wind turbines failures in a chronological time span. The hourly weather data of 5 years from 1997 to 2001 were obtained from BADC Met office MIDAS stations for Aonach UK area [115] and converted to 100m wind turbine wind speed using (4-6). It is shown that wind power output in winter is more frequently at the maximum power output level compared to spring and summer. On the other hand, spring and summer power outputs are at the half of the nominal power during the majority of the hours.



Figure 4-1: Wind Power outputs for Aonach UK area

4.2 Demand Response

4.2.1 Overview of the methodology

The basic steps of the proposed DR model will be discussed in this section, while the results of the model will be presented and discussed in Chapter 6.

Optimal probabilistic DR scheduling is determined using the sequential Monte Carlo probabilistic approach. The main features of the proposed DR modeling framework are: a) Load reduction scheduling driven by network security; b) Optimal scheduling of load recovery using both economic and security criteria, as shown in Figure 4-2.



Figure 4-2: Overview of DR scheduling

The load reduction technique under probabilistic analysis is realised in a separate module. Optimal power flow analysis is first deployed to assess whether network reliability is improved when demand response is triggered. If this is the case, contracted customers are sent demand respond signals to alter their consumption; else, no signal is sent and no demand response is triggered. Improvement in network operation and reliability can be achieved in both pre-fault and post-fault cases. For pre-fault analysis expected operating costs (generation and customer interruption costs) can be used, whereas for post fault analysis the EENS reliability index is used. Load recovery under network emergency conditions is a more complex problem, as it requires inputs regarding the expected duration of the system's violation, the most likely lowest marginal price under probabilistic analysis as well as load recovery profiles after different outage intervals and for different customer types. Once all these criteria are considered, OPF analysis is executed to ensure a secure system operation.

The overall methodology is realized within two independent sequential Monte Carlo simulation (SMCS) procedures [17]. The first SMCS is the initialization module, which is used to calculate several components required by the second SMCS that determines optimal day-ahead operation of the power system. The main building blocks of the first SMCS procedure are: a) Calculation of reliability indices needed for ranking of load types for demand reduction; and b) Determination of nodal marginal prices and several economic indicators used for finding the optimal schedule of load recoveries.

The second SMCS consists of four modules: a) The demand reduction scale module; b) The load recovery scale module; c) The demand reduction and load recovery (DRLR) control module, and d) The outputs module. The first module contains ranking of different load types for demand reduction, calculation of required amounts of voluntary and involuntary DR, as well as the customer revenues. The load recovery scale module considers load recovery profiles and sizes, and determines a matrix with the most appropriate schedule hours for load recovery. The DRLR-control module contains logics for initiation of load reductions and load recovery schedules, as well as reliability and financial indicators.

The equations used in the model and the case studies are presented in the following sections.

4.2.2 Methodology

The proposed demand scheduling methodology is aimed at determining the optimal demand response plan for the next day, when the committed generation units, status of network switching devices and forecast loads are well defined. However, several uncertainties in the day-ahead operation are still present, so that the overall problem is formulated as a probabilistic model and solved with the SMCS. The proposed DR methodology is applied for post contingency states; however it is general enough to also consider pre-contigency events. The main building blocks are described below.

4.2.2.1 Sequential Monte Carlo Simulation

SMCS performs analysis of time intervals in chronological order whilst taking into account various uncertainties [43]. It can model the chronological phenomena, such as load reduction and recovery, real-time thermal ratings and wind generations. The following uncertainties are assumed for a day-ahead operation of the transmission networks:

• Load varies in a window around the forecast hourly loads. The uncertainty window is defined by the Mean Absolute Percent Error (MAPE) of the short-term forecast by hourly intervals obtained using the neural network approach extensively described in Chapter 5.3.3.

- Availability of all generation and network units was modelled with the aid of two-state Markovian model with exponentially distributed up and down times.
- Hourly wind speed predictions and a window around the predicted values are applied within the random sampling. An alternative approach is to use wind speed probability distribution functions (PDFs) by hourly periods.
- The amount of voluntary load reduction varies by customer and DR type. For example, DR from residential customers responding to price signals is highly uncertain, whilst DR from incentive-based contracted commercial customers has much less uncertainty – section 4.2.4.

One SMCS period is equal to 24 hours and simulations are repeated until convergence is obtained. Any failure that goes over the planning horizon (i.e. 24:00) is considered in the 'next day' simulation. The same simulation principles were applied in both SMCS procedures.

4.2.2.2 Initialization module

The initialization module is used to calculate several quantities required by the main simulation loop. Following the data input, the network model with real-time thermal ratings and load customer characteristics is built and fed into the first SMCS procedure, as shown in Figure 4-3. The outputs from this stage are some pricing and reliability indicators.



Figure 4-3: Initialization Demand Response module

4.2.2.2.1 Input Data

The input data include network, reliability, customer, and economic data. Beside the standard network data, forecast in-service generation units with technical characteristics and chronological hourly load point demands are input. Reliability data are failure rates and repair times of all components, whilst customer data encompass customer and DR types, contracted voluntary load reductions, normalized load recovery profiles and customer availability to respond to a DR call. Essential economic data are generation costs, values of lost load (VOLL) and marginal offer prices for voluntary load reduction. Average VOLL data by customer types were obtained from the latest UK national study [116].

4.2.2.2.2 Nodal Marginal Costs

Dual variables μ are the nodal marginal costs of meeting the power balance at each system node for the considered operating regime. The nodal marginal costs have been extensively used for electricity energy and reserve pricing [117][58]. The nodal marginal prices vary over the system nodes and during the day due to load variation and congestion in the system [118]. The greatest variation of marginal prices is experienced due to unexpected failures of lines and/or generator units [119]. Consequently, these prices should be carefully considered for the load recovery scheduling.

In the proposed approach, a concept similar to the real time pricing scheme proposed in [120] is applied. The following quantities are calculated in each time step *t*:

• The revenue of generator *j*:

$$GR_{i}(t) = Pg_{i}(t) \cdot \mu_{i}(t) \tag{4-7}$$

where $Pg_j(t)$ is the active power output of generation unit *j* at hour t and $\mu_j(t)$ the marginal cost of the node at hour *t*, at which generation unit *j* is connected.

• The cost of demand *i* delivery:

$$LC_i(t) = P_{di}(t) \cdot \mu_i(t) \tag{4-8}$$

where $P_{di}(t)$ power supplied to load point *i* at hour *t* and $\mu_i(t)$ is the marginal cost of node *i* at hour *t*.

• Revenue for voluntary load *i* reduction:

$$VLR_{i}(t) = \sum_{s=1}^{s4} (\sigma_{i}^{s}(t) \cdot VL_{i}^{s}(t))$$
(4-9)

where σ_i is the marginal offer value for voluntary load reduction at load point *i* at hour *t* and $VL_i^s(t)$ amount for voluntary load reduction of load type *s*, hour *t*

• Revenue for involuntary load *i* reduction:

$$IVLR_{i}(t) = \sum_{s=1}^{s4} (VOLL_{i}^{s} \cdot IVL_{i}^{s}(t))$$
(4-10)

where $IVL_i^s(t)$ is amount of involuntary load reduction of load type *s* at load point *i* at hour *t*. Here *VOLL* is defined by load types in the initialization module, as presented in (4-10). However, in the second SMCS there is an option to use a look-up table where VOLLs are functions of interruption duration [121]. The interruption duration is estimated as:

$$D_{i}^{s} = \begin{cases} mean(D_{i}^{s \ BASE}), & if \ D_{i}^{s} \le mean(D_{i}^{s \ BASE}) \\ D_{i}^{s}, & if \ D_{i}^{s} > mean(D_{i}^{s \ BASE}) \end{cases}$$
(4-11)

where $D_i^{S BASE}$ denotes the interruption duration calculated in the initialization module. The estimated duration of interruption is equal to the mean base value unless the interruption already lasts for more than the base value; it then takes the actual duration value.

4.2.3 Demand Response Scheduling Outline



Figure 4-4: Optimal Demand Response computational framework

The computational framework for optimal demand response scheduling is illustrated in Figure 4-4. The load reduction and recovery scale modules feed into the DRLR control module. Load reduction and load recovery ranking lists are produced by the demand response initialization module introduced in section 4.2.2.2. When a constraint violation occurs on the network then demand response is activated and so *load reduction ranking list* is used to calculate available sizes for voluntary load reduction (i,s)^r at load point *i* and for load type *s* within the load reduction scale module. OPF analysis is run for the hour t_{RED} and if expected energy not supplied *EENS^{DR}* resulted from the load reduction is not improved as well as operational savings are not positive, then the next load reduction amount (i,s)^r on the load reduction ranking list is evaluated. The customers for whom the criteria on EENS and savings

are satisfied, proceed to the load recovery evaluation at hour t_{REC} . Load recovery ranking list gives load recovery amount $(i,s)^r$ at load point *i* and type s to proceed for load recovery evaluation. The customers who incur both improved *EENS^{DR}* and maintain savings are selected for DR scheduling. To summarise, both load reduction and recovery are managed by the DRLR control module in which the OPF is used to detertmine optimal voluntary and involuntary load reductions, and the developed control scheme gives the optimal load recovery profiles. The outputs module finally gives optimal DR and LR schedules, as well as financial and reliability indicators.

4.2.4 Load Reduction Scheduling module

Load reduction scale module is required for each load point and load type when load shedding takes place at the considered hour t_{RED} . The physics of demand response are presented first, which is followed by the ranking and sizing.

Four load types, industrial, commercial, large user and residential, have been defined in our approach. Different characteristics have been associated with these four types, such as temporal load variations, total amounts available for voluntary and involuntary load reductions, relative load recovery profiles and economic data. Two categories of demand response have been recognised, namely direct and indirect load control [122]. In direct load control, the contracted customers (usually large and industrial) are directly disconnected during emergency conditions and they receive revenue for participating in the 'reserve market' [123]. The contracted amounts are certain and they are of deterministic nature. In indirect load control, incentive- and price-based demand responses can be distinguished. The former group refers to the customers contractually incentivised to curtail load during system emergencies [124][125]. This category can be considered semi-probabilistic; here sampling is used within a window around the contracted value. Finally, in price based demand response customers move their consumption from periods of higher to periods of lower prices. This demand response is a probabilistic quantity, which can vary from zero up to the estimated maximum amount.

Load ranking at each node *i* and for each load type *s* at the considered hour t_{RED} is based on the financial implications of reducing the load. The ranking order is a product of the normalized value of the base expected duration interruption index (*BEDI_i*) calculated in the initialization module, the normalized marginal offer price for voluntary load reduction $\hat{\sigma}_i^s$ or customer interruption cost for involuntary load reduction, and the required load shedding Pc_i^s . This is shown in relations below:

$$\widehat{R}_{i}^{s}(t_{RED}) = \begin{cases} \widehat{BEDI}_{i} \cdot Pc_{i}^{s} \cdot \widehat{\sigma}_{i}^{s} \\ \widehat{BEDI}_{i} \cdot Pc_{i}^{s} \cdot VOLL_{i}^{s} \end{cases}$$
(4-12)

$$BEDI_{i} = \frac{\sum_{y=1}^{Y} \sum_{t=1}^{T} \sum_{s=1}^{S4} \zeta_{i}^{s} \cdot D_{i}^{s \; BASE}}{Y}$$
(4-13)

Relation (4-12) shows how independent ranking lists for voluntary and involuntary load reductions can be built. Ranking of all 'voluntary customers' is based on submitted marginal offer prices, which can be normalised with the average price of up-spinning reserve in the energy-reserve markets [126]. On the other hand, involuntary load reductions are ranked using VOLL. The VOLL is defined either by load types, or customer damage functions are used; it is normalised using the average VOLL in the entire GB [116]. The base expected interruption index *BEDI_i* is found from the number of interruptions ζ_i^s having duration $D_i^{s BASE}$ across the entire simulation period.

The total required amount of load reduction Pc_i^s is determined from the OPF model and it consists of voluntary and involuntary components. When considering industrial and large customers under the direct load control, it was assumed that available voluntary load reduction is equal to the contracted voluntary reduction (CVL_i^s). Then the (part of) voluntary load reduction is:

$$[\Lambda^{-}]_{i}^{s}(t_{RED}) = \begin{cases} Pc_{i}^{s}(t) & \text{, if } Pc_{i}^{s}(t) < CVL_{i}^{s}(t) \\ CVL_{i}^{s}(t), & \text{if } Pc_{i}^{s}(t) > CVL_{i}^{s}(t) \end{cases}$$
(4-14)

Available voluntary load reductions from industrial and commercial incentivised customers and residential customers contain a probabilistic component that can be determined using random sampling. It is calculated using the availability factor f_{RED}^s :

$$f_{RED}^{s} = \begin{cases} 1 + (rs - 1)win , industrial, commercial \\ rs , domestic customers \end{cases}$$
(4-15)

where *rs* is a random number generated from the uniform distribution between $\{0,1\}$ and *win* is the per unit window. In case of incentivised (industrial and commercial) customers, the available amount is based on average probability that the contracted amount is available. For these customers, the uncertainty is much smaller and it is defined by the size of window *win*. For example, if we assume that the average probability is 0.9, the range of variation is between 80% and 100%, so that *win=20%*. Residential customers respond to price signals and the uncertainty window is the entire available range. The available voluntary load reduction is then calculated by multiplying the availability factor (4-15) and the contracted value (CVL_i^s) in case of incentivised industrial and commercial customers, or estimated maximum load reduction of residential customers.

After having obtained available voluntary load reductions for all types of customers s at node i, the total voluntary and involuntary load reductions are calculated using the ranking order and a relation similar to expression (4-14). The minimum amount of involuntary load reduction is always used to meet the network security constraints.

4.2.5 Load Recovery Scheduling module

This module determines the amounts of potential load recoveries in the period following load reduction in the time slot t_{RED} . The actual load recovery is determined in the DRLR control module using the hourly nodal marginal prices.

Load recovery profiles can be very different for the considered customer types, and moreover, for different customers within a single group; a good example is industry [60]. Here a general normalized load recovery profile of triangular shape is applied, which is modelled by two straignt lines in disrete form. The upward line models load pick-up after the customer reconnection, whilst the downward line brings it back from the 'overshot point' to the pre-disconnection value. The discrete modelling is done using the upward/downward slope coefficients in consecutive time intervals.

The amount of load recovery at time period t_{REC+t} , $[\Lambda^+]_i^s(t_{REC} + t)$, is computed by using the following expression:

$$[\Lambda^{+}]_{i}^{s}(t_{REC} + t) = [\Lambda^{-}]_{i}^{s}(t_{RED}) \cdot \gamma_{i}^{s}(t_{REC} + t) \cdot f_{REC}^{s}$$
(4-16)

where $[\Lambda^{-}]_{i}^{s}(t_{RED})$ is amount of load reduction of load type *s* at node *i*, $\gamma_{i}^{s}(t_{REC} + t)$ is upward or downward slope coefficient and f_{REC}^{s} is the availability factor of type *s* load recovery. This factor was introduced because not all customers may come back when supplies are restored or signalled [59]. In the current approach, availability factors f_{REC} are deterministic quantities defined by customer types and network nodes. It is also worth noting that the load recovery can be higher than the amount of the initial load reduction [60]; the slope factors can take values greater than unity.

Modelling of load recovery profiles over a specified time period introduces additional complexities in the developed SMCS methodology. Each time a load recovery is initiated, the corresponding nodal load needs to be modified over a specified period in line with the load recovery profile. Besides, a record must be kept of all load recoveries at different time steps, because they cannot be considered for further load reduction. This is reflected in the next DRLR module.

4.2.6 Demand Response Load Reduction (DRLR) Scheduling module

The DRLR control module is used to control the initiation of load reductions and recoveries and to produce their optimal schedules within the forecast 24 hourly period. The control principles are listed below:

- Loads whose recovery process is underway cannot be considered for load reduction.
- Loads eligible for load reduction will not be disconnected if there is no improvement in the energy-not-served following the load reduction.
- Only those loads, whose reduction including recovery generates revenue to the customers, will be actually disconnected and reconnected.
- The best timing of load recovery is determined using the (forecast) nodal marginal prices over the recovery period.

When the OPF analysis has generated non-zero load curtailments, then the loads which are not a part of previous load recoveries are ranked and the sizes of voluntary and involuntary reductions are determined. The first load reduction from the ranking list is applied and is checked with the aid of the OPF whether the total energy-not-served has reduced. If this is the case, the nodal customer profits are computed based on the savings acquired due to the load reduction and the projected payback cost due to the load recovery. The optimum load recovery always takes place when the nodal marginal prices are 'low' over the recovery window. If the load customer projected profit is negative, the load reduction is not activated even if the reliability of the network might improve. Calculation of customer savings, costs and profits is presented below.

4.2.6.1 Customer Savings

The customer savings incurred during load reduction are the consequence of reduced load payments to the generators. These payments are valued at nodal marginal prices $\mu_i(t)$, as shown in equation (4-8), which are in turn dependent on the considered regime. The customer savings are therefore calculated from two OPF runs: the first without load reduction and the second with load reduction. The change in load payments, ΔLC , represents the customer savings at t_{RED} :

$$\Delta LC_i^s(t_{RED}) = LC_i^{s NO - DR}(t_{RED}) - LC_i^{s DR}(t_{RED})$$
(4-17)

The total savings are then found for the entire interval when the load reduction is in place:

$$Savings_{i}^{s}(t_{RED}) = \sum_{t=t_{RED}}^{t_{REC}} \Delta LC_{i}^{s}(t)$$
(4-18)

4.2.6.2 Payback costs

If customer *savings* are positive then the algorithm proceeds to the load recovery stage to project the optimal load recovery schedule. The optimization is based on the following principles:

 Load recovery is always scheduled after the corresponding load reduction and it can continue into the 'following' simulated day. There are periods within a day when the load recovery does not take place; for example between 12am and 5pm on weekdays for residential customers.

- Load recovery blocks due to involuntary load reduction are always committed before voluntary load recovery blocks. They are prioritized based on their VOLL; where the VOLL is the same; ranking is based on the size of load reduction, the largest loads being reconnected first. Similar criteria are applied to voluntary load reductions, where marginal offer prices are used instead of VOLL.
- Optimal timing of load recovery is determined by finding the weighted average of (base) nodal marginal prices over the recovery window. The weights are equal to the slope coefficients $\gamma_i^s(t_{REC} + t)$ of the normalized recovery profile. The window with the smallest average nodal marginal price is selected for the load recovery. This approach is the best for load customers, because they will be exposed to the least additional payback cost.
- After having determined the optimal starting hour of load recovery, it will only be
 materialized if there will be no new load curtailments within the recovery window. This
 is checked by running OPF over consecutive time periods within the recovery window;
 where curtailments occur, the next best recovery window is examined and so on.

The payback costs due to the selected optimal load recovery schedule are again computed from two OPF runs in each time step within the recovery window. Since load recovery increases the amount of load, additional cost ΔLC is calculated as the difference between costs with and witout load recovery over the load recovery period t_{REC} to t_{MAX}:

$$\Delta LC_i^s(t_{REC}) = LC_i^{s DR}(t_{REC}) - LC_i^{s NO - DR}(t_{REC})$$
(4-19)

$$C_{payback \, i}^{s} = \sum_{t=t_{REC}}^{t_{MAX}} \Delta L C_{i}^{s}(t) \tag{4-20}$$

4.2.6.3 Customer Profits

The total customer profit $\pi_i^s(t_{RED})$ needs to account for savings due to reduced load, costs due to load recovery, as well as rewards for voluntary and involuntary load shedding. This is summarised in the equation below:

$$\pi_i^s(t_{RED}) = Savings_i^s - C_{payback\,i}^s + \sum_{t=t_{RED}}^{t_{REC}} IVLR_i^s(t) + \sum_{t=t_{RED}}^{t_{REC}} VLR_i^s(t) \qquad (4-21)$$

where VLR_i^s revenue for voluntary load *i* and type s reduction and $IVLR_i^s$ revenue for involuntary load *i* and type *s* reduction.

Only load customer with a positive profit $\pi_i^s(t_{RED})$ evaluated at time t_{REC} proceeds into the DR strategy. The analysis continues until the convergence criterion on expected energy not served is met. After having completed the SMCS procedure, the algorithm goes straight to the outputs module. The outputs module includes optimal load reduction and recoveries, generation outputs, nodal marginal prices, reliability indices and financial indicators. The detailed outputs and simulation results are presented in Chapter 6.

4.3 Thermal Rating Modelling

In the current operation practice, a conservative constant thermal rating is usually considered for a transmission line. The system operator usually has a constant thermal rating for a transmission line, taking into account the worst possible weather conditions. However, in practice the thermal rating of transmission lines varies when the weather conditions change [127]. The constant thermal rating is usually lower than the real time thermal rating of transmission lines. Therefore, the transmission operator operates the system with a high security margin, which means the transmission assets are not utilized in an efficient way.

According to the deterministic approach included in IEEE standards [67], the maximum current that a line can carry can be derived by the steady state heat balance equation, which is in function of the joule heating, P_j ; the solar heating P_s ; the radiative cooling P_r ; and the convective colling P_c . Equation (4-23) presents this balance whilst the heat flows in a conductor are shown in Figure 4-5.

$$P_I + P_s = P_R + P_C \tag{4-22}$$

Joule heating, P_J, also known as ohmic heating is calculated using skin effect factor k, R_{DC} resistance at 20°C (Ω /m), current flow in the conductor I, average temperature T of the conductor and the temperature coefficient per degree of resistance per degree Kelvin α , as shown in equation (4-23). The solar heating is a function of several parameters including solar absorptivity of conductor surface a_s , the global solar radiation S and the external diameter of the conductor D, as shown in equation (4-24).



Figure 4-5: Heat flows [128]

$$P_{J} = kR_{DC}I^{2}(1 + a(T - 20))$$

$$P_{s} = a_{s}SD$$
(4-24)

(1 22)

The convection cooling Pc varies with the change in wind speed (V_m) , wind direction factor (K_{angle}) and the difference between the conductor (T_c) and ambient air temperature (T_a) , as described in (4-25). Additional variables are necessary for calculating convection cooling such as, the thermal conductivity K_f , the density of air ρ_f and the dynamic viscosity of air μ_f . Finally, radiative cooling P_r is the energy of the electromagnetic waves emitted to the ambient space; it is a function of the temperature difference between the conductor and air, and the emissivity of the conductor, ε as shown by equations (4-26) and (4-27).

Replacing relations (4-23) to (4-27) into the balance equation (4-22), the maximum current that a line can carry is derived by the equation (4-28).

$$P_{c} = \begin{cases} \left(0.0119 \left(\frac{D\rho_{f} V_{m}}{\mu_{f}} \right)^{0.6} \right) K_{f} K_{angle} (T_{c} - T_{a}), & High V_{m} \\ \left(1.01 + 0.0372 \left(\frac{D\rho_{f} V_{m}}{\mu_{f}} \right)^{0.52} \right) K_{f} K_{angle} (T_{c} - T_{a}), Low V_{m} \end{cases}$$
(4-25)

$$P_r = 0.0178D\varepsilon \left[\left(\frac{T_c + 273}{100} \right)^4 - \left(\frac{T_a + 273}{100} \right)^4 \right]$$
(4-26)

$$P_r = 0.0178D\varepsilon \left[\left(\frac{T_c + 273}{100} \right)^4 - \left(\frac{T_a + 273}{100} \right)^4 \right]$$
(4-27)

$$R(T_c) = \frac{R(T_{high}) - R(T_{low})}{T_{high} - T_{low}}$$

$$I = \sqrt{\frac{P_c(T_c, T_a, K_{angle}, V_m + P_r(T_a, T_c) - P_s)}{R(Tc)}}$$
(4-28)

4.3.1 Standard Thermal Ratings

Many transmission companies usually use fixed thermal ratings for short term and long term planning studies. These fixed thermal ratings are calculated assuming extreme weather conditions and the maximum temperature, which a conductor can tolerate before annealing. This results in a greater conductor sag and smaller ground clearance. The lowest fixed thermal rating is calculated for the summer period, since the ambient temperature considerably affects the maximum capacity of the line. The rating is usually called static (or seasonal) thermal rating (STR) and it is based on the following data: the ambient temperature Ta equals to 40°C, the wind speed equals to 0.61m/sec and the *Kangle*=1 [67]. These values along with the conductor temperature are used to give the static (seasonal) thermal rating of a transmission line in summer.

Transmission companies usually calculate the fixed thermal ratings for each season. In [129] three different ratings are considered: 1) for summer; 2) for spring and fall; and 3) for winter.

The assumed ambient temperatures, wind speeds and wind angle on the conductor for these seasons are shown in Table 4-2.

Conditions	Winter	Spring/Fall	Summer
Ambient Temperature (°C)	2	9	40
Wind speed (m/sec)	0.61	0.61	0.61
Angle onto the conductor	perpendicular	perpendicular	perpendicular

Table 4-2: Seasonal weather conditions

For both approaches, the conductor temperature needs to be set to one of the standard design values (i.e. 50°C, or 65°C, or 75°C) to get the OHL ampacity; an increased value can be used during system emergencies. This is specified in company policy.

4.3.2 Steady State Conductor Temperature

This section describes the importance of measuring and accounting for the real conductor temperature especially when real time thermal ratings need to be determined. Then the real time thermal ratings modelling will be introduced.

In the event of a sudden electrical current change in a transmission line, an almost immediate temperature-change occurs on the conductor (low thermal constant), as shown in Figure 4-6. It must be noted that the exponential trend of the conductor temperature depends not only on the current change on the line but also on the weather conditions the OHL is exposed to. Besides, the effects of high temperature conductor operation can considerably affect the electrical clearances of the conductor, the importance of which is the safe distance of the conductor to protect personnel, vehicles and equipment against inadvertent contact, or hazardous proximity, to exposed conductors. Additionally, elevated temperature creep should also be included in the simulation when the conductor temperature suggests that the emergency thermal rating will experience accelerated creep but not loss of strength.



Figure 4-6: Schematic non-linear relationship between conductor temperature and current

As a result the conductor temperature has a significant impact on the capacity of the line, and therefore the hourly steady state conductor ampacity model is developed, which calculates conductor permissible temperatures using equation (4-28), as presented in the next section. Consequently, the corresponding thermal rating of overhead lines can be applied in a reliability assessment analysis.

4.3.3 Real Time Thermal Ratings

Real time thermal rating (RTTR) is a smart grid technology that allows the rating of electrical conductors to be increased (or decreased) based on local weather conditions. The developed RTTR model calculates the real transmission capacities that are available on a given network using an iterative algorithm that gives the real time thermal ratings over a yearly period in relation to the chronological load curve. Towards this, the steady state conductor temperatures need to be measured or computed for the studied OHLs, which will be done for the most frequently overloaded lines.

Given the variability of the steady state conductor temperature versus time, it becomes necessary to determine: 1) conductor characteristics, 2) weather conditions and 3) load parameters, as the three inputs to be used for the calculation of the actual conductor ampacity and resistivity.

The conductor characteristics are defined by the diameter, the calculated resistance at 25°C and 75°C, as well as its reactance. The weather data consists of wind speed, direction, and ambient temperature. Finally, the load parameters constitute the OHL loadings calculated

using power flow analysis at given load levels. The steps of the methodology calculating the hourly thermal ratings are illustrated in Figure 4-7.

- 1. Initially, the conductor data and hourly weather data are used to identify the hourly varying maximum thermal rating.
- 2. The loadings (I_f) of the lines are calculated using load flow analysis.
- 3. The data obtained in step 1 and 2 along with randomly distributed conductor temperature Tc are plugged into the iteration based technique to calculate the maximum permissible current (I_m). It should be noted that Tc is randomly distributed only in the first iteration of real time thermal rating calculation. For the next iterations step 5 is used to estimate conductor temperature Tc. The calculated current I_m is set as the new maximum transmission line ampacity.
- 4. When I_m equals to I_f then store the Tc for the specified operating condition and identify the conductor ampacity and resistivity by using method from [130]; otherwise go to the next step.
- 5. Estimate the *Tc* taking into consideration percentage difference between I_f and I_m and continue the iteration based loop.
- 6. Stopping criteria: the process is continued until $I_f = I_m$.



Figure 4-7: Conductor Temperature-Ampacity Calculations

After the conductor ampacity is determined the MVA rating of the line is calculated considering the line-to-line voltage V_{LL} , as shown in the following equation:

$$S_{3\varphi} = I \times \sqrt{3} V_{LL} \tag{4-29}$$

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4.3.4 Network modelling considering OHL properties

For the application of thermal rating models the OHL properties should be considered. All the models developed were tested on the IEEE-RTS 96 network. The IEEE-RTS 96 test system does not provide any OHL data required for the hourly thermal ratings calculations. A simple ACSR technology is assumed with conductor sizes that provide similar ratings to those in the IEEE-RTS 96 system with AAAC and ACSR conductors. Table 4-3 provides the information on the conductors used in the analysis. The Rac 25 °C and 75 °C used as an input in equation (4-28) to determine the conductor resistance for certain conductor temperature Tc. Consequently the ampacity of the conductor and the MVA rating is computed as in (4-29) and (4-30) respectively. Under system normal operation, conductor temperature, *Tc*, is set to 60°C for Dove & Hawk conductors and 75°C for Drake & Grosbeak types and so the corresponding MVA rating of each conductor is depicted in the 4th column on the table. A line is considered in emergency state when another transmission line connected at the same bus fails. The maximum conductor temperature in emergencies is set to 75°C and 95 °C for Dove & Hawk, and Drake & Grosbeak respectively, based on avoidance of the conductor annealing.

NAME	Rac (Ω/Km)	Configuration	Snorm (MVA)	Sem-long (MVA)
Dove	0.1003 @ 25°C	Single bundle	95	138
(138kV)	0.1270 @ 75°C		[60°C]	[75°C]
Drake	0.0728@25°C	Single bundle	200	320
(138kV)	0.0868@25°C		[75°C]	[95°C]
Grosbeak	0.0902@25°C	Twin bundle	540	580
(230kV)	0.1220@75°C		[75°C]	[95°C]
Hawk	0.1154 @ 25°C	Twin bundle	308	365
(230kV)	0.1225 @ 75°C		[60°C]	[75°C]

Table 4-3: Conductor properties modelled in IEEE RTS network

4.4 FACTS

4.4.1 FACTS methodology

Due to the increased number of SVC and TCSC installed by the industry, the impact of those on reliability of the network, maximization of deployed wind energy as well as minimization of network operating costs is investigated. Their physical models are first analysed and then a best ranking methodology for connection in the power network is proposed.

Thyristor controlled series compensator (TCSC) devices have been developed to control power flows, to increase the transfer limits or to improve system stability. TCSC is well established technology, which is primarily used in the transmission systems to reduce transfer reactances. They additionally contribute to transient and voltage stability proliferation.

TCSC configuration considered in the studies is shown in Figure 4-8 (i). TCSC can be considered as an additional reactance -jXc on a line (i,j) with impedance Z_{Line} . Therefore the new impedance of the line can be expressed as $Z_{i,j}=Z_{Line}\pm jXc$. The value of Xc is adjusted according to the TCSC control scheme and it can take any value betwee minimum value $X_{c,Min}$ and maximum value $X_{c,Max}$. As shown in the figure, TCSC is connected between bus i and j and power is effectively injected at the sending and receiving ends of the line. The impedance of the line Z_{Line} (fixed parameter) is in series with the TCSC, Xc (variable parameter), which can either be capacitive (Xc<0) or inductive (Xc>0). The injected powers at buses i, j can be expressed as S_{ic} and S_{jc}.

Static Var compensators (SVC) are devices that can quickly and reliably control line voltages. An SVC will typically regulate and control the voltage to the required set point under normal steady state and contingency conditions and thereby provide dynamic, fast reactive power response following system contingencies (e.g. network short circuits, line and generator disconnections, etc.). In addition, SVCs increase lines transfer capability, reduce losses, mitigate active power oscillations and prevent over/under voltages at loss of load incidents.

SVC configuration considered in the studies, it is shown in Figure 4-8 (ii). SVC is a shunt connected static VAr generator/load, whose output is adjusted according to the required

capacitive or inductive current. The SVC is connected directly to the load bus, as a generator or absorber of controllable reactive power, as shown in Figure 4-8 (ii). SVC injects reactive power into the system $Q_{SVC}>0$ and absorbs reactive power from the system if $Q_{SVC}<0$ and thereby regulates the change of the voltage ΔV_{SVC} between buses i,j. The corresponding injected powers at buses i, j can be expressed as S_{is} and S_{js} .



Figure 4-8: Block diagram of considered FACTS [29]

The basic steps of the proposed optimal location of FACTS devices in the network will be discussed in this section, while the simulation results of the model will be presented in Chapter 7.

Ranking lists for both SVC and TCSC placements are developed based on reliability analysis without the use of FACTS on the network. Once their best placement is determined, FACTS are applied to the network to improve the security and economic criteria, as shown in Figure 4-9. Security criteria includes the improvement of expected energy not supplied (EENS), whilst economic criteria includes the reduction of network operational costs compared to the case of not using FACTS devises. If these criteria are not met, another FACTS device from the ranking list is installed.



Figure 4-9: Overview of FACTS framework

SVCs are usually installed to solve network voltage problems. As such, for the ranking of the SVCs, sequential Monte Carlo simulation was used to calculate the voltages at the nodes, as well as the expected energy not supplied due to violation of voltage constraints at nodes *i* $BEENS_i^{volt}$ and expected wind spillage due to voltage constraints $BESP_i^{volt}$. This is considered to be the base case where the system is operated with no flexible actions (FACTS, RTTR, etc).

TCSCs are usually installed when capacity constraints are violated. As such, for the ranking of TCSCs, sequential Monte Carlo was used to calculate the most frequently overloaded OHLs, as well as the expected energy not supplied and expected wind spillage due to violation of thermal constraints $BEENS_i^{th}$, $BESP_i^{th}$, respectively. The entire analysis and the equations used for the model are presented as follows.

4.4.1.1 Ranking of SVCs

Ranking of SVCs is based on the following assumptions: a) SVCs are installed when violation of voltage constraints exists or when voltages are close to the limits; and b) SVCs are placed at nodes where the voltage problems are highest.

Essential indicators used to build the ranking lists are expected curtailed loads *BEENS* and curtailed winds *BESP*. The nodal values are classified in the base SMCS as follows:

- Voltage related *BEENS* and *BESP* are at those nodes where the relevant voltage constraint is binding. The corresponding daily nodal curtailments are *BEENS*_i^{volt} and *BESP*_i^{volt}.
- Voltage histograms at nodes *i* are also relevant for SVC connection, because they can show nodes close to the limits that can be easily exceeded with varied conditions. If the histogram of base SMCS voltages at node *i* is $\gamma_i = \{V_i^1, ..., V_i^{t}, ..., V_i^{24Y}\}$, the following quantities can be defined:

$$\Delta \gamma_i^{V^{min}}(\eta) = \frac{1}{Y} \sum_{V^{min}}^{V^{min}+\eta} (\gamma_i - V^{min})$$

$$(4-30)$$

$$(4-30)$$

$$\Delta \gamma_i^{V^{max}}(\eta) = \frac{1}{Y} \sum_{V^{max}-\eta}^{V^{max}} (V^{max} - \gamma_i)$$
(4-31)

which represent total daily nodal voltage deviations from the lower (4-30) and upper limit (4-31) in a pre-specified per unit region η . These deviations are then included into the developed criterion for ranking of nodes for SVC connection:

$$\rho_{i} = \left(\tau_{1}BEENS_{i}^{volt} + \tau_{2} \cdot BESP_{i}^{volt}\right) \left[1 + \Delta\gamma_{i}^{V^{min}}(\eta) + \Delta\gamma_{i}^{V^{max}}(\eta)\right]$$
(4-32)

where τ_1 and τ_2 are weights showing relative importance of load curtailment compared to wind spillage. In systems where reliability is preferred to wind spillages, ratio τ_1/τ_2 can be set to the ratio of the value of lost load to the average spillage cost; where wind spillages play more important role, this ratio can be less or even $\tau_1 = \tau_2$ can be used. Relation (4-32) shows that ranking of SVC considers both reliability and spillage whilst also looking into uncertain future expressed through interior voltage deviations (4-30) & (4-31).

4.4.1.2 Ranking of TCSCs

Essential assumptions used for ranking of TCSCs are: a) TCSCs are installed when energy curtailments occur due to violation of capacity constraints; b) Numerical sensitivity analysis of OPF solutions is applied to define branches best candidates for TCSC installation; and c) The initial set of branches considered for TCSC placement is based on available thermal capacity margins of branches.

The essential idea is to find a set of branches whose reduction in reactance gives the maximum reduction in load and wind curtailments. Since placement of a TCSC in branch ij will change branch reactance x_{ij} and create a non-linear model, numerical sensitivity analysis of the OPF solution has been applied. The main algorithmic steps are:

- Consider a SMCS¹ OPF solution and find binding capacity constraints. If there are no such constraints, repeat step No. 1 for the next hourly period.
- 2) Find the set of branches $ij \varepsilon \beta_{br}$ which have sufficient capacity margin (typically, at least 20-30%). These branches will be further examined for TCSC installation. For example, if branches 10,13, 20 and 26 have capacity margins of 20-30% then the set β_{br} would be β_{br} ={10,13,20,26} for the considered hourly period. Note that the set β_{br} can be different in each hourly period; we are, however, looking for the total, accumulated impact of installing a TCSC within each branch with spare capacity.
- 3) Do two OPF runs with relaxed voltage constraints; the first is done with original reactances, whilst the reactance of the considered branch $ij \in \beta br$ is modified by prespecified increment in the second run. The reduction in load and generation curtailments at node *m* is denoted by $\Delta BEENS_{ij,m}^{th}$ and $\Delta BESP_{ij,m}^{th}$.
- 4) Step No. 3 can also be done to include the highly loaded branches into TCSC ranking, which is analogous to voltage interior regions (4-30) and(4-31). In that case, both OPF runs are done with thermal ratings of highly loaded branches reduced by η pu.
- 5) Find the total weighted daily reduction in load and wind curtailments due to change in reactance *x_{ij}*:

$$\Delta BENS \& SP_{ij} = \tau_1 \cdot \sum_{m \in \beta_{ENS}} \Delta BEENS_{ij,m}^{th} + \tau_2 \cdot \sum_{m \in \beta_{ESP}} \Delta BESP_{ij,m}^{th}$$
(4-33)

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which is used to establish a TCSC ranking list in descending order.

4.4.2 Optimal Placement of SVCs and TCSCs

Expected daily load curtailments due to violation of voltage and thermal constraints, *BEENS^{volt}* and *BEENSth*, as well as expected daily spillages caused by voltage and thermal constraints, *BESP^{volt}* and *BESPth*, are then used to define the optimal placement for SVCs and TCSCs:

1) Where linear combination of curtailed wind and load due to voltage problems $ce^{volt} = (\tau_1 \cdot BEENS^{volt} + \tau_2 \cdot BESP^{volt})$ is greater than the curtailed energy due to thermal problems $ce^{th} = (\tau_1 \cdot BEENS^{th} + \tau_2 \cdot BESP^{th})$, a top-ranked SVC is installed and SMCS is run; otherwise, the highest ranked TCSC is placed and SMCS is run.

2) The SMCS results give a new set of load and wind curtailments *BEENS^{volt}*, *BEENSth*, *BESP^{volt}* and *BESPth*. They are used to determine whether a SVC or TCSC is installed in the next step using the same logic as in step No. 1.

- 3) The above procedure is repeated until:
 - either improvement in load and wind curtailments is considered insignificant, or, the FACTS investment budget is spent.

4.5 Corrective Scheduling

The corrective unit commitment problem deals with disruptions in power systems operation caused by an unforeseen unit outage with stochastic duration [131]. As a result, a corrective scheduling of committed generating units that provides an immediate response to such a disruption is needed to update the original schedule in time. The system operator can exercise corrective control actions consisting of generator output adjustments of both real and reactive power, adjustments of transformers tap settings, switching of capacitors or reactors and if necessary load shedding. In the contemporary power systems, corrective scheduling can be also defined as the minimum reserve strategies for systems with high wind integration [109]. Similarly energy storage can be used as part of the control measures in a corrective form to alleviate power system violations [132]. Line switching is used in [133] on congested

networks to reduce generator dispatch cost. Corrective control strategy is deployed in [134] using FACTS to prevent voltage collapse as well as to relive transmission congestion under both normal and emergency operation regime. Normally open points (NOP) are used in [135] as corrective actions to provide alternative paths for supplying the customers when a fault occurs in a medium voltage distribution network. Demand response scheduling is applied in [17], as a corrective action in the event of an emergency condition in order to improve network reliability. Real time thermal ratings are implemented in [136] to quantify network reliability in terms of expected energy not supply (EENS), while minimizing generation costs.

In summary, historically corrective scheduling is usually planned for the generators, transformers, transmission lines and loss of load. In the modern power systems, corrective scheduling can be also applied in the form of new technologies installed on power systems such as FACTS, DR, energy storage, etc.

The developed studies use corrective scheduling to maintain the secure operation of the system, while looking for the most economical dispatch. The actions taken in the developed studies are the following:

- > Make adjustments of the flexible generation active and reactive outputs,
- Increase the conductor design temperature of transmission lines when there is a fault in the vicinity of this line,
- > Use shunt or series compensation connected to system nodes or branches,
- Apply involuntary load curtailment, if any of the above actions couldn't maintain the system within operating limits.

In addition to the above corrective actions, this thesis proposes flexible new technologies such as DR, FACTS and RTTR and wind curtailment control as corrective actions to keep the operation of the system secure in the event of unforeseen failures. Ranking lists for demand response customers are generated and included in the objective function to prioritize customers under emergency conditions to increase reliability of the system. For example, certain DR customers are selected to participate in load reduction and load recovery after reliability and finicial indicators are improved compared to not using DR scheduling. FACTS

devices are adjusted to improve voltage and thermal related load and/or generation curtailment with the goal to improve reliability and operational costs of the network under emergency conditions. Real time thermal ratings are included as maximum OHL ratings in the OPF analysis to facilitate energy transfer under high contingency events. Finally, corrective scheduling of wind curtailments is also implemented by prioritizing wind curtailments through cost coefficients associated with wind curtailments in the OPF analysis in order to maximize wind deployment and at the same time improve reliability and operational costs of the network. Probabilistic wind curtailment cost coefficients are assigned to every wind generator in the objective function because spillage cost values significantly contribute to spillage minimization, which is most probable to occur in the event of an unexpected contingency event. Consequently, the final goal of all developed corrective actions is to allow optimal integration of LCTs to maintain secure and reliable operation of the network.
5 Components of the Developed Reliability Assessment Methodologies

Summary:

A description of modelling of power system components in a probabilistic framework is given, such as, component failures, repairable failures, load demands and wind generation. This is followed by optimisation algorithms literature review, which accelerates computational time of Monte Carlo simulation. In recent years, many efforts have been made to improve the computational efficiency of algorithms, especially those that are applied to problems of greater complexity and high dimensionality. This chapter provides information on the major components of the reliability assessment methodologies used in this thesis. More specifically, it illustrates developed reliability assessment techniques such as non-sequential Monte Carlo simulation (NSMCS) combined with Particle Swarm Optimization (PSO); the approache is used to reduce the number of Monte Carlo iterations and speed up computation.

5.1 Probabilistic modelling of power systems components

Power system components modelling in the reliability analysis means the probabilistic representation of all events involved in the calculation of the reliability indices. There are three major input categories, which need to be considered in power system reliability assessment: component failure models, network models and load & weather models in conjuction with forecasting techniques.

5.1.1 Component failure modelling

The failure of a power system component is a stochastic event, whose time of occurrence is a random variable. In other words, in reliability studies the random variable, which must be modelled, is the time of occurrence of failure [137]. Stochastic events are usually modelled by probabilistic distributions. There are several forms of functions for interpreting probabilistic behaviour of random variables. The easiest is to explain the cumulative probability function (*cdf*). Generally, a cdf of any random variable gives the probability of the random variable being equal to or less than a specific value [1]. For example, if *d* is a random variable, the cdf (D) gives the probability of $d\leq D$. When projecting this concept to the time of occurrence of the failure, the *cdf*(*T*) defines the probability that a component will fail at time $\leq T$, which is simply the probability of failure. Therefore, in engineering reliability studies the *cdf* is known as the probability failure function, or simply failure function and it is commonly denoted by Q(t) [1]. The complementary function of the failure function is the reliability function R(t). Given that the total probability of any two complementary events equals one, R(t) can be calculated by (5-1).

$$R(t) = 1 - Q(t)$$
(5-1)

The value of Q(t) at t=0 equals zero, while $Q(\infty)=1$. In a similar way, the reliability of a component R(t)=1 when t=0, whereas R(t)=0 when $t=\infty$. The third form of probability distribution functions is the probability density function pdf, which is denoted as f(t) in reliability engineering. The f(t) is the first derivative of the cumulative distribution function as given by (5-2):

$$f(t) = \frac{dQ(t)}{dt}$$
(5-2)

The integral of *pdf* over a period of time gives the probability of the failure occurring during this period. Accordingly, the integral of *pdf* from zero to infinite equals one.

The hazard rate function is an alternative function interpreting the probabilistic distribution in the reliability analysis. This function is also known as the failure rate function and is designated as $\lambda(t)$. This function is introduced to define the instantaneous probability of failure at a specific point in time [138]. It gives probability that a component did not fail until time *t* but did fail in time period $t + \Delta t$ [139]. Subsequently, the hazard rate function has units 1/time. The relationship between $\lambda(t)$ and other distribution functions is given by (5-3) [1].

$$\lambda(t) = \frac{f(t)}{R(t)}$$
(5-3)

The hazard rate function for the exponentially distribution can be calculated in the following way. The pdf of the exponential distribution is given by (5-4):

$$f(t) = \lambda e^{-\lambda t} \tag{5-4}$$

where λ is the parameter of the exponential function. The reliability function of the exponential distribution function is given by (5-5):

$$R(t) = e^{-\lambda t} \tag{5-5}$$

Then using (5-3) the hazard rate function of the exponential distribution is calculated as shown in (5-6):

$$\lambda(t) = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda \tag{5-6}$$

The constant hazard rate function is very unique feature of the exponential distribution, and hence, exponential distribution is used to characterise failure events in the useful life stage of the component [140]. This feature is also the reason for referring to the parameter of the exponential distribution λ as failure rate.

A failure of a power system component can be repairable, where a component transits from in service state to repair state and spends some time in it. Consequently, the random variable in repair state is time to repair (TTR). If the TTR is exponentially distributed, the above equations apply with failure rate λ being replaced by repair rate μ .

5.1.2 Repairable Failure

The concept behind the repairable failure is that the component can be repaired to the same condition as before the failure. For power system components, the repair duration takes considerable time, and hence the repair process is also defined as a stochastic process. Based on this, the component outage can be modelled by two states: up and down states. The

transition rates between these two states are the failure rate and the repair rate. This is called Markov process and it is illustrated in Figure 5-1.



Time

Figure 5-1: Availability and unavailability limits based on Markov theory

In typical power system reliability studies, the failure and repair rates are assumed constant, which means the failure and repair processes have an exponential distribution [140]. With this assumption, the two state model meets the requirements of Markov process, which is characterised by the possibility of transitions between all states, lack of memory, and stationary transition rates between the states [1]. The first requirement is an inherent feature of the two state model, since the component transits between the states. The second and last requirements are satisfied by the exponential distribution assumption. It was shown that the exponential distribution has a constant hazard rate (or failure rate) function. In order to demonstrate that it is memory-less, one may assume that a component has operated for a period of time T and the probability of failure in the next period of time *t* has to be evaluated. The main consideration here is that the component cannot fail in T+t if it has failed in the previous time *T*. This is a conditional probability problem because what needs to be assessed is the probability of failure during *t* given that it has survived up to *T*. The conditional probability rule is given by (5-7) [1]:

$$P(A/B) = \frac{P(A \cap B)}{P(B)}$$
(5-7)

In the context of the the stated problem $P(A \cap B)$ is the probability of surviving up to *T* and failing during *t*. This probability can be estimated by integrating the pdf of exponential distribution from *T* to *T*+*t*, as illustrated in (5-8).

$$P(A \cap B) = \int_{T}^{T+t} f(t) dt = \int_{T}^{T+t} \lambda e^{-\lambda t} dt = e^{-\lambda T} - e^{-\lambda(T+t)}$$
(5-8)

P(B), which is the probability of survival up to T, is actually one minus the probability of failure during the previous period T given in (5-9):

$$P(B) = 1 - \int_0^T f(t)dt$$
 (5-9)

Given that the integration of the pdf from zero to infinity equals one, P(B) can then be expressed as:

$$P(B) = \int_0^\infty f(t)dt - \int_0^T f(t)dt = \int_T^\infty f(t)dt = \int_T^\infty \lambda e^{-\lambda t} = e^{-\lambda T}$$
(5-10)

Substitution of the so calculated probabilities in (5-7) gives ((5-11), which is the probability of failure during t given that the component has survived up to T.

$$P(A|B) = 1 - e^{-\lambda t} \tag{5-11}$$

From (5-11), it is obvious that the conditional probability calculated for the exponential distribution does not depend on the previous period T, but it only depends on the future study time t. Therefore, the exponential distribution is memory-less.

Markov process theory states that the probability of being found in any state (up or down) reaches a limiting value that is independent of the initial conditions (up or down). The probability of being found in the up state is called availability. Likewise, the probability of being found in the down state is known as the unavailability. The availability and unavailability are essential measures of component performance in system reliability. Referring to the Markov process, for the repairable failure, the availability and unavailability

of a component are constant in the long run. Figure 5-1 shows an illustrative example of the limiting values of availability and unavailability. The up state is denoted in the figure as 1 and the down state as 0. As shown, the availability and the unavailability reach the same limiting values regardless of the initial state of component.

The unavailability (U) and availability (A) are calculated by (5-12) and (5-13) respectively, which are the Markov limiting state probabilities [140]:

$$U = \frac{\lambda}{\lambda + \mu} \tag{5-12}$$

$$A = 1 - U = \frac{\mu}{\lambda + \mu} \tag{5-13}$$

where λ and μ are the failure and repair rate, respectively.

5.1.3 Network modelling in terms of reliability

The network modelling in power system reliability is classified into two categories. The first one is associated with load flow analysis, which determines whether the system state is a system success event or a system failure event. System success event is the one in which no system constraint is violated (no thermal, voltage violations or load shedding). On the other hand, system failure event is the one when voltage or thermal limits are exceeded and load curtailment is applied. The second category is associated with both unplanned and planned outages (maintenance). Planned outages can be treated in two ways. Firstly, the planned outage is modelled as a two state model, where the transition rates between the two states are estimated using the Markov process [141]. By doing this, planned outages are considered as random events. The second model is to have the predetermined schedule of planned outages for the period of study [44]. This model is more realistic because it ensures that maintenanceplanning criteria set by the utility are fulfilled. For instance, utilities commonly do not allow for more than one component in a substation or generation plant to be out of service for maintaince. This condition is not granted when considering the planned outages as random events.

5.1.4 Load model

The simplest approach in load modelling is to consider a single load level that remains constant over a yearly period. The peak load is usually employed for this model in order to account for the worse case scenario. The reliability indices calculated using this model are known as *annualised* indices. The major advantage of this model is that it reduces the computation time of the reliability assessment; however, it does not reflect the variation in the load demand throughout the year.



Figure 5-2: Load duration curve and its multi step model

For some system reliability applications, it is essential to consider the load variation during the study period. Accordingly, the annual curve has to be modelled and incorporated in these reliability analyses. There are two approaches for modelling an annual load curve [43]. The first approach is to consider the chronological annual load curve and to perform reliability assessment at each hourly period. The annual reliability indices are calculated using an equal probability 1/8760 for each hourly load. This approach is the most accurate, but it requires excessive computation time and effort. The second approach is to represent the annual load variation by the load duration curve and then convert this duration curve into a multi-step load model [43]. An illustrative model example is given in Figure 5-2. Clustering technique

is the most common method for obtaining multi-step load models. The basic steps of these techniques are described below:

- 1) Determine the number of steps.
- 2) Set an initial value of the load level for individual steps
- 3) Calculate the distance between hourly load points and all load levels. Then cluster the hourly points in that level.
- 4) Repeat steps 2 and 3 with an acceptable level of accuracy.

The calculated load levels and the number of hourly load points define the multi-step levels with the associated durations. The accuracy of the reliability results is proportional to the number of steps and thereby, proportional to the computational time. The selection of the number of steps is a trade-off between the required level of accuracy and the computational time of the evaluations. Different power networks have different sensitivities to the load levels, and therefore to the required number of steps in the load model.

In order to incorporate this multi-step model into system reliability assessmet, one can either enumerate the levels one by one or randomly sample them within the simulation iterations. For the former, the reliability indices are assessed at each level, and then the annual indices are calculated using the indices obtained for the individual levels and their associated probabilities. The latter approach is only applicable for reliability assessment techniques based on simulations. In this method, the probabilities of load levels are sorted from smallest to largest, and then accumulated. In each iteration of the reliability assessment, a random number between 0 and 1 is generated and compared to the accumulated probabilities to sample the load levels.

5.2 Sampling Reduction Techniques

In structural reliability analysis, where the probability of failure is generally relatively small, the direct Monte Carlo (MC) simulation procedure becomes inefficient. In this case, many simulations are required to estimate a reliability index and limit the uncertainty in the estimate. In MC simulation procedure dealing with a large number of random variables, a

large number of sampling sets is required. Thus, there are limitations to obtaining satisfactory occuracy for large-scale problems, because it requires large computational time and effort.

By reducing the variance of the probability density function of a random variable that results from a Monte Carlo simulation can decrease the standard deviation of the estimated quantity. Besides, decreasing the variance has a similar effect on the accuracy of a Monte Carlo simulation as increasing the number of samples, or equivalently, number of iterations. The application of variance reduction techniques is an important concept in Monte Carlo simulation [142]. The most commonly used variance reduction techniques in power systems reliability evaluation are control variates, importance sampling, stratified sampling, antithetic variates, and dagger sampling [1]. Even though variance reduction techniques successfully reduce the number of samples, they can alter the probability distribution of estimated quantities [143].

Alternatives to the traditional sampling reduction techniques are pseudo-chronological MCS [144][145], cross entropy quasi sequential [146][147], quasi cross entropy [148] and latin hypercube sampling [149], which are all combined with the conventional Monte Carlo simulation to accelerate its convergence. In addition, the population intelligence search method has been recently applied to the probabilistic reliability analysis of power systems [150]. The synergistic combination of the listed methods with the MCS has resulted in improved methods of sampling within the MCS methodologies. The latest developments are mainly focused on the use of optimization heuristic techniques, such as genetic algorithm (GA) [151] and particle swarm optimization (PSO) [152], but there are also some works including artificial immune system (AIS) [150] and ant colony optimization (ACO) [153]. In this thesis, Monte Carlo simulation is used to model the uncertainty in the availability of transmission lines and generation units, which form the total number of states of the system. For a system of realistic size, the number of states will be extremely large; however, most of those states play a small role in reliability evaluation. As a result the heuristic approaches mentioned above give enough precision through visiting sufficient states of high probability and this approach has been shown to be effective [154]. In particular, the goal of these techniques is to remove as many non loss-of-load states as possible (also called state space pruning) in order to generate a new state space where the density of failure states is quite high. This newly formed state space will encourage algorithms such as MCS to converge more quickly. Concequently, particle swarm optimization is used in combination with MCS to improve its computation time by identifying and reducing the number of systems states of interest.

To summarize, the full algorithm contains the following steps [155], which will be described in more detail in section 5.2.1.4:

- Prune the original state space using MOPSO
- Run MCS for the pruned state space until LOLP converges
- Convert MCS LOLP from the pruned state space back to LOLP for the original state space

The following sections will focus on particle swarm optimization combined with nonsequential Monte Carlo simulation. These approaches were developed to speed-up computations.

5.2.1 Binary Particle Swarm Optimization

The particle swarm optimization (PSO) is a population based optimization technique firstly proposed by Kennedy and Eberhart [156]. Few years later an alternative PSO, the binary PSO (BPSO), was investigated by Kennedy and Eberhart, which restricts the component values and the solution to the range (0,1). An introduction to the particle swarm optimization will be presented first and then BPSO equations will be given.

Some of the attractive features of the PSO include the ease of implementation and the fact that no gradient information is required. It can be used to solve a wide array of different optimization problems. In addition, PSO, similarly to the algorithms belonging to the evolutionary algorithm family, is a stochastic algorithm that can be used on functions where the gradient is either unavailable or computationally expensive to obtain. The PSO approach originates from sociological phenomena, since the original algorithm was based on the sociological behavior associated with bird flocking and school of fish [157]. The algorithm considers a population of particles, where each particle represents a potential solution to an optimization problem. If the size of the swarm, namely generations, is for example G, each

particle *i* can be represented as an object with several characteristics. As such originally these characteristics were assigned by Kennedy and Eberhart the following symbols:

x_i: the personal position of particle i;

vi: the personal velocity of particle i;

yi: the personal best position of particle i.

The personal best position associated with particle $i y'_i$ is based on the best position that the particle has visited (a previous value of x_i), yielding the highest fitness value for that particle. For a maximization task, a position yielding a larger function value is regarded as having a higher fitness. The symbol f will be used to denote the objective function that is being maximized. The update equation for the current best position is presented in (5-14):

$$\mathbf{y}'_{i} = \begin{cases} \mathbf{y}_{i} & \text{if } f(\mathbf{x}_{i}) \leq f(\mathbf{y}_{i}) \\ \mathbf{x}_{i} & \text{if } f(\mathbf{x}_{i}) > f(\mathbf{y}_{i}) \end{cases}$$
(5-14)

Each particle is characterized by the best global value, *gbest*, which denotes the best position discovered by any of the particles so far. The definition of *gbest* is given by (5-15).

$$g_{best} = \max(f(\mathbf{y}_0, \mathbf{y}_1, \dots, \mathbf{y}_G))$$
(5-15)

where *G* is the size (number) of the particles generations.

The algorithm was later developed to a two-vector velocity $v_{i,j}$ to help solve more complex problems [158]. For application in this work, the additional vector j represents the j^{th} system element (e.g a generation unit or a transmission line), whereas i represents the i^{th} particle. This is specific to the problem at hand, as one could assess failures in generation units only, in transmission lines only, or as is the case in this thesis failures in both generation units and transmission lines. This algorithm makes use of two independent random sequences, r_1 ~U(0,1) and r_2 ~U(0,1). These sequences are used to reflect the stochastic nature of the algorithm as shown in (5-16).

$$\boldsymbol{v}_{i,j}' = \boldsymbol{v}_{i,j} + c_1 r_{1,j} [\boldsymbol{y}_{i,j} - \boldsymbol{x}_{i,j}] + c_2 r_{2,j} [gbest - \boldsymbol{x}_{i,j}]$$
(5-16)

The values of r_1 , r_2 are scaled by constants c_1 , $c_2 \le 2$. These constants are called acceleration coefficients and they influence the maximum size of the step that a particle can take in a single iteration. The velocity update step is specified separately for each dimension j=1...n, so that $v_{i,j}$ denotes the j^{th} dimension of the velocity vector associated with the i^{th} particle. From the definition of the velocity update equation (5-16) it is clear that c_2 regulates the

maximum step size in the direction of the current best position of that particle. The value of $v_{i,j}$ is clamped to the range $[-v_{max}, v_{max}]$ to reduce the likelihood that the particle might leave the search space. If the search space is defined by the bounds $[-x_{max}, x_{max}]$, then the value of v_{max} is typically set so that $v_{max}=k^*x_{max}$, where $0.1 \le k \le 1$.

The position of each particle is updated using the new velocity vector for that particle so that:

$$x'_{i,i} = x_{i,i} + v_{i,i} \tag{5-17}$$

A binary version of the PSO was introduced by Kennedy and Eberhart in [159]. This alternative of PSO restricts the values of components x_i and y_i to the binary values (0, 1). There is no such restriction on the value of the velocity, $v_{i,j}$, of a particle, though. When using the velocity to update the positions, however, the velocity is bounded to the range [0, 1] and treated as a probability. This can be accomplished by using the sigmoid function, defined as,

$$sig(x) = \frac{1}{1 + exp(-x)}$$
 (5-18)

Note that this velocity update equation does not differ from the one used in the original PSO. The position update equation for the BPSO is expressed by relations (5-19):

$$\boldsymbol{x}_{i,j} = \begin{cases} 0, & \text{if } r_{3,j} \ge sig(\boldsymbol{v}_{i,j}) \\ 1, & \text{if } r_{3,j} < sig(\boldsymbol{v}_{i,j}) \end{cases}$$
(5-19)

where $r_{3,j}(t) \sim U(0,1)$ is a uniform random variate. It is clear from the equation that the value of $x_{i,j}$ will remain 0 if $sig(v_{i,j})=0$. This will happen when $v_{i,j}$ is approximately less than -10. Likewise, the sigmoid function will saturate when $v_{i,j}>10$. To prevent this it is recommended to clamp the value of $v_{i,j}$ to the range ±4 [160], resulting in a state-change probability that sig(4)=0.018. The original paper describing the binary PSO recommended a slightly larger v_{max}/v_{min} threshold of ±6, resulting in a probability of approximately 0.0025. In other words, equation (5-16) implies the sociocognitive concepts of particle swarm optimization, which are included in the function v_{ij} , which means that the disposition of each individual towards success is adjusted according to its own experience as well as of the community.

Note that the velocity update equation corresponds to the original velocity update equation without the inertia weight or constriction coefficients [159]. This is because the paper describing the binary PSO [159] was published before these modifications were introduced. A later paper used the binary PSO in a comparison with a Genetic Algorithms on a multi-modal test function generator [161]. That binary PSO made use of constriction coefficient, showing that the techniques usually applied to the continuous PSO are applicable to the binary PSO as well.

5.2.1.1 Rate of Convergence Improvements

Several techniques have been proposed for improving the rate of convergence of the PSO. These proposals usually involve changes to the PSO update equations, without changing the structure of the algorithm. This usually results in better local optimization performance, sometimes with a corresponding decrease in performance (i.e. worse performance) on functions with multiple local minima.

• Inertia weight

Some of the earliest modifications to the original PSO were aimed at further improving the rate of convergence of the algorithm. One of the most widely used improvements is the introduction of the inertia weight by Shi and Eberhart [162]. The inertia weight is a scaling factor associated with the velocity during the previous time step, resulting in a new velocity during the previous time step; the new velocity update equation is used:

$$\boldsymbol{v}_{i,j} = w \boldsymbol{v}_{i,j} + c_1 r_{1,j} [\boldsymbol{y}_{i,j} - \boldsymbol{x}_{i,j}] + c_2 r_{2,j} [gbest - \boldsymbol{x}_{i,j}]$$
(5-20)

where *gbest* is the global best value and it is given in (5-15).

The original PSO velocity update equation can be obtained by setting w=1. Shi and Eberhart investigated the effect of w values in the range [0, 1.4], as well as varying w over time [162].

Their results indicate that choosing $w \in [0.8, 1.2]$ results in faster convergence, but that larger w values (>1.2) result in more failures to converge.

The inertia weight governs how much of the previous velocities should be retained from the previous time step. To briefly illustrate the effect of w, set c_1 , $c_2=0$. Now, a w value greater than 1.0 will cause the particle to accelerate up to the maximum velocity v_{max} (or $-v_{max}$), where it will remain, assuming the initial velocity was non-zero. A w value less than 1.0 will cause the particle to slowly decelerate until its velocity reaches zero.

Another set of experiments was performed to investigate the interaction between v_{max} and the inertia weight [163]. For the single function studied in this experiment, it was found that an inertia weight of 0.8 produced good results, even when $v_{max}=x_{max}$ the best performance, however, it was again obtained by using an inertia weight that decreased from 0.9 to 0.4 during the first 1500 iterations. Consequently, the inertia weighting factor *w* is often specified as a real value in the interval [0.0, 1.0] and can be proportionally decreased with the iteration progress, using, for example, relation (5-21).

$$w = w_{max} - \frac{t}{t_{max}} (w_{max} - w_{min})$$
 (5-21)

where w_{max} and w_{min} are the maximum and minimum weighting values; *t* and t_{max} are the current and maximum counts of iterations, respectively.

Constriction Factor

Recently, work by Clerk [164] indicated that a constriction factor may help to ensure convergence. The constriction factor model describes, amongst other things, a way of choosing the values of w, c_1 , c_2 so that convergence is ensured. By choosing these values correctly, the need for clamping the values of $v_{i,j}$ to the range [- v_{max} , v_{max}] is required.

A modified velocity update equation, corresponding to one of several constriction models [164] is presented in (5-22).

$$\boldsymbol{v}_{i,j} = X \cdot \{ \boldsymbol{v}_{i,j} + c_1 r_{1,j} [\boldsymbol{y}_{i,j} - \boldsymbol{x}_{i,j}] + c_2 r_{2,j} [gbest - \boldsymbol{x}_{i,j}] \}$$
(5-22)

where:

$$X = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{5-23}$$

and $\varphi = c_1 + c_2$, $\varphi > 4$. If $c_1 = c_2 = 2.05$ substituting $\varphi = c_1 + c_2 = 4.1$ into equation (5-23) yields x = 0.7298, which in turn gives equation (5-22) in the form of:

$$\boldsymbol{v}_{i,j} = 0.7298 * (\boldsymbol{v}_{i,j} + 2.05 * r_{1,j} (\boldsymbol{y}_{i,j} - \boldsymbol{x}_{i,j}) + 2.05 * r_{2,j} (\boldsymbol{g}_{best} - \boldsymbol{x}_{i,j}))$$
(5-24)

Since 2.05*0.7298=1.4962, this is equivalent to using the values $c_1=c_2=1.4962$ and w=0.7298 in the modified PSO velocity update equation (5-24).

5.2.1.2 Application of PSO to Power Systems

The PSO has been applied to a vast number of problems. This section will briefly mention some of the applications that can be found in literature. Different types of PSO have been presented and categorized as shown below [164]:

- Reactive power and voltage control,
- Economic dispatch,
- Power system reliability and security,
- Generation expansion problem,
- State estimation,
- Load flow and optimal power flow,
- Power system identification and control,
- Controller tuning,
- System identification and intelligent control,
- Electric machinery,
- Capacitor placement,
- PMU placement,
- Generator maintenance scheduling,
- Short-term load forecasting,
- Generator contributions to transmission system,

5.2.1.3 Illustration of the proposed model on reliability analysis

The main goal of the proposed algorithm is to reduce the state space by removing the states that do not result in loss of load and so contribute less to the computation of the reliability indices. Consequently, computational time is saved from avoiding searching unecessary states. These states are characterized by "success state" if there is load curtailment on the network, while the states are considered "failure states" if no curtailment is needed. Therefore, the movement of the particle is accomplished in a 3-dimensional space by searching for the optimal solution along three coordinates. The first coordinate – objective function is based on the maximization of the probability of the system state as in [154], so the variable of the problem is the probability of the system state for each particle *i*, based on the probability of each network component state, and is given in equations (5-26), (5-27). Given a probability of failure for each network component, the total probability of each system state represents the product of the probabilities of every network component in a given system state. The first objective therefore searches for system states with probability close to 1 (maximum probability) and discards those states that do not lead to any loss of load (i.e.: no load curtailment) from the state space. As such, the states without loss of load occur with higher density compared to states with loss of load. The second objective function uses the minimization of load curtailment as in [154] to further encourage the particle's movement to a non-loss of load state, equation (5-28). The third objective function makes use of the maximization of the rating of the transmission lines to speed up the search for non-loss of load states. Indeed, under certain sets of combinations of failures, lines can be overloaded; in some cases this does not cause any loss of load, in other cases this causes loss of load. The third objective hence targets the former case, where lines are overloaded, in other words where line ratings are maximised, but do not cause any loss of load. The state space is hence reduced and thus speeds up the particle search. This third objective function further acts as a conflicting force to the two previous objectives. Because the first and second objective functions are complementary, it is possible for the particle to collapse towards one corner of the search space [154]. To avoid this, the opposing criterion from the third objective is used to control the particle dynamics and ensure that the particle visits all the states of interest. The formula of this objective is given in equation (5-33). The variable on this function is the ratings of the transmission lines, which depends of the systems components availability and unavailability. The first and the second objective functions used in this work is similar as in [155][154][159], whereas the third objective function is a novel extension of the algorithm and a contribution in this thesis. As such the algorithm is multi objective and so it is called

Multi Objective Particle Swarm Optimization (MOPSO). This function is explained in (5-25):

$$v_{i,j} = v_{i,j} + F_1 r_{1,j}(t) [PPrbest_{i,1} - x_{i,j}] + V_1 r_{2,j} (Gpbest - x_{i,j}) + F_2 r_{3,j} [PLCbest_{i,2} - x_{i,j}] + V_2 r_{4,j} [Glcbest - x_{i,j}] + F_3 r_{5,j} [PTRbest_{i,3} - (5-25) x_{i,j}] + V_3 r_{6,j} [Gtrbest - x_{i,j}]$$

$$\max PPrbest_{i,1} = \max \{PPrbest_{1,1}, PPrbest_{2,1}, \dots, PPrbest_{P,1}\}$$
(5-26)

$$PPrbest_{i,1} = \prod_{j=1}^{TC} p_j \tag{5-27}$$

$$minPLCbest_{i,2} = min\left\{\frac{LC}{TLoad}\right\}$$
 (5-28)

where the quantities denote:

PPrbest _{i,1} :	Addresses the highest system state probability;		
Gpbest :	Denotes the best position with the highest system state probability		
	discovered by any of the particles so far;		
PLCbest _{i,2} :	Addresses the minimum load curtailment;		
Glcbest :	Denotes the best position with the lowest load curtailment discovered		
	by any of the particles so far;		
$PTRbest_{i,3}$:	Addresses the loading of the transmission line;		
Gtrbest :	Denotes the best position with the highest rating discovered by any o		
	the particles so far;		
<i>F</i> , <i>V</i> :	Acceleration factors for each objective function respectively;		
<i>r</i> :	Independent uniformly distributed variables in the interval [0,1];		
<i>P</i> :	Number of particles;		
TC:	Total number of nentork components (generators and transmission		
	lines);		
p_j :	Probability of generator/transmission line j to be available or		
	unavailable;		
LC:	Load Curtailment for particle <i>i</i> ;		
TLoad:	Total Load in the network for particle <i>i</i> ;		

The Multi Objective Particle Swarm Optimization (MOPSO) algorithm is developed using power flow analysis to distinguish between a success or a failure system state. In order to keep track of the states visited by the particles, a dynamic array has been used. Whenever a state is encountered, its binary encoding scheme is computed. If the number is already present, then it means that this state has already been encountered before. Otherwise, this state is being encountered for the first time, and therefore the binary code is stored in the array. The steps of the proposed methodology for improved MCS are illustrated in Figure 5-3. They are explained below.



Figure 5-3: MOPSO flowchart

Initialization: PSO is initialized with a group of random particles P and then searches for optima by updating generations G. Generations G are comprised by a number of particles P. Both values are randomly selected until a combination of them results in a desired target, which in our case is to minimize computational time. In every iteration, each particle is updated by following two "best" values (the personal best and the global best value). The number of particles P and generations G are set for the simulation. The components of the

system (generators and lines) represent one dimension through a binary encoding scheme; 1 represents the up and 0 the down status of the dimensions of each particle. Dimension j equals to a binary encoding scheme representing the availability or not of the total number of generation units and transmission lines. For each dimension j of a particle i the initial positions and velocities are defined by the forced outage rate (FOR) of the j^{th} dimension, as follows.

$$X_{i,j} = \begin{cases} 0 & r \le FOR_{i,j} \\ 1 & otherwise \end{cases}$$
(5-29)

$$\boldsymbol{v}_{i,j} = \begin{cases} FOR_{i,j} & X_{i,j} = 0\\ 1 - FOR_{i,j} & X_{i,j} = 1 \end{cases}$$
(5-30)

where $X_{i,j}$ is the value of the position of the j^{th} dimension of the i^{th} particle and $v_{i,j}$ is the value of the velocity vector.

Since all the particles obtain a position vector at position $x_{i,j}$ and velocity vector $v_{i,j}$, they track a personal best solution and position that relates to the multi-function.

Filtering meaningless cases: The network status is considered as meaningless (i.e. it is not studied) in the following cases: a) The probability of the system state is lower than a very small number δ (e.g.: δ =10⁻⁷); b) A particle is the same as a particle of the same or previous generation; c) All components are in the up state.

Loss of load computation: The objective of using DC OPF here is to minimize the total load curtailments during peak demand. The state is considered to be a success state if there is curtailment, while the states are considered failure states if no curtailment is needed. The objective function is derived from the equations presented in section 2.5 and uses a piecewise linear approach for the minimization of loss of load and generation costs.

Weight index calculation: The novelty of this thesis is the use of a new index *WI* to weight the loading of the lines. Distinguishing more frequently highly loaded lines from less frequently highly loaded lines within deterministic analysis, we can find which lines contribute more or less to a non-loss load state when there is a failure in the system. Consequently, we can use the weights on the lines to direct the particle to states with no load

curtailment, which is the target of the proposed algorithm (state space pruning using PSO). As such, transmission lines with the highest loading contribute less to the non loss load state space and therefore a smaller personal best number is calculated for these lines; on the other hand, lines which are loaded less satisfy the load connected at their terminals and a higher personal best number is calculated for these lines so the particle will be directed to the nonloss load space. As a preparation, the deterministic (N-1) approach is first used for the calculation of the weight index as this is method is fast and provides an approximate indication of the index for the set of system states where transmission lines are overloaded but do not cause any loss of load. A sensitivity analysis is then performed, by varying the ratings of each line and considering N-1 transmission lines outages, the number of occurrences when a line is loaded above a given rating is recorded for the peak load. The analysis was implemented considering N-1 outages of the lines so as to give an indication of which lines are more frequently overloaded. Therefore for all system states the total probability must equal 1. The system is operated under the occurrence of a credible outage without causing voltage problems and load shedding. Probability of each state (P_i) is calculated by using the normalised value of (5-33), assuming that all outages are independent; normalization is done with $\Sigma PTRbest_{i,3}$ so that sum of all normalized probabilities is equal unity. The line overloadings are classified from 10% to 100% of the actual ratings into bins of 10%. This classification is applied because several actual transmission line ratings/flows are very low compared to their actual capacity margin. Therefore, the mean value of frequency of OHLs' overloadings $(TL_{s,l})$ is determined for the various rating limits, as shown in (5-32) with $\chi_{y,l}$ being the number of overloadings of transmission line *l* of scenario *S*. The average loading value for each OHL is given by WI_l in (5-31) aiming to show the importance of each line in the network:

$$WI_{l} = \frac{\sum_{s=1}^{S} TL_{s,l}}{S}$$
(5-31)

$$TL_{s,l} = \frac{\sum_{y=1}^{Y} \chi_{y,l}}{Y}$$
(5-32)

$$PTRbest_{i,3} = \frac{\sum_{l=1}^{L} \frac{1}{WI_l} \cdot Lflow_l}{Lflow_system}$$
(5-33)

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WI_l :	Weight index of transmission line l considering deterministic				
	scenarios S;				
<i>S</i> :	Number of deterministic scenarios;				
$TL_{s,l}$:	Mean value of thermal loading of line <i>l</i> at scenario <i>s</i> ;				
<i>Y</i> :	Total iterations of deterministic scenario S;				
$\chi_{y,l}$:	Number of overloadings of transmission line <i>l</i> of scenario <i>s</i> ;				
PTRbest _{i,j} :	Personal best considering thermal ratings;				
Lflow _l :	Load flow of transmission line <i>l</i> ;				
Lflow_system:	Total Load flow of the entire network;				
L:	Total number of transmission lines				

Assessing the dominant cases: If the particle is a success state then the algorithm includes the following steps: a) Store the binary sequence of the particle as pruned state; b) Store the probability calculated as in equation (5-27); c) Store if there is load curtailment in the system state; and d) Store the power flows of the transmission lines. Otherwise, set a low importance value to the personal best values and go to the next particle.

Population evaluation-formulation: Determine the personal best values by using the inputs of the network status. Update the velocities and positions for each dimension j of particle i using (5-25) and check the following constraints:

$$v_{i,j}^{k+1} > V_{max}$$
 then $v_{i,j}^{k+1} = V_{max}$ (5-34)

$$\boldsymbol{v}_{i,j}^{k+1} < V_{min} \text{ then } \boldsymbol{v}_{i,j}^{k+1} = V_{min}$$
(5-35)

 V_{max} and V_{min} are considered as thresholds for the velocity-probability of failure and make use different values for the lines and for the generators in order to make the algorithm more realistic.

Stopping Criteria: The simulation process is continued until the number of the particle generations is reached (k=G).

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5.2.1.4 BPSO within Monte Carlo Simulation

As discussed above in Section 5.2, the MOPSO algorithm is combined with Monte Carlo simulation to discard a large amount of success states and make the MCS converge quicker as proven in [155]. However, the advantage of including a third objective function introduced in this work is twofold: 1) this reduces computational speed by targeting the system states where overloaded lines do not cause loss of load, and 2) this opposing criterion from the third objective is used to control the particle dynamics and ensure that the particle does not collapse towards a corner of the search space. The MC algorithm used for this purpose is shown in Figure 5-4 and it can be divided into the following steps:



Figure 5-4: Pruned MCS flowchart

1) Set the number of samples *Y*

- 2) Use state sampling technique to determine the system state. For the sampling technique the random numbers are taken exponentially from the range (0, 1).
- 3) If the state has been pruned determine from the database whether it is a success or failure state. If it is a success state discard this event. If not, add the state into the calculation of LOLP.
- 4) If the state hasn't been pruned, run OPF and classify it as a success or failure state.
- 5) If it is a failure state then add the state into the calculation of LOLP using the following equations, as in [150][155]:

$$LOLP_{MOPSO-MCS} = LOLP_{MCS} * (1 - \sum P_i)$$
(5-36)

where P_i is the probability of occurrence of a pruned state generated by the MOPSO. In (5-36) we have used:

$$LOLP_{MCS} = \frac{1}{K} \sum_{i=1}^{K} D_i \tag{5-37}$$

$$D_i = \begin{cases} 1 & loss of load state \\ 0 & otherwise \end{cases}$$
(5-38)

where D_i is given in (5-38), K is the total number of states sampled so far in each iteration and $LOLP_{MCS}$ is the loss of load probability (LOLP) calculated via MCS and it is converted back to a LOLP relevant to the original state.

6) If the stopping criterion is fulfilled ($COV \le 0.04$), then stop simulations [43].

5.2.1.5 MOPSO algorithm with Thermal Ratings

Thermal ratings are included in the MOPSO algorithm to realistically identify faster the pruned states using standard and real time thermal ratings. The MOPSO algorithm is tested incorporating static, seasonal and real-time thermal ratings using probability distribution functions to sample thermal rating values. Real-time thermal ratings are modelled for winter

peak load and under a 30-year weather data corresponding to peak winter days. To create the probability distribution functions, chronological data such as wind speed, ambient temperature and wind direction were plugged in (4-28) to determine ampacities for each conductor type. Because MOPSO is implemented for non-sequential MCS, which means for a specific load level (in this case for the peak load), the PDFs are produced using 30 years of historical weather data for the peak load hour. For static thermal rating the peak hour during summer period is used, whilst for seasonal thermal ratings three periods are considered 1) peak summer hour, 2) peak spring/fall hour, and 3) peak winter hour. Then the median value of each PDF is used as the fixed value for each type of standard thermal ratings.

In the case of real thermal ratings, historical weather data during the peak hour (winter period) are plugged in (4-28) to calculate the PDF of real thermal ratings. While the median value of the PDFs are used for standard thermal ratings, in this case a random number is generated using the best PDF matching with the calculated real thermal ratings, which have mean value μ and standard deviation σ .

For either thermal rating approach, the PDFs generate the maximum thermal rating at each sample of system state. Subsequently, the load flow parameters of the lines are calculated after using DC (OPF) formulation, as described in Chapter 4.3.3 for the network considering the operating conditions (i.e. failures if any) and the initial maximum thermal rating. The thermal ratings are set in the MOPSO algorithm as it is shown in the flowchart of Figure 5-3 through the "assessing the dominant cases" step. The rest of the MOPSO procedure continues as described in the previous section.

5.2.2 Case studies

5.2.2.1 Validation of MOPSO algorithm

The MOPSO method was implemented using acceleration factors: F_1 =0.01, V_1 =0.1; F_2 =0.1, V_2 =0.1; F_3 =0.1, V_3 =0.1 and velocity limit V_{max} =4 and V_{min} =-4. The size of the swarm also plays a determining role in the convergence of the NMCS. Due to this, each simulation run has been done for a combination of particles and generations, which range from 5 to 30 particles and from 50 to 300 generations. After the various combinations of particles and

generations were completed, the data were sorted in ascending order in respect to the number of success states pruned. The probability threshold of system states is δ =10⁻⁷, stopping criterion for MOPSO is the number of generations *G* and the stopping criterion for NSMCS is 4%. NMCS is used as a baseline to calculate the LOLP and computational time of the original method. Both the effects of transmission lines and generators' failures are considered in the reliability modelling.

Three performance indicators were computed: LOLP, CPU time and number of iterations. Table 5-1 presents comparisons of system indices between NSMCS (baseline) and the proposed MOPSO. It is shown that the number of NSMCS iterations are reduced by 70%, when MOPSO algorithm is used. Similarly the CPU time is reduced by 73%, which shows that MOPSO technique is very efficient and accelerates significantly NSMCS simulation burden. As far as the accuracy of the indices is concerned, the MOPSO technique is very robust and achieves less than 0.1% error of the expected values of indices calculated.

RELIABILITY INDICES	NSMCS	MOPSO
LOLP	0.06261	0.06359
iterations	85534	24625
CPU(h)	3.23	0.86

 Table 5-1: Comparison of system indices using NSMCS and MOPSO

Figure 5-5 details the comparative results between single, bi, and multi objective functions for pruning the states. In particular, it indicates that the LOLP derived from the optimization algorithm shows high accuracy in the range of 0.004 in respect to the baseline LOLP. In addition, the proposed MOPSO displays slightly smaller LOLP fluctuation around the baseline throughout the total number of trials, which demonstrates that the novel method improves network performance indices.



Figure 5-5: MOPSO algorithm: LOLP reliability index

Figure 5-6 shows the total computational time required for MOPSO to complete the simulations. It is clear that the proposed MOPSO is faster than the single and bi-objective function. In particular, MOPSO needs 1.35 hr when the single objective function is used for pruning, while the proposed method (three objectives) decreases the MOPSO convergence time to about 0.85 hr, as it is shown in Figure 5-5. This is because the MOPSO prunes larger number of success states for the same combination of particles and particle generations as it combines the three objectives, while still superior to a single objective on its own. The spikes that occur in all three optimization algorithms mean that although the number of success states pruned is large, the number of MCS iterations is bigger because there is a possibility of MCS to randomly sample a success system state that wasn't captured by the optimization techniques (this is known as collision). Furthermore, it can be inferred from the graph that the computational time of MOPSO with a single and bi-objective function is almost the same between 20 and 40 trials. This is mainly because the bi-objective function identifies success states, which are not sampled so often by MCS, as well as because there are collisions between PSO method and MCS. In summary, the proposed MOPSO has a CPU time of 0.86 hours for trial 1, as given both in Table 5-1 and Figure 5-6 representing a 74% improvement in CPU time compared to the MCS algorithm alone (3.23 hours).



Figure 5-6: MOPSO Computational Time

Figure 5-7 demonstrates that the MOPSO method prunes more success states than both the probability based method and the probability-curtailment method. All methods prune up to 14500 success states for the first 40 simulations and then the pruning increase in an exponential manner.

It can be seen that the algorithm using one objective function prunes more success states than the method with two objective functions. This is evident, since the algorithm with two objective functions is mainly affected by the curtailment objective function, which plays dominant role in the selection of the success states. However, PSO using three objectives shows better results, see Figure 5-7, because the occurrence of success states pruned by three objectives are more frequently compared to one objective function.



Figure 5-7: Success States Pruned

The Weight Index (WI_{crude}) used to validate the proposed MOPSO uses the capacity data of the transmission lines given by the IEEE RTS. The loading of each transmission line is computed after deterministic analysis implementation using the peak load of IEEE RTS for the WI_{crude} and 2.5 times the peak load of the network for the WI_{str} (static thermal rating) and WI_{RTTR} (real time thermal rating). It is illustrated in Figure 5-8 that for the 138 kV voltage IEEE RTS network line 11 is the most frequently overloaded, whereas for the 230kV network lines 23 and 28 show very high loading probability. Therefore, it can be implied that the indexes of the most critical lines boost the intelligent movement of particles to search and track more success system states. This is due to the ability of particle to discover the states that the lines are overloaded subject to generator and line failures in order to satisfy the total demand and eventually result in a non-loss of load state.



Figure 5-8: Weight indices used by the proposed MOPSO for the different thermal rating scenarios

5.2.2.2 MOPSO algorithm using Thermal Ratings results

The additional scenario with increased load to 2.5pu of its peak load is also used to consider the thermal ratings of the OHLs.

The probability distribution functions (PDFs) of Seasonal Thermal Rating (SeTR) for Aonach UK area are shown in Figure 5-9. The thermal ratings of winter, spring/fall, and summer are shown for both Drake (138kV voltage level) and Grosbeak (230kV voltage level) conductor. This graph indicates the probability density for different thermal rating levels. As a result, system operators can not only use the median rating value for operating the OHLs, but they can also estimate the range of minimum and high thermal ratings under the event of probabilistic failures. It can be seen that the Drake conductor has smaller rating values than Grosbeak and that the risk of Grosbeak conductor's ratings taking high values is larger than Drakes conductors. This is because Grosbeak conductors are utilized more as well as because of their electricity OHL's properties. Consequently any failure at the north part of the network, which is comprised of higher rating Grosbeak conductors, results in a need for even higher ratings.



Figure 5-9: Probability distribution functions of SeTR of Aonach UK area for two different conductors $x10^{-3}$



Figure 5-10shows the PDF functions of both Drake and Grosbeak conductors when real thermal ratings are applied on the network. Among all standard distributions, the best distribution function matching with calculated hourly thermal ratings is the log-logistic. As such, log-logistic distribution function can be used to estimate the real thermal rating of a certain conductor and specific load level. In this way system operators can conduct studies offline using real time thermal ratings and thereby quantify network performance when thermal ratings of OHLs are critical to power system operation.

Chapter 5 - Components of the Developed Reliability Assessment Methodologies



Figure 5-10: Probability distribution functions of RTTR of Aonach area for two different conductors

It is also shown in the figure that the real thermal rating of Grosbeak conductor covers wider range than Drake conductor. In particular, Grosbeak thermal rating ranges from 500 MVA to 3500 MVA whereas Drake conductor rating ranges from few MVA to almost 1000MVA. As a result, Grosbeak conductor is utilised more than the Drake especially under probabilistic analysis. Therefore, by applying real thermal ratings under probabilistic analysis one can identify the whole range of the MVA values a conductor can take as well as estimate the thermal rating of a particular hour and load so system operators can consider it and optimize system operation.

Table 5-2 presents the reliability indices and CPU times for the various thermal-rating scenarios. It is demonstrated that RTTR facilitates MOPSO algorithm. This is more likely because the more detailed parameters of OHLs enhance the efficiency of the algorithm as well as the various thermal ratings values enable the proposed algorithm to escape from local minima and maxima. In particular, MOPSO_{RTTR} is 73.5% faster than NSMCS_{RTTR}, whereas MOPSO_{STR} is 67.2% faster than NSMCS_{STR}. At the same time MOPSO calculates accurately the LOLP and EENS indices. In addition, the RTTR model resulted in 46.54% lower EENS than the STR model. This is mainly due to the increased capacity of transmission lines provided from the RTTR model.

	LOLP	EENS (MWhr/y)	iterations	CPU (hr)
NSMCS _{STR}	0.3898	28.25	14146	0.55
NSMCS _{Setr}	0.3574	21.01	32983	0.98
NSMCS _{RTTR}	0.3429	15.1	59402	1.62
MOPSO _{STR}	0.3885	28.13	3879	0.18
MOPSO _{Setr}	0.3591	20.87	7916	0.27
MOPSO _{RTTR}	0.3418	15.1	10710	0.43

Table 5-2: Comparison of system indices considering OHLs Thermal Ratings

5.3 Input data estimation

Before an optimal demand response plan can be scheduled for the next day, the load must be forecasted one day-ahead. In addition, the unit commitment schedule and the status of network switching devices must also be known [17]. The load is forecasted in this work using an artificial neural network as presented below in section 5.3.1. This load forecast will then be used as an input to the unit commitment scheduling in chapter 6. This unit commitment schedule is determined using Matlab Matpower, while the status of network switching devices are determined through Monte Carlo simulation, as explained previously in chapter 2.

Further inputs to the model include wind predictions, which are required for wind generation modelling and real-time thermal rating modelling. For wind estimation, values are simulated to create a full distribution of results that has the same statistical properties as the observed data. Instead of taking observed data only, which is limited to one data point per hour, a large number of data points are generated through simulation as this allows taking stochasticity into account and thus allows a probabilistic quantification of risk. Although not done here, further work using this simulation framework could be done by modifying some properties of the wind distribution, such as mean and standard deviation, in order to test different scenarios and sensitivities on network costs and risks.

5.3.1 Load forecasting

A load-forecasting model has therefore been developed using a neural network algorithm and applied to demand response scheduling. The proposed demand scheduling methodology is aimed at determining the, when the committed generation units, status of network switching devices and forecast loads are well defined. The forecasting model uses an artificial neural network (ANN) algorithm that provides high forecasting performance when dealing with nonlinear and multivariate problems involving large datasets, as is the problem of short term load prediction. This algorithm was tested against a linear regression and proved to outperform the latter in all cases. The performance of the algorithm is quantitatively assessed using mean absolute percent error (MAPE) and mean absolute error (MAE). Further analysis gives comparison plots of actual and forecast loads, histograms of errors, and R-values outputted from the linear regression that determines the accuracy of the results.

An overview of the linear regression model used within the analysis is given first and the building blocks of neural networks are described next. Results and a comparison between the two models are presented in the case study section.

5.3.2 Linear Regression

Linear regression is the most common method to give information between a dependent variable and one or more explanatory variables, because it is simple to implement and the relationship between an input matrix of explanatory variables x and an output vector y is easy to understand [165]. In linear regression, the model specification is that the dependent variable at point z, y_z , is a linear combination of the explanatory variables at z, x_z . For example, in simple linear regression for modelling data points z=1,...,n there is one independent variable, x_z , and two parameters, β_0 and β_1 , as shown in (5-39).

$$y_z = \beta_0 + \beta_1 x_z + \varepsilon_z \tag{5-39}$$

In multiple linear regressions, one models the relationship between two or more explanatory variables and a dependent variable by fitting a linear regression to the observed data. The form of the multiple linear regression functions for two explanatory variables is:

$$y_z = \beta_0 + \beta_1 x_z + \beta_2 w_z + \varepsilon_z \tag{5-40}$$

This represents a linear regression expression in variables x_z and w_z , and it is linear in parameters β_0 , β_1 and β_2 . In both cases, ε_z is an error term and the subscript *z* indicates a certain observation point. Considering a sample of observation points within the whole population, the unknown parameters of simple regression (5-39) can be estimated. If they are replaces in (5-40), one gets:

$$\hat{y}_z = \hat{\beta}_0 + \hat{\beta}_1 x_z \tag{5-41}$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are estimated unkonen parameters, whilst residual, $e_z = y_z - \hat{y}_z$, is the difference between the value of the dependent variable predicted by the model, \hat{y}_z , and the true value of the dependent variable, y_z .

However, when weather variables are included, linear regression algorithms assume a linear relationship between weather parameters and load. Yet, this relationship is neither linear nor stationary [1], [7]. For instance, it is shown in [166] that the correlation between temperatures and load considering a day of the week, hour of the day and the previous 20th minute load is non-linear. A more efficient method is the artificial neural network (ANN) approach, which models non-linear relationships between variables and can more accurately model the relationship between load and weather variables. Artificial neural network method for load forecasting is described in the following section.

5.3.3 Artificial Neural Network (ANN) Approach

Artificial neural networks (ANN) use previous load data to predict future load patterns, like time series, but they are also coupled with regression techniques that do not require linear assumption. They can perform complex nonlinear mappings between input variables x_z and output variables y_z . Inspired by biological nervous systems, they create connections between elements, known as neurons or nodes [167], to perform a task or function by adjusting the values of the connections, weights w_z , between elements so that a particular input leads to a specific target output. The multi-layer perceptron (MLP) is the most common ANN in many forecasting applications [168]. It is composed of several layers j of nodes n, where input and output layers are separated by processing stages known as hidden layers [169]. As shown in Figure 5-11, the inputs first pass through the hidden layers, where non-linear functions are used. These allow the network to learn nonlinear relationships between input and output vectors. The values then pass through a linear output layer for function fitting. Non-linear functions, like log-sigmoid and tan-sigmoid functions, are usually used for pattern recognition problems [170], while linear output neurons are used for fitting problems [171]. These functions are the most common but others can also be used.



Figure 5-11: Feed Forward neural network [172]

The output of each neuron, y_g , is a function of the input signals, representing the sum of the weighted inputs, combined with a bias term v and mathematically presented in (5-42):

$$y_g = f(\sum_{p=1}^n w_{gp} x_p - v)$$
 (5-42)

The adjustment of the weights is done based on training samples taken from different operating points of the electricity load forecast. Each node receives information from a number of input nodes, contained in the input layer, processes it locally, first linearly and then through a nonlinear activation or transfer function f, to produce a transferred output signal to other nodes until it reaches the final output layer. The activation function used here is a logistic sigmoid function (5-43), but can be different as in [173]:

$$f = \frac{1}{1 + e^{-x}} \tag{5-43}$$

The output of each neuron is used as input for the transfer function at each node. Starting from a random initial point, the learning algorithm determines the weights so that the error
for mapping the inputs of the training samples to their outputs is minimized with the expectation that a low error will be obtained for an unseen test sample. The choice of learning algorithm is a tradeoff between objective, speed and memory. Some training algorithms are better suited for function approximation, others for pattern recognition [174]. The Levenberg-Marquardt (LM) training algorithm was chosen as it is often the fastest and most efficient training function for small size problems, while achieves lower mean square errors compared to other training functions. It also performs best on function approximation, as is the problem of nonlinear regression. Nonetheless, for larger size networks with a very large number of weights, the LM algorithm can require a lot of memory, unlike other algorithms. The BFGS Quasi-Newton for instance performs similarly to the LM algorithm and requires less memory, but this comes at the expense of computation time. Quantifying the accuracy of the model is essential and is assessed using the mean absolute error (MAPE). The mean absolute error is the absolute value of the residuals, r_z , averaged over the total number of observations, *n*. The errors are first calculated as:

$$r_z = actual \ load_z - \ predictions_z$$
 (5-44)

The MAE and MAPE are then calculated as follows:

$$MAE = \frac{\sum_{z=1}^{n} |r_z|}{n}$$
(5-45)

$$MAPE = \frac{\sum_{z=1}^{n} |r_z / actual \ load_z| \times 100}{n}$$
(5-46)

5.3.4 Case Study Analysis

The following section describes the results of both neural network algorithm and linear regression for four sites in the U.K., which include loads for residential load sector. Each site is modeled first using a linear regression before being modeled with the developed ANN algorithm. Starting from Matlab's neural network toolbox and using a generic function fitting algorithm, the ANN for site1 was run with 10 hidden layers, while ANNs for sites 2 to 4 were run with 2 hidden layers as these settings proved to give most accurate results. Several tests

are made to show the effects of previous load data, weather data and the number of hidden layers on the accuracy of the forecasts. Two types of data were used; inputs variables that are site dependent and input variables that are site independent. The site independent variables are comprised of date (the date of historical load data allows the consideration of patterns in a given season), time (the time for each historical data point, in particular, the hour of the day allows considering patterns in night and day consumption), day of the week (the day of the week is set from Monday to Sunday while a flag indicates a workday, a weekend or a holiday). A list of U.K. bank holidays is also input so that these days are not considered, as they are outliers. Office Heating, Ventilation and Air-Conditioning (HVAC) loads, for example, would commonly be switched on during workdays and off during weekends, which the algorithm needs to consider. The site dependent variables include past load data and temperature.

A predictor matrix containing the date, the hour of the day, the day of the week, the binary element of whether it is a weekday or a weekend and several lagged vectors of the load data based on its correlation with previous minute's load (e.g. previous 10th minute load, previous 20th minute load and previous 20 minutes' average load) is first created for each site. This predictor matrix is used as input data for training the ANN algorithm, at the data selection stage in the neural network toolbox. The target data, defining the desired network output, is the load data for each site. At the next step, 70% of the data is selected for training, 15% of the data is selected for validation and 15% is used for testing. Finally, at the "network architecture" stage, the number of hidden neurons is chosen. These are selected based on which number of neurons gives the most accurate results. The model is finally trained using the Levenberg-Marquardt backpropagation algorithm.

Two case studies are performed considering lags of 24 to 168 hours: the first case does not consider weather data while the second one incorporates weather data.

5.3.4.1 Case study 1

In this case study, it is considered the 1st, 10th and 20th minute lags, as these show high serial autocorrelation in the prediction matrix, but the weather data are omitted for now. The prediction matrix is given in Table 5-4.

Number	Input	Description	Unit
1	Days	Date (06-November-2000)	-
2	Hours	Hour of the Day (0-23:00)	-
3	Day of week	Weekday (Monday to Sunday)	-
4	Previous minute load	Previous load 10 minutes apart	MWh
5	Previous load 10 min apart	Previous load 20 minutes apart	MWh
6	Previous 20 minutes average load	Previous 20 minutes' average load	MWh

Table 5-3: Prediction Matrix

Table 5-4: Summary of linear Regression and Artificial Neural network results (ANN) without weather data

Indices	Linear Regression	ANN		
MAE	0.12MW	0.10MW		
MAPE	437.42%	168.51%		
Training time(mm:ss)	n/a	05:31		
Number of iterations	n/a	171		
Memory Reduction	n/a	1		

It is shown in Table 5-4 that the linear regression has a MAPE of 437.42% and a MAE of 0.12 MW, while an ANN, significantly improves the forecast, with MAPE of 168.51% and MAE of 0.10 MW. This demonstrates that ANN considerably outperforms linear regression technique.

The forecasting accuracy can be observed visually in Figure 5-12 for linear regression and Figure 5-13 for ANN. Results are very good and the neural network seems to perform a lot better than using linear regression. Using the correlated lags definitely improves results and provides quite high forecasting accuracy. The next case study tests if the accuracy can be improved by including the weather data.

These results prove to be very accurate. The errors are consistently very small, with most errors contained around -6.81 and 8.15 MW (Figure 5-14). Both MAPE and MAE are extremely low, while the R-values of the regression plots are all contained close to 1. In particular, it is 0.99382 for linear regression and 0.99462 for ANN, as shown in Figure 5-15.



Figure 5-12: Linear Regression Forecasts



Figure 5-13: Neural Network Forecasts



Figure 5-14: Error Histogram for Neural Network



Figure 5-15: Site3 – Regression plots with R-values for the linear regression (left) and the artificial neural network (right)

5.3.4.2 Case study 2 (with weather data)

Table 5-5: Prediction Matrix						
Number	Input	Description	Unit			
1	Temp	Ambient temperature	°C			
3	Days	Date (06-November-2000)	-			
4	Hours	Hour of the Day (0-23:00)	-			
5	Day of week	Weekday (Monday to Sunday)	-			
6	Previous minute load	Previous load 10 minutes apart	MWh			
5	Previous load 10 min apart	Previous load 20 minutes apart	MWh			
6	Previous 20 minutes average load	Previous 20 minutes' load average	MWh			

Considering weather data the prediction matrix becomes, as shown in Table 5-5.

Table 5-6: Summary of linear Regression and Artificial Neural network results (ANN) with weather data

Indices	Linear Regression	ANN
MAE	0.12MW	0.11MW
MAPE	453.37%	121.11%
Training time(mm:ss)	n/a	03:46
Number of iterations	n/a	112
Memory Reduction	n/a	1

Table 5-6 shows that the inclusion of the weather data does improve slightly the MAPE, which can be seen from Figure 5-16 and Figure 5-17 presented below for the linear regression and the neural network forecasts, respectively. In particular, the MAPE is reduced by 4% and 29% for the linear regression and the ANN, respectively. On the contrary, the MAE value remains the same for the linear regression, whereas it decreases by 0.0.11MW for the ANN. As a result, weather data show a great effect on the ANN compared to the linear regression because the ANN can handle linear and non-linear relationships between parameters. Also, the errors are mostly all around zero, with the majority of errors contained between -5 and 5 MW, as shown in Figure 5-17. Finally, the R-values considerably increase and take values between 0.99621 and 0.99724 meaning the correlation coefficients are even closer to 1.



Figure 5-16: Linear Regression Forecasts



Figure 5-17: Neural Network Forecasts

5.3.5 Wind speed model

Several wind speed models have been used in the power system reliability assessment, such as Weibull distribution model, multi-state wind speed model and auto regressive moving average (ARMA) model [175][176][177]. However, the ARMA model has proved to be the most commonly used. Historical hourly wind speed data collected from the wind farm site can be used to calculate the mean wind speed m_t and its standard deviation σ_t . The normalised time series y(t) is then calculated from the expression [178]:

$$Vm_t = m_t + \sigma_t y_t \tag{5-47}$$

where Vm_t is the wind speed at time *t*.

The ARMA time series is shown in (5-48) where y(t) denotes the output value at time *t*, *na* is the number of of autoregressive terms, *nc* is the number of error terms, y(t-1)...y(t-na) represent the previous outputs on which the current output depends and e(t-1)...e(t-nc) are the white noise error terms.

$$y(t) + a_1 y(t-1) + \dots + a_{na} y(t-n_a) = c_1 e(t-1) + \dots + c_{n_c} e(t-n_c) + e(t)$$
(5-48)

In a more compact way the above equation is described as follows:

$$A(n)y(t) = C(m)e(t)$$
(5-49)

A(n) is a function showing the autoregressive order number 'n' and C(m) is a function showing the moving average order number 'm'. Model (5-49) is usually referred to as ARMA(n,m) stochastic process.

The partial autocorrelation function (pacf) is applied in order to consider whether y(t) and y(t-k), k=1,2,..., are directly correlated. The partial autocorrelation function measures the correlation between an observation k periods ago and the current observation, after controlling for observations at intermediate lags (i.e all lags<k). This means that the correlation between y(t) and y(t-k) is sought, after removing the effects of y(t-k+1), y(t-k+2),..., y(t-1). For example, the pact for lag 3 would measure the correlation between y(t) and y(t-3) after removing the effects of y(t-1) and y(t-2). At lag 1, the autocorrelation and partial autocorrelation coefficients are equal, since there is no intermediate lag effect to eliminate. Partial autocorrelation plays an important role, since one could determine the appropriate order n in an AR(n) model.

In order to evaluate the accuracy of the ARMA model, the Akaike information criterion (AIC) is used [179]. It provides a measure of model quality by simulating the situation where the model is tested on a different data set. After computing several different models, the AIC can be used for comparison purposes. According to Akaike's approach, the most accurate model has the smallest AIC. Akaike information criterion is defined by (5-50):

$$AIC = V\left(\frac{1+\frac{d}{N_e}}{1-\frac{d}{N_e}}\right)$$
(5-50)

where *V* is the loss function, *d* is the number of estimated parameters and N_e is the number of values in the estimation data set.

Consequently, the main steps for ARMA modelling used to forecast wind speed are the following:

- a) Normalize historic wind speeds at hour t using the mean and standard deviation at the same hour t.
- b) Estimate parameters of the ARMA(n,m) stochastic process fitted to the normalized historic wind speeds, where n is order of AR terms and m is order of the MA terms.
 ARMA (4,3) model was the best fit in many cases [175].
- c) Analyze the partial autocorrelation function to determine the best ARMA model.
- d) Evaluate the ARMA model goodness using AIC (low AIC values show higher accuracy). Determine the ARMA model orders n and m.
- e) Transform back the forecast normalized wind speeds to get absolute values in the considered hourly period t.

The forecast wind speeds were then used to calculate either thermal rating of OHLs, or generations of wind turbines.

5.3.5.1 Case study analysis

The ARMA model is applied to one-year hourly data from the Aonach area in the UK. The process is split into two components: the first is the deterministic component for the expected wind speed in each individual hour of the day which is modelled as the sum of sine functions representing the daily peaks and troughs observed in the data. The deterministic component takes into account the relationship between electricity prices, temperatures, hour of the day, day of the week and holidays. Therefore a matrix of these predictors for every observation is generated.

The second component is a stochastic component with a random noise process that characterizes the ARMA model. A seasonal autoregressive term with order 4 and a moving average of order 3, an ARMA(4,3), was found to be the best fit for wind estimation. The parameters of the model are estimated by fitting this function. Figure 5-18 (i) shows a sequence of one-hour ahead forecasts for the estimated wind speed data compared to the actual data and their residuals in time series (from 1 to 100 hours). It is illustrated that the estimated hourly peak wind speeds follow the actual data. The residuals are differences between the actual wind speeds and the simulated wind speeds and they are shown in Figure 5-18 (ii). While the initial residuals fluctuate around -2 and 2 m/s for hours between 1 and around 50, the highest residual value of almost 3 m/s is obtained in the 90th estimated hour.



Figure 5-18: Hourly wind speed estimation (i) and residuals (ii)

The serial correlation is analyzed in Figure 5-19 (i) to define the serial correlation of wind speed data at hour t=1 with hour t=2. The wind speed values examined have been converted to 100m height wind speed. When there is a significant correlation between the data then the residuals are outside the blue line in the Figure, whereas there is insignificant correlation of the data when the residuals are inside the blue lines. For instance, it is inferred from Figure 5-19 (i) that wind speeds at hours t=1 and t=12 show significant correlation in the data.

Similarly, the partial autocorrelation is depicted in Figure 5-19 (ii), where the correlation of between wind speeds at hour t=12 and t=1 is illustrated after removing the effects of wind speed at t=2,3,..,11. As a result, lag12 measures the correlation between wind speed at t=1 and t=12. Overall, it is shown that few lags take values higher than -0.5, whereas the majority are not significant as indicated by the blue lines. After removing the autocorrelation using a lag matrix of hours 1 and 12, the residuals are no longer correlated and they can be modelled as independent variables with an appropriate distribution.



Figure 5-19: Sample autocorrelation (i) and sample partial autocorrelation (ii)

The appropriate distribution is determined by aggregating the two components and plotting the cumulative distribution function of the wind data, which is then compared to several probability distributions. After first comparing to a normal distribution, then to t-location scale distribution, finally a Pareto Tail distribution seems to provide the best fit, since the wind data presents fat tails and skeweness at each end of the distribution as shown in both Figure 5-20 and Figure 5-21. The t-location scale is modelled from the student's t-distribution, which has a bell-shaped probability density function just like a normal distribution but asymmetric and with heavier tails (where it is more likely that values are further from the mean).



Figure 5-20: Comparison of T-Location Scale and Pareto Tail cumulative distribution function of wind speed data.



Figure 5-21: Histogram of actual wind speed data

From the model described above, 3,000 stochastic paths for the wind speed data can now be simulated. The reason for simulating these paths is that historic data is only available for a few years and does not provide enough observations to reach a statistically sound conclusion regarding the data set. Instead, simulated paths provide a large number of observations that are mathematically and statistically consistent with the actual data. It also allows to take into account stochasticity in wind and can be modified (by changing its mean and volatility for instance) to test different scenarios (e.g. higher/lower wind days, higher/lower intermittency), something that cannot be done using historic data.

An example of 20 simulated paths is presented in Figure 5-22. The hourly wind speed prediction, calculated as the average hourly values of the simulated paths (thick black line), is very close to the hourly values of the actual data. Yet, each path produces a new random time series that takes into account the random nature of wind speed and its temporal variations across time. The predicted wind speed values follow the same pattern as the actual data, thus highlighting the high accuracy of the model. These simulated paths will then be used as inputs to the probabilistic model for calculating the reliability indices.



Figure 5-22: Data & Model prediction

5.4 Conclusions

Two sampling reduction techniques were introcuded in this chapter, namely the Latin Hypercude Sampling (LHS) and Multi Objective Particle Swarm Optimization (MOPSO). The newly developed method based on multi-objective PSO for reliability assessment is proposed using three objective functions. The method has shown significant advantage regarding both the performance indices and the reduction of the simulation time of the NSMCS. Furtheremore, thermal ratings (static, seasonal and real time thermal rating) of transmission lines using OHL's properties are used to assess the effectiveness of the proposed model. It is highlighted that the computational effort required by the proposed MOPSO algorithm using real time thermal rating is only 26.5% compared to

the Monte Carlo Simulation (baseline). Then the power systems components probabilistic modelling is described including component failure modelling, load and weather forecasting modelling as well as network modelling. Finally, two optimal power flow models are presented and they are used for assessment of power system adequacy.

Summary:

This chapter presents the modelling objectives, case studies description and results of the probabilistic framework for optimal demand response scheduling in the day-ahead planning of transmission networks with real time thermal ratings, as described in Chapter 4.2. Optimal load reduction plans are determined from network security requirements, physical characteristics of various customer types and by recognising two types of reductions, voluntary and involuntary. Ranking of both load reduction categories is based on their values and expected outage durations, whilst sizing takes into account the inherent probabilistic components. The optimal schedule of load recovery is then found by optimizing the customers' position in the joint energy and reserve market, whilst considering several operational and demand response constraints. The developed methodology is incorporated in the sequential Monte Carlo simulation procedure and tested on several IEEE networks. Here, the overhead lines are modelled with the aid of either seasonal or real-time thermal ratings. Wind generating units are also connected to the network in order to model wind uncertainty. The results are determined for two case studies. The first case study presents the benefits of RTTR alone in a stressed modified IEEE network. The second case study results show that the proposed demand response scheduling improves both reliability and economic indices, particularly when emergency energy prices drive the load recovery.

6.1 Simulation modelling framework

The overall methodology is realized within two independent sequential Monte Carlo simulation (SMCS) procedures. The first SMCS is the initialization module, which is used to calculate several components required by the second SMCS that determines optimal day-ahead operation of the power system. Also, from the first SMCS module the most frequently overloaded OHL's are determined, which are then used to select the most critical OHL's for real time thermal ratings used in the second SMCS. The main building blocks of the first SMCS procedure are: a) Calculation of reliability indices needed for ranking of load types for demand reduction; b) Calculation of most critical OHLs for real-time thermal ratings; and c) Determination of nodal marginal prices and several economic indicators used for finding the optimal schedule of load recoveries.

The second MCS includes application of DR methodology described in chapter 4.2 and RTTR model described in chapter 4.3 within the developed optimal power flow (OPF) model, which is presented in sequel.

6.1.1 First Sequential Monte Carlo Simulation

The input data include network, reliability, customer, economic data, overhead line (OHL) data and weather data, as shown in Figure 6-1. Beside the standard network data, forecast inservice generation units with technical characteristics and chronological hourly load point demands are input. Reliability data are failure rates and repair times of all components, whilst customer data encompass customer and DR types, contracted voluntary load reductions, normalized load recovery profiles and customer availability to respond to a DR call. Essential economic data are generation costs; values of lost load (VOLL) and marginal offer prices for voluntary load reduction.

Weather data include ambient temperatures, wind speeds and directions required for the calculation of RTTRs of OHLs, as well as either forecast hourly wind speeds or hourly wind speed PDFs used to calculate wind generations over the next 24 hours. OHL data include conductor design properties and environmental parameters required for the RTTRs. It should

be mentioned that before an optimal demand response plan can be scheduled for the next day, the wind speed should be forecasted one day-ahead for determining not only wind generation outputs, but also real-time thermal ratings, as they are highly dependent on wind speeds. In addition, load forecasting, the unit commitment schedule and the status of network switching devices must also be known for the next 24 hours.



Figure 6-1: Computations within initialization module

The input data are fed into the thermal ratings and network modelling modules, whose outputs are generation nodal prices, base expected customers interruptions duration index (BEDI) and base expected thermal overloading index for overhead lines (BETOI). These are then used by the second SMCS procedures.

6.1.2 Second Sequential Monte Carlo Simulation

The initialization module is used for three puposes; the first is to determine the most frequently overloaded OHLs based on the index (BETOI), which is then used to choose most appropriate OHLs candidates for real time thermal rating implementation. The second purpose is to determine the base expected duration interruption (*BEDI*) index of loads needed

for ranking of loads within the demand reduction scale module. The third is to compute the probabilistic energy nodal prices used within the DRLR-control module to find the optimal load recovery strategy. The probabilistic nodal prices at different confidence intervals ψ are used to make decision about the most appropriate load recovery times.

Each hour within the simulation period is characterized by available generating units, transformers and circuits, as well as nodal loads and operational constraints. Availability of all generation and network units was modelled with the aid of two-state Markovian model with exponentially distributed up and down times [1], as introduced in section 5.1. An optimum power flow (OPF) model based on the DC load flow is solved to find the levels of voluntary and involuntary load reductions and revenues to generator and demand customers. The formulation of the OPF model is a modification of the market-clearing model proposed in [126]; the main difference is that there is no preventive control and corrective scheduling is applied to the already sampled contingent case. The mathematical equations of the model are:

$$Min\left\{\sum_{j\in J}C_{gj}\cdot P_{gj} + \sum_{i\in I}\sum_{s\in S}VOLL_i^s\cdot IVL_i^s + \sum_{i\in I}\sum_{s\in S}\sigma_i^s\cdot VL_i^s\right\}$$
(6-1)

$$P_g - P_d - B\theta = 0 \quad (\mu) \tag{6-2}$$

$$P_f = H\theta \tag{6-3}$$

$$-P_f^{max} \le P_f \le P_f^{max} \tag{6-4}$$

$$-P_g^{min} \le P_g \le P_g^{max} \tag{6-5}$$

$$0 \le VL_i^s \le VL_i^{s,max} \tag{6-6}$$

$$0 \le IVL_i^s \le IVL_i^{s,max} - VL_i^{s,max}$$
(6-7)

$$P_d^{max} - \sum_s IVL^s - \sum_s VL^s \le P_d \le P_d^{max}$$
(6-8)

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The objective function to be minimized (6-1) is the sum of the offered cost functions C_{gj} for all generating power plants with active power outputs Pg_j where $j \in J$ plus the sum of the cost of involuntary load reductions IVL_i^s for all load nodes $i \in I$ and types $s \in S$ plus the sum of offered costs σ_i^s for voluntary load reductions VL_i^s for all load nodes and types. The involuntary load reduction is valued at *VOLL* that is dependent on the general load type; dependency on the connection node is taken into account because there may exist special loads whose curtailment must be avoided. Voluntary load reduction is priced at the rates offered by consumers to provide this service. They are closely linked to the offers made by generators for the 'up-spinning reserve' in the joint energy and reserve market [126]. It is again envisaged that the rates can vary with customer type and connection location. Finally, note that the time index *t* is omitted for simplicity.

Using the DC load flow model, constraints (6-2) represent the nodal power balance equations for the considered state, which include potential contingencies within the system matrix *B* with phase angles of nodal voltages θ . Note that these equations contain both voluntary and involuntary load reductions which are 'equivalent' to nodal generations. P_d represents the active power supplied to load; they are problem unknowns. A Lagrange multiplier (or dual variable) μ_i is associated with each of the equations. Constraints (6-3) express the branch flows P_f in terms of the nodal phase angles, while constraints (6-4) enforce the corresponding branch flow capacity limits. Here, modelling of OHL ratings can be done using the RTTR model, in which case limit P_f^{max} is a function of the time step *t*.

Constraints (6-5) set the generation limits P_g^{min} and P_g^{max} for the considered state, while considering available units and requirements for the down- and up-spinning reserve in the analysed time step [126]. Reserve requirements depend on the system peak load and contingency state considering N-1 condition. Reserve requirements include spinning reserve generation. The spinning reserve is based on the sum of the largest generation unit and a proportion of the load; in our case the largest generation unit is 400 MW (nuclear generation unit) and a proportion of the load (equal to 5%). The IEEE RTS 96 network [180] has a total installed capacity of 3405 MW in 32 generating units and a peak load of 2850 MW, therefore having a spinning reserve requirement of 555 MW. This generation reserve capacity scales

up to peak load per unit level. For the non-controllable units, such as wind turbines, upper and lower limits are the same.

Constraints (6-6), (6-7) and (6-8) set the limits on the demand; they are expressed as inequality constraints on the voluntary and involuntary load reductions and the total delivered load. The upper limit of the voluntary load reduction $VL_i^{s,max}$ can contain a probabilistic component for some DR types, which is dependent on the considered time step. As a consequence, the upper limit of the involuntary load reduction is the difference between the absolute limit $IVL_i^{s,max}$ and the voluntary load reduction limit $VL_i^{s,max}$. Finally, the delivered demand P_d is equal to the forecast load in the considered time interval P_d^{max} if there is no load reduction. The lower limit is specified in terms of the forecast load, voluntary and involuntary load reductions, which are a part of the optimal solution.

Solving the optimization model (6-3) to (6-8) gives the optimal values of the unknown variables, as well as dual variables associated with the constraints of this problem [181]. The signifance of the dual variables was discussed in Chapter 4.2.2.

6.1.3 Outputs

The outputs module generates several results related to the load reductions, nodal prices, generation outputs, reliability and financial indicators. These are briefly discussed below.

• Optimal Load Reductions and Recoveries

PDFs of voluntary and involuntary load reductions by load types and/or nodes are calculated for each hour in the 24-hourly period. These can be directly converted into energy not served PDFs. The corresponding mean and percentile values show the 'likely' distributions in the next 24-hourly period. PDFs of daily totals are also computed. Besides, conditional PDFs of the load recovery initiation times given the load reduction at certain hour are also produced.

• Generation Outputs

PDFs of generator hourly productions and costs, as well as total daily costs are computed.

• Nodal Marginal Prices

PDFs of nodal marginal prices are produced for each hour in the considered 24-hourly period. Their expectations can be used as an indicator of what the prices for rewarding generation and charging load customers would be in the next day.

• Reliability Indices

Reliability indices relating to energy not served as well as frequency of customer interruptions and duration of interruptions are computed. For example, expected energy not supplied (EENS), expected frequency of custommers interruptions (EFI) and expected duration of interruptions (EDI) are calculated as:

$$EENS = \sum_{y=1}^{Y} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{s=1}^{s4} Pc_i^s / Y$$
(6-9)

$$EFI = \sum_{y=1}^{Y} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{s=1}^{s4} \zeta_i^s / Y$$
(6-10)

$$EDI = \sum_{y=1}^{Y} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{s=1}^{s4} \zeta_i^s \cdot D_i^s / Y$$
(6-11)

where *s4* is the number of customer types, Pc_i^s is the total load shedding of load type *s* at load point *i* at hour *t*, ζ_i^s is the number of customers interruptions having durations D_i^s and *Y* is the number of Monte Carlo simulation days.

• Financial Indicators

PDFs of load customer payments (LC), voluntary (VLR) and involuntary load reduction rewards (IVLR) are computed by hours and for the considered day. The latter curves are then used to quantify the financial risk of implementing the proposed demand response

scheduling. The concept of value-at-risk (VaR) [30] was applied to measure the potentially 'low' revenues or 'excessive' payments.

Assuming network reward (*NR*) denotes any category of revenues, the corresponding cumulative distribution function (*CDF*_{NR}) is used to calculate the network reward *NR*_X that exceeds the network reward at the confidence level ψ , NR_{ψ}, with probability $1 - \psi$. The value at risk is [182]:

$$VaR_{\psi}^{NR}(NR_{\chi}) = inf\{NR_{\psi} \in \mathcal{R}: CDF_{NR_{\chi}}(NR_{\psi}) \ge \psi\}$$
(6-12)

Similarly, the *CDF* of any network cost (*NC*) can be used to determine value-at-risk at confidence level ψ . In this case, network cost *NC_X* that does not exceed the network cost with probability $1 - \psi$, *NC*_{1- ψ}, is calculated as:

$$VaR_{1-\psi}^{NC}(NC_x) = \sup\{NC_{1-\psi}\in\mathcal{R}: CDF_{NC_x}(NC_{1-\psi}) \le 1-\psi\}$$
(6-13)

6.2 Case study analysis

The IEEE-RTS 96 is composed of 38 lines circuits, 32 generating units and 17 load delivery points [183]. It is studied by using the algorithms developed in Matlab that make use of a modified version of Matpower and MIPS solver for the power flow calculations [184]. Essential study cases are developed for the six scenarios related to network performance improvement when different thermal rating models are deployed. This is followed by the description of eight scenarios for optimal demand response scheduling related to the availability for load reduction, impact of nodal marginal prices, load recovery profile – availability, and impacts of RTTR, DR and wind generation.

6.2.1 Case studies 1 (RTTR)

OHL thermal ratings are modelled as static thermal ratings (STR), seasonal thermal ratings, (SeTR) or real time thermal ratings (RTTR). The analysis is performed for the whole year

using both deterministic and probabilistic thechniques. The sequential modelling of the seasons is set to 1 to 1416 hours and 8017 to 8760 hours for winter, 3625 to 5832 hours for summer, as well as to 1417 to 3624 hours and 5832 to 8016 hours for spring and fall. Conductor temperature T_c of OHLs is set to 75°C for normal operation (no failures on the network), whereas 95°C is used when there is a failure on the generation units or transmission lines connected to the considered transmission line.

Six scenarios are described in Table 6-1, where "0" and "1" shows binary number to indicate if a variable and or/method is implemented on the simulation. The first factor, n, indicates whether a deterministic (n=0) or SMCS analysis (n=1) is done. Scenario S1 models STR considering fixed values for conductor temperature (Tc=0), resistance (r=0) and weather data ($w_d=0$). Scenario S2 models the SeTR with the only diferrence being that weather data are different for each season (winter, summer, fall, see Table 4-2), as opposed to STR, which considers only summer data. Scenario S3 models real time thermal ratings where conductor temperature (Tc=1) and resistance (r=1) are calculated from the hourly weather and loading conditions. Scenario S4 models real time thermal ratings considering fixed values for conductor resistance and temperature in order to assess the impact of conductor temperature and resistance on RTTR performance. Finally, Scenario S5 is similar to S1 and S6 is similar to S4 with the only difference being consideration of the deterministic framework.

		L.				
	S 1	S2	S 3	S4	S5	S 6
n	1	1	1	1	0	0
Tc	0	0	1	1	0	1
r	0	0	1	1	0	1
W_d	0	1	0	1	0	1

Table 6-1: Modelling Scenarios of RTTR methodology

The AC OPF is used to minimize the load curtailment and the generation cost. AC OPF is used as opposed to DC OPF given that the conductor's resistance is a variable that needs to be included in the simulation. The original IEEE-RTS 96 was modified: all scenarios assume an increase in load by 1.3pu compared to the original load, as well as increase of 1.3pu in generation capacity. A single Drake conductor configuration for the 138 kV part and twin Grosbeak configuration for the 230 kV part is assumed (the relevant OHL properties are given in Table 4-3).

6.2.2 Case studies 2 (DR)

OHL thermal ratings are modelled as STR or RTTR, as shown by parameter p in Table 6-2 below. Three seasons (winter, summer and fall), denoted as $\lambda_s=1$, 2, 3, are studied. The first day of the 50th week of the year is used for winter peak (hours: 8425-8449); the 2nd day of the 22nd week of the year is used for summer (hours: 3721-3744), whilst the 2nd day of the 32nd week is used for fall (hours: 5401-5424). Availability factor f_{RD}^s is a random number, whilst availability factor for load recovery f_{REC}^s varies in the specified range. Load recovery is based on either hourly emergency energy prices (i.e. $\vartheta_{REC}=1$) or load profiles (i.e. $\vartheta_{REC}=0$). The presence of wind generators is denoted by wg=1.

	S1	S2	S 3	S4	S5	S 6	S 7	S 8
р	STR	STR	STR	STR	RTTR	RTTR	STR	STR
λ_s	1,2,3	1	1,2,3	1	1	1	1	1
f_{RD}^{s}	0	1	1	1	0	1	0	1
f_{REC}^s	0	1	1	0-1.2	0	1	0	1
ϑ_{REC}	-	0	1	1	-	1	-	1
wg	0	0	0	0	0	0	1	1

Table 6-2: Modelling scenarios of DR methodology

Eight scenarios are described in Table 6-2. Scenario S1 is the base case, where the system is evaluated in all seasons without DR scheduling and with STR for OHLs. Scenario S2 models load recovery by using the hourly load curve at each load point (g_{REC} =0). Scenario S3 models all seasons and load recovery on the basis of expected marginal prices at each load point (g_{REC} =1). Scenario S4 models time-varying load recovery profiles. Sensitivity studies are done here in order to assess the impact of different recovery sizes and profiles on DR performance. Factor f_{REC}^s is set from 0 to 1.2pu increasing in 0.2pu increments; the 1.2pu is taken as a high-risk scenario. Scenario S5 incorporates the RTTR of OHLs without DR operation, while Scenario S6 includes the DR scheduling. Finally, Scenario S7 incorporates wind farms without DR, while in Scenario S8 the benefits of demand response are evaluated by incorporating wind generation (wg=1) for pricing. Therefore in AC OPF case, marginal costs are equal to Lagrange multipliers and therefore will give revenue that is completely different from the total cost due to non linearity of the problem

DC OPF is used for optimal demand response scheduling. DC OPF is used as opposed to AC OPF due to the proposed DR method uses marginal costs for pricing. Therefore in the AC OPF case, revenues will be completely different from the total cost when marginal costs are equal to Langrange multipliers due to non-linearity of the problem. As a result, DC OPF is used, as in linear programming marginal costs are equal with dual variables and thereby costs are completely recovered. The original IEEE-RTS 96 was modified: all scenarios assume an increase in load by 1.3pu compared to the original load, as well as increase of 0.55pu and 0.6pu transmission capacity for the 138kV and 230kV levels, respectively, and 1pu in generation capacity. Next, the WTGs are connected at seven sites and it was assumed that they operate at power factor mode with power factor equal to 35% [185]. Wind farms are designed to deliver 20% of the peak load [186], equivalent to 684MW on the studied power network. Geographically, 70% of the wind farms' maximum capacity is installed in the northern part of the network at buses 15, 17, 19, 20, 22, while in the southern part of the network, the remaining 30% of the wind capacity is installed at buses 1, 2, 7, 8 (Figure 6-2). The total wind farm capacity is 2394 MW obtained from a total number of 240 WTG, each representing a nominal capacity of 10MW. There is significant transmission utilization in this modified system as the bulk of the generating capacity is located mainly in the northern areas and considerable power is transferred from the north to the south aiming to represent the existing topology of the UK network.



Figure 6-2: Modified IEEE RTS network

6.3 Simulation Results

6.3.1 Results for Case study 1

When the different thermal rating models are considered for the reliability performance assessment, then the most secure and economic scenario is the application of the RTTR. This can be observed in Figure 6-3 where the EENS reliability index for the three thermal rating scenarios is shown. The RTTR model using actual conductor temperature (S4) resulted in 24.79% lower EENS than the STR model (S1). This is mainly due to the increased capacity of transmission lines provided from the RTTR model and the change in resistance that is considered in the OPF model. From Figure 6-3 it can also be derived that the SeTR (S2) improves the network performance by 17%. However even when the more conservative

scenario (S3) is used the improvement in network performance is substantial to the tune of 14.68% indicating that RTTR can contribute in all seasons.



Figure 6-3: EENS considering STR, SeTR and RTTR

To quantify the impact of different thermal rating approaches in the studied scenarios, the average capacity of the lines is illustrated in Figure 6-4. As shown in Table 6-1, S1 models static thermal rating (STR), S2 models seasonal thermal rating (SeTR) and S4 models real time thermal ratings (RTTR). It can be inferred that the ratings of L11, L23 and L28 are higher when using RTTR strategy with the capacity of L23 showing the most notable increase, from 474 MVA (STR) to almost 560 MVA. It can also be observed that other lines (e.g. L3, L18, L22, L31, L32, L33 and L38) demonstrate equal or lower capacities when the RTTR strategy is utilised. The reason for this is that the increase in the power flows of other lines (due to increased ampacity from the RTTR) resulted in reduction of the power flow through those lines and in some cases due to weather conditions incurring lower thermal ratings.



Figure 6-5 depicts the average values of the thermal ratings for scenario S6 under deterministic analysis. It displays several features about the transfer capacity of transmission lines; these are the median of rating value, the upper quartile (representing the amount of population which is higher than the median population-75th percentile), the lower quartile (representing the amount of population which is lower than the mean population-25th percentile), as well as the line which extends from each box and represents the largest or the smallest point within 1.5 interquartile range from the previous quartile. These characteristics can provide system operators with vital inputs suggesting network reinforcement under conservative-deterministic operation regime. The most critical lines are utilized less compared to the probabilistic case, by a factor of 3.6%, which occurs due to the power margins set to the network by the deterministic approach. The upper and lower quartiles of OHL nos. 6, 23, 24, 27 and 28 show high variance, which indicates that they are occasionally overloaded and hence system operators' should take actions to further utilize them. In summary, the results of thermal rating analysis show that RTTR capacities are associated with higher levels of utilization.

÷ 500 Đ Thermal Rating (MVA) 400 300 þ ₿ 200 Ŧ 100 Ţ 0 10 1112 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 2 7 8 9 3 4 5 6 1 Transmission Lines

Chapter 6 - Optimal Demand Response Scheduling with Real Thermal Rating for Network Reliability

Figure 6-5: MVA rating for RTTR model under deterministic scenario (S6)

Figure 6-6 compares the operational costs of STR (S5) under deterministic operation and the proposed RTTR under probabilistic simulation (S4). The operational costs are higher in the deterministic approach. In particular, operational costs of generation units 8-9, 21-23, 30- 32 have been considerably reduced due to RTTR (S4) model, while a slight difference is seen in operational costs of 1-7 and 10-20 generators. Consequently, the deterministic dispatch under STR model is inefficient with respect to total hourly costs and increased by a factor of 2.1%. This is mainly because RTTR under the probabilistic analysis allows the cheapest generators to generate more energy considering the higher thermal loading capability of the OHL.



Figure 6-6: Hourly operational cost for deterministic and probabilistic studies

6.3.2 Results for Case study 2

6.3.2.1 Load Forecasting uncertainty values used for Demand Response scheduling

The developed ANN model is used for load forecasting. Certain input parameters are varied (e.g. atmospheric variables, activity levels, etc.) and the mean absolute percentage errors (MAPE) are generated for each hour showing the hourly variation of load forecast. In this way, hours, which have the highest MAPE, will have the largest uncertainty window in the proposed Monte Carlo simulation procedure. The methodology used for the short-term load forecasting of each *customer sector* is developed, as presented in Chapter 5.1.4. To illustrate the developed methodology, load forecasting uncertainties for a 24 hour ahead forecast for residential, industrial and commercial types of customers are shown in the Figures 6-7, 6-8 and 6-9 below. It is shown that residential load has higher MAPE during evening hours or around 18:00 because most people come back from work, but the arrival time can vary. On

the other hand, industrial loads are more uncertain during the day and they are a function of manufacting loads. The same is true for commercial loads (offices).



Figure 6-7: MAPE values for forecast residential loads



Figure 6-8: MAPE values for forecast industrial loads



Figure 6-9: MAPE values for forecast commercial loads

6.3.2.2 Customer Availability for Load Reductions

In this section, the impact of the availability of customers responding to a DR call is examined. Uncertainty in load availability for each customer type is given by (4-15). In particular, domestic customers' load reduction takes values from the entire possible range, while for industrial and commercial loads it is within the assumed window, win=0.8-1pu. Scenario 3 (S3) is used to evaluate the impact of customers responding to a DR on the EENS, mean and VaR values of voluntary (VLR) and involuntary load reductions (IVLR) – equations (4-9) and (4-10). For VLRs, Figure 6-10 generated over the entire MCS period shows that the probability for residential loads to give 'small' response (up to 25 MWh) is much higher than to produce 'large' response (up to 50MWh).

However, industrial, commercial and large users are more likely to give 'larger' responses as they have bigger contracted amounts compared to residential users, and the uncertainty in response (if any) is much lower (Fig. 6-10). For low load reductions, industrial loads have higher probability to respond than commercial and large users, while large users have the highest probability for larger amounts of load reductions; they are followed by commercial and industrial users.



Figure 6-10: Probability to respond to a DR signal for different customer types based on the voluntary load reduction amount at 17h00

The PDFs for voluntary (VL) and involuntary load reductions (IVL) for different hours in a day are illustrated in Figure 6-11 and compared with the PDFs of IVL without DR (IVL^{NO} DR). The results show that the probability of having IVL is reduced when doing higher amounts of DR (IVL^{DR}) (right side of x-axis), while the probability is much higher for low amounts of IVL^{DR}. This clearly shows the effectiveness of voluntary DR on the EENS. In particular, the mean value of IVL^{DR} at 17h00 is around 60% less than the mean value of IVL^{DR} at 21h00 and 22h00 is, respectively, 61% and 60% lower when applying the voluntary DR. Applying voluntary load reduction (VL) helps eliminate the need for involuntary one (IVL^{NO} DR), particularly when larger VL amounts are used. This is further highlighted when converting VL and IVL into the EENS index (see Table 6-4 in Section 6.3.2.3).

Table 6-3 shows the mean (VaR_{50%}) and the 90% confidence VaR (VaR_{90%}) for the costs of supplying load demand (LC), as well as for customer VLR and IVLR revenues, for the most critical load points (B6, B8 and B14) under scenarios S1 and S3. Both the $VaR_{50\%}^{LC}$ and $VaR_{90\%}^{LC}$ are much lower under scenario S3 for all load points, since under DR, demand is recovered under cheaper nodal marginal prices.

In addition, $VaR_{90\%}^{VLR}$ is much larger than $VaR_{50\%}^{VLR}$ since marginal nodal prices are significantly higher under severe emergency conditions. Furthermore, the $VaR_{50\%}^{IVLR}$ is much lower under S3 than under S1, where the decrease is by 60% for B6, 44% for B8 and 47% for B14. This also shows that voluntary DR significantly decreases the need for IVL (an average VOLL value was assumed for all customer types).



Figure 6-11: Probability of voluntary and involuntary load reductions under DR for different hours in a day

	<i>B6</i>		B 8		B14	
Critical buses	S1	S 3	S1	S 3	S1	S 3
$VaR_{50\%}^{LC}$	31.43	19.59	55.13	22.91	57.55	41.72
$VaR_{90\%}^{LC}$	55.64	52.81	75.11	61.24	95.39	89.08
$VaR_{50\%}^{VLR}$	-	1.3	-	1.8	-	1.5
$VaR_{90\%}^{VLR}$	-	5.6	-	2.5	-	2.8
$VaR_{50\%}^{IVLR}$	600	240	578	320	480	252
$VaR_{90\%}^{IVLR}$	1344	420	1260	604	1284	546

Table 6-3: VaR values of customer costs and rewards (k£)

6.3.2.3 Impact of Nodal Prices on Reliability Analysis

Most DR studies would recover reduced-curtailed load during load troughs and/or system normal operation if only network adequacy was looked at. However, in this thesis an approach is used to investigate impact of hourly nodal prices on load recovery and customers' wellbeing. Figure 6-12 shows an example of the nodal marginal price and the demand variation over 24 hours for the most frequently interrupted bus in the network (B6) under both intact and emergency conditions.

When no failures occur, load can be recovered almost at any time since intact prices do not change significantly with respect to load variation. However, nodal prices under emergency conditions may vary considerably. For instance, a significant difference in magnitude between intact and emergency nodal prices is shown at 15h00. The proposed analysis has proven that the magnitude of the emergency nodal price can be almost 5 times higher than the intact one. Thus, scheduling of 'optimal' load recoveries based on marginal nodal prices has proven effective in providing system security and customer benefits. Furthermore, comparative studies were conducted to quantify the improvements from implementing load recovery under nodal marginal prices rather than under load profile only.



Figure 6-12: Hourly marginal prices and demand curve under emergency for bus 6

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The hourly nodal price at bus B6 for different confidence levels is given in Figure 6-13. In the event of an outage linked to bus B6, TSOs may be provided with the illustrated confidence level dependent prices to decide which load recovery hour would be the most appropriate to restore load. For example, the TSO can know that if a violation occurs at 11h00, the load can be recovered between 13h00 and 16h00, since there is an 80% probability that the price will be between zero and 90£/MWh and a 90% probability that the price will be between zero and 420£/MWh. In this thesis, a conservative confidence level of $\psi=95\%$ was selected. This gives flexibility to TSOs to apply operational decisions so they can guarantee making a profit for the demand customers for almost all nodal prices in the feasible range, since the load recovery will ideally be costed at (lower) intact prices.



Figure 6-13: Emergency marginal price at node B6 for different confidence intervals

For the marginal offer prices, the 60th percentile of the hourly prices of the system (i.e. average prices over relevant nodes) is used, as shown in Figure 6-14. It is assumed that marginal offer prices are similar to the prices in the up-spinning reserve market as discussed previously in the DR methodology development. It can be inferred that offer prices are low between 1 and 8am (less than 25£/MWh), while between 17:00pm and 21:00pm offer prices take larger values, with the highest of almost 120£/MWh at 18:00pm. Overall, all the hourly offer prices show significant fluctuations around the median for all the hours except for the period 23:00pm-2:00am.


The results presented in Table 6-4 give a comparison of reliability indices for scenarios S1, S2 and S3 during winter, summer and fall. For example, the DR strategy under scenario S3 improves the reliability of the network in terms of EENS by 66% in winter ($\lambda_s = 1$) compared with scenario S1, allowing for almost a 5% decrease in EENS compared to scenario S2. The S3 strategy also substantially improves reliability indices for summer ($\lambda_s = 2$) and fall ($\lambda_s = 3$), which demonstrates the effectiveness of the algorithm throughout the entire year.



Table 6-4: Reliability Indices for Scenarios 1, 2 and 3

In order to show the necessity to quantify the economic risk of DR operation, results for the base case S1 are compared to scenario S3 to investigate the VaR of the load cost (LC). Figure 6-15 illustrates the frequency of occurrence of various load costs seen at the most critical bus,

B6, with and without DR. In particular, it is shown that there is a high variation in nodal costs at 11h00, resulting from outages of lines 12 and 13 that connect bus B6 with cheaper generators. Consequently, $VaR_{90\%}^{LC}$ is 55.64k£ under the base case, whereas it is only 52.81k£ under S3, which shows that DR can help reduce nodal costs by 5% (2.83k£). Clearly, both reliability and financial indices can be improved using nodal energy prices (S3) rather than the load profile only (S2) for optimal decision on load recovery.



Figure 6-15: Distribution of demand costs for load at bus B6

6.3.2.4 Impact of customer availability to recover the load

The load recovery of a DR customer can be of different size compared to the corresponding load reduction. As a result, this can affect both the network performance and customer profits, as exemplified by scenario S4.

Assuming load recovery size is specified by availability factor f_{REC}^s , Table 6-5 shows an increase of around 5% in EENS for f_{REC}^s =1.2pu compared to f_{REC}^s =1pu. When load recovery

sizes are lower than 100%, network reliability is improved compared to $f_{REC}^s=1$ pu. This is due to the higher probability of implementing voluntary DR since less load recoveries are required. There is also a substantial decrease in reliability indices EDI and EFI.

$f_{}^{s}(nu)$	1.2	1	0.8	0.6	0.4	0.2
1 REC (pu)	1.2	1	0.8	0.0		•
EENS(MWh/day)	205.8	196	192.34	191.13	191.08	188.12
EDI(h/day)	0.2334	0.2331	0.2330	0.229	0.227	0.227
EFI(int/day)	0.0386	0.0383	0.0383	0.038	0.038	0.0378

Table 6-5: Reliability Indices for Scenario S4

Differences in the mean (VaR_{50%}) and VaR_{90%} values for demand costs (LC) and customer profits (π) between scenarios S4 and S3 are shown in Table 6-6 for different load recovery sizes f_{REC}^s . This table gives the cost and revenue differences following various load payback sizes compared to applying DR with a load payback of 100% for a winter day-ahead operation. For instance, when S4 is modeled with f_{REC}^s =1.2pu, the $VaR_{50\%}^{LC}$ is 912£ higher than under scenario S3. This is because as load recovery gets larger, the operating conditions become more difficult and the marginal prices increase, implying higher costs for demand. For low load recovery sizes, however, very high profits can be incurred (over 2,100£) as the demand cost VaR shows the largest decrease.

		S4-S3 V	alues				
	(difference in costs)						
-	$VaR_{50\%}^{LC}$	$VaR_{90\%}^{LC}$	$VaR_{50\%}^{\pi}$	$\mathrm{VaR}_{90\%}^{\pi}$			
f _{REC} =1.2	+912	+1932	+0.05	+0.2			
$f_{REC}=0.8$	-89	+775	+5.3	+8.1			
$f_{REC}=0.6$	-101	-198	+6.3	+9.5			
$f_{REC}=0.4$	-257	-2102	+8.8	+9.5			
$f_{REC}=0.2$	-463	-2124	+10.2	+12.8			

Table 6-6: Difference in mean and VaR for LC and profits (£/kWh) for S4 vs. S3

6.3.2.5 Impact of RTTR and DR on Network Reliability and Customer Costs & Revenues

In scenario S5 only RTTR is used, whilst scenario S6 combines DR with RTTR. Table 6-7 shows that the more reliable and cheapest scenario is S6.

The use of RTTR and DR under S6 results in, respectively, 61% and 6.6% reduction in EENS compared with DR alone (S3) and with S5. Indices EFI and EDI are also improved. When RTTR is considered alone (S5), the greater utilization of the three most critical lines improves network performance by 18% compared to S1. Besides, the load cost index for S3 $VaR_{50\%}^{LC}$ is slightly higher than $VaR_{50\%}^{LC}$ for S5. This is because RTTR on OHLs allows extraction of greater generation from cheaper units.

In terms of VLR and IVLR, both average values are lower under S6. It is noted that DR provides the greatest benefits since all indices are drastically improved with DR, whilst benefits are only slightly higher under RTTR.

Scer	narios	S3(DR)	S5(RTTR)	S6(DR&RTTR)
	EENS(MWh/day)	196	475	183
Reliability	EFI (int/day)	0.0383	0.0381	0.0379
malees	EDI*10 ⁻² (h/day)	23.31 23.34	23.18	
	$VaR_{95\%}^{CG} VaR_{50\%}^{LC}$	135.9	134.9	131.3
Financial indices	Mean ^{CG}	142.7	136.1	134.8
(k£)	π^{CIC}_{mean}	1.6	-	1.2
	$\pi^{CIC}_{95\%}$	2352	-	2196

Table 6-7: IEEE RTS network evaluation with RTTR and DR

6.3.2.6 Impact of Wind Farms and DR on Network Reliability and Customers Costs and Revenues

In scenario S7, only wind farms are connected, whilst scenario S8 uses DR in conjunction with wind farms. Table 6-8 shows that the more reliable and less expensive scenario is S8;

the wind farms contribute to improving network reliability by 4% in EENS compared to S3 alone. Besides, a considerable reduction in EDI is achieved, whilst the frequency of interruptions, EFI, remains the same as under S3. If compared with S1, wind farms alone (S7) improve network performance by 14% due to wind farms' integration on the network. Also, $VaR_{50\%}^{LC}$ for S3 is slightly higher than $VaR_{50\%}^{LC}$ for S7 as wind farms are considered to have near-zero marginal costs. When wind farms are used in conjunction with DR (S8), this has the best effect on network performance and customer costs & revenues. This is because DR implementation helps when wind output is low and network components fail. Next, when wind output is high, spillage can occur as there is not enough capacity on the network to transfer the total amount of wind, thus leading to congestion when using STR for OHL operation. In this case, RTTR can be used to further reduce EENS and improve power system reliability.

Scen	arios	S3(DR)	S7(wind)	S8(wind&DR)
	EENS(MWh/day)	196	496	189
Reliability	EFI (int/day)	0.0383	0.0388	0.0383
mulees	EDI*10 ⁻² (h/day)	23.31 23.8	23.19	
	$\mathrm{VaR}^{\mathrm{CG}}_{95\%}\mathrm{VaR}^{\mathrm{LC}}_{50\%}$	135.9	135.3	129.3
Financial indices	Mean ^{CG}	142.7	141.9	136.8
(k£)	π_{mean}^{CIC}	1.6	-	1.05
	$\pi^{CIC}_{95\%}$	2352	-	2268

Table 6-8: IEEE RTS Network evaluation of wind farms and DR

6.4 Conclusions

A probabilistic methodology for optimal scheduling of load reductions and recoveries in a day-ahead planning of transmission networks is proposed in the thesis. The methodology recognizes several types of uncertainties, and finds optimal demand response scheduling using the network security and customer economics criteria. Impacts of wind generation and real-time thermal ratings of overhead lines are also studied.

The developed case studies have demonstrated that the value of optimal demand scheduling combined with real-time thermal ratings can be significant when using nodal marginal prices compared to using the hourly loads to determine the optimal load recovery periods. In particular, both reliability and financial metrics can be improved by a factor of around 66% for expected energy not served and around 5% for value at risk for costs of demand. Improvements in other reliability indicators and expected generation costs were also observed. Nonetheless, the selection of the reliability indicator to base the operational decisions on demand scheduling can be of highest importance; having multiple indices can therefore help system operators to make more informed decisions on 'best' demand response practice.

Summary:

This chapter presents the modelling concepts and objectives, description of case studies and results of a probabilistic framework for minimizing wind spillage and maximizing capacity of the deployed wind generation, whilst improving system reliability, as described in Chapter 4.1. Capacities of the wind units connected to the network are initially determined by using the industry-based criteria. A probabilistic approach is applied for the day-ahead planning to determine maximum deployable wind sources so that the prescribed wind spillage level is not exceeded. This is done in an iterative way using the optimum power flow, in which wind spillages are weighted with the probabilistic 'cost coefficients'. Further improvement of wind energy utilization is achieved by installing FACTS devices and making use of real-time thermal ratings (RTTR). Two ranking lists are proposed to find the best placement of static VAr systems (SVSs) and thyristor controlled series compensators (TCSCs). The developed methodology is incorporated into two sequential Monte Carlo simulation procedures. The probabilistic simulation results are then compared with the state enumeration results. It was shown that the proposed methodology improves economics of network operation as well as its reliability.

7.1 Simulation modelling framework

The objectives of the proposed probabilistic approach for day-ahead planning of systems with large penetration of wind are threefold: a) Maximize deployed wind generation to meet contractual obligations; b) Increase overall system reliability; and c) Reduce system operation cost including costs of non-delivered load and curtailed wind generation. These objectives are achieved by following corrective actions: a) Reschedule dispatchable generation; b) Curtail load and wind generation; c) Deploy SVC and TCSC devices; and d) Deploy RTTR on overhead lines (OHL).

The probabilistic framework consists of two simulation stages, as shown Figure 7-1. The first, SMCS¹, is preparatory and it delivers outputs, which are required by the second stage SMCS². The main building blocks of the first stage are:

• Connection of wind generation using industry criteria (method is described in Chapter 4.1.2).

• Probabilistic analysis of the 24-hour period with the base SMCS¹ with unity costs associated with wind spillages.

• Calculation of base expected energy not supplied (BEENS), base expected spillage (BESP), wind spillage 'cost coefficients' (method is described in Chapter 4.1.3), voltage histograms for ranking of SVCs, as well as BEENS and BESP increments for TCSC ranking.

• Procedure for optimal FACTs placement (method is described in Chapter 4.4.2).

The second simulation stage is then used to find the optimal utilization of wind sources whilst applying different controls. Two different methodological approaches are developed: a) The SMCS² procedure; and b) The state enumeration based on (N-1) outages. The essential building blocks are the same in both methodologies – Figure 7-1. In this stage, several independent corrective action scenarios are executed:

• 'Scheduling scenario': generation rescheduling and curtailment of wind and load is considered to maximize wind utilization. RTTR may be included.

• 'Scheduling and FACTS scenario': rescheduling of generation and load with placement of SVC and/or TCSC is done; RTTR may also be included.

• 'Increased deployed wind scenario': this can be either 'scheduling' or 'scheduling & FACTs scenario' whereby wind capacities are increased until contractual limits are met.



Figure 7-1: Optimal deployed wind generation computational framework

7.1.1 First Simulation Stage

Computation of maximum wind generation connection is initially done considering static thermal ratings for OHLs. The amount of wind generation connected at each node is based on a mathematical formula used by the industry – equation (4-1). After nodal wind generations are defined, AC OPF analysis is run to calculate minimized spillage values under state enumeration framework. Probabilistic analysis is run using SMCS¹, to determine the stochastic behaviour of nodal wind spillages. The probabilistic cost coefficients of wind spillages are then incorporated in the objective function of the OPF model to prioritize wind spillages and contributed to the improved system operation under under emergency conditions.

The first simulation stage, also includes ranking lists of SVCs and TCSCs, as well as finding locations for optimal placement of these devices. The ranking lists are formulated using expected energy not supplied (*BEENS*) and expected wind spillage (*BESP*) produced by the SMCS¹. *BEENS* and *BESP* are categorised as voltage related (*BEENS^{volt}* and *BESP^{volt}*), and thermal realted (*BEENSth* and *BESPth*) and they are used for ranking of, respectively, SVCs and TCSCs, and finding their most appropriate locations. As such, a ranking list of nodes in a desceding order is calculated for SVC placement and a ranking list of circuits in desceding order is calculated for TCSC placement. These two lists are finally used in the optimal FACTs placement block, which gives the optimal SVC and TCSC installations based on the reductions of load and wind energy curtailments.

All procedures accomplished in the first stage use a number of different data for network modelling. The most important are:

Network topology and impedance, reliability, wind data, overhead line (OHL) data, FACTS data and weather data. Beside the standard network data, forecast in-service generation units with technical characteristics and chronological hourly load point demands are input. Reliability data are failure rates and repair times of all components (conventional generation units, wind turbines and transmission lines), whilst wind data encompass wind generators nominal power rates and wind speed cut-in, cut-off and cut-rated data. OHL data include conductor design properties and environmental parameters required for the RTTRs. FACTs data include operating ranges for SVCs and TCSCs as well as failure and repair rates of FACTs. Finally weather data includes ambient temperature, wind speeds and wind directions.

7.1.2 Second Simulation Stage

The models specific to the second simulation stage are presented below. Other models, such as prioritization of SVCs and TCSCs and their optimal placement, are already given in chapter 4.

7.1.2.1 AC Optimal Power Flow (OPF) analysis

The OPF model is adapted to include load and wind curtailments and FACTS devices. It is based on the AC power flow model and its mathematical formulation is given by equations (7-1) to (7-13):

$$min\left\{z = \sum_{j} C_{gj} \cdot P_{gj} + \sum_{i} VOLL_{i} \cdot Pc_{i} + \sum_{j} \xi_{j} \cdot VSP_{j} + \sum_{j} \xi_{j} \cdot IVSP_{j}\right\}$$
(7-1)

$$\left(P_{gi} - VSP_i - IVSP_i\right) - \left(P_{Di} - Pc_i\right) - \sum_{ij} P_{ij}(\cdot) = 0$$
(7-2)

$$Q_{Gi} + Q_{SVCi} - (Q_{Di} - tg(\varphi_i) \cdot Pc_i) - \sum_{ij} Q_{ij}(\cdot) = 0$$
(7-3)

$$I_{ij}(\cdot) \le I_{ij}^{STR/RTTR} \tag{7-4}$$

$$V^{\min} \le V_i \le V^{\max} \tag{7-5}$$

$$P_{gj}^{min} \le P_{Gj} \le P_{gj}^{max} \tag{7-6}$$

$$Q_{gj}^{min} \le Q_{gj} \le Q_{gj}^{max} \tag{7-7}$$

$$P_{WGj}^{up} \le P_{WGj} \le P_{WGj}^{up} \tag{7-8}$$

$$0 \le VSP_j \le VSP_j^{max} \tag{7-9}$$

$$0 \le IVSP_j \le IVSP_j^{max} - VSP_j^{max}$$
(7-10)

$$0 \le Pc_i \le P_{Di} \tag{7-11}$$

$$Q_{SVCi}^{min} \le Q_{SVCi} \le Q_{SVCi}^{max} \tag{7-12}$$

$$X_{TCSCij}^{min} \le X_{TCSCij} \le X_{TCSCij}^{max}$$
(7-13)

where C_{gj} is marginal cost of generation P_{gj} at node *j*, $VOLL_i$ is value of the lost load [116] (load curtailment) Pc_i at node *i*, ξ_j is cost of either voluntary VSP_j or involuntary spillage $IVSP_j$ at node *j* (see relation (4-3)), Q_{gi} and Q_{SVCi} are reactive power productions of a generator and an SVC at node *i*, P_{Di} , Q_{Di} and φ_i are active load, reactive load and load angle at node i, $P_{ij}(\cdot)$, $Q_{ij}(\cdot)$ and $I_{ij}(\cdot)$ are active power, reactive power and current flows in branch ij, $I_{ij}^{STR/RTTR}$ is either STR or RTTR rating of branch ij, V_i is voltage magnitude at node *i*, P_{WGj} is active wind generation at node *j* set at the selected value P_{WGj}^{up} , and X_{TCSCij} is reactance of TCSC in branch *ij*. The lower and upper limit values are denoted by superscripts min and max, respectively.

The objective of the optimization model (7-1)–(7-13) is minimization of the hourly operational costs, which consist of four terms: generation cost, cost of curtailed loads and costs of voluntary and involuntary wind spillages. Equations (7-2) and (7-3) model active

and reactive power balances at all nodes; it is assumed that wind generators operate at unity power factor, so there is no curtailment of reactive wind generations in (7-3). A constant power factor is assumed for each nodal load, giving reactive power curtailment $tg(\varphi_i) \cdot Pc_i$ in (7-3). Active $P_{ij}(\cdot)$ and reactive power flows $Q_{ij}(\cdot)$ in branches *ij* are functions of terminal voltage magnitudes and angles [187] which are problem unknowns.

Thermal constraints of all branches are expressed by inequalities (7-4), in which either STR or RTTR is used for OHL. Branch currents $I_{ij}(\cdot)$ are again functions of terminal voltage magnitudes and angles [188]. Voltage constraints at all nodes are given by (7-5), whilst limitations of dispatchable generation are modelled with inequalities (7-6) and (7-7). Inequalities (7-8) specify the level of wind generation, which is obtained either from the forecasting model, or within the iterative process of spillage level adjustment. Limits on voluntary and involuntary wind spillages are defined by (7-9) and (7-10); note that the total spillage $IVSP_j^{max}$ must be less than wind production P_{WGj}^{up} . Limits on load curtailments are shown in (7-11), whilst constraints on SVC and TCSC devices are defined by (7-12) and (7-13), respectively. The former shows that SVCs are modelled as reactive power sources; however, inequalities (7-13) are implicitly modelled by adjusting branch reactances.

7.1.2.2 Maximization of Wind Deployment

In several analyzed scenaria, particularly when FACTS and/or RTTR are deployed, wind spillage levels can be below the contractual values. In such cases, it is possible to increase capacities of installed wind units.

The SMCS results are delivered on an hourly basis and for the whole day. The expected hourly spillages are compared against the contractual spillage and deployed wind generations are uniformly increased in hours with spillages smaller than contractual obligations. A heuristic relation between the wind generation increase and spillage increase is used to decide how much to increment deployed wind generation in each step. The procedure is iteratively repeated and maximum deployable wind generations are calculated on an hourly basis.

This procedure can be extended to increase and/or decrease deployable hourly wind generation in such a way that the expected daily spillage does not exceed contracted threshold.

7.1.2.3 Outputs from the simulation stage

The calculated nodal and system reliability indices are expected energy not served (EENS), expected frequency of load interruptions (EFI) and expected duration of load interruptions (EDI). The indices related to wind spillage are expected relative (percentage) value of spillage (ESP), expected frequency of spillage (ESPF) and expected duration of spillage (ESPD). The expressions used within the SMCS are given in [17]; relations related to state enumeration are presented in [43].

The calculated hourly operational cost OC(t) contains four terms, as shown by expression (7-1): a) Cost of generations $C_G(t)$ valued at marginal prices; b) Cost of load curtailments $C_{LC}(t)$ valued at VOLL; c) Cost of voluntary wind spillage $C_{VSP}(t)$ valued at contracted price; and d) Cost of involuntary wind spillage $C_{IVSP}(t)$ valued at μ^p . When studying two alternative solutions (e.g. with and without FACTS devices), change in daily operational costs is:

$$\Delta OCOST = \sum_{t=1}^{24} [\Delta C_G(t) + \Delta C_{LC}(t) + \Delta C_{VSP}(t) + \Delta C_{IVSP}(t)]$$
(7-14)

The PDFs of operational costs, as well as costs of voluntary and involuntary spillages and load curtailments are calculated for each hour in the studied 24-hour period. These curves can be used to quantify the financial risk of implementing a particular strategy. The concept of value-at-risk (VaR) [189] was applied to measure potentially 'excessive' costs. Assuming network cost (NC) denotes any category of costs, the corresponding CDF can be used to determine the value-at-risk at confidence level ψ [189]:

$$VaR_{1-\psi}^{NC}(NC_X) = \sup\{NC_{1-\psi} \in R: CDF_{NC_X}(NC_{1-\psi}) \le 1-\psi\}$$
(7-15)

where NC_X is the network cost that is not exceeded with probability $1 - \psi$.

7.2 Analysis of case studies

Combinations of several factors are done to define the study cases – first column of Table 7-1. All scenarios use both state enumeration and SMCS analysis. The deployed wind sources can be maximized to meet contractual obligations ($\vartheta_{SPL} = +1$), or no modification of wind capacities is done ($\vartheta_{SPL}=0$). The second factor shows whether the prioritized cost of wind spillages is included ($\xi \neq 0$) or not ($\xi = 0$) in the OPF. The installation of an SVC is denoted by $f_1=1$, whilst $f_2=1$ means a TCSC is present. The last factor, p, shows whether OHL STR is used (p=0) or RTTR is calculated (p=1). All studies are repeated for winter peak demand (first day of week 50) and summer minimum demand (7th day of 38th week).

Nine developed scenarios are shown in Table I. Scenario *S1* is the base case, where unity spillage costs are used in the OPF. No corrective actions are modelled before FACTs optimal placement and STR is applied for OHL. In this scenario the ranking lists of FACTs are initially defined ($f_1=0$ and $f_2=0$) and then used for the optimum FACTs placement ($f_1=1$ and $f_2=1$). Scenario *S2* doesn't adjust deployed wind capacities ($\vartheta_{SPL} = +0$) and applies wind spillage costs in the OPF, as a corrective control action to find reduced wind spillage values. Scenario *S3* maximizes deployable wind ($\vartheta_{SPL} = +1$) using wind spillage costs in order to meet contractual obligations on wind spillage. Scenario *S4* is similar to *S2* but incorporates RTTR of OHL as a corrective action, whilst scenario *S5* maximizes deployed wind ($\vartheta_{SPL}=+1$) and applies RTTR. Scenario *S6* incorporates SVC or TCSC to find minimum wind spillages, whereas scenario *S7* deploys SVC or TCSC device to maximize deployed wind ($\vartheta_{SPL}=+1$). Scenarios *S8* and *S9* are similar to *S6* and *S7*, the only difference being the modelling of SVC and TCSC as well as RTTR.

	S1	S2	S 3	S4	S5	S6	S7	S8	S9
ϑ_{SPL}	0	0	+1	0	+1	0	+1	0	+1
ξ	0	≠0	≠ 0	≠0	≠0	≠0	≠ 0	≠0	≠0
f_1	0,1	0	0	0	0	1	1	1	1
f_2	0,1	0	0	0	0	1	1	1	1
р	0	0	0	1	1	0	0	1	1

 Table 7-1: Modelling scenarios for optimal wind deployemnt

The original test network IEEE-RTS 96 [183] was modified in the following way: all scenarios assume an increase in load by 1.31pu compared to the original load, an increase of 0.55pu and 0.6pu transmission capacity for the 138kV and 230kV levels, respectively. Next, wind farms are connected at nine sites in an attempt to emulate 7 UK areas as shown in Figure 7-2. It was assumed that they operate at PQ mode with wind factor *wf* equal to 16.6% [185] and that they deliver 20% of the peak load [186], which is equivalent to 745MW on the studied network. Geographically 80% of the wind farms' maximum capacity is installed in the northern part of the network (buses 13, 14, 15, 18 & 19), while 20% of the wind capacity is installed in the southern part (buses 1, 2, 7 & 8). The total wind farm capacity is 4470MW delivered from 447 wind turbines.

To calculate power outputs of wind turbines (WTGs), it was assumed that cut-in, rated, and cut-out speeds are 14.4, 36, and 80km/h, respectively [190]. The failure rates and average repair times of WTG are two failures/year and 44 hours [105]. As the original network does not provide data for RTTR calculation, a simple ACSR technology was assumed with conductor sizes that give ratings similar to those in the IEEE-RTS 96 system [17]. Conductor temperature is set to 60°C for system normal operation and to 75°C for system emergencies [17]. Average values of 5-year hourly weather data are obtained from the BADC MIDAS metheorogical stations in 7 UK areas listed in Figure 7-2 [115]. Finally, SVCs operated in the range -100MVar to 100MVar, whilst reactances of TCSCs were in the range X_{TCSCij}^{min}

 $0.7X_{ij}$ to $X_{TCSCij}^{max} = 1.2X_{ij}$. The initial weights τ_1 and τ_2 were set to 0.5; they were later changed in sensitivity studies.



Figure 7-2: Modified test network

7.3 Simulation Results

7.3.1 SVC and TCSC Ranking Lists

Scenario S1 (Table 7-1, first column) is used to produce FACTs ranking lists after the SMCS1 and then to define optimal locations for SVCs and TCSCs, as explained in chapter 4.4.1. Table 7-2 shows SVC ranking list, the base expected spillages BESP^{volt} and the base expected energy not supplied BEENS^{volt} due to voltage constraints, as well as the voltage deviations $(\Delta \gamma^{Vmin/max})$ from minimum (0.95pu) and maximum limits (1.05pu) within the internal region

of $\psi=1\%$. The presented ranking was obtained for $\tau_1=\tau_2=0.5$ and it remains unchanged until $\tau_1=0.7$ and $\tau_2=0.3$. The SVC ranking list is based on criterion (4-32) and it shows that the best locations are buses b18, b7, b19, b14, b8 and b1 if $\tau_1=\tau_2$. This is because voltage spillages BESP^{volt} are very high at these buses, whilst BEENS^{volt} is high only at b7 and b8. Had we chosen $\tau_1 \gg \tau_2$, nodes b7 and b8 would be on the top of the list. The lowest feasible-internal voltages are at b13 and b15, whilst b18 has highest feasible voltages; this may indicate problems at these nodes in future.

The ranking list of branches for TCSC placement is shown in Table 7-3. The thermal reductions Δ BEENSth indicate that lines (7,8), (8,9) & (2,6) are the best locations, whilst lines (15,24), (8,9) and (15,16) give highest thermal spillage reductions Δ BESPth. The maximum spillage reduction of 13.16 MW is on line (15,16) where the initial BESPth was 58MW.

Wind buses	$ ho_i$	$BESP_i^{volt}(MW)$	$BEENS_i^{volt}(MW)$	$\Delta \gamma_i^{V^{min}}$	$\Delta \gamma_i^{V^{max}}$
b18	14.1288	27.82	0.02	0.008	0.007
b7	12.0456	5.50	18.40	0.008	0
b19	11.4408	22.66	0.04	0.008	0
b14	11.2687	22.37	0.1	0.002	0.001
b8	10.9218	9.52	12.28	0.001	0.001
b1	10.8990	21.73	0.003	0.002	0.001
b13	3.7004	7.07	0.2	0.018	0
b2	2.8721	5.73	0	0.001	0.0015
b15	2.0694	3.87	0.16	0.017	0.01

Table 7-2: SVC Ranking List

Table 7-3: TCSC Ranking List									
Line	$\Delta BENS\&SP_{ij}$	$\Delta BESP_{ij}^{th}(MW)$	$\Delta BEENS^{th}_{ij}(MW)$						
(15,24)	8.11	16.2	0.02						
(7,8)	7.64	10.9	4.38						
(8,9)	7.6	12.12	3.14						
(15,16)	7.5	13.16	0.01						

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(2,6)	5.073	7.42	2.72
(13,23)	3.9	7.87	0.028
(8,10)	3.32	4.6	2.04
(14,16)	2.61	5.12	0.1

	Ce ^{volt}	> <	ce th		Ce ^{volt}	> <	ce th
baseSMC	88.74	<	104.13	b14	80.80	>	76.71
(15,24)	96.12	>	95.02	b8	76.01	<	76.93
b18	94.97	>	94.42	(15,16)	75.75	>	74.31
b7	89.05	<	93.82	(2,6)	74.08	>	70.28
(7,8)	88.58	>	86.01	b1	74.01	IS	70.12
b19	85.11	<	86.29	b13	74.99	IS	71.01
(8,9)	86.94	>	76.87	(13,23)	74.06	IS	70.03

Table 7-4: Optimal FACTS Placement

Optimal placement strategy of SVCs and TCSCs is illustrated in Table 7-4. It is based on the comparison of wind and load curtailments due to voltage ce_{volt} and thermal constraints ce_{th} . Where $ce^{th} > ce^{volt}$ the first TCSC from the ranking list is placed in line (i,j); otherwise, the first SVC is connected to bus "b". Every time an SVC or TCSC is installed, the difference in EENS and ESP is checked against the threshold value and if considered insignificant ('IS'), the next device is studied. Here, TCSC on line (15,24) reduces ceth but increases cevolt compared to the base SMCS¹; however, the total curtailed energy cevolt plus ceth is always reduced. The last three cases in Table 7-4 show no desired improvement in curtailed energy. Consequently, nodes b18, b7, b19, b14 and b8 should be considered for SVC installation, whilst lines (15,24), (7,8), (8,9), (15,16) and (2,6) for TCSC placement. The available budget will determine the actual FACTS installations.

7.3.2 Prioritisation of wind spillages

Scenario S1 with unit spillage costs in the OPF is used to evaluate base wind spillages BESP and marginal prices μ , required for the calculation of wind spillage cost coefficients

(equations (4-3), (4-4)) that are used in the OPF for scenario S2. Figure 7-3 compares S1 and S2 and shows how the mean percentage value of wind spillage at each wind generation node decreases for both days and both study methods when cost coefficients are applied in S2. The largest decrease (33%) in spillage occurs at bus 8 in winter, whilst in summer, wind spillage decreases by 20% at bus 13. The SMCS reduces wind spillage in the total system by 10.8% in winter and 13.11% in summer, whilst these figures are respectively, 24% and 22% for the state enumeration analysis. Although wind spillage prioritization can substantially reduce optimal spillage levels under the probabilistic SMCS analysis that considers all combinations of outages, the state enumeration approach gives less wind curtailment because only N-1 outages are taken into account.



Figure 7-3: Wind spillages under scenario S1 and S2

7.3.3 Impact of Controls and Maximized Deployed Wind Capacity

The initially installed wind capacity of 4470MW, found from (4-1) and (4-2), are first used to calculate optimized wind spillages. The box plots of optimized wind spillages for the SMCS analysis of scenaria S1, S4, S6(f_1), S6(f_2) & S8 with initially connected wind sources are shown in Figure 7-4. Spillages are higher in all cases in winter due to increased network stress. Scenario S8 with a combination of SVC&TCSC&RTTR gives the best minimized

spillages; the reduction is 31.65% in winter and 33.44% in summer. The second best spillage is for $S6(f_2)$ giving reduction of 22.8% (winter), and reduction of 22.3% for $S6(f_1)$ (summer). A normal distribution was found to best-fit the wind spillage PDF in winter, whilst a log-normal distribution best fit summer spillage PDF.

The maximum integrated wind power that meets contractual obligations are calculated using the SMCS and state-enumeration for the following cases (Figure 7-5): a) S3 with non-zero spillage costs; b) S5 with RTTR; c) S7 with SVC (f_1 =1); d) S7 with TCSC (f_2 =1); and e) S9 with SVC&TCSC&RTTR. In all cases, it was possible to deploy more wind in the winter and summer day, where deployed wind in winter was always higher than in summer mainly because winter STR is higher than summer STR and winter wind speeds are higher than in summer.



Figure 7-4: SMCS wind spillages for scenaria S1, S4, S6(f1), S6(f2) & S8



Figure 7-5: Maximum deployed wind capacity under scenaria S1, S3, S5, S7 & S9

Finally, comparison of results from Figure 7-4 and Figure 7-5 shows that although installation of TCSCs can give slightly higher wind integration than with SVCs (Figure 7-5), probabilistic wind spillages in the system with SVCs can be lower than with TCSCs (Figure 7-4). This means that both problems need to be studied separately, and it is likely that the preferred solution will be the one, which maximizes wind deployment.

Table 7-5 summarises reliability indices for SMCS studies. It is shown that S8 is the most reliable scenario, both in terms of load and spillage indices; reduction in EENS is 24% in winter and 79% in summer when compared to S1. The spillage indicators are significantly lower; for example, ESPD has dropped from 5.93 to 3.13h/d. S2 with non-zero spillage costs gives significantly reduced ESP and ESPF, whilst EENS is slightly lower. The use of RTTR in S4 results in substantial reduction in EENS, which is consequence of greater utilization of the three most critical lines (16,14), (16,17) and (7,8); the wind spillage indicators are also reduced. Installation of FACTS contributes to improved network reliability by 9.38% in EENS for SVC (S6-f₁) and 14.2% for TCSC (S6-f₂) compared to S1. SVCs and TCSCs also improve expected spillages indices; in different seasons the former or the latter contribute more to the reduction of wind spillages.

		S 1	S2	S4	S6(SVC)	S6(TCSC)	S 8
EENS	Wint	86.4	84.7	75.1	78.3	74.1	65.9
(MWh/d)	Sum	6.42	4.16	3.72	3.81	3.75	1.34
EDI	Wint	2.67	2.65	2.41	2.65	2.63	2.12
$(*10^{-2}h/d)$	Sum	0.47	0.54	0.51	0.53	0.52	0.50
EFI	Wint	2.39	2.37	1.98	2.03	2.01	2.01
(*10 ⁻² int/d)	Sum	0.19	0.12	0.09	0.12	0.11	0.10
ESP	Wint	15.8	14.1	13.1	12.5	12.2	10.8
(%/d)	Sum	12.2	10.6	8.53	9.5	9.8	8.12
ESPF	Wint	1.9	1.51	0.73	1.19	1.24	1.07
(int/d)	Sum	1.24	1.02	0.08	1.12	1.15	0.09
ESPD	Wint	5.93	5.84	3.69	5.15	4.76	3.15
(h/d)	Sum	5.66	4.76	3.58	3.86	4.51	3.12

Table 7-5: Load and Spillage Reliability Indices

7.3.4 Impact of FACTS and RTTR on Operation Costs

Operation costs for different scenaria and cost savings between the scenaria and base case S1 are quantified in terms of VaR metrics at different confidence levels ψ . Figure 7-6 shows VaR metrics for scenario S4 with RTTR, S6 with SVC, S6 with TCSC and S8 with SVC&TCSC&RTTR. Black area indicates savings between S6(SVC) and base case S1, dark grey between S6(TCSC) and S6(SVC), less dark grey between S4(RTTR) and S6(TCSC), and light grey area between S8(SVC&TCSC&RTTR) and S4(RTTR). Scenario S8 (SVC&TCSC&RTTR) shows the highest savings compared to the base case S1 by 45% considering VaR^{NC}_{95%}. It is apparent that applied interventions give greater savings for higher confidence intervals. However, when ψ =60% the savings are almost negligible, showing that averaged conditions give little information about wind systems.



Figure 7-6: Operating cost for S4 (RTTR), S6 (SVC), S6 (TCSC) and S8 (SVC & TCSC & RTTR)

7.3.5 Computational CPU times

All simulations are done on a PC with i7-3820 processor & 32GB RAM; optimization model (7-1)-(7-13) is solved using MIPS Matpower solver under Matlab. The CPU times are presented in Table 7-6 for scenario S1 and all scenaria related to maximized deployed wind. Times required to solve optimal location of FACTs devices are high due to iterative nature of the algorithm – section 4.4.1.

Table 7-6: Computational CPU Times for Main Scenaria

	S1		S 3	S5	S7	S7	S9
	Base case	FACTs Opt.	ξ≠0	RTTR	SVC	TCSC	SVC&TCSC &RTTR
CPU(s)	3689	7273	3812	5129	3720	5248	6664

7.4 Conclusions

A probabilistic methodology for maximizing deployed wind sources whilst minimizing curtailed wind to meet contracted obligations is proposed in this paper. Impacts of wind spillage prioritization, deployment of FACTS devices and real-time thermal ratings on optimal wind utilization, system reliability and operation costs are investigated in the day-ahead planning.

Case studies have shown that wind spillage prioritization using spillage costs in the OPF can substantially reduce optimal spillage levels, up to 10.08% in winter- and 13.11% in summerday. It was also shown that implementation of SVC&TCSC&RTTR allows for higher integration of wind sources, up to 23%. However, ranking of the applied controls based on optimal utilization of wind sources can be different when applying the SMCS and state enumeration studies. Improvements in EENS and other reliability indices were also observed. It can be concluded that application of multiple reliability indicators can be a good choice for operational decisions on optimal wind management.

8 Conclusions and Future Work

8.1 Conclusions and Discussions

The thesis has made three important contributions: i) a critical review of smart solutions for reliability improvements in energy systems is presented and research gaps are identified; ii) a probabilistic framework for quantifying the reliability and profitability of flexible smart solutions, such as demand response, real time thermal ratings and FACTS is developed, iii) a novel probabilistic model that maximizes capacity of the deployed wind generation whilst decreasing wind curtailment levels is proposed. In completing this research, a probabilistic methodology and a tool have been developed to assisst system operators in decision making when operating modern and highly uncertain transmission systems.

Each contribution is now discussed in more detail:

1. A critical review of smart solutions for reliability improvements

This thesis presented a critical assessment of current reliability based methodologies for systems with smart energy solutions, with the objective to identify the gaps or inconsistencies in the so-far developed approaches. This investigation is used to propose comprehensive probabilistic methodologies that will quantify both reliability and economic risks. For instance, it is shown that demand response strategies currently under investigation are usually considered at the distribution level, but their potential in transmission networks is often

overlooked. In addition, physical characteristics of customers participating in the demand response are often neglected, and the research related to the impact of demand response on network reliability is very limited. Even if a probabilistic approach is used to assess the demand response contributions, often only single contingencies of network components are analysed. Similarly, real time thermal ratings of overhead lines are usually studied to find benefits compared to standard thermal ratings, to provide additional wind integration in the transmission system, and to determine conductor sag, conductor loss of strength due to annealing and limitations of the conductor fittings. Yet, the benefits of real time thermal ratings in terms of reliability increase and reduction of operating costs under probabilistic analysis versus deterministic analysis are not investigated in the aforementioned studies. Another smart technology that can substantially contribute to optimal power system operation is FACTS devices. Although, several approaches for optimal placement and sizing of FACTS have been developed, with the objective to minimize real power losses, to improve system loadability, to improve system voltage profile and additionally to minimize the total fuel cost, there is no investigation quantifying the impact of FACTS on the optimal utilization of wind energy sources within a probabilistic framework. So far, different aspects of deploying wind energy sources are implemented; for example, energy storage, stochastic unit commitment and deterministic security criteria are used to maximize or increase integration of wind energy. Besides, studies that include probabilistic wind-modelling usually do not include wind spillages, which can create high operating costs if these are not carefully considered in the power flow and economic analyses.

2. Quantify demand response benefits in network reliability and economic analyses

As a consequence of the gaps highlighted in point 1, this thesis first proposes a probabilistic approach for optimal demand response scheduling in the day-ahead planning of transmission networks. Uncertainties related to forecast load, network component availability, available amount of demand response and wind speeds are incorporated into a sequential Monte Carlo simulation framework. Synchronous and wind generating units, as well as four types of load customers (large, industrial, commercial and residential) are modelled. Optimal nodal load reductions are calculated using the optimum power flow model, and are then dissagregated into voluntary (i.e. demand response) and involuntary components. Recognizing that

directly-controlled loads can certainly be shed and indirectly-controlled loads contain a probabilistic component that can affect the shedding, then optimal amounts of voluntary and involuntary nodal load reductions are determined using these principles. Different load recovery profiles for customer types are considered within 'payback periods' and they are initiated when the load customer's profit is highest.

In addition, the whole modelling is implemented from the load customer's perspective to maximise their revenues, whilst the load recoveries are controlled by the transmission system operator (TSO); they may represent either physical paybacks from specific appliances or controlled paybacks whereby the TSO schedules its customer loads so as to have the desired shape.

3. Quantify the benefits of real time thermal ratings uisng a probabilistic methodology

Real time thermal ratings are used in probabilistic analysis to reduce power systems congestions. The developed model considers the real conductor temperature, resistance and ampacity on a sequential hourly basis, so the true impact of real thermal ratings is captured in the sequential network analysis. It is shown that when real time thermal rating is used in the probabilistic analysis, operating costs are significantly reduced compared to operating costs based on standard thermal ratings. This is because additional capacity margins are available and the system operator can resolve a post fault contigency in a cheaper way.

4. Quantify the maximum wind deployment using flexible smart solutions

A probabilistic methodology for maximizing the deployed wind sources whilst minimizing curtailed wind to meet contracted obligations is proposed in this thesis. Impacts of wind spillage prioritization, deployment of FACTS devices and real-time thermal ratings on optimal wind utilization, system reliability and operation costs are investigated for the day-ahead planning. Wind spillages are classified as 'voluntary' and 'involuntary'. The first category relates to the quantity limited by the contracted average annual spillage, whereas involuntary spillages are limited by the maximum allowed wind curtailment. The main objective is to determine maximum deployable wind generations by hourly intervals so that

the expected minimized wind curtailment satisfies contractual constraints. This is realized within the developed sequential Monte Carlo simulation (SMCS) procedure, in which corrective rescheduling is done with the aid of the AC optimum power flow (OPF) whose composite objective function contains both load and wind curtailments. Results of the developed SMCS procedure give the maximised hourly deployable wind capacities, minimised wind spillages, as well as reliability and operation cost indicators. Additional investigations are then done to find impact of FACTS and RTTR on the maximum utilisation of wind sources. It was also shown that implementation of RTTR and FACTS allows for additional integration of wind sources. It was concluded that application of multiple reliability indicators can be a good choice to base operational decisions on optimal wind management.

5. Determine ranking lists and optimal placement of FACTS devices based on their contribution towards load and wind curtailment reduction

A ranking list of nodes most appropriate for the SVCs connection is developed using the load and wind curtailments due to violation of voltage limits. Branches best candidates to install TCSCs are ranked based on their contribution towards reduction of load and wind curtailments caused by violation of thermal constraints. In particular, optimum FACTS placement is applied after checking probabilistic indices such as expected energy not supplied (EENS) and expected wind spillage (ESP). Only when there is an improvement in the EENS and ESP, FACTS devices are installed to enable additional integration of wind sources. More specifically, an SVC is installed when EENS and ESP caused by violation of voltage constraints prevail, whilst a TCSC is placed when thermal-capacity constraints caused the majority of EENS and ESP. It is shown that FACT devices can considerably improve reliability indices and that they can allow for significant reduction in total operation costs. Considering FACTS operation in a probabilistic framework leads to an added value, which may be otherwise overlooked under a deterministic analysis.

8.2 Future work

The work presented within this thesis has fulfilled all research aims, which were initially defined. Nevertheless, there are a number of areas where this work could be extended to further develop the ideas and methods, which have been established. They are briefly presented below.

1. Reduction of the computational time of the sequential Monte Carlo simulation.

According to the information provided in Chapter 5.2, the reduction of the simulation time, when using MCS is a big challenge. The development of new algorithms, which modify the crude - original MC method will play a great role in the acceleration of the simulation process. Firstly, the multi-objective PSO can be further extended to be used in the sequential analysis (apply the same approach for hourly loads or for a multi-level load model), and secondly include more objectives to solve problems that contain multiple goals or fitness functions. In that case the intelligent search of the particles will become more time efficient and this will enable the particles to visit less non-loss load states and also to minimize multiple visits to already visited states. Besides, studies can be made on improving the performance of classification stages of the MCS. These techniques may be combined in order to develop a hybrid algorithm that outperforms the current state of the art approaches. Such hybrids could produce very good results. An area that is still under investigation is application of Intelligent State Space Pruning methods in large and complex systems. Such applications may include larger and more reliable test systems, models of real life power systems, and various models that incorporate some aspects of the smart grid such as FACTS, renewable generation, and communication units.

2. To investigate the thermal capacity of a specific section of an OHL by using Spatial Correlation Prediction Model (SCPM).

As the thermal rating of a line is considerably affected by the wind speed, it is worthwhile to develop a model that uses the correlated relationships between wind speeds at neighbouring locations in order to predict wind speed at target locations. Hence, correlation analysis can help to determine which section of a transmission line has the lowest thermal capacity, which

is relevant to the system operators to make decisions. The basic model, Augmented Kriging Model (AKM), can be further analysed and extended to a multivariate Kringing model that will include wind direction and temperature profiles of various areas to predict spatially distributed and correlated variables at unmeasured locations.

3. Quantify demand response for investment planning decisions

The probabilistic demand response model proposed in this thesis calculates the revenues of demand response customers for different confidence intervals. The work was illustrated taking a particular winter, summer and spring week in a year; however, further analysis is required to assess the potential of demand response over longer periods (for instance over a month or over the whole year). Having determined the benefits of demand response scheduling for the entire year, the system operators then can take investment decisions about appropriate equipments to be installed at customers' premises and/or DNO control center, for example smart meters, ICTs, SCADA, etc. The model proposed in this thesis has been applied only for post contingency system states. However, the described process and methodology can also be applied for system normal operation (i.e. pre-contingency states), where voluntary load reductions (i.e. demand response) will be used if they are cheaper than committing some expensive generation units. The quantitave results of such studies might result in higher or lower revenues for either customers or system operators. Therefore, it would be interesting to incorporate demand response to precontigency states in order to quantify the maximum possible revenues by deploying optimal demand response scheduling.

In addition, it would be appropriate to extend the demand response model with the load recovery profiles that are dependent on different network outage durations. In this way, modelling of realistic load recovery sizes and shapes will contribute to a complete and accurate network assessment.

4. Incorporation of energy storage model in conjunction with the demand response model

The proposed demand response model was included in the analysis with the renewable energy sources, such as wind generation, because it can have a significant impact on smart grid

operation. The illustrated work doesn't consider the event that the customer can cogenerate all of its energy requirements and as a result the network failure will have no effect on its consumption. However, in the case where a customer is still reliant on the grid connection, the network failure will interrupt its consumption which can be aggrevated by the highly intermittent generation from renewables (e.g. when the sun is not shinning or when the wind is not blowing). This can be further mitigated if a customer had energy storage. This would also affect the energy prices in a joint energy and reserve market. As a result, the contemporary price profile should be incorporated for valuing load reduction as well as load recovery. Hence, it is likely that the quantitative results of studies will change when storage is involved in the network operation.

5. Maximize wind connection capacities in the presence of energy storage

A probabilistic methodology for maximizing the deployed wind sources was illustrated on two cases. The first is analysis of the peak week in winter in order to find the impact of wind generation when the sytem is very stressed; the second is analysis of the minimum demand week in summer in order to find the levels of wind curtailment when the load is low while the wind generation is high. This model can be extended to a yearly planning to find the optimal connection of wind capacities. This study would result in both maximum wind generation connections as well as in maximum revenues for system operators, which will be based on a probabilistic approach. Then, the same analysis could be performed by incorporating optimal management of energy storage within wind systems. Energy storage can contribute to alleviate wind fluctuations especially when wind curtailment is required to alleviate asset overloads or voltage violations. Consequently, this would allow reduction in wind spillage and give room to integrate more wind generation on the system.

6. Maximize wind connection capacities incorporating smart energy solutions

In this thesis, maximum wind deployment has been quantified in the presence of FACTS devices and RTTRs of OHLs. There is still no research that finds maximum wind connections when demand response is employed before load (and wind) curtailment. For instance, it would be interesting to determine maximum wind energy connection –

utilization when load recovery is higher than the load reduction, as well as when load reduction is partly met by wind generation and the rest from demand response strategies. After quantifing maximum wind utilization due to demand response, energy storage could be also added beside RTTR and FACTS devices. In this way, network performance would be determined considering the majority of smart energy solutions under both probabilistic and deterministic approaches.

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