Risk-based Assessment for Distribution Network via An Efficient Monte Carlo Simulation Model

Yang Yang

Department of Electrical and Electronic Engineering

Imperial College London

This dissertation is submitted for the degree of

Doctor of Philosophy

Control and Power Group May 2016

Copyright Declaration

Declaration of Originality

As required by the college, I hereby confirm that this thesis is the result of my own work. Any ideas or quotations from the work of other people, published or otherwise, are fully acknowledged through standard referencing practices of the discipline.

Yang Yang

Imperial College London

30 May 2016

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Professor Goran Strbac, for his thought-provoking insights into the power system reliability problems and constant guidance through my PhD study. I also thank him for providing financial assistance to support my last three years' study.

A special thank you to Dr Simon Tindemans, for his wisdom, kindness and generousness. I really enjoyed this PhD study thanks to all the fruitful discussion, idea sharing, and methodology exploration with him.

I gratefully acknowledge the Control and Power research team at Imperial. I would like to thank Predrag Djapic, Zhe Feng, Feng Teng, Jingjing Jiang, Ming Ge, Manuel Castro and other colleagues for their support in my study.

Finally, this study cannot be completed without the unlimited love, support and confidence in me from my dear wife Zhanghuiqi Tu, and my parents. Thank you for all dedication to the family during my busiest time.

ABSTRACT FOR THE THESIS

Given the fact that Smart Grid technologies are implemented mainly in distribution networks, it is essential to build a risk-based assessment tool which can model the operational characteristics of distribution networks operation. This thesis presented a distribution network model which captures the features of distribution network restoration, based on approximations of real-time switching actions. It enables the evaluation of complex distribution network reliability with active network control. The development of an explicit switching model which better reflects actual network switching actions allows for deliberate accuracy and efficiency trade-offs. Combined with importance sampling approach, a significant improvement in computational efficiency has been achieved with both simplified and detailed network switching models. The assessment model also provides flexibility for users to analyse system reliability with various levels of complexity and efficiency.

With the proposed assessment tool, different network improvement technologies were investigated for their values of substituting traditional network constructions and impacts on network reliability performances. It has been found that a combination of different technologies, according to specific network requirements, provide the best solution to network investments. Models of customer interruption cost were analysed and compared. The study shows that using different cost models will result in large differences in results and lead to different investment decisions. A single value of lost load is not appropriate to achieve an accurate interruption cost quantification. A chronological simulation model was also built for evaluating the implications of High Impact Low Probability events on distribution network planning. This model provides the insights for the cost of such events and helps network planners justify the cost-effectiveness of post-fault corrections and preventive solutions.

Finally, the overall security of supply for GB system was assessed to investigate the impacts of a recent demand reduction at grid supply points (for transmission networks) resulting from the fast growing of generation capacity in distribution networks. It has been found that the current security standard may not be able to guarantee an acceptable reliability performance with the increasing penetration of distributed generation, if further balancing service investment is not available.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF PUBLICATIONS

Y. Yang, S. Tindemans, G. Strbac, “An implicit Switching Model for Distribution Network Reliability Assessment”, accepted by the 19th Power System Computation Conference 2016.

Y. Yang, S. Tindemans, G. Strbac, “Snapshot Model for Distribution Network Reliability Analysis with Variable Restoration Accuracy”, submitted to IEEE Transaction on Power Systems.

Y. Yang, S. Tindemans, G. Strbac, “Generation System Adequacy Performance Under the Current UK Reliability Standard” to be submitted to IET Generation, Transmission & Distribution.

Goran Strbac, Predrag Djapic, Rodrigo Moreno, Ioannis Konstantelos, Dimitrios Papadaskalopoulos, Jose Calvo, Danny Pudjianto, Simon Tindemans, Sana Kairudeen, **Yang Yang**, Hadi Karimi, Enrique Ortega, Marko Aunedi, “Review of Distribution Network Security Standards - Extended Report”, submitted the Energy Network Association, 2016.

List of Acronyms

DECC	Department of Energy and Climate Change
SQSS	Security and Quality of Supply Standards
ER	Engineering Recommendation
DER	Distribution Energy Resources
DG	Distributed Generation
ES	Energy Storage
DSR	Demand Side Response
MCS	Monte Carlo simulation
NOP	Normally Open Point
ENS	Energy Not Supplied
CI	Customer Interruption
CML	Customer Minute Lost
DNO	Distribution Network Operator
OFGEM	Office of Gas and Electricity Markets
CIC	Customer Interruption Cost
HILP	High Impact Low Probability
LOLE	Loss of Load Expectation
LOLD	Loss of Load Duration
LOLF	Loss of Load Frequency
PNS	Power Not Supplied

BS	Balancing Service
PDF	Probability Distribution Function
GB	Great Britain
VOLL	Value of Lost Load
OHL	Overhead Line
UG	Underground
FMEA	Failure Mode Effect Analysis
CB	Circuit Breaker
EHV	Extra High Voltage
HV	High Voltage
LV	Low Voltage
LP	Load Points
EENS	Expected Energy Not Supplied
ECI	Expected Customer Interruption
ECML	Expected Customer Minute Lost
IS	Importance Sampling
NSMCS	Non-sequential Monte Carlo Simulation
TSMCS	Time-sequential Monte Carlo Simulation
RBTS	Roy Billinton Test System
RTS	Reliability Test System
GSP	Grid Supply Point
COV	Coefficient Of Variation
MTTR	Mean Time To Repair

CDF Cumulative Distribution Function

CCDF Complementary Cumulative Distribution Function

CDF Customer Damage Function

ECC Equivalent Circuit Capacity

SAIFI System Average Interruption Frequency Index

SAIDI System Average Interruption Duration Index

PV Photovoltaic

WTA Willingness To Accept

WTP Willingness To Pay

GVA Gross Value Added

Chapter 1 INTRODUCTION

1.1 MOTIVATIONS

1.1.1 NEED FOR A FUTURE LOW CARBON POWER SYSTEM

There is an increasing consensus that to ensure a sustainable human future, a low carbon energy system is required to be built. To address global climate change, commitments have been made in a number of countries to radically reduce CO2 emission and deploy more renewable energy resources. Some of the related initiatives are:

- From the Climate Change Act 2008 [1], the UK government is committed to reducing greenhouse gas emissions by at least 80% by 2050, relative to 1990 levels.
- It is expected by DECC that in the UK, electricity sectors would be significantly decarbonised by 2030.
- The EU has set the legislation to achieve 40% cut in greenhouse gas emission, 27% energy production from renewables and 27% improvement in energy efficiency by the year 2030 [2].
- On 30 June 2015, China submitted its Intended Nationally Determined Contribution (INDC), lower the carbon emissions per dollar of economic output by 60% to 65% below 2005 levels, and increase the proportion of non-fossil in total primary energy supply to around 20%, by the year 2030 [3].
- Japan sets a target that by 2030 carbon emission from all sectors will be reduced to 80 percent of those in 2013 [4].
- Other main CO2 emitting countries like the US have also set up their legislation framework to ensure a low carbon system development.

To deliver these ambitious targets, tighter regulations and generous incentives have been set to promote and stimulate the transition from conventional fossil fuels to lower carbon technologies. For instance,

- The Zero Carbon Buildings policy [5] requires that from 2016 all new homes in the UK need to achieve zero carbon emission for energy consumption including heating and lighting.

- Feed-in tariffs [6] have been set in a number of countries in the EU for subsidising the wind and solar energy generation installed by domestic and commercial electricity consumers.
- Low CO2 emission cars can be exempt from road tax in the UK [7]; Full electric vehicles are free from congestion zone fee in London [8] and free to park and recharge in the City of Westminster [9].

The fast growing incorporation of heat and transport sectors can lead to a sharp increase in electricity demand. However, most electricity networks in the UK, EU and other developed countries have been in service from the booming construction era in the late 1950s to 1960s. These network infrastructures are approaching their designed useful lifetime and are waiting for decommissioning and replacement. To meet the ever increasing electricity demand and prevent customers from shortages and outages, the network capacity requires urgent upgrades.

1.1.2 Need for a better network investment efficiency

In the UK, the system security and quality of supply standards (SQSS) [10] for transmission networks and Engineering Recommendation P2 [11] for distribution networks are based on the “n-k” criteria for system reliability. The methodology is that a system needs sufficient redundancy capacity to ensure a reliable supply for a set of specific system failures.

In this traditional asset-based philosophy, substantial generation installation and grid construction are required to meet the rising demand. The current planning standard has delivered secure and reliable electricity services to end users in the last century, the key concern is whether it can deliver reliable service economically.

Rather than increasing system capacity by building more centralised generators to produce power, upgrading the rating of grid lines in transmission and distribution networks to deliver power to customers, the concept of Smart Grid proposes another route to achieve a potentially better investment efficiency.

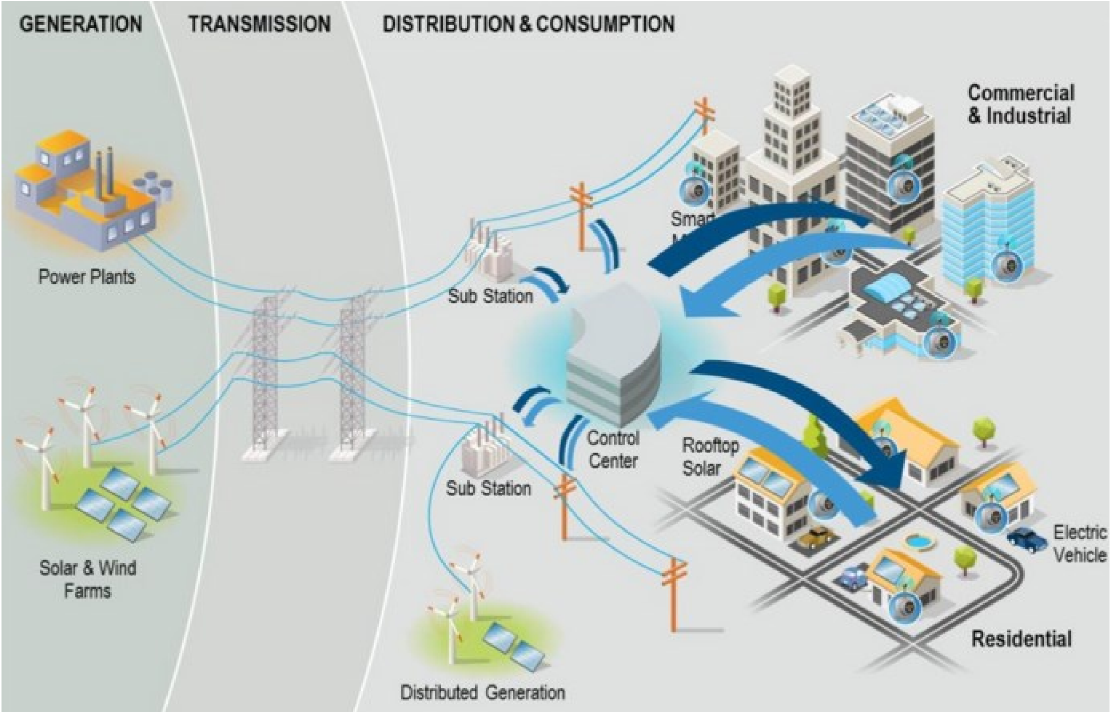


FIGURE 1-1 AN EXAMPLE OF THE VISION OF SMART GRID [12]

By integrating renewable distributed energy resources (DER) (including photovoltaic panel, wind turbine, biomass power plant, and other types of DG) and flexible demand side response (DSR) (including smart demand control in domestic appliances, electric cars, heat pumps and energy storage) into distribution networks, in combination with active network control and automation, the Smart Grid may be able to achieve a higher utilisation of existing network assets and therefore deliver a cheaper alternative to traditional asset-based solutions.

1.1.3 Need for efficient distribution network assessment tools

Even if the Smart Grid is able to deliver an economic solution for meeting the booming electricity demand whilst avoiding/reducing extra network asset constructions, it is essential to ensure that network reliability is not compromised. A distribution network reliability assessment model is required that is able to reflect the operational characteristics of distribution network service operation and restoration and also the stochastic performance for long term planning.

Distribution network operation includes complex network restoration schemes [13]. Up to recently, substantial works [14]–[21] have been focused on optimising specific network failure service restorations, minimising load shedding and the number of switching actions. These works are usually for analysing the operational properties of system security but not for long term time domain interruption and restoration characteristics. The analysis of probabilistic study on distribution network reliability for planning has also been developed for decades [22]–[24]. However, most studies investigating system performances make approximations which simplify network restoration and compromise the accuracy of modelling chronological distribution network operation in system planning. The bottle-neck is that the mixed integer optimisation for determining the optimal switching actions in distribution network operation brings huge computational burden and long-term chronological simulation is very slow to converge for large and complex distribution networks.

The operation of Smart Grid technologies such as the charging and discharging of energy storage is naturally a time domain optimisation problem. Capturing the chronological characteristics of these technologies in combination with active distribution network control requires efficient distribution network assessment tools.

1.2 Scope of the work

This thesis focuses on the challenges of reliability assessment for complex time domain distribution network operations. The research aims to develop an efficient distribution network operation model that allows, via Monte Carlo simulations, the implications of Smart Grid technologies, various customer interruption cost models and high impact low probability events to be analysed. The following research questions were identified:

A. How to model distribution network reliability performance considering the essential aspects of real-time operations?

   It is required to develop a network reliability model which captures the stochastic characteristics of network components' failure, repair and maintenance, and reflects key features of real-time service restoration actions including fault clearing, fault isolation and supply rerouting. This model needs to determine the optimal switching actions in real time distribution network operations, whilst satisfying network constraints and minimising load curtailment at all times.

B. How to overcome the computational challenges in evaluating distribution network reliability metrics?

   Optimal switching actions are determined by solving mixed integer optimisation problems with multiple objectives including restoring as many customers as possible by network reconfiguration, employing minimal number of switching actions, maintaining power flows within line ratings, keeping radial network topology, minimising network losses, etc. Meanwhile, for a network with n switches (including controllable circuit breakers, switches and NOPs), there exist at least 2^n possible switching combinations, in which each switch is either closed or open. The number of possible solutions expands exponentially with the growing size of networks.

Such an optimisation problem brings a huge computational burden. To assess predictive reliability properties for distribution networks, it may need to simulate thousands of years, and in each simulation year there exist a large number of system states, each of which requires solving the corresponding optimisation problems.

Therefore, there is a need for efficient methods that allow for deliberate accuracy and efficiency trade-offs.

C. What are the impacts of different network improvement options on reliability performance in distribution networks?

Apart from upgrading the capacity limit of substation transformers and distribution lines/cables, there exist a number of network improvement options. These include but are not limited to installing DG and energy storage in the LV network, replacing switches operated manually by automatic switches that operated remotely with very short response time, allocating mobile generation for emergency supply for disconnected areas. These options, via the proposed simulation tool, are investigated and compared for their different impacts on ENS, CI and CML, the main security of supply indicators monitored by the UK DNOs [25].

D. What are the implications of customer interruption cost (CIC) on network planning?

OFGEM and DECC have set a headline weighted-average value of lost load of £16940/MWh for peak winter workdays in GB. This figure is used as a reference for security of supply calculations including for setting capacity levels and calculating cost in cash-out [26]. However, a general consensus on the value of customer interruption cost has not been yet achieved as the values proposed by different sources vary significantly. The value of CIC is affected by unsupplied energy, the timing (time of day, day of week, month of year) of the supply interruption, the duration of the supply interruption, the frequency of interruptions, the availability of advance warning before the interruption takes place and the category of different customers. The dependency of the interruption cost to customers on these factors needs to be thoroughly evaluated by chronological simulations. Our studies have demonstrated that the adopted model and estimate of interruption costs can have a profound impact on the obtained planning solution.

E. What is the importance of assessing impacts of high impact low probability (HILP) events on distribution network reliability?

   Reliability indices used for assessing the reliability performance of electricity networks are usually based on predictive “average” or “expected” values derived from historical data. This methodology is not valid for those exceptionally rare events whose probability of occurrence is not predictable. Those events with large impacts, even though occurring infrequently, can lead to significant changes in the dynamic behaviour of the network and result in prolonged interruptions of supply. It is of great importance to understand the reason and consequences of HILP events and identify the role and quantify the value of emergency operation actions and emergency network development. This requires tools for estimating reliability performances including HILP events.

F. Is the transition in distribution networks making any difference to the whole GB system security of supply under the current reliability standard, i.e. 3h/year LOLE?

   OFGEM has set 3h/year LOLE for GB electricity system as the generation adequacy standard. It is expected that under the 3h LOLE standard [27], the system operator should be able to achieve a secure and reliable supply to customers, with the current level of balancing service. However, there has been an ever expanding reduction in demand at grid supply points (from the transmission networks’ perspective) due to the fast growing embedded capacity from distribution networks. It is essential to understand, under the same reliability standard, the impacts on system security of supply, and to inspect whether the standard is appropriate and the amount of balancing service is sufficient.

1.3 Original contributions

The original contributions of this thesis are described in chapters 2, 3, 4 and 5.

Chapter 2 proposes an implicit switching model for the reliability analysis of active distribution networks. The resulting reliability model is approximate, but has the following advantageous properties:

- The model captures the qualitative benefits of network restoration by switching but foregoes explicit computation of switching actions.
- Complex distribution network composition and topologies can be represented using the graphical method in a simplified fashion whilst switching operations such as failure isolation, network rerouting, restoration can still be modelled;
- The impact of a given state does not depend on its history but the current state of network components. This property enables the use of state sampling Monte Carlo schemes (a 'snapshot' analysis of network states) and associated variance reduction schemes (e.g. importance sampling) so that very large speedups can be obtained;
- Network constraints and load shedding can be conveniently embedded using a simple linear optimisation;
- The approximations in network restoration are gradually becoming less artificial as future networks become smarter and deploy technologies such as soft open points and demand response.

The existing studies on distribution network reliability either oversimplify restoration actions, or consider step by step operations in details. The former methods include analytical analyses such as failure mode effect analysis (FMEA) which calculates the impact of each possible system contingency on reliability performance and weighting the impact with the corresponding probability of occurrence to obtain the expected annual reliability indices. An important shortfall is that due to the size of network, it is infeasible to consider all possible contingency events so that approximations on the model need to be taken including ignoring overlapping failures and specific restoration processes. The latter methods consider exact network restoration actions in detailed sequences. The optimal switching action is obtained by solving mixed integer programming which can be very time consuming in long-term predictive reliability analysis. The proposed implicit switching model is able to consider overlapping failures and network restoration operations and also presents a good computational efficiency by applying importance sampling in non-sequential Monte Carlo analyses.

In Chapter 3, the implicit switching model of Chapter 2 is extended to include the explicit operation of network switches. Optimal network reconfigurations in service restoration are determined by mixed integer optimisation to minimise demand curtailment, whilst maintaining network constraints and a radial topology.

- An exact mathematical model for finding the optimal radial topology is proposed in this chapter. The radiality constraints ensure every node has a maximum one upstream node connection to achieve radial distribution network topology.
- The sampling of system states is still independent of its history so that large speedups are available in reliability assessment benefits from state sampling Monte Carlo methods with variance reduction techniques.

It is worth noting that, an exact mathematical optimisation for radial network topology is considered complicated and extremely time-consuming in [28]–[30]. Heuristic algorithms for network restoration optimisation have been rapidly developed in the recent decades can provide a near-optimal solution but the radiality constraints are controlled implicitly [31]. In this chapter, an exact mathematical model for radiality constraints is formulated which does not compromise the precision of switching optimisation and a high simulation efficiency is still able to be achieved by applying state sampling Monte Carlo with importance sampling.

Chapter 4 contains three parts. Firstly, a real-time operation model for DG and a ‘greedy’ energy storage model - aiming for maximising their ability in improving reliability were formulated. Based on the proposed implicit switching model with time-sequential Monte Carlo simulation, non-network solutions for enhancing distribution network reliability/capacity have been analysed taken into consideration the real-time distribution network restoration. Different network improvement options including automatic switching, mobile generation, energy storage and DG were assessed for their impacts on network reliability performances in terms of ENS, CI and CML. Based on the results, it has been found that non-network solutions can greatly contribute to distribution network capacity. However, the impacts on network performance indices can vary significantly with different technologies. According to the results and analyses for different non-network solutions, it can be concluded that the optimal network reinforcement for matching the future demand growth should be a combination of various network and non-network solutions.

Part Two focuses on assessing the impacts of customer interruption cost on network planning. This part has firstly discussed the main methodologies previously employed for the quantification of CIC. Secondly, it has discussed the highlights of a comprehensive literature survey on CIC and VoLL quantification, demonstrating the significant variations and the lack of consensus. The main outcomes of the latest relevant studies in the UK context have been discussed and form the core of the customers' supply valuation assumptions adopted throughout this chapter. Furthermore, different modelling approaches to customer interruption costs have been presented and discussed, including constant VoLL as well as interruption duration-dependent VoLL in the form of customer damage functions. Our study has demonstrated that the adopted model and estimate of interruption costs can have a profound impact on the obtained planning solution.

The third part study models the impact of HILP events. The reliability performance of a test distribution network has been evaluated through time-sequential Monte Carlo simulation. Impacts of HILP events with different severity levels have been studied considering the contribution of an emergency generation with different supply rate and preparation time as mitigation measures. The results demonstrate that severe HILP events can lead to significant cost of lost load which may justify development of more resilient networks, e.g. transformation to underground (UG) network, supported by the provision of fast and high capacity emergency generation, especially during very severe HILP events.

Chapter 5 evaluates the security of supply for a generic GB electricity system. From the analysis, it is found that there is a relatively low-level risk of customer interruptions given a 3 hours LOLE system where the System Operator has access to balancing services (for the current level around 2GW). However, the drop in peak demand in recent years mainly from the contribution of fast growing embedded generation and rising demand response services in distribution networks can expose the system to fewer minor but more serious customer disconnections. The analysis has shown that the 3h LOLE standard for a high wind penetration system may not be able to ensure an acceptable level of security of supply, especially for adverse events when high demand coincides with lower available generation capacity. The potential solution can be a more stringent reliability standard or increased capacity of balancing services.

It needs noting that, following publications form the basis of this thesis:

- Chapter 2 is based on the material of the paper
  Y. Yang, S. Tindemans, G. Strbac, "An implicit Switching Model for Distribution Network Reliability Assessment", accepted by the 19th Power System Computation Conference 2016.
- Chapter 2, Chapter 3 and part 1 of Chapter 4 are from the material of paper

Y. Yang, S. Tindemans, G. Strbac, "Snapshot Model for Distribution Network Reliability Analysis with Variable Restoration Accuracy", submitted to IEEE Transaction on Power Systems.

- Part 2 and Part 3 of Chapter 4 present the material that has been published in the consultation report "Review of Distribution Network Security Standards - Extended Report", authored by Goran Strbac, Predrag Djapic, Rodrigo Moreno, Ioannis Konstantelos, Dimitrios Papadaskalopoulos, Jose Calvo, Danny Pudjianto, Simon Tindemans, Sana Kairudeen, **Yang Yang**, Hadi Karimi, Enrique Ortega, Marko Aunedi, submitted the Energy Network Association. I was the main contributor to sections reproduced in this thesis (section 2.4, 2.11, 2.12, 9.4, 13.2 of the report)
- Chapter 5 is formed from the material of the paper
  Y. Yang, S. Tindemans, G. Strbac, "Generation System Adequacy Performance Under the Current UK Reliability Standard" to be submitted to IET Generation, Transmission & Distribution.

1.4 THESIS STRUCTURE

The structure of this thesis is outlined below:

Chapter 2: This chapter proposes an approximate reliability analysis method where switching actions are modelled implicitly. It can be used graphically as a model reduction method, and simulated using time-sequential or state sampling Monte Carlo methods. The method is illustrated on a simple distribution network, and reliability indices are reported both as averages and distributions. Large speedups result from the use of biassed non-sequential Monte Carlo sampling.

Chapter 3: In this chapter, we propose an extended model where switching actions are explicit. Optimal switching actions for each switching devices are determined to minimise demand curtailment, maintain network constraints and radial topology. Although simulation time consumption is compromised for conducting mix integer optimisation, most of the benefits achieved by the implicit model in Chapter 2 are maintained that it can still be used graphically as a model reduction method, and simulated using time-sequential or state sampling Monte Carlo methods which enable potential large speedups in reliability assessment.

Chapter 4: In this chapter, we propose three aspects of studies on distribution network reliability evaluation via the proposed implicit switching model. In the first part, the impacts of non-network solutions including automatic switching, mobile generation, energy storage and DG on distribution network reliability/capacity are analysed. Part Two focuses on the evaluation of VoLL and CIC. Impacts of different customer interruption cost models on network planning are investigated by conducting time-sequential Monte Carlo simulation with the proposed assessment model. Various customer damage functions are applied and compared for different customer categories. The third part is for distribution network reliability in High Impact Low Probability events (HILP). In the final section of this chapter, the impact of HILP on reliability performance is investigated and the preventive and corrective mode of investment are compared.

Chapter 5: In this chapter, we use chronological Monte Carlo simulations to analyse a simplified GB electricity system for its reliability performance at the level of the GB Reliability Standard, i.e. LOLE=3h/year. The effects of the drop in peak demand in recent years mainly from the contribution of fast growing embedded generation and rising demand response services in distribution networks are analysed.

Chapter 6: The final chapter summarises the main conclusions and indicates research questions for future researches.

Chapter 2 An Implicit Switching Model for Distribution Network Reliability Assessment

Abstract

Modern active distribution networks make use of intelligent switching actions to restore supply to end users after faults. This complicates the reliability analysis of such networks, as the number of possible switching actions grows exponentially with network size. This chapter proposes an approximate reliability analysis method where switching actions are modelled implicitly. It can be used graphically as a model reduction method, and simulated using time-sequential or state sampling Monte Carlo methods. The method is illustrated on a simple distribution network, and reliability indices are reported both as averages and distributions. Large speedups result from the use of biassed non-sequential Monte Carlo sampling – a method that is hard to combine with explicit switching models.

2.1 INTRODUCTION

An understanding of network reliability performance relies significantly on quantitative reliability modelling of distribution networks because distribution networks are the source of the majority of outages that affect end users [23]. Distribution networks are undergoing significant changes with increased penetration of distributed generation, flexible demand and new monitoring and automation technologies, and their adoption is further affected by changes in transmission networks and market arrangements [13]. Developing realistic future network scenarios thus necessitates rapidly assessing the reliability performance for a large range of parameters and network configurations. This, in turn, requires the use of reliability assessment methods that are both flexible and efficient.

Reliability modelling of complex distribution systems has been extensively discussed in [32]. The minimal cut-set technique is a common method employed for system simplification, and failure mode effect analysis (FMEA) is well developed for evaluating the impact of specific failure modes. It is pointed out in [13] that FMEA requires the development of a complete table of failure modes with their probability and the corresponding reliability impact. FMEA has been used for network reliability evaluation in [23], [32] and [22].

Whereas FMEA and other analytical methods typically take a passive view of the network, realistic distribution networks take a more active approach to fault management. For maximising distribution network reliability, system protection and restoration actions including failure isolation, network rerouting, load shedding and restoration are achieved by coordination of circuit breakers (CBs), sectionalizing switches and normally open points (NOPs). The active operation of networks, therefore, requires real-time decision-making with the objective to improve reliability for end users.

A particular computational challenge stems from the range of discrete switching actions available to network operators, including control of normally open points, fault isolation and restoration and load shedding. In [16], the (near) optimal post-fault network configuration is first identified by applying load acceptance and load transfer algorithms and then a switching synthesis algorithm is employed to create (near) optimal switching sequences. In general, the optimal allocation and control of switches results in mixed integer optimisation problems (see e.g. [20]), which result in a significant computational burden especially for large and increasingly controllable networks.

In this chapter, a simplified model for distribution network reliability analysis is proposed. Its defining feature is the implicit incorporation of switching actions instead of direct control of switches in the network. This is done by splitting and portioning the network into sets of components that are separated by switches (normally closed or normally open) or circuit breakers. These sets are represented by nodes, connected by links where switchable components are located.

When a fault occurs it propagates to the nearest enclosing circuit breakers or NOPs. After a characteristic switching time, it is assumed that network switches are operated to locally isolate the fault, converting the affected node to a non-conducting node. Remaining nodes are assumed to be supplied if a conductive path to a grid supply point exists, even if it passes through a NOP (closing it is implicit).

The resulting reliability model is approximate, but has the following advantageous properties:

- Complex distribution network composition and topologies can be represented using the graphical method in a simplified fashion whilst switching operations such as failure isolation, network rerouting, restoration can still be (approximately) modelled;
- The impact of a given state does not depend on its history. This property enables the use of state sampling Monte Carlo schemes and associated variance reduction schemes (e.g. importance sampling);
- Network flow constraints and load shedding can be embedded using a simple linear optimisation.

2.2 DISTRIBUTION NETWORK RELIABILITY MODELLING

UK distribution networks are composed of EHV, HV and LV voltage levels. EHV (132kV-33kV) is mainly used for connecting the national transmission network and usually in meshed distribution network, and residential end users are supplied at the LV level (0.4kV). This chapter focuses on the intermediate HV level (33kV-11kV) at which most protection and restoration actions take place [23].

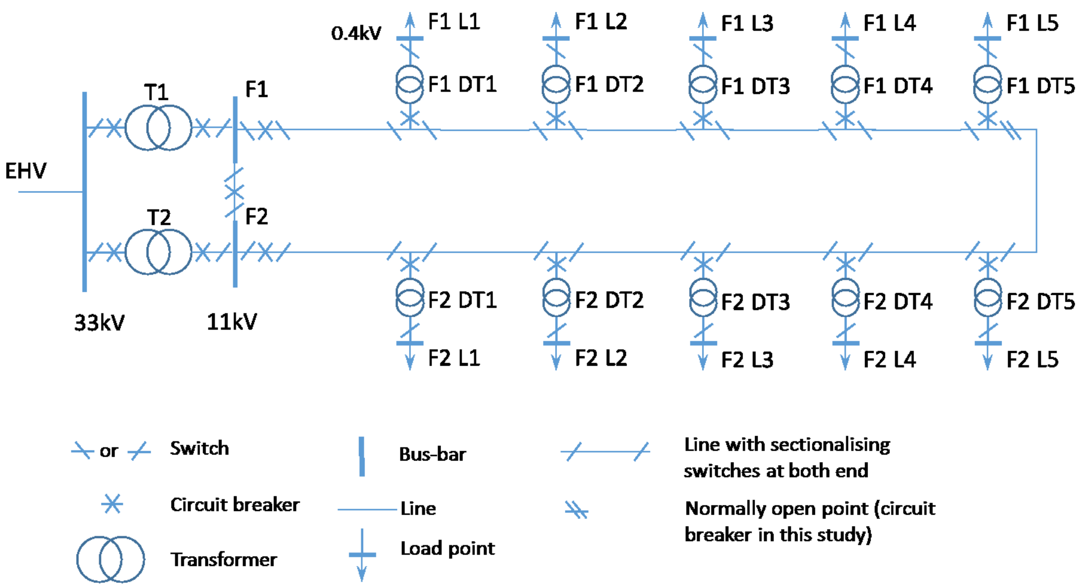


FIGURE 2-1 AN ILLUSTRATIVE HV DISTRIBUTION NETWORK

An example of a radially operated HV distribution network is shown in Figure 2-1. The HV network is connected to an EHV network through a primary substation which is composed of bus-bars, 33-11kV transformers, switches and circuit breakers. At the 11kV level, the substation is connected to feeders equipped with a protection circuit breaker (indicated by a cross). Two feeders (F1 and F2) are connected in this example but more feeders can be supplied by the same substation. Feeder sections can be overhead lines or underground cables depending on local requirements. Sections are equipped with sectionalizing switches (diagonal lines) at one or both ends. The LV network is represented as load points (L1, L2,…) in this example, connecting to the HV network via an 11-0.4 kV distribution transformer and a circuit breaker or fuse for protection. Although the network is radially distributed, a normally open point (NOP; a circuit breaker or switch) is deployed for alternative connection when needed.

Reliability analysis of such a network must consider a number of possible failure modes. When a 33-11kV transformer (T1 or T2) fails, the circuit breakers/switchgears isolate the transformer so that other parts of the network will not be affected. These transformers usually satisfy the N-1 criterion so that one transformer is adequate to supply the peak demand of network.

When a short circuit fault occurs in HV lines or cables, the corresponding fault clearing device, usually the circuit breaker connecting the substation, will trip the downstream branch instantly without interrupting upstream or other branches. This fault clearing action may disconnect an entire feeder, so a switching action is required to restore the power supply to as many customers as possible. In this example network, the 11kV network is operated as a radial network with a normally open circuit breaker (NOP) that connects different branches for back-feeding during an outage. Furthermore, all network lines/cables are equipped with normally closed switchgears at both sides. When the fault location is identified, a switching action is performed. First, the failed line/cable is isolated by opening the nearest sectionalizing switches (upstream and downstream). Second, the affected downstream load points can then be resupplied by closing the NOP to the adjacent branch. At the same time, the upstream circuit breaker can be reclosed to supply upstream load points. At the LV level, a circuit breaker or fuse serves to disconnect the load point from the HV network. This way, the HV network is not affected by faults of the LV transformer or LV network.

There are a number of challenges for quantitative reliability analysis of distribution networks. Analytical methods are not well-suited to analyse multi-step processes, such as fault-restoration sequences, or duration-dependent interruption costs. Furthermore, in complex networks, the number of possible switching actions grows exponentially, and the optimal sequence of switching actions often depends on historical decisions. Modelling this in detail requires running a simulation with an embedded mixed integer optimisation problem for switching actions, which is computationally very demanding.

2.3 IMPLICIT SWITCHING MODEL

2.3.1 FEATURES OF THE PROPOSED MODEL

A simplified reliability analysis model is proposed that qualitatively captures the ability to reroute power using switches, but does not require explicit computation of the switching actions. The model is based on the following observations and assumptions:

- Connected components between switches and circuit breakers are always in the same electrical state. We label such an aggregation an ‘electrical node’. It is similar to the concept of a ‘section’ in [20].
- When a short circuit fault occurs within a node, the fault propagates to all connected electrical nodes, until it is stopped by a circuit breaker, NOP or isolated network section. The affected nodes are immediately disconnected from the electricity supply.
- After a fault occurs, there is a characteristic switching time before the fault is diagnosed and switching actions are initiated. These consist of node isolation (opening sectionalizing switches) and restoration (closing CBs and NOPs). Switches are operated simultaneously.
- It is assumed that NOPs and sectionalizing switches are intelligently controlled so that if a node can be supplied then the power to the node will be restored.

- The operation of CBs, NOPs and switches is assumed to be 100% reliable.
- Lack of available capacity due to network constraints does not prevent switching but results in load curtailment so that the constraint is satisfied.

2.3.2 Network composition and operation modelling

2.3.2.1 Node model

System components and the associated switches are aggregated into electrical nodes. The fault state of each node is modelled as a four-state Markov process shown in Figure 2-2 and the associated transition rates:

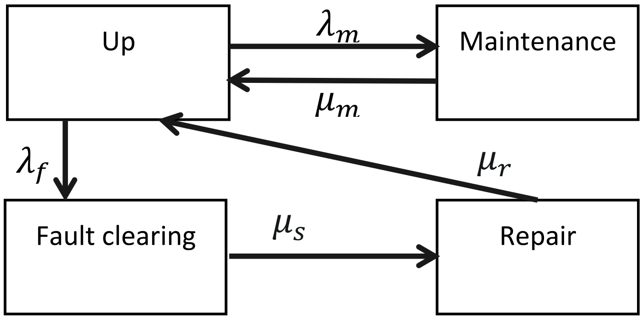


FIGURE 2-2 NODE STATE IN MARKOV MODEL

a) "Up state": the component is working
b) "Fault clearing state": the component is faulty; the fault has been cleared by opening the corresponding feeder circuit breaker, and therefore also affects neighbouring nodes.
c) "Repair state": switching action has been taken to isolate the component for repair. This allows neighbouring nodes to be resupplied if possible.
d) "Maintenance state": the component is in scheduled service and it is isolated.

It is worth noting that, the Markov model for system components can be more complicated according to different purposes. For example, the faults studied here refer to permanent faults but if temporary faults are considered, the effect of network recloser can be analysed in an extended Markov model shown in Appendix B Figure B-3.

2.3.2.2 Network model conversion

In order to use the implicit switching model for reliability analysis, distribution network models must be expressed in a graph representation with four node types:

a) Electrical nodes with fallible components, as described above. Their reliability parameters depend on the physical components they represent. In the case of transformers, it may be convenient to embed circuit breakers in this component, thus effectively skipping the 'fault clearing' state in Figure 2-2.

b) Supply nodes that represent the EHV network supply points.

c) Load nodes that represent end users (the LV network).

d) Circuit breaker / NOP nodes that arrest faults on the network.

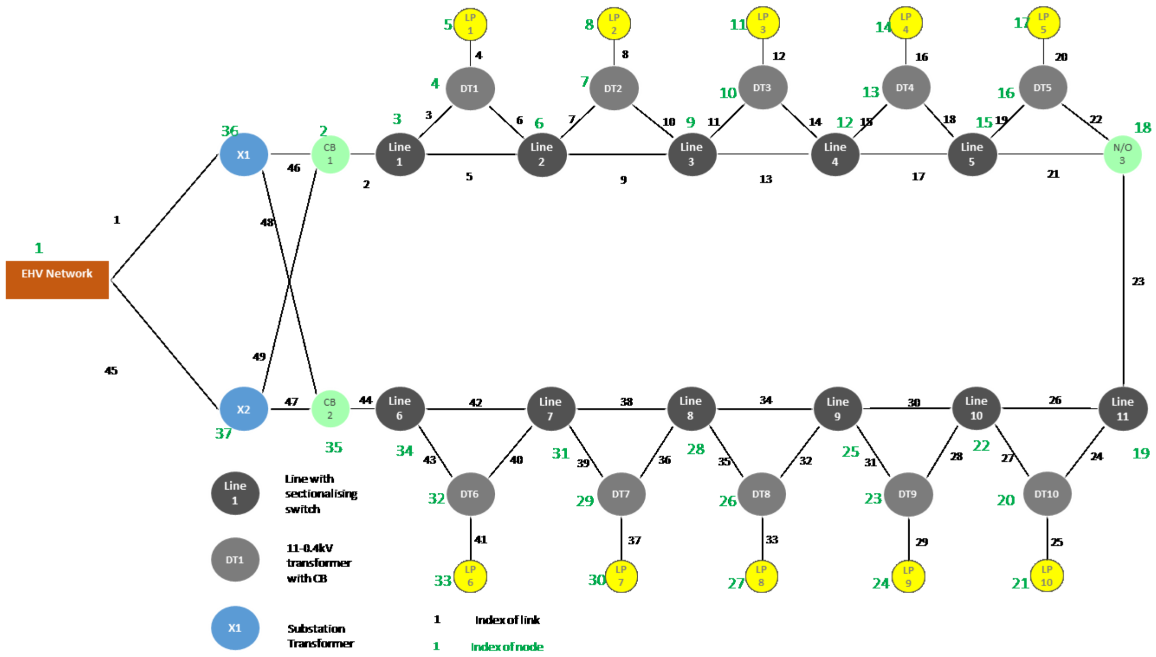


FIGURE 2-3 GRAPH REPRESENTATION OF HV NETWORK FOR RELIABILITY ASSESSMENT

Figure 2-3 depicts the graph representation of the example network in Figure 2-1. Different node colours are used to indicate that the underlying components have different reliability parameters. Arcs represent logic linkage of the network topology. The following steps are taken to translate a real network into its corresponding node representation.

a) Network data requisition: The physical network is described in terms of its components (with their attributes, including reliability parameters) and their connections.

b) Construct full node + link network: Convert the component data into a graph, where the nodes are physical components and logical links represent their connections.

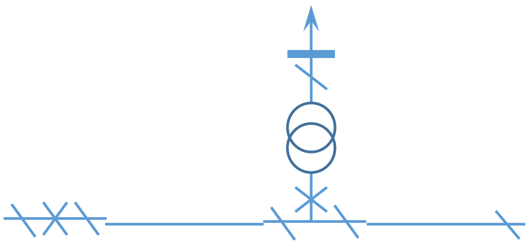


FIGURE 2-4 REAL COMPONENT NETWORK CONSTRUCTED FROM NETWORK DATA

c) Merge components into electrical nodes: Identify electrical components that have no intermediary switches/NOPs/CBs and merge them into electrical nodes. For the purpose of the model a node operates as a single component, so its constituent reliability parameters, i.e. length, failure rate, switching time, repair time, should be aggregated. Load points at this step are not aggregated with other network components. Shown in Figure 2-4, between two switches there is only one line component which can be several line sections in raw network data but connected directly without switching components. Line sections are aggregated for network simplification whilst not compromising any original network switching property.

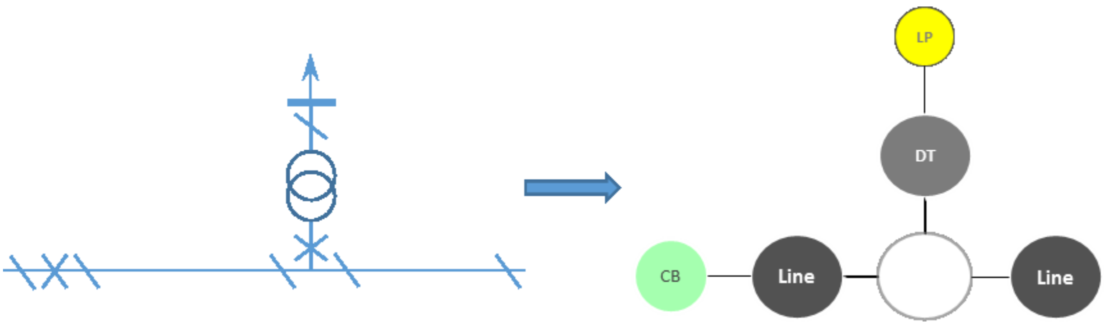


FIGURE 2-5 COMPONENTS MERGES TO FORM NODES; SWITCHES ARE REMOVED SINCE THEY ARE MODELED IMPLICITLY IN NODES

d) Remove switches: At this step, the graph consists of circuit breakers/NOPs/sectionalizing switches, supply nodes, load points and aggregated electrical nodes (on the left of Figure 2-5, before removing switches). Shown in the right part of Figure 2-5 sectionalizing switches are removed because their actions can be represented implicitly in the electrical nodes. Circuit breakers connected to transformers can also be removed since transformers are assumed to be isolated immediately after a fault happens without affecting other parts of the network (i.e. they have no 'fault clearing' state). NOPs are modelled the same as circuit breakers that work as fault clearing devices (which can trip network instantly), so for NOPs and circuit breakers a 'CB' type of node will be used. The connection part between distribution transformer circuit breaker and line section sectionalising switches is represented as a node which will never fail.

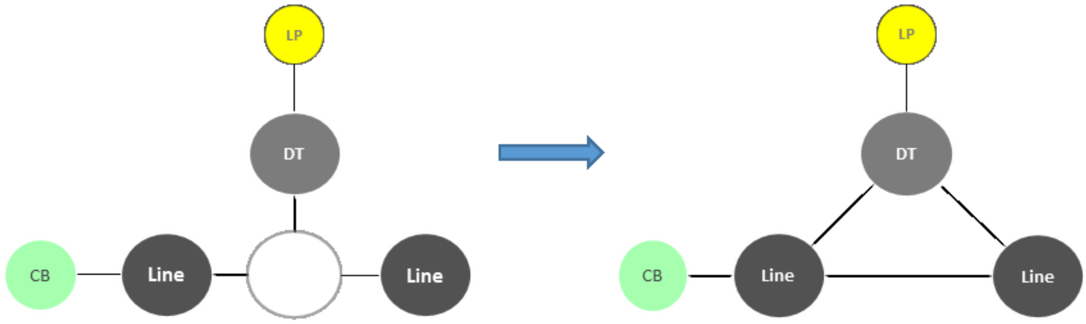


FIGURE 2-6 REMOVE NO-ACTION NODES TO ACHIEVE FEWER NODES OR LINKS, THUS SIMPLER STRUCTURE

e) Complete connections: After removing switches, the physical connections once linking back-to-back switches remain. These may remain as no-action nodes (cannot fail, only serve to connect other nodes) or be replaced by links (see for example the triangular motifs in Figure 2-6) for fewer nodes in the network and therefore smaller size of problem formulation in optimisation.

2.3.2.3 NODE STATUS MODELLING

The electrical status of a node is a dynamic property that is affected by the fault state of the node itself, and that of other nodes. There are four possible states:

a) "Supplied": The node is not faulty and a live route from this node to a power source exists.
b) "Interrupted": The component at this node is affected by an active fault that caused a circuit breaker to interrupt the power supply. This happens if the node itself or a connected node is in the 'fault clearing' state.
c) "Isolated": The component node has experienced a fault and is being repaired. In practice, this usually results from switchgear at the ends of the component being opened. In this state, the node interrupts power flow but does not otherwise affect flows in the network, thus allowing neighbouring nodes to be reconnected using load transfer via a normally open point if a live route to a power source exists.
d) "Unsupplied": The node has no live route to a power source, and is, therefore, unsupplied.

The electrical state of a node is determined as follows from the node fault states and the network topology. Network searches are performed using a depth-first network searching algorithm [33].

a) Tag all nodes as unsupplied

b) Tag all nodes that are in the "repair state" or "maintenance state" as isolated.

c) Tag all nodes that are in the "fault clearing state" as interrupted.

d) From each interrupted node, iteratively search and tag all connected nodes as interrupted until an isolated node, or a circuit breaker/NOP node is encountered.

e) From each node power supply node, iteratively search and tag all connected node as supplied until an isolated or interrupted node is encountered.

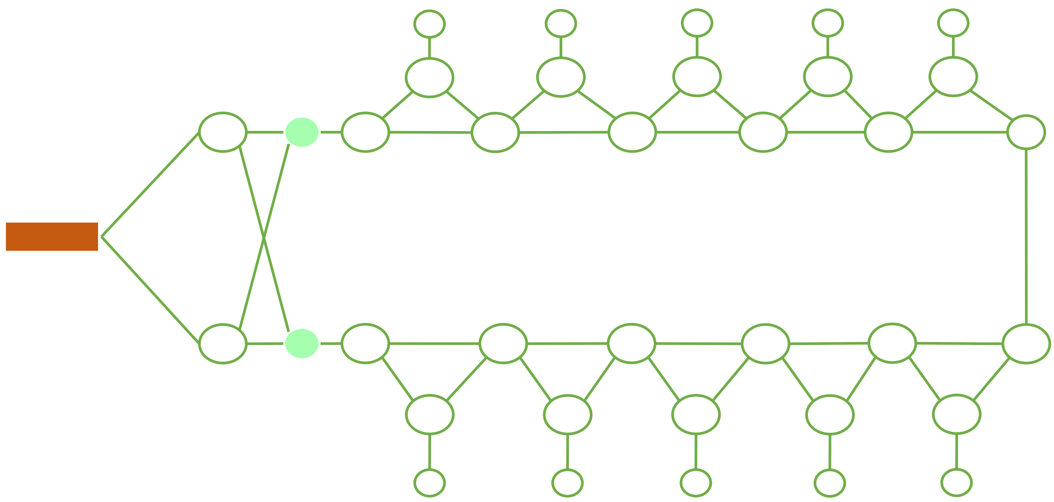


FIGURE 2-7 A) TAG ALL NODES AS UNSUPPLIED

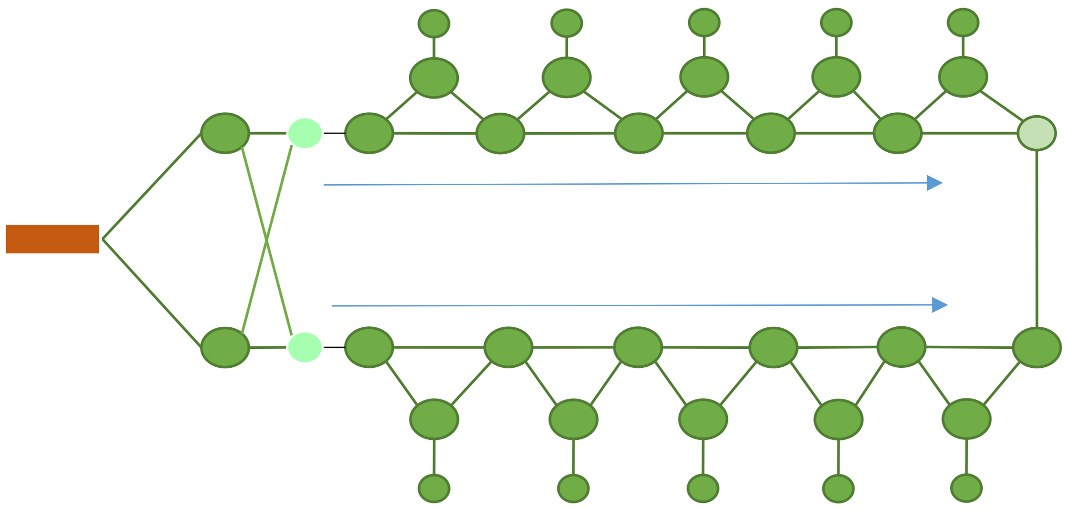


FIGURE 2-8 IF NO FAULT, DO E) PROPAGATE FROM POWER SOURCE TO EACH NODE

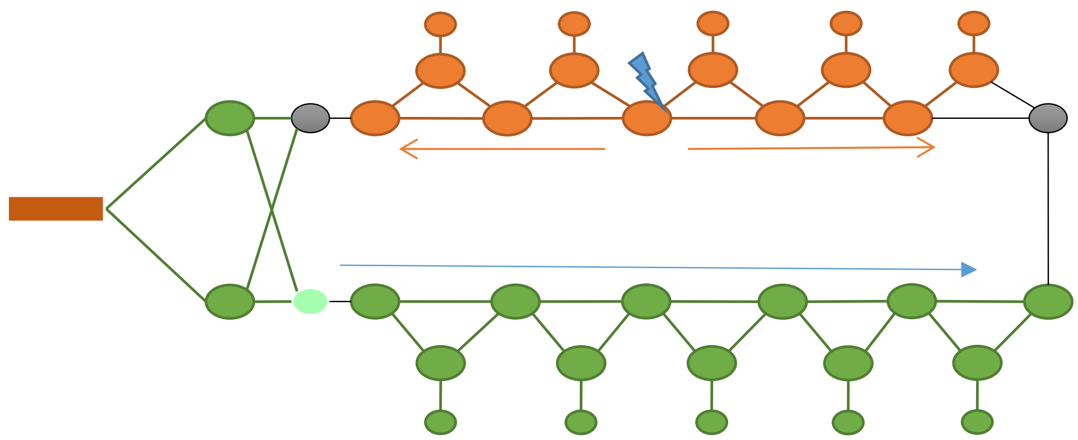


FIGURE 2-9 IF A FAULT OCCURS, DO C) AND D) FAULT CLEARING PROPAGATE TO NEAREST CB/NOP; OTHER NODES SUPPLIED BY POWER SOURCE BY DOING E)

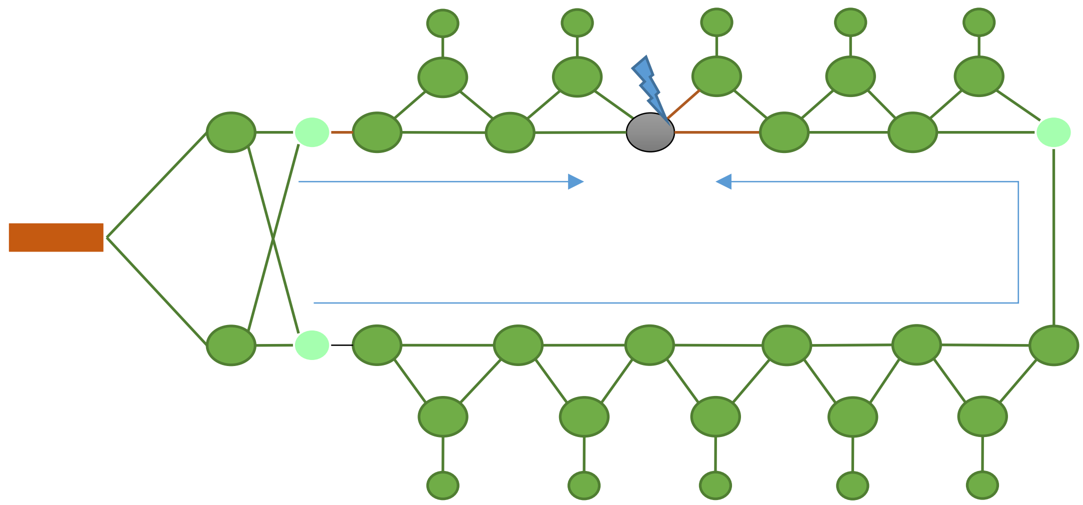


FIGURE 2-10 IF THE FAULT IS ISOLATED DO B); OTHER NODES SUPPLIED BY POWER SOURCE BY DOING E)

The status of each node can be identified by applying this tagging method, and then the load curtailment can be computed by solving optimisation for the connected areas. It is worth noting that, even though a single fault example is given here, this model can also analyse multiple faults overlapping in the network with the tagging and network searching method.

2.3.2.4 Network constraints

Capacity constraints for lines, circuit breakers and transformers need be considered in planning and operation of the distribution network. When there is a fault, switching actions may happen to restore interrupted customers that could potentially be resupplied by other network power sources. In this situation, the capacity constraints for system components may limit the system restoration ability. In a model where switching actions are explicitly considered, this may result in a decision not to restore power to a section of the network. In this implicit switching approach, we instead curtail demand in order to satisfy capacity constraints.

The constraint-driven load curtailment can be formulated as a linear optimisation problem. The input parameters are:

L_i load level sampled from load profile at node i

f_k^{max} flow constraint between nodes connected by link k

π_{ik} directed incidence matrix of node i and link k: 1 if out from node i; -1 if towards node i; otherwise 0

The optimisation objective is to minimise load curtailment:

$$\min_{\{c_i, f_k\}} \sum_i c_i \cdot L_i \tag{2.1}$$

subject to the constraints

$$-f_k^{max} \leq f_k \leq f_k^{max}, \qquad \forall k \tag{2.2}$$

$$c_i \cdot L_i - \sum_k \pi_{ik} \cdot f_k = L_i, \quad \forall i \tag{2.3}$$

where f_k is the power flow between the nodes connected by link k. c_i represents the fraction of curtailed demand at node i. In a passive distribution network, load points can be disconnected by opening circuit breaker/switch at the LV transformer when a power shortage happens. In that case, $c_i \in \{0,1\}$ are binary variables indicating the interruption of load points. With the development of active network technologies, flexible demand control could be used to reduce the load in smaller steps. For those smart networks, c_i is continuous between 0 and 1 – allowing for reduced curtailment and faster computation.

It is worth noting that, throughout this thesis, the commercial mathematics software MATLAB [34] and the open source OPTimization Interface (OPTI) Toolbox [35] were used for constructing and solving optimisation problems. The relevant solvers are supplied within OPTI and the default solvers were used for solving the optimisation problems in this thesis, despite that users can flexibly choose different supplied solvers or use interfaced solvers from other sources.

2.4 MONTE CARLO SIMULATION

The reliability of the model introduced in the previous section is analysed using Monte Carlo (MC) sampling. Both state-based (non-sequential) and time-sequential MC sampling are discussed.

2.4.1 NON-SEQUENTIAL MONTE CARLO SIMULATION (NSMCS)

With the proposed network switching model, network switching actions are implicit and the electrical status of nodes does not depend on the history of the system. This feature enables the application of non-sequential MC simulation. The reliability indices are estimated as follow:

$$\hat{E}(H) = \frac{1}{N}\sum_{i=1}^{N} H(X_i) \tag{2.4}$$

where H is the estimation function of a reliability index such as energy not supplied (ENS); N is the number of simulated system states; X_i represents a sampled system state which includes the fault states of all components in the network according to their Markov model and the load profile for each load point.

Network components such as line sections and transformers are usually very reliable. This means that unbiased sampling of states will be very inefficient, as most sampled states will have no components in the fault state – and will therefore not contribute to the result. To improve simulation computational efficiency, one of the variance reduction techniques, Importance Sampling (IS) [36][37], is applied in company with the proposed implicit switching model for a considerably faster convergence. No load is assumed shed if all components are in the 'up' state. Therefore, the sampling is biased by forcing at least one component to be in a 'down' (i.e. not-'up') state. For each sample, one component is randomly selected according to its probability to be in the 'down' state. This component is forced to be in the 'fault clearing', 'maintenance' or 'repair' state according to their relative probabilities. All other components are sampled without bias. After reliability indices are quantified for the sampled system state, a weighting factor is used to correct the bias from the adjusted sampling distribution.

The weighting factor is derived as the ratio of the probability of a system state in original distribution and that in the adjusted distribution. For independent components, it can be shown that the relation is:

$$Pr'(X_i) = \frac{N_f(X_i)}{\sum u_k} Pr(X_i) \tag{2.5}$$

$Pr(X_i)$ is the probability of system state X_i in the original sampling distribution. $Pr'(X_i)$ is the probability of system state X_i in the adjusted sampling distribution. $N_f(X_i)$ is the number of 'down' components in system state X_i. $\sum u_k$ is the sum of unavailabilities (i.e. probability of being in the 'down' state) of all components. If we denote by X'_i sampled states that have been sampled according to the adjusted distribution, reliability indices can be calculated as:

$$\hat{E}(H) = \frac{1}{N} \sum_{i=1}^{N} H(X'_i) \frac{Pr(X'_i)}{Pr'(X'_i)} \tag{2.6}$$

2.4.2 Time sequential Monte Carlo Simulation (TSMCS)

The time-sequential Monte Carlo simulation is a method in which time-dependent system operation is reproduced by sampling stochastic sequences and durations of system states. The system states are sampled according to the Markov models of the system components. By randomly sampling durations of component states, a random sequence of system states is produced. The stochastic sampling of system states for period of one year is described below:

Step 1: Generate the initial state of each system component according to the steady state probability distribution of its Markov model. The initial load state is generated by randomly sampling a starting time in a year and selecting the corresponding load level from the load profile.

Step 2: Sample the transition time from the current state to the next possible state for each component. For those components that have multiple possible transitions, choose the first transition event. The transition time for the load state is obtained by calculating the time to the next half hour boundary.

Step 3: List and sort all component transition times in ascending order. The set of all component states is the current system state and its duration is the shortest component transition time T_{min}. Set system simulation time as $T = T_{min}$.

Step 4: Identify the status for each node in the system and conduct the capacity constraint optimisation so that, at each load point, reliability indices can be computed for the current system state.

Step 5: Deduct the shortest transition time from all component transition times and update the component state as the next sampled state. Sample the time to the next transition for the recently switched component.

Step 6: Repeat steps 3-5 until the system simulation time exceeds 1 year. In step 3, set the system simulation time as $T = T + T_{min}$. If step 5 results in load point switching from supplied to unsupplied status, the counter of customer interruption events is incremented by 1; otherwise it is recognised as a continued interruption. A disconnection priority order is established to prevent spurious rotation of disconnections across load points.

Step 7: Evaluate and record the reliability indices of the system for this year.

The expectation value and distribution of reliability indices can be evaluated by repeating the above sampling for N independent years. Using the coefficient of variation, the convergence of simulation result is monitored, which has been used as the stopping criterion.

The unbiased estimation of coefficient of variation is calculated as below:

$$\hat{v}(x) = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \frac{1}{N}\sum_{i=1}^{N}x_i\right)^2 \tag{2.7}$$

$$coefficient\ of\ variation = \frac{\sigma}{\mu} \approx \frac{\sqrt{\hat{v}(x)}}{\frac{1}{N}\sum_{i=1}^{N}x_i} \tag{2.8}$$

The coefficient of variation is computed after each iteration and the simulation stops when the coefficient of variation reaches a certain level (e.g. smaller than 1%).

2.5 Case Study

The proposed implicit switching model is applied using non-sequential and sequential MCS in different distribution networks to test its accuracy, efficiency and applicability.

2.5.1 The illustrative HV network

The illustrative HV network is shown in Figure 2-1, and in reduced form in Figure 2-3. The network consists of two branches, each with five load points connected through distribution transformers and line sections. Each line is equipped with sectionalizing switches at both ends. A NOP is employed to connect the ends of both branches as an alternative supply route. The network parameters are given in Table 2-1. The network data used in this thesis are calculated from data received from several UK DNOs. Those data are available from Regulatory Reporting

Pack [38] and Quality of Service Reporting [39] for up to 5 years. The analysis of raw data is given in APPENDIX E.

TABLE 2-1 PARAMETERS OF THE ILLUSTRATIVE NETWORK

Parameters	**Values**
Failure rate for lines	0.2 occ./km.year
Failure rate for transformers	0.006 occ./year
Maintenance rate for primary transformer	0.2occ./year
Switching time	30 min
MTTR for lines	24 hours
MTTR for primary transformers	299 hours
MTTR for distribution transformers	24 hours
Maintenance restoration time for primary transformer	24 hours
Line section length	0.25 km
Line capacity constraint	5MW (N-1) / 2.5MW (N-0)

Each load point is assumed to connect 500 customers, with a peak demand of 500kW, or 2.5MW per feeder. A normalised UK load profile with 17520 levels for each half hour is used. For line sections and 33-11kV transformers, a capacity constraint of 5MW and 2.5MW is applied for N-1 (regular utilisation, with redundancy at peak load) and N-0 (full utilisation at peak load), respectively.

With the proposed implicit switching model, the impact of a given state does not depend on the history. This property enables the use of state sampling Monte Carlo schemes and associated variance reduction schemes. In Table 2-2, a comparison study for the illustrative HV network and N-0 loading level is taken for testing the computational efficiency of different simulation methods. It is clear that the computations with discrete load shedding (columns 3-4) are generally slower due to the use of binary variables in the optimisation. The resulting EENS values are also higher than those corresponding to ‘smart’ systems (continuous c_i). Furthermore, for the same coefficient of variation (CoV) of 1%, applying importance sampling reduces the convergence time to 140s, which is only 0.2% that of conventional NSMCS. TSMCS in this case is still faster than NSMCS since the time sequence sampling also “forces” the next state after an “all good state” to be a state with fault, not the same as the current state. But the convergence speed is significantly restricted by the half-hourly load profile: the simulation must update the load level each half hour.

TABLE 2-2 COMPARISON OF COMPUTATIONAL EFFICIENCY FOR DIFFERENT MONTE CARLO SIMULATIONS

Computation time	Continuous c_i		Discrete c_i		CoV
	EENS (MWh/y)	Time (s)	EENS (MWh/y)	Time (s)	
NSMCS	4.11	78978	5.22	108541	1%
NSMCS+IS	4.10	140	5.14	204	1%
TSMCS	4.14	7114	5.23	12139	1%

TABLE 2-3 EENS FOR DIFFERENT HV NETWORK LINE FAILURE RATES AND LOADING LEVELS

Network EENS	Line Failure Rate (occ./km.year)	N-1		N-0	
		Continuous (MWh/y)	Discrete (MWh/y)	Continuous (MWh/y)	Discrete (MWh/y)
	0.02	0.04	0.04	0.41	0.58
	0.05	0.11	0.10	1.00	1.38
	0.1	0.22	0.22	2.04	2.76
	0.2	0.44	0.44	4.14	4.96

TABLE 2-4 EXPECTED CUSTOMER INTERRUPTION (ROUNDED) FOR DIFFERENT HV NETWORK LINE FAILURE RATES AND LOADING LEVELS

Network ECI	Line Failure Rate (occ./km.year)	N-1		N-0	
		Continuous (occurrence/ 100custusto mer/y)	Discrete (occurrence/ 100custusto mer/y)	Continuous (occurrence/ 100custusto mer/y)	Discrete (occurrence/ 100custusto mer/y)
	0.02	3	3	3	3
	0.05	7	7	7	7
	0.1	14	14	15	15
	0.2	28	28	28	28

TABLE 2-5 EXPECTED CUSTOMER MINUTE LOST (ROUNDED) FOR DIFFERENT HV NETWORK LINE FAILURE RATES AND LOADING LEVELS

Network ECML	Line Failure Rate (occ./km.year)	N-1		N-0	
		Continuous (min/customer /y)	Discrete (min/custom er/y)	Continuous (min/custo mer/y)	Discrete (min/custo mer/y)
	0.02	1	1	7	9
	0.05	2	2	16	22
	0.1	4	4	33	44
	0.2	9	9	66	80

In the UK, distribution network reliability performance is reviewed by regulatory authority OFGEM with three main indices [40]: Energy Not Supplied (ENS) [used implicitly for the P2 distribution reliability standard], Customer Interruption (CI)[1] and Customer Minute Lost

[1] "The number of customers interrupted per year (CI). This is the number of customers whose supplies have been interrupted per 100 customers per year over all incidents, where an interruption of supply

(CML)[2]. Table 2-3, Table 2-4, and Table 2-5 show the expected values of these 3 indices with a different failure rate and loading levels using TSMCS (1% coefficient of variation). Results are given for both active (continuous c_i) and passive (discrete c_i) networks. The higher N-0 loading level results in a significant increase in ECML and EENS compared to the N-1 case, but the frequency of interruptions (ECI) is unaffected.

TABLE 2-6 EENS COMPOSITION

Network EENS	N-1 (MWh/y)	N-0 (MWh/y)
Fault clearing	0.43	0.43
Thermal constraint	0.00	3.71
Single failure	0.43	4.13
Double overlapping failure	0.01	0.01

It is worth noting that the implicit switching model also enables the recognition of different types of failures in the network. Table 2-6 shows the EENS composition (for the active network with continuous c_i) for the case with a line failure rate of 0.2occ/year.km. At the N-0 loading level, EENS from fault clearing is 0.43MWh/y, similar to that of N-1, for the outages that occur when a circuit breaker trips the whole feeder. EENS from thermal constraints is the load curtailment after switching actions when the alternative network capacity is not able to fully supply the restored areas. The result shows that, at the N-0 loading level, thermal constraints are the main source of undelivered energy to customers. Table 2-6 also breaks down the contributions caused by single and overlapping failures, for system planners to check the network performance of rare overlapping failures.

The proposed method can be used to obtain probability distributions of network reliability indices, although this does require the use of a sequential method (TSMCS). An example is

lasts for three minutes or longer, excluding re-interruptions to the supply of customers previously interrupted during the same incident." This is defined in OFGEM RIIO report [40]

[2] "The duration of interruptions to supply per year (CML). This is the average customer minutes lost per customer per year, where an interruption of supply to customer(s) lasts for three minutes or longer." [40]

presented for the case where the network feeder capacity conforms with N-0. Figure 2-11 shows the complementary CDF distribution of annual ENS for various cable failure rates.

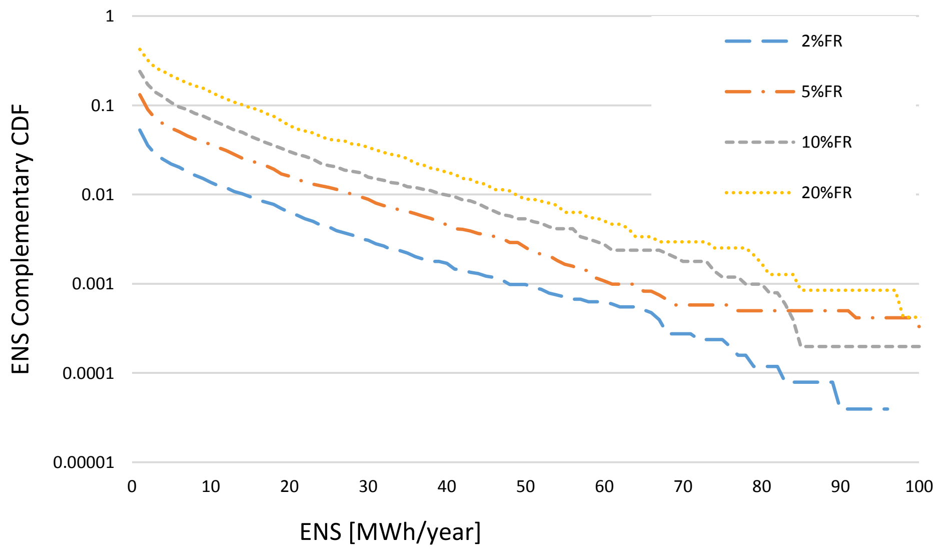


FIGURE 2-11 CCDF OF ANNUAL ENS FOR FAILURE RATE OF 2%, 5%, 10%, 20%/KM.YEAR

2.5.2 RBTS BUS 4 NETWORK

A second case study was carried out on the well-known distribution network RBTS Bus 4 [24]. Its graphical representation is shown in Figure 2-13. Active load shedding (continuous c_i) has been assumed for all calculations, and computed reliability indices are listed in Table 2-7 for two scenarios, labelled 'N-1' and 'N-0'. The capacity limit of each feeder line is equal to the peak demand of all load points in the associated branch for 'N-0' and double of that for 'N-1'. The half-hourly load profile is applied instead of the average data in [24]. Table 2-8 compares the time required using different simulation approaches to compute the ENS with a coefficient of variation of 1% for the 'N-0' scenario. Mirroring the results for the smaller network, the importance sampling variant of the non-sequential method is vastly more efficient than both other methods.

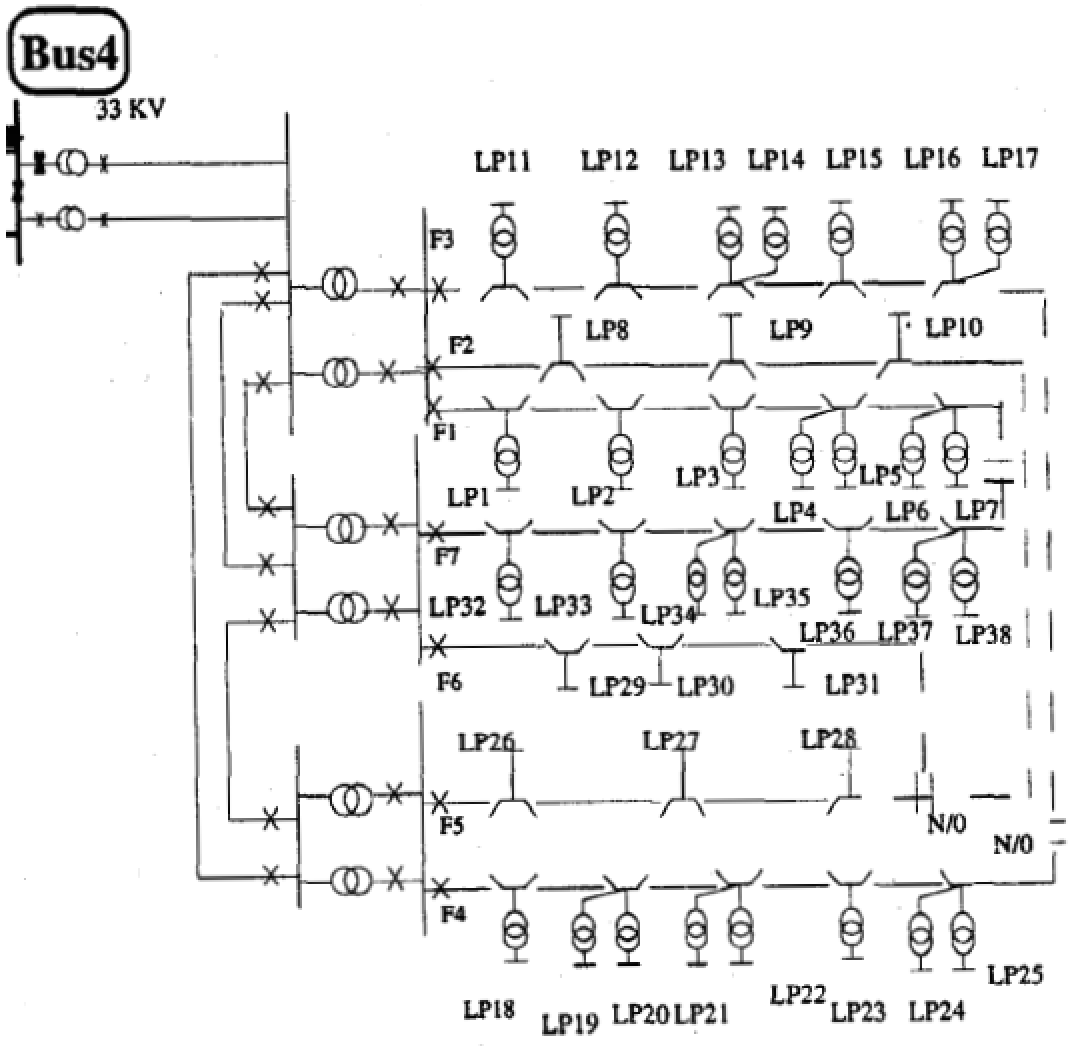


FIGURE 2-12 RBTS BUS 4 NETWORK [24]

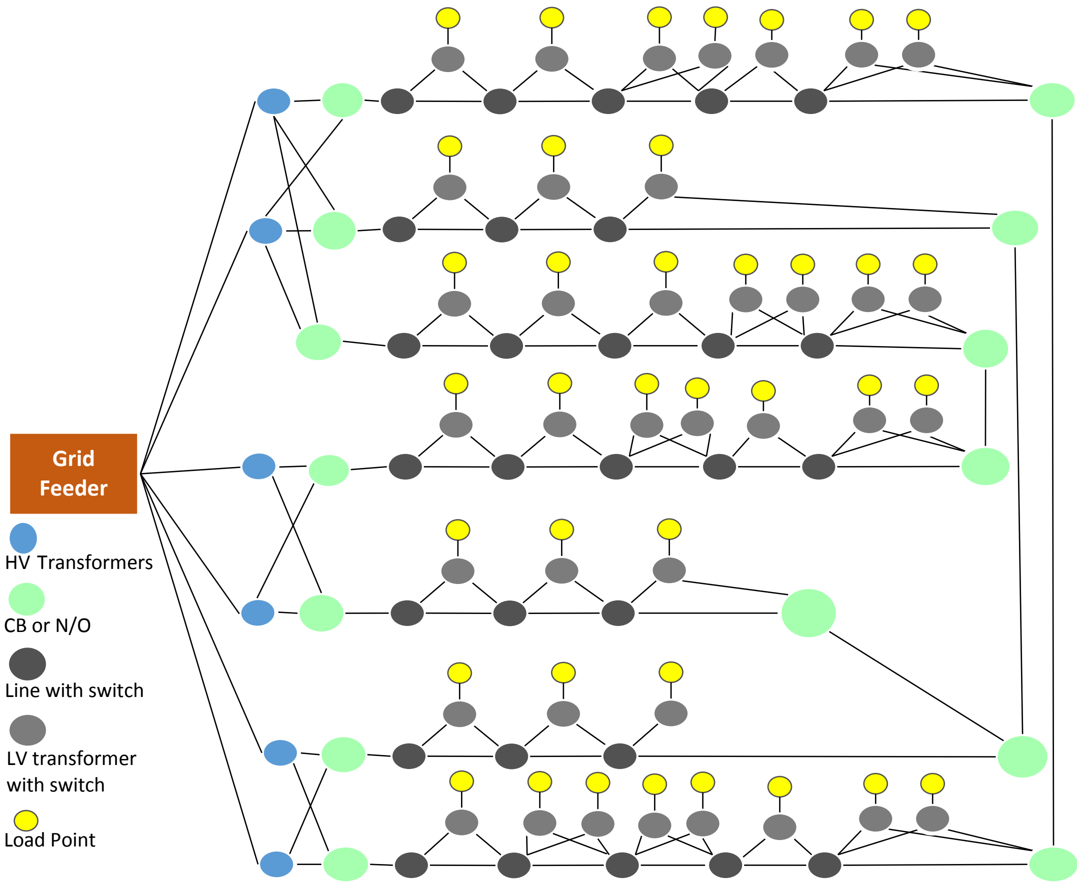


FIGURE 2-13 THE GRAPHICAL REPRESENTATION FOR RBTS BUS 4

TABLE 2-7 RELIABILITY PERFORMANCE OF RBTS BUS 4

Reliability indices	N-1	N-0
EENS (MWh/y)	11.5	16.5
ECI (occ./100cust./y)	57.5	56.7
ECML (min/cust./y)	31.2	43.2

TABLE 2-8 COMPARISON OF COMPUTATIONAL EFFICIENCY FOR DIFFERENT MONTE CARLO SIMULATIONS FOR RBTS BUS 4

Computational Efficiency	EENS (MWh/y)	Time (s)	Coefficient of Variation
NSMCS	16.33	57615	1%
NSMCS+IS	16.52	118	1%
TSMCS	16.29	1900	1%

2.6 CONCLUSIONS

A simplified model has been introduced for the reliability analysis of active distribution networks. The model captures the qualitative benefits of restoration by switching but foregoes explicit computation of switching actions. Instead, a simplified implicit switching approach is used to approximate the fault clearing, isolation and restoration processes. In addition, power flow constraints can be assigned to network bottlenecks, potentially limiting restorative power flow adjustments. Although the implicit switching model is based on a number of approximations, these are gradually becoming less artificial as future networks become smarter and deploy technologies such as soft open points and demand response.

The approximations greatly simplify the analysis and – among other things – enable a 'snapshot' analysis of network states that only depends on the current state of network components. This snapshot analysis forms the basis of a non-sequential Monte Carlo technique. In combination with importance sampling approach, very large speedups were obtained, versus sequential simulations and – especially – unbiased non-sequential simulations. The significant improvement in computational efficiency is achieved by enforcing the non-sequential MCS to sample those "important" system states which are with at least one fault and ignore those "all good" states which do not contribute to the final results. This is done by disturb the probability distribution of a randomly picked component in the system. Because of the interference to the original probability distribution, the simulation will sample the "more desired" states more often. However, this also introduces distortion to the final results and so requires a weighting factor to restore them. The mathematical formula for distorting distribution function and results restoration have been provided in section 2.4.1.

There exist drawbacks with the application of Importance Sampling. Since the original probability distribution functions of components are deliberately modified, the distribution functions of final reliability indices are distorted and hard to restore. In the case that the variability of the indices is required, the time-sequential simulation described in section 2.4.2 can be used to obtain the unbiased distributions of reliability measures.

In the implicit model, switching actions are represented implicitly. This approximation enables efficient network analysis but can also bring inaccuracy to the final results. Chapter 3 proposes an extended model in which switching actions are explicitly analysed. The study will compare these two models with their strengths and drawbacks.

Thanks to the simplicity of the proposed switching model, various active network technologies can be modelled in an efficient way. Future studies include the extension of the linear optimisation considering distributed generation, storage and responsive demand in the system, which is introduced in Chapter 4 section 1. Furthermore, in combination with time-sequential Monte Carlo simulations, the method can be used to analyse customer interruption costs with non-linear customer damage functions, which is demonstrated in Chapter 4 section 2.

Chapter 3 AN EXPLICIT SWITCHING MODEL FOR DISTRIBUTION NETWORK RELIABILITY ASSESSMENT

Abstract

In this chapter, an extended model is proposed where switching actions are explicit. Optimal switching actions for each switching devices are determined to minimise demand curtailment, maintain network constraints and radial topology. Although simulation time consumption is compromised for conducting mix integer optimisation, most of the benefits achieved by the implicit model in Chapter 2 are maintained that it can still be used graphically as a model reduction method, and simulated using time-sequential or state sampling Monte Carlo methods which enable potential large speedups in reliability assessment.

This chapter builds on the node-link model and Monte Carlo simulations for distribution network reliability introduced in the implicit switching model. For a full description, the reader is referred to Chapter 2.

3.1 INTRODUCTION

In Chapter 2, a simplified model was applied in which switching actions are reflected implicitly, based on the assumption that in future distribution networks power flow and switches can be fully and intelligently controlled by system operators. However, this may be over-optimistic for a less active network. To investigate the reliability performance of such a network, specific requirements of distribution network topology and reconfiguration are crucial to consider.

Finding the optimal real-time switching for loss reduction, load balancing and service restoration can be very complex. First, the optimal solution of the switching action decision comes from a large number of options. For a network with n switches (including controllable circuit breakers, switches and NOPs), there exist at least[3] 2^n possible switching combinations, in which each switch is either closed or open. The number of possible solutions expands exponentially with the growing size of networks. Second, switching actions must be determined not to violate any network constraints. The service restoration can be a series of switching actions; in each step all constraints must be considered. The work in this problem can be found in [14], [15], [16]. Third, distribution network need to be maintained as radial topology to minimise any potential outages affecting large areas. Fourth, switching actions need to recover the service to as many customers affected as possible whilst employing as few switching operations as possible, since a higher number of devices being switched means a higher risk the network is exposed to [18], [19]. However, in a real case shown in [41], restoration can be multiple stages instead of fewer operations to achieve a better network reliability.

Many studies have been proposed in this area for decades. The most recent studies include [20], and [21] in which heuristic algorithms (sometimes referred to as evolutionary algorithms) are used for finding a near-optimal solution for distribution network switching decisions whilst achieving multiple objectives including minimising load disconnection, minimising number of switching operation, minimising loops in the network, maintaining network constraints. It is worth noting that, in [21] one of the most recent publications, it requires 3 min for analysing one possible system state (in the paper, for a branch is faulty and removed) and 92 hours for enumerating all N-1 states for their test network which contains 460 branches. It shows that the significant computational burden for analysing long-term operation in distribution

[3] Some switches can be connecting more than 2 terminals.

network planning, especially for large and increasingly controllable networks, can be unacceptable.

In this chapter, an extended model is proposed where switching actions are explicit. Optimal switching actions for each switching device are determined to minimise demand curtailment, not violate flow constraints and maintain the radial topology. Although, simulation time consumption is longer compared with the implicit model in Chapter 2 for conducting mix integer optimisation, most of benefits achieved by the implicit model are maintained that it can still be used graphically as a model reduction method, and simulated using time-sequential or state sampling Monte Carlo methods which enable potential large speedups in reliability assessment.

In this explicit switching model, the node-link model is stilled used as introduced in Chapter 2. By splitting and portioning the network into sets of components that are separated by switches (normally closed or normally open) or circuit breakers, we are able to represent the network by nodes, connected by links and status of switches are determined by solving mixed integer optimisation problems. For details, please see Chapter 2.

3.2 Explicit switching model

3.2.1 Features of the proposed model

A reliability analysis model is proposed which captures the ability to reroute power using switches, but also determine optimal explicit the switching actions. The model is based on the assumptions introduced in section 2.3 but also include:

- Switching actions for the connected areas where there exists a live route to the grid are determined by solving mixed integer optimisation with objectives to minimise load point curtailment, maintain radial topology, and not violate network constraints.
- Upstream and downstream switches are operated simultaneously.
- Lack of available capacity due to network constraints does not prevent switching but can result in load curtailment when load point disconnection is continuous so that the constraint is satisfied.

3.2.1.1 Node status modelling

The electrical status of a node is a dynamic property that is affected by the fault state of the node itself, and that of other nodes. There are four possible states:

a) "Potentially supplied": The node is not faulty and a live route from this node to a power source exists. A potentially supplied node in this explicit switching model can still be unsupplied if the optimal solution of switching action decides to isolate this node.
b) "Interrupted": The component at this node is affected by an active fault that caused a circuit breaker to interrupt the power supply. This happens if the node itself or a connected node is in the 'fault clearing' state.
c) "Isolated": The component node has experienced a fault and is being repaired. In practice, this usually results from switchgear at the ends of the component being opened. In this state, the node interrupts power flow but does not otherwise affect flows in the network, thus allowing neighbouring nodes to be reconnected using load transfer via a normally open point if a live route to a power source exists.
d) "Unsupplied": The node has no live route to a power source, and is, therefore, unsupplied.

3.2.1.2 Network optimisation model

Using the node status tagging method above, the nodes which are potentially supplied can be identified. In the implicit switching model, which assumes full control on power flow and switching actions, load curtailment can be obtained by solving the optimal flow and load point disconnection. In this explicit switching model, to better reflect switching actions and operational network constraints, a network optimisation model is built to determine optimal switching actions, search for load points that are actually supplied and minimise overall load disconnection subject to:

- power flow constraints between nodes
- discrete network switching for radial network topology
- discrete/continuous load point disconnection

Parameters for the model:

i index of node;

k index of link;

π_{ik} directed incidence matrix of node *i* and link *k*: 1 if the link is oriented away from node *i*; -1 if towards node *i*; 0 if not connected;

f_k^{max} flow constraint between nodes connected by link *k*

L_i load level at node *i*;

GSP the set of nodes that are grid source points, i.e. transmission / EHV network feeders

Variables for the model:

c_i the fraction of curtailed demand of node *i*;

f_k power flow between nodes connected by link k, positive if flow in the direction defined by π_{ik};

w_{ik} 1 if node i is connected with an upstream node through link k, and the switch of the connection is closed; otherwise, 0;

s_k the status of physical connection, i.e. switch status between nodes connected by link k;

u_k 1 if the intrinsic orientation of link k is towards upstream; 0 for downstream;

As described in the introduction, the network model in this chapter aims to determine the optimal switching actions to achieve minimal load curtailment whilst respecting in network constraints and maintaining radial topology.

Capacity constraints for lines, circuit breakers and transformers need be considered in planning and operation of the distribution network. When there is a fault, switching actions may happen to restore interrupted customers that could potentially be resupplied by other network power sources. In this situation, the capacity constraints for system components may limit the system restoration ability. In a model where switching actions are explicitly considered, this may result in a decision not to restore power to a section of the network.

The optimisation objective is to minimise load curtailment:

$$\min_{\{c_i, f_k\}} \sum_i c_i \cdot L_i \tag{3.1}$$

Subject to constraints:

1. Switching on/off and flow limit

Switches are explicit in the model of this chapter. To reflect switching actions, a binary variable s_k is associated with each link. The status of switches be OPEN or CLOSED gives additional constraint to power flow between nodes.

$$-s_k f_k^{max} \leq f_k \leq s_k f_k^{max}, \qquad \forall k \tag{3.2}$$

$$s_k \in \{0,1\}$$

The power flow through link k is limited by the corresponding capacity constraint f_k^{max}. The binary variable s_k represent the status of the switch between the nodes connected by link k. If k is open, the value of s_k becomes 0 and the flow limit through link k f_k is therefore limited as 0.

2. Power balancing

The power available at node i must be balanced with the supplied demand.

$$c_i \cdot L_i - \sum_k \pi_{ik} \cdot f_k = L_i, \qquad \forall i \tag{3.3}$$

$$c_i \in [0,1] \; or \; c_i \in \{0,1\}$$

$c_i \cdot L_i$ is the curtailed demand at node i. The directed incidence matrix π_{ik} is positive for direction point out from node i, thus $\sum_k \pi_{ik} \cdot f_k$ represents the sum of power flows out from node i. c_i represents the fraction of curtailed demand at node i. In a passive distribution network, load points can be disconnected by opening circuit breaker/switch at the LV transformer when a power shortage happens. In that case, $c_i \in \{0,1\}$ are binary variables indicating the interruption of load points. With the development of active network technologies, flexible demand control could be used to reduce the load in smaller steps. For those smart networks, c_i is continuous between 0 and 1 – allowing for reduced curtailment and faster computation.

3. Radial topology

Distribution networks are commonly built in radial topology for rural areas since this topology is simple and does not require complex protection systems which are cost prohibitive [13]. For areas which require higher reliability, meshed network topology could be designed with much more interconnection within the network. But these networks are commonly operated radially with NOP for lower operation cost and reduced impact from fault clearing.

For areas with the highest reliability requirements (e.g. London central business district), highly interconnected spot network topology may be built. These networks are usually equipped with fast response protection devices that multiple failures would not interrupt the continuity of supply [42]. The study of these networks is out of the scope of this thesis, nevertheless, they can be analysed using the implicit switching model.

The radial topology of distribution networks is represented by two auxiliary variables u_k and w_{ik} with the corresponding constraints below.

In a radial or radially operated network, each component has a unique route to the grid feeder. The direction towards the feeder is upstream and that away from the feeder is downstream. This direction can be reflected by links that the intrinsic orientation of each link is either upstream or downstream. To describe the direction of upstream or downstream, an auxiliary variable u_k is created for each link. u_k is a binary variable showing whether the intrinsic orientation of link k defined by π_{ik} points to upstream: 1 for upstream and 0 for downstream.

Particularly, the direction away from a power source node is always downstream, thus it satisfies:

$$u_k = \frac{1}{2}(1 - \pi_{ik}), \qquad \forall i \in \{GSP\}, \pi_{ik} \neq 0 \tag{3.4}$$

$$u_k \in \{0,1\}$$

For all grid source point (GSP) nodes, the connected nodes are all downstream. Therefore, if π_{ik} is 1 for the intrinsic orientation of link k is away from GSP node i, the value of u_k is 0 showing the orientation points to downstream; if π_{ik} is -1 for the intrinsic orientation towards GSP node i, the value of u_k is 1 showing the orientation points to upstream; if π_{ik} is 0, it means no connection exists for link k and node i. The value of u for other links (not connected to GSP nodes) will be determined by other constraints.

In a radially operated network, since each component has a unique route to the grid feeder, each node cannot have more than *one* upstream connection. An auxiliary variable w_{ik} is introduced for representing the connection property of node i and link k. w_{ik} is a binary variable as 1 if node i is connecting to a node through link k to upstream; 0 to downstream. In radial topology, there should exist no more than one upstream connection for all nodes, thus it satisfies:

$$\sum_k w_{ik} \leq 1, \qquad \forall i \tag{3.5}$$

$$w_{ik} \in \{0,1\}$$

In order to identify the value of w_{ik} which represents the relation between a link and a node, link k is an upstream link of node i is defined by:

$$s_k = 1\ AND\ \pi_{ik} \cdot (2u_k - 1) = 1 \tag{3.6}$$

Hence, $w_{ik} = 1$ should be the sufficient and necessary condition to the equations above.

a. If $s_k = 1\ AND\ \pi_{ik} \cdot (2u_k - 1) = 1$ is true, then $w_{ik} = 1$. This is achieved by the inequality:

$$w_{ik} \geq 1 - (1 - s_k) - \big(1 - \pi_{ik}(2u_k - 1)\big), \qquad \forall i, k \tag{3.7}$$

When $s_k = 1\ AND\ \pi_{ik} \cdot (2u_k - 1) = 1$ is true, the binary variable $w_{ik} \geq 1$, thus it can only be 1. If either condition is not true, w_{ik} is not constrained.

b. If either $s_k = 1\ OR\ \pi_{ik} \cdot (2u_k - 1) = 1$ is not true, then $w_{ik} = 0$. This is achieved by the inequality:

$$w_{ik} \leq \frac{1}{3}(s_k + \pi_{ik}(2u_k - 1) + 1), \qquad \forall i, k \tag{3.8}$$

When $s_k = 1\ AND\ \pi_{ik} \cdot (2u_k - 1) = 1$ is true, the binary variable $w_{ik} \leq 1$, thus w_{ik} is not constrained. If either $s_k = 1\ OR\ \pi_{ik} \cdot (2u_k - 1) = 1$ is not true, the binary variable $w_{ik} \leq$ a number smaller than 1 but larger than 0, thus the binary variable w_{ik} must be 0.

With the constraints introduced above, the studied distribution network is ensured to be radial topology. This is a stronger constraint than that in the implicit model of Chapter 2, where different branches can be implicitly connected as a ring or meshed topology for service restoration. Therefore, the assessment results from the explicit model are less optimistic than that of the implicit model.

This optimisation model enables us to find the optimal switching actions to minimise load curtailment and maintain radial topology whilst not violate flow limit. A simplification of this model is that we do not determine the sequence of switching actions from the original network (before switching) to the target (final optimal switching status). The model effectively assumes that all switching actions can be done simultaneously so that the switching actions do not depend on the history of the system, which enables us to apply state-sampling techniques in Monte Carlo simulations for network planning assessments.

3.3 CASE STUDY

The same as Chapter 2, the proposed explicit switching model is applied using non-sequential and sequential MCS in different distribution networks to test its accuracy, efficiency and applicability.

3.3.1 THE ILLUSTRATIVE HV NETWORK

The illustrative HV network is shown in Figure 2-1, and in reduced form in Figure 2-3. The network consists of two branches, each with five load points connected through distribution transformers and line sections. Each line is equipped with sectionalizing switches at both ends. A NOP is employed to connect the ends of both branches as an alternative supply route. The network parameters used in this chapter has been given in Table 2-1.

With the proposed explicit switching model, the impact of a given state does not depend on the history. This property enables the use of state sampling Monte Carlo schemes and associated variance reduction schemes.

In Table 3-1, a comparison study for the illustrative HV network and N-0 loading level is taken for testing accuracy and the computational efficiency of the implicit switching model and the explicit switching model. It is clear from the table that the computations with discrete load shedding (columns 3-4) are generally slower due to the use of binary variables in the optimisation with the implicit switching model. However, the time difference is less obvious with the explicit switching model. This may result from that the explicit switching model is already a mixed integer optimisation problem, having discrete load shedding only add in more binary variables.

TABLE 3-1 COMPARISON OF COMPUTATIONAL EFFICIENCY FOR DIFFERENT SWITCHING MODELS

Computation time	Continuous c_i		Discrete c_i		CoV
	EENS (MWh/y)	Time (s)	EENS (MWh/y)	Time (s)	
Implicit switching NSMCS+IS	4.10	140	5.14	204	1%
Explicit switching NSMCS+IS	4.14	20856	5.28	21453	1%
Explicit switching TSMCS	4.2	68839	5.6	70846	10%

The resulting EENS values are also higher for less active load point disconnection (discrete c_i) than those corresponding to 'smart' systems (continuous c_i). For the explicit switching model with non-sequential Monte Carlo simulation, the time required for achieving the same coefficient of variation (CoV) is much longer as 20856s and 21453s for continuous and discrete load shedding, respectively. However, for a worse CoV of 10%, applying Time Sequential Monte Carlo simulation, the required simulation time is even longer than 68839s. It means that although the explicit switching model compromises its computational efficiency for solving mixed integer optimisation, applying state sampling combined with variance reduction techniques, it still enables great speed up for distribution network reliability assessment.

Although there exists some difference in results among the three simulations, it is believed that this comes from Monte Carlo simulation error and the EENS values are actually very close if not the same.

In the following part, we repeat the sensitivity study conducted in the previous chapter but using the explicit switching model.

TABLE 3-2 EENS FOR DIFFERENT HV NETWORK LINE FAILURE RATES AND LOADING LEVELS

Network EENS	Line Failure Rate (occ./km.year)	N-1		N-0	
		Continuous (MWh/y)	Discrete (MWh/y)	Continuous (MWh/y)	Discrete (MWh/y)
	0.02	0.04	0.04	0.41	0.58
	0.05	0.11	0.10	1.00	1.38
	0.1	0.22	0.22	2.04	2.76
	0.2	0.44	0.44	4.14	4.96

TABLE 3-3 EXPECTED CUSTOMER INTERRUPTION (ROUNDED) FOR DIFFERENT HV NETWORK LINE FAILURE RATES AND LOADING LEVELS

Network ECI	Line Failure Rate (occ./km.year)	N-1		N-0	
		Continuous (occurrence/ 100custustomer/y)	Discrete (occurrence/ 100custustomer/y)	Continuous (occurrence/ 100custustomer/y)	Discrete (occurrence/ 100custustomer/y)
	0.02	3	3	3	3
	0.05	7	7	7	7
	0.1	14	14	15	15
	0.2	28	28	28	28

TABLE 3-4 EXPECTED CUSTOMER MINUTE LOST (ROUNDED) FOR DIFFERENT HV NETWORK LINE FAILURE RATES AND LOADING LEVELS

Network ECML	Line Failure Rate (occ./km.year)	N-1		N-0	
		Continuous (min/customer/y)	Discrete (min/customer/y)	Continuous (min/customer/y)	Discrete (min/customer/y)
	0.02	1	1	7	9
	0.05	2	2	16	22
	0.1	4	4	33	44
	0.2	9	9	66	80

Similarly, Table 3-2, Table 3-3, Table 3-4 show the expected values of Energy Not Supplied (ENS), Customer Interruption (CI) and Customer Minute Lost (CML) with a different failure rate and loading levels using TSMCS (1% coefficient of variation). Results are given for both active (continuous c_i) and passive (discrete c_i) networks. The higher N-0 loading level results in a significant increase in ECML and EENS compared to the N-1 case, but the frequency of interruptions (ECI) is unaffected.

TABLE 3-5 EENS COMPOSITION

Network EENS (MWh/y)	N-1	N-0
Fault clearing	0.43	0.43
Thermal constraint	0.00	3.71
Single failure	0.43	4.13
Double overlapping failure	0.01	0.01

It is worth noting that the both implicit and explicit switching models also enable the recognition of different types of failures in the network. Table 3-5 shows the EENS composition (for the active network with continuous c_i) for the case with a line failure rate of 0.2occ/year.km. At the N-0 loading level, EENS from fault clearing is 0.43MWh/y, similar to that of N-1, for the outages that occur when a circuit breaker trips the whole feeder. EENS from thermal constraints is the load curtailment after switching actions when the alternative network capacity is not able to fully supply the restored areas. The result shows that, at the N-0 loading level, thermal constraints are the main source of undelivered energy to customers. Table 3-5 also breaks down the contributions caused by single and overlapping failures, for system planners to check the network performance of rare overlapping failures.

The proposed method can be used to obtain probability distributions of network reliability indices, although this does require the use of a sequential method (TSMCS). We present an example for the case where the network feeder capacity conforms to N-0. The figure below shows the complementary CDF distribution of annual ENS for various cable failure rates.

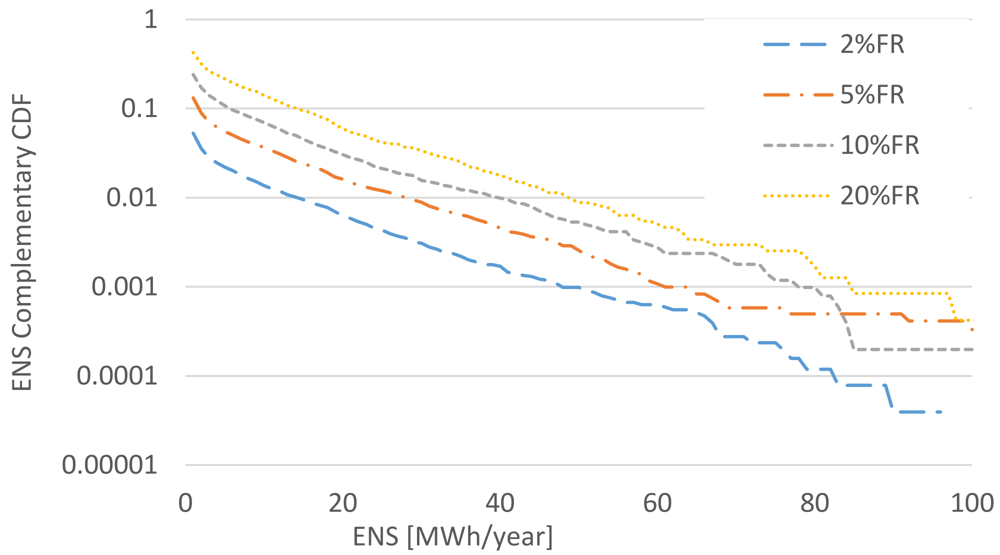


FIGURE 3-1 CCDF OF ANNUAL ENS FOR FAILURE RATE OF 2%, 5%, 10%, 20%/KM.YEAR

3.3.2 RBTS Bus 4 network

Similarly, a second case study was carried out on the well-known distribution network RBTS Bus 4 [24]. Its implicit switching representation is shown in Figure 2-13. Active load shedding (continuous c_i) has been assumed for all calculations, and computed reliability indices are listed in Table 3-6 for two scenarios, labelled 'N-1' and 'N-0'. The capacity limit of each feeder line is equal to the peak demand of all load points in the associated branch for 'N-0' and double of that for ‘N-1’. The half-hourly load profile is applied instead of the average data in [24]. Table 3-6 and Table 3-7 compare the accuracy and the simulation time required with implicit and explicit switching model to compute the ENS and SAIDI for the ‘N-0’ scenario.

TABLE 3-6 EENS COMPOSITION OF THE IMPLICIT AND EXPLICIT MODELS FOR RBTS BUS 4

	Continuous c_i		Discrete c_i		CoV
EENS	EENS (MWh/y)	Time (s)	EENS (MWh/y)	Time (s)	
Implicit switching NSMCS+IS	16.5	118	17.0	445	1%
Explicit switching NSMCS+IS	21	3711	36	5102	5%

TABLE 3-7 SAIDI COMPOSITION OF THE IMPLICIT AND EXPLICIT MODELS FOR RBTS BUS 4

	Continuous c_i		Discrete c_i		CoV
SAIDI	SAIDI (min/customer/y)	Time (s)	SAIDI (min/customer/y)	Time (s)	
Implicit switching NSMCS+IS	46.2	118	47.4	445	1%
Explicit switching NSMCS+IS	48	3711	99	5102	5%

Table 3-6 shows that for RBTS network, the explicit switching model may lead to a worse reliability result in terms of EENS. This can be caused by that, the illustrative network has only 2 branches and if outages happen, network reconfiguration does not create a loop, in other words, still a radial network. However, in RBTS a more complex network, when failures occur there exist multiple combinations of network switching to form a loop that can resupply adjacent disconnected branches. The explicit switching model limits this to happen for maintaining a radial topology, but the implicit model allows it as long as a conducting route can be found to the grid feeder. This mean that the explicit model can lead to more load curtailment (but better reflect the reality of less-active distribution networks).

Table 3-7 demonstrates the results of SAIDI for RBTS network. Similarly, the values of SAIDI are worse with the explicit switching model. Discrete load point disconnection can also lead to prolonged outages. The SAIDI for this network with the implicit model and continuous switching is 46.2 min/customer/year, which is very close to the value obtained in Chapter 2 for CML as 43 min (in the computation of CML, interruptions shorter than 3min are ignored). Considering that CML can only be obtained by running time-sequential Monte Carlo simulation (aiming for excluding interruptions shorter than 3min), which is very inefficient with explicit switching, we can use snapshot Monte Carlo simulation with importance sampling to efficiently obtain the SAIDI for an approximate CML value.

3.4 Conclusions

We have introduced an extended model for the reliability analysis of active distribution networks where switching actions are explicit. Optimal switching actions for each switching devices are determined to minimise demand curtailment, whilst respecting network constraints and enforcing a radial topology through switches. Combined with the node-link network model developed in Chapter 2, the explicit model can benefit from the approximations that greatly simplify the analysis and – among other things – enable a 'snapshot' analysis of network states that only depends on the current state of network components. Although the explicit switching model, which is based on mixed integer optimisation, compromises the simulation time consumption compared with the implicit model, it is still able to be analysed by snapshot simulation. In combination with importance sampling approach, very large speedups were obtained, versus sequential simulations and – especially – unbiased non-sequential simulations. This suggests that the explicit switching model can be used for complex distribution networks considering realistic topology constraints.

Compared with the implicit model, the explicit switching model better reflects the actual switching actions in distribution networks. The studies simulated for the illustration network show that very close results can be obtained by the two models. However, for larger and more complex networks such as RBTS Bus 4, the results are different – worse reliability performance has been obtained with the explicit switching model. This results from that the RBTS Bus 4 can form meshed topology during network restoration and the radiality constraint in the explicit model prevents it to happen, which leads to more load curtailment. It, therefore, can be concluded that for a large and complex network which must keep radial topology the implicit model which allows meshed network topology could bring inaccuracy. In that case, the explicit switching model should be applied for accurate reliability assessment and relatively good computational efficiency can be achieved using non-sequential Monte Carlo methods with variance reduction techniques (e.g. importance sampling). However, the analysis of time dependent operations (e.g. energy storage) which needs time-sequential Monte Carlo can be very slow to run.

Considering the development of active network control, future distribution networks may be allowed to have meshed or ring topology during contingency restoration. In a system with smart control, the implicit switching model can be applicable and achieve a considerable higher computational efficiency and still good accuracy (close results shown in the illustration network).

Chapter 4 APPLICATIONS OF DISTRIBUTION NETWORK RELIABILITY EVALUATION VIA THE PROPOSED ASSESSMENT MODEL

Abstract

In this chapter, a number of studies on distribution network reliability evaluation were proposed via the proposed implicit switching model.

In the first part, non-network solutions on enhancing distribution network reliability/capacity are analysed. A mathematical model for optimising the operation of DG and storage to reduce load curtailment is created. Four network improvement options including automatic switching, mobile generation, energy storage and DG are assessed for their impact on network reliability performances.

Part Two explores various models for customer interruption cost (CIC) quantification. Different CIC models are investigated by conducting time-sequential Monte Carlo simulation with the proposed assessment model. The CICs using customer damage functions (CDF) for different customer sectors, interruption durations are evaluated and compared. The implications of choosing CIC models on network planning are also discussed.

The third part models distribution network reliability in High Impact Low Probability events (HILP). A chronological simulation model is built to analyse different severity HILP events when component failure rates are radically increased and repair durations prolonged. Based on this model, the role and value of emergency operation actions and network development is discussed.

4.1 DISTRIBUTION NETWORK RELIABILITY EVALUATION FOR DISTRIBUTED GENERATION AND ENERGY STORAGE VIA THE PROPOSED MODEL

4.1.1 INTRODUCTION

Traditionally, network security of supply relies on the redundancy of system capacity. Security standards in the UK have been designed to deterministically use the level of asset redundancy as the planning criteria. In Engineering Recommendation P2/6 [43], the regained level of system security is defined in terms of the available redundant capacity for the different size of group demand, which is the aggregation of all demand at the same and lower voltage levels.

The planning criteria relying on capacity redundancy, though delivered good service to customers, may result in very high expenditure. Decreasing asset utilisation means that the corresponding cost of upgrades to end customers could become unacceptable.

To deliver an economic power supply, power systems need to be designed in a more advanced way based on Smart Grid technologies which envisage a penetration of various forms of distribution energy resources (DER), such as demand side response (DSR) technologies in distribution networks, including demand-led DSR in the form of controllable / responsive loads and generation-led DSR in the form of DGs and energy storage (ES) technologies. DSR and ES devices are growing in their role in facilitating cost-effective evolution to lower carbon systems due to their ability to provide a wide array of services across all voltage levels.

A crucial emerging question is centred on assessing the contribution of these DER technologies to network security i.e. their ability to displace network reinforcement. An illustrative example of this issue is indicated in Figure 4-1, in which several solutions are considered: (a) traditional network reinforcement through network-based solutions (the third transformer is for illustrative purposes only), (b) distributed generation-based solution, (c) storage-based solution and (d) demand-side management-based approach (which can for instance include flexible commercial demand).

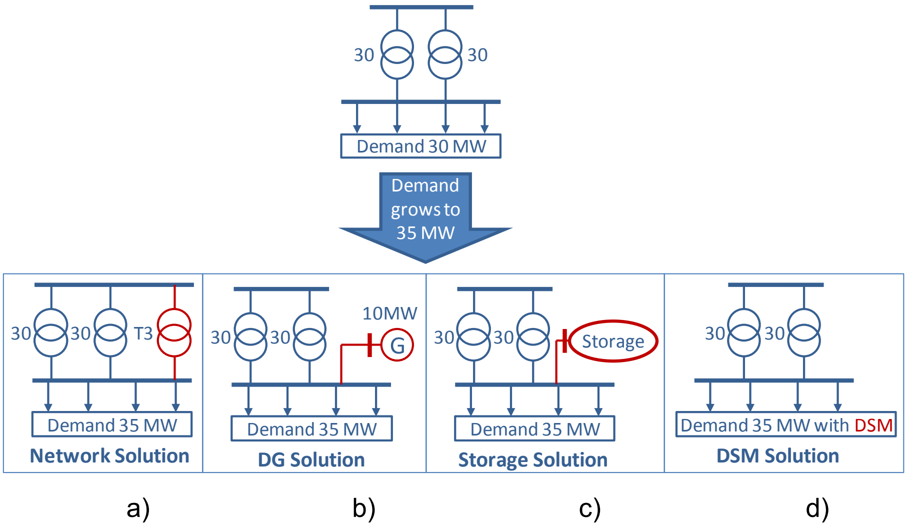


FIGURE 4-1 RANGE OF NETWORK AND NON-NETWORK SOLUTIONS FOR RESOLUTION OF NETWORK SECURITY PROBLEMS

In the case of load increase, as indicated in Figure 4-1, traditional planning approaches would require network reinforcement (e.g. installation of a third transformer) as indicated in the solution (a) of Figure 4-1. Regarding the other three non-network solutions, the challenge lies in assessing the ability of these alternative solutions to substitute network reinforcement. In one approach, the network planners will need to determine the “capacity value” of the alternative non-network solutions, which requires assessment of the reliability performance.

The present distribution network planning standard, Engineering Recommendation P2/6 [43] employs the concept of Equivalent Circuit Capacity (ECC) that is used to quantify the security contribution of DG without considering the reliability properties of the actual distribution network. Since the reliability delivered to end consumers is ultimately a property of the system as a whole, including the combined effects of the distribution network and DER, the P2/6 approach offers limited insight into the actual reliability implications associated with the use of DER in particular scenarios.

This section aims at quantitatively assessing the security contribution of non-network solutions include automatic switching, emergency supply, DG and ES technologies by accounting for the combined effects of the distribution network and non-network properties. Sensitivity analyses have been carried out in this section to investigate the impact of different levels of network redundancy.

The evaluation of the capacity credit of DG is based on the representation of demand through load duration curves. This is driven by the assumptions that DG would have no restrictions regarding fuel availability and their operation is not coupled to past system states. ES is different to DG technologies in a variety of ways. First of all, whereas DG is solely constrained by its technical availability, ES facility must have both sufficient power output capability and energy stored to supply the load. In other words, whereas conventional resources, such as DG, typically face only power constraints, storage facilities can face both power and energy constraints. A second point is that whereas fuel supply of DG is considered unconstrained (e.g. diesel generators operating for relatively short periods of time are considered to have no fuel limitations, but this assumption may be reconsidered when extended operation is required) or stochastic (e.g. wind generators), ES's state-of-charge (SOC) is tightly linked to the network's available transfer capability as well as preceding events. The former consideration relates to the fact that ES does not generate power but rather make use of existing network assets (i.e. transformers) to draw power from the upstream grid. The degree to which this import capability is limited or not determines how much energy can be stored in a given period, for subsequent discharging at a time of need. As such, the supply headroom of network is an important factor to ES contributions. In addition, whereas transformer outages do not have an impact on DG's output capability, in the case of ES they do influence substantially its ability to store energy. Given that the ES state-of-charge is coupled to preceding operating points and outage events, the proposed implicit switching model with Time-Sequential Monte Carlo simulation is employed for evaluating network reliability performances.

4.1.2 DG AND ENERGY STORAGE MODEL

Parameters for the model:

i	index of node;
k	index of link;
π_{ik}	intrinsic incidence matrix of node *i* and link *k*: 1 if out from node *i*; -1 if towards node *i*; 0 if no connection;
f_k^{max}	flow constraint between nodes connected by link *k*
G_i^{max}	maximum generation available at node *i*
e_i^{max}	energy rating of the storage at node *i*
Δt	time to next system state transition
L_i	load level at node *i*;
e_i	energy stored in the storage at node *i*

ε weighting factor, e.g. 0.001

Variables for the model:

c_i fraction of curtailed demand of node *i*;

f_k power flow between nodes connected by link *k*, positive if flow in the direction of pre-set orientation of link *k*;

g_i generation output at node *i*

p_i power of charging (discharging if negative) of the energy storage at node *i*

Based on the implicit switching model, this section proposes an operation model to optimise the reliability for networks with DG and storage units.

The model introduced in Chapter 2 is used for this section, in which the switching actions are modelled implicitly to realise network fault isolation, load rerouting and service restoration. Capacity constraints for lines, circuit breakers and transformers need be considered in planning and operation of the distribution network. When there is a fault, switching actions may happen to restore interrupted customers that could potentially be resupplied by other network power sources. In this situation, the capacity constraints for system components may limit the system restoration ability. In a model where switching actions are implicitly considered, this may result in a decision not to restore power to a section of the network.

In addition to the existing network constraints, the power output limitation of distributed generation and the rating of power and energy stored in energy storages are also considered in the model in this chapter.

In order to optimise the network reliability, two objectives are set in the objection function:

- Minimise load curtailment;
- Maximise the state of charge of energy storage (as 2nd priority)

$$\min_{\{c_i, f_k\}} \sum_i c_i \cdot L_i - \varepsilon \cdot p_i \tag{4.1}$$

The second part of this multi-objective function $-\varepsilon \cdot p_i$ is aiming for a system in which storage devices would be charged at the largest possible rate to maintain a maximum state of charge, whilst not increasing curtailment. Such a system, sometimes referred to as the “greedy” storage operation, is used for investigating the extreme (maximum) value of energy storage on network reliability.

When the network is in normal condition, load curtailment of the network is 0 so that the optimisation of objective function will lead to maximise the charging power of storages. This allows storage devices to be charged in advance when the network has capacity surplus. When there is a deficit of capacity to meet the demand, the optimisation aims to minimise load curtailment. A weighting factor ε is used in the objective function to ensure the minimum load curtailment as the first priority. The value of ε should be small enough so the charging of storage would not affect the minimised load curtailment – when load curtailment happens, storage devices won't be charged to make the situation worse.

It is worth noting that, the value of weighting factor would be system specific. Using an inappropriate ε may bring inaccuracy to the optimal result. A precise solution to this issue is applying the first part of the objective function as the constraints of the second part, in the form of the Karush-Kuhn-Tucker (KKT) conditions. A discussion is given for the future work in section 6.2.

In practice, storage appliances can be operated for other purposes, e.g. energy arbitrage, load shedding and etc. The state of charge would not be always at its possible maximum. An appropriate storage operation scheme should consider the balance between the profitability from energy arbitrage and the ability for restoring outage during contingencies.

Constraints:

4. Active power flow limit

$$-f_k^{max} \leq f_k \leq f_k^{max}, \qquad \forall k \tag{4.2}$$

The power flow through link k is limited by the corresponding capacity constraint f_k^{max}.

5. Power balancing

$$g_i + c_i \cdot L_i - \sum_k \pi_{ik} \cdot f_k - p_i = L_i, \qquad \forall i \tag{4.3}$$

$$c_i \in [0,1] \; or \; c_i \in \{0,1\}$$

The power available at node i must be balanced with the supplied demand. $c_i \cdot L_i$ is the curtailed demand at node i. The directed incidence matrix π_{ik} is positive for direction point out from node i, thus $\sum_k \pi_{ik} \cdot f_k$ represents the sum of power flow out from node i. c_i represents the fraction of curtailed demand at node i. In a passive distribution network, load points can be disconnected by opening circuit breaker/switch at the LV transformer when a power shortage happens. In that case, $c_i \in \{0,1\}$ are binary variables indicating the interruption of load points. With the development of active network technologies, flexible demand control could be used to reduce the load in smaller steps. For those smart networks, c_i is continuous between 0 and 1 – allowing for reduced curtailment and faster computation.

6. DG constraints

$$0 \leq g_i \leq G_i^{max} \tag{4.4}$$

In this study, we assume distributed generation can be controllable when required within its rated generation limit. In general, the DG in distribution network can be the wind, photovoltaic (PV), biomass and other conventional generations. It is worth noting that, not all generation technologies are fully flexible, especially renewable generations are often intermittent.

Islanding situations may happen when no conductive route is available from DGs to the grid. Islanded operation of DG is not permitted in this study, though this situation may further reduce demand curtailment and achieve a better network reliability. In our study for this chapter, if a DG is not connected to the grid, it is assumed not contributing to mitigating load curtailment. However, in reality, this situation may happen under specific regulations and contracts.

7. Energy storage constraints

$$\max\left(-p_i^{max}, -\frac{e_i}{\Delta t}\right) \leq p_i \leq \min\left(p_i^{max}, \frac{e_i^{max} - e_i}{\Delta t}\right) \tag{4.5}$$

This inequality implicitly includes the constraint to the energy stored in storage devices, $0 \leq e_i \leq e_i^{max}$ and the constraint to the charging/discharging power, $-p_i^{max} \leq p_i \leq p_i^{max}$. Δt is the time length of the system state (time to the next state transition). It is assumed that the storage would charge/discharge at a constant rate during the period of the system state. Since a half-hourly load profile is applied in this study, the period of a system state is usually shorter than or equal to 30 min (the time period for electricity market is cleared in the UK), the assumption of constant charging/discharging is reasonable. e_i is the state of charge at the start of the system state, therefore, at the end of the state the stored energy in the storage unit will be $e_i \coloneqq e_i + p_i \cdot t$.

4.1.3 CASE STUDY

As introduced in Chapter 2, case studies are conducted with the illustrative distribution network in Figure 2-1. The network data used in this thesis are calculated from data received from several UK DNOs. Those data are available from Regulatory Reporting Pack [38] and Quality of Service Reporting [39] for up to 5 years. The analysis of raw data is given in APPENDIX E.

TABLE 4-1 PARAMETERS OF THE ILLUSTRATIVE NETWORK

Parameters	**Values**
Failure rate for lines	0.05 occ./km.year
Failure rate for transformers	0.006 occ./year
Maintenance rate for primary transformer	0.2occ./year
Switching time	30 min for manual, 3 min for automatic
MTTR for lines	24 hours
MTTR for primary transformers	299 hours
MTTR for distribution transformers	24 hours
Maintenance restoration time for primary transformer	24 hours
Line section length	1 km
Load point peak demand level	500kW (N-1), 625kW (N-0.75), 750kW (N-0.5), 875kW (N-0.25), 1000kW (N-0)
DG availability	85%
DG mean time to repair	100 h
DG peak generation capacity	200 kW
Energy Storage charging / energy rating	200 kW / 400 kWh
Emergency generation capacity	500 - 1000 kW according to load point

Each load point is assumed to connect 500 customers, with a peak demand of 500kW (N-1), 625kW (N-0.75), 750kW (N-0.5), 875kW (N-0.25), 1000kW (N-0). A normalised UK load profile with 17520 levels for each half hour is used. For line sections and 33-11kV transformers, a capacity constraint of 5MW is applied for N-1 (for each load point as 500kW, in total 5MW for the network).

Non-network reliability enhancement solutions:

- Base case: The original illustrative network with manual switching which can be finished averagely in 30min, the probability of switching time is exponentially distributed.
- Automatic switching: network switching actions for service restoration can be finished in 2min after a fault occurs.
- Emergency generation: emergency generators can be arranged to supply interrupted load points after a waiting time of 3h. It is assumed that a mobile generator can fully supply any single load point that is fully or partly curtailed.
- Energy storage: Storage power/capacity rating in this study is 200kW/400kWh. It is assumed to be fully reliable. Storage units are operated to be fully charged when possible and used for only reliability purposes. Storage in this study is assumed connected to load directly, e.g. in room battery. The energy stored can be utilised during load curtailment before switching is finished (allows for islanded operation).
- Distributed generation: DG in this study is assumed to have an availability of 85%, mean time to repair as 100h, and peak generation as 200kW. DG is assumed to be isolated from the rest of network when it is faulty and would not incur an interruption to the network.

Comparison studies are performed for the base case and the 4 network improvement options, including automatic switching, mobile supply, storage and DG. In Table 4-2, the expected results of ENS, CI and CML are demonstrated for different demand levels. Different from the study in Chapter 2 where N-0 is with an unchanged demand but lowered line rating, demanding levels reflect the increase of demand but the line rating is constant.

It is worth noting that all studies in this section are based on the implicit switching model, assuming that load points can be curtailed partly according to the level of power shortages (continuous c_i) rather than tripped entirely (discrete c_i).

It can be seen from the table, in the base case, with increased demand at load points, ENS and CML are raising significantly. After switching actions, the fault is isolated and the affected customers are supplied via available routes. The branch with no faulted line has to supply customers in two branches (partly for the faulted branch). When demand level is N-1, the line rating is safe to restore all customers, thus ENS is very low for the network but non-zero for curtailment during the fault clearing stage. When network redundancy is low, even if service restoration is available after switching, the number of recovered customer is limited by the line rating.

The differences of CI between demand levels are small. With a low network redundancy, it is expected to experience more interruptions to customers, since the lack of redundant capacity may lead to load curtailment that one power source cannot fully supply the whole of restored area after a fault. The result of nearly unchanged CI for different redundancy levels, however, is caused by the specific methodology for the computation of CI. Since for DNOs in the UK, the number of customer service interruption will be counted once for *a* network failure. If the service is recovered but suspended again for the same fault, it would not be counted as a second interruption for the affected customers [40]. Meanwhile, if the available capacity is not sufficient for all connected customers, the DNO would first disconnect the customers from the faulted branch, which won't be recorded as a new interruption (this is reflected in our model by applying priority orders to the already affected and unaffected load points). The small differences between the results are likely to be simulation errors (the coefficient of variation is 2.5% for this study), and the real values of CI are generally unchanged.

TABLE 4-2 RELIABILITY PERFORMANCES FOR FOUR NETWORK IMPROVEMENT OPTIONS AT DIFFERENT DEMAND LEVELS

	Demand level	ENS (MWh/y)	CI[4] (occ/100customer/y)	CML[5] (min/customer/y)
Base case	N-1	0.44	28.0	8.4
	N-0.75	0.67	27.9	9.8
	N-0.5	1.77	28.5	19.4
	N-0.25	4.24	27.8	38.5
	N-0	7.93	28.3	63.6
Automatic switching	N-1	0.04	0.0	0.2
	N-0.75	0.18	0.3	1.6
	N-0.5	1.19	1.6	11.2
	N-0.25	3.72	4.0	30.3
	N-0	7.40	7.0	55.8
Mobile supply	N-1	0.46	28.2	8.8
	N-0.75	0.57	28.4	8.9
	N-0.5	0.81	28.3	10.1
	N-0.25	1.22	28.3	12.1
	N-0	1.69	28.0	14.6
Storage/DR	N-1	0.17	9.0	2.9
	N-0.75	0.30	13.3	4.3
	N-0.5	1.01	16.0	10.7
	N-0.25	2.90	18.6	25.8
	N-0	6.12	20.1	48.1
DG	N-1	0.43	27.8	8.2
	N-0.75	0.54	28.2	8.1
	N-0.5	0.66	28.3	8.2
	N-0.25	1.12	27.8	11.1
	N-0	2.38	28.5	19.2

For comparison study between different options and the base case, Figure 4-2, Figure 4-3 and Figure 4-4 present the improvement (shown as positive) of ENS, CI and CML from the base case, respectively.

[4] "The number of customers interrupted per year (CI). This is the number of customers whose supplies have been interrupted per 100 customers per year over all incidents, where an interruption of supply lasts for three minutes or longer, excluding re-interruptions to the supply of customers previously interrupted during the same incident." This is defined in OFGEM RIIO report [40]

[5] "The duration of interruptions to supply per year (CML). This is the average customer minutes lost per customer per year, where an interruption of supply to customer(s) lasts for three minutes or longer." [40]

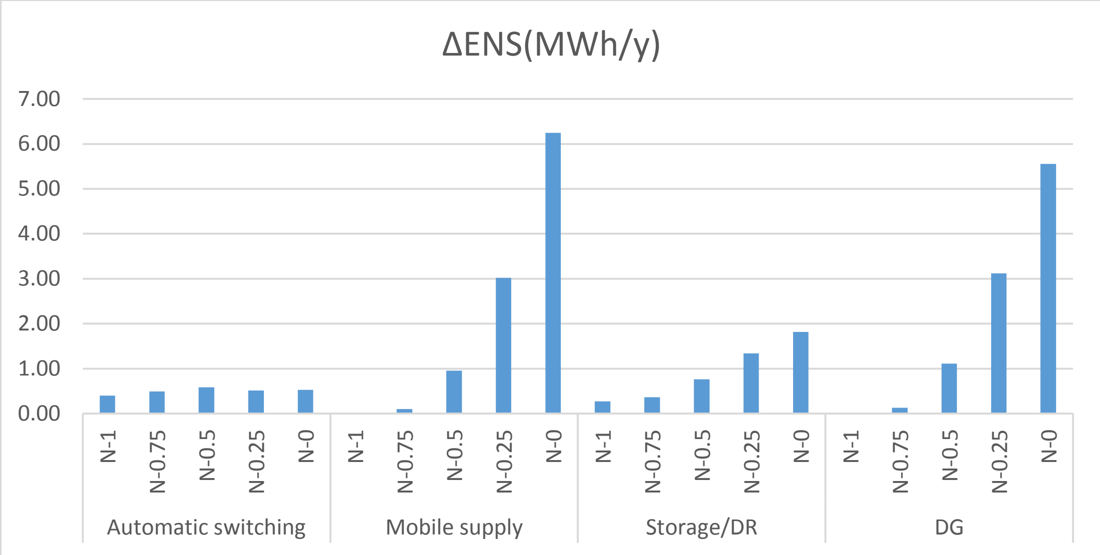


FIGURE 4-2 THE ENS IMPROVEMENT FOR FOUR OPTIONS AT DIFFERENT DEMANDING LEVELS

From Figure 4-2, automatic switching can reduce the energy curtailed during switching action preparation, the period starting from the fault's happening to the completion of switching actions. The switching time in a traditional distribution network is 30 min (it can be shorter or longer depending on the importance of the network). The automatic switching can shorten this interruption to 3 min before the network isolates the faulted line and restores customers affected. However, this option of network improvement cannot help reduce ENS for the period after switching actions are completed. When demand level increases, the ENS for the whole system is rising (shown in Table 4-2), but the improved ENS (ENS reduction) from exploiting automatic switching is almost unchanged at around 0.5MWh/y, the amount due to the reduction in the whole branch fault clearing outage.

Mobile generation and DG can significantly reduce the ENS, especially for low network redundancy cases. This may be mainly for that generators are not restricted with energy constraints (we assume, in this study, that resources for generators are unlimited). When the capacity from the feeder, which supplies its own branch and the recovered customer in the other branch where a fault happened, is not sufficient, DG and mobile generators can help prevent customers from disconnection, thus lowering the potential energy curtailment. Given the fact that mobile generators can fully supply load points (with a peak as 500kW-1000kW) but DG used in this study is merely 200kW, DG performs similarly to mobile generation for high redundancy cases. It may result from that load deficiency in high redundancy is still relatively low and real-time demand level is not always at peak so that 200kW DG capacity is sufficient to greatly reduce load curtailments. Additionally, DG can resupply the load immediately after switching actions are completed, rather than waiting for 3h to arrange mobile generators. However, for low redundancy such as the N-0 situation when outages are more likely longer and deeper, mobile generators with the ability to fully supply the whole load points can make a greater contribution to lower energy curtailment.

Storage/DR are usually installed with loads at LV level (there are, however, grid level storages which are out of the scope of this thesis). It is assumed in our study that these devices, e.g. battery in building or electric vehicles, can help mitigate load curtailment immediately after an outage occurs (working in islanding mode). From the results in the figure, 200kW/400kWh storage/DR performs well for high redundancy levels (N-1 and N-0.75) when mobile generators and DG cannot make a decent improvement in ENS. When load level is increased, the reduction of energy curtailment from storage is relatively humble. Considering that the storage has the same power rating at 200kW as the DG, the energy constraint of storages is the main factor limiting their ability to improve ENS further.

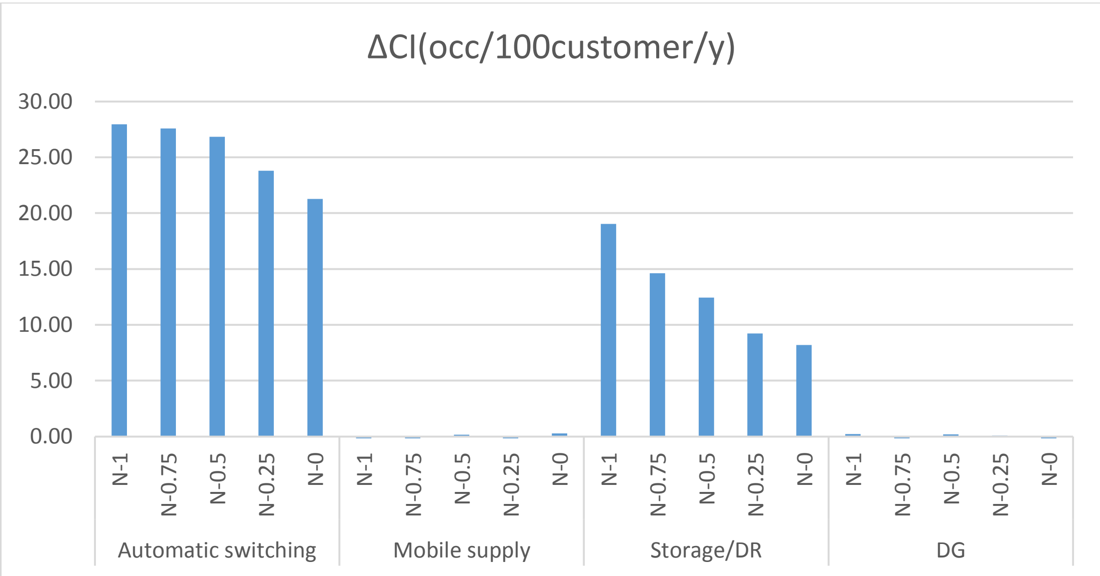


FIGURE 4-3 THE CI IMPROVEMENT FOR FOUR OPTIONS AT DIFFERENT DEMANDING LEVELS

Shown in Figure 4-3, among all 4 network improvement options, automatic switching is found to be the best way to improve (lower) CI. This is caused by that, in the UK, an interruption is not recorded as a customer interruption if shorter than 3 minutes [40]. By upgrading manual switching which lasts for averagely 30min to automatic switching as 2min, most interruptions due to fault clearing (trip the whole branch) no longer contribute to CI (even though customer still experience them, they are not shown in CI measurement). The CI reduction slides down with higher demanding levels since in those cases interruptions can happen after switching actions due to the lack of capacity from the adjacent feeder. For those cases, automatic switching is less effective in improving CI.

Storage/DR can also help in reducing CI since these devices/services are immediately available at LV so that the customers at load points are not affected or only partly affected before switching actions are complete; after network reconfiguration is finished, storages can be connected to the grid and start charging if redundant capacity is still available. As network redundancy level lowers, the improvement in CI will be restricted by the capacity of storage/DR services.

The results for mobile generators and DG show that their contribution in improving CI is negligible. The small measured differences exist are believed to be simulation error (coefficient of variation as 2.5%). These results are caused by that when a fault happens, the corresponding fault clearing device (circuit breaker connected to the substation) trips the whole branch and generators are assumed not working when disconnected from the grid (no islanding mode). After switching actions are finished, generators can work to supply the network but the customers who have experienced the fault clearing are recorded for CI. When network redundancy becomes lower, the recovered area could face another interruption if all connected load points cannot be supplied by one feeder. However, as a network operator, it is reasonable to first disconnect the customers in the branch who have been already recorded for CI. Thus, no matter how much capacity is available from DG or mobile generators, CI would not be affected.

Nevertheless, for the same reason, we can expect that DG is potentially able to reduce CI further if automatic switching is available. Since with automatic switching, customers in the branch with a fault are not recorded to increase CI for the switching is shorter than 3 minutes. When network redundancy is low, DG can significantly reduce the possibility to have a shortage in the recovered area, thus improve CI.

However, for mobile generators, even they can resupply the recovered area if a shortage exists due to low redundancy, customer disconnection is inevitable before the service is ready (which averagely take 3h). Thus, even automatic switching is available, mobile generators still cannot effectively reduce CI.

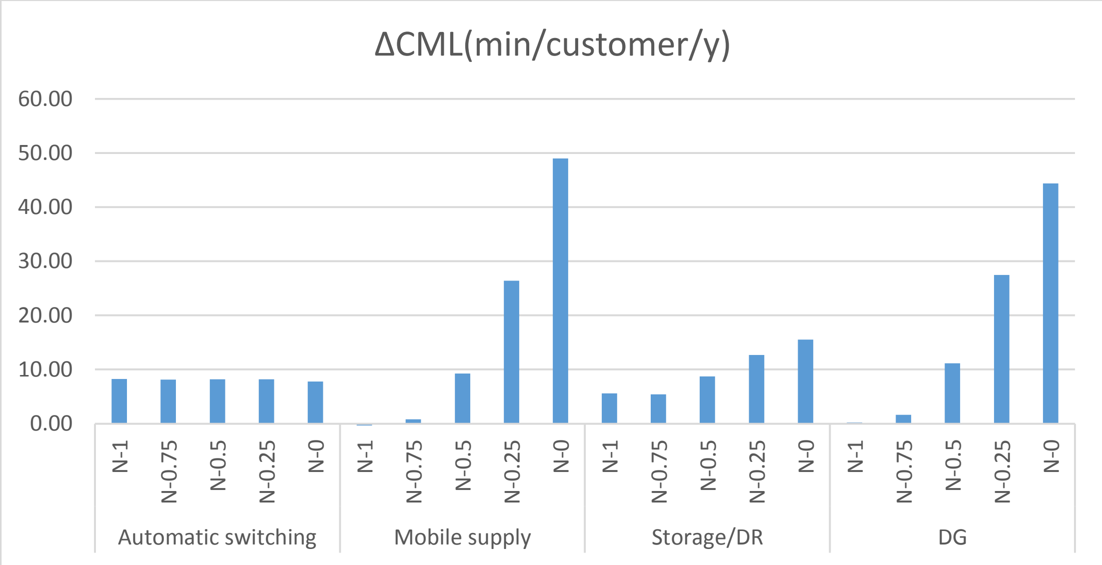


FIGURE 4-4 THE CML IMPROVEMENT FOR FOUR OPTIONS AT DIFFERENT DEMANDING LEVELS

Similar to Figure 4-2, in Figure 4-4, automatic switching can considerably reduce the average duration of interruption by about 8min per customer a year. The improvement is achieved since the period of fault clearing is reduced from 30min to 2min. However, this option of network improvement does not help reduce CML for the period after switching actions are completed. When demand level increases, the CML for the whole system is rising (shown in Table 4-2), but the improved CML from exploiting automatic switching is almost unchanged at around 8min/customer/y.

Mobile generation and DG can significantly reduce the CML, especially for low network redundancy cases. This is mainly because generators are not restricted with energy constraints (we assume, in this study, the resources for generators are unlimited). When the capacity from the feeder, which supplies its own branch and the recovered customer in the other branch where a fault happened, is not sufficient, DG and mobile generators can help prevent customers from disconnection, thus shorten customer interruptions. Given the fact that mobile generators can fully supply load points (500kW-1000kW peak demand) but DG used in this study is 200kW, DG performs similarly to mobile generation for high redundancy cases. The similarity of results may be due to the fact that load deficiency in high redundancy is still relatively low and real-time demand level is not always at peak so that 200kW DG capacity is sufficient to greatly reduce load curtailments. Additionally, DG can resupply the load immediately after switching actions are completed, rather than waiting for 3h to arrange mobile generators. However, for low redundancy such as the N-0 situation when outages are more likely longer and deeper, mobile generators with the ability to fully supply the whole load points can make a greater contribution to reducing the duration of customer disconnections.

Storage/DR are usually installed with loads at LV level. We assume in our study these devices can help mitigate load curtailment immediately after an outage occurs. From the results in the figure, 200kW/400kWh storage/DR performs well for high redundancy levels (N-1 and N-0.75) when mobile generators and DG cannot make a decent improvement in CML. When load level is increased, the reduction of energy curtailment from storage is relatively humble. Considering that the storage has the same power rating at 200kW as the DG, the energy constraint of storages is the main factor limiting their ability to improve CML further.

4.1.4 CONCLUSIONS

In this section, a number of studies for the values of non-network solutions on improving distribution network reliability/capacity were analysed. The reliability assessment model for DG and energy storage was created based on the proposed implicit switching network framework in Chapter 2. With the illustrative distribution network, four network reliability improvement options including automatic switching, mobile generation, energy storage and DG were investigated via time-sequential Monte Carlo simulation. ENS, CI and CML were used as the standard reliability indices for DNOs in the UK.

It was found that automatic switching can significantly reduce CI since fault clearing can be shortened to 2min so that the interruption before switching actions are not recorded in CI. The contribution is less effective for lower network redundancy since that automatic switching is not able to mitigate the power shortage. The contribution from automatic switching to reduction of ENS and CML is rather humble.

Energy storage units can also greatly improve network CI performance since they are usually available at LV level and can immediately supply the loads even when a fault happens. But if operated without islanding operation, the ability of storage in reliability enhancement can be limited. Storage can be an effective option to lower ENS and CML, but this ability is constrained by not only the power rating but also the maximum energy that can be stored.

Mobile generators for emergency supply, which in our study is assumed to be available in 3 hours after an outage happens, are found effective in improving ENS and CML, especially for low network redundancy situations. The effect on CI from mobile generators is negligible.

Similar to mobile generators, considerable contribution in improving ENS and CML can be achieved with increased network demand by installing DG. Different from mobile generators, if combined with automatic switching, DG can potentially have a significant contribution to CI reduction since it does not require a long waiting time to supply.

4.2 Quantification and Implications of Customer Interruption Cost (CIC)

Historically, electricity networks are planned on the basis that all consumers place the same value on continuity of supply and use of their appliances when required. Furthermore, it has been assumed that the continuity of supply is binary: electricity supply is 100% available under normal operating conditions (all devices can be used) or not at all under outage conditions (none of the devices are used). This approach is usually characterised by valuing avoided interruptions using a single value of the value of lost load (VoLL) [44], which is widely recognised as an oversimplification. First of all, the estimation of VoLL is subject to considerable uncertainty, driven by the fact that the damage caused by interruptions is different for different classes of consumers, different locations, durations, and different times of the year, week and day. Furthermore, in future distribution networks, smart metering coupled to in-home energy management devices could change the way customers value supply continuity through facilitating reliability-based consumption choices. By setting design standards that allow networks to be planned in accordance with the differing priorities of different categories of in-house demand, it may be possible to develop and operate networks at lower costs to customers.

4.2.1 Significance of customer interruption cost

The basis of network planning standards lies in balancing the cost of network investments against the customer interruption cost (CIC) in order to identify network capacity levels minimising the total expenditure. This network planning process is illustrated in Figure 4-5. As the level of network capacity and redundancy increases, the reliability of supply for the served customers is increased (i.e. customer interruption costs are decreased) at the expense of higher network investment costs. The optimal network capacity achieves the best trade-off between these two cost components. The CIC can be quantified through different measures, such as the cost per interruption (£/interruption), the cost per unit peak demand/annual energy consumption (£/kW, £/MWh) and the Value of Lost Load (VoLL) (£/MWh), representing the estimated value a consumer puts on an unsupplied unit of energy [45].

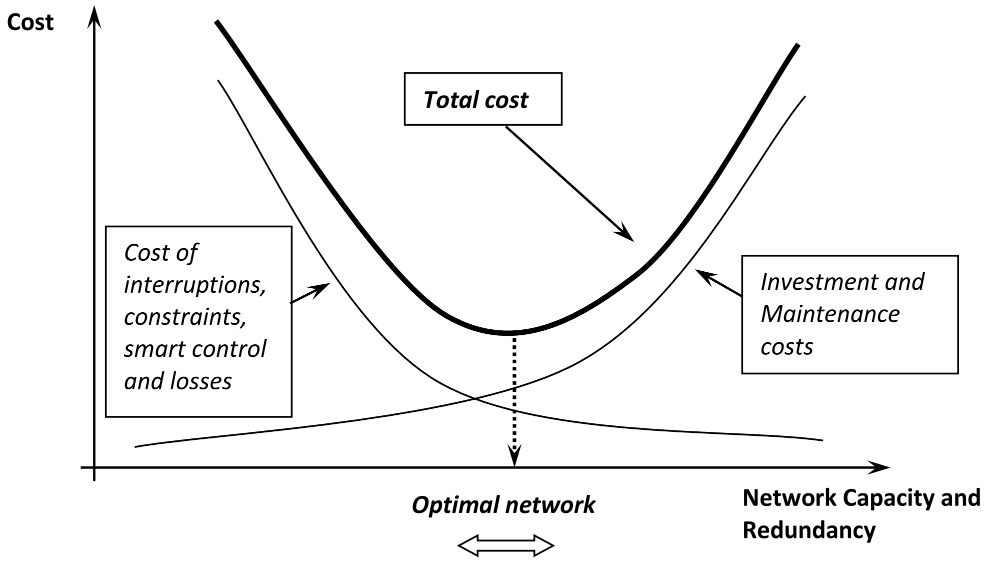


FIGURE 4-5 BALANCING OF NETWORK INVESTMENT COSTS AGAINST CUSTOMER INTERRUPTION COSTS FOR NETWORK PLANNING

4.2.2 Methodologies for CIC quantification

The published key CIC data summarised in [46] are from Canada [47]–[57], USA [58]–[62], Austria [63], [64], Denmark [65], Finland [65], Netherlands [66], Norway [67], Iceland [65], Italy [68], Ireland [69], Spain [70], Sweden [71]–[73], Germany [74] and United Kingdom [26], [45], [75]–[77] are tabulated in Appendix A in Table A.1. Additional information could be found in [78], [79] and for other jurisdictions in [80]–[84]. European guidelines for estimating the cost of interruptions can be found in [85]. A literature survey of consumer interruption cost is presented in [86],[46]. Customer survey design is described in [87]–[93]. This part of data for CDFs are tabulated in Appendix A in Table A.2.

Various methodologies for CIC data acquisition are discussed in [46] and these are summarised below:

- ***Ratio of Gross Economic Output to Energy Consumption (EO/C)*** is a very rough estimate of VoLL and it is calculated by dividing a gross economic measure by the total energy consumed,
- ***Customer surveys (CS)*** provide the evaluation of the statistically significant VoLL by different customer sectors from data provided directly by the end users,
- ***Amalgamated Customer Surveys (ACS)*** combine multiple sets of survey data from various regions of a country,
- ***Mapped Customer Surveys (MCS)*** approach maps data from one country and modifies it to suit the context of another country,

- ***Black Out Case Study (BOCS)*** approach is mainly the post-event analysis of blackouts providing more detailed cost estimates.

As discussed in [46], the EO/C approach is simple since it uses readily available data but it does not account for all drivers. CS is the preferred approach but it is costly and time intensive. ACS is less expensive and less time intensive than CS but only captures common key features and lose regional differences. MCS might not capture differences between countries. BOSC provides more detailed cost estimates but findings are limited to the geographic region and to the characteristics of the considered outage. The information such probability of occurrence can be also difficult to obtain because of the rarity of blackout events.

A large number of studies have employed different approaches to quantify the CIC. However, a general consensus on the value of CIC has not been achieved, as the values proposed by different sources vary significantly. The main reason is that CIC depends on a large number of diverse factors, the cost implications of which cannot be unambiguously quantified even by the consumers themselves. These factors include the activities affected by unsupplied energy, the categories of customer sectors, the timing (time of day, day of week, month of year), the duration, the frequency of interruptions and the availability of advance notification before the interruption takes place.

This lack of consensus is aggravated by the fact that CIC have been quantified in different currencies and different years in the past, introducing significant difficulties in comparative analysis. This lack of consensus gives network planners a great deal of freedom in their choice of the CIC parameters for system models. The final selection might be based on averaging different available values or on the values giving the “most sensible” results.

4.2.3 Customer Damage Function and VoLL

The dependency of the CIC on the factors aforementioned is modelled by the customer damage function (CDF). The original data of CDF in published key literature is presented in Appendix A. A common format of CDF represents the value of customer interruption cost with respect to interruption duration for different customer categories. The value of lost load (VoLL) which is “the value an average customer puts on an unsupplied kWh” [44][94], is effectively a particular function of CDF for an interruption of one hour [36], [45]. In this section, the latest published data for CDF and VoLL for the UK is introduced below.

The data of CDF for the UK was obtained from the survey presented by Kariuki and Allan in [45], [95], [96], which is based on a Preparatory Action survey of British Regional Electricity Company areas. For Large Users (consumers with demand of at least 8 MW), the cost of an interruption lasting 20 minutes is only slightly higher than the cost of a momentary interruption (<1sec). The industrial processes of these users can be interrupted by a very short outage, and it can take a significant amount of time to restore operations after the power supply is restored. As a result, interruptions costs are fairly insensitive to the duration of the outage.

Table 4-3 shows four customer damage functions adopted from the UK Survey [45] and all values are indexed by RPI-X [97] for 2012. The function represents the cost of per unit peak demand of load point according to various demand sectors and interruption durations.

TABLE 4-3 UK SURVEY [45]

Time	Customer damage function (£/kW)			
	Residential	Commercial	Industrial	Large user
momentary	0.27	1.76	10.95	12.00
1 minute	0.27	1.82	11.51	12.00
20 minutes	0.27	6.92	25.40	12.21
1 hour	0.96	18.95	44.96	12.78
4 hours	6.62	69.48	128.53	15.77
8 hours	14.17	139.98	213.76	17.28
24 hours	44.35	177.94	267.63	23.76

Kariuki and Allan [45] use the results of a UK Survey to convert the customer interruption cost (given in £ per interruption) into a customer damage function (given in £/kW per unit peak demand and £/MWh per-unit annual energy consumption). Both parameters are given as a function of interruption durations. Even though from the survey they found CIC in the UK is less related to unserved energy than interruption duration, which is contrary to the concepts of ‘implied cost per kilowatt-hour saved’ and VoLL, they have identified an expected VoLL of £19,363/MWh across all outage durations with VoLL for a one-hour interruption being £32,480/MWh by converting the CDF obtained in their survey (data shown here are indexed by RPI-X).

Furthermore, a recent report by London Economics [26] estimates the VoLL for domestic, small and medium-sized enterprises (SME) and industrial and commercial (I&C) electricity users. They estimate the VoLL in terms of willingness-to-accept (WTA) payment for an outage and willingness-to-pay (WTP) to avoid an outage. The WTA estimates are larger than the respective WTP estimates since customers desire a larger monetary amount in order to bear a loss of supply than the one they are willing to pay to retain it. For domestic customers, the statistically significant estimate of the VoLL ranges from £1,651/MWh (WTP) to £11,820/MWh (WTA) for a one-hour electricity outage during Winter Peak conditions with a headline figure of £10,289/MWh. For SME the respective range is from £19,271/MWh (WTP) to £39,213/MWh (WTA) for all conditions with a headline figure of £35,488/MWh. For I&C customers the overall value is about £1,400/MWh obtained using the gross value added (GVA) method. They have derived the load-share weighted average VoLL across domestic and small and medium enterprise users for winter, peak, and weekday as £16,940/MWh. The summary is shown in Table 4-4.

TABLE 4-4 HEADLINE VOLL IN £/MWH [26]

Domestic customers	Small and medium enterprise (SME)	Load-share weighted average across domestic and SME	Industrial and commercial
10,289	35,488	16,940	1,400

4.2.4 IMPACT OF CDF ON NETWORK PLANNING

Models for evaluating customer interruption cost are developed such as (i) the value of interruptions is simply at VoLL, (ii) the valuation of avoided interruptions is represented by a customer damage function such that value depends on the customer type(s) affected and duration of the outage. The Monte Carlo simulation approach described in Chapter 2 is used to assess the cost of interruptions in terms of expected values and distributions.

To understand the implications of CDF on the value of interruptions, different customer damage functions (CDFs) are considered:

- CDF0: Constant value £17,000/MWh (headline value of the VoLL for load-share of residential and small and medium enterprise customers)
- CDF1: Constant value £10,289/MWh (headline value for residential customers)
- CDF2: Constant value £35,488/MWh (headline value for small and medium enterprise customers)
- CDF3: Linearly increasing without capping starting from 0, reaching £54,000/MWh for a duration of 18 hours and continuing further
- CDF4: Linearly increasing without capping starting from 0, reaching £108,000/MWh for a duration of 18 hours and linearly increasing at a slower rate by adding £54,000/MWh for each additional day
- CDF5: Linearly increasing starting from £13,500/MWh, reaching £54,000/MWh for a duration of 18 hours and linearly increasing further without capping.

- CDF6: using 'residential' customer damage function from Table 4-3
- CDF7: using 'commercial' customer damage function from Table 4-3
- CDF8: using 'industrial' customer damage function from Table 4-3
- CDF9: using 'large user' customer damage function from Table 4-3

Figure 4-6 illustrates the curves of customer interruption cost corresponding to CDF0 - CDF5 during the first 24 hours of an interruption. These CDFs have been expressed as VoLL with regard to interruption duration that the y-axis is representing interruption cost per unit unserved energy. It can be seen that CDF0 - CDF2 are constant VoLL for all interruption durations. CDF3 - CDF5 are duration-dependent VoLL and representing three possible trends.

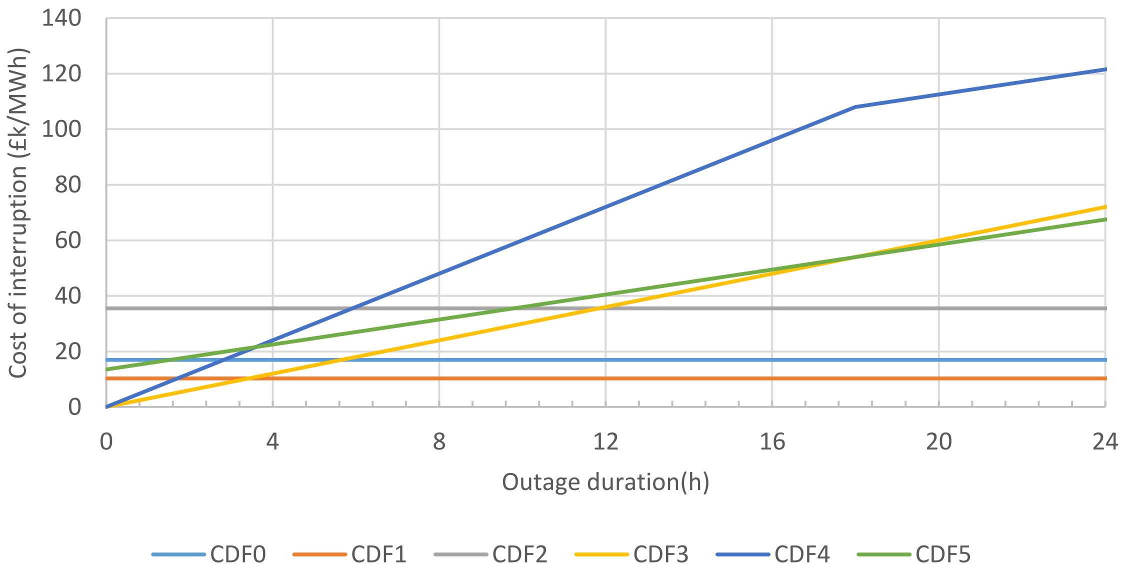


FIGURE 4-6 GENERIC CUSTOMER INTERRUPTION COSTS FOR CONSTANT AND DURATION DEPENDENT VOLL

Customer damage functions for different customer categories presented in [45] and shown in Table 4-3 are used for this analysis as CDF6-9. Different from the Voll, the quantification of CIC using these CDFs does not relate to unserved energy but the duration of interruptions and the peak demand/annual energy consumption of load points. It is worth noting that, the data in Table 4-3 gives values of critical interruption durations. The data for other durations is obtained with linear interpolation between critical durations and linear extrapolation for beyond 24h.

Case studies

In this section, time-sequential Monte Carlo simulation with the implicit switching model introduced in Chapter 2 is applied with the test illustrative network for conducting the evaluation of customer interruption costs using input parameters shown in Table 4-5.

TABLE 4-5 CASE STUDY PARAMETERS FOR CIC EVALUATION, HV LEVEL

Parameters	Values
Failure rate for overhead lines (%/km.year)	8.4
Switching time (minutes)	30
Normal repair time (hours)	120
Restoration time (hours)	24
Section length (km)	1
Peak demand of each load point (kW)	500, 625, 750, 875, 1000
Loading level	N-1, N-0.75, N-5, N-0.25, N-0
Feeder capacity (MVA)	5

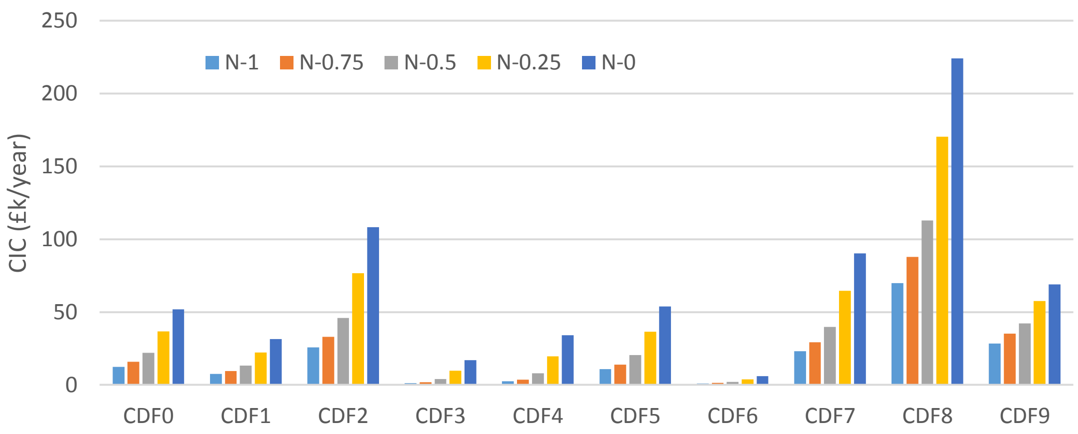


FIGURE 4-7 CUSTOMER INTERRUPTION COST WITH CONSTANT AND OUTAGE DURATION DEPENDENT VOLL, HV LEVEL

Figure 4-7 shows the customer interruption cost calculated using different CDFs. It can be observed that for less network redundancy, customer interruption costs increase with all CDFs due to increased customer disconnection. Costs corresponding to CDF0 to CDF2 (constant VoLL) are increased more than 4 times when redundancy decreases from N-1 to N-0, same as EENS.

CIC corresponding to duration-dependent CDF3 to CDF5 show that for N-1 the interruption costs can be very low since in a sufficient redundancy network interruptions are rare and short. The results for low redundancy become worse but still generally better than that of CDF0 and CDF2. It may be caused by that the durations of interruptions for this particular network are usually shorter than 12h according to Figure 2.2.

Costs corresponding to CDF6 to CDF9 increase as system redundancy decreases even though the cost using these methods is not related to unserved energy. This indicates that the duration of outages is increasing as redundancy decreases for the studied network. The cost to residential customers (using CDF6) is lower than that to commercial, industrial or large users (using CDF7, CDF8 and CDF9, respectively). The cost to commercial sectors is lower than that to larger users for N-1 redundancy but higher for N-0 redundancy which might indicate that commercial customers will be affected more by longer outages than large users. This table provides an insight of implications of different durations on the cost of per unit unserved energy.

Table 4-6 presents the interruption costs corresponding to the different CDFs as a percentage of the costs corresponding to the use of a constant VoLL of £17,000/MWh. This table provides an insight of implications of different durations on the cost of per unit unserved energy.

TABLE 4-6 INTERRUPTION COSTS RELATIVE TO VOLL=£17,000/MWH

Redundancy	CDF0	CDF1	CDF2	CDF3	CDF4	CDF5	CDF6	CDF7	CDF8	CDF9
N-1	100%	61%	209%	10%	20%	87%	8%	186%	565%	229%
N-0.75	100%	61%	209%	11%	22%	88%	9%	186%	556%	222%
N-0.5	100%	61%	209%	18%	36%	93%	10%	181%	514%	192%
N-0.25	100%	61%	209%	27%	54%	100%	11%	176%	463%	157%
N-0	100%	61%	209%	33%	66%	104%	12%	174%	432%	133%

Shown in Table 4-6, the percentages corresponding to CDF0-CDF2 remain constant with the redundancy level given that these CDF are constant with the interruption duration. The percentages corresponding to CDF3 and CDF4 increase about 3 times as the level of redundancy decreases from N-1 to N-0. The percentage for CDF5 increases about 20%, showing a mild growth which is consistent with its flatter trend shown in Figure 2.1.

The percentage value for CDF6, representing residential customers, increases about 50%, while the percentage value for CDF7 to CDF9, representing commercial, industrial and large users respectively, decreases. These results are in line with Table 4-3 that, for residential customers, interruption costs are not as high as other business but sensitive to duration increases. This is because domestic customers are usually not able to change their living style (e.g. cannot put off washing or heating for very long) but other business sectors may be able to rearrange their production schedule to reduce the cost for longer outages.

The selection of CDFs can have a profound impact on the planning solution. Use of conservative CDFs would underestimate the interruption cost to end users and result in a lower optimal degree of redundancy. The impact of the differentiated estimation of customer interruption costs is demonstrated through a simple example on the LV network of Figure 4-8. The planning problem lies in whether to design a system with a reserve cable and selecting the optimal number of feeder sections.

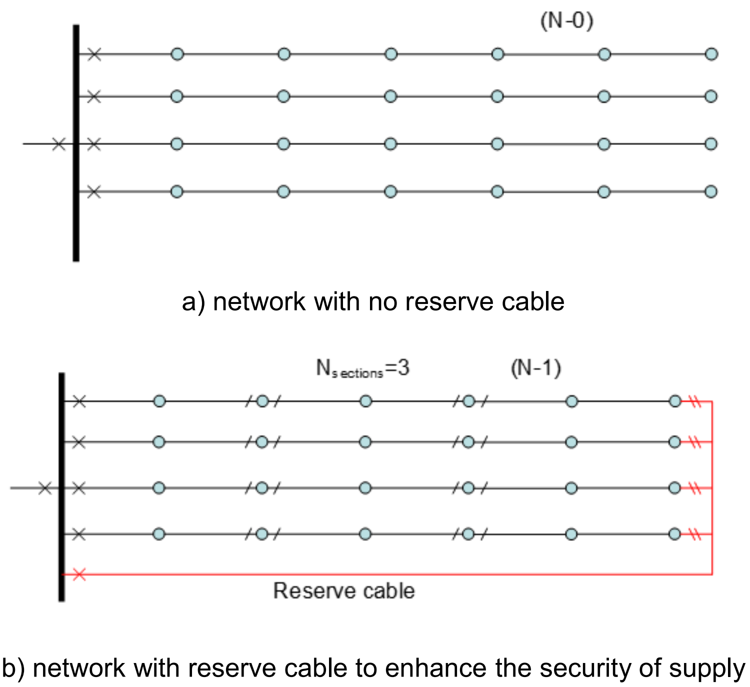


FIGURE 4-8 TEST NETWORK A) WITHOUT AND B) WITH RESERVE CABLE

Test network design a) consists of four radial feeders which do not provide for redundancy in case of a fault while design 2) can provide back-feed to some customers depending on the number of sections on a feeder.

The following two figures compare the planning solutions for two different selections of the VoLL, namely the ones corresponding to CDF6 and CDF0, respectively. In the first case presented in Figure 4-10, the low VoLL reduces the customer interruption costs and as a result, the optimal planning solution lies in not investing in extra reserve cable and switchgears.

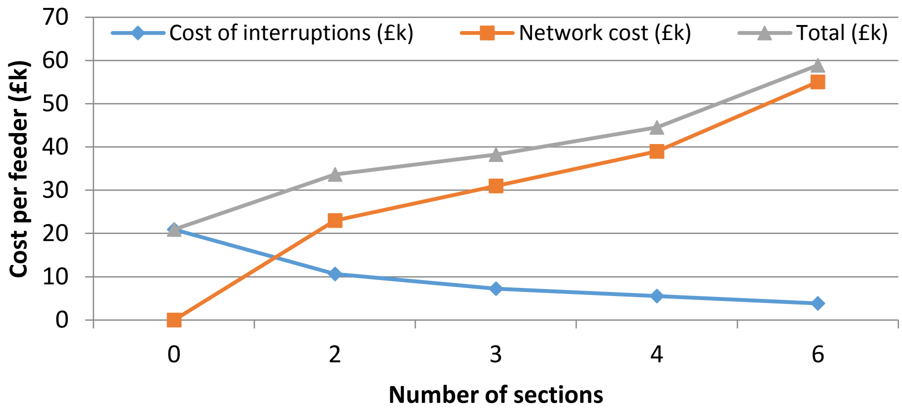


FIGURE 4-9 PLANNING SOLUTION CORRESPONDING TO CDF6

In the second case, shown in Figure 4-10, the relatively higher VoLL increases the customer interruption cost and as a result, the optimal planning solution lies in investing in reserve cable and creating three feeder sections.

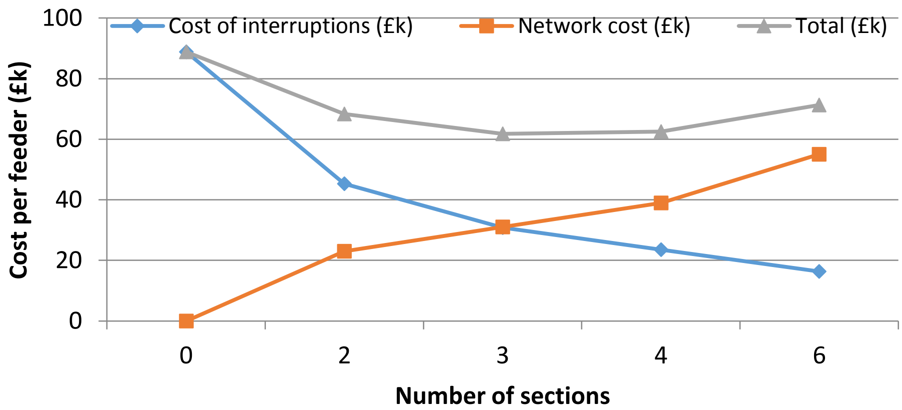


FIGURE 4-10 PLANNING SOLUTION CORRESPONDING TO CDF0

This example indicates that the selection of different interruption cost models (CDFs) can change fundamentally the obtained planning solution.

4.2.5 Conclusions

A large number of studies have employed different approaches to quantify the customer interruption costs (CIC) for different categories of consumers. However, a general consensus on the value of these costs has not been yet reached, as the values proposed by different sources vary significantly. The main reason is that CIC depends on a large number of diverse factors, the cost implications of which cannot be unambiguously quantified even by the consumers themselves. These factors include the activities affected by unsupplied energy, the timing (time of day, day of week, month of year) of the supply interruption, the duration of the supply interruption, the frequency of interruptions and the availability of advance warning before the interruption takes place. This lack of consensus is aggravated by the fact that CIC have been quantified in different currencies and different years in the past, introducing significant difficulties in comparative analysis.

This section has firstly discussed the main methodologies previously employed for the quantification of CIC. Secondly, it has discussed the highlights of a comprehensive literature survey on CIC and VoLL quantification, demonstrating the significant variations and the previously discussed lack of consensus. The main outcomes of the latest relevant study in the UK context, by London Economics, have been discussed and form the core of the customers' supply valuation assumptions adopted throughout this chapter. Furthermore, different modelling approaches to CIC have been presented and discussed, including constant VoLL as well as interruption duration-dependent VoLL in the form of customer damage functions. Case studies have demonstrated that the adopted model and estimate of interruption costs can have a profound impact on the obtained planning solution.

4.3 Reliability assessment for distribution networks considering High Impact Low Probability (HILP) events

4.3.1 Introduction

Traditionally, the reliability parameters used for assessing the reliability performance of electricity networks are based on "average" characteristics derived from historical data. This kind of assessment is typically employed for selecting a set of network designs that meet the reliability criteria. However, exceptional rare events such as extreme weather conditions leading to floods could have an effect on the dynamic reliability parameters. For example, it could increase the failure rates of network components affected by the events and also increase repair times. HILP events, even if anticipated, can lead to significant and prolonged interruptions of supply.

In this context, a set of studies has been carried out with the objective to:

- Assess the consequences of HILP events with different severity, focusing on the impact of extreme weather conditions on the increased failure rate of network components and prolonged restoration system,
- Consider how to include HILP explicitly in network design optimisation through considering robust network operation and design measures, taking into account emergency operation actions such as the provision of emergency supply (mobile generation) to improve the restoration process, and

- Identify the role and quantify the value of emergency operation actions and emergency network development.

4.3.2 Impact of HILP on reliability performance and the use of emergency generation as a mitigation measure

Case studies have been carried out to investigate the impact of a HILP event with different severity on the reliability performance of the system. During a HILP event (e.g. very adverse weather), the failure rate of line sections is increased and the repair time of component is accordingly prolonged. There are 2 HILP failure factors used in the studies: (i) 10 and (ii) 50 (the latter is 5 times more severe than the former). A HILP failure factor of 10 and 50 means that the asset failure rate is 10 times and 50 times higher than the average, respectively. As the HILP events may also prolong the restoration or repair time, the studies also investigate 3 different HILP factors that affect the MTTR: 2, 5 and 10. This means the MTTR during the HILP events will be 2x, 5x or 10x larger than the MTTR in normal operating conditions (24h is used as a reference value). The example is illustrative and should provide insights into the issues that would be important to consider in the context of future network design standards.

The studies also investigate the impact of the availability of emergency supply schemes (mobile generation). Two parameters, i.e. the waiting time for deploying emergency (mobile) generation and the supply rate, are varied. For the waiting time, the values used in the studies are 3 h and 24 h. Typically, the deployment time for mobile emergency generation is about 4.5 h on average, which is within the range of the studies. In terms of the supply rate, the emergency power may not be able to fully supply the load interrupted, therefore two scenarios with supply rate of 25% and 100% of full demand are studied. Depending on the size of the network in outage, the amount of mobile generation which could be deployed might be lower than 25%. In this illustrative example with a total affected region of 5 MW during the peak period, the assumption that 100% of the demand could be picked up by mobile generation is considered reasonable.

HILP events (e.g. gale, flooding and even earthquake) can last for varied time length from 1 day to weeks. In this study, the duration of a HILP event is assumed to be 2 days (nonetheless, sensitivity studies can be produced). It is worth noting that, even an adverse weather condition stops, the impact of the condition on networks may exist longer. To analyse the detailed dynamic characteristics of network reliability performance during a HILP event, a chronological simulation model is developed:

Step 1: Generate the initial state of each system component enforcing that all components are normal. The initial load state is generated by randomly sampling a starting time in a year and selecting the corresponding load level from the load profile.

Step 2: Sample the transition time from the current state to the next possible state for each component using the transition rate in normal condition. The transition time for the load state is obtained by calculating the time to the next half hour boundary.

Step 3: A HILP event starts when the first fault is identified in the network (recorded as T0). The failure rate and repair time for all components are increased by applying HILP factors. The transition time of each component is then resampled with the increased rates.

Step 4: Evaluate load point curtailment for each system state using the proposed implicit switching model as described in this thesis.

Step 5: Sort the list of transition time and find the next transition state, update transition time list using the method introduced in Chapter 2, section 2.4.2.

Step 6: Repeat step 4-5 until the system simulation time exceeds T0+48h (the 48h can vary for sensitivity study). If at t=T0+48h, there exist failures in the network, the simulation will continue until all faults are repaired.

Step 7: Evaluate and record the reliability indices of the system for the HILP event. Repeat the simulation for statistic results.

A set of parameters used in the studies is shown in Table 4-7.

TABLE 4-7 CASE STUDY PARAMETERS

Parameters	Values
Failure rate for overhead lines (%/km.year)	10
Switching time (minutes)	30
Restoration time (hours)	24
Section length (km)	2
Peak demand of each load point (kW)	500
Loading level	N-0
HILP failure factor	10, 50
HILP repair factor	2, 5, 10
Emergency generator preparing time (h)	3, 24
Emergency generator supply rate	25%, 100%
Value of Lost Load (£/MWh)	17,000
HILP event duration (h)	48

The studies have been carried out on a HV distribution network shown in Figure 2-1. The studies assume that each HV section has installed disconnectors on both sides. This allows any single circuit fault to be isolated and supply restored in switching time which reduces the supply interruption. The 11 kV network is designed as a radial network with a normally open circuit breaker (NOP) that connects the two main feeders for back-feeding during contingencies. The part of the network affected by the fault(s) can be isolated by opening the corresponding switchgear and the affected load points can be resupplied by the adjacent branch. At each load point, a distribution transformer is connected.

The studies have been carried out using the year-round load profile with 30-min time resolution.

Results

Time-sequential Monte Carlo method is conducted to model the impact of HILP events on network reliability performances. The results of the studies are presented in Table 4-8.

It is worth noting that, the “event” for EENS/cost is referring to the whole period of a HILP situation lasting for 48h or longer until all faults are repaired. Therefore, here the “event” is not an outage or interruption, it is possible to have multiple faults overlapping but also possible that there is no fault/interruption in the network for a short while.

TABLE 4-8 SYSTEM RELIABILITY AND COST PERFORMANCES UNDER VARIOUS HILP AND PROVISION OF EMERGENCY SUPPLY SCENARIOS

Network Reliability			No HILP	HILP FRx10			HILP FRx50		
HILP MTTR			x1	x2	x5	x10	x2	x5	x10
No emergency supply		EENS (MWh/event)	1.33	3.2	5.1	11.6	15.4	55.2	157.8
		Cost of EENS (k£/event)	22.6	54.4	86.7	197.2	261.8	938.4	2,682.6
25% emergency supply rate	3h	EENS (MWh/event)	1.29	2.5	3.3	7.4	9.8	33.4	111.2
		Cost of EENS (k£/event)	21.9	42.5	56.1	125.8	166.6	567.8	1,890.4
	24h	EENS (MWh/event)	1.33	2.9	4.3	9.2	13.2	39.6	126.5
		Cost of EENS (k£/event)	22.6	49.3	73.1	156.4	224.4	673.2	2,150.5
100% emergency supply rate	3h	EENS (MWh/event)	1.26	1.6	1.8	1.8	3.2	4.7	5.7
		Cost of EENS (k£/event)	21.4	27.2	30.6	30.6	54.4	79.9	96.9
	24h	EENS (MWh/event)	1.32	2.6	3	4.2	11.1	19.2	27.2
		Cost of EENS (k£/event)	22.4	44.2	51	71.4	188.7	326.4	462.4

Table 4-8 shows the results of case studies for distribution network reliability with different HILP factors and emergency supply. Expected Energy Not Supplied (EENS) and cost of ENS are computed to summarise the reliability performance and related cost of HILP events. It can be seen that under normal weather conditions, i.e. no HILP event, the EENS for each failure event is relatively low, in the range between 1.26 MWh (with emergency supply) and 1.33 MWh (without emergency supply). The improvement of EENS due to the emergency supply is relatively modest, i.e. 0.06 MWh or £1.2k cost savings. Marginal improvement of the EENS performance and the small benefit obtained indicate that the emergency supply may not be justified in normal conditions.

When a HILP situation happens, the failure rate of network components increases by 10 or 50 times of the original and repair time is prolonged to 2, 5, 10 times of the original as 2 days, 5 days, 10 days (as high impact may cause significant damage to overhead lines that would require long repair times). If no emergency supply is available, the system EENS can be as high as 157.8 MWh/event and the corresponding cost is £2.68m/event for a case with the HILP failure factor of 50 and the repair factor of 10. The system EENS increases when the failure rate goes up and repair time increases. If emergency supply is available in the HILP event, the system EENS can be significantly reduced. For example, for a case with the HILP failure factor of 10 and the repair factor of 2, the EENS in a case with no emergency supply is 3.2 MWh and with the emergency supply, it can be reduced down to 1.6 MWh, i.e. a reduction of 50%. The improvement is considerably higher for a severe HILP event. For a case with the HILP failure factor of 50 and the repair factor of 10, the EENS with emergency supply is down to 5.7MWh which is merely 4% of the original 157.8 MWh, saving £2.58m for reducing the duration of supply interruptions. Considerable improvement of the EENS performance and the savings obtained indicate that the emergency supply is an effective method to mitigate the impact of HILP situations.

In order to show more clearly the impact of HILP with different severity, the reliability performances of the system for cases with HILP failure factor of 10 and 50 are compared in Figure 4-11.

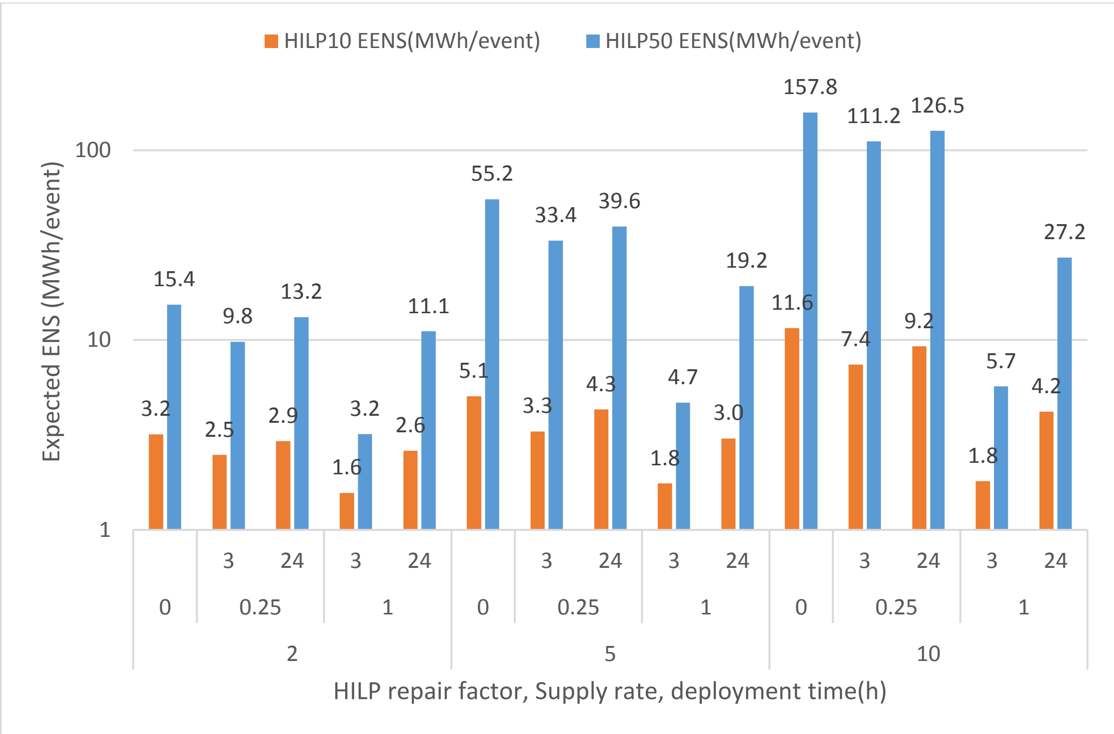


FIGURE 4-11 RELIABILITY PERFORMANCES OF THE SYSTEM FOR HILP CASES CONSIDERED IN THE STUDIES

The results demonstrate that higher EENS would be associated with more severe HILP situation, longer repair time, lower supply rate and longer deployment time of mobile generation. Improvement of the EENS can be made by shortening the deployment time of the emergency generation and increasing the supply rate.

Figure 4-12 shows the cost of EENS using VoLL of £17,000/MWh for cases with HILP failure factor of 10 and 50. When there is no emergency supply, the costs of EENS vary between £54.2k and £2683k in different conditions. If the emergency generation is available, the cost savings in the case with the HILP failure factor of 10, the repair factor of 2, 25% supply rate and 24h deployment time are relatively low, i.e. £4.3k (£54.2k-£49.9k). This savings increase to £2.586m (£2683k-£96.9k) in the case where the HILP failure factor is 50, the repair factor is 10, with 100% supply rate and 3h waiting time.

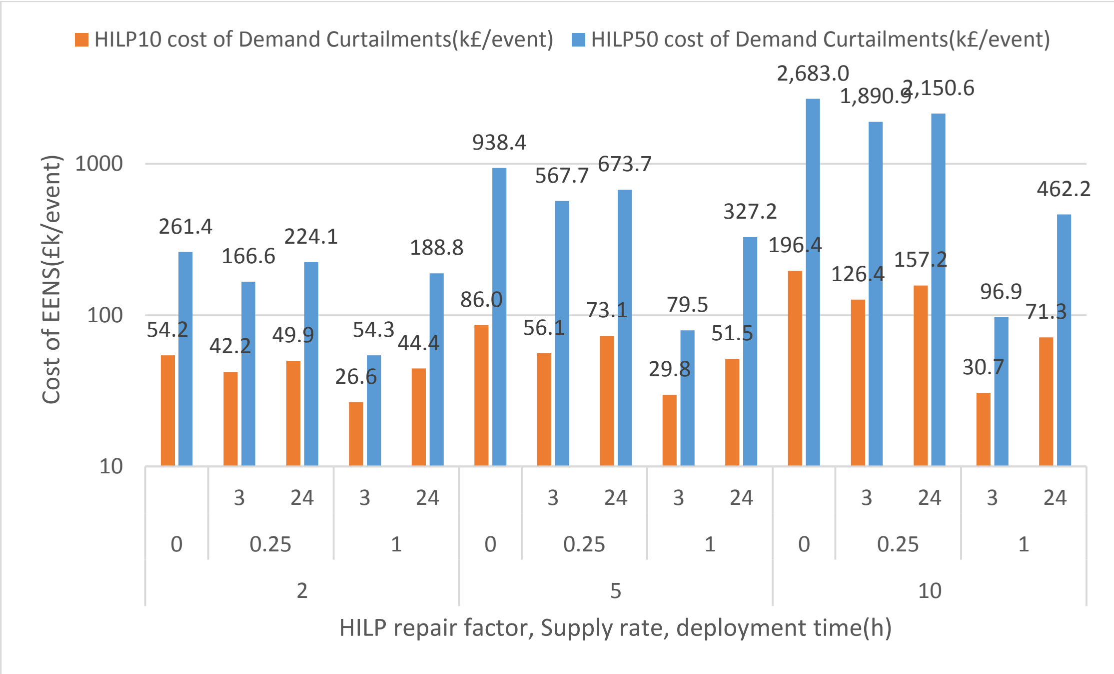


FIGURE 4-12 COST OF EENS FOR HILP CASES CONSIDERED IN THE STUDIES

This kind of analysis can also be used to inform the development of alternative actions for improving the resilience of the system, for example, by transforming the overhead network which is prone to extreme weather conditions to an underground network. Considering the cost per km for replacing overhead lines with underground cables is £110k/km, the cost of transforming the test network is 22km*£110k/km=£2.42m. From the above study, during a HILP event (e.g. a storm), the expected interruption cost can be as high as £2.682m. In that case, the loss incurred in a HILP event can justify the cost of transforming the network. As an alternative, the provision of emergency mobile generators, especially when these can be deployed fast, could improve considerably the reliability performance of the system affected by a HILP event and reduce the associated cost of EENS.

In order to get more insight on the impact of improving the deployment time of Figure 4-13 shows the distribution function of ENS for different deployment times of emergency generation, i.e. 3, 6, 12 and 24 h in cases with HILP repair factor of 2 and HILP failure factor of 50.

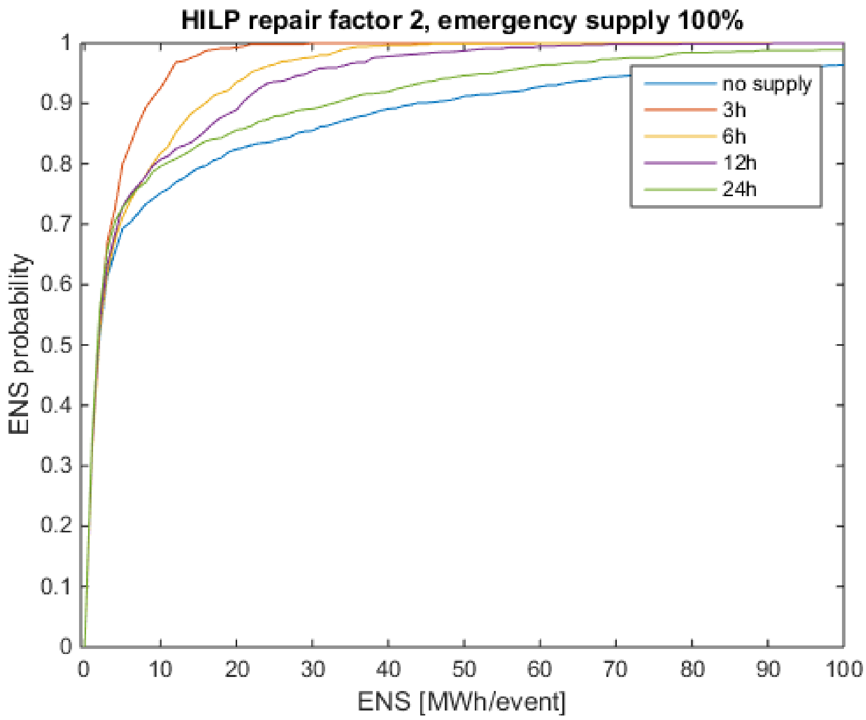


FIGURE 4-13 CUMULATIVE PROBABILITY DISTRIBUTION OF ENS FOR HILP EVENTS

The analysis demonstrates that decreasing deployment time of emergency generation would significantly reduce the probability of high levels of ENS. For example, there is 90% chance that the ENS due to the HILP event is smaller than 10 MWh, 17 MWh, 19 MWh, 22 MWh, 35 MWh, 56 MWh for cases with an emergency generation deployment time of 3h, 6h, 12h, 24h and no emergency generation, respectively.

4.3.3 Conclusions

This study modelled the impact of HILP events. The reliability performance of a test distribution network has been evaluated through time-sequential Monte Carlo simulation. Impacts of HILP events with different severity levels have been studied considering the contribution of an emergency generation with different supply rate and preparation time as mitigation measures. The results demonstrate that severe HILP events can lead to the significant cost of lost load which may justify development of a more resilient network (transformation to UG network), supported by the provision of fast and high capacity emergency generation, especially during very severe events.

Chapter 5 Generation System Adequacy Performance Assessment

Abstract

In this chapter, the chronological Monte Carlo model was used to analyse GB electricity system. It is aimed to investigate a simplified GB system with reliability performance at the level of the GB Reliability Standard, i.e. LOLE=3h/year, to evaluate the system characteristics such as the frequency and duration and magnitude of the shortfall in energy and power, as well as the variability around expected indices. System risks are analysed for different yearly demand profiles, generator properties, system margins, balancing services under the OFGEM reliability standard. The effect of the recent years' reduction in demand due to the increase in renewable (mainly wind) generation is also analysed and compared.

This work was cooperated with the Department of Energy and Climate Change (DECC).

5.1 INTRODUCTION

Generation adequacy is the ability of a system with installed generators to meet electricity demand. A power system is expected to be built adequately that sufficient generation capacity can meet the load consumption considering demand fluctuation and expansion, weather changing, generator planned and unplanned outages, and other possible unexpected issues in a long term time span. Building a system with absolutely sufficient capacity, which always meets the demand, is senseless in terms of the investment cost, whilst a system with insufficient capacity will lead to frequent blackouts which interrupt industrial production and domestic needs. Therefore, it is important to determine the suitably installed capacity that will give an acceptable system reliability performance while considering the cost of construction and operation.

The assessment of generation adequacy enables the evaluation of performances for alternative system planning for specific customer demand and requirements, which is essential for planners in the decision of building sufficient generation capacity when various investments are available.

The determination criterion of generation adequacy was firstly proposed in terms of a percentage reserve. A system is considered to be adequate if the installed capacity margin, the excess of total installed generation over the peak demand, meets or exceeds a given level of a percentage of the peak demand.

In the UK, the similar concept used in National Grid capacity assessment is the de-rated margin. Instead of the total installed generation, the de-rated margin is the average excess of the available generation over peak demand [98].

This criterion is simple to understand and straightforward to apply in system capacity planning and assessment. However, the methodology is deterministic and it ignores the various characteristics of the system in two aspects: 1. only the peak demand is used that it ignores the differences in demand profiles with the same peak demand; 2. Considering only the total installed generation ignores the generator properties including the availability, size, type, repair time and etc. For the same installed generation, the effective capacity and its corresponding reliability performance can vary significantly.

Another generation adequacy performance indicator, applied in National Grid capacity assessment, sometimes referred to as the risks to the security of supply, is the Loss of Load Expectation (LOLE). This index reflects the expected number of hours per year a system is insufficient in power supply. This insufficient status means that the sum of all available generators' output is lower than the system demand for the moment. In industry, this index is usually under the context that system intervention actions are not applied by the system operator. While in academia, LOLE can also be computed for comparing the impact of various intervention actions on system performances.

In the UK, the government has set the level of generation adequacy for the Great Britain (GB) electricity system referred to as the Reliability Standard [27], which sets a 3 hour/year LOLE as an acceptable/target reliability level for the GB system. Expectation values of risks to the security of supply are straightforward in understanding system reliability performances. However, a single value of LOLE ignoring the variability of the index can be very limited to represent the whole system reliability. The LOLE is the average time length of capacity shortage which, by definition, excludes the property of shortage event frequency. For instance, a 3 hour/year LOLE system can result from an average of three 1-hour outages in a year or six half-a-hour outages in a year. The frequency and duration of system outage are not recognised within LOLE. The LOLE in different years can also vary significantly in a real system. It can be 3 h/year for all single years, but also possible to have many very reliable years (LOLE is near 0 hour/year) and some very serious (LOLE is much higher than 3h). A single expectation value cannot reflect these variations, thus may eventually lead to inferior system planning.

For reliability indices quantification, the analytical methods which enumerate all system states with their probabilities and the corresponding impact of the state has been well applied in power system planning. Through analytical methods, only expectation values of reliability performances can be obtained. Monte Carlo simulation is a method via stochastic sampling to analyse system performance. Using this method, probability distributions of indices can also be achieved in addition to expectation values. Furthermore, the sequential Monte Carlo simulation, which simulates the chronological behaviours of system components including generators and demand, is naturally suitable to estimate the frequency and duration of system outages. Thus, the system status in real time can be thoroughly assessed and other reliability properties evaluated.

In this chapter, we use the chronological Monte Carlo model to analyse GB electricity system. We aim to investigate a simplified GB system with reliability performance at the level of the GB Reliability Standard, i.e. LOLE=3h/year, evaluate the system characteristics such as the frequency and duration and magnitude of the shortfall in energy and power, as well as the variability around expected indices. System risks are analysed for different yearly demand profiles, generator properties, system margins, balancing services under the same reliability standard. The effect of the recent years' demand reduction due to the increase in renewable (mainly wind) generation in distribution systems is also analysed and compared.

5.2 METHODOLOGY

5.2.1 GENERATION MODEL

To assess the reliability performance of a power system and investigate its behaviours as a function of time, the available generation needs to be simulated chronologically.

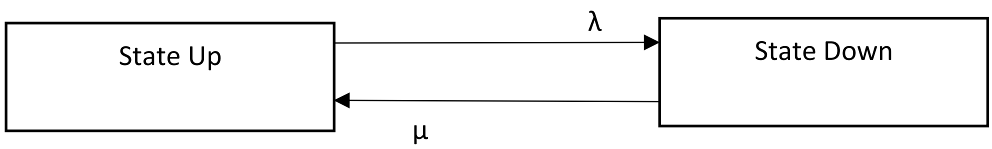


FIGURE 5-1 TWO-STATE MARKOV MODEL FOR CONVENTIONAL GENERATOR

The operations of conventional generators are modelled as a two-state Markov process, i.e. up and down.

The failure rate of a generator, λ, represents the average rate of outage per year for a generator to occur. $\lambda = 1/m$, where m is the mean time for generator to stay in the up state.

The repair rate of a generator, μ, reflects the rate of a generator being repaired from failure state. The mean time to repair (MTTR) is the expected time required for repairing a generator, usually using hour as the unit, which is more common in the industry to represent μ that $\mu = 1/r$, r is MTTR.

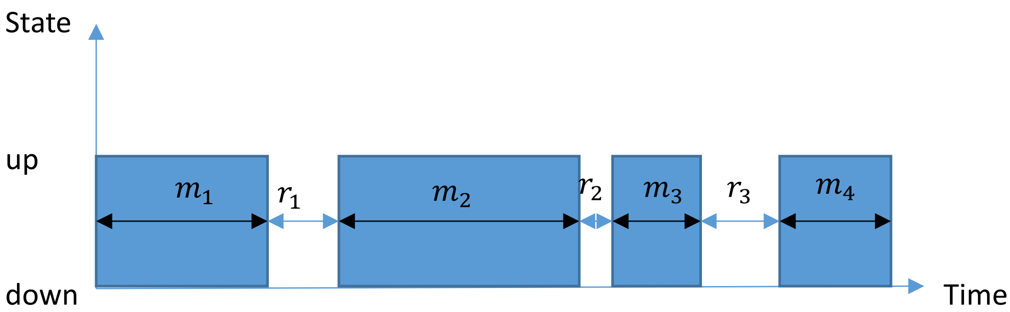


FIGURE 5-2 STATE TRANSITION OF A GENERATOR AS A FUNCTION OF TIME

The state transition of generators is modelled as Markov process and it is found in [32] that the failures can be reasonably modelled exponentially distributed. Although [32] also pointed out that repair times may not be always conforming to exponential distribution. For simplicity and the relatively small impact from using exponential distribution, in this thesis, we assume all generator failures and repairs are exponentially distributed.

5.2.2 LOAD MODEL

With sequential Monte Carlo simulation, system behaviours in real time are enabled to be simulated. Rather than using load duration curve, which provides only the demand levels and their corresponding probabilities, chronological demand profile has been applied in this study. The demand in this chapter is firstly using the normalised yearly demand profile of IEEE Reliability Test System [99] as a typical system demand model. The hourly demand profile is scaled to a desired peak demand level.

In the second part, National Grid Company historical demand data for the year 1995-2011 is exploited for investigating the yearly difference in reliability performance. This demand profile, excluding demand by pumped storage plants but including losses, has been scaled to a common level of underlying demand in each year, currently 331 TWh. The scaling is in proportion to the weather–adjusted TWh demand for that year, conforming to average cold spell (ACS) conditions. This should preserve day-to-day variations from weather and chance events. There has been no attempt to correct for changes in the mix of demand over time (e.g. de-industrialisation).

A sharp drop of about 6 GW in ACS peak demand has been found between winter 2005/06 and winter 2014/15 seen from NGC transmission network [100]. The reduction in demand is believed to be mainly from the contribution of fast growing embedded generation and rising demand response services in distribution networks. In this study wind generation was used to represent the embedded capacity from distribution networks. Wind factors are derived from the Virtual Wind Turbine Model [101]. The wind capacity in the model is a mix of existing and planned turbines, onshore, offshore and Round 3 sites [102]. The mix represents National Grid’s Gone Green Scenario, with 13.7 GW onshore and 12.6 GW offshore. The wind output is derived as a continuous hourly profile for years from 1995 to 2011, corresponding to the NGC load profile. The impact of the wind on the whole system security of supply is then analysed.

5.2.3 RELIABILITY INDICES

- Loss of Load Expectation (LOLE)

$$LOLE = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N_i} lold_{i,k}}{N} \tag{5.1}$$

Where N is the total number of simulation years, i is the index of simulation year, N_i is the total number of system states in simulation year i, k is the index of system state in year i. $lold_{i,k}$ is the loss of load duration for the kth system state in ith year, if the total generation in the state is lower than load level, then $lold_{i,k} = t_{i,k}$, $t_{i,k}$ is the duration of that system state, otherwise 0.

$$LOLD_i = \sum_{k=1}^{N_i} lold_{i,k} \tag{5.2}$$

$LOLD_i$ is the total interruption duration for ith year.

- Energy Not Supplied (ENS) per year

$$ENS = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N_i} pns_{i,k} * t_{i,k}}{N} \tag{5.3}$$

$pns_{i,k}$ is the power curtailed for the kth system state in ith year. If the total generation in the state is higher or equal to load level, then $pns_{i,k} = 0$.

- Loss of Load Frequency (LOLF)

$$LOLF = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N_i} llo_{i,k}}{N} \tag{5.4}$$

$llo_{i,k}$ is the loss of load occurrence for the kth system state in ith year, if the total generation in the state is lower than load level for the state, and in $(k-1)th$ system state the total generation is higher or equal to load level so the corresponding state, then $llo_{i,k} = 1$, otherwise 0.

- Outage Duration

$$Outage\ Duration = \frac{\sum_{m=1}^{N_{outage}} d_m}{N_{outage}} \tag{5.5}$$

Where N_{outage} is the total number of simulated outage events, m is the index of outage, d_m is the time length of the mth simulated outage. In a chronological simulation, a simulated outage event represents a set of adjacent system states in all of which total generation is lower than demand level for their corresponding state. d_m is the sum of durations of all these system states.

- Energy Not Supplied (ENS) per event

$$ENS\ per\ event = \frac{\sum_{m=1}^{N_{outage}} ens_m}{N_{outage}} \tag{5.6}$$

ens_m is the energy not supplied in the mth simulated outage. ens_m is the sum of energy curtailed in all system states in the outage event.

- Power Not Supplied (PNS) per event

$$PNS\ per\ event = \frac{\sum_{m=1}^{N_{outage}} pns_m}{N_{outage}} \tag{5.7}$$

pns_m is the power not supplied of the mth simulated outage. Since an outage event could contain multiple system states, the value of pns_m is obtained by choosing the highest power not supplied in all these states.

5.3 IMPLEMENTATION

In this chapter, the chronological Monte Carlo model was used to analyse a generalised GB electricity system. A case study was firstly analysed to investigate the system performance of a generic power system. As a world widely well-known system in academia, the IEEE-RTS load profile was used as a reference system. Following that the study was extended to explore the reliability properties for GB system with the load profile data from National Grid Company. We aimed to investigate a typical GB system with reliability performance at the level of the GB Reliability Standard, i.e. LOLE=3h/year, to evaluate the system characteristics such as the frequency and duration and magnitude of the shortfall in energy and power, as well as the variability around expected indices. System risks were analysed for different yearly demand profiles, generator properties, system margins, balancing services under the same reliability standard. The effect of the recent years' reduction in demand due to the increase in renewable (e.g. wind) generation was also analysed and compared.

5.3.1 CASE STUDY 1: GENERATION ADEQUACY WITH ONE-YEAR DEMAND PROFILE

5.3.1.1 ORIGINAL BASE CASE SYSTEM

Assumptions for a UK power system are given as:

- Generators are standardised as 500MW unit
- Generator availability is 85%
- Generator MTTR as 100h
- Yearly peak demand is 50GW

- System target LOLE as 3 hour/year

In reality, generator parameters vary significantly for different individual generation plant. To investigate the generation reliability performance of UK power system, in this section, the studied system was simplified to be comprised of identical generators.

The standardised generation was obtained from [103] that Combined Cycle Gas Turbine (CCGT) plants, which are the majority of the Capacity Agreements provisionally awarded in the UK, are averagely 473MW per unit. The average generator size for nuclear is 492MW and 318MW for coal/biomass plants. Therefore, 500MW was chosen as the generator capacity size in this study and 300MW was also investigated in sensitivity studies.

The chosen generator availability relies on the data from OFGEM report [100] which provides the generator availability achieved in the UK is from 82% to 89%. Thus, 85% has been used for the base system and 90% in sensitivity analysis.

From [104], a technical assessment report for UK conventional generator including coal and gas fired plants, the average mothball timescale is given for CCGT and coal as 2 days and 4 days, respectively. According to this data, 100h generator mean repair time (MTTR) was chosen for the base system and 50h was used in sensitivity studies.

With generator availability and MTTR, the failure and repair rate can be obtained using the following formula:

$$availability = \frac{\mu}{\lambda + \mu} = \frac{\frac{1}{MTTR}}{\lambda + \frac{1}{MTTR}} \tag{5.10}$$

Therefore, the generator failure and repair rate can be derived as

$$\lambda = 15.45\ occ/year \tag{5.11}$$

$$\mu = 87.6occ/year \tag{5.12}$$

In this section, a normalised IEEE RTS hourly load profile with 8760 values is used to represent a year. It is shown in Figure 5-3.

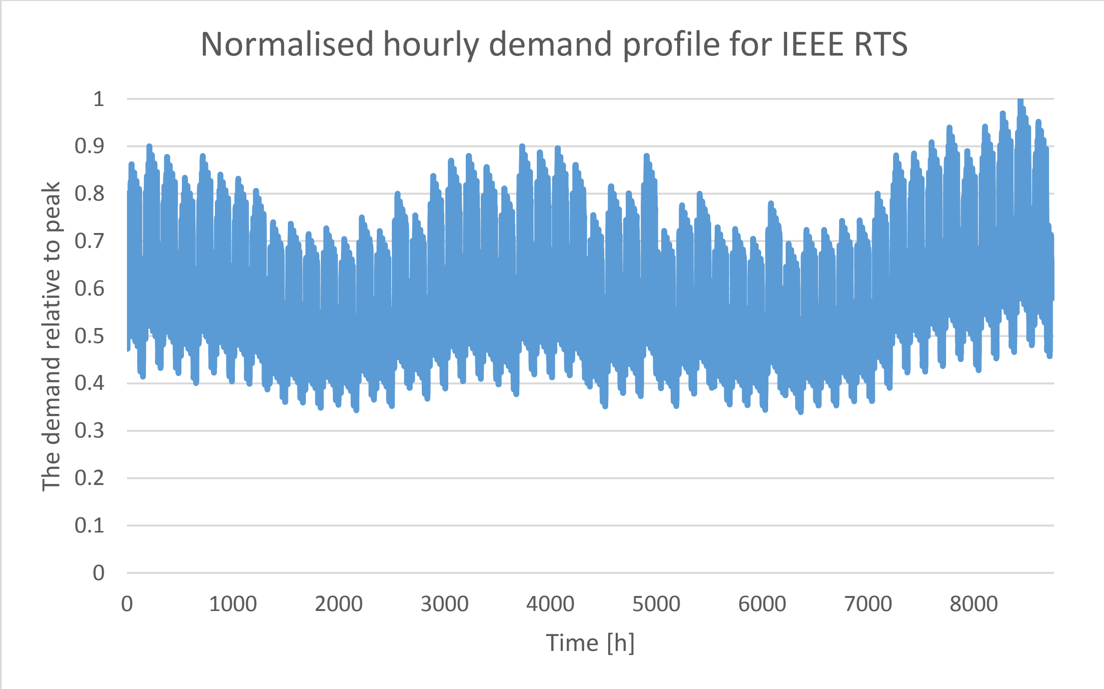


FIGURE 5-3 HALF-HOURLY LOAD PROFILE FOR A YEAR, NORMALISED [99]

The available generation in this system is assumed independent from the demand. In Table 1, the installed generation is determined by adjusting the number of generators in the system to achieve a nearest LOLE value to 3h per year. Other than only LOLE, the yearly ENS and interruption frequency are obtained in this table. In all simulation time, the average duration, ENS and PNS of outage/shortage events are also computed. The system is simulated with the coefficient of variation as 1%.

TABLE 5-1 THE ADEQUACY INDICES FOR THE GENERALISED GB POWER SYSTEM

Installed Generation [GW]	LOLE [h/year]	ENS [GWh/year]	LOLF [occ/year]	Duration [h/event]	ENS [MWh/event]	PNS [MW/event]
60.5	3.11	2.87	2.85	1.09	1008.0	928.9

Apart from expectation values, the probability distribution of system adequacy indices is estimated by the sequential MSC. To aid interpretation, results are shown in histograms depicting the expected number of occurrence in 100 years. It is worth noting that, bar with x-axis value as 0 representing indices equal to 0. Bars with x-axis value as N (N is not 0) representing indices larger than N-1 and equal or smaller than N. For example, the bar $LOLD = 1h/year$ represents $LOLD \in (0, 1]\ h/year$.

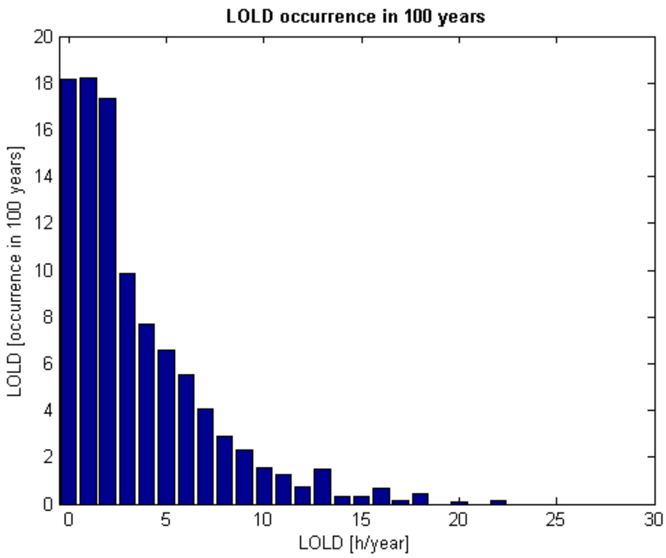


FIGURE 5-4 LOLD PER YEAR OCCURRENCE DISTRIBUTION IN 100 YEARS

From Figure 4, it can be seen that even LOLE is 3h/year, in 100 years there are still 18 years the LOLD is actually 0 meaning that no outage happens in these years. Similarly, there are very high occurrences for LOLD less than 2h/year. However, for a system conforms to the target Reliability Standard, there are still inevitable occurrences of very serious reliability performances. LOLD per year can be above 20h from this graph which means that the average 3h LOLE system cannot prevent very long yearly shortage in a single year.

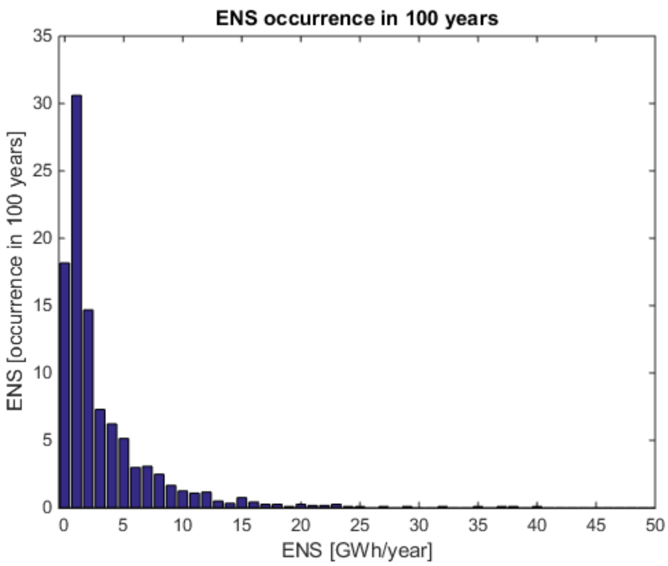


FIGURE 5-5 ENS PER YEAR OCCURRENCE DISTRIBUTION IN 100 YEARS

Figure 5 shows the occurrence distribution of ENS. ENS equals or smaller than 1 GWh/year (excluding 0) happens 31 times in 100 years, approximately once in 3 years. The occurrence of yearly ENS is then decreasing for higher ENS.

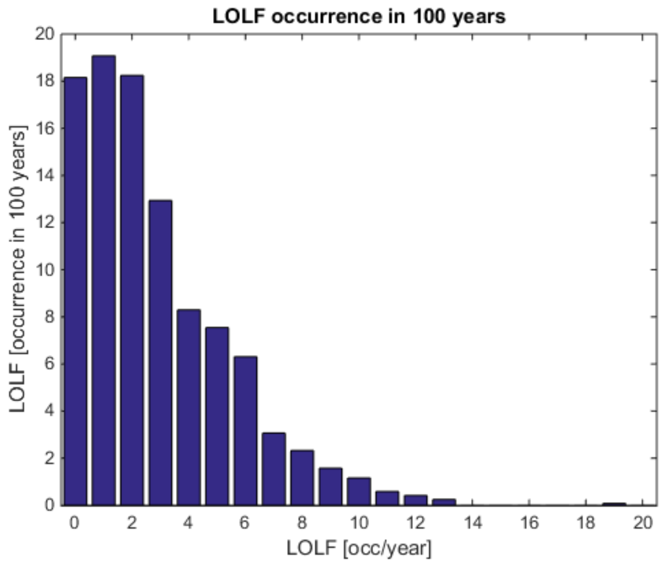


FIGURE 5-6 LOLF OCCURRENCE DISTRIBUTION IN 100 YEARS

In Figure 6, yearly LOLF distribution shows a similar trend as LOLD. The same occurrence of 0 outage as 18 times in 100 years. The most possible frequency of outage is once in a year. Still, a number of outages up to 19 in a year was observed in simulations.

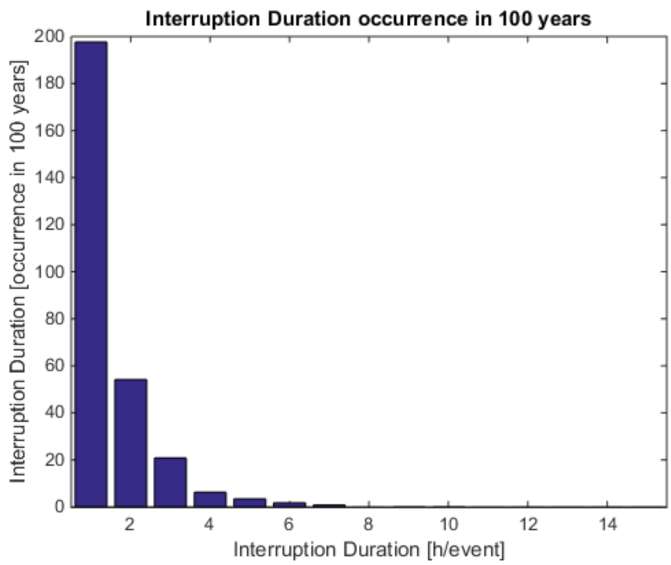


FIGURE 5-7 INTERRUPTION DURATION OCCURRENCE DISTRIBUTION IN 100 YEARS

From Figure 7, the indices are for per event rather than per year. The occurrence of a 1-hour interruption in 100 years is around 200 means on average 2 interruptions lasting for 1 hour are expected in a simulation year. From the same graph, it can be found that except for 1-hour shortages, the number of a longer shortage is less than 1 in a year.

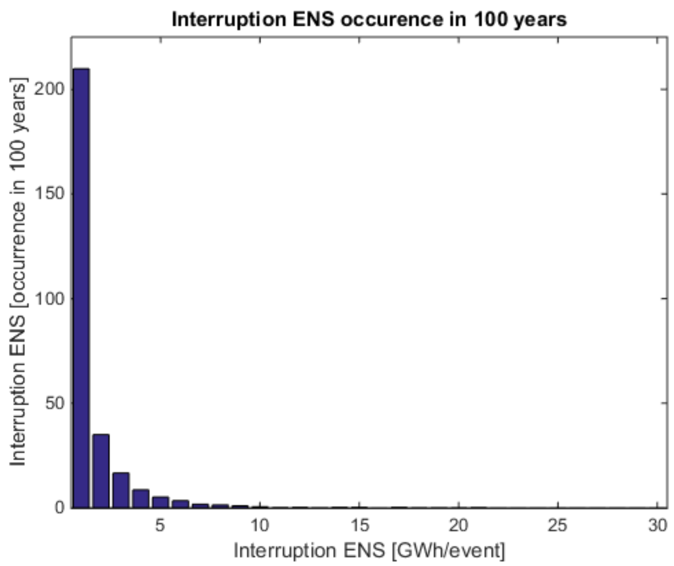


FIGURE 5-8 INTERRUPTION ENS PER EVENT OCCURRENCE DISTRIBUTION IN 100 YEARS

Similarly, the occurrence of 1GWh/year ENS event is slightly higher than 200 in 100 years. The occurrence of larger ENS events slides down dramatically. A shortage event with ENS as 10GWh is approximately the total consumption of 2500 UK households in a year or that of 21.9 million UK households for an hour on average.

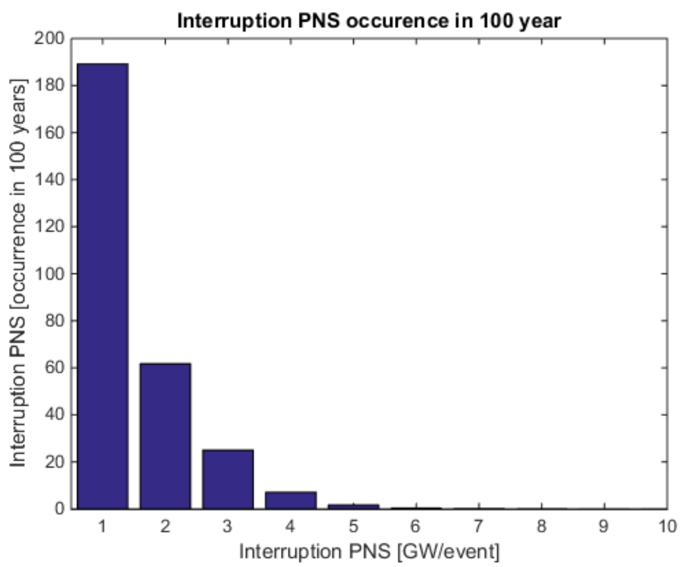


FIGURE 5-9 INTERRUPTION PNS PER EVENT OCCURRENCE DISTRIBUTION IN 100 YEARS

The PNS occurrence distribution shows that most of the interruption event has a PNS less than 6 GW/event. In other words, the studied system can avoid almost all interruptions if a 6 GW capacity is standing by for all time.

5.3.1.2 Sensitivity to different LOLE levels

Even though the target UK reliability standard is set as 3h/year for LOLE, this value can be questioned may not guarantee a suitable level of security of supply. In power systems, system operators can apply balancing services during a system shortage to prevent a real blackout to customers. It is, therefore, essential to investigate the occurrence of extreme events when customer disconnection would have to happen.

In this section, 5 systems with different LOLE levels are assessed to find out how much impact can be on reliability performances for extreme events. The reliability indicator is shown as the likelihood of controlled disconnections in the metric format of 1 in n years [100].

Table 5-2 Probability of occurrence in a generic GB system meeting different reliability standards

	Probability of occurrence in a generic GB system meeting a reliability standard of:				
Event	6.9 h/year LOLE	4.6 h/year LOLE	3.0 h/year LOLE	1.3 h/year LOLE	0.8 h/year LOLE
LOLD > 10h/year	4	6	1 in 12 years	39	75
>10GWh energy unserved in one year	4	7	1 in 13 years	38	70
2 or more power shortages in one year	2	3	1 in 4 years	11	19
Interruption lasting >10 hrs	11	17	1 in 30 years	79	135
Interruption of >10GWh unserved energy per event	5	9	1 in 16 years	44	75
Interruption of >4GW power not served	12	20	1 in 35 years	102	182

Table 5-2 summarises results across 5 systems which meet increasingly stringent reliability standard from left to right. The central case shows the probability of occurrence in 100 years of a number of "extreme events" in a system meeting the current GB 3 hours LOLE reliability standard.

With less stringent reliability standard (i.e. a smaller number of hours' shortage), there is less installed capacity required, and therefore the occurrence of unserved energy events increases.

While a more stringent reliability standard does reduce the probability of consumer interruptions, it does not completely insure against unserved energy.

Results show that in all systems, regardless of the target LOLE, some risk of unserved energy will exist. This is due to the probability of plants being unavailable at the same time from planned and unplanned outages.

However, unserved energy events do not necessarily lead to consumer disconnections. In reality, the System Operator is able to call on a number of "balancing services" to avoid resorting to consumer disconnections.

5.3.1.3 Effects of balancing service

There are three types of balancing services the system operator (SO) can use to prevent consumer disconnections: voltage reduction, max gen service and Emergency Assistance from interconnectors [27].

Table 5-3 summarises results presented across 3 systems which meets a reliability standard of 3 hrs LOLE, where the SO has access to (a) no balancing services, (b) 1 GW or (c) 2 GW of balancing services (a realistic assumption given Grid's current tools; however, procurement volume for balancing service is decided by National Grid and DECC and can be higher in other cases).

TABLE 5-3 PROBABILITY OF OCCURRENCE IN A 3H/YEAR LOLE SYSTEM

	Probability of occurrence in a 3hrs LOLE system with		
Event	No balancing services	1 GW of balancing services	2 GW of balancing services
Yearly LOLD > 10hrs	1 in 12 years	1 in 53	1 in 267
>10GWh energy unserved in one year	1 in 13	1 in 51	1 in 226
2 or more power shortages in one year	1 in 4	1 in 14	1 in 67
Interruption lasting >10 hrs	1 in 30	1 in 97	1 in 361
Interruption of >10GWh unserved energy per event	1 in 16	1 in 57	1 in 236
Interruption of >4GW power not served	1 in 35	1 in 151	1 in 840

Overall, results show that the existence of balancing services significantly reduces the risk of consumer disconnections. With 2GW of balancing services available, the probability of occurrence of extreme consumer interruptions is very low in a generic 3 hours LOLE system, as they could occur less than once in 226 years in all categories.

Therefore, the analysis shows that there is a relatively low level risk of consumer interruptions given a 3 hours LOLE system where the SO has access to balancing services.

5.3.1.4 Sensitivity to generator and peak demand variations

In the original base case system, 100h MTTR, 500MW unit size, 85% availability and 50GW peak demand are chosen for a generic UK power system. In reality, generator parameters can vary considerably as well as peak demand changes in different years. These parameters may affect the whole system reliability performance even under the same LOLE standard.

- Generator average repair time sensitivity

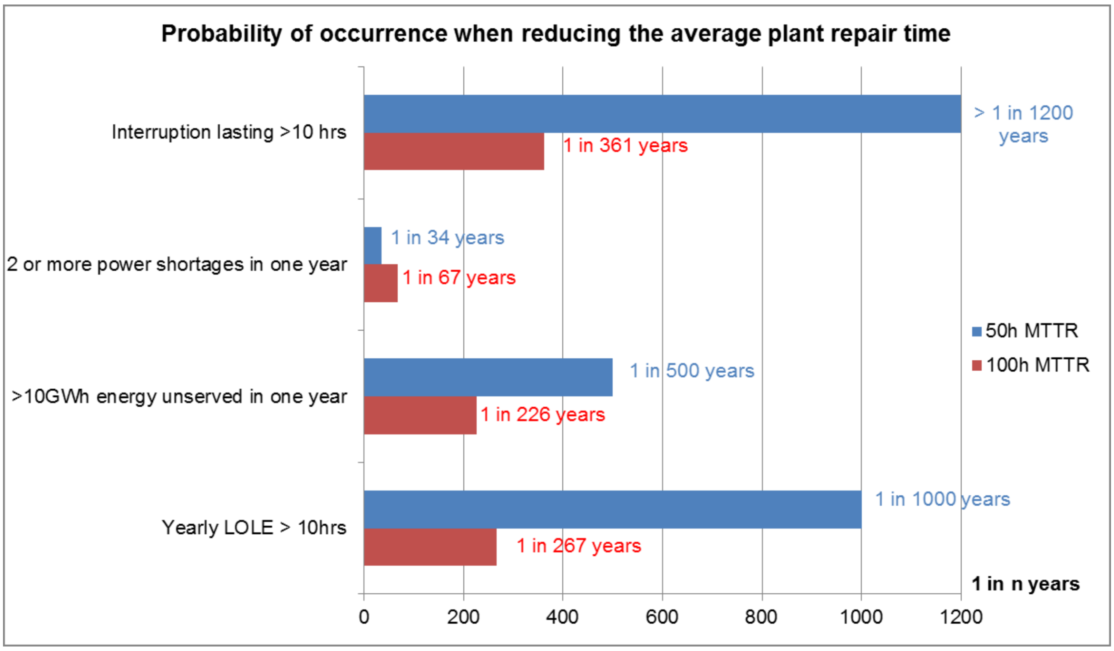


FIGURE 5-10 PROBABILITY OF OCCURRENCE WITH MTTR AS 50H AND 100H

In Figure 10, when changing the assumed plants' Mean Time To Repair (MTTR) from the original 100 hours down to 50 hours, the same LOLE level can be achieved on average (with the same overall plant availability of 85%), however, the probability of most extreme events becomes even lower.

For example, the probability of large LOLE materialising in a given year (e.g. probability of a LOLE exceeding 10 hours) changes from 1 in 267 with 100 hours MTTR, to 1 in 1000 with 50 hours MTTR. While it increases the frequency of interruptions, reducing the mean repair times of plant also reduces the average length of a given interruption.

Indeed, with reduced repair time, plants fail more often, but come back online more rapidly as well. This results in a reduced average amount of unserved energy in a given year, i.e. the probability that we get >10Gwh of energy unserved in one year changes from 1 in 226 years to 1 in 500 years.

Results of sensitivity analysis show that these conclusions are robust to changing assumptions about plant repair times.

- Generator size sensitivity

Similarly, a sensitivity analysis was also conducted on the assumed size of plants on the system and the results shown in Figure 11. Moving from the central assumptions of a generic 500MW plant size to 300 MW units also changes the risks of the consumer disconnections for a given 3 hours LOLE target, as the expected average frequency, duration and size of interruptions changes.

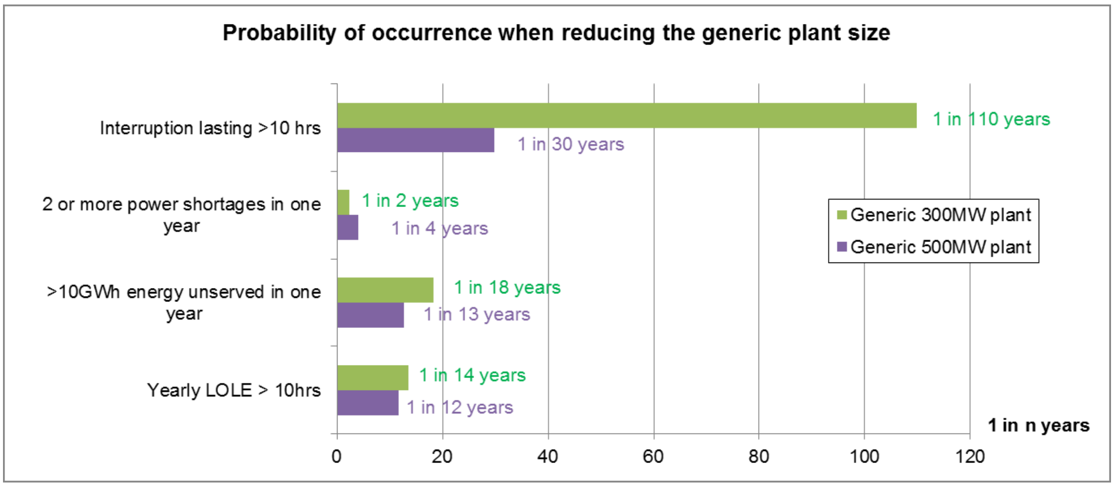


FIGURE 5-11 PROBABILITY OF OCCURRENCE WITH PLANT SIZE AS 300MW AND 500MW

With smaller plants on the system, a 3 hours LOLE target on average is associated with more frequent but smaller and shorter interruptions. The probability of large unserved energy amounts within one year is decreased since smaller plants mean more frequent failures (larger in number of generators), but if independent from each other, less capacity gets disconnected at a single time, reducing the depth of interruptions.

This is an interesting finding, as these suggest that with large units on the system (e.g. large nuclear), while the occurrence of power shortages would be less frequent, each interruption could be more damaging to consumers.

- Sensitivity to peak demand

Figure 12 shows the expectation values of system adequacy indices for a system with the same load profile but different peak demand. The number of generators is adjusted to achieve the nearest possible LOLE to 3h/year. It can be found a slightly higher LOLE (less than 10%) with the 60GW system. For that, we expect these two systems have very similar performance while the 60GW may be slightly less reliable in terms of LOLE.

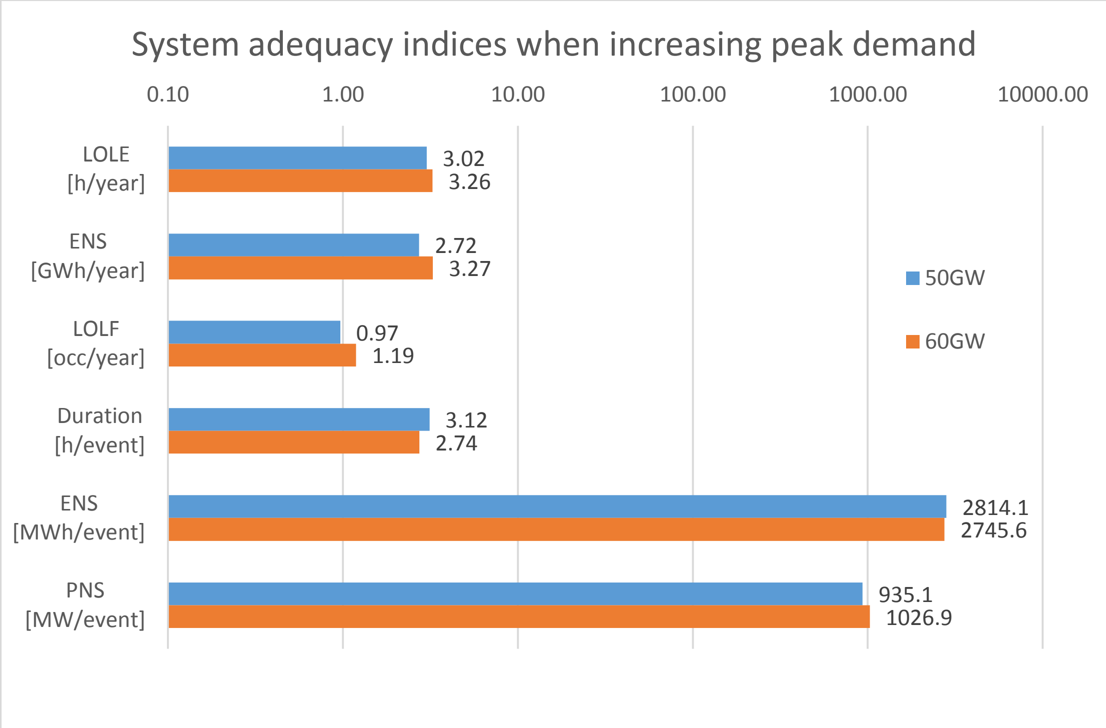


FIGURE 5-12 SYSTEM ADEQUACY INDICES WITH PEAK DEMAND AS 50GW AND 60GW

Under the 3h LOLE condition, compared with the base case, when peak demand is increased from 50GW to 60GW (20% increase), the ENS and LOLF are 20% higher than the former. The rise of these values is aligned with the increase of system size, though as aforementioned the larger system is slightly less reliable in terms of LOLE.

The average outage duration decreases from 3.12 to 2.74 h/event, about 10% lower. ENS for each interruption event is almost unchanged. PNS per event increases as the increase of LOLE. This can be explained that averagely PNS is increased with the LOLE but with a shorter duration, the change in ENS per event is neutralised. It can be found that, under the same reliability standard (by adjusting the number of generators), average yearly ENS and LOLF can be higher and duration of outages shorter with increased peak demand.

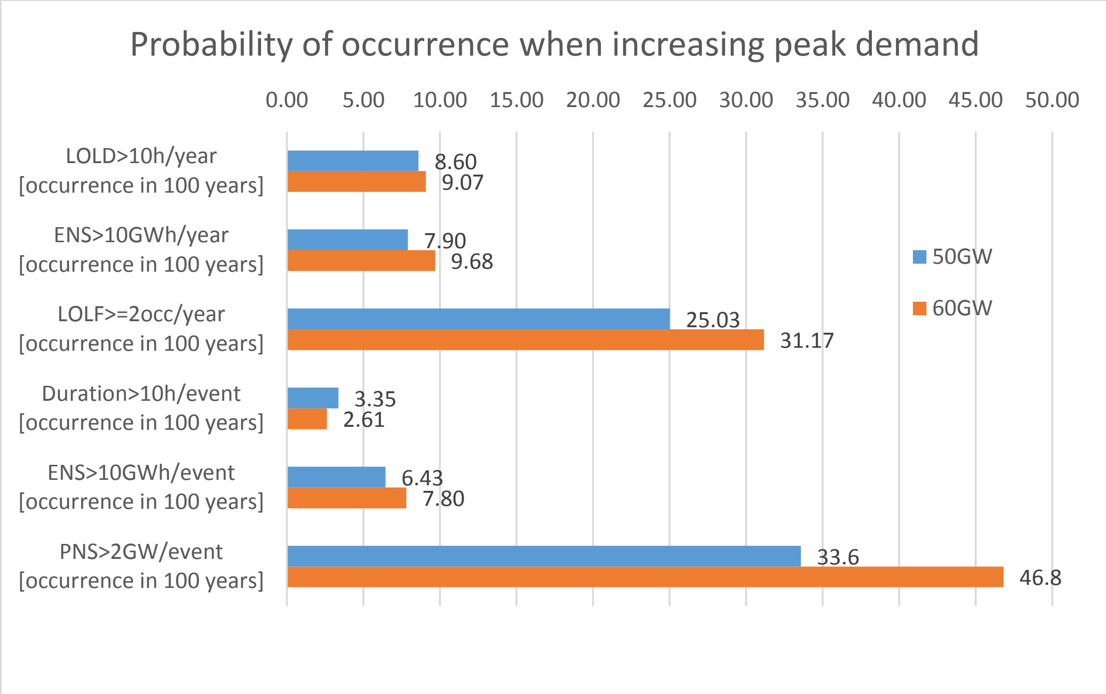


FIGURE 5-13 PROBABILITY OF OCCURRENCE WITH PEAK DEMAND AS 50GW AND 60GW

Similarly, when peak demand is increased from 50GW to 60GW, the occurrence of large ENS and LOLF are higher than before conforms to the increase of LOLE (a slightly less reliable system due to discrete generation increasing). The same as expectation values, increase in high yearly ENS and LOLF is more obvious than that of LOLE.

Long outage events are much rarer within the 60GW system that occurrence falls from 3.35 to 2.61 times in 100 years. Different from an unchanged average ENS per event and slightly increased PNS per event, extreme ENS and PNS events are much more frequent than the base case.

It can be concluded that, under the same 3h/year LOLE, increased peak demand, or in other words a larger system, would lead to more frequent but averagely shorter outages. With the unchanged generator size in a larger system, the size of generator compared with the size of the whole system relatively shrinks. This finding is then aligned with the sensitivity study of generator size in which smaller generator means a larger number of outage frequency (for a larger number of generators).

With regard to the magnitude of shortage, the increased occurrence of large ENS event in a larger system is due to the increased frequency of shortage (considering that the expectation values are close); extreme events in the larger system have a higher probability to last shorter but more serious in depth.

- Sensitivity to generator availability

In this part, system reliability is assessed with 2 generator availability levels: 0.85 and 0.90. Similarly, both systems are under then 3h LOLE standard by adjusting the number of generators. Repair time and generator size are kept the same as the base case system.

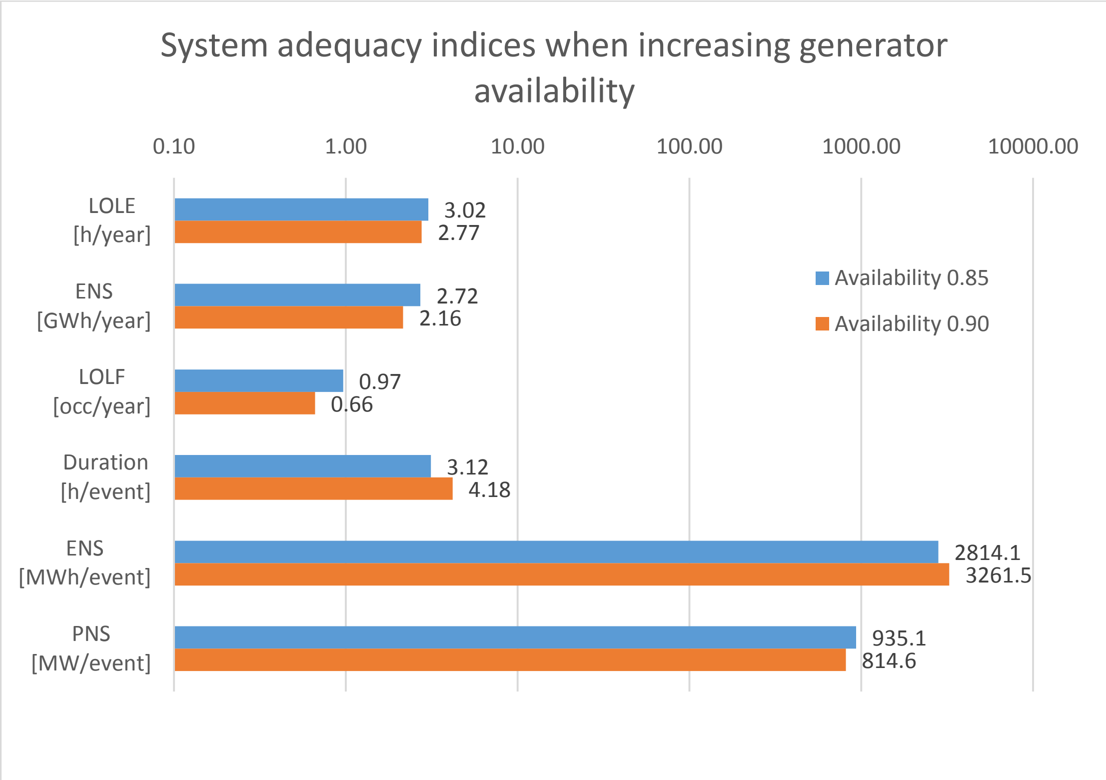


FIGURE 5-14 SYSTEM ADEQUACY INDICES WITH GENERATOR AVAILABILITY AS 0.85 AND 0.90

In Figure 14, the system with 0.90 availability generators is with a slightly lower LOLE at 2.77h/year (about 10% lower than the base case system). This results from the discrete generator number in achieving the closest 3h LOLE (subtracting one generator from the system may lead to a LOLE much higher than 3h).

ENS per year is decreased from 2.72 to 2.16 GWh/year, a larger fall than that of LOLE. The frequency of outage is much depressed, whilst duration of interruption per event is much longer. Although, PNS per event is down as LOLE, the average ENS per event goes up in the 0.90 system.

The frequency of shortage in 0.90 availability system is lower can be resulted from the smaller number of generators – the system requires fewer generators to achieve the same LOLE if they are more reliable. This result can also be related to the decreased failure rate of this generator.

$$availability = \frac{\mu}{\lambda + \mu} = \frac{\frac{1}{MTTR}}{\lambda + \frac{1}{MTTR}} \tag{5.13}$$

Hence,

$$\lambda_{availability=0.85} = 15.5\ occ/year \tag{5.14}$$

$$\lambda_{availability=0.90} = 9.7 occ/year \tag{5.15}$$

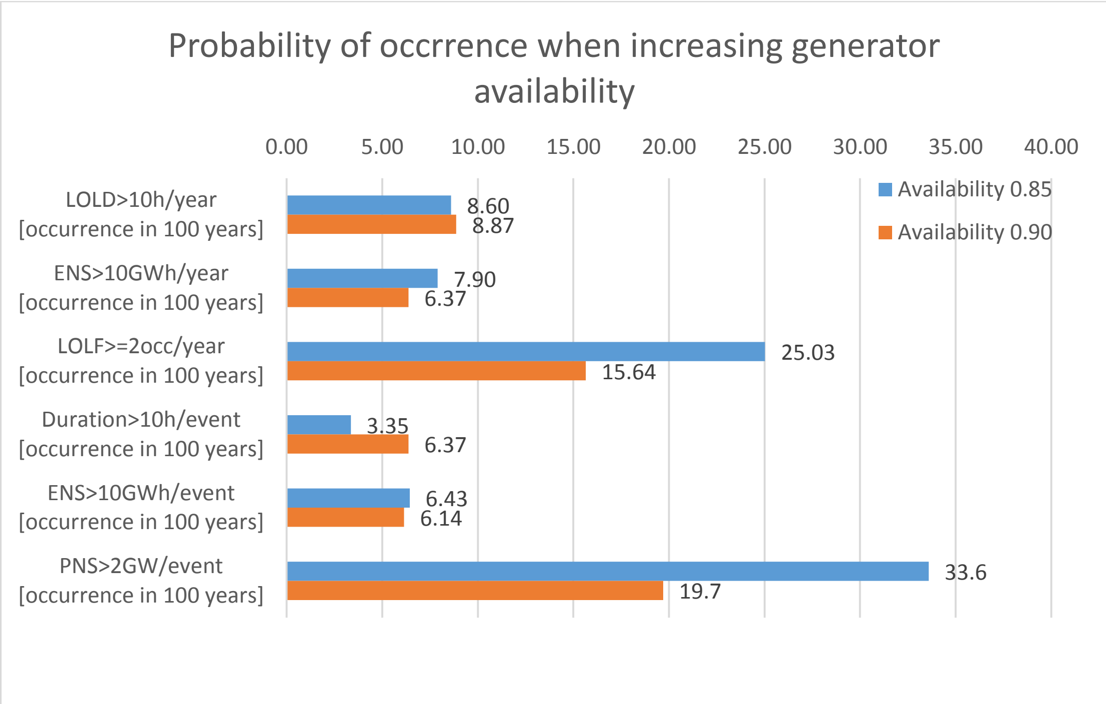


FIGURE 5-15 PROBABILITY OF OCCURRENCE WITH GENERATOR AVAILABILITY AS 0.85 AND 0.90

Figure 15 shows the indices for large events between 0.85 and 0.90 availability. When the single generator is more reliable (a higher availability), the occurrence of yearly shortage over 10h is increased, considering that the average LOLE is slightly lower in 0.90 system. The same as average yearly ENS, the occurrence of large ENS events is less frequent with reliable generator system. An obvious improvement is achieved in shortage frequency that the LOLF over once a year has fallen from 25 to 15 occurrence in 100 years, and the large PNS events are also much rarer. The drawback of the 0.90 system is that shortages over 10h can be much more frequent to occur.

This is an interesting finding that better generators can guarantee a big fall in expected frequency of outages and the number of very serious events in terms of power unserved. But the duration of such outages can double of that before. If the prolonged but light in depth shortage can be limited or dealt with actions to shorten the duration, better generators can contribute to a very healthy reliability performance.

5.3.2 Case study 2: Generation adequacy with 17 years demand profile

In this section, the demand profile is based on National Grid Company data from 1995 to 2011, excluding demand by pumped storage plants but including losses. The profile has been scaled to a common level of underlying demand in each year, currently 331 TWh. The scaling is in proportion to the weather–adjusted TWh demand for that year. This should preserve day-to-day variations from weather and chance events. There has been no attempt to correct for changes in the mix of demand over time (e.g. de-industrialisation). The rescaled peak demand for each year is shown in Figure 16. The estimated output from embedded wind stations is excluded in this figure but added back to demand in the study of 3.2.2.

The wind generation profile in this study has been derived from the Virtual Wind Turbine Model [101]. It is for a mix of existing and planned turbines, onshore, offshore and Round 3 sites. The mix represents National Grid's Gone Green Scenario, with 13.7 GW onshore and 12.6 GW offshore.

5.3.2.1 17 years vs individual year performance (500MW+100h)

Rather than section 3.1 in which normalised IEEE RTS yearly demand profile is used and scaled to preferred level (50GW), the NGC historic demand profile in this section contains specific demand levels in function of time for each hour from the year 1995 to 2011 for GB electricity system. The system security can, therefore, be assessed with the whole continuous 17 years' demand profile.

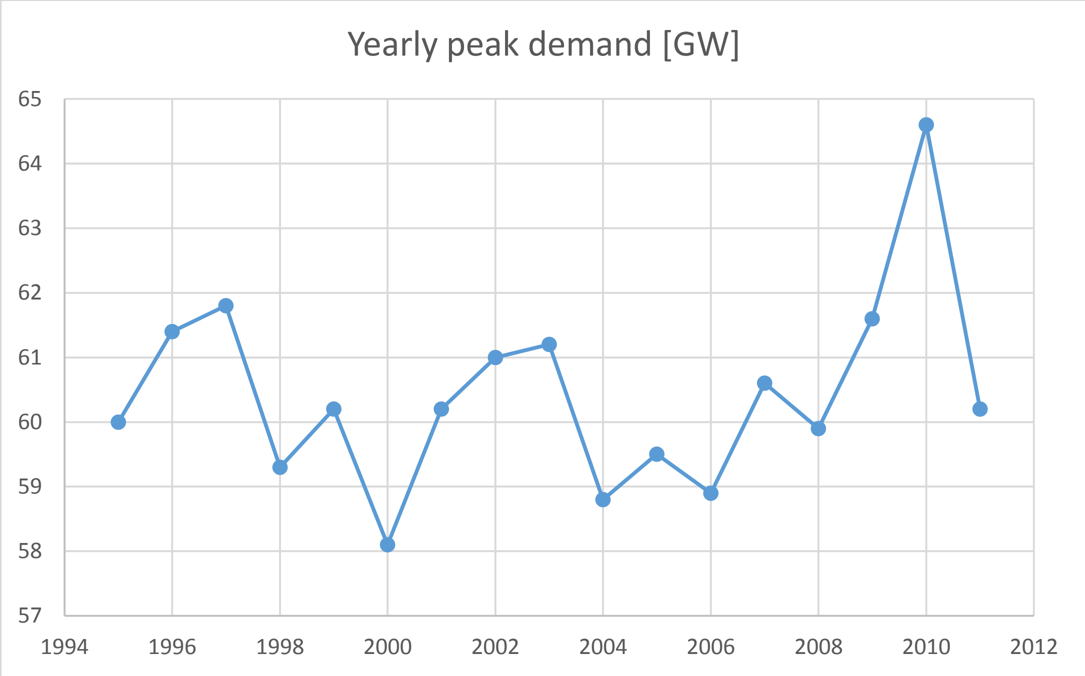


FIGURE 5-16 YEARLY PEAK DEMAND FOR GB ELECTRICITY SYSTEM 1995 TO 2011

System reliability performance of individual years can vary significantly. Shown in Figure 16, yearly peak demand can change over 10%. This is affected by many factors such as big events, weather changing, raise of environment awareness, appliances efficiency improvement and etc. Given the same generation capacity, the yearly system security indices can be a very low system for good years, such as the year 2000, but it can also be extremely high for adverse years, e.g. 2010, highly possible to be over the UK 3h LOLE Reliability Standard. Therefore, in this part, we aim to analyse the system adequacy for the whole 17 years, but also estimate the system performance in each individual year and based on the results discuss suitable arrangements.

In this section, assumptions for a generic GB power system are given as:

- Generators are standardised as 500MW unit
- Generator availability is 85%
- Generator MTTR as 100h
- System target LOLE as 3 hour/year

Yearly peak demand is no longer prescribed separately since the specific demand level for each hour can be obtained from NGC data.

The number of generators is adjusted to achieve the LOLE closest as possible to 3h for all 17 years. With the same installed generation capacity, LOLE and other reliability performance indices are checked for individual annual demand profiles.

TABLE 5-4 SYSTEM PERFORMANCE FOR THE WHOLE PERIOD FROM 1995 TO 2011: YEARLY EXPECTATION

	LOLE [h/year]	*ENS [GWh/year]*	*LOLF [occ/year]*	*Duration [h/event]*	*ENS [MWh/event]*	*PNS [MW/event]*
17-Year	3.16	4.10	1.78	1.78	2305.6	1360.5

TABLE 5-5 SYSTEM PERFORMANCE FOR THE WHOLE PERIOD FROM 1995 TO 2011: LARGE EVENTS OCCURRENCE IN 100 YEARS

	LOLE>10 h/year [occurrence in 100 years]	*ENS>10GWh /year [occurrence in 100 years]*	*LOLF>=2occ /year [occurrence in 100 years]*	*Duration>10h /event [occurrence in 100 years]*	*ENS>10GWh /event [occurrence in 100 years]*	*PNS>2GW /event [occurrence in 100 years]*
17-year	8.8	9.4	30.1	1.4	8.9	18.0

Table 5-4 shows the expectation adequacy values for the whole period from 1995 to 2011. The installed generation is adjusted to achieve a LOLE as 3.16h/year (add or subtract one generator will lead to a LOLE away from 3h) that the system is adequate according to the Reliability Standard. Table 5-5 provides the results for large event occurrence in 100 years for the 17 years’ profile.

TABLE 5-6 SYSTEM PERFORMANCE USING INDIVIDUAL ANNUAL LOAD PROFILES: YEARLY EXPECTATION

Year	*LOLE [h/year]*	*ENS [GWh/year]*	*LOLF [occ/year]*	*Duration [h/event]*	*ENS [MWh/event]*	*PNS [MW/event]*
1995	1.24	1.17	0.97	1.28	1200.1	948.2
1996	2.94	3.06	2.22	1.32	1378.0	1077.7
1997	3.04	3.39	2.01	1.51	1688.0	1190.2
1998	0.61	0.57	0.51	1.19	1109.6	947.9
1999	0.79	0.76	0.60	1.32	1271.8	970.4
2000	0.24	0.20	0.20	1.20	998.5	902.5
2001	1.04	1.01	0.78	1.33	1284.1	998.5
2002	1.61	1.73	1.11	1.45	1553.8	1115.2
2003	1.78	1.90	1.26	1.42	1513.3	1123.3
2004	0.56	0.48	0.43	1.31	1115.2	854.1
2005	1.12	1.04	0.83	1.35	1251.6	991.7
2006	0.65	0.55	0.49	1.32	1123.8	865.2
2007	1.10	1.00	0.74	1.49	1352.3	929.8
2008	1.26	1.24	0.91	1.38	1362.4	1018.1
2009	2.89	3.10	1.85	1.56	1681.3	1145.5
2010	28.01	41.15	12.96	2.16	3174.7	1634.8
2011	2.44	2.39	1.65	1.48	1448.9	1026.4

With the same generation capacity, individual annual demand profile was assessed via MCS. From Table 5-6, most of the years in the studied period have shown that the system is adequate in terms of yearly LOLE. However, in 2010, the LOLE can reach as high as 28h/year, other indices are almost 10 times of the average. In most years, except 2010, the indices are all under the average performance shown in Table 5-4.

TABLE 5-7 SYSTEM PERFORMANCE USING INDIVIDUAL ANNUAL LOAD PROFILES: LARGE EVENT FREQUENCY

Year	*LOLD>10h/year [occurrence in 100 years]*	*ENS>10GWh/year [occurrence in 100 years]*	*LOLF>=2occ/year [occurrence in 100 years]*	*Duration>10h/event [occurrence in 100 years]*	*ENS>10GWh/event [occurrence in 100 years]*	*PNS>2GW/event [occurrence in 100 years]*
1995	1.1	2.2	25.2	0.1	0.3	2.4
1996	5.5	7.5	52.7	0.9	2.4	10.1
1997	5.1	9.1	51.6	1.2	3.3	12.3
1998	0.2	0.8	12.3	0.0	0.2	1.4
1999	0.5	1.1	14.9	0.0	0.6	2.2
2000	0.1	0.2	3.7	0.0	0.0	0.4
2001	0.7	1.8	19.8	0.0	0.7	2.5
2002	2.1	4.0	29.1	0.0	1.6	5.0
2003	2.3	4.9	33.0	0.1	1.8	7.9
2004	0.1	0.5	10.4	0.0	0.2	0.9
2005	1.0	1.8	21.9	0.0	0.5	2.3
2006	0.4	0.8	11.7	0.0	0.4	0.8
2007	1.1	2.1	18.7	0.0	1.0	2.9
2008	1.5	2.5	23.5	0.1	1.4	3.6
2009	6.2	8.6	45.2	0.4	4.0	10.4
2010	90.4	91.2	100.0	20.5	109.6	209.6
2011	4.1	6.3	40.5	0.3	1.5	6.4

Similarly, with the same generation capacity as the average demand study, individual annual demand profile was assessed via MCS. Shown in Table 5-7, most of the years in the studied period have shown a very low occurrence for extreme situations. However, with the load profile of year 2010, serious events are almost inevitable to happen.

Above results show that when generation capacity is planned to be adequate for all years achieving 3h LOLE, the performance in individual years can vary considerably. In terms of LOLE, the system shows high reliability since above 50% years LOLE is lower than 2h/year. For achieving the target 3h/year, it may be more economical to lower the capacity of generation but applying emergency reserve for those adverse years.

5.3.2.2 System planning with wind

Embedded renewable energy is growing dramatically in recent years due to the well-increased environment awareness and government commitment and incentives. The UK has the world's largest installed capacity of offshore wind since 2008 [105]. It is essential to understand that how wind is to affect the UK total system reliability performance, whether it is advisable to build more wind, and whether the current Reliability Standard can ensure an acceptable security of supply for the future.

A sharp drop of about 6 GW in ACS peak demand has been found between winter 2005/06 and winter 2014/15 seen from NGC transmission network [100]. The reduction in demand is believed to be mainly from the contribution of fast growing embedded generation and rising demand response services in distribution networks. Since wind is playing a main role in the embedded capacity in the UK, in this study we use wind generation to represent the capacity from distribution networks. The wind capacity profile is derived from the Virtual Wind Turbine Model [101]. The wind capacity in the model is a mix of existing and planned turbines, onshore, offshore and Round 3 sites [102] [106]. The mix represents National Grid's Gone Green Scenario, with 13.7 GW onshore and 12.6 GW offshore. The wind output is derived as a continuous hourly profile for years from 1995 to 2011, corresponding to the NGC load profile. The impact of wind on the whole system security of supply is then analysed.

The analysis in this part is implemented by using the combined wind output and load profile and adjusting the number of generators to achieve the closest LOLE to 3h/year for the whole period from 1995 to 2011. In this section, we investigate generators as 500MW 100h MTTR and 300MW 50h MTTR, availability as 0.85 and 0.9, 3 levels of balancing service, 0GW, 1.5GW and 3GW, for sensitivity studies.

A. System performance in expectation values

TABLE 5-8 SYSTEM RELIABILITY PERFORMANCE IN EXPECTATION VALUES

Installed capacity [MW]			*LOLE [h/year]*	*ENS [GWh/year]*	*LOLF [occ/year]*	*Duration [h/event]*	*ENS [GWh/event]*	*PNS [GW/event]*
74000	500MW 100h MTTR	no wind:0GW BS	2.99	3.82	1.72	1.74	2.22	1.31
		no wind:1.5GW BS	1.20	1.39	0.73	1.64	1.91	1.22
		no wind:3GW BS	0.43	0.47	0.28	1.57	1.69	1.14
73200	300MW 50h MTTR	no wind:0GW BS	3.23	3.91	2.14	1.51	1.83	1.21
		no wind:1.5GW BS	1.02	1.09	0.73	1.41	1.51	1.09
		no wind:3GW BS	0.34	0.31	0.26	1.27	1.17	0.94

Table 5-8 shows the system reliability performances in expectation values. It can be found that for the system with 500MW unit and 100h MTTR, the required generation capacity is slightly higher than that with 300MW unit and 50h MTTR. Both systems are with LOLE as around 3h/year, conforming to the UK Reliability Standard. It can be seen that the frequency of system outage is much lower as 1.72 than the 300MW system where the LOLF is 2.14 occ/year. This is because the 300MW system has a higher number of generators so that the number of failures from generators can also increase. Meanwhile, the generator availabilities are both 85%, and the 300MW system's MTTR is 50h, the failure rate for each generator is larger, accordingly. The formula for failure rate can be given as followed

$$availability = \frac{\mu}{\lambda + \mu} = \frac{\frac{1}{MTTR}}{\lambda + \frac{1}{MTTR}} \tag{5.16}$$

Therefore, the values can be derived as

$$\lambda_{MTTR=50h} = 30.9 occ/year \tag{5.17}$$

$$\lambda_{MTTR=100h} = 15.45\ occ/year \tag{5.18}$$

With a higher average shortage frequency per year, the 300MW+50h system is reasonable to have longer average duration per event for the same LOLE at 3h. Since the expected ENS per year are almost the same for both systems, the ENS per event is therefore expected to be higher in the 500MW+100h system due to the lower frequency of events. However, the PNS per event is affected by ENS per event and duration per event which are both higher in the 500MW+100h system, the difference of PNS per event between those two systems is relatively small.

For the same amount of balancing service, it is interesting to see that, the improvement is more obvious with 300MW systems in all reliability indices. It may be because, in 300MW+50h systems, shortages are comparatively lighter in severity but more frequent to happen. Thus, with the same amount of balancing service, the smaller outages, though occur frequently, can be covered but larger outages may only be resolved when generators are repaired.

TABLE 5-9 SYSTEM PERFORMANCE FOR THE WHOLE PERIOD FROM 1996 TO 2011: WITH WIND

Installed capacity [MW]			*LOLE [h/year]*	*ENS [GWh/year]*	*LOLF [occ/year]*	*Duration [h/event]*	*ENS [GWh/event]*	*PNS [GW/event]*
69000	500MW 100h MTTR	wind:0GW BS	2.75	4.20	1.30	2.12	3.24	1.55
		wind:1.5GW BS	1.15	1.66	0.58	1.98	2.85	1.45
		wind:3GW BS	0.53	0.73	0.27	1.94	2.65	1.42
68100	300MW 50h MTTR	wind:0GW BS	2.94	4.52	1.53	1.92	2.96	1.49
		wind:1.5GW BS	1.35	1.93	0.73	1.83	2.63	1.42
		wind:3GW BS	0.57	0.74	0.33	1.72	2.24	1.32

Table 5-9 is the reliability performance for the systems with wind. Thanks to the wind capacity, only 69000MW conventional generation is required to achieve 3h LOLE, 5000MW less than that of the system without wind.

In Table 5-9, the 500MW+100h system with wind shows a lower frequency of outage (1.3occ/year to 1.53occ/year) and a longer duration per event (2.12h/event to 1.92h/event). The PNS and ENS per event are also lower in the 300MW+50h system. These results show a similarity as those for no wind system.

Between the systems with and without wind, it can be seen that, with LOLE as 3h/year (some differences are from the discrete number of generator, the same as other results in this chapter), the frequency of shortages is much improved from 1.72 occ/year to 1.3 occ/year with wind. However, customers have to suffer a longer duration of an outage event from 1.74h/event to 2.12h/event (comparing the 500MW+100h system data). The average results also show that both ENS and PNS per event are much worse when systems are installed with wind.

B. System performance in distribution functions

The system reliability indices are expressed as the distribution functions of frequency of occurrence in 100 years in this section. The value for LOLD=0h/year in the curve represents the occurrence of LOLD=0h/year; the value for LOLD=1h/year represents $LOLD\epsilon(0,1]h/year$; this applies to all other distribution diagrams. In each diagram, the range of reliability performance for different system specifications are also evaluated and shown as colour filled areas (red for no wind systems, blue for with wind systems). These system specifications include generator unit size as 300MW and 500MW, MTTR as 50h and 100h, generator availability as 0.85 and 0.9 and all systems are ensured to be 3h LOLE on average.

In addition to the distribution curves, the values of complementary cumulative frequency of occurrence are given for large events.

- Reliability performance per year

TABLE 5-10 RELIABILITY PERFORMANCE PER YEAR FOR LARGE EVENT IN NO WIND AND WITH WIND SYSTEMS (PER YEAR)

	LOLD>10h/year [occurrence in 100 years]	*ENS>10GWh/year [occurrence in 100 years]*	*LOLF>=10occ/year [occurrence in 100 years]*
No wind	7.8-9.7	7.8-9.8	3.3-6.6
With wind	7.9-8.3	8.9-10.3	0.5-1.2

In Figure 17, the distributions of LOLD per year for systems with no wind and with wind are drawn. It can be found that a slightly higher frequency of LOLD=0occ/year is observed for the system with no wind. However, most areas are overlapping for both systems meaning that the LOLD per year performance in distribution is very close for with and without wind. In Table 5-10, the frequency values of LOLD>10h/year for both systems are similar, though no wind system can have slightly more high LOLD per year.

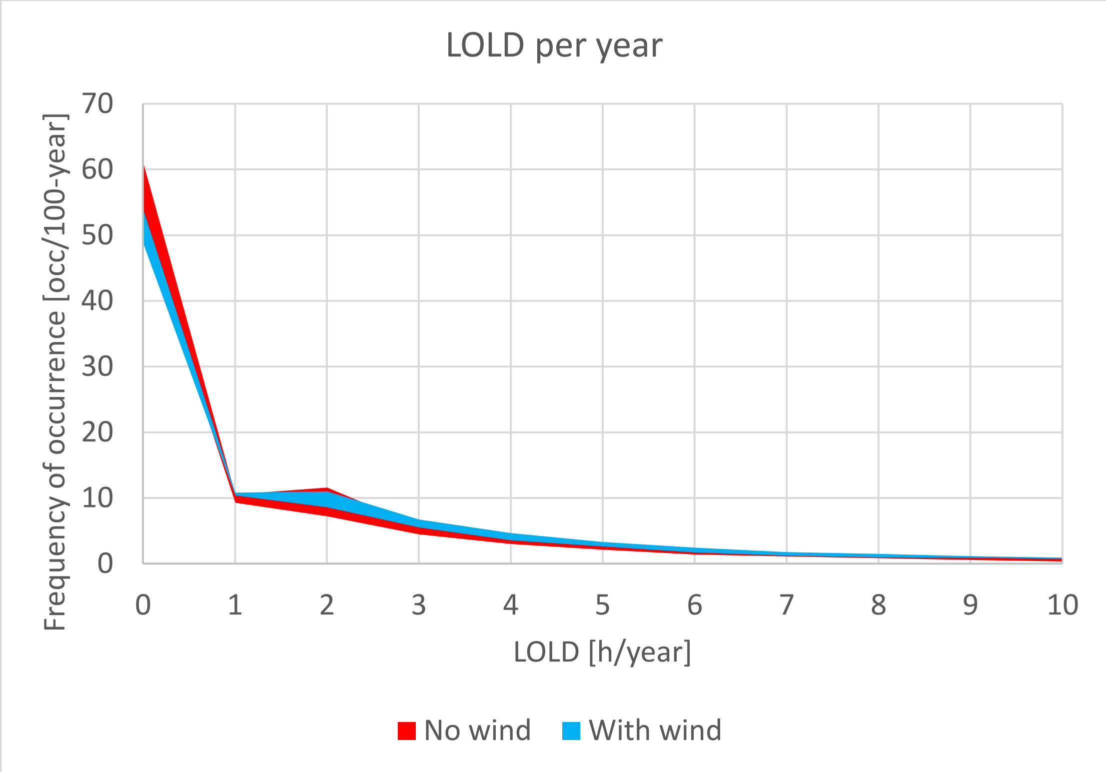


FIGURE 5-17 LOLD PER YEAR FREQUENCY OF OCCURRENCE

This also applies to ENS per year in Figure 18. No wind system has a higher ENS=0GWh/year, but the difference for higher ENS per year between two systems is very small.

Opposite to LOLD, the result for ENS>10GWh/year in Table 5-10 shows that with wind system can be slightly riskier to have large ENS years, even though the difference is not obvious.

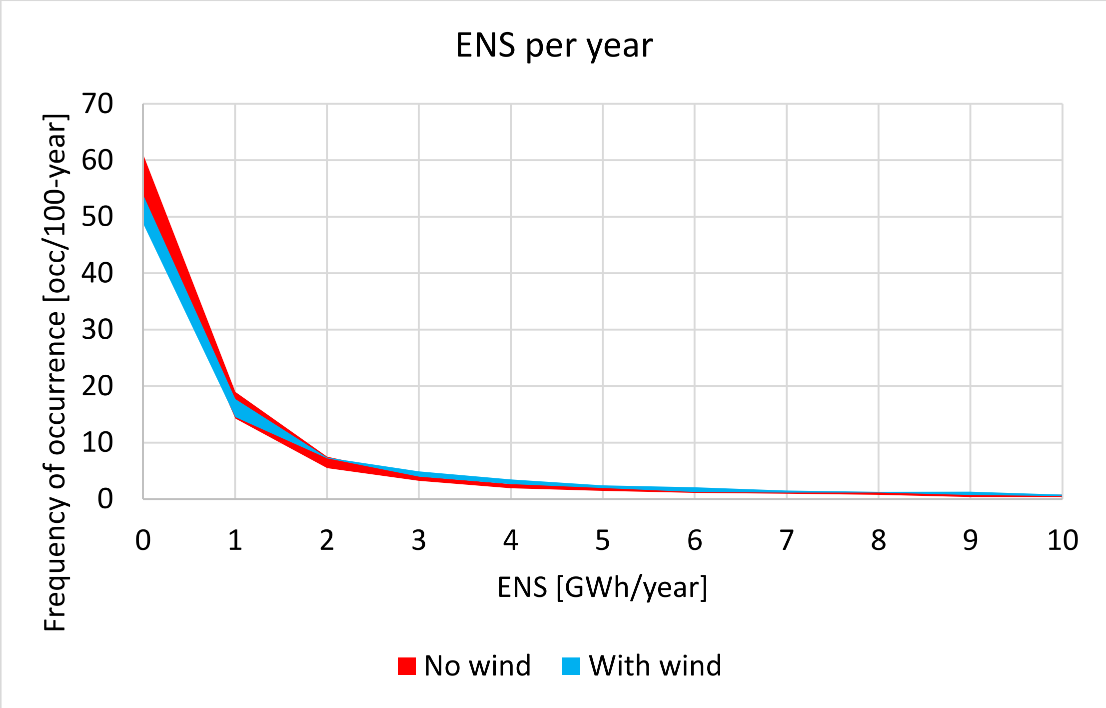


FIGURE 5-18 ENS PER YEAR FREQUENCY OF OCCURRENCE

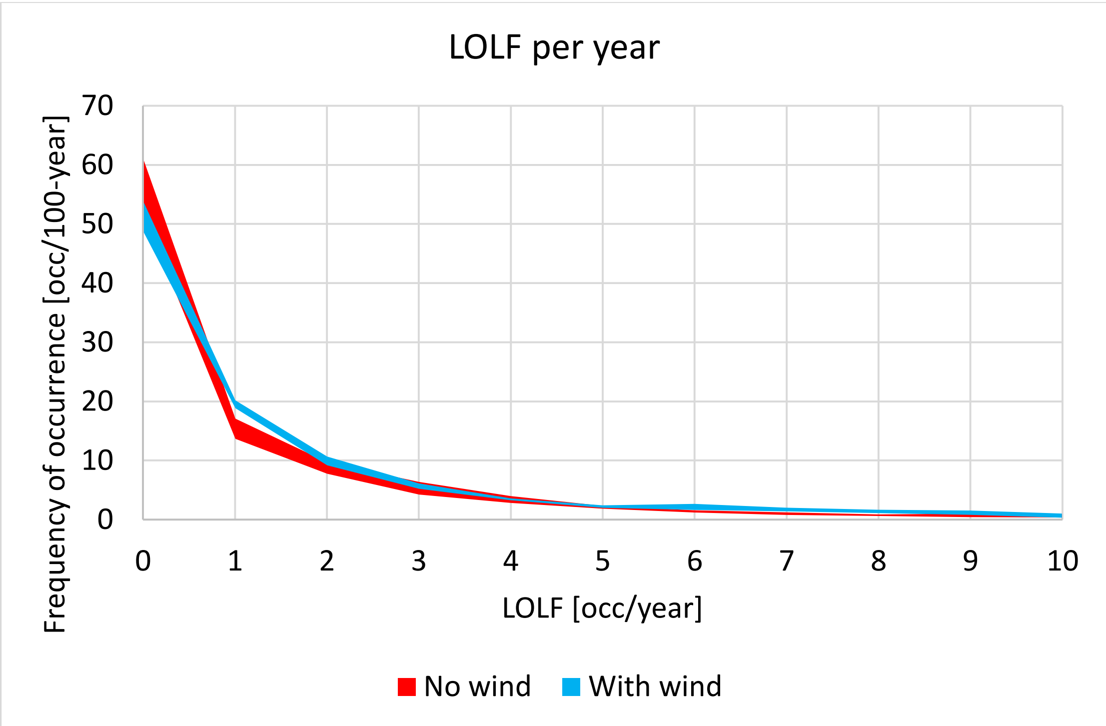


FIGURE 5-19 LOLF PER YEAR FREQUENCY OF OCCURRENCE

In Figure 19, the frequency of occurrence for LOLF=1 and 2occ/year is slightly higher in the system with wind. For large LOLF in this diagram, the values are very close. However, Table 5-10 shows that the frequency of occurrence for LOLF>10occ/year in no wind system is 3.3-6.6occ/100-year, which is considerably higher than that of the system with wind, i.e. 0.5-

1.2occ/100-year. It means that the system without wind can have a much higher probability of a high number of shortages per year, but through installing wind in distribution networks, the chance of very high shortage occurrence will be much reduced.

- Reliability performance per event

TABLE 5-11 RELIABILITY PERFORMANCE PER YEAR FOR LARGE EVENT IN NO WIND AND WITH WIND SYSTEMS (PER EVENT)

	Duration>10h /event [occurrence in 100 years]	*ENS>10GWh /event [occurrence in 100 years]*	*PNS>8GW /event [occurrence in 100 years]*
No wind	0.2-1.3	4.8-6.1	0-0.2
With wind	2.8-3.5	9.7-12.0	0.2-0.4

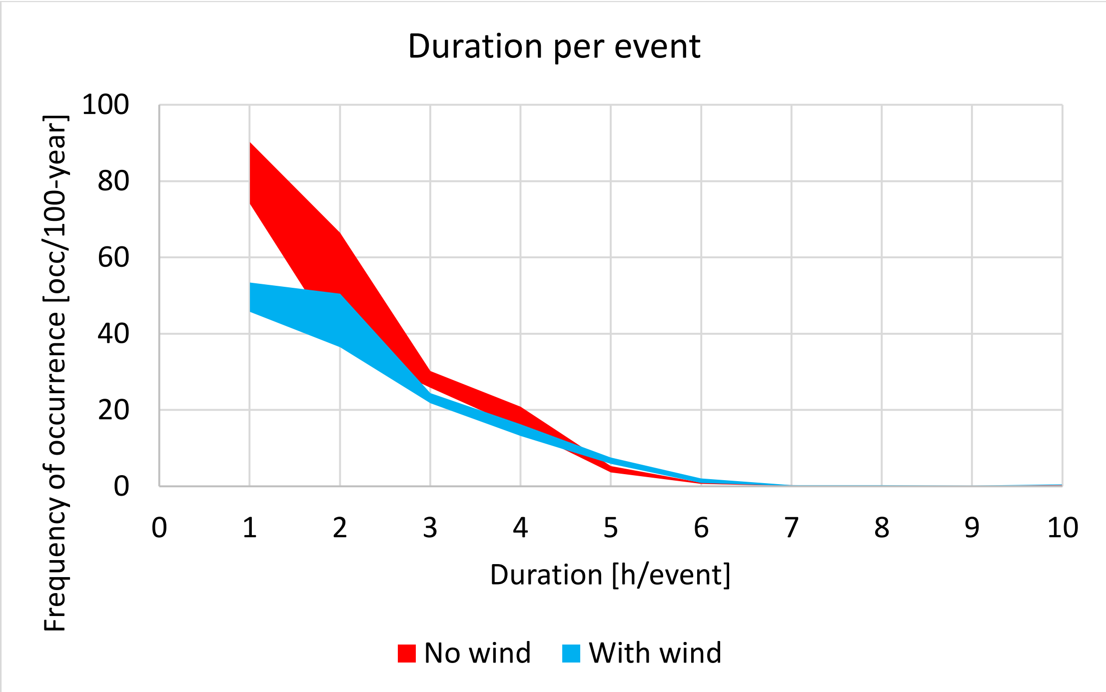


FIGURE 5-20 DURATION PER EVENT FREQUENCY OF OCCURRENCE

Figure 20 shows the distribution of occurrence for shortage duration per event. It can be found that the frequency of occurrence of short shortage events is much lower in the system with wind than the no wind system. But it becomes higher for duration events longer than 5h.

Duration>10h/event for the system with wind is 2.8-3.5occ/100-year almost three times of that for the system without wind. This means that system with wind can be much riskier to experience very long outages. However, since the occurrence of duration below 5h/event is much lower than that of the system with no wind, it can be seen that the system with wind has less frequent short duration outages.

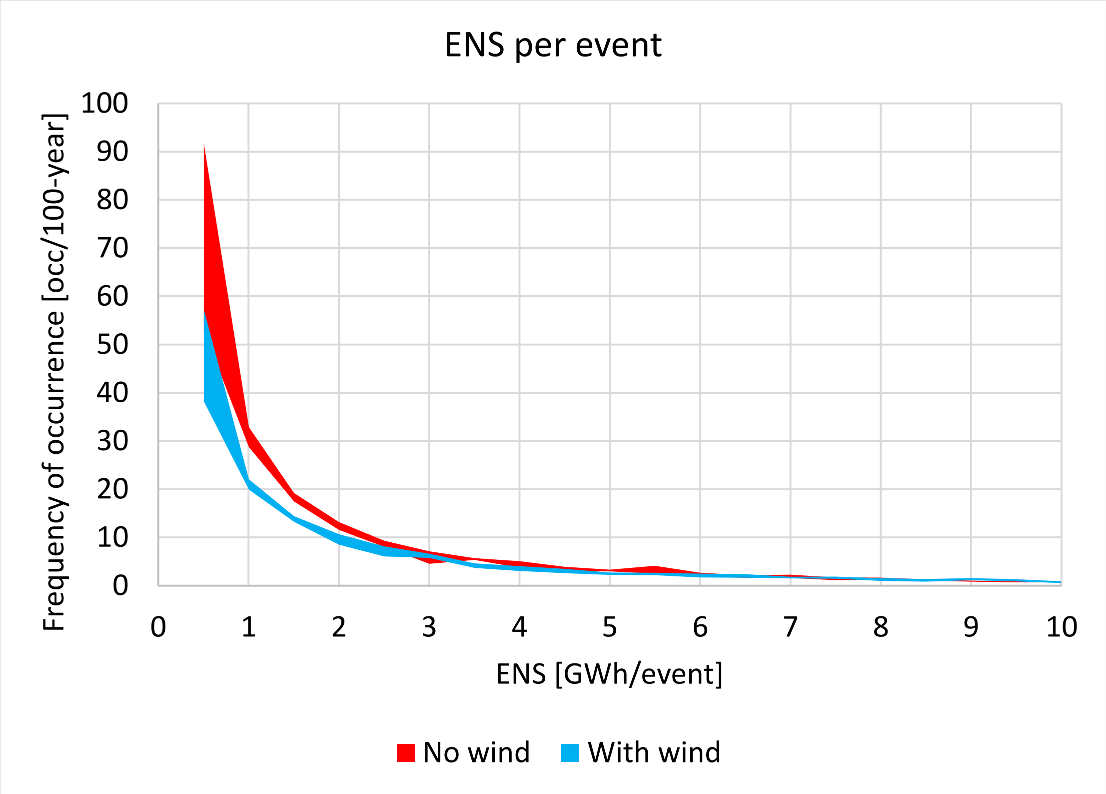


FIGURE 5-21 ENS PER EVENT FREQUENCY OF OCCURRENCE

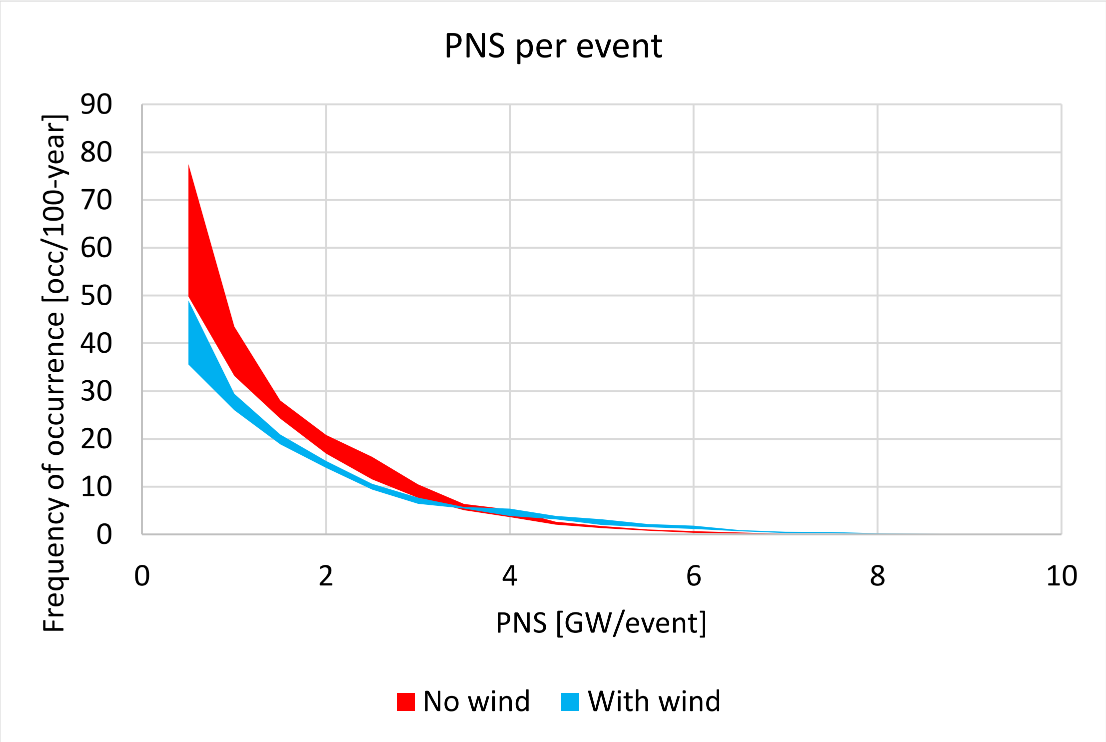


FIGURE 5-22 PNS PER EVENT FREQUENCY OF OCCURRENCE

In Figure 21, the frequency of occurrence for ENS<3GWh/event is found much lower for the system with wind. The difference is not obvious for ENS>3GWh/event. However, shown in Table 5-11, the ENS>10GWh events are twice frequent in the system with wind as that without wind.

Similarly, the system with wind has a lower frequency of events with power shortage less than 3GW, but more high PNS events are observed when the deficit is over 4GW. In Table 5-11, PNS per event larger than 8GW is much more frequent in the wind system.

Comparing wind and no wind, it is interesting to find that, the system with wind can have fewer events which are small in energy and power not supplied and short in time, but could potentially be more likely to experience very serious events than the system without wind.

C. Effects of balancing service for system with and without wind

In the UK power system, balancing services can be called on to mitigate a real blackout in unexpected situations. System operators can use the capacity standing from voltage reduction, max gen service and Emergency Assistance from interconnectors to prevent customer disconnection. According to OFGEM yearly GB capacity assessment report, the current GB balancing service capacity for NGC is around 2.56GW [100].

The effects of balancing service are analysed in section 3.1.3 in the generic GB system. However, even for the same capacity, the benefits in reliability improvement may vary in the systems with wind and without wind. It is essential to assess that whether the existing balancing service capacity is sufficient in the context that embedded generation (mainly as wind in the UK) and demand response capacity is booming in distribution networks.

Similarly, since balancing services are used during extreme situations, we will analyse the system reliability performance for very large events.

In this section, bar charts are used for representing the range of system security performances above a certain level to show that occurrences of very large issues in these systems. The ranges of values are evaluated in generator parameter sensitivity studies on unit size (500MW and 300MW), MTTR (100h and 50h), availability (0.85 and 0.90). All sensitivity studies conform to the 3h LOLE standard by adjusting the number of generators.

Since the results are obtained by Monte Carlo simulation, the ranges of values will contain simulation errors. The coefficient of variation for the simulation is 1% for LOLE, according to probability theory, the simulation error can be believed to be less than 2% (for 95%

confidence). But for other indices, the error range can be smaller or larger, though the difference should not be large.

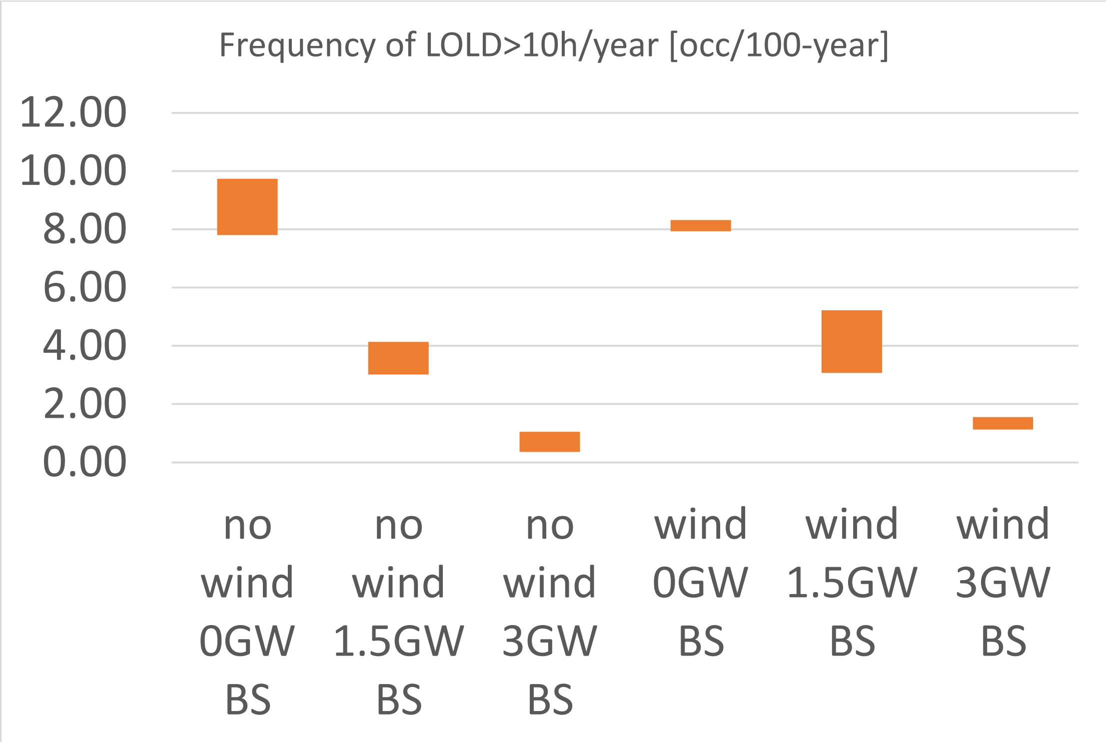


FIGURE 5-23 LOLE PER YEAR FREQUENCY OF OCCURRENCE WITH BALANCING SERVICE

In figure 23, both systems perform similarly for with wind and no wind. For different levels of balancing service, the system with wind has a slightly higher frequency of large LOLD.

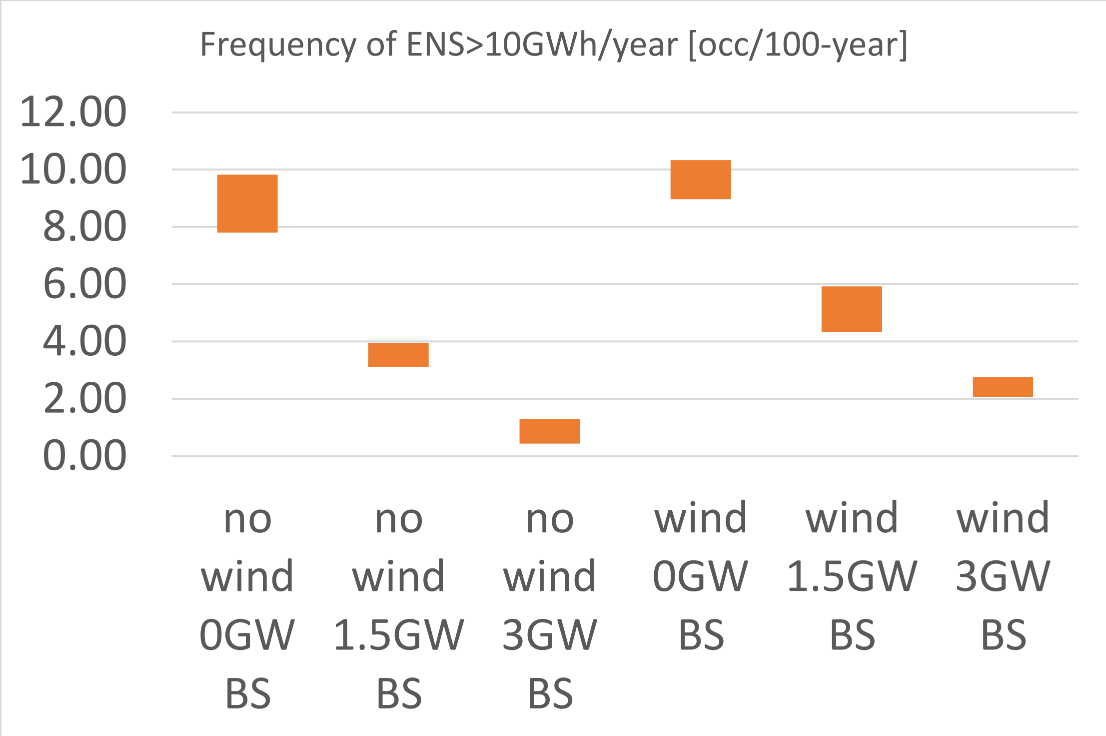


FIGURE 5-24 ENS PER YEAR FREQUENCY OF OCCURRENCE WITH BALANCING SERVICE

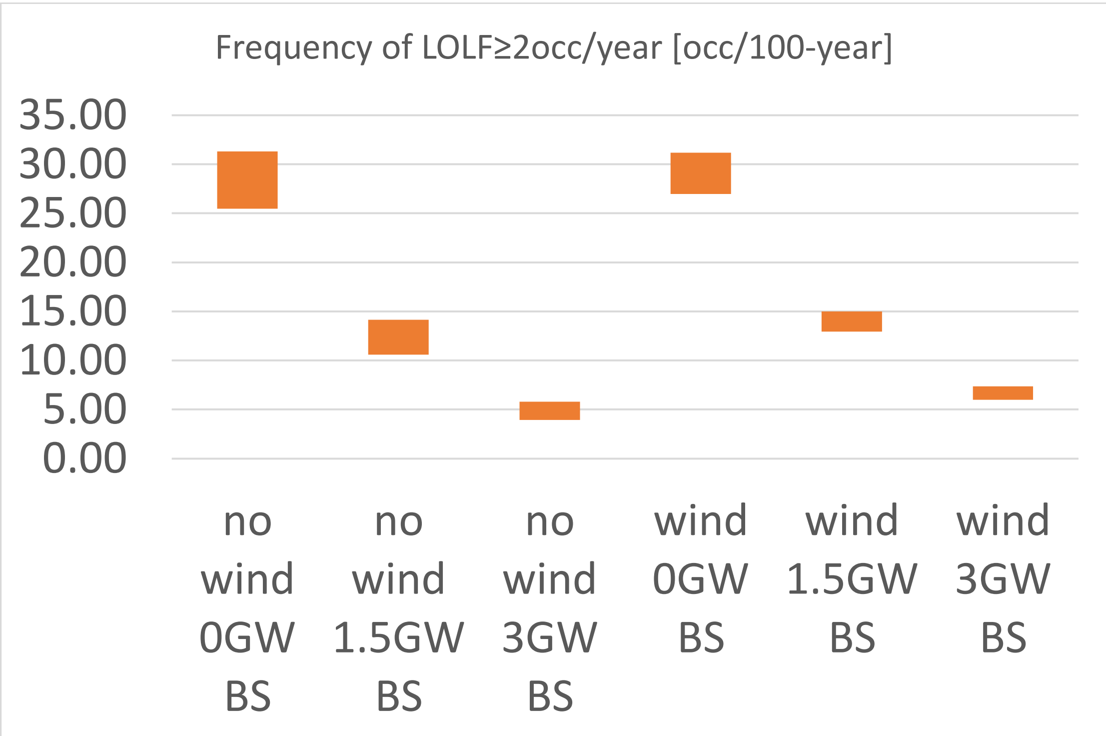


FIGURE 5-25 LOLF PER YEAR FREQUENCY OF OCCURRENCE WITH BALANCING SERVICE

Figure 24 and Figure 25 show us a similar result. It can be seen that, for yearly indices, the difference between wind and no wind with balancing service is very small.

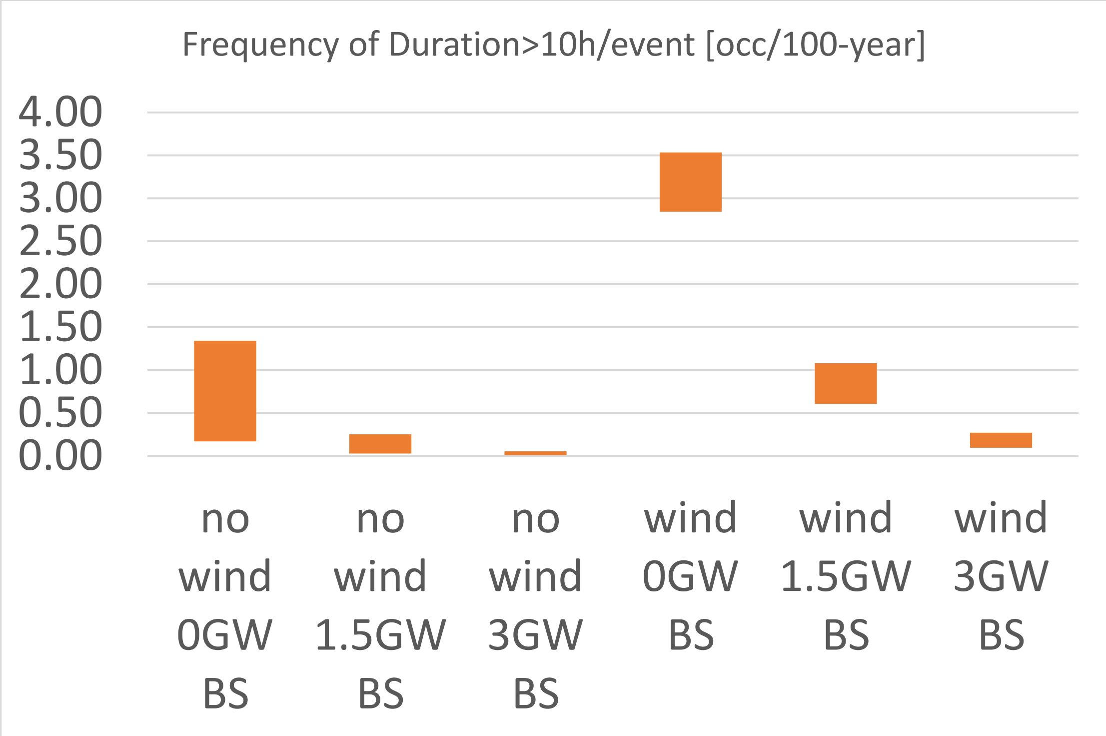


FIGURE 5-26 DURATION PER EVENT FREQUENCY OF OCCURRENCE WITH BALANCING SERVICE

In figure 26, the frequency of occurrence for duration per event larger than 10h is very high with wind. This can be seen that large events in wind system are much more frequent than that in no wind system. Balancing service can make a significant improvement for preventing outage occurrence. However, with the same level of balancing service, the reliability of system without wind is still better than that of with wind.

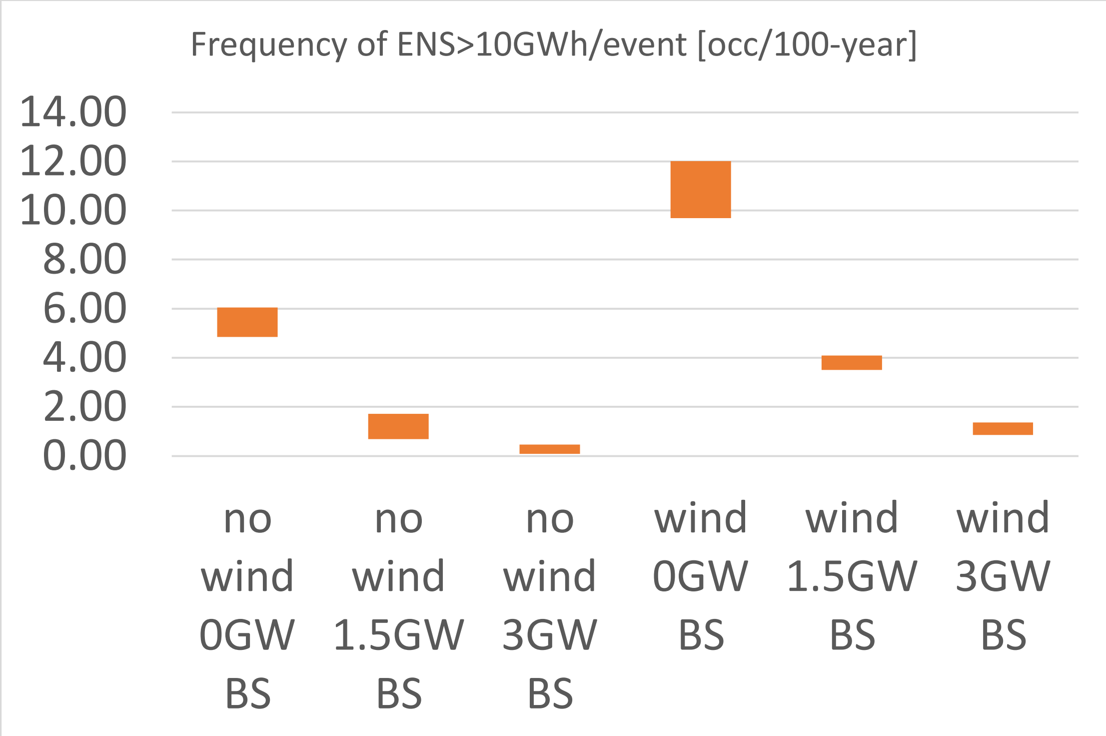


FIGURE 5-27 ENS PER EVENT FREQUENCY OF OCCURRENCE WITH BALANCING SERVICE

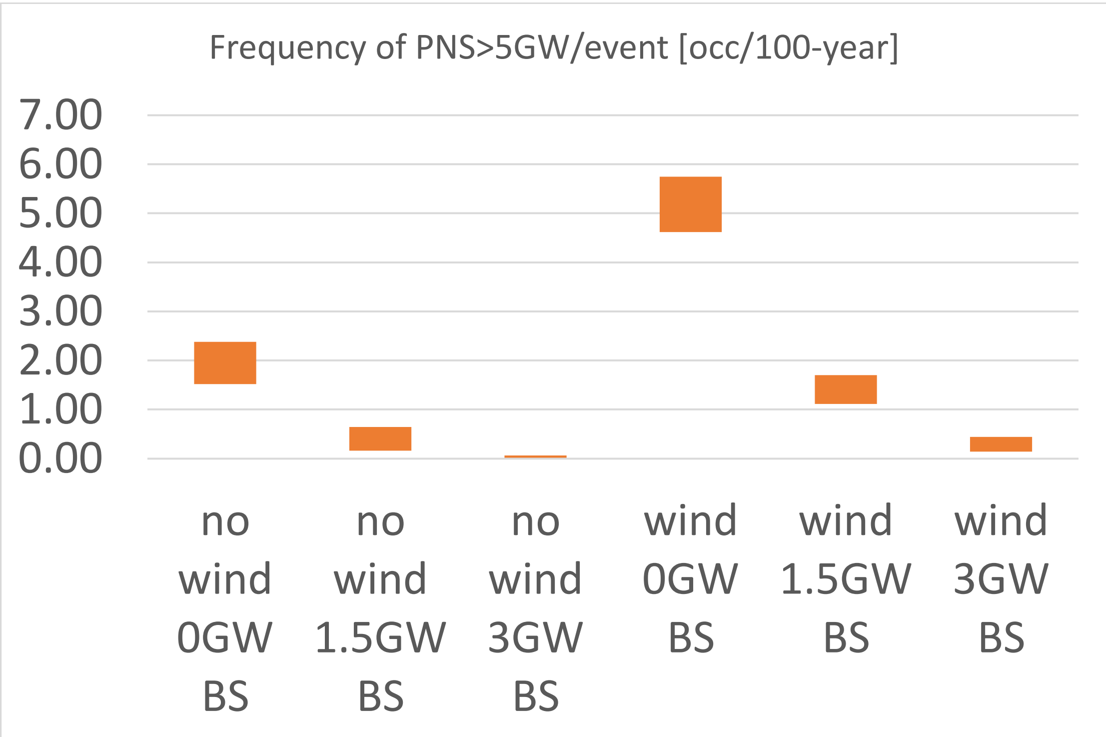


FIGURE 5-28 PNS PER EVENT FREQUENCY OF OCCURRENCE WITH BALANCING SERVICE

Figure 27 and Figure 28 show the frequency of serious events with very large energy and power curtailment. Similarly, adverse outages are much more frequent in a system with wind generation, even though high balancing service can make the difference much reduced.

It can be found that the effects of balancing service for both systems are very similar in annual indices. However, huge differences exist in shortage event duration, power in deficit, and energy curtailment. Extreme events mean that uncontrollable customer connection can be inevitable. The existing balancing service may be insufficient to prevent customers from more outages if the embedded generation capacity continues to grow.

5.4 CONCLUSIONS

In this chapter, the security of supply for a generic GB electricity system was assessed via chronological Monte Carlo simulation. The system under the 3h/year LOLE reliability standard was tested to evaluate its adequacy performance in an extended range of measurements, reflecting frequency and duration of event, magnitude of power and energy curtailment. The indices were represented as both expectation values and probability distribution functions.

Under the assessment model, two case studies were conducted. In the first case study, the normalised IEEE-RTS demand profile was applied to analyse the system adequacy with different LOLE levels for checking if 3h/year is a suitable system standard. Results show that in all systems, regardless of the target LOLE, some risk of unserved energy will exist. This is due to the probability of plants being unavailable at the same time from planned and unplanned outages. However, unserved energy events do not necessarily lead to consumer disconnections. In reality, the System Operator is able to call on a number of "balancing services" to avoid resorting to consumer disconnections. The study results for systems with different levels of balancing service show that the existence of balancing services significantly reduces the risk of consumer disconnections. With 2GW of balancing services available, the probability of occurrence of extreme consumer interruptions is very low in a generic 3 hours LOLE system, as they could occur less than once in 226 years in all categories. Therefore, the analysis shows that there is a relatively low level risk of consumer interruptions given a 3 hours LOLE system where the SO has access to balancing services.

In case study 2, a 17-year NGC data was used and individual year performance was evaluated to help recognise the variation of system behaviour in different years. The results show that when generation capacity is planned to be adequate for achieving 3h LOLE, the performance in individual years can still vary considerably. In terms of LOLE, the system shows high reliability since above 50% years LOLE is lower than 2h/year. For achieving the target 3h/year, it may be more economical to lower the installed capacity of generation but applying emergency reserve for those adverse years.

The drop of peak demand in recent years mainly from the contribution of fast growing embedded generation and rising demand response services in distribution networks was analysed by adding wind generation in the adequacy assessment. A wind profile model was applied for evaluating the impact of the growing wind capacity on system reliability. It was found that, under the same 3h LOLE standard, the system with wind could have fewer shortages per year on average. Light events in terms of shortage power, energy, duration are less frequent for that with wind. However, it was seen a larger risk to experience much more serious events than that of no wind. Balancing service for future GB system which could build more embedded wind and other types generation capacity from distribution networks may need more procurement for protecting customers from disconnection in more frequent extreme events. The 3h LOLE standard for a high wind penetration system may not be able to ensure an acceptable level of security of supply, especially for adverse events. The potential solution can be a more stringent reliability standard or increased capacity of balancing services.

Chapter 6 CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

In this thesis, the challenges of reliability assessment for distribution networks with complex time domain distribution network operations were identified and investigated. An efficient distribution network operation model was developed that allows, via Monte Carlo simulations, the implications of Smart Grid technologies, various customer interruption cost models and high impact low probability events to be analysed. The impacts of fast growing embedded generation in distribution networks on GB system generation adequacy were also investigated.

The hierarchy of the proposed reliability model for distribution network is shown in Figure 6-1. Taken together, the research described in this thesis has produced a single distribution network reliability model with various options to trade accuracy and computational efficiency:

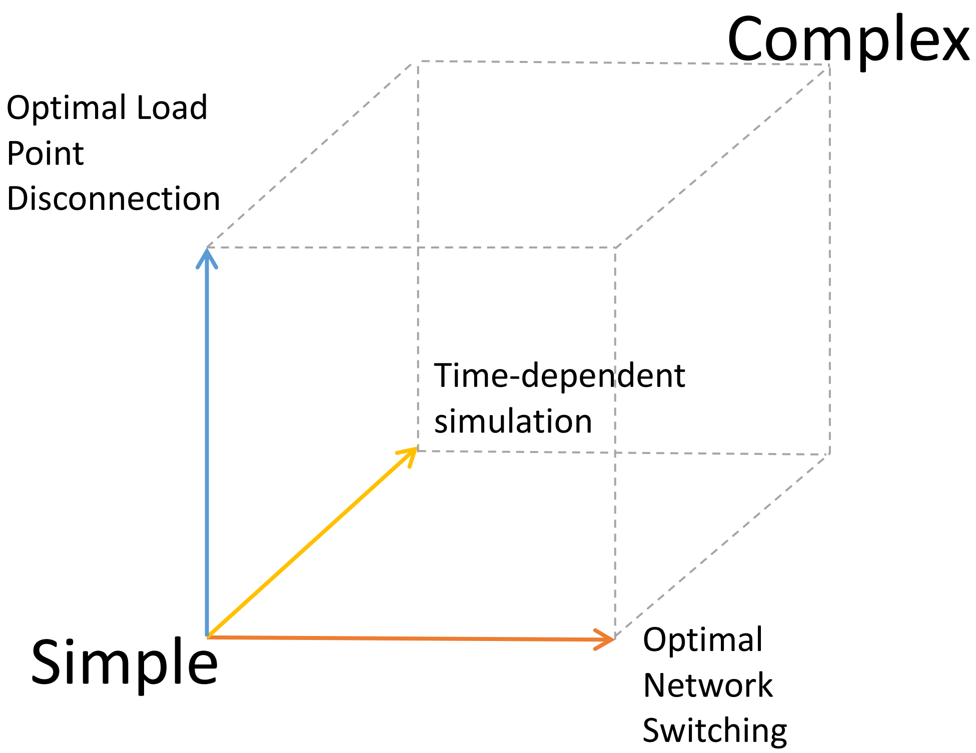


FIGURE 6-1 THE HIERARCHY OF MODELS

1) State space or time-dependent simulation:

With the proposed reliability assessment model, distribution network planning and operation can be analysed in a snapshot model in which the sampling of system state is independent to time or sequence of state. This feature enables the use of state space Monte Carlo simulation in which system states are sampled randomly and the result for each state is not affected by other states. Applying delicately controlled distortions to system state probability distribution functions to sample “important” states more frequently and restore the biased value in final results – the method often referred to as importance sampling – significantly improved the computational efficiency of network simulations. The proposed method still ensured accurate expected results, although the probability variability of reliability indices was compromised (achievable if not using importance sampling but lose computational efficiency); chronological characteristics of network operations which are related to actions in history, such as the charging and discharging of storages considering state of charge (SOC), were analysed with the proposed assessment model using time-sequential Monte Carlo method. With this method, the variability (probability distribution functions) of reliability performance indices was able to obtain with a better speed of result convergence than the unbiased state space Monte Carlo simulation, but slower than the simulation with importance sampling.

2) Continuous and discrete load point disconnection:
   Discrete load point disconnection represents passive LV network switching with which customers are fully curtailed after the occurrence of a fault by opening the circuit breaker/switch at the LV distribution transformer. The continuous load point disconnection represents the systems with active demand response so that the load at LV level can be disconnected partially by the amount required for network balancing and the power curtailment is dynamically controlled reflecting the real time network information updates. These two systems can both be analysed with the proposed assessment model by solving the optimisation of load curtailment with the corresponding constraints for two disconnection schemes.

3) Implicit and explicit network switching: the explicit network switching model has been proposed to reflect detailed switching actions in distribution network restoration considering network constraints and radial topology; the implicit switching model was created for distribution systems assuming that with future Smart Grid technologies

radial topology would not be necessary and optimal control over power flows in each section of networks can be applied automatically. The two network switching models enable the analysis for the different levels of future network simulation fidelity and computational efficiency.

Using the proposed system model via Monte Carlo simulation, applications of risk assessment in power system reliability have been conducted and some results have been concluded below:

A. <u>Impacts of different network improvement options on distribution network reliability were analysed and discussed.</u>

Based on the proposed simulation model in Chapter 2, non-network solutions for enhancing distribution network reliability/capacity were analysed in Chapter 4 part 1. An operation model for DG and a greedy model for energy storage aiming for maximising their ability in improving reliability were formulated. Different network improvement options including automatic switching, mobile generation, energy storage and DG are assessed for their impacts on network reliability performances in terms of ENS, CI and CML.

It has been found that non-network solutions can greatly contribute to distribution network reliability, but the impacts on network performance indices can vary significantly with different technologies. The following are the features of the studied solutions to network reliability:

- Automatic switching can significantly reduce CI since fault clearing can be shortened to 2min so that the interruption before switching actions are not recorded in CI. The contribution is less effective for lower network redundancy since that automatic switching is not able to mitigate the power shortage. The contribution from automatic switching to reduction of ENS and CML is relatively small.
- Energy storage units can also greatly improve network CI performance if they can support islanded operation (e.g. battery on the wall). Storage can be an effective option to lower ENS and CML, but this ability is constrained by not only the power rating but also the maximum energy that can be stored.
- Mobile generators for emergency supply, which in our study is assumed to be available in 3 hours after an outage happens, are found effective in improving ENS and CML, especially for low network redundancy situations. The effect on CI from mobile generators is negligible.

- Similar to mobile generators, considerable contribution in improving ENS and CML can be achieved with increased network demand by integrating DGs. Different from mobile generators, if combined with automatic switching, DGs can potentially have a significant contribution to CI reduction since it does not require a long waiting time to supply.

Therefore, the optimal network reinforcement for matching the future demand growth may be a combination of various network and non-network solutions.

B. Investigation on the quantification of customer interruption cost (CIC) and its implications on distribution network planning.

In Chapter 4 part 2, we reviewed the main methodologies for the quantification of customer interruption cost (CIC). To investigate the value customer might place on interruptions, different customer damage functions (CDF) were identified. In combination with the OFGEM adopted constant value of lost load (VoLL), the expected CIC were computed using the different CDFs within the same distribution network. It can be observed that for reduced network redundancy, customer interruption costs increase with all CDFs. The cost to residential customers is lower than that to commercial, industrial or large users. This is caused by that most interruptions experienced by customers in the network being studied are shorter than 8 hours. Interruptions longer than that may incur a higher cost per unit peak demand for residential customers than that for large users. The cost to commercial sectors is lower than that to large users for N-1 redundancy but higher for N-0 redundancy which indicates that commercial customers could be affected more by longer outages than larger users. Our study also showed that the selection of different customer damage functions can change fundamentally the obtained planning solution for distribution network operators. An average value of VoLL for quantification of customer interruption cost may therefore not lead to a truly optimal network planning and potentially result in extra costs to customers.

C. Modelling of High Impact Low Probability (HILP) events and evaluation of their impacts on network planning.

High impact low probability events are by definition very rare so that their impacts on network reliability and the cost to network operators are difficult to quantify. The third part of Chapter 4 modelled HILP events and evaluated the reliability performance through time-sequential Monte Carlo simulation. Impacts of HILP events with different severity levels have been studied considering the contribution of an emergency generation with different supply rate and preparation time as mitigation measures. The results demonstrate that severe HILP events can lead to a significant cost of lost load which may justify development of more resilient networks, e.g. transformation to underground (UG) network, supported by the provision of fast and high capacity emergency generation, especially during very severe events.

D. Exploration of the influence of the fast growing generation capacity in distribution networks to the whole GB system security of supply under the current reliability standard.

Chapter 5 evaluated the security of supply for a generic GB electricity system. From the analysis, it is found that there is a relatively low level risk of customer interruptions given a 3 hours LOLE system where the System Operator has access to balancing services (currently around 2GW). However, the drop in peak demand in recent years mainly from the contribution of fast growing embedded generation and a future increase of demand response services in distribution networks can expose the system to fewer but more serious customer disconnections. The analysis shows that the 3h LOLE standard for a high wind penetration system may not be able to ensure an acceptable level of security of supply, especially for adverse events when high demand coincides with lower available generation capacity. The potential solution to this issue could be a more stringent reliability standard or increased capacity of balancing services.

6.2 Directions for Future Work

A. Network model

The proposed network simulation tool models distribution network restoration in two stages. The first stage is node status modelling (described in section 2.3.2.2 of Chapter 2) which identifies sections of the network that are potentially supplied and the second stage solves optimisation problems to compute the optimal demand curtailment. This simplification can bring inaccuracy if compared with real distribution networks in which upstream and downstream switching actions do usually not happen simultaneously. Therefore, a method which can model the actions of different switches separately may improve the accuracy of the reliability assessment.

It is also assumed that switches including circuit breaker, sectionalizing switchgears, normally open points are 100% reliable. Operational failure may be modelled in future study that switches can potentially fail to respond.

B. Storage model

The proposed "greedy" model for the storage operation aims to maximise the ability of storage devices to contribute to network reliability. A weighting factor has been used to prioritise the optimisation problems: in the condition of minimising load curtailment, maximise the state of charge. The choice of the value for the weighting factor can be difficult since the reasonable range of it varies for different systems.

A precise solution to this issue is applying the first part of the objective function as the constraints of the second part, in the form of the Karush-Kuhn-Tucker (KKT) conditions.

An example for the optimisation problem with multiple objectives and their weighting factors is shown as:

$$\min f(x) + w \cdot g(x) \tag{6.1a}$$

$$s.t. \qquad Ax \leq b \tag{6.1b}$$

It can be reformulated by the introduction of the Lagrangian function or the KKT conditions to avoid the weighting factors as:

$$\min g(x) \tag{6.2a}$$

$$s.t. \qquad Ax \leq b \tag{6.2b}$$

$$\frac{\partial}{\partial x}\big(f(x) + \lambda \cdot (Ax - b)\big) \leq 0 \tag{6.2c}$$

$$\frac{\partial}{\partial \lambda}\big(f(x) + \lambda \cdot (Ax - b)\big) \leq 0 \tag{6.2d}$$

$$\lambda \geq 0 \tag{6.2e}$$

$$\frac{\partial^2}{\partial \lambda^2}\big(f(x) + \lambda \cdot (Ax - b)\big) > 0 \tag{6.2f}$$

$$\frac{\partial^2}{\partial \lambda^2}\big(f(x) + \lambda \cdot (Ax - b)\big) > 0 \tag{6.2g}$$

The constraints (6.2c)-(6.2g) are the sufficient conditions for achieving the minimal value for f(x).

This example demonstrates the method to prioritise multiple objectives without the use of weighting factors, despite some loss in computational efficiency.

In the proposed greedy model for the storage operation, it is aimed to maximise the state of charge (SOC) when connected to the grid and discharge only if outages happen. Although this operation scheme is straightforward for reliability purposes, it may not be a cost-effective scheme since a maximum SOC does not guarantee the optimal profitability of storages. Arbitrage of energy may be combined within the operation optimisation so that it can also make a profit when the network is not in an outage. This results in more complex time domain simulations, ideally using model predictive control (MPC) [107] for energy storage operation.

C. Customer Interruption Cost

In future distribution networks, smart metering coupled to in-home energy management devices could change the way customers value supply continuity through facilitating reliability-based consumption choices. By setting design standards that allow networks to be planned in accordance with the differing priorities of different categories of in-house demand, it may be possible to develop and operate networks at lower costs to customers.

A possible model of this ‘smart disconnection’ is briefly described here. It is assumed that some fractions of the load can be interrupted at a lower cost than others, and it is allowed to control the disconnections so that there is an increasing cost per unit of power as disconnecting more load. It might also be achieved by identifying ‘cheap’ vs. ‘expensive’ customers, but it’s more likely that some sort of demand response mechanism is used to disconnect ‘easy’ loads within each household whilst keeping essential services going.

Considering that some fractions of the load can be interrupted at a lower cost than others and we always disconnect the cheapest load first, it may be assumed that the cost of per unit power curtailment is linearly increasing with a higher percentage of demand disconnected.

$$Cost\ of\ \Delta p = £17000 * \frac{p}{Demand} \tag{6.1}$$

p is the curtailed power level, $Demand$ is the original load level, Δp is the curtailed power per MW. That means for a load, the cost of the first 1% load curtailment is cheapest and the cost of per unit power curtailment reaches the costliest level when fully curtailed.

The function of the cost of marginal load curtailment can be much more complex in a real network than the example given above. The factors affecting this function include but are not limited to the development of 'smart disconnection' technologies, the contract between customers and service providers and the degree of customer involvement in the network.

D. High Impact Low Probability events

The Part 2 of Chapter 4 proposed a novel method to analyse HILP events. It can be improved by investigating more detailed time-domain modelling of HILP.

a. Fragility

The *fragility* approach [108], which was originally invented to describe the probabilistic relationship between nuclear plant failure and ground acceleration in an earthquake, can be applied in the reliability analysis to express the probability of distribution network line section failure with respect to the severity of HILP events.

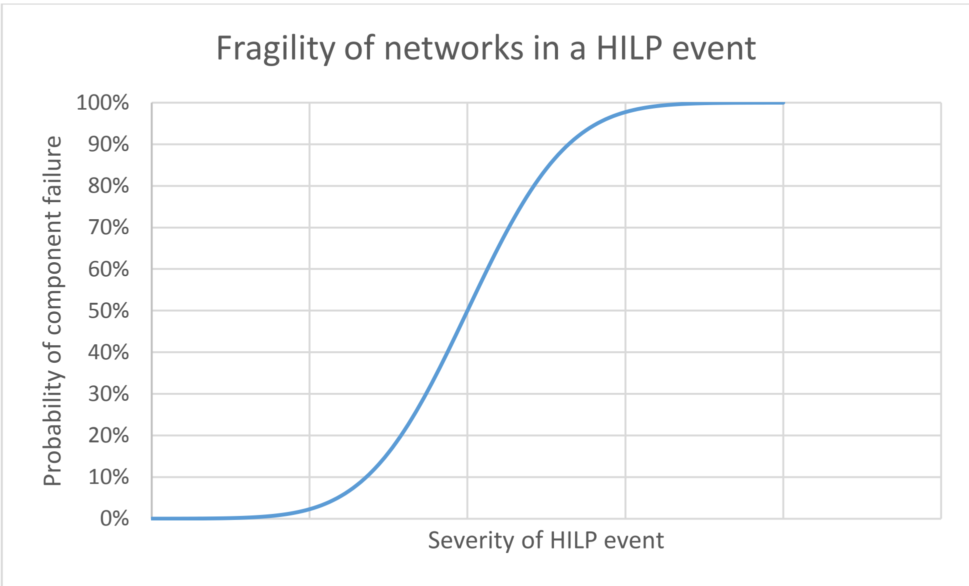


FIGURE 6-2 FRAGILITY OF NETWORKS IN A HILP EVENT

The generic shape of the fragility function is shown in Figure 6-2. The trend indicates that the probability of a network component failure increases as a HILP event, e.g. storm, becomes more profound.

Even though HILP events are infrequent and their "weighted-average" probability is difficult to be calculated / estimated accurately due to the lack of data, considering the fragility of networks in a HILP event, a distribution of HILP events could be assumed and used to estimate the failure rates for various confidence levels and enables reliability assessments. The expected risk for a specified confidence level could then be estimated.

b. Preventive vs corrective

Some case studies have been produced for assessing the impacts of HILP events with preventive (underground cable) and corrective (emergency generation) network reliability improvement measures. The fundamental idea has been introduced in section 9.4.3 of the P2 report "Review of Distribution Network Security Standards" section submitted to OFGEM.

There is a number of fundamental questions associated with the optimal portfolio of investments that may increase the network resilience against occurrence of natural hazards such as:

- To what extent a portfolio of merely post-contingency mitigation actions (such as the deployment of mobile generation and transfer cables) would be efficient to deal with outages caused by natural hazard? (historically, network infrastructure has been installed to deal with "credible" rather than rare events)
- Can network resilience be efficiently improved through network reinforcements rather than through a portfolio of post-contingency mitigation actions?
- How the set of post-contingency measures that may include deployment of provisional cables from neighbouring substations can affect the design of network infrastructure?

Overall: what is the right balance between preventive and mitigation (post-contingency) measures that can efficiently improve network resilience? In this thesis, we have developed a simulation model that could be applied to analyse different specific cases. A more comprehensive analysis can be undertaken but scenarios would need to be defined.

E. Equivalent Load Carrying Capacity

We investigated the implications of different non-network solutions for enhancing network reliability. The impacts of these solutions on network performance is represented by changes of ENS, CI and CML. However, it is still difficult to compare the capability of different techniques since the change of reliability indices is case specific. The methods could be developed further to be compatible with the concept of Equivalent Load Carrying Capacity (ELCC) [109], which measures the amount of additional demand by installing an alternative technique whilst maintaining the original reliability performance. This enables the direct comparison of different network improvement solutions.

REFERENCES

[1] Parliament of the United Kingdom, “Climate Change Act 2008,” 2008.

[2] European Council, “European Council (23 and 24 October 2014 - Conclusions),” 2014.

[3] National Development and Reform Commission of China, “Enhanced Actions on Climate Change: China’s intended nationally determined contributions,” 2015.

[4] Government of Japan, “Japan’ s First Biennial Report,” 2013.

[5] Zero Carbon Hub, “Zero Carbon Homes and Nearly Zero Energy Buildings UK Building Regulations and EU Directives,” 2014.

[6] Ofgem, “Feed-in Tariff (FIT) Generation & Export Payment Rate Table,” 2016.

[7] GOV.UK, “Vehicle tax rate.” [Online]. Available: https://www.gov.uk/vehicle-tax-rate-tables.

[8] Transport for London, “Congestion Charge.” [Online]. Available: https://tfl.gov.uk/modes/driving/congestion-charge/discounts-and-exemptions#on-this-page-0.

[9] Westminster City Council, “Electric Vehicle.” [Online]. Available: https://www.westminster.gov.uk/electric-vehicles.

[10] National Grid, “National Electricity Transmission System Security and Quality of Supply Standard,” 2012.

[11] OFGEM, “To distributors, customer groups and other interested parties,” 2007.

[12] Trilliant Holdings Inc., “Vision of Smart Grid.” [Online]. Available: http://trilliantinc.com/smart-grid.

[13] R. Brown, *Electric Power Distribution Reliability*, Second Edi. CRC Press, 2008.

[14] K. Aoki, K. Nara, M. Itoh, T. Satoh, and H. Kuwabara, “A new algorithm for service restoration in distribution systems,” *IEEE Trans. Power Deliv.*, vol. 4, no. 3, pp. 1832–1839, 1989.

[15] K. Aoki, K. Nara, T. Satoh, M. Itoh, H. Kuwabara, M. Kitagawa, and K. Yamanaka, "Totally automated switching operation in distribution system," *IEEE Trans. Power Deliv.*, vol. 5, no. 1, pp. 514–520, 1990.

[16] J. Nahman and G. Strbac, "A new algorithm for service restoration in large-scale urban distribution systems," *Electr. Power Syst. Res.*, vol. 29, no. 3, pp. 181–192, 1994.

[17] D. Shirmohammadi, "Service Restoration in Distribution Networks," *Transm. Distrib. Conf. 1991., Proc. 1991 IEEE Power Eng. Soc.*, vol. 7, no. 2, pp. 626–632, 1991.

[18] H. Kim, Y. Ko, and K. Jung, "Algorithm of Transferring the Load of the Faulted Substation Transformer Using the Best-First Search Method," *IEEE Trans. Power Deliv.*, vol. 7, no. 3, pp. 1434–1442, 1992.

[19] E. N. Dialynas and D. G. Michos, "Interactive Modeling of Supply Restoration Procedures in Distribution System Operation," *IEEE Trans. Power Deliv.*, vol. 4, no. 3, pp. 1847–1854, 1989.

[20] L. S. de Assis, J. F. V. Gonzalez, F. L. Usberti, C. Lyra, C. Cavellucci, and F. J. Von Zuben, "Switch Allocation Problems in Power Distribution Systems," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 246–253, 2015.

[21] A. Mendes, N. Boland, P. Guiney, and C. Riveros, "Switch and tap-changer reconfiguration of distribution networks using evolutionary algorithms," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 85–92, 2013.

[22] G. Kjolle and K. Sand, "RELRAD-an analytical approach for distribution system reliability assessment," in *Transmission and Distribution Conference, 1991., Proceedings of the 1991 IEEE Power Engineering Society*, 1991, pp. 729–734.

[23] R. Billinton and R. Allan, *Reliability evaluation of power systems*. New York, 1984.

[24] R. N. Allan, R. Billinton, I. Sjarief, L. Goel, and K. S. So, "A reliability test system for educational purposes--Basic distribution system data and results," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 813–820, 1991.

[25] Ofgem, "How we report on electricity distribution company performance − next steps," 2015.

[26] London Economics, "The Value of Lost Load (VoLL) for Electricity in Great Britain: Final

report for OFGEM and DECC," 2013.

[27] OFGEM, "Electricity Capacity Assessment Report 2014," 2014.

[28] H. P. Schmidt, N. Ida, N. Kagan, and J. C. Guaraldo, "Fast reconfiguration of distribution systems considering loss minimization," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1311–1319, 2005.

[29] E. Ramos and A. Expósito, "Path-based distribution network modeling: application to reconfiguration for loss reduction," *Power Syst. IEEE …*, vol. 20, no. 2, pp. 556–564, 2005.

[30] S. Haffner, L. F. A. Pereira, L. A. Pereira, and L. S. Barreto, "Multistage model for distribution expansion planning with distributed generation - Part I: Problem formulation," *IEEE Trans. Power Deliv.*, vol. 23, no. 2, pp. 915–923, 2008.

[31] M. Lavorato, J. F. Franco, M. J. Rider, and R. Romero, "Imposing radiality constraints in distribution system optimization problems," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 172–180, 2012.

[32] R. Billinton and R. N. Allan, *Reliability Evaluation of Engineering Systems*, 2nd editio. New York: Springer Science, 1992.

[33] R. Tarjan, "Depth-first search and linear graph algorithms," *12th Annu. Symp. Switch. Autom. Theory (swat 1971)*, vol. 1, no. 2, pp. 114–121, 1971.

[34] MathWorks, "MATLAB The Language of Technical Computing." [Online]. Available: http://uk.mathworks.com/products/matlab/?requestedDomain=uk.mathworks.com.

[35] O. TOOLBOX, "What Is OPTI." [Online]. Available: http://www.i2c2.aut.ac.nz/Wiki/OPTI/index.php/Main/WhatIsOPTI?

[36] K. Bell and P. R. Allan, "Computation of the Value of Security," *Manchester Cent. Electr. Energy, Dep. Electr. Eng. Electron. UMIST*, 1999.

[37] A. B. Owen, "Importance Sampling," in *Monte Carlo theory, methods and examples*, vol. 85, no. 7, 2012.

[38] OFGEM, "Regulatory Reporting Pack (RRP) version 2.2 Cost and Data tables." [Online]. Available: https://www.ofgem.gov.uk/publications-and-updates/regulatory-reporting-pack-rrp-version-2.2-cost-and-data-tables.

[39] OFGEM, "Quality of Service Interruptions reporting workbook." [Online]. Available: https://www.ofgem.gov.uk/ofgem.../46653/qos-interruptions-reporting-workbook.xls.

[40] OFGEM, "RIIO-ED1 glossary of terms," pp. 1–29, 2000.

[41] R. E. Brown and A. P. Hanson, "Impact of two-stage service restoration on distribution reliability," *IEEE Trans. Power Syst.*, vol. 16, no. 4, pp. 624–629, 2001.

[42] J. J. Burke, *Power Distribution Engineering: Fundamentals and Applications*. Marcel Dekker, 1994.

[43] R. Allan, G. Strbac, P. Djapic, and K. Jarrett, "Developing the P2 / 6 Methodology," *OFGEM*, 2004.

[44] National Grid, "National Grid EMR Electricity Capacity Report," no. June, pp. 1–109, 2014.

[45] K. K. Kariuki and R. N. Allan, "Evaluation of reliability worth and value of lost load," *IEE Proc. - Gener. Transm. Distrib.*, vol. 143, p. 171, 1996.

[46] D. Cheng and B. Venkatesh, "Literature survey and comparison of consumer interruption costs in North America and Europe," *Can. Conf. Electr. Comput. Eng.*, pp. 1–7, 2014.

[47] G. Wacker and R. Billinton, "Customer Cost of Electric Service Interruptions," *Proc. IEEE*, vol. 77, no. 6, pp. 919–930, 1989.

[48] P. Kos, R. Billinton, and G. Wacker, "Cost of electric power interruptions in the agricultural sector--Statistical analysis," *IEEE Trans. Power Syst.*, vol. 6, no. 4, pp. 1432–1438, 1991.

[49] B. R. and W. G. Subramaniam R.K., "Understanding Industrial Losses Resulting from Electric Service Interruptions," *Annu. Meet. IEEE Ind. Appl. Soc.*, 1990.

[50] B. R. and W. G. Subramaniam R.K., "Understanding Commercial Losses Resulting from Electric Service Interruptions," *IEEE Trans. Ind. Appl.*, vol. 29, 1993.

[51] G. Wacker and R. Billinton, "Farm losses resulting from electric service interruptions-a canadian survey," *IEEE Trans. Power Syst.*, vol. 4, no. 2, pp. 472–478, 1989.

[52] G. Tollefson, E. Chan, and J. Aweya, “A Canadian Customer Survey To Assess Power System Reliability Worth,” *IEEE Trans. Power Syst.*, vol. 9, no. 1, 1994.

[53] J. Gates, R. Billinton, and G. Wacker, “Electric service reliability worth evaluation for government, institutions and office buildings,” *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 43–49, 1999.

[54] K. H. Tiedemann, “Estimating the Value of Reliability for Residential Customers (a),” *8th Int. Conf. Probabilistic Methods Appl. to Power Syst.*, pp. 742–746, 2004.

[55] K. H. Tiedemann, “Estimating the Value of Reliability for Residential Customers (b),” *8th Int. Conf. Probabilistic Methods Appl. to Power Syst.*, pp. 747–751, 2004.

[56] G. Wacker, E. Wojczynski, and R. Billinton, “Interruption Cost Methodology and Results - A Canadian Residential Survey,” *IEEE Trans. Power Appar. Syst.*, vol. PER-3, no. 10, pp. 34–35, 1983.

[57] E. Woiczynski, R. Billinton, and G. Wacker, “Interruption Cost Methodology and Results A Canadian Commercial and Small Industry Survey,” *IEEE Power Eng. Rev.*, vol. PER-4, no. 2, pp. 39–40, 1984.

[58] P. D. Michael Sullivan, P. D. Michael Perry, M. A. Josh Schellenberg, M. P. P. Jason Burwen, B. A. Sam Holmberg, B. A. Sarah Woehleke, and S. & C. Freeman, “Pacific Gas & Electric Company ’ s 2012 Value of Service Study The FSC Group Table of Contents,” *Rep. Prep. Pacific Gas Electr. Co. by Free. Sullivan Co.*, pp. 1–84, 2012.

[59] P. Balducci, J. M. Roop, L. A. Schienbein, J. G. Desteese, and M. R. Weimar, “Electrical Power Interruption Cost Estimates for Individual Industries, Sectors, and U.S. Economy,” 2002.

[60] J. L. Corwin and W. T. Miles, “Impact Assessment of the 1977 Ney York City Balackout,” *Prep. United States Dep. Energy by Syst. Control Inc.*, pp. 1–155, 1977.

[61] M. J. Sullivan, M. Mercurio, J. Schellenberg, and S. & C. Freeman, “Estimated Value of Service Reliability for Electric Utility Customers in the United States,” *Lawrence Berkeley Natl. Lab.*, no. June, p. 98, 2009.

[62] K. T. Centolella P., Farber-DeAnda M., Greening L. A., “Estimates of the Value of Uninterrupted Service for The Mid-West Independent System Operator,” 2010.

[63] M. Bliem, “Economic Valuation of Electrical Service Reliability – Experiences from Austrian,” *Counc. Eur. Energy Regul. Work. Contin. Supply Regul. by Incent. - Willingness to Pay Accept*, no. September, pp. 1–27, 2008.

[64] M. Bliem, “Economic Valuation of Electrical Service Reliability in Austria – A Choice Experiment Approach,” *Inst. Adv. Stud. Carinthia*, no. August, 2009.

[65] V. T. T. Energy, P. O. Box, and F.- Vtt, “COMPARISON OF THE METHODS FOR ASSESSING THE CUSTOMERS’ OUTAGE COSTS Matti Lehtonen and Bettina Lemstrom, VTT Energy, P.O.Box 1606, FIN-02044 VTT, Finland,” *Proc. EMPD*, no. 95, pp. 1–6, 1995.

[66] M. de Nooij, C. Koopmans, and C. Bijvoet, “The value of supply security. The costs of power interruptions: Economic input for damage reduction and investment in networks,” *Energy Econ.*, vol. 29, no. 2, pp. 277–295, 2007.

[67] G. H. Kjølle, K. Samdal, B. Singh, and O. A. Kvitastein, “Customer costs related to interruptions and voltage problems: Methodology and results,” *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1030–1038, 2008.

[68] a. Bertazzi, E. Fumagalli, and L. Lo Schiavo, “The use of customer outage cost surveys in policy decision-making: the Italian experience in regulating quality of electricity supply,” *18th Int. Conf. Exhib. Electr. Distrib. (CIRED 2005)*, vol. 2005, no. 6, pp. v6–41–v6–41, 2005.

[69] E. Leahy and R. S. J. Tol, “An estimate of the value of lost load for Ireland,” *Energy Policy*, vol. 39, no. 3, pp. 1514–1520, 2011.

[70] P. Linares and L. Rey, “The costs of electricity interruptions in Spain: Are we sending the right signals?,” *Energy Policy*, vol. 61, pp. 751–760, 2013.

[71] F. Carlsson and P. Martinsson, “Willingness to pay among Swedish households to avoid power outages: A random parameter Tobit model approach,” *Energy J.*, vol. 28, no. 1, pp. 75–89, 2007.

[72] F. Carlsson, P. Martinsson, and A. Akay, “The effect of power outages and cheap talk on willingness to pay to reduce outages,” *Energy Econ.*, vol. 33, no. 5, pp. 790–798, 2011.

[73] F. Carlsson and P. Martinsson, “Does it matter when a power outage occurs? - A choice experiment study on the willingness to pay to avoid power outages,” *Energy Econ.*, vol.

30, no. 3, pp. 1232–1245, 2008.

[74] A. J. Praktiknjo, A. Hähnel, and G. Erdmann, “Assessing energy supply security: Outage costs in private households,” *Energy Policy*, vol. 39, no. 12, pp. 7825–7833, 2011.

[75] Accent Scotland, “Quantitative Research into Non Domestic Customer Engagement and Experience of the Energy Market Report November 2012,” *OFGEM*, 2012.

[76] Accent, “Expectations of DNOs & Willingness to Pay for Improvements in Service,” *OFGEM*, no. July, 2008.

[77] Accent Marketing & Research, “Consumer Expectations of DNOs and WTP for Improvements in Service,” *OFGEM*, no. June, pp. 1–117, 2004.

[78] OakleyGreenwood, “Valuing Reliability in the National Electricity Market: Final Report,” *Aust. Energy Mark. Oper.*, 2011.

[79] M. Delfanti, E. Fumagalli, P. Garrone, L. Grilli, and L. Lo Schiavo, “Toward voltage-quality regulation in Italy,” *IEEE Trans. Power Deliv.*, vol. 25, no. 2, pp. 1124–1132, 2010.

[80] D. F. Layton and K. Moeltner, “The Cost of Power Outages to Heterogeneous Households,” in *Applications of Simulation Methods in Environmental and Resource Economics*, R. Scarpa and A. Alberini, Eds. Dordrecht: Springer Netherlands, 2005, pp. 35–54.

[81] K. G. Willis and G. D. Garrod, “Electricity supply reliability,” *Energy Policy*, vol. 25, no. 1, pp. 97–103, 1997.

[82] M. Beenstock and E. Goldin, “Priority pricing in electricity supply: An application for Israel,” *Resour. Energy Econ.*, vol. 19, no. 3, pp. 175–189, 1997.

[83] S. Feature, “Quality of supply — Attitudes of Business and Domestic Electricity Customers,” *OFFER*, no. June 2000, pp. 108–114, 2001.

[84] K. Y. Nam, S. B. Choi, H. S. Ryoo, S. H. Jeong, J. D. Lee, and D. K. Kim, “A survey on interruption costs of Korean industrial customers,” *Proc. IEEE Power Eng. Soc. Transm. Distrib. Conf.*, pp. 781–787, 2006.

[85] M. Hofmann, H. Slejeseth, G. Holst Volden, G. H. Kjolle, and SINTEF Energy Research, “Guidelines of Good Practice on Estimation of Costs due to Electricity Interruptions and Voltage Disturbances,” *Counc. Eur. Energy Regul.*, no. December, pp. 1–72, 2010.

[86] RECKON, "Desktop review and analysis of information on Value of Lost Load for RIIO-ED1 and associated work," 2012.

[87] N. Hanley, S. Mourato, and R. E. Wright, "Choice Modelling Approaches : a Superior Alternative for Environmental Valuation ?," *J. Econ. Surv.*, vol. 15, no. 3, pp. 435–462, 2001.

[88] R. Scarpa and J. M. Rose, "Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why," *Aust. J. Agric. Resour. Econ.*, vol. 52, no. 3, pp. 253–282, 2008.

[89] I. Journal and R. H. Muconsult, "The ' no-choice ' alternative to conjoint choice experiments," no. January, 2001.

[90] D. Pearce, "The role of 'property rights' in determining economic values for environmental costs and benefits," *Environ. Agency*, no. December, 2002.

[91] B. Vermeulen, P. Goos, and M. Vandebroek, "Models and optimal designs for conjoint choice experiments including a no-choice option," *Int. J. Res. Mark.*, vol. 25, no. 2, pp. 94–103, 2008.

[92] J. P. C. Grutters, A. G. H. Kessels, C. D. Dirksen, D. Van Helvoort-Postulart, L. J. C. Anteunis, and M. A. Joore, "Willingness to accept versus willingness to pay in a discrete choice experiment," *Value Heal.*, vol. 11, no. 7, pp. 1110–1119, 2008.

[93] S. The, Q. Journal, N. Feb, M. J. Doane, and C. Woo, "Consumer Rationality and the Status Quo Author (s): Raymond S . Hartman , Michael J . Doane and Chi-Keung Woo Published by : Oxford University Press Stable URL : http://www.jstor.org/stable/2937910 Accessed : 17-04-2016 21 : 24 UTC Your use of the JSTOR," vol. 106, no. 1, pp. 141–162, 2016.

[94] R. N. Allan, "VOLL - fact or fiction?," *IEE Power Eng. J.*, vol. 9, no. 1, p. 2, 1995.

[95] K. K. Kariuki and R. N. Allan, "Factors affecting customer outage costs due to electric service interruptions," *IEE Proceedings - Generation, Transmission and Distribution*, vol. 143, no. 6. p. 521, 1996.

[96] K. K. Kariuki and R. N. Allan, "Applications of customer outage costs in system planning, design and operation," *IEE Proc. Gener. Transm. Distrib.*, vol. 143, no. 4, pp. 305–312, 1996.

[97] Office of National Statistics, "Inflation and price indices." [Online]. Available: https://www.ons.gov.uk/economy/inflationandpriceindices.

[98] P. Ochoa, "Electricity Capacity Assessment Report 2013," *OFGEM, UK*, 2013.

[99] "IEEE Reliability Test System," *IEEE Trans. Power Appar. Syst.*, vol. PAS-98, no. 6, pp. 2047–2054, 1979.

[100] K. Marr, "Electricity security of supply - A commentary on National Grid ' s Future Energy Scenarios for the next three winters," *OFGEM, UK*, pp. 1–24, 2015.

[101] I. Staffell and R. Green, "How does wind farm performance decline with age?," *Renew. Energy*, vol. 66, pp. 775–786, 2014.

[102] "Offshore Wind (UK)," 2014. [Online]. Available: http://www.renewableuk.com/en/utilities/document-summary.cfm?docid=534FCE8C-D4DB-490D-A58E6B14B4B72BE4. [Accessed: 01-Dec-2012].

[103] DECC and National Grid, "Provisional Auction Results: Capacity Auction 2014," 2014.

[104] Parsons Brinckerhoff, "Technical Assessment of the Operation of Coal and Gas Fired Plants," no. December, 2014.

[105] RenewableUK, "Offshore Wind Energy Figures." [Online]. Available: http://www.renewableuk.com/en/renewable-energy/wind-energy/offshore-wind/index.cfm.

[106] RenewableUK, "Offshore Wind Development Rounds." [Online]. Available: http://www.renewableuk.com/en/renewable-energy/wind-energy/offshore-wind/development-rounds.cfm.

[107] M. Arnold and G. Andersson, "Model Predictive Control of Energy Storage Including Uncertain Forecasts," *Power Syst. Comput. Conf.*, vol. 22, no. 1, pp. 60–71, 2012.

[108] K. Porter, "A Beginner' s Guide to Fragility, Vulnerability, and Risk," *Univ. Color. Boulder SPA Risk LLC, Denver CO USA*, no. May, 2016.

[109] C. Dent, D. Miller, N. P. Uk, P. Davison, D. Roberts, and S. Blake, "Capacity Value of Distributed Generation for Network Capacity Planning," *Cired 22*, no. 0827, pp. 10–13, 2013.

[110] Jamasb T., L. Orea, and M. G. Pollitt, “Estimating marginal cost of quality improvements: The case of the UK electricity distribution companies,” *Ewepa*, no. September, 2011.

[111] D. S. Kirschen, “Power Systems Test Case Archive,” *University of Washington*. [Online]. Available: https://www.ee.washington.edu/research/pstca/rts/pg_tcarts.htm.

APPENDIX A. TABLE OF KEY CDF DATA

The Table A.1 is a copy from the literature [46], Table A.2 is summarised data of [26], [36], [45]–[94], [97], [110] in the format of A.1 (but excluding data already existed in A.1).

TABLE A.1 LIST OF PUBLISHED CIC DATA [46]

References	Country	Date of Data	Method	Key Findings €=Euro, C$= Canadian Dollar, $=US Dollar, £= UK Pound, NOK=Norwegian Krone
Nooij et al (2006)	Netherlands	2001	EO/C	Agriculture € 3.90/kWh Manufacturing € 1.87/kWh Construction € 33.05/kWh Transport € 12.2/kWh Services €7.94/kWh Government € 33.50/kWh Residential € 16.38/kWh Total € 8.56/kWh
Leahy et al (2010)	Ireland	2007	EO/C	Industrial € 4/kWh Commercial € 14/kWh Residential € 24.6/kWh Total € 12.9/kWh
Linares et al (2012)	Spain	2008	EO/C	Agriculture € 4.40/kWh Manufacturing € 1.38/kWh Construction € 33.37/kWh Transport € 8.53/kWh Services € 8.47/kWh Government € 6.23/kWh Residential € 8.11/kWh Total € 5.98/kWh
Wacker et al (1989a)	Canada	1980	Customer survey	*1min* *20min* *1hour* *4hours* *8hours* Larger User C$1.80/kW C$2.22/kW C$3.19/kW C$6.89/kW C$10.47/kW Small Industrial C$0.70/kW C$2.88/kW C$5.19/kW C$13.87/kW C$27.60/kW Commercial C$0.28/kW C$2.05/kW C$5.88/kW C$21.51/kW C$63.06/kW Residential - C$0.06/kW C$0.31/kW C $3.16/kW -
Tollefson et al (1994)	Canada	1991	Customer survey	Industrial C$ 6.5264/kW (1 hour interruption) Commercial C$ 15.0650/kW (1 hour interruption) Residential C$ 0.1626 /kW (1 hour interruption)
Tiedemann (2004a, 2004b)	British Columbia, Canada	2000	Customer survey	*20min* *2hours* *4hours* *12hours* $/kWh lost $/kWh lost $/kWh lost $/kWh lost Business 806 299 216 107 Residential 3.23 0.54 0.44 0.18
Kjølle et al (2008)	Norway	2001-2002	Customer survey	Industrial NOK123/KWh not supplied (1 hour Interruption) Commercial NOK201.5/KWh not supplied (1 hour Interruption) Large Industry NOK 23.8/KWh not supplied (1 hour Interruption) Public service NOK19.9/KWh not supplied (1 hour Interruption) Agriculture NOK16.6/KWh not supplied (1 hour Interruption) Residential NOK11.5/KWh not supplied (1 hour Interruption)
Lehtonen et al. (1995)	Denmark	1992-1993	Customer survey	Industrial $22.10/kW (1 hour Interruption) Commercial $8.50/kW (1 hour Interruption) Residential $6.60/kW (1 hour Interruption) Agricultural $66.80/kW (1 hour Interruption)
Lehtonen et al. (1995)	Finland	1992-1993	Customer survey	Industrial $14.50/kW (1 hour Interruption) Commercial $16.40/kW (1 hour Interruption) Residential $2.90/kW (1 hour Interruption) Agricultural $15.50/kW (1 hour Interruption)

Lehtonen et al. (1995)	Iceland	1992-1993	Customer survey	Industrial $12.50/kW (1 hour Interruption) Commercial $21.00/kW (1 hour Interruption) Residential $3.20/kW (1 hour Interruption) Agricultural $5.60/kW (1 hour Interruption)
Bliem (2008)	Austria	2007	Customer survey	Households € 73.5/KWh not supplied (1 hour Interruption) Business € 203.93/KWh not supplied (1 hour Interruption)
Sullivan et al (2012)	Pacific & Gas Electric, San Francisco USA	2012	Customer survey	***Note: SMB = Small and Medium Business*** Cost per Outage Event ***Outage Duration*** | ***Residential ($/Event)*** \| ***SMB ($/Event)*** | ***Large Business ($/Event)*** \| ***Agricultural ($/Event)*** 5 minutes | $7.41 | $379.8 | $454,675 | $146.1 1 hour | $11.89 | $1,848.8 | $449,655 | $453.5 4 hours | $16.82 | $4,774.3 | $596,675 | $1,230.7 8 hours | $22.89 | $10,568.7 | $617,196 | $2,549.4 24 hours | $31.67 | $21,339.4 | $1,472,497 | $5,842.4
				Cost per Average kW ***Outage Duration*** | ***Residential ($/kW)*** \| ***SMB ($/kW)*** | ***Large Business ($/kW)*** \| ***Agricultural ($/kW)*** 5 minutes | $9.75 | $43.3 | $319.3 | $18.1 1 hour | $14.86 | $205.2 | $327.4 | $52.1 4 hours | $21.03 | $540.1 | $436.9 | $143.9 8 hours | $28.61 | $1,136.4 | $449.7 | $288.7 24 hours | $40.09 | $2,403.1 | $1,047.5 | $700.5 Cost per Unserved kWh ***Outage Duration*** \| ***Residential ($/kWh)*** | ***SMB ($/kWh)*** \| ***Large Business ($/kWh)*** | ***Agricultural ($/kWh)*** 5 minutes | $123.50 | $493.3 | $3,769.8 | $205.7 1 hour | $14.86 | $195.6 | $318.5 | $50.3 4 hours | $5.08 | $127.5 | $107.5 | $35.6 8 hours | $3.44 | $138.4 | $55.6 | $35.9 24 hours | $1.67 | $99.7 | $43.7 | $28.8
Balducci et al (2002)	USA	1992 and 1996 Canadian data	MCS	| ***20min*** | ***1hour*** | ***4hours*** Industrial | $ 6.29/kW | $ 13.93/kW | $29.94 /kW Commercial | $ 4.74/kW | $ 12.87/kW | $44.37/kW Residential | $ 0.03/kW | $ 0.15/kW | $1.64/kW Transport | $ 8.91/kW | $ 16.42/kW | $45.95/kW Wt. Average | $ 3.59/kW | $ 8.76/kW | $24.90/kW
Sullivan et al (2009)	USA	1989-2005	ACS	**Medium& Large Commercial & Industrial (Av. Consumption = 7,140,501 kWh/year)** | ***Momentary*** | ***30min*** | ***1 hour*** | ***4 hours*** | ***8 hours*** *Cost Per Event* | $11,756 | $15,709 | $20,360 | $59,188 | $93,890 *Cost Per Average kW* | $14.4 | $19.3 | $25.0 | $72.6 | $115.2 *Cost Per Un-served kWh* | $173.1 | $38.5 | $25.0 | $18.2 | $14.4 *Cost Per Annual kWh* | $1.65E-03 | $2.20E-03 | $2.85E-03 | $8.29E-03 | $1.31E-02 **Small Commercial & Industrial (Average Consumption = 19,214kWh/year)** | ***Momentary*** | ***30min*** | ***1 hour*** | ***4 hours*** | ***8 hours*** *Cost Per Event* | $439 | $610 | $818 | $2,696 | $4,768 *Cost Per Average kW* | $200.1 | $278.1 | $373.1 | $1,229.2 | $2,173.8 *Cost Per Un-served kWh* | $2,401.0 | $556.3 | $373.1 | $307.3 | $271.7 *Cost Per Annual kWh* | $2.28E-02 | $3.18E-02 | $4.26E-02 | $0.1403 | $0.2482 **Residential (Average Consumption =13,351kWh/year)** | ***Momentary*** | ***30min*** | ***1 hour*** | ***4 hours*** | ***8 hours*** *Cost Per Event* | $2.7 | $3.3 | $3.9 | $7.8 | $10.7 *Cost Per Average kW* | $1.8 | $2.2 | $2.6 | $5.1 | $7.1 *Cost Per Un-served kWh* | $21.6 | $4.4 | $2.6 | $1.3 | $0.9 *Cost Per Annual kWh* | $2.06E-04 | $2.48E-04 | $2.94E-04 | $5.81E-04 | $8.05E-04
Centolella et al (2010)	USA MidWest	1989-2002	ACS	**Large Commercial & Industrial (Consumption > 1 million kWh/year)** *Agriculture* $24.83/kW (1 hour interruption) *Mining* $77.53/kW (1 hour interruption) *Construction* $24.83/kW (1 hour interruption) *Manufacturing* $42.09/kW (1 hour interruption) *Transport/Communication/Utilities* $24.83/kW (1 hour interruption) *Wholesale/Retail* $24.83/kW (1 hour interruption)

				Finance/Real Estate	$24.83/kW (1 hour interruption)	
				Services	$15.56/kW (1 hour interruption)	
				Public Admin	$24.83/kW (1 hour interruption)	
				Small Commercial &Industrial (Consumption < 1 million kWh/year)		
				Agriculture	$49.51/kW (1 hour interruption)	
				Mining	$49.51/kW (1 hour interruption)	
				Construction	$40.06/kW (1 hour interruption)	
				Manufacturing	$35.81/kW (1 hour interruption)	
				Transport/Communication/Utilities	$29.30/kW (1 hour interruption)	
				Wholesale/Retail	$49.51/kW (1 hour interruption)	
				Finance/Real Estate	$35.64/kW (1 hour interruption)	
				Services	$15.25/kW (1 hour interruption)	
				Public Admin	$33.35/kW (1 hour interruption)	
				Residential		
				Willingness-to-Pay	$1.60/kW(1 hour interruption)	
System Control Inc. (1978)	New York City	1977	BOCS	**Direct ($ million)**	**Indirect ($ million)**	
				Business	34.0	160.4
				Government (Non-public Services)	-	12.5
				Consolidated Edison	12.0	65.0
				Insurance	-	33.5
				Public Health Services	-	1.5
				Other Public Services	9.1	17.26
				Westchester County	0.44	-
				Total	55.54	290.16

TABLE A.2 LIST OF PUBLISHED CIC DATA/2, SUMMARISED FROM [26], [36], [45]–[94], [97], [110] **EXCLUDING DATA EXISTED IN A.1**

References	**Country**	**Date of Data**	**Method**	**Key Findings** **€=Euro, C$= Canadian Dollar, $=US Dollar, £= UK Pound, NOK=Norwegian Krone**				
London Economics	UK	2011-2013	Customer survey	VOLL	WTA	WTP		
				Domestic	£6957/MWh-£11820/MWh	£1651/MWh-£2766/MWh		
				small and medium sized businesses (SMEs)	£33358/MWh-£44149/MWh	£19271/MWh-£27859/MWh		
				Industrial and commercial	£1075/MWh -£1654/MWh			
Kariuki and Allan	UK	1992	Customer survey	SCDFs(£/MWh) for per unit annual consumption				
				Duration	Residential	Commercial	Industrial	Large user
				Mom	-	0.46	3.02	1.07
				1min	-	0.48	3.13	1.07
				20min	0.06	1.64	6.32	1.09
				1h	0.21	4.91	11.94	1.36
				4h	1.44	18.13	32.59	1.52
				8h	-	37.06	53.36	1.71
				24h	-	47.58	67.10	2.39
				SCDFs(£/kW) for per unit peak demand				
				Mom	-	0.99	6.15	6.74
				1min	-	1.02	6.47	6.74
				20min	0.15	3.89	14.27	6.86
				1h	0.54	10.65	25.26	7.18
				4h	3.72	39.04	72.22	8.86
				8h	-	78.65	120.11	9.71
				24h	-	99.98	150.38	13.35
Carlsson and Martinsson	Sweden	2004	Customer survey	Willingness to pay to avoid an interruption: worst case scenario (£)	Mean	Median	Max	Share of zero WTP
				Planned interruption				
				1 hour	0.59	0	46.80	0.9
				4 hours	2.66	0	93.60	0.74
				8 hours	7.90	0	187.20	0.51

				24 hours	17.71	4.68	280.80	0.39
				Unplanned interruption				
				1 hour	0.88	0	46.80	0.86
				4 hours	3.49	0	70.20	0.68
				8 hours	10.12	1.40	187.20	0.46
				24 hours	20.87	8.42	280.80	0.36
				Of uncertain duration: between 2 and 6 hours	6.44	0.00	112.32	0.59
Carlsson and Martinsson	Sweden	2007	Customer survey	Duration and day of interruption	November — March	April — October		
				4 hour weekday	£0.69	£1.00		
				8 hours weekday	£1.98	£2.47		
				24 hours weekday	£8.95	£7.24		
				4 hours weekend	£2.76	£1.88		
				8 hours weekend	£3.53	£3.76		
				24 hours weekend	£11.71	£9.85		

(Table continues)

References	Country	Date of Data	Method	Key Findings			
Bertazzi et al	Italy	2003	Customer survey	Duration of interruption	Domestic customers		
					Direct costs(£/kW for 3 minute interruption, £/kWh for other, annual consumption)	WTA(£/kW for 3 minute interruption, £/kWh for other, annual consumption)	WTP(£/kW for 3 minute interruption, £/kWh for other, annual consumption)
				3 mins	7.3	4.9	1.3
				1 hour	23.0	15.5	3.4
				2 hours	18.5	12.6	2.4
				4 hours	14.3	10.2	2.0
				8 hours	8.8	6.3	1.2
					Business customers		
				3 mins	50.1	31.0	4.5
				1 hour	107.2	72.5	9.7
				2 hours	76.1	51.9	7.0
				4 hours	61.0	44.0	6.0
				8 hours	36.3	26.3	3.6
Accent	UK	2004-2008	Customer survey	Domestic customer: willingness to pay and to accept for a change in number of annual interruptions(£ per interruption per year)			
					Deterioration in service	Improvement in service	
				DNOs	From –£19.52 to –£4.52	From £4.49 to £15.04	
				Domestic customers' willingness to pay and to accept change in average duration of a power cut by a minute (£ per minute change)			
					Deterioration in service	Improvement in service	
				DNOs	From –£0.22 to –£0.04	From £0.04 to £0.18	
Bliem (2009)	Austria	2009	Customer survey	**Summary of estimates on willingness to pay (% of annual bill)**			
				Attribute	Households	Businesses	
				Duration 3 mins	–1%	5%	
				Duration 4h	–16%	–10%	
				Duration 10 h	–22%	–20%	
				Frequency	–1%	–6%	
				Time of day (night)	–1%	14%	

				Day of the week (Sunday)	–7%	16%
				Notification (yes)	3%	–2%
Praktiknjo, A.J. et al	Germany	2011	EO/C	Estimates of costs of interruption for household customers		
				Duration of interruption	VOLL (£/kWh)	
				1 hour	13.7	
				8 hours	8.1	
				Estimates of costs of interruption for business customers		
				Sector	VOLL (£/kWh)	
				Agriculture	2.0	
				Industry	2.2	
				Commerce, service and transportation	14.2	
				Weighted average	5.3	

APPENDIX B. EXAMPLES OF RELIABILITY SIMULATION MODELS AND RESULTS

Reliability indices evaluation through sequential Monte Carlo simulation

Sequential Monte Carlo simulation is a method in which time-dependent system operation is simulated by sampling stochastic sequences and durations of system states. The system states are sampled according to the Markov model of each system component. By randomly sampling durations of component states, the stochastic sequence of system states can then be produced. The estimate of reliability indices for chronological system operation is computed as below:

$$\hat{E}(H) = \frac{1}{N}\sum_{i}^{N} H(X_i)$$

H is the estimation function of a reliability index such as Energy Not Supplied (ENS) or Customer Interruptions (CI). N is the number of simulated years, and X_i represents the chronological system state sequence and duration for year *i*.

Stochastic sampling of system state for a pre-set time period (here we use a year but other time horizons can be used if required) is described as follows:

The expected value and probability distribution of reliability indices can be evaluated by repeating the above procedure for *N* years. Convergence of the simulation is calculated using confidence intervals or coefficients of variation, which also serve as stopping criteria for the simulation.

As discussed before, the reliability indices used for measuring the DNOs performance in the UK are ENS, CI and CML (Customer Minute Lost). Time-sequential Monte Carlo simulation allows for calculating the real-time information of outages at each load point. An illustrative example of a load point outage can be seen in Figure B-1. In this example, the sampled outage covers 3 system states with the critical time points at t1, t2, t3 and t4, and system unserved power varying in time across P1, P2 and P3.

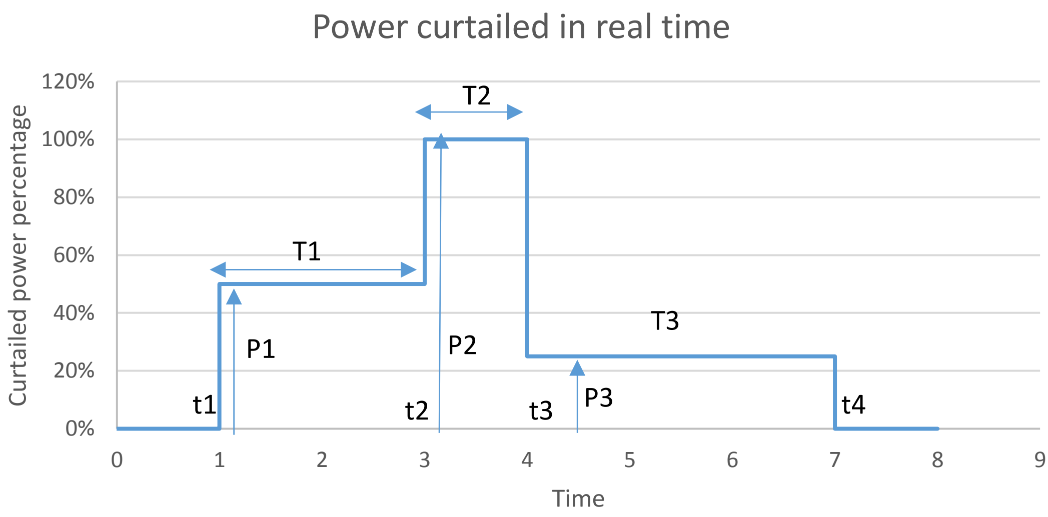


FIGURE B-1 AN ILLUSTRATIVE EXAMPLE FOR LOAD POINT OUTAGE IN REAL TIME

The ENS for this outage is:

$$ENS = P_1 * (t_2 - t_1) + P_2 * (t_3 - t_2) + P_3 * (t_4 - t_3) = P_1 * T_1 + P_2 * T_2 + P_3 * T_3$$

The CML index for this load point is calculated as follows:

$$CML_i = \frac{P_1}{D_1} * N * T_1 + \frac{P_2}{D_2} * N * T_2 + \frac{P_3}{D_3} * N * T_3$$

Where D_i is the load point demand for the system state i and N is the number of customers at the load point.

System CML is adjusted as follows (note the multiplication by 60 to convert hourly values of CML_i to minutes):

$$CML_{system} = \frac{\sum_k CML_k}{\sum_k N_k} * 60$$

where k is the index of load point.

Finally, the CI index for the load point is found as:

$$CI_i = \max\left(\frac{P_1}{D_1}, \frac{P_2}{D_2}, \frac{P_3}{D_3}\right)$$

System CI is adjusted as follows (note the multiplication by 100 to convert the values per customer into the value per 100 customers):

$$CI_{system} = \frac{\sum_k CI_k}{\sum_k N_k} * 100$$

where k is the index of load point.

Figure B-2 illustrate four Markov models for transformer and lines. They are used for representing distribution transformers, primary and bulk supply substations, and lines and cables.

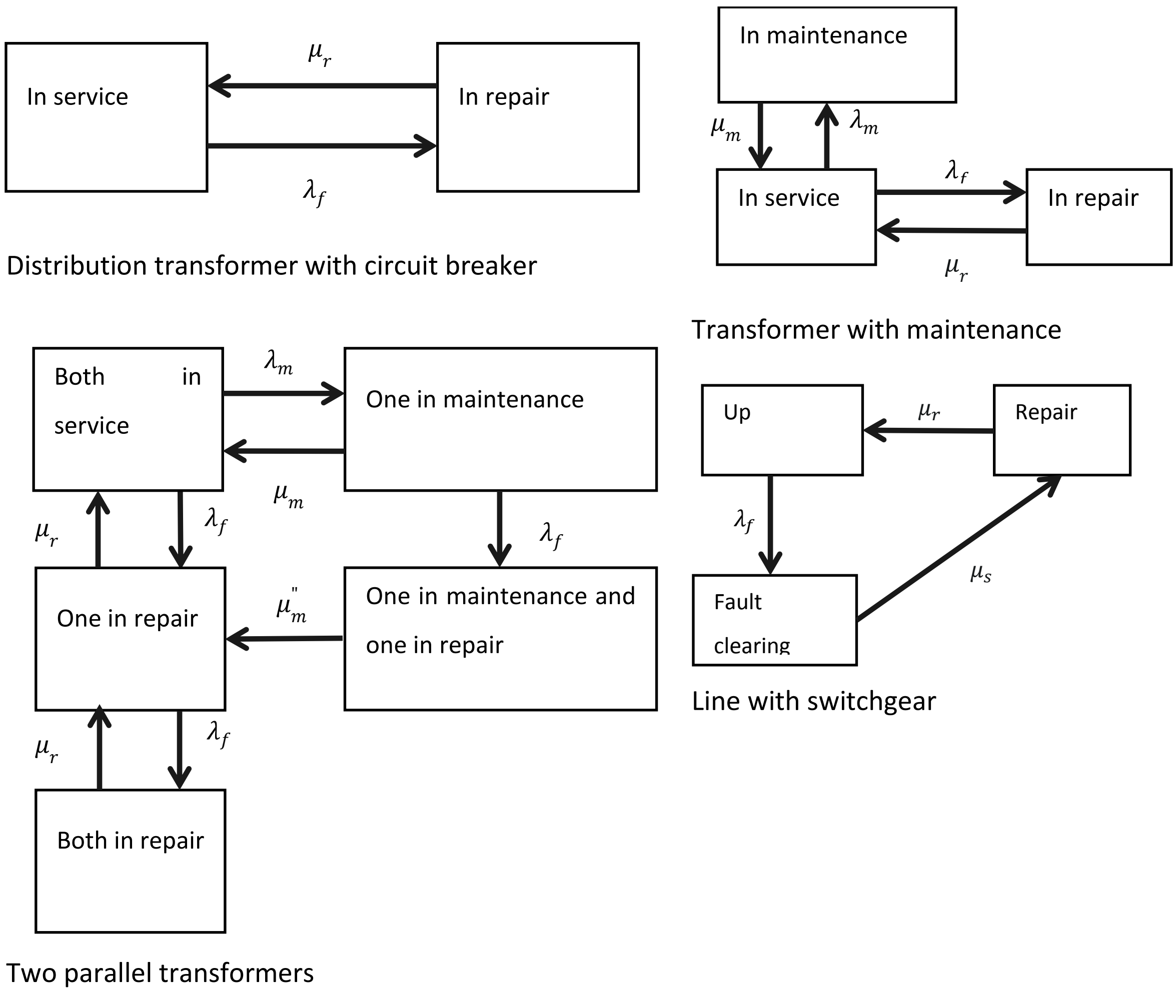


FIGURE B-2 ILLUSTRATION OF FOUR MARKOV MODELS FOR TRANSFORMERS AND LINES

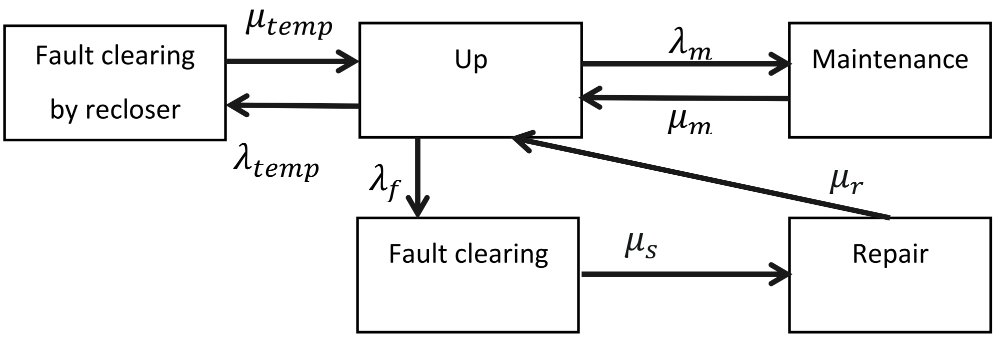


FIGURE B-3 NODE MARKOV MODEL CONSIDERING TEMPORARY FAULT

Figure B-3 provides the Markov model for network with recloser. In the case of a temporary fault in the network, the circuit breaker works as a recloser which trips the whole branch for fault clearing and attempts to close itself after the fault is healed without conducting a repair action or network restoration switching (with sectionalising switches and NOPs). Otherwise, in the case of a permanent fault, it works as presented in Chapter 2.

Illustrative case studies

In order to illustrate the use of analytical and numerical techniques in reliability analysis, a range of studies has been carried out on a typical radial HV distribution network, as shown in

Figure B-4 shows the PDF (probability distribution function)bars and CDF (cumulative distribution function) curves for ENS for line failure rates of 2%, 5%, 10% and 20% per km and year. Depicted range of ENS values is between 0 and 10 MWh/year.

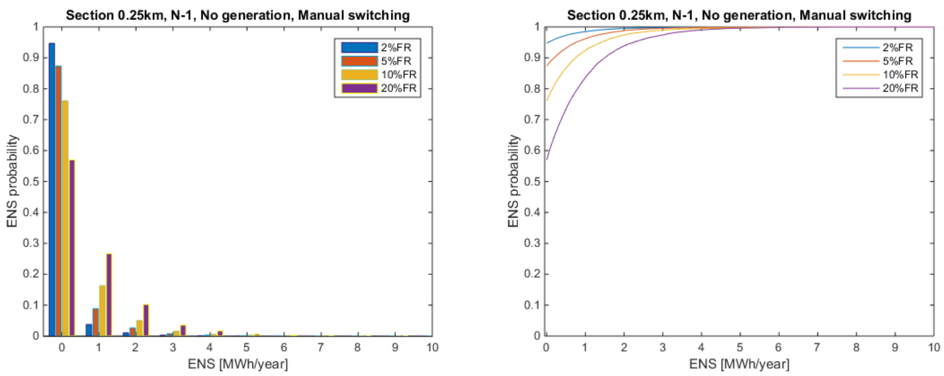


FIGURE B-4 PDF AND CDF OF ENS FOR FAILURE RATE OF 2%, 5%, 10% AND 20%/KM.YEAR

The results suggest that the probability of annual ENS being zero is up to 95% for low failure rates (associated with underground cables), while it is about 57% for high failure rates (more common for overhead lines). The PDF bars in Figure B-4 follow an exponential distribution. It can further be seen from the CDF chart that there is a 95% likelihood that ENS is lower than

0.1 MWh/year for the failure rate of 2%, 0.8 MWh/year for 5%, 1.4 MWh/year for 10% and 2.2 MWh/year for 20% failure rate.

Figure B-5 shows PDF bars and CDF curves for CI for network failure rates of 2%, 5%, 10% and 20% per km and year, with CI ranging between 0 and 250 occ./100customer/year.

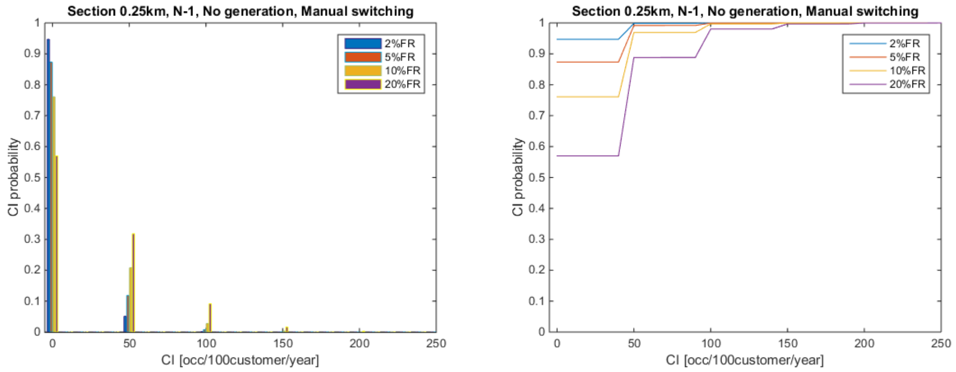


FIGURE B-5 PDF AND CDF OF CI FOR FAILURE RATE OF 2%, 5%, 10%, 20%/KM.YEAR

The probability of annual CI being 50 occ./100customer.year is around 5% for low failure rates, but is as high as 32% for high failure rates. The PDFs again suggest an exponential distribution. The CDF chart suggests that the probability of CI index being 50 occ./100customer.year or below is 99.9% for failure rate of 2%, 99.2% for 5%, 96.9% for 10% and 88.8% for 20%.

Figure B-6 shows the PDF bars and CDF curves for the CML index, again looking at failure rates of 2%, 5%, 10% and 20% per km and year.

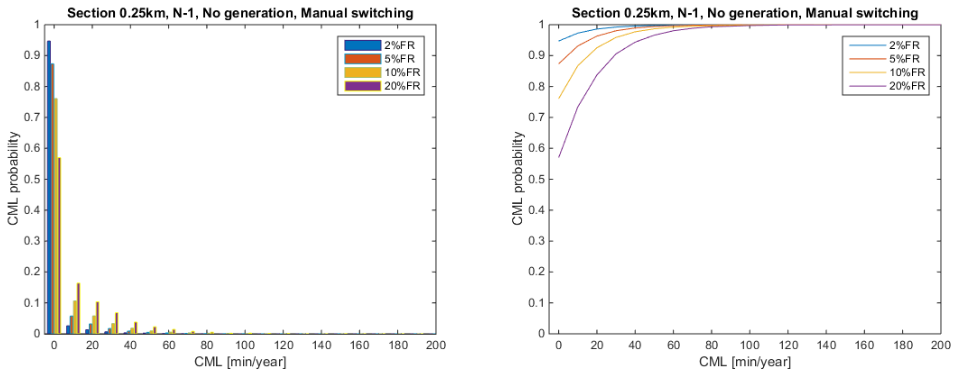


FIGURE B-6 PDF OF CML FOR FAILURE RATE OF 2%, 5%, 10%, 20%/KM.YEAR

According to the results, the probability of annual CML being at the level of 10 min/customer.year is about 2% for low failure rates and about 16% for high failure rates. The CDF curves further suggest that the probability of CML being at or below 20 occ./customer.year is 98.6% for 2% failure rate, 96.3% for 5%, 92.5% for 10% and 83.7% for 20%.

Expected ENS, CI and CML

A set of further case studies has been carried out for different values of input parameters shown in Table B.1.

TABLE B.1 CASE STUDIES PARAMETERS

Parameter	Values
Failure rate for overhead lines (%/km.year)	5 and 20
Failure rate for underground cables (%/km.year)	2 and 10
Switching time (minutes)	2 (automatic) and 30 (manual)
Restoration time (hours)	3 (mobile generation) and 24 (repair)
Section length (km)	0.25 and 1
Loading level	N-1 and N-0

Table B.2 shows the resulting expected values of ENS for different HV network reliability parameters, switching times and loading levels.

TABLE B.2: EENS FOR DIFFERENT HV NETWORK RELIABILITY PARAMETERS, SWITCHING TIME AND LOADING LEVEL

Network ENS (MWh/year)	Failure Rate (%/km.year)	Automatic switching				Manual switching			
		MTTR 3h		MTTR 24h		MTTR 3h		MTTR 24h	
		N-1	N-0	N-1	N-0	N-1	N-0	N-1	N-0
Section length 0.25 km	2%	0.00	0.10	0.00	0.71	0.04	0.17	0.04	0.84
	5%	0.01	0.25	0.01	1.85	0.10	0.40	0.11	1.93
	10%	0.02	0.53	0.02	3.71	0.22	0.85	0.22	4.21
	20%	0.03	0.97	0.04	7.69	0.43	1.66	0.45	8.52
Section length 1 km	2%	0.01	0.40	0.01	2.87	0.17	0.68	0.17	3.24
	5%	0.03	1.07	0.04	7.51	0.46	1.68	0.45	8.22
	10%	0.07	2.03	0.11	15.16	0.90	3.35	0.88	16.86
	20%	0.15	4.03	0.31	29.97	1.74	7.29	1.95	35.84

Table B.3 shows the results for the expected values of CI for different HV network reliability parameters, switching times and loading levels.

TABLE B.3 ECI FOR DIFFERENT HV NETWORK RELIABILITY PARAMETERS, SWITCHING TIME AND LOADING LEVEL

Network ECI (occ./100 cust.year)	Failure Rate (%/km.year)	Automatic switching				Manual switching			
		MTTR 3h		MTTR 24h		MTTR 3h		MTTR 24h	
		N-1	N-0	N-1	N-0	N-1	N-0	N-1	N-0
Section length 0.25 km	2%	3	3	3	4	3	3	3	4
	5%	7	8	7	10	7	8	7	9
	10%	14	15	14	19	14	15	14	20
	20%	27	29	27	39	27	30	28	41
Section length 1 km	2%	11	12	11	15	11	12	11	15
	5%	29	31	27	38	31	30	28	40
	10%	54	59	55	78	57	58	55	79
	20%	109	124	110	156	110	128	111	166

Finally, Table B.4 shows the expected values of CML for different HV network reliability parameters, switching times and loading levels.

TABLE B.4 ECML FOR DIFFERENT HV NETWORK RELIABILITY PARAMETERS, SWITCHING TIME AND LOADING LEVEL

Network ECML (min/customer.year)	Failure Rate (%/km.year)	Automatic switching				Manual switching			
		MTTR 3h		MTTR 24h		MTTR 3h		MTTR 24h	
		N-1	N-0	N-1	N-0	N-1	N-0	N-1	N-0
Section length 0.25 km	**2%**	0	1	0	6	1	1	1	7
	5%	0	2	0	14	2	3	2	15
	10%	0	4	0	29	4	7	4	34
	20%	1	8	1	61	8	15	9	69
Section length 1 km	**2%**	0	3	0	23	3	6	3	26
	5%	1	8	1	59	9	15	9	66
	10%	1	16	2	119	17	29	17	136
	20%	3	32	6	237	33	64	37	290

Comparison between sequential Monte Carlo simulation and analytical method

Differences between results obtained using sequential Monte Carlo simulation and the analytical method applied to the same network are presented in Table B.5.

TABLE B.5 DIFFERENCE OF EENS OBTAINED BY MONTE CARLO SIMULATION AND BY ANALYTICAL METHOD

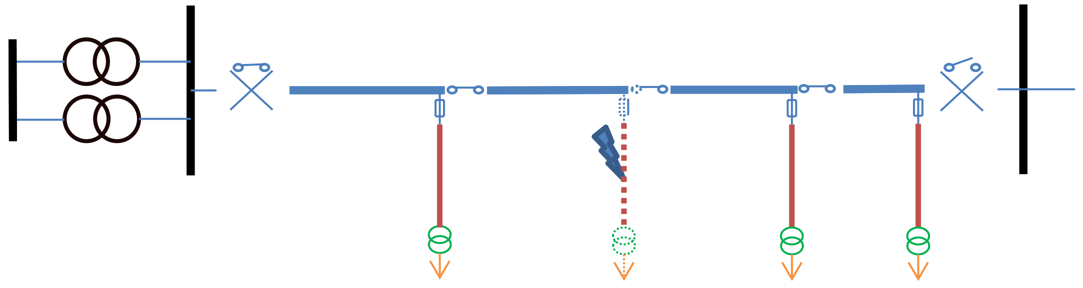
Network ENS (MWh/year)	Failure Rate	Automatic switching				Manual switching			
		MTTR 3h		MTTR 24h		MTTR 3h		MTTR 24h	
		N-1	N-0	N-1	N-0	N-1	N-0	N-1	N-0
Section length 0.25 km	**2%**	-4.1%	-4.9%	-2.8%	-8.5%	-7.2%	-3.6%	-0.1%	-0.3%
	5%	-2.8%	-1.2%	-0.2%	-3.9%	-4.1%	-8.7%	-0.4%	-8.7%
	10%	5.3%	5.0%	-10.5%	-3.8%	-0.1%	-3.1%	-0.1%	-0.4%
	20%	-5.9%	-4.6%	2.4%	-0.5%	-1.5%	-4.7%	2.4%	0.7%
Section length 1 km	**2%**	2.0%	-2.1%	0.1%	-6.9%	-0.9%	-1.9%	-1.4%	-4.1%
	5%	0.4%	5.3%	11.0%	-2.8%	6.6%	-3.9%	2.4%	-2.8%
	10%	5.3%	0.3%	9.7%	-2.0%	4.1%	-4.1%	-3.1%	-0.5%
	20%	7.1%	-0.7%	5.3%	-3.4%	0.3%	4.3%	3.0%	5.5%

The simulation stopping criteria for all case studies in the sequential Monte Carlo simulation was when a Coefficient of Variation (CoV) of 5% or less was achieved. According to the statistical theory, the simulation error greater than two standard deviations occurs with less than 5% probability. Thus, in this distribution network reliability study, the probability of simulation error greater than 10% of the actual value is about 5%. From Table B.5, there are 2 cases (out of 64) with errors greater than 10%. This corresponds to 3% of cases being beyond the (-10%, +10%) interval, which is within the adopted range for CoV of 5%.

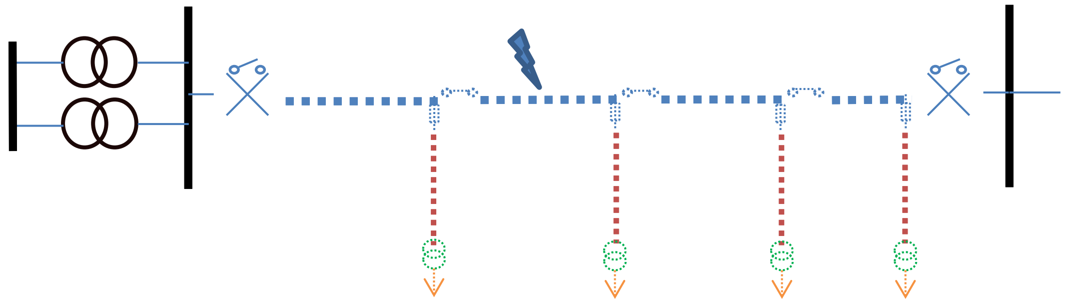
APPENDIX C. ILLUSTRATIONS OF FUNDAMENTAL DISTRIBUTION NETWORK RESTORATION

Fault clearing: Fuse

- Failure occurs in distributed line (red) would be cleared by the operation of fuses
- Fuses perform in a similar way as circuit breaker which isolate the faulty network from the main
- No switching action in this case. Load points recovered only if the faulty line is repaired.

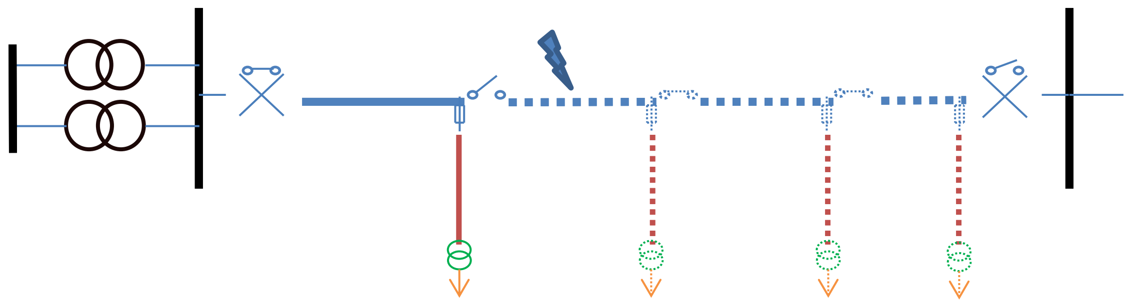


Fault clearing: Circuit breaker



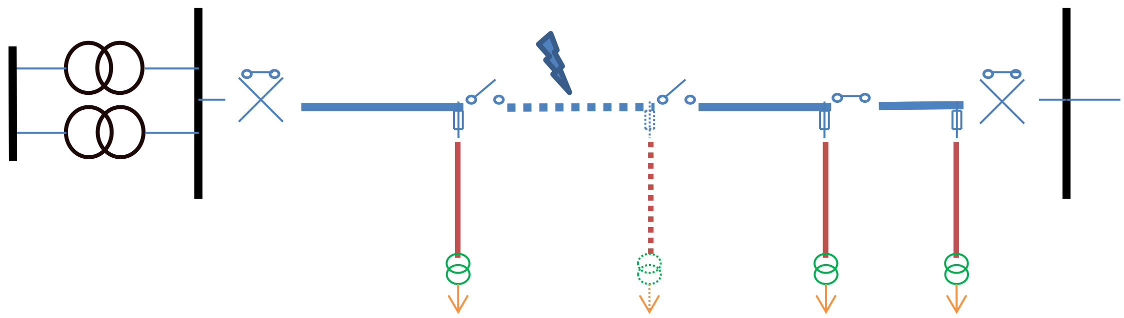
- Failures occur in main lines, circuit breaker would isolate the faulty network from higher voltage level network immediately
- The network would be restored when the faulty line is repaired or switching action is operated

Fault switching: Upstream and downstream switching



Upstream switching action:

- Search for the nearest upstream switch to the failure
- Check that closing the CB whether failures existed in potential recovered area
- Close the main circuit breaker to resupply customers isolated from the failure

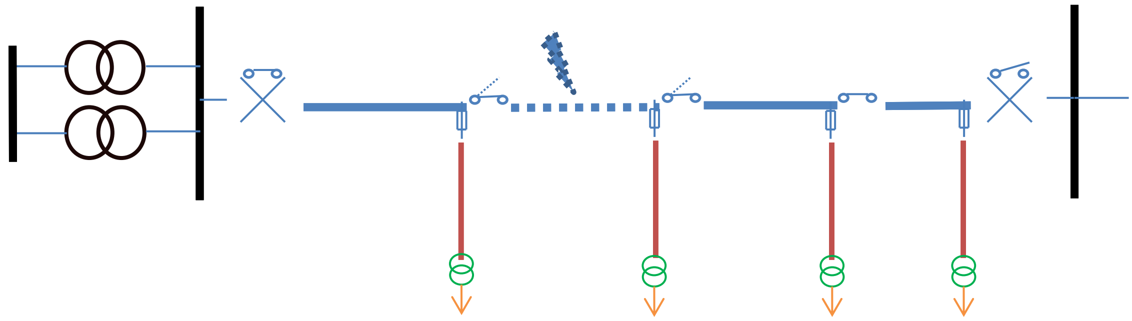


Downstream switching action:

- Search for the nearest downstream switch to the failure
- Check that closing the NOP whether customers existed in potential recovered area

- Check that closing the NOP whether failures existed in potential recovered area (including the failure in other side of NOP)
- Close the NOP to resupply customers isolated from the failure

Fault repair and restoration



Restoration action:

- Check that closing the opened switches whether there exists any failure in potential recovered area
- Close switches and open the NOP

APPENDIX D. IEEE RELIABILITY TEST SYSTEM PARAMETERS

This data is available from [99] and [111]

The IEEE Reliability Test System (IEEE-RTS)

I. Load data:

Annual peak load: 2850 MW

Table 1: Weekly peak load in percent of annual peak

W: Week
PL: Peak load in percent of annual peak

(W)	(PL)	(W)	(PL)	(W)	(PL)	(W)	(PL)
1	86.2	14	75.0	27	75.5	40	72.4
2	90.0	15	72.1	28	81.6	41	74.3
3	87.8	16	80.0	29	80.1	42	74.4
4	83.4	17	75.4	30	88.0	43	80.0
5	88.0	18	83.7	31	72.2	44	88.1
6	84.1	19	87.0	32	77.6	45	88.5
7	83.2	20	88.0	33	80.0	46	90.9
8	80.6	21	85.6	34	72.9	47	94.0
9	74.0	22	81.1	35	72.6	48	89.0
10	73.7	23	90.0	36	70.5	49	94.2
11	71.5	24	88.7	37	78.0	50	97.0
12	72.7	25	89.6	38	69.5	51	100.0
13	70.4	26	86.1	39	72.4	52	95.2

Table 2: Daily peak load in percent of weekly peak

PL: Peak load in percent of weekly peak

(Day)	(PL)
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94

Saturday	77
Sunday	75

Table 3: Hourly peak load in percent of daily peak

Winter: Winter weeks (1-8 and 44-52)
Summer: Summer weeks (18-30)
Sprint/Fall: Spring and Fall weeks (9-17 and 31-43)

Wd: Week day load in percent of daily peak
We: Week end load in percent of daily peak

	[Winter]		[Summer]		[Spring/Fall]	
(Hour)	(Wd)	(We)	(Wd)	(We)	(Wd)	(We)
12-1 am	67	78	64	74	63	75
1-2	63	72	60	70	62	73
2-3	60	68	58	66	60	69
3-4	59	66	56	65	58	66
4-5	59	64	56	64	59	65
5-6	60	65	58	62	65	65
6-7	74	66	64	62	72	68
7-8	86	70	76	66	85	74
8-9	95	80	87	81	95	83
9-10	96	88	95	86	99	89
10-11	96	90	99	91	100	92
11-Noon	95	91	100	93	99	94
Noon-1 pm	95	90	99	93	93	91
1-2	95	88	100	92	92	90
2-3	93	87	100	91	90	90
3-4	94	87	97	91	88	86
4-5	99	91	96	92	90	85
5-6	100	100	96	94	92	88
6-7	100	99	93	95	96	92
7-8	96	97	92	95	98	100
8-9	91	94	92	100	96	97
9-10	83	92	93	93	90	95
10-11	73	87	87	88	80	90
11-12	63	81	72	80	70	85

II. Generation System data:

Type: Type of generating units
Cap: Capacity of each unit (MW)
N: Number of units
MTTF: Mean time to failure (hours)
MTTR: Mean time to repair (hours)

(Type)	(Cap)	(N)	(MTTF)	(MTTR)
Oil	12	5	2940	60
Oil	20	4	450	50
Hydro	50	6	1980	20
Coal	76	4	1960	40
Oil	100	3	1200	50
Coal	155	4	960	40
Oil	197	3	950	50
Coal	350	1	1150	100
Nuclear	400	2	1100	150

APPENDIX E. DISTRIBUTION NETWORK PARAMETERS

Below is a part copy from the Appendix B of "Review of Distribution Network Security Standards - Extended Report", submitted the Energy Network Association 2016, for which I was one of the authors. This part provides the source of the network data used in this thesis.

HV network of seven DNOs have been used to estimate the typical characteristics of HV main and spur part of networks. Load profiles from Low Carbon London project and Elexon's electricity user demand profiles have been used to establish load duration shape and typical load factors per voltage levels. Regulatory reporting pack and quality of supply reporting data are analysed. These data and in consultation with data working subgroup the range of asset upgrade cost, asset register quantity and statistic associated with network failures, outages and service restoration procedures are established.

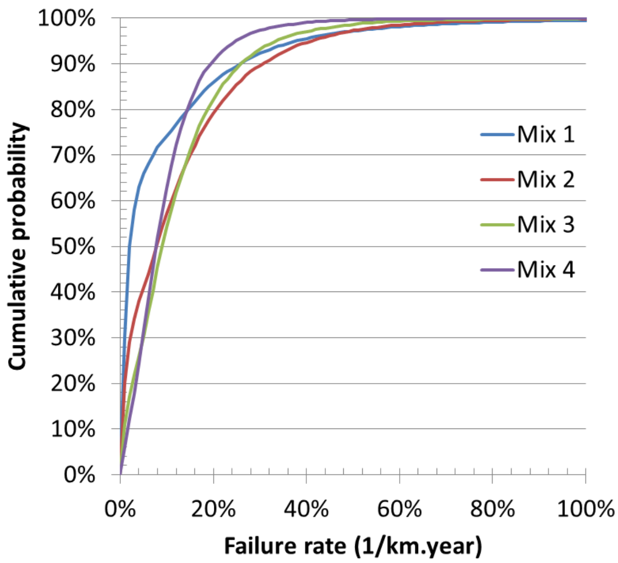
HV feeders are split into 4 mixes as shown in Table E.1. Mix 1 represents a system dominated with underground cables, e.g. urban systems. Mix 2 is a system with 75% or more underground cables and 25% or less overhead lines, e.g. semi-urban systems. Mix 3 and Mix 4 are systems dominated by overhead lines. The share of overhead lines in Mix 3 is less than 75% but greater than 50%, while in Mix 4, the share of overhead lines is greater than 75%. Mix 3 and Mix 4 constitute semi-rural and rural systems respectively.

TABLE E.1 SYSTEMS WITH DIFFERENT MIXES OF UNDERGROUND CABLES AND OVERHEAD LINES

Percentage of	Mix 1	Mix 2	Mix 3	Mix 4
Underground cables	100%	≥75% (89% avg)	>25% (45%)	≤25% (11%)
Overhead lines	0	≤25% (11%)	<75% (55%)	≥75% (89%)

The GB HV systems are grouped into the 4 network categories (mix 1 – mix 4). For each mix, the number of HV systems is estimated and shown as a pie chart in Figure E-1 (right). Data we have analysed show that the majority (67%) of HV feeders are Mix 1 type followed by Mix 3, Mix 4 and the last one is Mix 2 type.

Figure E-1 (left) shows the cumulative probability of feeder's failure rates for each of mixes. A majority of the feeders have relatively low failure rates (<0.1 occurrence per km per year). The number of networks with higher failure rates decreases, Figure E-1 (left) shows rapid saturation for networks with failure rates more than 0.3 occurrence per km per year.



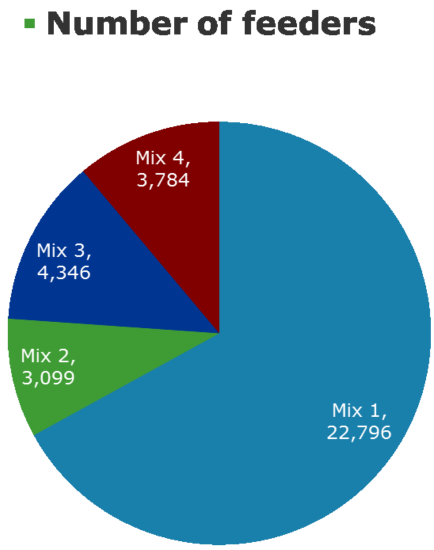


FIGURE E-1 CUMULATIVE PROBABILITY OF FEEDER'S FAILURE RATES AND DISTRIBUTION OF MIXES

Other details that have been modelled in the studies are the number of distribution transformers and the average distance between distribution transformers. Figure E-2 shows the distribution for Mix 1 feeders. We find that the majority of Mix 1 feeders supply six distribution transformers with average distance of transformers between 400 and 500 m. The database contains significant number of a single supplied distribution transformer per feeder with distance to primary less than 100 m.

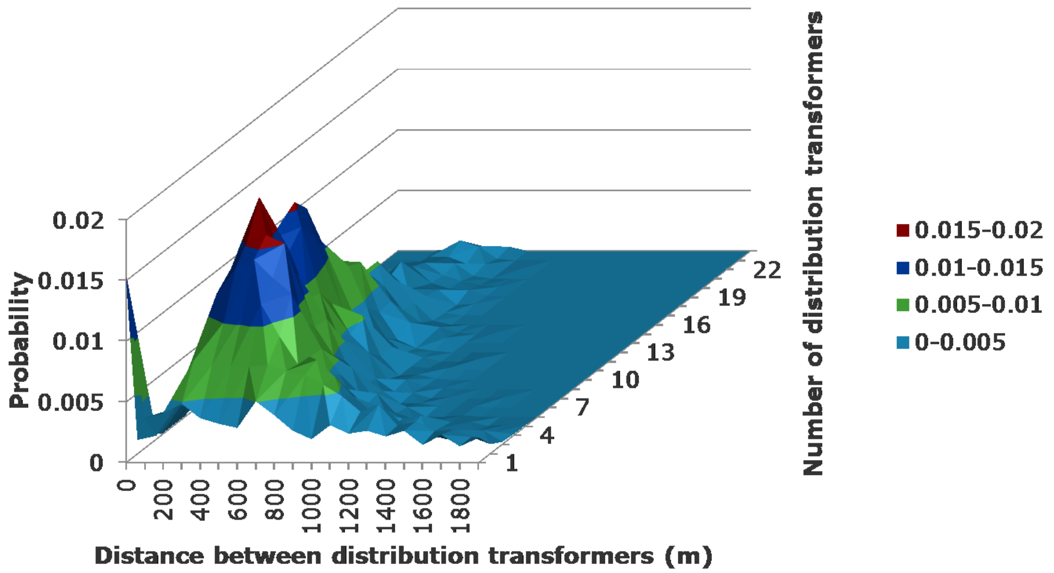


FIGURE E-2 BREAKDOWN OF MIX 1 FEEDERS PER NUMBER OF DISTRIBUTION TRANSFORMERS AND THE AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS

Figure E-3 shows the case for Mix 2 feeders. Data show that the majority of Mix 2 feeders supply 16-17 distribution transformers with the average distance between 500-600 m. This is followed by feeders connected with 8-9 distribution transformers and 12-13 with the same average distance.

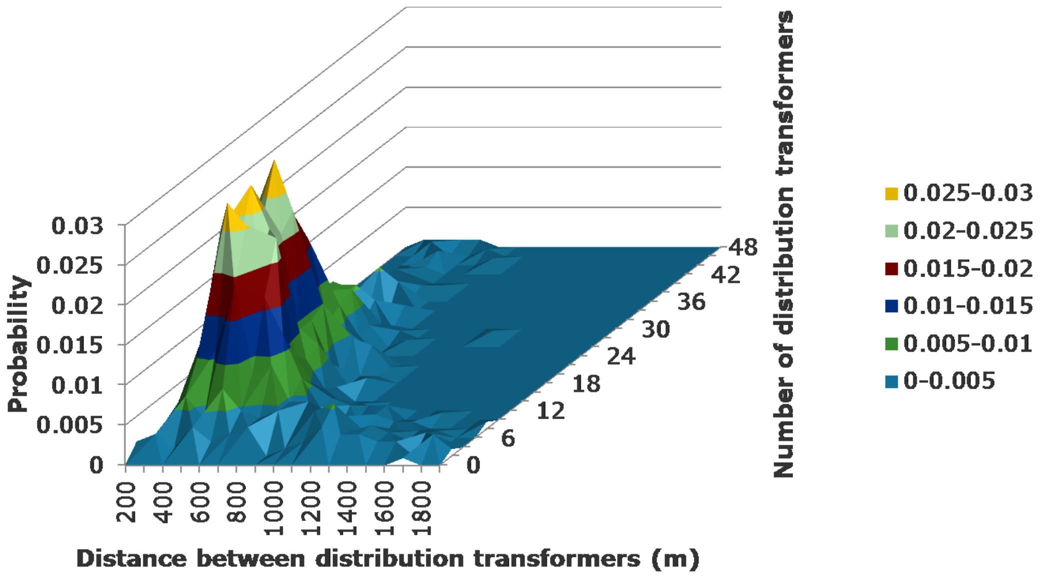


FIGURE E-3 BREAKDOWN OF MIX 2 FEEDERS PER NUMBER OF DISTRIBUTION TRANSFORMERS AND THE AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS

Figure E-4 shows the case for Mix 3 feeders. Data show that the majority of Mix 3 feeders supply 25 - 29 distribution transformers with the average distance of transformers between

500 and 600 m. This is followed by feeders connected with 15 - 19 distribution transformers with the same average distance.

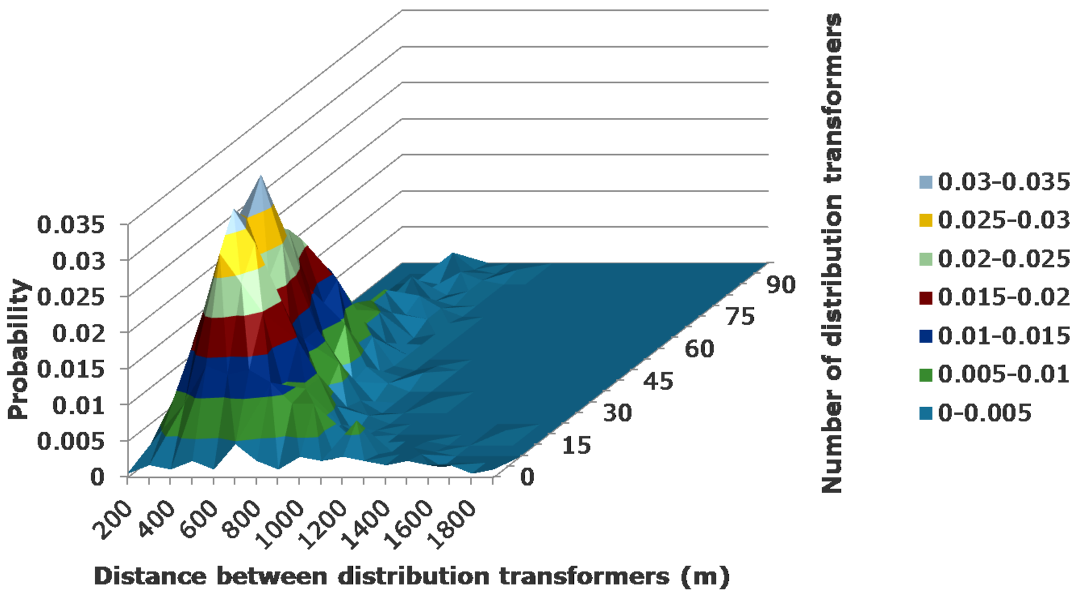


FIGURE E-4 BREAKDOWN OF MIX 3 FEEDERS PER NUMBER OF DISTRIBUTION TRANSFORMERS AND THE AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS

Figure E-5 shows the case for Mix 4 feeders. Data show that the majority of Mix 3 feeders supply 35 - 39 distribution transformers with the average distance of transformers between 600 and 700 m. This is followed by feeders connected with 15 - 19 distribution transformers with the same average distance.

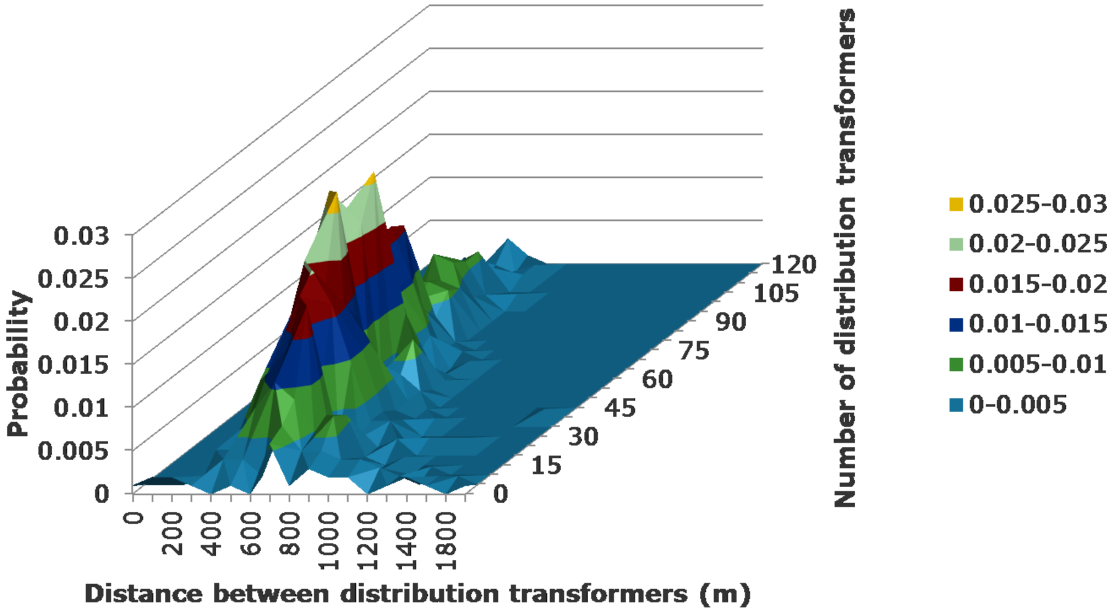


FIGURE E-5 BREAKDOWN OF MIX 4 FEEDERS PER NUMBER OF DISTRIBUTION TRANSFORMERS AND THE AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS

Figure E-6 to Figure E-9 show distribution of average distance between distribution transformers and number of distribution transformers per HV spur for Mix 1 to 4 type of networks, respectively.

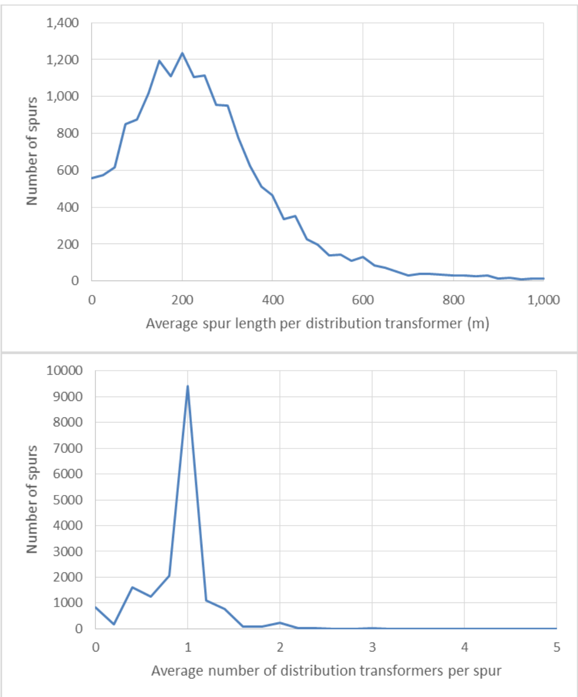


FIGURE E-6 DISTRIBUTION OF AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS AND NUMBER OF DISTRIBUTION TRANSFORMERS SUPPLIED FROM HV SPUR IN MIX 1 TYPE NETWORKS

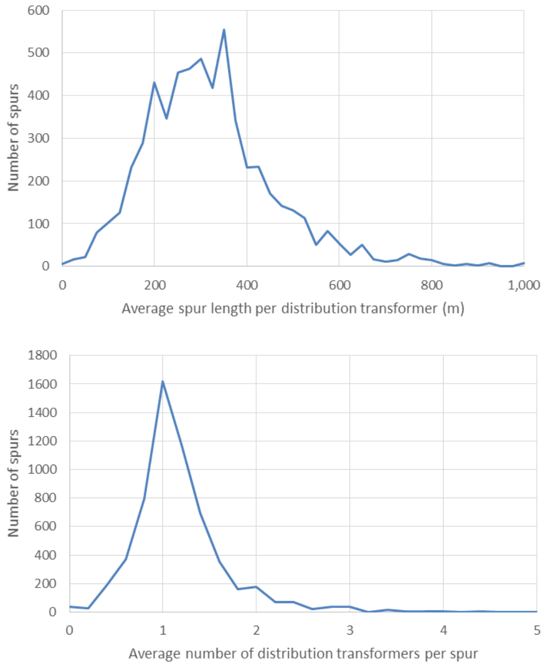


FIGURE E-7 DISTRIBUTION OF AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS AND NUMBER OF DISTRIBUTION TRANSFORMERS SUPPLIED FROM HV SPUR IN MIX 2 TYPE NETWORKS

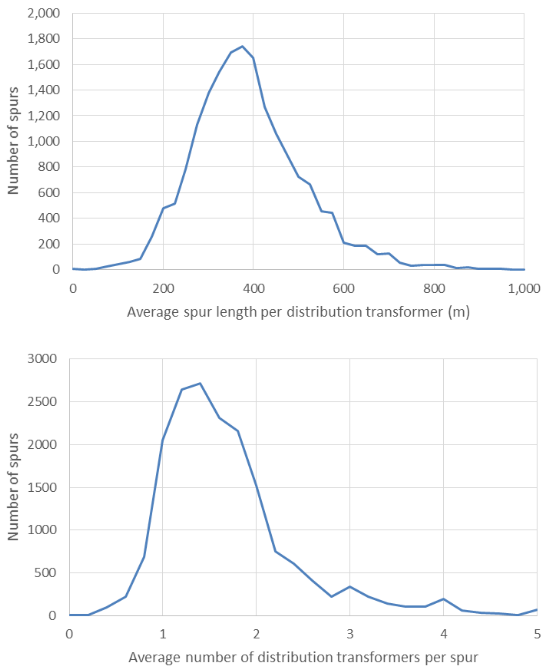


FIGURE E-8 DISTRIBUTION OF AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS AND NUMBER OF DISTRIBUTION TRANSFORMERS SUPPLIED FROM HV SPUR IN MIX 3 TYPE NETWORKS

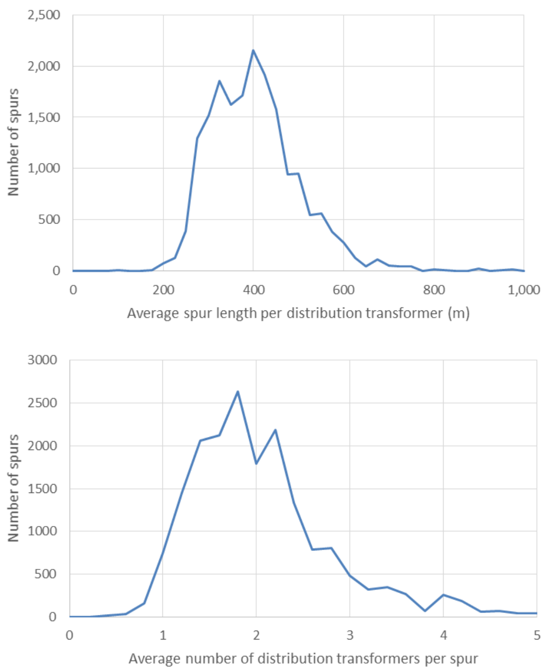


FIGURE E-9 DISTRIBUTION OF AVERAGE DISTANCE BETWEEN DISTRIBUTION TRANSFORMERS AND NUMBER OF DISTRIBUTION TRANSFORMERS SUPPLIED FROM HV SPUR IN MIX 4 TYPE NETWORKS

Figure E-10 shows the number of simultaneous faults per day for nine GB DNOs during five-year period.

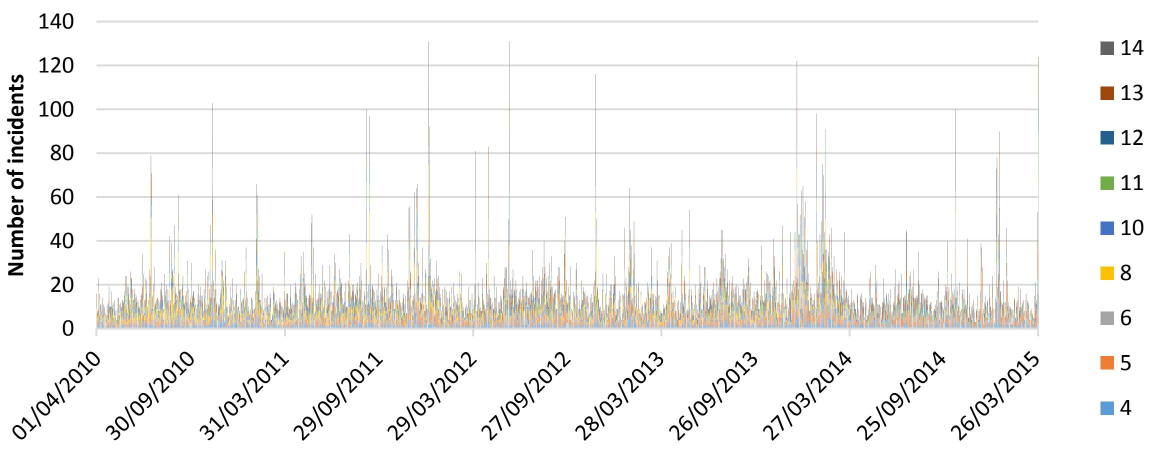


FIGURE E-10 STATISTICS OF THE NUMBER OF SIMULTANEOUS FAULTS PER DAY FOR GB DNOS DURING FIVE YEAR PERIOD

Table E.2 shows agreed range of failure rates, repair times, and upgrade and repair cost.

TABLE E.2 RELIABILITY RELATED PARAMETERS

Asset	Failure rate (%/unit.year)	Urgent repair time (hours)	Average normal repair time (hours)	Upgrade cost (£k/unit)	Repair cost (£k)
132 kV overhead line (km)	2-15	24	240	87	3.8
132 kV underground cable (km)	2-8	48-120	240	1,215	50
132kV/EHV transformer	1-10	240	720	1,100	1,000
EHV overhead line (km)	2-15	12	120	39-46	3.8
EHV underground cable (km)	2-8	24-72	240	290	19.5
EHV/HV transformer	1-10	192	720	400	250
EHV and HV busbars	0.1	24	240		
HV overhead line (km)	5-8.4-20	6	120	30	2.1
HV underground cable (km)	2-4.8-10	6-18	120	110	8.4
HV/LV PMT transformer	2-20	8-10	24	4.3	4
HV/LV GMT transformer	2-20	24	48	15	7
LV overhead line (km)	10-50	4	4	19	1.1
LV underground cable (km)	10-50	8	8	101	3.3

Note: average normal repair time assumes a half of regular repair time; OH line common mode failure rate sensitivity 0, 5% and 10% of single outage failure rate

Table E.3 shows agreed transformer feeder maintenance parameters.

TABLE E.3 TRANSFORMER FEEDER MAINTENANCE PARAMETERS

Asset	Typical frequency (%/year)	Emergency return to service time (hours)	Outage time (hours)
132kV/EHV transformer circuit maintenance	12.5%	12	240
EHV/HV transformer circuit maintenance	12.5%	9	120
HV/LV GMT	10%	8	8

Note: depending on the number of operations of OLTC maintenance might be carried out sooner

Table E.4 shows agreed durations of networks reconfiguration.

TABLE E.4 NETWORK RECONFIGURATION DURATION

Switching	Feeder resupply time (minutes)	Backfeed resupply time (minutes)
Protection	0	0
Automation	3	3
Remote control	10	10
Manual switching	30-60	50

Note: each additional stage of manual switching adds another 20 minutes; remote control of switchgear assumed as available in all primary and bulk supply substations, EHV and 132 kV networks.

List of alternative supply options:

- Resupply with mobile generation within 3-6 hours for HV outages and on average 4.5-10 hours for primary and bulk transformers, EHV, and 132 kV circuits with maximum of 10 MW of units used. Renting cost of 500 kW and below unit is £500-1,750/day while of 1,000 kW unit is £1,000-3,500/day.
- Temporary cable laying within 36 hours at a cost of £50,000-200,000. This option is relevant for outage of EHV/HV and 132kV/EHV, HV transformers and 132kV underground cables.
- Voltage reduction within 3 minutes and each 1% V corresponds to 1.15% MW reduction.