CRANFIELD UNIVERSITY

Jesús Nieto Martín

SMART GRID EVOLUTIONARY PLANNING & MODELLING FUTURE POWER NETWORKS

SCHOOL OF AEROSPACE, TRANSPORT
AND MANUFACTURING

DOCTOR OF PHILOSOPHY

Academic Year: 2014 - 2017

Supervisors:

Professor Mark A. Savill

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This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor on Philosophy.

Declaration of Authorship

I, Jesus Nieto Martin, declare that this thesis titled, 'Smart Grid Evolutionary Planning & Modelling Future Power Networks' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given.
- With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ________________________________

Date: ________________________________

"It is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is most adaptable to change"

Attributed to Charles Darwin, 1809-1882

"All models are wrong but some are useful"

George Box, 1919-2013

Abstract

The volatility and associated uncertainties of a rapid evolving power sector, along with the digitalisation of the sector, have triggered the necessity of answering questions faster while dealing with more granularity in data. The primary hypothesis underlying this research is that evolutionary meta-heuristics methods could be used to provide planners exploration capabilities of trade-off in system when conflicting objectives appear. The aim of this research is to apply a set of novel evolutionary techniques to make better informed decisions that are capable of a) develop detailed quantitative representation of real-world power systems suitable for being optimised, b) fit existing meta-heuristics evolutionary techniques to real-world size problems, c) evaluating non-traditional system flexibility services, d) validate, visualise, and evaluate performance metrics for power systems optimisation.

Dynamic optimisation encompasses the important challenge in real-world applications of capturing evolving behaviours of complex systems. The literature review identifies key problems in the sector for evolving pathways to a low-carbon 2050. Issues on power networks relate to the reactive nature of intervention planning, which leads to horizoning and locally optimal solutions. In that context, and as interventions are triggered by network failures, locational case studies are presented in this research. Applying a bespoke Graph search algorithm (A*) and Multi-Objective Evolutionary Algorithms (MOEAs) can

be say that where the first evaluates just one solution at a time, MOEAs are a better approach for global optimisation due to its capability of developing multiple alternative solutions to a problem simultaneously.

Historically, electricity distribution networks have been designed to provide reliable connections to the customers by virtue of asset ratings sufficient to cope with peak demand. With the proliferation of low carbon technologies such as electric vehicles, heat pumps and distributed generation, the network is starting to experience congestion both, load and generation driven. The congestion restricts further deployment of distributed energy generation, making it more difficult to meet the emission reduction targets.

This motivated three case studies contained in this thesis: a large power system case study modelling the Independent System Operator of New England in the US with high wind penetration and storage; A 11kV distribution network for investment planning in the UK evaluating smart grid interventions, and finally, a non-traditional flexibility service propositions evaluation using Real Options for Multi-Utility dynamic investments.

Keywords

Power distribution, Evolutionary Optimisation, Strategic Planning, Meta-heuristics.

Acknowledgements

I would like to express my thanks to Professor Mark A. Savill and Dr. Timoleon Kipouros for their help, good guidance, and valuable support to my approaches throughout this PhD program and development of this work.

Also, it is mandatory to thank many mentors that have contribute to with their valuable expertise to improve my research and skills. Starting with the sponsor of the research, Western Power Distribution and personalising it in Jenny Woodruff who always has been helpful as a technical advisor of this thesis.

From the Cranfield research team, I would like to highlight the contributions from Dr. Eugene Butans, for the technical contributions and support with the SIM, IPSA, and the FALCON project, and also for all of the co-supervising of MSc students experience which enriched me as a person and mentor. Likewise, this thesis would not be the same without Ganesh and Dr. John Oliver's work.

Some chapters of this thesis have been developed during secondments so recognition for them need to be addressed. First, to Professor Derek W. Bunn, from London Business School, for the chats and his time, where while he was challenging my mind I was learning by osmosis from him immense knowledge, having great impact on how I foresee my career. Lastly, to my mentors at NREL in the US, for giving me the opportunity to be researcher that make better questions, Dr. Carlo Brancucci Martinez-Anido, Dr. Bri-Mathias Hodge, and Dr. Anthony Florita.

I wish to acknowledge the financial support from the Low Carbon Network Fund through the WPD FALCON project. Without it, or Prof. Savill's opportunity, I would not have been able to take part in this thrilling moment of the energy sector.

Finally, I cannot find words, and that is not usual on me, to express my most sincere gratitude and admiration to my parents, brother, and friends for their continuous love and support throughout the endless hours that led to the completion of this thesis.

Contents

List of Acronyms

ALT	Automatic Load Transfer
BEIS	Business, Energy & Industrial Strategy
CAPEX	Capital Expenditure
CfDs	Contract for Differences
CHP	Combined Heat and Power
CI	Customer Interruptions
CML	Customer Minutes Lost
DAR	Dynamic Asset Rating
DECC	Department of Energy and Climate Change
DERs	Distributed Energy Resources
DG	Distributed Generation
DLTs	Distributed Ledger Technologies
DNO	Distribution Network Operator
DSM	Demand Side Management
DSOs	Distribution System Operators
EA	Evolutionary Algorithms
EC	Evolutionary computing
EN&S	Electricity Networks and Storage
EP	Evolutionary Programming
ES	Evolution Strategies
ES	Energy storage
FALCON	Flexible Approaches for Low Carbon Optimised Networks
FiT	Feed in Tariff
GA	Genetic algorithms
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GAs	Genetic algorithms
GHG	Greenhouse Gas
HFT	High-Frequency Trading

ICTs	Information and Communication Technologies
ISO	Independent System Operator
ISO-NE	ISO of New England
LMP	locational Marginal Pricing
LRE	Load Related Expenditure
MO	Multi Objective
MOEA	Multi Objective Evolutionary Algorithm
MOP	MO problem
MURRA	Multi-Utility Resilience Rating Assessment
NMT	Network Modelling Tool
NSGA	Non Sorted Genetic Algorithms
OCGT	open cycle gas turbine
OF	Objective Function
OFGEM	Office of Gas and Electricity Markets
OPEX	Operating Expense
R&D	Research and Development
RIIO	Revenue=Incentives+ Innovation+Outputs
RIIO-ED1	RIIO for distribution
RIIO-TD1	RIIO for transmission
RO	Renewable Obligations
ROV	Real Option Valuation
SEC	Smart Energy Code
SIM	Scenario Investment Model
T&D	Transmission and Distribution

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To my father, for being an example of perseverance.

To my mother, for instilling me the love of reading.

To my brother, for his critical thinking.

Chapter 1

Introduction

This chapter addresses the following:

- To introduce the research of the thesis
- To provide motivation for the research
- To highlight the novelties of the work
- To describe the structure and publications resulted from this thesis

1.1 Background and motivation

In the past, electricity industry has delivery a secure reliable supply. The sector now is going to a massive fast-pathed digital and data transition. It has to both, decarbonise, as well as, deliver low affordable reliable electricity prices. The sector has committed large investments on the transmission and distribution sector upon 2050 in order to ensure grid resilience. 10 trillion of dollars are required world-wide in electricity sector' investments to make this low carbon transition a reality over the next 25 years (World Economic Forum, 2015). The volatility and uncertainty linked to the digital transition have an effect on investability, causing policy makers, regulators, businesses and investors to look harder at the lessons learnt from the recent past in which at European level, countries have not picked the best technology for its natural resources producing a sub optimal energy mix.

Future strategic investments need a holistic approach to ensure that the energy trilemma - energy security, energy equity, and environmental sustainability, is accomplished (World Energy Council, 2013) (World Energy Council, 2013). These three objectives, define the complexity of the relationships among actors in the energy sector: public and private sector, governments,regulators, economic and social factors, national resources, environmental limitations, and customers behaviours.

The share of renewables within the world-wide energy mix, their intermittency, and their required flexibility of a system designed to operate coal and gas is leading to a century ageing grid operating far from optimal (Milligan et al., 2010). That makes power supply networks sector a key player in the planning to come for achieving these low-carbon targets while reducing system volatility (Strbac et al., 2016) (Ketterer, 2014).

The rising number of stakeholders in the energy planning sector increases the complexity of the problems to solve. The planning horizon for this fast evolving sector is not providing quick enough answers to all questions that are being raised. Beside the number of decision makers, the power planning sector is facing a data revolution. These new data are now available to predict and improve how these commercial and technical innovation investments decisions can be made. The UK has a novel regulatory framework, RIIO (Revenue=Incentives+ Innovation+Outputs) (Ofgem, 2014), which incentivise investment on smart techniques at electricity transmission and distribution level, as well as in the gas sector, and being therefore a great opportunity for the case studies presented in this thesis to test how much non-traditional approaches are encouraged.

How model-driven engineering systems are designed have been divided into two main pathways to be discerned. Whether, models have to be, aggregated (top-down), disaggregated (bottom-up) or a combination of both has being discussed since late 1970s (Van Horn and Van Meter, 1977) (Sabatier and Mazmanian, 1979). Most of the studies within the energy sector, have focused on CO_2 emissions (Wing, 2006), whole-system modelling (Neij, 2008) (McFarland et al., 2004) or energy economics (Koopmans and te Velde , 2001) (Rivers and Jaccard, 2005). As for the power network sector, in the UK, (UK Power Networks, 2013) proposed for their RIIO-ED1 (2015-2023) business plan a mixed approach as (Sabatier, 1986) did.

Multi-objective Evolutionary Algorithms (MOEA), and specifically, Non Sorted Genetic Algorithms (NSGA) have been used in the past for testing power systems such as the IEEE 30 bus (Oliver, 2014) or for economic-environmental dispatch (Gjorgiev et al., 2013), as well as being proved in other sectors such as aerospace, manufacturing, defence or design (Subbu et al., 2006). Real-world systems addressed in this thesis combine non-linearity, non-convexity and highly constrained issues on a multidimensional solution space with a no unique optimal solution and, therefore, customised visualisation techniques like parallel coordinates will be addressed (Inselberg, 1997).

This thesis will provide insights for looking after disaggregated, i.e. bottom-up, optimising multiple objectives (MO) at the same time, at a planning resolution, where some conflicting interest might appear among them and in most of the cases cannot be handled using conventional single optimization approaches, while MO methods fit naturally (Oliver, 2014). Evolutionary methods capable of MO optimisation are becoming more necessary as the complexity of optimisation problems in power networks increases. Smart and traditional interventions will reinforce the network, optimising its performance, using techno-economic evolutionary scenarios. A working definition of optimised scenario is the configuration of the power system model obtained once the planning techniques have obtained an optimised solution. The combination of new availability of digital data and their combination with evolutionary planning approaches motivates the research behind this thesis.

1.2 Thesis structure and layout

For this thesis, there are four case studies presented within three chapters of the thesis, two at a transmission level in chapter 4, and two at distribution level, chapters 5 and 6. As chapter 3, a methodology, where applied evolutionary planning using heuristics is presented and a brief literature review in chapter 2. Chapter 7, summarises final conclusions and recommendations for future work resulting from this thesis.

Chapter 3, discusses the implementation of dynamic modelling for evolutionary planning, where trade-off methodologies are required for planning and operating evolutionary power systems. Meta-heuristics, and particularly the implementation of Graph search algorithms and Multi-Objective Evolutionary Algorithms (MOEAs) are discussed.

The Independent System Operator of New England (ISO-NE) in the US have been modelled using PLEXOS as energy market plus operation modeller tool. The purpose of the two case studies within Chapter 4 is to evaluate the impact of different wind power topologies in the first one, and Massachusetts' Storage Target impact on ISO-NE using MOEAs. The model, analysed at nodal level, has integrated 770 wind farms candidate locations with a total of

30GW of installed capacity. For the stylised case study has been decided to install 10GW of wind capacity due to the projections of wind commitments in New England's energy mix up to 2030. The hourly standard deviation of prices and total generation costs will be the system performance indicators to optimize in order to measures how different wind topologies might impact on planning strategies. In the optimisation section of the chapter, the variability of prices, wind curtailed, and ramping events are reduced modelling the Massachusetts' Storage Mandate, producing a Pareto-set of feasible locations while evaluating its impact on ISO-NE.

The aim of Chapter 5 is to assess the suitability and cost-effectiveness of smart distribution techniques along with traditional reinforcements for electricity distribution networks, in order to analyse expected investments up to 2047 under different DECC scenarios. These novel techniques are evaluated under different demand scenarios to assist decision makers in future power networks planning. The evaluation of assets planning is based on the FALCON project network. The area of study is Milton Keynes (East Midlands), being composed of six 11kV primaries. To undertake this analysis is used a novel tool for electricity distribution network planning, called Scenario Investment Model (SIM). In this context, this study summarises the benefit of novel techniques versus traditional reinforcements, comparing short-term versus long-term planning, highlighting, triggering new research questions as the impact that high penetration of electrical vehicles will have on the test network and comparing that load with Industrial and Commercial loads from the FALCON trials, recommending finally an investment planning strategy.

Finally, Chapter 6, goes a step beyond Chapter 5 as one of the learnings was that smart techniques do provide flexibility to the grid but do not create extra firm capacity in the system. This chapter will provide Real Options valuation for contracting the required flexibility from a range of service propositions where final decision maker will evaluate the granularity of how much and for how long they are willing to pay for their flexibility portfolio.

1.3 Thesis aim

The primary hypothesis underlying this thesis is to apply a set of evolutionary techniques to address decision making in a big digital data industry such as the electrical utilities sector. This thesis aids decision makers to make better informed decisions in an adequate planning time horizon. Having a more robust understanding of how off-line selection of optimal scenarios among various alternatives will impact on long-term planning decisions leading to evaluate the emergence impact of new non-traditional business propositions.

1.4 Research objectives

In order to achieve the aim of the thesis, a set of specific objectives are established as followed:

1. To develop problem detailed quantitative representation of real-world power systems suitable for being optimised.

2. To fit existing algorithms and heuristics evolutionary techniques to real-world size problems.

3. To visualise performance criteria for case studies decision making.

4. To propose non-traditional flexibility services for creating capacity within distribution networks.

5. To validate and evaluate performance metrics for power systems optimisation and customise optimisation frameworks for measuring their performance.

1.5 Contribution to knowledge

- Chapter 3 details how a set of Meta-heuristics can be customised to different types of evolutionary power systems design depending on the dynamics of the optimisation problem.

- Chapters 4 proposes a detailed real-world modelled power systems, focused on large integration of wind, and how Genetic Algorithms aid in decision location planning to accomplish a storage mandate.

- Chapter 5 presents an evaluation using a customised bottom-up Graph search algorithm with memory, the SIM A* algorithm, for short-term and long-term investment planning on an 11 kV smart grid.

- Chapter 6 details a non-traditional methodology, MURRA, for creating capacity in the 11kV network with a Real Options valuation of flexibility business propositions comparing it with Chapter 5 SIM' outcomes.

1.6 Publications

1. Nieto-Martin, J., Butans, E., Woodruff, J.A., Kipouros, T., Savill, M. (2017) "Automation of Smart Grid Technologies for Low Voltage Evolutionary Networks", Special Issue on *Technologies and methodologies in modern distribution grid automation*, Sustainable Energy, Grids and Networks, [accepted]

2. Butans, E., Nieto-Martin, J. and Orlovs, I. (2017), "SIM: Scenario Investment Model - Smart Planning for Distribution Networks", in *Sustainable Energy Grid and Networks*, [accepted]

3. Nieto-Martin, J., Bunn, D., Savill, M., "Dynamic Investments in Flexibility Services for Electricity Distribution with Multi-Utility Synergies", Special Issue on *IAEE 40th International Conference: Meeting the Energy Demands of Emerging Economies: Implications for Energy and Environmental Markets*, Energy Journal, [accepted]

4. Nieto-Martin, J., Butans, E., Varga, L. (2017) "Model-driven Nodal Network Planning: A bottom-up investment approach for Smart grids", Special issue on *Complexity and Real World Applications. Using the Tools and Concepts from the Complexity Sciences to Support Real World Decision Making Activities*, Emergence: Complexity and Organization (E:CO), [Under review]

5. Nieto-Martin, J., Butans, E., Woodruff, J.A., Bunn, D., Kipouros, T., Savill, M., "Techno-Economic Planning for the UK 11 kV Distribution Network Using Evolutionary Self-Healing Network States", in *Applied Energy* [Under review]

6. Nieto-Martin, J., Bunn, D., Savill, M., "Pricing Distribution Networks Flexibility Options with Multi-Utility Business Models", in *Journal of Operation Management* [Under review]

7. Nieto-Martin, J., Brancucci Martinez-Anido, C., Kipouros, T., Hodge, B.M., Savill, M., "Addressing Utility-Scale Storage for Massachusetts Capacity Targets using Multi-Objective Evolutionary Optimisation", in *Energy Policy* [In progress]

8. Nieto-Martin, J., Brancucci Martinez-Anido, C., Florita, A., Kipouros, T., Hodge, B.M., Savill, M., (2016) "Impact of Impact of Wind Topologies on the ISO of New England Nodal Electricity Prices", in *EWEA WindEnergy Summit, 27-29 September 2016*, Hamburg, Germany.

9. Nieto-Martin, J., Butans, E., Kipouros, T., Varga, L., Savill, M., (2016) "Model-driven Nodal Network Analysis and Investments Planning in Smart Grids", in *4th Numerical Evolutionary Optimization Conference, 20-24 September 2016*, Mexico City, Mexico

10. Nieto-Martin, J., Butans, E., Woodruff, J.A., Kipouros, T., Savill, M., "Smart Grids Evolutionary Planning: A model-driven nodal investment optimisation for the 11kV network", in *7th Hubnet Smart Grid Symposium, 13-14 September 2016*, Glasgow, United Kingdom

11. Nieto-Martin, J., Brancucci Martinez-Anido, C., Florita, A., Kipouros, T., Hodge, B.M., Savill, M., "Impact of Wind Topologies on Nodal Electricity Price", in *3rd WholeSEM conference, 4-5 July 2016*, Cambridge, United Kingdom

12. Nieto-Martin, J., Butans, E., Correa-Castillo, P., Fontaine, J., Gonnelle, A., Lahjibi, M., Vrancken, C., "Scaling Milton Keynes power require-

ments for electrical transportation", in *IEEE ENERGYCON 2016, 4-8 April 2016*, Leuven, Belgium

13. Zafred, K., Nieto-Martin, J., Butans, E., "Electric Vehicles-effects on domestic low voltage networks", in *IEEE ENERGYCON 2016, 4-8 April 2016*, Leuven, Belgium

14. Peláez J.M.E, Nieto-Martin, J., Butans, E., "Assessing smart grid interventions for future power networks", in *7th Asset Management Conference, 25-26 November 2015*, London, United Kingdom

15. Nieto-Martin, J., Kipouros, T., Savill, M., "Smart Grids Modelling and Simulation for Distributed Power Supply Networks", in *5th Hubnet Smart Grid Symposium, 9-10 September 2014*, Glasgow, United Kingdom

1.7 Software and Models produced

The following items were produced in the course of this PhD as contribution from the author (code and models are upon request to the author and depending of ownership of data), these being:

1. The set of plugins necessary for self-adaptive multi-objective evolutionary algorithm case studies. Bespoke optimisation problem definition and plugins for vectors optimisation using GANESH environment.

2. PLEXOS ISO-NE 770 wind turbines (30% generation mix) model

3. SIM 2015-2023-2047 DECC2 and DECC4 demand scenarios planning for Milton Keynes

4. SIM patch framework for including Real Options Valuation of Multi-Utility flexibility services (MURRA)

Chapter 2

The pathway towards a Low-Carbon 2050

2.1 Motivation

Managing the transition to a low carbon economy, while continuing to ensure energy supply and affordability, is one of the greatest challenges of our age. Moving to a secure, sustainable energy system will require the deployment of new technologies, many of which are still at the development stage (Nieto-Martin, 2015).

The UK is mandated by the 2008 Climate Change Act to achieve a 34% reduction in its Greenhouse Gas (GHG) emissions by 2020 and an 80% reduction by 2050, compared to 1990 levels (Xenias et al., 2015), (Li and Trutnevyte, 2017).The UK energy sector has become an important focus as part of this drive to deliver this transition to a low-carbon economy, given the significant proportion of GHG emissions that can be attributed to energy generation and consumption in the UK. For instance, in 2011, the energy supply sector accounted for approximately 35% of the UK's GHG emissions in 2011 (EA Technology, 2012), (Hannon et al., 2013).

Additionally, the residential and business sectors accounted for a further 29% of GHG emissions, with the vast majority of this attributable to fossil fuel combustion for heat and electricity (Strbac et al., 2016).

Innovation, starting with Research & Development (R&D) initiatives, in energy technologies will be a critical factor when considering the transition of the energy system over the coming decades. However, it is a complex, non-linear process with multiple inputs and feedbacks (MacKay and Winser, 2010).When this is overlaid with the complexity of scenario modelling and forecasting, the uncertainties of the future become even greater. Figure 2.1 shows the innovation steps diagram for new technologies deployment.

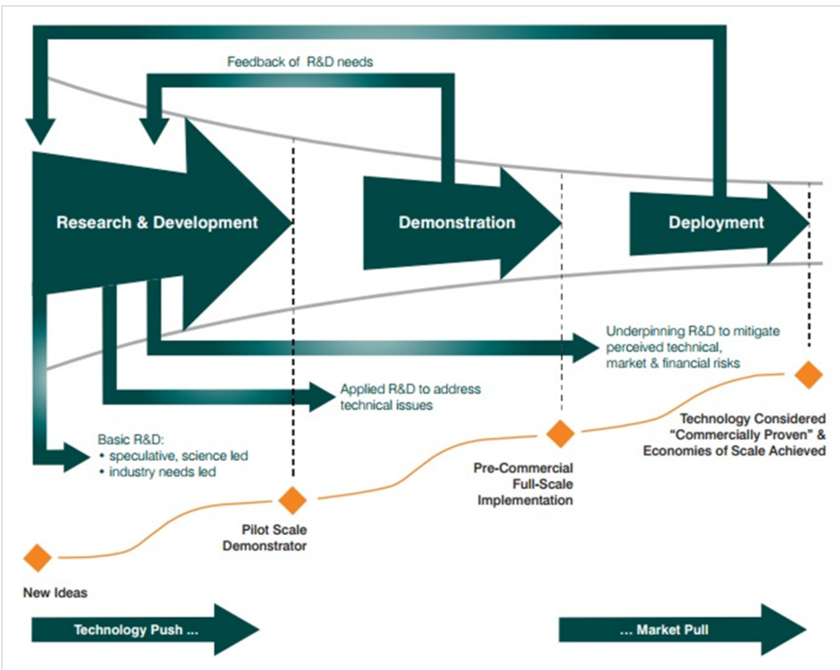


Figure 2.1: Energy Research Partnership innovation diagram (Hannon et al., 2013)

In the last decade, R&D initiatives have developed the concept of a 'smart grid'. It has emerged in as a core element of a more sustainable electricity system. There is no single agreed definition of a smart grid, but the basic principle is the application of information and communication technologies (ICTs) to electricity networks to allow: greater observation of the state of wires and other assets; control of power flows; automation of management of power fluctuations of outages, and integration of new low carbon generation and demand side technologies, such as solar PV, heat pumps and electric vehicles.

On a cold winter's day the electricity network will deliver around 1.1 TWh, while the gas network can deliver five times that amount of energy (Bolton and Foxon, 2015). The two networks have quite different characteristics, with electricity able to travel the length of Britain almost instantaneously while gas takes many hours. The way that energy networks operate will be different as many more coal-fired power stations have to shut down.

This literature seeks to uncover and examine the complex set of governance challenges associated with transforming energy networks, which play a key enabling role in a low carbon energy transition. Appendix A serves for uncovering the different sectors that are currently playing a role in this transition towards 2050, while Appendix C positions this thesis and its impacts. The importance of such infrastructure networks to sustainability and low carbon transitions in the energy is clear; there is relatively little understanding of the social and institutional dimension of these systems and appropriate governance strategies for their transformation.

2.2 From Electricity Regulation to Low-Carbon Technologies

2.2.1 Electricity Regulation

The two network-infrastructure-based natural monopolies, as well as, the wholesale and retail markets are regulated in the UK through the Office of Gas and Electricity Markets Authority (Ofgem).

Transmission assets, due to its large nature, can be evaluated disaggregated, whereas distribution facilities need to be aggregated for evaluation by areas, or set of assets (Skea et al., 2012).

Smart grids present major potential benefits in terms of economic, environmental, and social considerations. The deployment of instrumentalised smart grids however requires not only technological advancement but also the ability to overcome many regulatory barriers. Potentially will allow to gain better insights on how to operate and invest at disaggregated distribution level.

Regulatory challenges are particularly significant for the development of those smart grids. The design and operation are fundamentally different from traditional power grids. Traditional systems are predominantly centralised, however the existence of a more decentralised power system requires a flexible management of the grid. Smart meters play here a vital role, enabling to generators real time data to help industry to balance energy demand. Ofgem and the Department of Energy and Climate Change (DECC) [1] have created several frameworks for control and supervise the correct operation of these devices, such as, Data and Communications Company (DCC), Smart Energy Code (SEC) and Smarter Markets Programme (Connor et al., 2014). A summary,

[1] In July 2016, DECC became part of the Department of Business, Energy & Industrial Strategy (BEIS). For consistency across the thesis just DECC will be named.

in the form of a time-line, regarding ongoing regulation and actors involved within the UK electricity sector is presented in Appendix A.

The approach to regulation of electricity networks aims to enhance outputs rather than simply cost. Former RPI-X@20 regulatory framework led to a new regulatory model for networks, called "RIIO", namely "Regulation = Incentives + Innovation + Outputs" (Ruester et al., 2014).RIIO applies across both gas and electricity, and to transmission and distribution. The new price control started being effective in April 2015 and it is known as RIIO-ED1 (for distribution) and RIIO-TD1 (for transmission) and will run for eight years, from 2015 to 2023. Subsequent RIIO periods will run up to 2047. Those will be assessed in Chapter 5 of this thesis.

The smart grid agenda involves not only technological innovation, but also innovation in business models, network operation and social practices. It is widely recognised that it will also need major changes in policy and regulatory frameworks, particularly because the entities currently responsible for distribution network operation and investment in the UK are vertically integrated monopolies (Great Britain, 1989) (Beesley and Littlechild, 1989), whose actions are largely determined by those regulatory frameworks. In February 2017, OFGEM opened up an innovation sandbox to promote engagement with innovators that are willing to challenge current regulatory paradigms.

2.2.2 Wholesale market design

Renewable sources are planned to provide up to 15% of the UK's total energy needs by 2020. In February's 2015 auction, CfDs (Contract for Differences) were divided in two sections, one for established technologies, such as solar and onshore wind, and one for emerging technologies, which is primarily offshore wind.

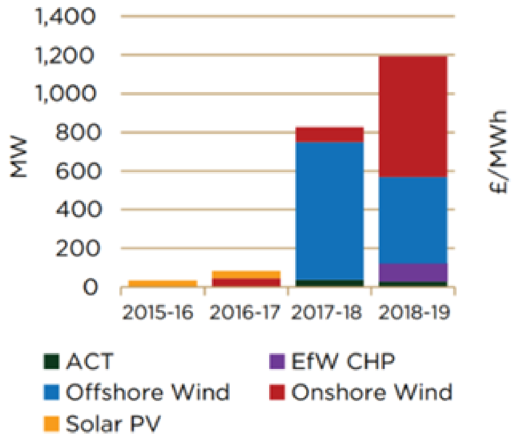


Figure 2.2: CfD Projects awarded by technology and award date (Porter and Roberts, 2015)

Competition during the auction will delivered savings to consumers, as future allocation rounds to will continue to do so. But how much money can be expected to be made available to renewable projects through future allocation rounds up to 2020?

The initial allocation of over 300m from the Levy Control Framework (LCF) in 2020/21 is a cautious start. In this section is important to consider: first, how the LCF in 2020/21 will be allocated, and what this implies for the gap in renewable generation to meet the 2020 Renewables Target; second, what this might mean for future CfD allocation rounds (Porter and Roberts, 2015). Ensuring a regulation framework that solves those questions will provide as an accurate projection of renewable penetration of the GB generation mix.

Figure 2.2 projects GB renewable generation as a proportion of total generation out to 2020/21, using the following assumptions:

1. Maintaining the current levels of renewable generation for committed RO (Renewable Obligations), FiT (Feed in Tariff) and unsupported generation.

2. Projecting future levels of renewable generation from new RO and FiT plant based on published spend projections, and assuming the current spend to renewable generation ratios are maintained.

3. Projecting future levels of renewable generation from FIDeR (Final Investment Decision Enabling for Renewables) and allocated CfD plant, based on the load factors assumed in the CfD allocation framework budget calculation. Total generation based on DECC's central forecast.

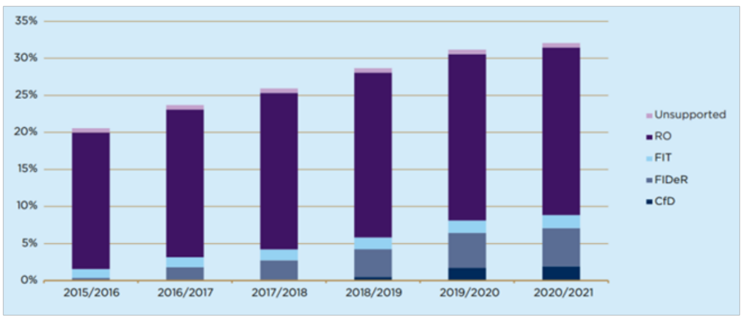


Figure 2.3: Share of UK generation from renewable sources (Porter and Roberts, 2015)

Due to the more advanced development of lower carbon options in the electricity sector and once that wholesale market and T&D improvements have been settled, as has been mentioned in Figure 2.1, technologies to enable 2050 pathway have to be defined.

2.2.3 Electricity Generation

The demonstration of carbon capture and storage technologies (CCS) on coal and gas fired power stations are critical in determining what generation technologies will be deployed for electricity generation out to 2050, as is shown in Figure . CCS have proven to be too expensive or unable to deliver on the scale required but, both wind and nuclear power will face challenges that are not all technical and which might restrict the scale and rate of their deployment. This could lead to an increase in gas fired power stations being built in the short term to meet the electricity demand, emphasising how gas CCS could be an important technology (MacKay and Winser, 2010).

Once the real capability of CCS to reduce emissions is established, an assessment can be made about progress towards decarbonisation of electricity generation on which other parts of the energy system are dependent - in particular, heat and transport. By 2020, a clearer picture will be available of the scale of deployment of other technologies and what impact they will have on the development of the generation system, including grid reinforcement, demand reduction, and decentralised generating technologies.

For a CCS Commercialisation Programme there is up to 1bn in capital support available for CCS projects. It is hard to estimate the level of support, given that this will be the outcome of the procurement process currently underway. However, it is not unreasonable to expect a figure in the region of 400m in 2020/21 based on DECC's published cost estimates for CCS (Department of Energy, 2014).

About the consensus on the need for rapid decarbonisation of power generation, new generation of nuclear plans will potentially help to decarbonised the power mix (Parkinson, 2014).

2.2.4 Road transport

A range of road transport technologies is likely to be used in the transition to 2050. Digitalisation and bundling of private and public electric vehicle services appear to offer promising technology adoption and development for a decarbonised electricity mix.

An evolution from the current range of hybrids to full hybrids reaching the mass market, transition to plug-in hybrids and eventually electric vehicles can be expected during the 2020s. However, a failure to improve battery technology, offset by breakthroughs in low-carbon hydrogen production and storage, may make fuel-cells a viable low-carbon option.

The role of biomass and biofuels in the energy system is very sensitive to competing demands from energy and other sectors and sustainable alternatives to current biofuels have yet to be fully demonstrated. Given the uncertainties, a period over this decade should be used to assess technology development of electric (including plug-in) and fuel-cell vehicles.

There has been demo studies around the UK (Nieto-Martin, 2015) (Zafred et al., 2016) to scale and demonstrate what outcomes and impact could be achieved with wider uptake. With some projects already underway, there should be strategic coordination both nationally and internationally (Forrest et al., 2016). This will also give time to further our understanding of the issues around the sustainability of sustainable transportation (Porter and Roberts, 2015), (Crispim et al., 2014).

2.2.5 Built environment

For heating technologies, heat pumps are favoured by scenarios and other analysis into how to meet the heat demand of domestic buildings. However, the performance of heat pumps in the UK's climate and housing stock, and by real consumers, has not been fully tested so far. Promoting moving heat from gas to electrical devices is the challenge to come in the next years to come (Wade et al., 2010).

Similarly, the performance of domestic Combined Heat and Power (CHP) for single households has yet to be proven on a large scale, and new CHP models are expected to be marketed widely in coming years. Digitalisation of assets at consumer premiss will allow to characterise disaggregated variable and fixed loads, aiding to respond to price signals or automated through an aggregator providing extra flexibility capacity to the network (Zeifman, 2012) (Berges et al., 2010).

2.2.6 Demand Side Management

An area where energy systems will be important for a low carbon transition is in integrating with the demand side and promoting demand side management (DSM). In the electricity sector, the traditional role of a distribution network has been to reliably deliver power to the customer in a one way direction. However, as we move away from this "predict and provide" paradigm, the demand side, along with increased storage capacity and interconnection will become a more active component in the electricity system in order to deal with the issue of intermittency.

The UK government plan to roll out smart metres, as mention before, will become an increasingly important part of developing a more interactive engagement between consumers and electricity providers. Such issues have become central to debates surrounding smart grids. The changes required to develop a supporting energy infrastructure to accomplish a the low carbon transition go wider than just technical issues which were highlighted in (MacKay and Winser, 2010), (Crispim et al., 2014) and (Wade et al., 2010).

2.2.7 Energy storage

Energy storage technologies will play a relevant role in the forthcoming decades. This technology will help to increase the amount of renewables to be integrated in the grid (Xenias et al., 2015), (Jamasb el al., 2012) but also in the market as recently proposed by the US Energy regulator (Federal Energy Regulatory Commission , 2017). Beside renewable integration, broader value propositions are being discussed in Figure 2.4.

Figure 2.4: Grid-Scale Energy Storage Use Cases and Value Propositions (Massachusetts Department of Energy, 2016)

Benefits can be summarised as (Denholm et al., 2013):

- Voltage control: Support a heavily loaded feeder, provide power factor correction, reduce the need to constrain DG, mitigate flicker, sags and swells.

- Power flow management: Redirect power flows, delay network reinforcement, reduce reverse power flows, minimise losses.
- Restoration: Assist voltage control and power flow management in a post fault reconfigured network.
- Energy market: Arbitrage, balancing market, reduce DG variability, increase DG yield from non-firm connections, replace spinning reserve.
- Commercial/regulatory: Assist in compliance with energy security standard, reduce Customer Minutes Lost (a GB regulatory incentive designed to improve quality of service that will be used in this thesis), reduce generator curtailment.
- Network management: Assist islanded networks, support black starts, switch ES between alternative feeders at a normally open point.

2.3 Transmission and Distribution

The future of energy distribution in the context of the 2050 low carbon transition is of course highly complex and uncertain and likely to be shaped also by a range of innovations in other areas of the energy chain (generation, transmission, end consumers). With this in mind, in this section, is identified the regulation framework for Transmission and Distribution (T&D), challenges and learning from other countries where distribution systems are likely to act as important enablers for a low carbon transition across alternative low carbon pathways (Ruester et al., 2014).

In the UK, there is one System Operator, National Grid, and currently 14 DNOs, each of which distributes electricity to all consumers in their geographical area. While generation and supply (retail) of electricity have been liberalised, networks remain regulated as natural monopolies. In Europe, the United Kingdom pioneered unbundling and privatising the electricity industry (Great Britain, 1989) into different sub-sectors aforementioned not being able of holding more than one operation license for enhancing competition.

Focusing now at distribution level, RIIO regulatory framework is a mechanism to prevent overestimation by DNOs when declaring future investment plans.

Gómez (2013, p.199) illustrates the investment planning at DNO level with the three consecutive steps:

1. Each DNO sends OFGEM an ex-ante expenditure forecast in line with what it expects to spend ex-post.

2. Once the expenditure forecasts have been established by the DNOs, OFGEM sets the target or baseline for each company and a DNO power ratio is calculated for each.

3. Every DNO has an incentive to spend as little as possible through efficient operation. Rewards increase as actual DNO expenditures decrease (Gomez, 2013).

The smart grid agenda applies largely to the low voltage distribution networks, as the high voltage transmission system is already 'smart' to some degree. Existing electricity distribution infrastructure has been developed to serve predictable and regular patterns of demand and generation.

Until now, power networks historically have been conceived as a problem with multiple objectives, but have been treated individually. Among the performance targets that have been under consideration in the evaluation of such distribution networks are the reduction of customers without service, voltage

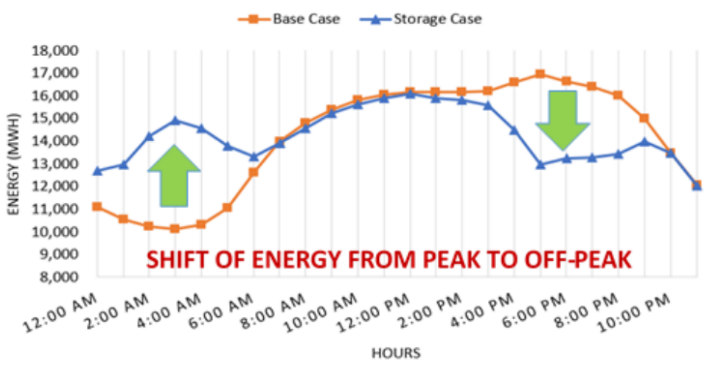


Figure 2.5: Efficient system utilisation with storage implementation

deviations, losses, imbalance in power feeders, and reliability indexes (Gan et al., 2009), (Stoft, 2002). The performance indicators used are intended to answering questions such as which are the relevant indexes to prioritize in a future power network or how might a new infrastructure be composed (UK Power Networks, 2013), (Zheng and Cai, 2010).

Restoration of operation services is nowadays a difficult optimization problem to solve. Therefore, it has generally been implemented using combinatorial non-linear optimization tools. For designing proper solutions it is necessary to consider the constraints of the network operation (Bernal-Agustin et al., 2011), (Dolan et al., 2009).

Deferral on grid operations to shift demand from peak to off-peak with storage is an example on how future T&D networks will operate (Chang et al., 2015). The assets on those networks can use the storage as smart technique to decrease the thermal and voltage stressing, extending thus the life time of the network assets. Figure 2.5 represents how storage enhance a more efficient utilisation of the network by shifting loads.

Figure 2.6 represents the ability of energy storage in New England, US (ISO-NE, 2016) to generate peak shaving when coupled with solar, compared with the same power system where solar was used alone. The Storage device gets charged over night and non-peak peak periods of the day, shifting system load curve, red line, and is being discharged during peak time providing both advantages, providing lower prices and reducing ramping events on the system operation.

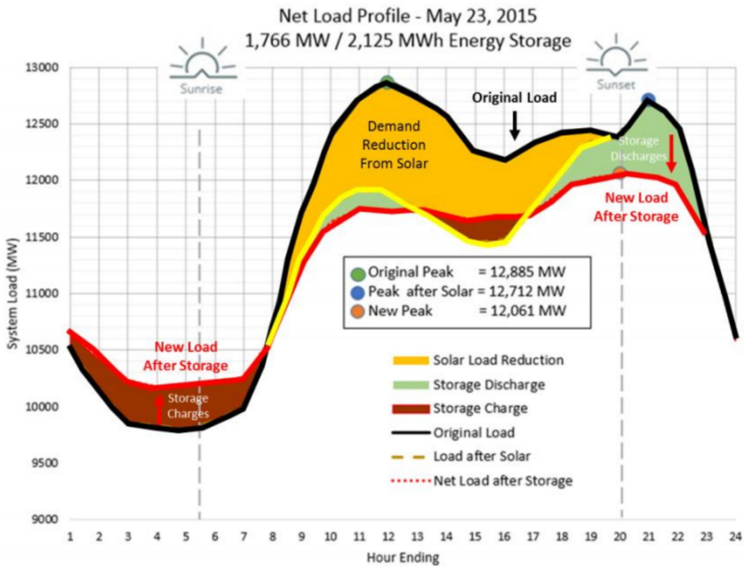


Figure 2.6: Storage contributes to peak shaving and time-shifting of solar resource

California Public Utilities Commission (2014, p.24) published the California's Energy Storage Mandate, aiming to install 1.325 GW of storage at transmission, distribution and consumer level by 2024 (California Public Utilities Commission, 2014). Oregon and Massachusetts are the next US states committing resiliency through storage or promoting storage combined with microgrids (Massachusetts Department of Energy, 2016). The impact and locational optimisation of installing 600MW Storage in Massachusetts across the ISO-NE will be debug in chapter 4 of this thesis.

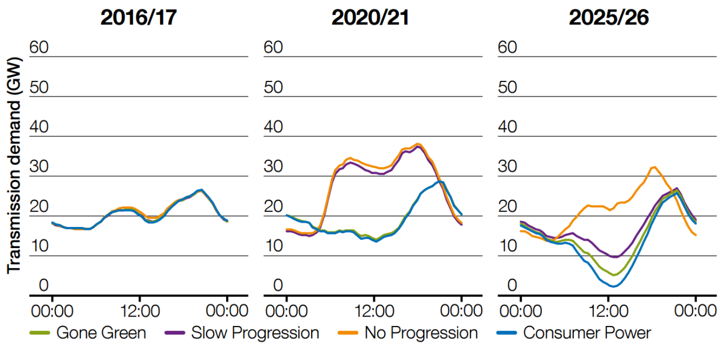


Figure 2.7: Transmission demand profiles according to (National Grid, 2016)

Back to the UK, the system operator presented in 2016 their System Operability Framework (National Grid, 2016) where some their Future Energy Demand Scenarios evaluated, present "duck curve" shapes (Figure 2.7) leading to high ramping events on system operations.

The task to reconfigure networks is not a simple task. A set of switches can be settling to open and close, for minimizing the power losses of the system under constraints. A MO method has to be conducted through a modelling tool with performance indicators. Distribution networks connect locations through power lines. Where several lines converge or where a line meet sat a generator or a load, it is called: bus. Node is the intersection of paths in any type of network. Buses and nodes will be a way to measure the size of the future network model domain (Kirschen and Strbac, 2004).

Current network reinforcement treatments do not evaluate long term consequences of network changes, but act on a short-term horizon. Power distribution network value will convert the cost factors associated through a costing model to a financial factor. This indicator is then used for future optimisation of the models displayed in this thesis (Western Power Distribution, 2015).

According to projections in Figure 2.8, from RIIO-ED2, a rapid ramp up will incentivise the investments on Low Carbon projects. Those investments will be driven by changes in demand (LRE- Load Related Expenditure) while other network investment that is disassociated with load (NLRE) will be as an example, asset replacement. RIIO framework will reduce the uncertainty about future network needs and operation while promoting innovation (Jenkins, 2011).

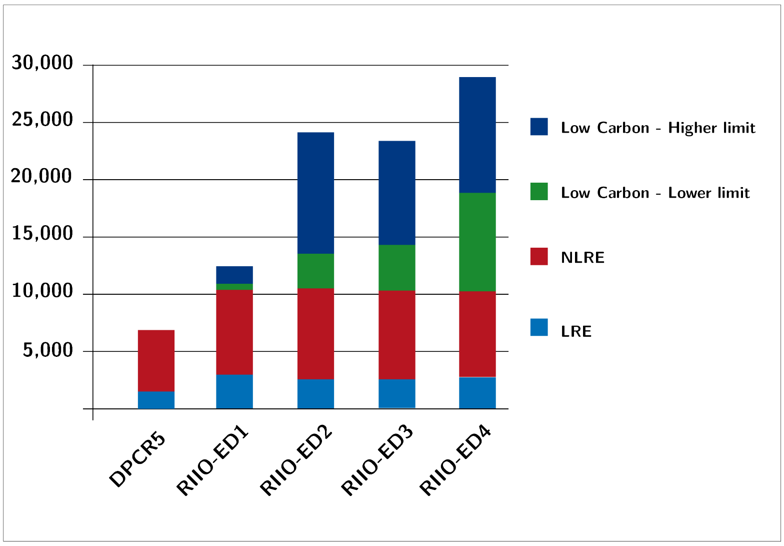


Figure 2.8: Gross GB network related investment for the next four RIIO periods

(EA Technology, 2012)

The power network can be improved technically and economically though the inclusion of reinforcement interventions. Six Smart Grid intervention techniques have been identified to be assessed in this thesis and detailed in following subsection namely, Dynamic Asset Ratings (DAR), Automated Load Transfer (ALT), Meshed Networks, Battery Storage, Distributed Generation and Demand-Side Management (DSM) (Western Power Distribution, 2015).

2.4 Smart Grid Techniques Characterisation

Distribution networks investment uncertainty is a complex problem, where traditional deterministic models are in need to be revised overcome present and future decision-making challenges. Proliferation of distributed renewable generation and other low carbon technologies are creating new challenges for Distribution Network Operators, increasing alternatives to conventional reinforcement in order to reduce network operation costs, increase security of supply and allows a more reliable renewable generation to be connected to the grid. Selecting the most optimal combinations of interventions in regards to long-term cost and performance of the network is something that the current tools and approaches used by the industry cannot adequately do (Papaefthymiou and Dragoon, 2016).

The cost and limited flexibility of traditional approaches to 11kV network reinforcement threaten to constrain the uptake of low carbon technologies (Nieto-Martin et al., 2017). Current 11kV network modification practices do not evaluate long term consequences of network changes, acting on a short-term horizon. Long term capacity planning is based on historical estimates that assume gradual ramp-up of energy demand (Patti et al., 2015).

As part of the FALCON project four Engineering intervention techniques were proposed as alternatives to traditional network reinforcements. The technical and commercial benefits of the intervention techniques will be quantified during field trials. The technique description and trials data would be used to create accurate technique models that will allow us to automate decision-making for optimising network interventions.

2.4.1 Automated Load Transfer

A large number of circuits at 11kV on WPD distribution networks are run in an 'open ring' configuration (McDonald, 2008). On these circuits, feeders from the same or adjacent primary substations are electrically connected together at the feeder extremity, via a switching device that is normally in the open position. These feeder inter-connection points are referred to as Normal Open Points (NOPs). All loads on such circuits are ordinarily associated and fed from a specified feeder/Primary Substation. It is possible to close these normal open points and create an open point elsewhere on the network (maintaining the open ring nature of the network), and change the feeder/primary substation that a load (or number of loads) are fed from. Routinely this is done under maintenance or fault circumstances. The positions of NOPs on a mature portion of network have been established for a variety of reasons, including: limiting load/number of customers on a single feeder; managing network voltage; and allowing immediate access for switching purposes. In many instances, these NOPs have been in place for lengthy periods of time (years). As such, their position may no longer be optimal with respect to losses, voltage, and feeder capacity headroom, particularly where incremental growth in load on a network (within authorised supply capacities) has occurred.

ALT (Western Power Distribution, 2015) Western Power Distribution (2015) on the 11kV network is the process of changing the state of switching devices on the network to shift the location of the normally open points (NOPs), and cause an improvement in the network's performance. Deliberately changing the open point, and consequentially what loads are supplied from which primary substations, affects the key network parameters of losses, voltage, and capacity headroom. This technique seeks to change the power flows on the network through alternative NOP locations. However, there are other potential benefits that may be gained when considering automatic load transfer as a more flexible operational tool within an electricity distribution network. These benefits include:

- Active management of network feeding arrangements to maximise utilisation of existing capacity
- Automated load transfer at peak times
- Voltage regulation
- Even load profile of circuits and feeders
- Even customer number profile to assist with Customer Interruptions (CI) and Customer Minutes Lost (CML)
- Real-time transfer of load or generation across feeders and primary substations
- A positive impact on Carbon resulting from reduced losses due to more even loading, better voltage regulation and reduced reinforcement.

The implementation of ALT depends on the network configuration and connected load. Network reconfiguration is a highly complex, non-differentiable, constrained, non-linear (due to the on-off nature of the circuit breakers) mixed integer optimization problem, due to the high number of switching elements in a distribution network. Thus, evaluation of all possible configurations is time consuming. In addition, the process behind how benefits can be validated using measured network data on a practical scale taking into account the issue of substation time varying loading uncertainty is complex. From a theoretical perspective, a network reconfiguration is an optimisation problem that may have different objective functions, such as minimum switching operations, minimum power loss, balanced feeder load balancing, or their combination (Narimani et al., 2014) (Tsai and Hsu, 2010) to comply with a set of operational constraints such as bus bar voltage limits, line or cable capacity ratings and fault levels. Generally these methods can be grouped into several categories; classic optimisation techniques (Botea et al., 2012), (Mendes et al., 2013), sensitivities analysis methods (Jabr el al., 2012), knowledge-based heuristic methods (Gonzalez et al., 2012), (Ferdavani et al., 2013), and Genetic Algorithms (Queiroz and Lyra, 2009). Sensitivities analysis methods and knowledge-based heuristic methods can provide practical results with short computing time but may not be global solutions. Heuristic techniques including "Sequential Switch Opening" (Merlin and Back, 1975) (Shimohammadi and Hong, 1989), and "Branch Exchange' (Civanlar et al., 1988) (Baran and Wu, 1989) deal with a branch at a time. Sequential switch opening is where all the switches of the network are initially closed forming a meshed network, then, to eliminate network loops, the switches are opened sequentially starting with the switch that has the lowest current. The process is repeated until the network reaches a radial structure. Branch exchange methods are different from sequential switching, the method starts from the initial configuration of the network and performs pairs of open/close switching actions to produce new network topologies while maintaining the radial nature of the system.

2.4.2 Meshed Networks

Meshed networks (Western Power Distribution, 2015) is the process by which circuit breakers on the network are switched in order to feed loads from a multiple of locations (Amanulla et al., 2012) (Asuhaimi et al., 2012). This approach fundamentally allows the load on each feeder in a meshed circuit to deviate according to the routine variations in the connected load, without the need for pre-existing analysis and changes to switch states.

However, simply closing Normal Open Points (NOPs) exposes more connected customers to supply interruption following a network fault. Therefore any planned closure of open points for long term operation is routinely accompanied by the installation of along-the-feeder fault sensing and interruption equipment (protection relays and circuit breakers). The installation of along-the-feeder protection devices restores, and potentially improves (i.e. reduces), the probability of customer interruption under fault conditions with mesh operations. Meshing is primarily done to improve the security of supply. However, there are other potential benefits that may be expected when considering a meshed network. These benefits could include:

- Improved capacity margins
- Voltage regulation
- Increased penetration of distributed generation
- Reduced losses
- Power quality improvements

There are however disadvantages to meshing and these include increased fault levels, increased complexity of protection and automation, leading to additional cost.

2.4.3 Energy Storage

Energy Storage was addressed in subsection 2.2.7. This subsection details the demo trial (Western Power Distribution, 2015) and looked at understanding the implementation and operational capability of installed battery energy storage connected at existing substations on a single 11kV feeder from the Fox Milne Primary substation. The potential benefits that may be expected when considering energy storage within an electricity distribution network include:

- Improved capacity margins
- Increased penetration of distributed generation
- Deferring network reinforcement by reducing peak loads in branches of the network (above the point of battery connection), where the unmodified peak loads would ordinarily have approached or exceeded effective circuit capacity
- Power quality and phase balance improvements through active filtering that counters harmonic distortion, and prioritises output to more lightly loaded phases
- Provision of frequency response and other ancillary services by utilising the stored energy outside times of peak load (primary purpose)
- Improvements in control of voltage at the point of connection

However, batteries in particular have specific operational drawbacks and limitations that include:

- Any reduction in the peak circuit loading is heavily dependent on the prevailing shape and duration of load peaks (e.g. short sharp peaks vs.

long relatively flat peaks), the power rating and capacity of the energy storage system and the strategy used to trigger the start of energy output

- Worsening of network power quality due to the connection of power electronics
- An operational life that is dependent on the pattern of usage (e.g. repeated high depth of discharge operation)
- Provision of land, construction costs
- Operating noise
- Operating costs (maintenance, plus the net cost of electricity for commercial services)

2.4.4 Dynamic Asset Rating

Traditionally overhead lines (OHL) (Western Power Distribution, 2015), transformers and cables have been assigned capacity ratings intended to ensure operation within safe operating limits, and allow assets to achieve nominal service life. These ratings may be fixed for specific periods of time (e.g. summer and winter ratings of OHLs), or may relate to a load that has a daily cyclic characteristic (e.g. transformer and cables). However, these ratings essentially do not take the current/present environmental conditions into account, nor do they take into account the current/present thermal state of the asset. In this respect, the ratings are regarded as 'static'– not responsive to the current thermal or environmental conditions of the asset. These 'static' ratings make assumptions about prevailing environmental conditions (air temperature, wind speed and direction etc.) and set a limit on electrical current passing through the asset such that safety and service life of the assets are maintained.

DAR seeks to allow operation of these assets beyond the static limits, through dynamic assessment of the asset's actual thermal state (derived from preceding operating circumstances), and the present environmental factors. Whilst seeking to increase capacity, this technique can also identify periods where the dynamic rating is calculated as less than the static rating, thereby potentially reducing the asset's rating under some circumstances.

The dynamic rating is often referred to as 'ampacity'- the maximum current that can pass through an asset before the temperature limits are reached. The ampacity may be defined as either 'sustained' or 'cyclic' where sustained refers to the asset seeing a steady load, whereas as cyclic refers to the asset seeing an ever-changing load following a set pattern. This technique seeks to properly increase the capacity of assets during peak usage periods to alleviate constraints, whilst maintaining safety and managing impact on asset life. DAR can also constrain use of assets (e.g. generation) when environmental/load conditions are not favourable.

2.4.4.1 Transformer Dynamic Asset Rating

The practice of using transformer dynamic asset rating (Western Power Distribution, 2015) is to assess transformer oil and winding temperatures (the prevailing thermal state of the asset) and to estimate the additional load that the transformer could carry and still remain within a stated highest winding temperature (known as hot-spot), for a given ambient air temperature.

For a given transformer, the temperature of the insulation (limiting factor for operation) is governed by the heating effect of current flowing through the windings, and the cooling of the transformer oil. The temperature of the oil (and cooling effect on the insulation) is governed by the ambient air temperature, the heating from load current, and cooling process due the cooling arrangement of the transformer. Sustained load and cyclic load ratings are given by manufacturers, sometimes with different cooling mechanisms, to limit operating insulation temperatures (typically to less than 98°C or 110 °C for a range of ambient temperatures e.g. 20°C up to 30°C) to guarantee that an acceptable service life of at least 20 years can be achieved.

In reality, primary transformers are typically installed as multiple units, where the loss of one unit from service does not interrupt supply, and many transformers are located outdoors where the ambient temperature rarely reaches 30°C. Therefore, the transformers tend not to be operating close to their temperature limits resulting in a longer service life span. It is possible to take advantage of the conditions to rate the transformer dynamically based on hot spot temperature rather than on a static basis. It should be noted that the hot-spot temperature exists somewhere around the windings but is difficult to exactly locate. The hot-spot location and temperature is a function of transformer design and cooling functionality, ambient air temperature, oil temperature, and winding losses amongst other parameters. This makes the hot-spot temperature complex to assess with any degree of certainty. Although direct measurement methods do exist, they can only be applied to newly built units, for which the manufacturer can install bespoke technically advanced measuring facilities (for instance sensors with fibre optic cables). Therefore, for existing in-service applications, the hot-spot temperature may only be computed. To establish a dynamic asset rating for a transformer, two elements are necessary:

- a thermal model of the transformer is required to assess prevailing transformer oil and winding temperature given previous load and ambient air temperatures; and

- a process is required that will iteratively increase modelled load current and calculate consequential hot-spot temperature (using the thermal model) until the limiting hotspot temperature is reached. The load current that results in this limiting hot-spot temperature is the dynamic asset rating, or ampacity of the transformer. This can be either sustained or cyclic.

The potential benefits that may be expected when considering dynamic asset rating of transformers within an electricity distribution network include:

- Deferring network reinforcement by allowing more current to pass through the transformer when the weather conditions are favourable to cooling without adversely affecting life
- Assisting with ratings when highly fluctuating loads are connected (i.e. average rate of loss-of-life of the transformers are still within specified limits even if temporarily the transformer is overloaded compared to nameplate rating).

2.4.4.2 Cables Dynamic Asset Rating

The static calculated current ratings of underground cables (Western Power Distribution, 2015) are based on the rise of temperature of the cable insulation (90°C for cross-linked polyethylene (XLPE) insulation and 65°C for oil impregnated paper or 75°C for other paper insulation types (Narimani et al., 2014)). The temperature is limited to avoid insulation breakdown leading to cable failure. The cable temperature increases by the passage of current through the cable. This current is limited to a static summer and winter current rating and a cyclic summer and winter rating as defined in UK Engineering recommendation P17 (Bernardon et al., 2010). These values are reduced (the cable is de-rated) when the cable is ducted or in close proximity to other cables. The ratings contained within P17 are typically calculated using representative values for soil characteristics, taking the thermal resistivity of soil as a set seasonal value. Although this is fine for a generalised answer that will fit the large majority of cables on the UK distribution network, it does not allow the full realisation of individual cables current carrying capability. The ratings within P17 have been used over 30 years by the majority of UK DNO's.

P17 consists of three documents relating to the rating of 11kV and 33kV solid paper insulated cables and polymeric cables. The 'distribution rating' is the most common rating basis applied throughout the distribution network (the maximum current that can be carried for five days whilst keeping the insulation below a maximum temperature). In addition a cable has two static ratings throughout the year, 'summer' and 'winter'. The 'winter' rating takes into account the ability of the cables to carry larger currents and therefore power flows in winter months due to colder temperatures, and generally wetter ground. This rating is broadly independent of the laying depth of an underground cable, provided the burial depth is at least 600mm.

The DAR technique looks to maximise network capacity usage by monitoring soil temperature and moisture. This data will be used to calculate 'real-time' asset capacity, potentially allowing for higher ampacity for limited periods rather than the current 'static rating' current used by distribution network operators. The DAR technique will allow the underground cable to be temporarily run above its continuous current rating providing it remains below the critical temperature set out by the manufacturer. A dynamically rated cable would provide the option of running underground cables to incorporate short term increases in load that might defer capital expenditure on network reinforcement. Research into the dynamic capabilities of underground cables undertaken worldwide, has led to the development of a number of monitoring techniques and simulation software applicable to the transmission and distribution network.

2.4.5 Learnings from Smart Grid trials

2.1 provides a high level summary of which techniques impact what network metric, with the remainder of the section providing comparison of each technique with other trials, on a network-metric basis. It must be said that the automation of the grid trials would have not be possible without WiMAX, the based Telecommunications System to Support for the FALCON project (Poidevin, 2008). ICT plays a core function when planning the automation and increase of smartness of the network. Detailed learnings from the trials can be found in (Nieto-Martin et al., 2017b).

Table 2.1: Cross-smart technique comparison of impacts

	DAR-OHL	DAR-Tx	DAR-Cables	ALT	Mesh	Energy Store
Thermal limits /capacity headroom	✓	✓	✓	✓	∼	✓
Voltage limits	No impact	No impact	No impact	✓	∼	✓
Faut levels	No impact	No impact	No impact	No impact	×	×
PQ	No impact	No impact	No impact	∼	∼	✓
Enablement of DG	✓	✓	✓	✓	✓	✓
Losses	×	×	×	✓	✓	×
CI/CMLs	No impact	No impact	No impact	∼	∼	No impact
Grid /Network services	No impact	No impact	No impact	No impact	No impact	✓

Key: ✓ Positive impact; × negative impact; ∼ network dependant, may have positive or negative impact

2.4.5.1 Network capacity

- All techniques altered capacity on the network.

- DAR evaluates capacity more accurately than static ratings which may suggest additional or in some cases less capacity. OHLs are predominately affected by wind speed/direction meaning significant variations occur both across seasons and within short time scales (minutes). When this variability of rating is combined with the low thermal capacities of OHLs (i.e. the OHL temperatures respond rapidly to the environmental changes), taking advantage of this technique is limited to particular circumstances. The dynamic ratings of both cables and transformers are dependent on ambient temperatures, meaning diurnal (for transformers only) and seasonal variations are clearly present, and the larger associated thermal capacities means short-time duration changes in ambient conditions cause less short term variability in asset ampacity.

- ALT and mesh shift load from one part of a network to another, thereby potentially relieving constraints. ALT offers a far more intuitive mechanism, whilst mesh is continually dynamic by its very nature. The extent to which benefits exist is highly dependent on the connectivity of any candidate network, and loads/generation connected to the network, and the extent to which the loads vary relative to each other.

- Energy storage shifts load in time, reducing load at a capacity constrained key point in time, only to increase the load at a less critical point in time. The specified power and storage energy capacity clearly need to be appropriately matched to the network load; and adaptive triggering is required to deal with individually daily variations in load, to optimise the impact that the installed system can have on the network. Energy Storage may complement DAR by providing a mechanism to alter load patterns such that constrained assets might make the best use of available ampacity.

2.4.5.2 Voltage

- Three of the techniques offer some potential for benefits (ALT, Mesh, ES)

- ALT demonstrated the largest benefit (4%), on some of the rural circuits that were trialled, but no significant benefit was found on urban circuits

- Mesh considered a small urban network and for this example there was no significant impact on voltage

- Energy storage shifts load in time, reducing load at a capacity constrained key point in time, only to increase the load at a less critical point in time. The specified power and storage energy capacity clearly need to be appropriately matched to the network load; and adaptive triggering is required to deal with individually daily variations in load, to optimise the impact that the installed system can have on the network. Energy Storage may complement DAR by providing a mechanism to alter load patterns such that constrained assets might make the best use of available ampacity.

- In general the voltage benefit of the ALT and mesh techniques networks will depend on the voltage difference across pre-existing NOPs, and does not directly address voltage issues at the end of branches

- The installed energy storage systems achieved little impact. In general, the reactive power capacity in relation to the magnitude and power factor of the adjacent load is modest, and can be expected to be expensive to deliver for this benefit alone

2.4.5.3 Fault levels

- As is clearly already recognised, introducing generation (including ES) to a network will ordinarily increase fault level, in this instance the ES were small compared to pre existing fault levels, and so had negligible impact. Meshed networks will also increase fault level due to the reduced circuit impedance. For the mesh technique trial, this was within the ratings of all circuit equipment

2.4.5.4 Power Quality (PQ)

- Mesh trials showed no discernible impact on power quality. Superposition theory and the feeding of harmonic loads via different sources means that harmonics presently fed from one source could be fed from two sources (depending on Network impedances), however, it is unlikely that larger scale trials will show any marked appreciable benefits as the majority of loads are within limits defined by standards and as such it will be difficult to differentiate small changes

- The installed energy storage equipment did not specifically have functionality aimed at improving PQ. At one site, improvement was noted, however this was a beneficial coincidence arising from the nature of a local (within standards) PQ disturbance and the inductance/capacitance smoothing network in the Energy storage system

- More targeted studies of a network that has a known PQ issue could be identified to further examine the potential of mesh/ALT techniques to beneficially impact this issue

2.4.5.5 Losses

- As discussed in the preceding technique-trial specific section, ALT and Mesh offer some potential, though the magnitude is network specific
- The trialled ES systems increased losses, and DAR will tend to increase losses if higher circuit loads are facilitated

2.4.5.6 CIs and CMLs

- ALT changes NOP positions and consequently affects numbers of connected customers per feeder. The trial algorithms:
  - Increased one feeder numbers by 15% (whilst optimising capacity headroom) on a rural/OHL network
  - Increased one feeder numbers by 50% (whilst optimising losses/voltage) on an urban/cable network
- Meshing networks does not improve customer security as such; the improvement only occurs if additional automatic sectioning/unitising occurs beyond that offered by the pre-existing NOP. Due to communication system limitations, the implemented trials did not increase the number of sections, essentially maintaining the pre-existing customer security

2.4.5.7 Network services

- Whilst these trials have demonstrated that frequency response is possible with the ES technique, a marketable service is not fully delivered by the installed equipment. In addition, further work would be required to put DNO owned energy storage on an appropriate commercial basis

We can use the learning from the dynamic asset rating work to understand the impact of loads on the ageing of assets and use this to inform our assumptions on asset health and our asset replacement policies. We are unlikely to monitor 11kV assets widely but dynamic asset rating systems may be cost effective for higher value assets at higher voltages.

The learning from automatic load transfer suggested that a review of normal open points would be beneficial. We are considering the methods for this optimization which may benefit from optimizing against a set of objectives rather than for losses alone. e.g. losses, CML/CI impact, accessibility for manual switching, etc. Meshed networks remain an option for sharing 11kV network capacity and are supported by the existing modelling tools.

DNO owned storage at 11kV is unlikely to be adopted as business as usual but work continues to investigate storage potential at higher voltages and to create regulatory frameworks that allow for multiple revenue streams to be combined.

Therefore, it is unlikely to implement the engineering techniques into business as usual as alternatives to conventional reinforcement in the form undertaken during the trial, because although they may be used in the future as short to medium term remedies they do not currently appear to represent value for money under the current regulatory framework.

In order for the technologies and techniques to be more viable we believe that there needs to be more work done to establish other ways of using the technology or finding ways to reduce the overall cost of the technique. As short term remedies they appear to work well, but on longer time horizons the case is weakened.

In addition we recommend to undertake the following exploratory analysis:

- Open point review
- Primary transformer DAR- further based on results of FALCON
- Energy storage: Optimisation, regulatory rules and technologies

2.5 Conclusions

An essential element in the future UK low-carbon energy system will be the electricity infrastructure that can facilitate more flexible demand, the balancing of variable renewable generation, and the incorporation of local small-scale technologies such as solar PV, and upcoming large deployment of technologies such as electric vehicles or energy storage.

In Figure 2.9 are represented the major challenges for UK network regulation until 2050 (beside ongoing TSO-DSO market roles). Electricity markets need regulators to oversee the effective functioning of the electricity sector through rule-setting, monitoring, and enforcement. Specifically, regulators (OFGEM in the case of the UK) have important roles to play in two main areas: market structure and innovation enhancement.

Figure 2.9: Regulation challenges for 2050

In terms of market structure, regulators can determine ownership, access to the market, and contractual relationships, market planning as well as the mechanisms of allocations. In terms of conduct, regulators are concerned about the production of electricity and the security of supply. Regulation may influence the fuel mix, production technologies, the environmental impacts of electricity and tariffs.

Proposed learnings can be summarised as:

Implementation of the 2050 Pathway for the deployment of Smart Grids in the UK. It is mandatory to create a collaborative information environment for the following Ofgem current programs: Data and Communications Company (DCC), Smart Energy Code (SEC) and Smarter Markets Programme

Such 'smart grid' infrastructure will need to incorporate greater observation, control, and automation, through incorporation of information and communication technologies, that ICTs need to have a framework for the utilities being able to measure their performances and the security of the data they are DECC renewable scenario projects to have at least 30% in the generation mix. Maximising the renewable penetration when available despite its intermittency will mean a curtailment of fossil fuels. A program to close non-environmental friendly generators can be implemented moving to Non-traditional business models.

Energy storage is the only 'green technology' without subsides. For making it competitive on the medium term, has been proved scalable, this technology not only will play a role itself, also will help other low-carbon interventions to be more reliable, i.e., wind or solar.

The prevalent model of infrastructure governance in the energy and other sectors has prioritised short term time horizons and static efficiencies. Technologies that currently are at R&D or on a pilot scale, as CHP (at utility scale) or CCS, will contribute with 2050, are receiving large investments. Regulation for the time horizon scalability of these projects is needed.

The electrification of both heating and transport. In a low carbon future, the Government anticipates that a significant proportion of heating will come from low carbon electricity using heat pump technologies. At the same time, internal combustion engines are likely to be replaced by batteries in electric vehicles.

Transmission & Distribution networks have moved in April 2015 from RPI-X to RIIO price control. The RIIO model is an incentive-based regulatory framework, providing innovation stimulus to the long-term regulated operators.

Network operators will want to be able to observe how much power is flowing where, in real-time. They will want to be able to manage and optimise demand as far as possible, effectively evolving from network operators to local electricity system operators. This vision contrasts with the grid that the UK has at present. Parts of the distribution network date back to the early part of the last century.

Building a smart grid is therefore a major undertaking for promoting Demand Side Management. Currently, there is not tariff may not offer a clear platform or guidance for smaller disaggregated distributed energy resources (DER) to participate effectively in the market. Unlike traditional supply resources, individual DER may be too small to meet this minimum size requirement - for example, at the residential level a rooftop photovoltaic solar system may have a maximum generation capacity of 5 kilowatts and a battery storage system may have a maximum discharge capacity of 2-3 kilowatts. The relationships between those DER, energy companies and regulatory authorities need to have a framework that allows further development of self-generation (CAISO, 2015), (Greentechgrid, 2015).

Advancements in technologies and services are changing the way energy is generated, transmitted, transacted and stored, and how consumers make decisions about their energy uses and sources and even becoming producers for some periods of the day. These advancements will provide opportunities to make the electric system more secure and sustainable, however, the complexity of the power system also increases, therefore, dynamic modelling approaches, to answer uncertainties that Internet of Things (IoT) and digitalisation will bring along are required.

Chapter 3

Meta-heuristics for Evolutionary Power Systems

This chapter provides the characterisation of the methodologies implemented in this research, namely evolutionary optimisation, heuristics, and visualisation techniques. In doing so, the application of those methodologies to specific optimisation domains, namely distribution and transmission power systems are detailed.

3.1 Unravelling bottom-up power systems modelling

The smart grid agenda applies largely to the low voltage distribution networks, as the high voltage transmission system is already 'smart' to some degree. Existing electricity distribution infrastructure has been developed to serve predictable and regular patterns of demand and generation.

Until now, power networks historically have been conceived as a problem with multiple objectives, but have been treated individually. Among the performance targets that have been under consideration in the evaluation of such distribution networks are the reduction of customers without service, voltage deviations, losses, imbalance in power feeders, and reliability indexes (Gan et al., 2009), (Stoft, 2002). The performance indicators used are intended to answering questions such as which are the relevant indexes to prioritize in a future power network or how might a new infrastructure be composed (UK Power Networks, 2013), (Zheng and Cai, 2010).

Restoration of operation services is nowadays a difficult optimization problem to solve Mendoza et al. (2006). Therefore, it has generally been implemented using combinatorial non-linear optimization tools. For designing proper solutions it is necessary to consider the constraints of the network operation (Bernal-Agustin et al., 2011), (Dolan et al., 2009).

Deferral on grid operations to shift demand from peak to off-peak with storage is an example on how future T&D networks will operate. The assets on those networks can use the storage as smart technique to decrease the thermal and voltage stressing, extending thus the life time of the network assets. Figure 3.1 represents how storage enhance a more efficient utilisation of the network by shifting loads.

A decentralised system like the one needed for integrating the technologies mentioned in chapter 2 is complex and need to be adaptive. It will consist on large number of adaptive agents (in our current case lines, cables, transformers, substations...) acting at local level. These local distributed interactions analysis will provide macro-decision making, in our case, investment of distribution and transmission grids (Burstedde, 2012). This intricate both-way information feed between bottom and top decision makers has been discussed in economics for a long time leading to application in several fields such as manufacturing, operations, water distribution, environmental policy and lately, IoT (Tesfatsion, 2002); (Gurung et al., 2014); (Reaidy et al., 2015).

Model-Driven Engineering (MDE) uses analysis, construction, and development of frameworks to formulate meta-models. Those models are usually characterised using domain-specific modelling approaches (Sánchez-Cuadrado et al., 2012), containing appropriate detail abstraction of particular domain through an specific meta-model. The use of meta-models require therefore inputs from domain experts which can be used to generate aggregated or disaggregated models. Top-down and bottom-up are the conceptual definition of aggregated and disaggregated models (Kim et al., 2014). These two modelling paradigms are frequently used to epitomise domain interactions among the operation of the energy system, the econometrics related and the technical performance indicators (Bohringer, 1998).

From a bottom-up modelling approach (Bower, 1974); (Mintzberg and Waters, 1985), the top-down perspective is a simplistic characterisation of how electrical power networks combine locational events and individual assets performance with high level objectives like improving the CML of a certain congested area (Carragher et al., 2012). From an engineering point of view, both are still valid since outputs and strategic forecast are produced in both. How those outcomes are calculated, validated and transformed to strategy is presented in Figure 3.1 (top-down) and Figure 3.2 (bottom-up).

The ability of bottom-up to capture discrete locational impacts of technologies on the system and their disaggregated costs is triggering the following subsections. $Trade-off$ methodologies are needed for planning evolutionary power systems where observing disaggregated results strategic forecasts are to be produced. These methodologies need to be *interactive* in the sense that starting from an initial state and after a testing or learning phase, the network is able to accommodate techniques that have improved the system, providing a *exploratory* set of solutions that can be expanded or discarded as the model evolves through time.

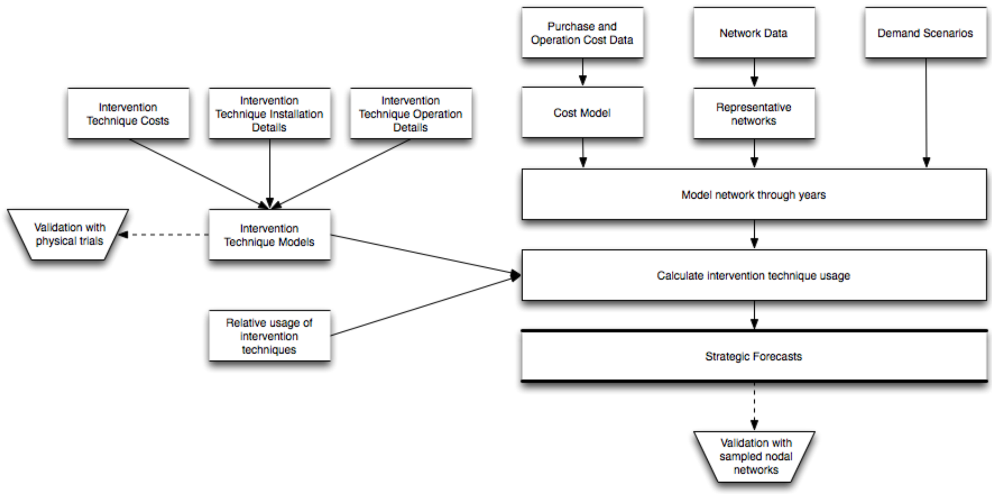


Figure 3.1: Top-down conceptualisation of evolutionary power networks planning

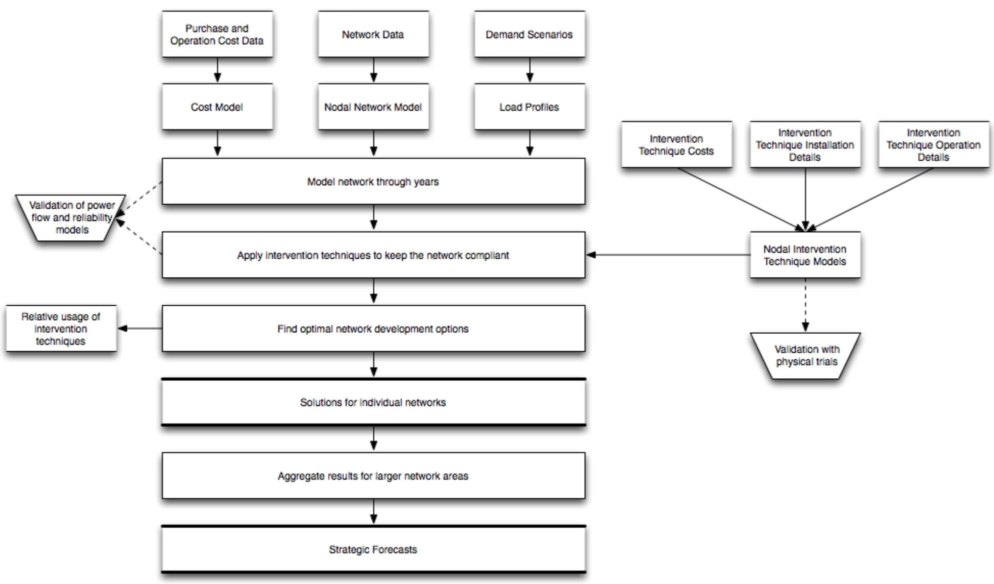


Figure 3.2: Bottom-up conceptualisation of evolutionary power networks planning

3.2 Optimisation

Most problems in nature have several, usually conflicting, objectives to be satisfied. Many of theses problems are frequently treated as single-objective optimisation problems by transforming all but one objective into constraints (Coello, 2016).

As an informal definition of optimisation can be defined as the process to minimise or maximise the proposed function, evaluating under certain conditions the variables and objective functions under results are obtained. However, there are essential limitations imposed upon candidate solutions that may otherwise be considered optimal; a solution must be both feasible and legal (Gen and Cheng, 2000).

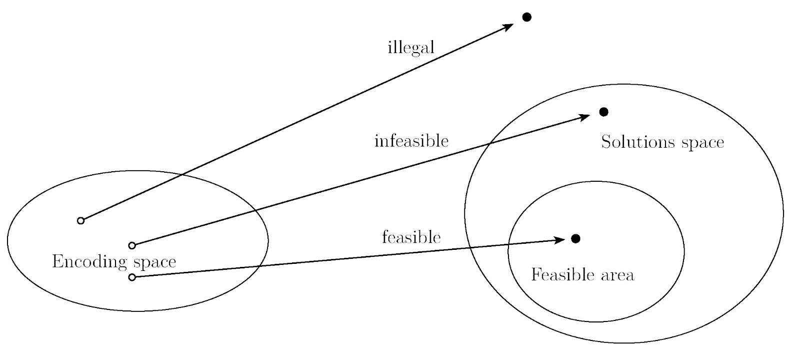


Figure 3.3: Solution space characterisation by nature of solution region

A legal solution is one that can successfully be translated from the internal representation of the optimiser into the problem domain, whereas a feasible one is legal and resides in the feasible solution region of the domain, as in Figure 3.3. For example, a solution could represent a theoretically possible configuration of the grid and hence be legal, but not being able to solve network constraints and therefore would not be a feasible for the real world.

When optimising a function, there is the possibility that OF has two or more locally optimal solutions, in which case it is known as multi-modal (Deb et al., 1993). An extreme example is given in Figure 3.4 which shows a surface plot from the *R* language of Rastrigin's function in its 3D form (Mühlenbein et al., 1991), being a highly multi-modal function having many local minima and maxima, and the global minimum. Multi-modal optimisation seeks to obtain a set of good solutions, comprising the best of the local optima along with, ideally, the global optimum if it can be found. When using methods which do not guarantee to find the global optimum, then it is more important to have a set to choose from since the global optimum may not be present and there may be different advantages and disadvantages between one local optimum and another.

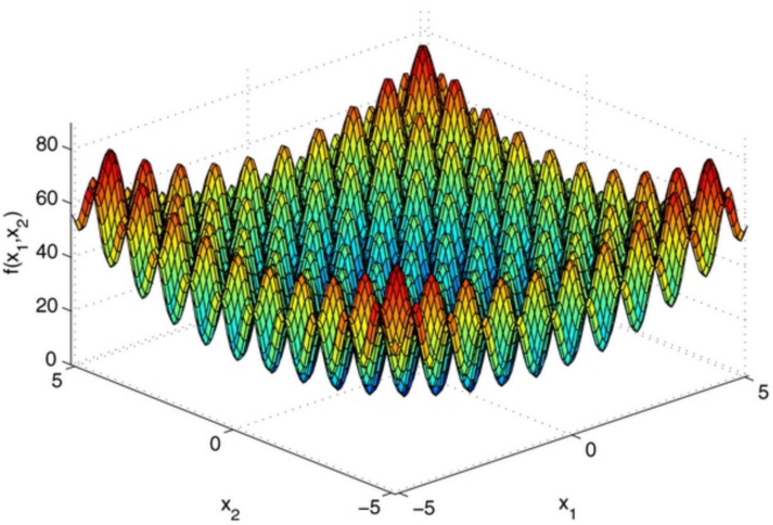


Figure 3.4: Rastrigin's function as a 3D surface plot, displaying its many local minima and maxima, where the global maximum is at (2.5, 2.5) and equal to 80.

In most of the real-world optimisation problems the optimiser has no inbuilt 'knowledge' about the subject domain of the problem upon which it works, thus the optimiser acts as a black-box process (Schaefer and Nolle, 2006), transforming the input into an output (Figure 3.5). On these types of applied optimisation, evolutionary computing is particularly relevant, especially when more than two objectives are being optimised at the same time. That motivates the following subsection.

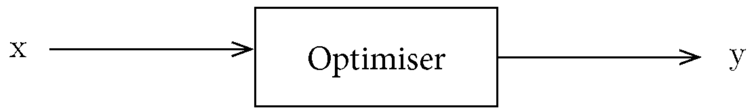


Figure 3.5: *Black−box* optimisation representation that finds the combination of variables x to provide feasible outcomes for y.

A barrier when optimising many objectives, imposed by our three-dimensional habitation and perceptual experience, is the visualisation of many dimensions. The accurate visualization of multidimensional problems and multivariate data unlocks insights into the role of dimensionality. The ||-coords technique (Inselberg, 2009) enables multidimensional results to be plotted uniquely and without loss of information, together in one plot. The results shown in the ||-coords plots and related scatter plots contain all of the results from all of the feasible solutions, the dominated and the non-dominated ones (Figure 3.5).

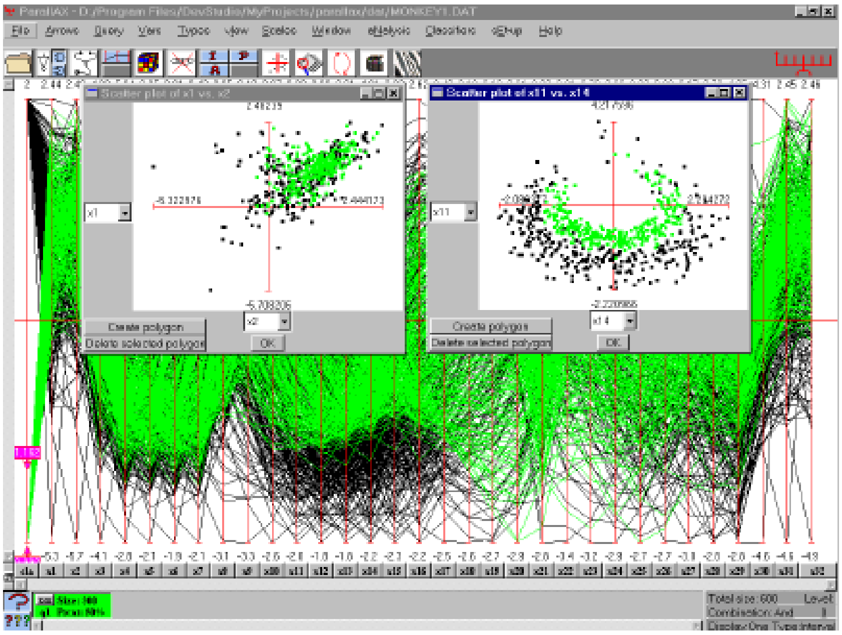


Figure 3.6: ‖-coordinates representation of many dimensions and ‖-2D scatter plots of Pareto optimal

Case studies within chapters 4, 5, and 6, deal with three or more objectives to be optimised and are modelled as a two-stage. The objectives are effectively $black - boxes$, which depend on the iterative learnings from data feeding the optimiser from either Plexos (chapter 4) or IPSA Power (chapters 5 and 6), commercial software that that performs market and operations analysis of power networks in the first case, and the second has been customised for modelling smart grid performance techniques describes on Chapter 1. The outcome of those experiments are fed to the meta-heuristic of each case study, a Genetic Algorithm (GA) for Chapter 4, graph search algorithm for Chapter 5 and a combination the last one with Real Options valuation for Chapter 6.

Non of these algorithms have itself information, therefore cannot start without some a priori knowledge of the problem. In the case of A* graph search algorithm, it starts with a valid network state of the grid with no faults in year one. As for the GA, the optimiser used, Ganesh, has been trained for supervised learning by genetic programming with the goal of making the GA experiment runs shorter. Both meta-heuristics used in this thesis, despite one is nature-inspired and the other is not, have in common their ability to deal with multiple objectives, being the motivation of the next subsection.

3.2.1 Multi-objective optimisation

The work in this thesis is focussed on characterising the transformation of power systems using more than one OF to be optimised at the same time. This subsection therefore addresses the area of multi-objective optimisation. The general Multi-objective Optimization Problem (MOP) can be formally defined by Coello (2006, p. 28) as:

Find the vector:

$$\vec{x}^* = [x_1^*, x_2^*, ..., x_n^*]^T \tag{3.1}$$

which will satisfy the m inequality constraints:

$$g_i(\vec{x}) \leq 0, \qquad i = 1, 2, ..., m \tag{3.2}$$

the p equality constraints:

$$h_i(\vec{x}) = 0 \qquad i = 1, 2, ..., p \tag{3.3}$$

and will optimize the vector function:

$$\vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), ..., f_k(\vec{x})]^T \tag{3.4}$$

It has been already discussed that optimisation constraints can also be taken as hard objectives, needing to be satisfied prior to the optimisation of the further OFs. In the past that has led to problems having many objectives have been transformed into single objective ones, with hard constraints, in order to solve them (Fonseca and Fleming, 1998). However, the essence of MOPs are that each of the conflicted OFs need to be optimised at the same time.

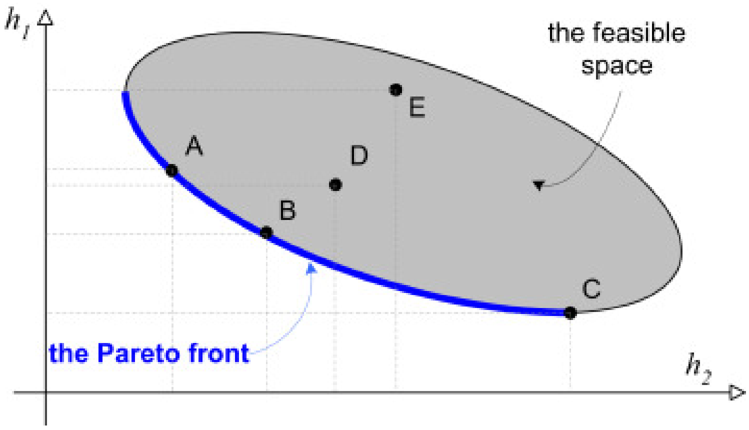


Figure 3.7: The Pareto-optimal front of a bi-objective minimising optimisation problem.

In MOPs that do have conflicting objectives, it naturally arises that there are a set of optimal solutions rather than just one, because no one solution can be better than all of the others with respect to all OFs, since to improve one OF necessarily degrades the other OFs (Deb, 1999). The global optimal set, in the feasible decision space) is known as the Pareto-front (Figure 3.7), but other solution sets which approximate the global one, may be found and would be termed the local Pareto set or front (Deb and Karthik, 2007).

In words, this definition says that $\vec{x^*}$ is Pareto optimal if there exists no feasible vector of decision variables $\vec{x^*} \in F$ which would decrease some criterion without causing a simultaneous increase in at least one other criterion. Unfortunately, this concept almost always gives not a single solution, but rather a set of solutions called the *Pareto optimal set*. The vectors $\vec{x^*}$ correspoding to the solutions included in the Pareto optimal set are called *nondominated*. The plot of the objective functions whose nondominated vectors are in the Pareto optimal set is called the $Pareto\ front$.

We say that a vector of decision variables $\vec{x} \in F$ is *Pareto optimal* if there does not exist another $\vec{x} \in F$ such that $f_i(\vec{x}) \leq f_i(\vec{x^*})$, for all $i = 1, ..., k$, and $f_j(\vec{x}) < f_j(\vec{x^*})$ for at least one j.

In objective space, the optimal set is known as the non-dominated set, since each solution cannot be said to be dominated (be more optimal) by any other. Hence MOO requires trade-offs to be made, by some higher-level decision maker, in choosing a compromise solution to be the answer to the problem, as Figure 3.8 illustrates.

Moreover, Coello (2006, p. 28) note, referencing Bäck (1995, p. 2) , that for a general MOP for a global optimum is an *NPcomplete* problem (Garey and Johnson, 1979) for any system that is of more than minimal complexity, due to the exponential increase in the size of the search space, which depends upon the cardinality of both the decision vector and its components(Coello, 2006), (Back, 1995).

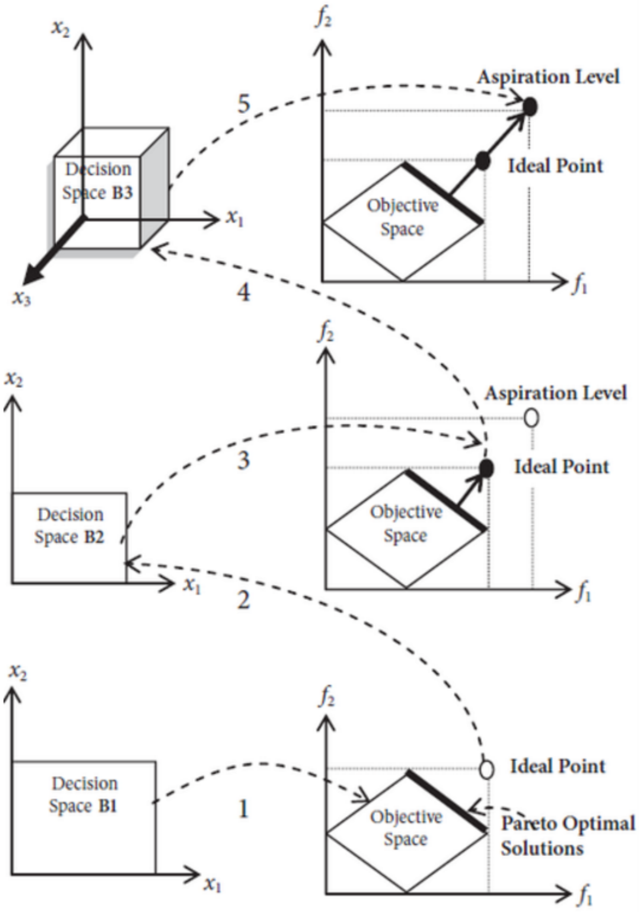


Figure 3.8: Multi-objective (3) optimisation Pareto front projections of OFs f1 & f2

The Pareto dominance relation can then be defined as follows (assuming minimisation as above): A given vector $u = (u_1, \ldots, u_n)$ is said to dominate another vector $v = (v_1, \ldots, v_n)$ if and only if u is at least partly less than $v(u_p < v)$;stated formally thus:

$$\forall i \in \{1, \ldots, n\}, u_i \leq v_i \land \exists i \in \{1, \ldots, n\} \, u_i \leq v_i \tag{3.5}$$

In practice, optimisation problems may be subject to restrictions on the values that one or more of their decision variables may take, or on the values held to be useful in the problem solution. Such constraints can usually take the form expressed as a function inequality: $f(x) \leq c$, or $f(x) < c$, where c is a constant value and f is real-value function of x.

Hu (2013, p. 1188) and Zitzler (2003, p. 117) broaden the definition of dominance and recognising that in real-world size MOPs is very difficult to obtain a true global Pareto front, whereas one or more local Pareto sets may suffice to provide choices of good enough solutions (Hu et al., 2013) (Zitzler et al., 2003).

3.3 Meta-heuristics for evolutionary planning

Dynamic optimisation encompasses the important challenge in real-world applications of capturing evolving behaviours of complex systems. It has been previously discuss in this chapter that MOPs are often hard to solve as they tend not to be amenable to analytical methods due to their usual non-linearity and multidimensionality, within the decision and the objective space, and also often or usually, having very large search spaces from which solutions must be chosen (Abramson et al., 2011) (Rao, 1996). In dynamic optimisation problems, the OF is deterministic at a given time but varies over time:

$$f_{dynamic}(x) = f_t(x) \tag{3.6}$$

where t represents the time at which OF is evaluated (Jin and Branke, 2005).

The inherent characteristics and sizes of real-world problems lead to the adoption of other methods for exploring the solution space where solutions found may not always a unique optimal, but returning solutions often "good enough".

Unlike exact methods, meta-heuristics allow to tackle large-size problem instances by delivering satisfactory solutions in a reasonable time. There is no guarantee to find global optimal solutions or even bounded solutions. They have gained popularity in the past 30 years. Their use in many applications shows their efficiency and effectiveness to solve large and complex problems. Meta-heuristics then, are "criteria, methods, or principles for deciding which among several alternative courses of action promises to be the most effective in order to achieve some goal." (Pearl, 1984, p. 3). Heuristic methods require knowledge about the problem domain, and may be of a stochastic nature, but tend to have simple, incomplete or unreliable information about the exact problem. The term meta-heuristic was introduced by Glover (1986, p. 533) in his discussion of the Tabu search algorithm (Jaeggi et al., 2008), which uses a heuristic, as above, but upon which is imposed a further strategy - that of penalizing moves that take a path already taken, and an organised memory mechanism (Glover, 1986).

It is frequently the case that in pursuing difficult problems, especially real-world engineering ones, that the Pareto-front, is neither known, nor indeed knowable analytically (Van Veldhuizen and Lamont, 200), therefore until proven otherwise, it is usually necessary to assume that a given set of solutions obtained in the front are an approximation characterisation to the global solution.

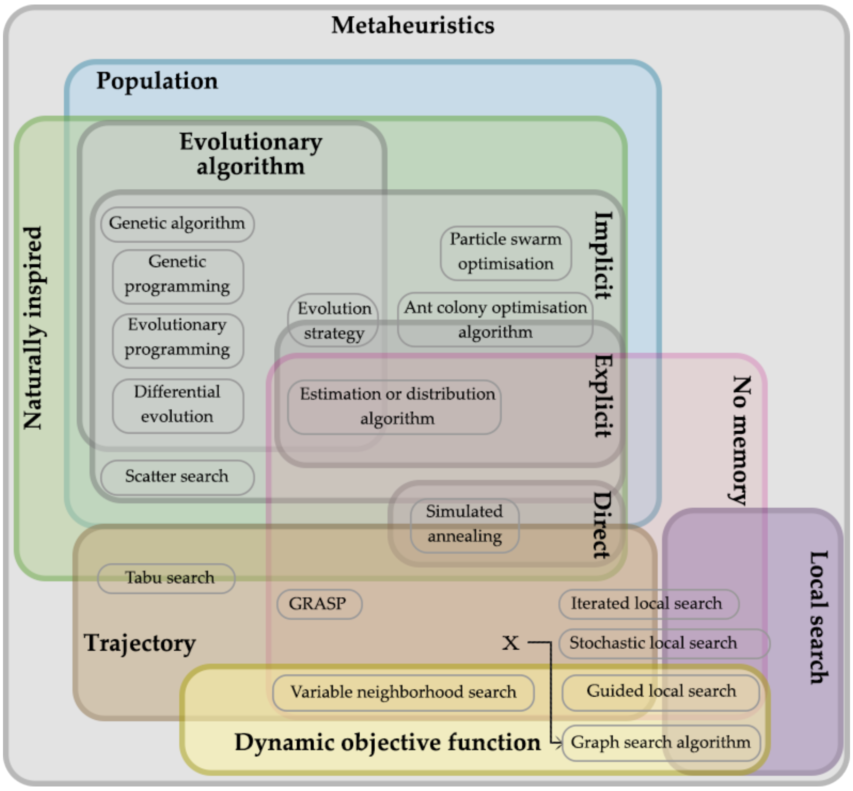


Figure 3.9: Methauristics characterisation by domains (Polymathian, 2017)

For classifying meta-heuristics (Figure 3.9) many criteria have been used (Talbi, 2009) (Blum and Roli, 2003):

- **Nature inspired versus non-nature inspired:** Many meta-heuristics are inspired by natural processes: evolutionary algorithms (Fraser, 1957) and artificial immune systems from biology; ants (Dorigo et al., 1996), bees colonies, and particle swarm optimization from swarm intelligence into different species (social sciences); and simulated annealing from physics.

- **Memory usage versus memoryless methods:** Some meta-heuristic algorithms are memoryless; that is, no information extracted dynamically is used during the search. Some representatives of this class are local search, GRASP, and simulated annealing (Pearl, 1984). While other meta-heuristics use a memory that contains some information extracted online during the search. For instance, short-term and long-term memories in tabu search.

- **Deterministic versus stochastic:** A deterministic meta-heuristic solves an optimization problem by making deterministic decisions (e.g., local search, tabu search). In stochastic meta-heuristics, some random rules are applied during the search (e.g., simulated annealing, evolutionary algorithms). In deterministic algorithms, using the same initial solution will lead to the same final solution, whereas in stochastic meta-heuristics, different final solutions may be obtained from the same initial solution. This characteristic must be taken into account in the performance evaluation of meta-heuristic algorithms (Sorensen and Glover, 2013).

- **Population-based search versus single-solution based search:** Single-solution based algorithms (e.g., local search, simulated annealing) manipulate and transform a single solution during the search while in population-based algorithms (e.g., particle swarm, evolutionary algorithms) a whole population of solutions is evolved. These two families have complementary characteristics: single-solution based meta-heuristics are exploitation oriented; they have the power to intensify the search in local regions. Population-based meta-heuristics are exploration oriented; they allow a better diversification in the whole search space. In the next chapters of this book, we have mainly used this classification. In fact, the algorithms belonging to each family of meta-heuristics share many search mechanisms.

- **Iterative versus greedy:** In iterative algorithms, we start with a complete solution (or population of solutions) and transform it at each iteration using some search operators. Greedy algorithms start from an empty solution, and at each step a decision variable of the problem is assigned until a complete solution is obtained. Most of the meta-heuristics are iterative algorithms.

Meta-heuristic based evolutionary case-studies have been broadly used within the power sector for structural planning (Gupta et al., 2014), Network reconfiguration (Tomoiaga et al., 2013), Power loss minimisation (Rao et al., 2013), Reactive power operation (Lai and Ma, 1997) or Generation dispatch (2012). That motivates the rest of this chapter where novelty of the two selected meta-heuristics implemented in this thesis are detailed and their particularities highlighted: A bespoke (hybrid) Graph Search algorithm and a Genetic Algorithm.

3.4 Graph Search algorithm: SIM A* algorithm

Distribution network planners usually alter the network topology or deploy interventions in response to external events such as new customer connection, thermal or voltage overloads, reliability issues, asset diversion or end-of-life or condition related replacement. This reactive approach naturally lends itself towards being represented as a time series sequence of network states with transitions between states corresponding to network configuration or load changes. (Goldberg and Harrelson, 2005) proposed and implementation based on (Tarjan, 1972), (Imai and Asano, 1986) and (Goldberg and Holland, 1988) of a path algorithm that use A* search to find a point-to-point shortest path in weighted, directed graph. The novelty of the A* implemented within this thesis is that has moved out Graph Search Algorithms from the No memory domain (Figure 3.9).

Alternative evolution pathways of the network over a period of time would therefore arrange into a phylogenetic tree of network states with branching points being alternative decisions of planning engineers. The root of the tree corresponds to the network configuration and loading conditions at the start of the modelling, while the leaf nodes represent boundaries of the search space that are furthest in time from the origin.

The phylogenetic tree representation of the search space using graph search algorithms closely mirrors existing processes within a DNO and can be easily understood by planners, managers and other stakeholders. Assembling the tree based on automated application of intervention techniques and finding least cost path from the root to the leaf nodes constitutes an optimisation problem of finding the best sequence of interventions to keep the network compliant under changing loading conditions over time. In this context, "least cost" can be defined in terms of technical performance of the network, economic expenditure to keep the network compliant, incentive costs or any combination of the above.

3.4.1 SIM algorithm

The SIM algorithm is a scenario-dependent, optimal-seeking feed-forward heuristic. For an exogenously defined scenario, each year is specified as a network state. The exogenous variables that are going to be consider for Chapter 5 and 6 case studies defining network states are namely, Customer Minutes Lost

(CML), Customer Interruptions (CI), Losses, Average Network Utilisation, Average of Maximum Network Utilisation.

The SIM search always starts with an unevaluated network state in the first year of the experiment (initial network state). Following a power flow study, the search either moves on to the following year, or, if the network state has failures, saves it into failed network states store. Evaluation then moves to the next year, so that the failed network states store accumulates all failed states contingent upon the scenario to its end date, before seeking to remedy any of them.

To remedy the failed states, SIM selects each failed network state from the failed network states store and applies a "patch". The set of patches is exogenously defines and may include one of the smart intervention techniques, storage or a conventional reinforcement to resolve failures. Depending on the outcome of patching, the SIM saves a new failed network state or moves on to the following year until the network state fails again.

To select the sequence of patching in the failed network states store, the SIM uses one of three algorithms, $depthfirst$, $widthfirst$ and A*. The depth first algorithm always tries to reach the end year of experiment as fast as possible by always selecting the last saved network state. The width first algorithm performs an exhaustive exploration of the search space by always selecting the first network state from the failed network states store . Both depth first and width first algorithms do not take costs of interventions into account when deciding which network state to expand next.

In contrast, A* algorithm aims to find the least-cost path through the search space. As A* traverses the search space, it builds a tree of partial paths. The leaf nodes of this tree (failed network states) are stored in a priority queue that is ordered using a cost function, which combines a heuristic estimate of the path cost to reach the goal $h(x)$ and the distance travelled from the initial node $g(x)$. In particular, the cost function is:

$$f(x) = g(x) + h(x) \tag{3.7}$$

where $g(x)$ is the TOTEX incurred so far and $h(x)$ is a heuristic estimate of TOTEX to reach the end of experiment. The algorithm removes the next network state in the priority queue to apply intervention techniques. The search stops when the queue is exhausted or a termination criterion, such as the number of evaluated network states, is satisfied.

3.4.2 A* in SIM

Unlike path finding tasks in which A* search is typically used (Ababei and Kavasseri, 2011), network evolution is a challenging problem, making calculation of $g(x)$ and $h(x)$ not straightforward.

$$g(x_i) = (c_i + o_i) + \sum_{j=1}^{i-1}(c_j + o_j + m_j) \tag{3.8}$$

Equation 3.8 defines $g(x)$, for a network state where c_i is CAPEX in the current year, o_i is OPEX in the current year, and c_j, o_j and m_j are CAPEX, OPEX and metrics costs of ancestor network state in year j with no issues. The heuristic estimate of cost to reach the end year is given.

$$h(x_i) = (\overline{c}_{REM_i} + \overline{m}_i) + \sum_{k=i+1}^{n} (\overline{c}_k + \overline{o}_k + \overline{m}_k) \tag{3.9}$$

Equation 3 requires knowing average CAPEX, OPEX and metrics costs of descendant network states, which might not be known in advance. This section details how the SIM estimates these costs.

3.4.3 CAPEX estimation

The SIM ranks all network states according to the number of failing asset groups. Thus, a fully compliant network state has a rank 0 and a network state with 5 failing assets has a rank 5. For each year of the experiment, the SIM has a vector c_{AVG} of historical average CAPEX to increase a rank of a network state by 1. For a year that has no network states in the database, the vector has a single constant value of $DEFAULT\_YEARLY\_CAPEX = 2000.0$, but any suitably low value would work. In reality, fixing a noncompliant network state in most cases costs well over $DEFAULT\_YEARLY\_CAPEX$, making the SIM to use a learning process to adjust the average estimated CAPEX for years that have expanded network states in the database. For each year with at least a single network state in the database, the SIM computes two vectors c_{AVG} and p. Vector c_{AVG} is predicted average CAPEX to increase a rank of a network state. Vector p is learning pressure, which increases with the number of network states of each rank in the database. The learning pressure exponentially increases with the number of network states of a given rank, reaching its maximum after 7 network states are expanded. Referring to Equation 4,

$$p_i = min(0.8, 0.05 \cdot l_{i,k}^{1.5}) \tag{3.10}$$

where $l_{i,k}$ is the number of network states of rank i in year k. At the end of each iteration, an updated historical average CAPEX vector is computed according to Equation 5

$$c_{AVG} = c_{AVG} + (c'_{AVG} - c_{AVG}) \circ p \tag{3.11}$$

In turn, the average CAPEX cost for entire year is obtained using Equation6

$$\overline{c} = c_{AVG}^T j \tag{3.12}$$

where j is a column vector of ones.

At the end of each iteration, an updated historical average CAPEX vector is computed.

3.4.4 OPEX estimation

Initially the SIM assumes no OPEX costs are incurred. As the expansion progresses, some patches start to incur OPEX costs. Unlike CAPEX, OPEX continues to be incurred in the following years after the patch has been applied. An average OPEX value for a year can be obtained using Equation 7

$$\overline{o} = j^T o_c (j^T j)^{-1} \tag{3.13}$$

where j is a column vector of ones, and o_c is an OPEX vector of compliant network states in that year.

3.4.5 Metrics cost estimation

Metric cost is estimated like the OPEX. Initially the SIM assumes no metric costs in a year. Once compliant networks states appear in a year, the metric cost for that year is updated according to Equation8

$$\overline{m} = j^T m_c (j^T j)^{-1} \tag{3.14}$$

where j is a column vector of ones, and m_c is a vector of metric costs of compliant network states in that year.

The average remaining CAPEX in the year a network state is in is calculated using the vector of historical average CAPEX c_{AVG} and the network state's rank according to Equation 9

$$\overline{c}_{REM} = \sum_{i=0}^{r-1} c_{AVG_i} \tag{3.15}$$

wherer is the rank of the network state.

3.4.6 Ranking of network states

Initially the SIM was using a single average CAPEX value for each year to predict future expansion costs. During verification runs it was observed that the costs to fix an asset group could change by a factor of 1000 depending on the asset group type, which would make the estimation of remaining expenditure in a year very coarse and, consequently, result in a slow expansion. To address this issue it was decided to rank network states according to the number of asset groups with failures remaining and maintain a set of averages for each year and for each rank.

The SIM calculates metrics costs from metrics data obtained as a result of $analyseIntactNetwork$ function call. Consequently this cost can be directly calculated only for network states with no constraint violations. This presents a problem as the fixed network states and their descendants in following years are becoming more expensive because of metrics costs suddenly being added to them once the network states are fixed. This prevents the A* search from expanding descendants of fixed network states. The issue can be solved in two ways, namely, by not including metrics costs in A* cost function or by making sure the metrics costs are correctly propagated to the ancestor network states once a fixed network state is found. The SIM adopted the latter approach by initially assuming the metrics costs for all years to be 0 and updating them with an actual average value once fixed network states appear in a year.

In the early versions A* was using the number of failures as an indicator of progress within a year. Statistical analysis of SIM expansion trees has revealed that the costs to fix a network state with constraints are not correlated with the number of issues. Instead, the costs and number of applied patches were strongly correlated with the number of asset groups with constraints. Latest A* search versions use the number of asset groups with failures as an intra-year progress indicator.

Solving the network optimisation problem represented as a tree with graph search algorithms such the one above detailed A*, has its downsides, however. The main problem stems from the fact that least cost path algorithms produce a single solution at a time, and obtaining alternative solutions is generally difficult. In contrast, planners are interested in exploring trade-off between alternative network development scenarios, e.g., balancing initial investment vs. ongoing maintenance and operating costs. The remainder of the issues relate to the reactive nature of intervention planning, which leads to horizoning and locally optimal solutions. As interventions are triggered by network failures, what is considered a failure plays a defining role in the way a solution is developed. For example, tightening voltage constraints applicable to a contingency operation mode would likely to trigger different interventions earlier in the life-cycle. For that reason, this research considers the transition to Evolutionary Algorithms as a step-forward for future research (Jiang and Yang, 2016).

3.5 Multi-Objective Evolutionary Algorithms

Multi-Objective Evolutionary Algorithms (MOEAs) are a better approach for global optimisation, that is capable of developing multiple alternative solutions to a problem simultaneously. The network design optimisation can be presented either as a static problem with performance functions capturing whole-life performance and costs of the network or a dynamic receding horizon problem, suitable for optimisation with model predictive control multi-objective dynamic approaches. A caveat of the suggested approach is discrete search space of network interventions, e.g., transformers and batteries come only in certain sizes and can only be installed at substations, meshing and automatic load transfer can occur only at normally open points, etc. This may require a hybrid approach between MOEAs and graph search combined with Pareto ranking of leaf nodes instead of an A* priority queue.

3.5.1 Introduction

Within the work of this thesis, in Chapter 4, a meta-heuristic optimisation framework and multi-objective evolutionary algorithm was implemented and bespoke plug-ins were designed for Ganesh optimiser [1]. The optimiser is a novel approach for MDE that incorporates real-world size problems with algorithms that capture external mechanisms that will inform the optimisation formulation.

[1]The name Ganesh comes from borrowing some letters from 'GA with non-domination ranking and elitism' (Oliver et al., 2015)

The MOEA part of Ganesh is a genetic algorithm (GA), a non-sorted genetic algorithm second generation (NSGA-II) employing elitism and Pareto non-dominance. This approach was originally suggested by (Holland, 1975) and Goldberg (1989), first implemented by (Fonseca and Fleming, 1993), and are active research lines for Coello (1994, p.331) and Deb (1989, p. 42)(Coello, 1994) (Deb and Goldberg, 1989). As an example, during the life of this thesis, Professor Deb and Haitham Seada unified and developed a NSGA-III for single, multiple and many objectives (Seada and Deb, 2015) for aiding the convergence of Pareto-dominance in optimisation problems of four or more objectives (Mkaouer et al., 2014) (Mkaouer et al., 2015).

The GA with Ganesh uses a novel crossover mechanism in order to recombine the mutation and crossover rates, as well as each of their perturbation control parameters, and unlike other GAs, provides a novel tunable control for the number of duplicate chromosomes in each generation (Oliver et al., 2013). It also provides the choice of using not just 1 or 0 as values of the genes, but up to 64-bit integers. That will be extremely valuable when feeding into the optimiser values of real-world engineering problems like the case in chapter 4 of this thesis.

Because MOEAs contain a population of solutions, rather than just one, they are inherently more suitable for optimising MDE providing multiple solutions per run. In theory, according to Coello (2006, p.28), a single EA run could find all of the feasible Pareto optimum solution, whereas non EA approaches would be able to find one only per run and have to be run n times to find n further optimum (Coello, 2006).

MOEAs are able to manage discontinuousness, non-differentiated, noisiness in optimisation problems, which make them able to be applied in a broad field of real-world applications. Fonseca and Fleming (1995, p.1) highlighted that

EAs are by their nature high likely to be parallelised due to being population-based, that will be extremely important for the future scalability of case studies presented in chapter 4(Fonseca and Fleming, 1995). MOEAs according to Back (1997, p. 3) are "especially well suited for solving difficult optimization problems", and all these attributes of MOEAs provide a solid foundation for using them to tackle real world-engineering problems (Back et al., 1997).

3.5.2 Ganesh: Algorithm and Implementation

3.5.2.1 The GA Algorithm

The GA implemented in this research was designed by Oliver (2013, p.261) and inspired by the NSGA-II algorithm (Deb et al., 2000) and its predecessors including Fonseca and Fleming's (1993) MOGA and that of Goldberg (1989), with some modifications, to: initialisation of population and solution, the non-domination sorting method, the construction of the new generation, the addition of repairable Hard Constraints, the adoption of a plugin architecture, and of course the self-adaptive aspect, as well as some practical considerations given below.

An initial population of random solutions is created and through the evaluation of their fitnesses for selection for reproduction, and by the introduction of variation through mutation and recombination (crossover), the solutions are able to evolve towards the optima populating a Pareto front.

Usually, while discussing a GA mechanisms and structures the biological terminology is brought in. The decision vector of the solution is termed the chromosome which is composed of a set of genes, each of which is a variable of the appropriate data type which may be primitive or a class and whose value is an allele. The result of the evaluation of the OFs, which depends on the chromosome, is then the fitness. The chromosomes may then be subject to manipulation by certain functions, termed operators, the most common of which are crossover and mutation. Crossover, also known as recombination in the biological domain, occurs during the creation of new solutions, in which two existing solutions (parents) are combined to create one or more new ones (children) by mixing the chromosomes in certain defined but stochastic ways. This is metaphorical sexual reproduction. Mutation is the process of altering one or more genes in one solution's chromosome. A variety of other similar operators exist which in some specific way also alter the chromosome(s) or gene(s) in order to explore the search space, and whose quality depends upon the specific details of the problem concerned.

The non-domination sorting is amended from NSGA-II to ensure that each solution is compared with every other one once in a simple and efficient manner which is entirely for-loop based, with the number of comparisons being of the same order as that of the continuously updated method (Deb, 2001), and the method of updating dominated-by count and dominated-solutions lists are modified accordingly. Figure X shows a high level view of the algorithm as a flow-chart.

Following characterisation highlights Ganesh uniqueness and novelty (Oliver et al., 2015):

- **Self-adaptation** Ganesh allows mutation and crossover rates to be specified for the initial population, or to be set to random values in a uniform distribution, or to default to certain values. The default mutation rate of each solution would be set to 1/n where n is the number of variables of the objective functions (OFs).

- **Constraints** Constraints, either soft or hard can be added to the problem by creating sub-classes of the appropriate type, such as Hard Constraint. A soft constraint is one that can be relaxed, by allowing it to be exceeded but acquiring a penalty associated with it proportional to the excess, which is reflected in the fitness of the solution when solutions are ranked. A hard constraint is one which must be adhered to, so solutions which break it must either be repaired or removed from the population.

- **Chromosome and Population Initialisers** Each chromosome type has its own default initialiser, that defines how its genes are assigned appropriate values when a solution is created, and the default is that each gene is randomly given a value within its permitted range, assuming a uniform distribution.

- **Resume from previous run** Real-world optimisation problems such as those presented in chapters 4, 5 & 6, tend to have objective functions that are computationally expensive to evaluate and which are therefore time-consuming. In these cases, an optimisation problem can take days, weeks or even months to run, which increases the chance that they may be interrupted by some unexpected external event, risking the loss of data, progress made and much time.

  Ganesh obviates these problems by providing the ability to resume from a previous run, in two ways, that differ by whether the default text log or optional binary log is used. The text log by default contains, in text form, the decision vector, objective function values and where applicable, the self-adaptive control parameters, for each solution in the population, for each entire generation produced and evaluated (with respect to the objective function values and non-dominated sorting).

Ganesh enables either the text log or the binary log or both to be used, moreover it enables Ganesh to retain the last generation only, as a binary log. The latter option enables Ganesh to execute optimisation problems which have objective functions that are quick to evaluate but require vary large numbers of generations to be run, which may otherwise create undesirably large text log files.

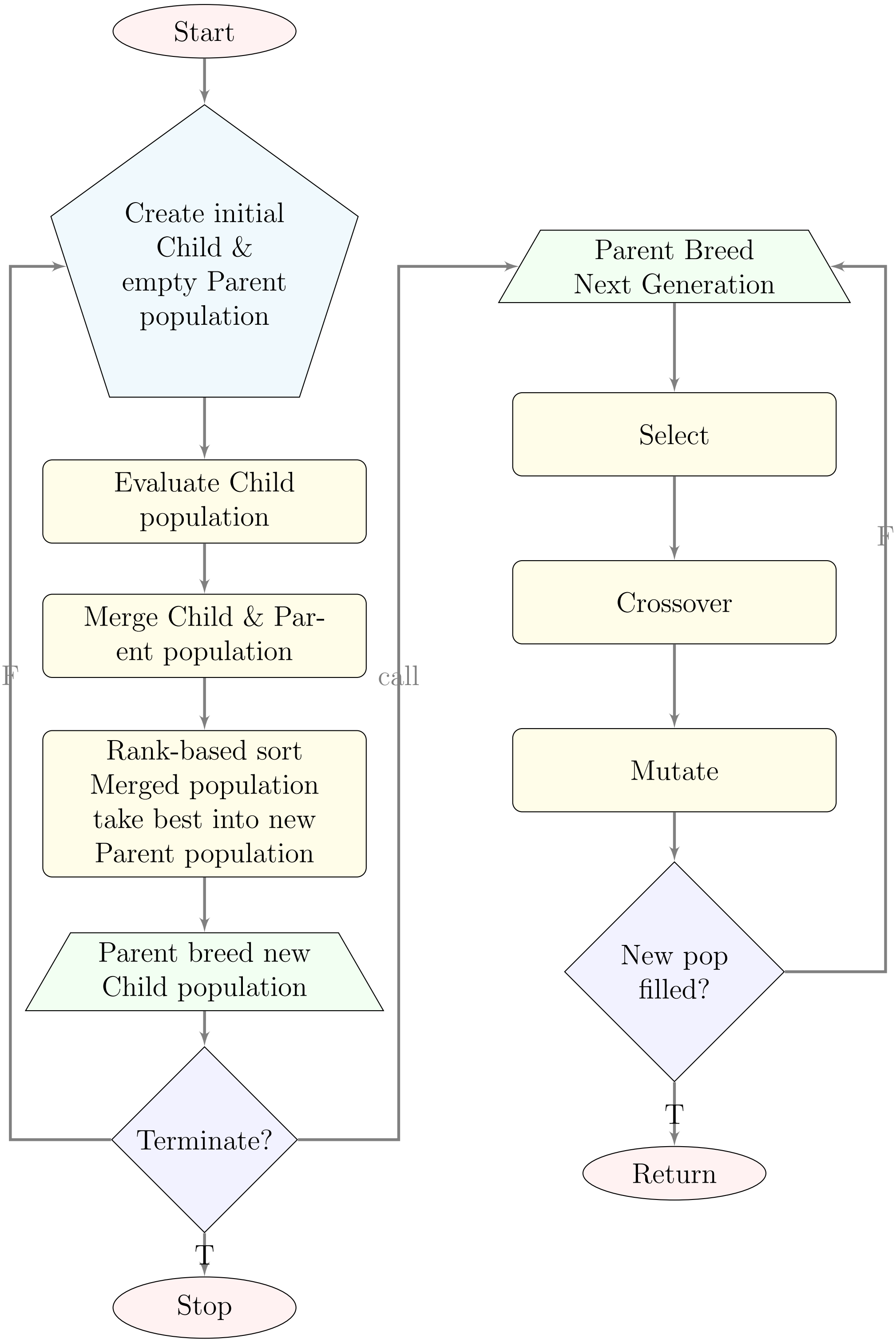


Figure 3.10: High level representation of the GA Ganesh algorithm (Oliver, 2015) expressed as a flow-chart, in which the production of the next generation population is shown as a sub-process for clarification

3.5.2.2 Multi-Objective Evolutionary Power Networks

In brief, the GA within Ganesh creates a random population of solutions at the start, which is to say, each solution has by default a set of pseudo-randomly chosen values for its decision vector. The resulting population is evaluated and the solutions ranked by comparing the values obtained for their objective functions, and the "best" ones are selected for breeding to create the new generation. The off-spring generation is then evaluated, and so on. This is repeated until the termination criteria are satisfied (Oliver, 2015).

For defining the optimisation problem using Ganesh MOEA a Java plug-in must be defined with its decision vector by choosing a Chromosome of the desired type and a list of the desired number of Variables, and also defining the OFs. Ganesh provides a default initialiser for the population and a default initialiser for each Chromosome type, thus the problem is fully defined. The problem class may then be compiled into an independent library named GA-Plugins.jar, which may contain as many different optimisation problems as desired.

In this way, the optimisation problem is created completely separately and without needing to change any of the source code of Ganesh. In order to execute a particular optimisation problem, Ganesh is simply called from the command line with the name of the problem class as a parameter. The independent file containing the plug-in may contain as many different optimisation problems as is desired, enabling easy testing or switching between problems.

Ganesh takes a number of parameters at run-time to control its behaviour, but these are all concerned with the general operation of the algorithm and apply to any problem that Ganesh might run. Some optimisation problems will have behaviours that the user might wish to parameterise, rather than hard-

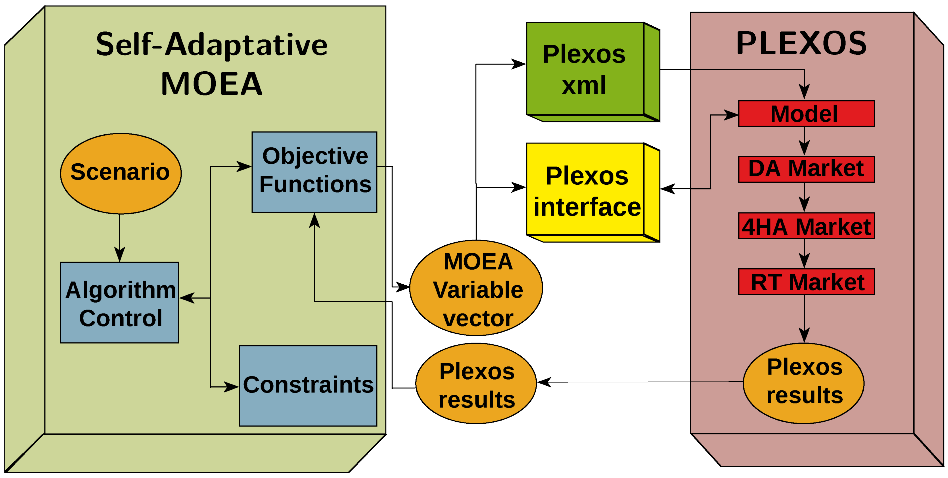


Figure 3.11: Domain characterisation of optimisation flow using Ganesh as MOEA and PLEXOS as market-operations solver

coding them as part of the problem class, so the Experiment class provides a default empty initialise method, supplying a parameter file when given, which plug-ins may override, to read and initialise themselves with values from that le. This is used, for example, to run the generations of PLEXOS scenarios optimisation concurrently, to gather the results of the OFs for the analysis of its performance, as detailed in Chapter 4.

3.6 Methods and materials

As described in the thesis introduction, having performed a literature review and described the meta-heuristic frameworks, test cases of real-world problems are due to implement aforementioned methodologies. In Chapter 4, Ganesh is to be applied for integrating storage in a certain area of the US. SIM A* search algorithm will be used in Chapter 5 for evaluating a 11 kV distribution network, where in combination with Real Options Valuation, in Chapter 6 will unlock flexibility services for distribution networks.

Ganesh framework, algorithm, and the plugins encoding the optimisation problems were developed in Java (Oracle, 2014). The software from which Ganesh is built is dependent upon features which were new to an older version, Java 2 Platform, Standard Edition 5.0 (J2SE 5.0), in particular Enumerations and Generics, therefore Ganesh will not run on versions of Java older than that (Oliver et al., 2015).

SIM A* search algorithm and the interface with Ipsa 2 software are managed using Python 2.7. For debugging and clustering some results can be directly queried by SQL. Python scripts were created to produce Excel, Word and JSON result datasets. Real Option Valuation algorithm was coded in Python for a future integration within SIM A* search algorithm.

All across the thesis, as a multi-dimensional visualisation technique, ParallAX (2009) and PACO Heinrich (2015) are implemented for the case studies contained in chapters 4, 5 & 6.

The source of the thesis was created using LaTeX with TeXstudio as editor.

Matlab language (MathWorks, 2015) was used to post-process some result data and to produce graph plots.

The use of PLEXOS as techno-economical solver made this work needed to be carried out on a Windows machine. Most of the runs were produced on an Intel Core i7 @2.20GHz 32GB machine, where validation runs were conducted using an Intel Xeon 3.30GHz 255.93GB machine.

Chapter 4

Addressing Massachusetts' Storage Target under High Wind Penetration in the ISO-New England using Multi-Objective Evolutionary Optimisation

4.1 Introduction

The case study presented in this chapter explores in two phases system configuration and evolutionary planning at transmission level and it is motivated by the volatility and recent uncertainty of large deployments of renewables and their impact on operations and prices. During the first phase, several high penetration of wind topologies are explored. Total generation costs, as well as, impacts on nodal electricity prices are explored. For the second phase, a solution from section 1 is explored further to include Massachusetts' Storage Mandate. Using PLEXOS (PLEXOS, 2016) production cost tool for modelling the power system operated by the Independent System Operator New England (ISO-NE, 2013), a multi-objective optimisation is conducted for evaluating the impact of that mandate on electricity volatility, total generation cost (TGC) and Dump/Unserved Energy. Production cost models are used extensively in the electric power industry to simulate bulk power system operations, generations costs, and prices.

One of the challenges of integrating wind power generation into the power sector is geographical and network locations. The best wind resources are generally located far from the load centre (Nieto-Martin et al., 2016) (Morales et al., 2011). Suitable locations for distributed wind power turbines depend both on topological and network conditions. In many cases, that provides an uncertainty degree for transmission asset investments (Conejo et al., 2016) (Gautam and Mithulananthan , 2007). In addition, the impact of wind power on bulk power system operations, generation costs, and electricity prices (main focus of this chapter) may vary significantly depending on its topological distribution (Papaefthymiou and Dragoon, 2016).

PLEXOS, a commercial software, is used to represent the production cost model of the ISO-NE power system by simulating the day-ahead (DA), four hour-ahead (4HA) and real-time (RT) markets Figure 3.11. Yearly simulations are run for six different wind power topologies. In order to populate a Pareto front that co-optimise price variability, productions costs and system performance, this chapter assess Massachusetts' Storage Mandate to study the impact of high penetration distributed wind power topologies on aforementioned objectives.

4.2 ISO-NE PLEXOS model

This chapter presents a renewable integration study that aims to assess the impact of wind on a real-world size power system with minimal or no upgrades to the distribution or transmission electricity systems. Firstly, it is investigated the impacts of integrating large amounts of utility-scale distributed wind power on bulk system operations by performing a case study on the power system of the ISO-NE (Brancucci et al., 2014). On a second stage, a multi-objective optimisation is performed for locating most suitable location for accomplishing the Massachusetts Storage Mandate.

The analysis is performed by modelling the ISO-NE power system for the year 2010 using PLEXOS with an academic license. For the first part, the model is run for six different deterministic scenarios with 10GW of wind power penetrations, being that up to 33% of the generation mix. The six scenarios represent different wind topologies using curtailment, DA, and 4HA forecasts. In one approach, wind power generation is modelled allowing wind power curtailment, and it includes simulated DA and 4HA operational wind power forecasts (Martínez-Anido et al., 2016).

The modelling approaches are analysed and compared to each other to simulate a more realistic case in which a system operator has neither visibility nor control over the turbines because of their distributed nature, and to simulate a case in which a system operator could curtail power generation and use wind power forecasts during the commitment of conventional power plants.

4.2.1 Transmission Network

The ISO-NE model includes a wide representation of the ISO-NE transmission network: 3,314 nodes (or substations); 2,485 transmission lines; and 1,830 transformers. Table 4.1 shows the number of nodes and lines for the different voltage levels represented within this model. All the wind power due to the large size of the wind farms (and computation convergence time efficiency) will be connected at high voltage levels, 345kV and 230kV. The transmission data set was slightly modified by eliminating 9 nodes and 7 transmission lines in northern Maine that are connected to Canada and separated from the rest of the transmission network, being 99.6% the similarity with the real ISO-NE network (ISO-NE, 2013).

Table 4.1: Nodel and Lines of the ISO-NE Model

(Brancucci et al., 2014)

Voltage Level (kV)	Number of Nodes	Number of Lines
345	157	186
230	32	30
120-191.5	10	6
115	1412	1677
99	80	0
69	171	186
44-48	97	90
34.5	200	125
24-33	44	18
23	187	75
14-22.8	97	1
13.8	505	66
<13.8	322	25

4.2.2 Generation

The ISO-NE model includes 468 electricity generators with a total installed capacity of 35,967 MW, excluding wind and solar generators. Wind farms for this study are distributed all along the ISO-NE territory simulating different topologies. Details about wind farms locations for each scenario are displayed in the results section. Table 4.2 shows the number of generators and installed capacity for each electricity generation source.

Maintenance is only considered for nuclear generators by scheduling it during the time periods with the lowest load. The maintenance schedule is planned such that it is never conducted on two nuclear generators at the same time. The maintenance schedule of the other generators is not considered, because it has only a very small impact on the generators' capacity factor. In addition, maintenance does not impact the analysis of the results, and it is outside the scope of this study. For the same reason, unplanned outages of generators and transmission lines are not considered in the model.

In the DA and 4HA market runs, DA and 4HA load and wind forecasts are considered. Nuclear, biomass and coal power plants are committed in the DA run; CC and steam turbines (STs) are committed in the 4HA run. All of these units may be redispatched within generator operating limits in the RT run. Hydropower plants are committed and dispatched in the DA run. All other power plants are committed and dispatched in the RT run.

Table 4.2: Generators and Installed Capacity in ISO-NE Model (Brancucci et al., 2014)

Generator Type	Number of Generators	Installed Capacity (MW)
Nuclear	5	4,878
Coal	19	3,740
Gas	159	17,101
Oil	131	5,691
Hydro	111	1,675
Biomass	36	844

4.2.3 Load

Hourly DA forecast and actual load time series used in the ISO-NE model were provided by ISO-NE (ISO-NE, 2013). For 4HA load forecasts have been based on (Brancucci et al., 2014).

For the analysis of different scenarios with high wind penetration levels, 1-hour DA, 1-hour 4HA, and 1-hour RT electricity demand time series are used, RT can be as precise as 5-minutes resolution, but its computational requirements was not worthy for this study. The total electricity system load in New England in 2010 was 130,773 TWh, with a peak system load of 27,102 MW.

4.2.4 Wind Topologies Scenarios

This subchapter describes the windfarm sites used to design different distributed wind scenarios with a wind power penetration from 30% to 33% of de scenario generation mix, see Table4.3. The six scenarios main difference is the location of each windfarms and therefore the transmission node that are connected to.

Suitable locations for distributed wind power turbines depend both on geographical and network constraints. For example, wind turbines are more likely to be connected to the distribution network in rural areas because of the difficult permitting issues in urban areas. Moreover, wind resource and some terrain features are important considerations when choosing a suitable site for a utility-scale wind turbine. With regard to network conditions, the voltage level and other feeder characteristics, such as rating and length, are important considerations when selecting suitable sites for distributed wind turbines.

The recent Wind Integration National Data Set (WIND) Toolkit (King et al., 2014), (Draxl et al., 2015) funded by the U.S. Department of Energy Wind Program, is the source of wind data for the distributed wind site selection exercise as well as for the production-cost modelling. The WIND Toolkit was created by 3TIER using a mesoscale numerical weather prediction model run on a 2-km by 2-km grid with 5-minute resolution from 2007 to 2013. The WIND toolkit provides data for more than 120,000 onshore and offshore wind power production sites in the United States. For each suitable wind site, the available data includes a 5-minute wind power production time series and simulated operational forecasts for 1-hour-, 4-hour-, 6-hour-, and DA forecast horizons for the entire 7-year period.

Table 4.3: Wind Topologies characterisation for ISO-NE PLEXOS Model

Scenario	Lat-Long dispersion	Wind penetration (%)	Number of wind sites	Installed wind capacity (MW)
1	2.008 (approx. 2.8km)	32.96	341	10,000
2	1.912 (approx. 5.6km)	33.68	89	10,000
3	1.947 (approx. 8.3km)	32.99	188	10,000
4	0.825 (approx. 2.8km)	33.55	228	10,000
5	3.076 (approx. 5.6km)	30.43	212	10,000
6	2.057 (approx. 13.9km)	32.55	92	10,000

Table4.3 provides a summary of the onshore wind site locations present in the WIND Toolkit database that are located in New England and from which a smaller number of wind sites are selected for each of the scenarios based on network constraints. Table 4.4 provides the number of sites and the total wind power capacity (from 2007 to 2012) for New England as well as for each of the six states that comprises it. In order to simplify the model and foreseen a prospective optimisation, 2,738 wind sites seemed to be an enormous number

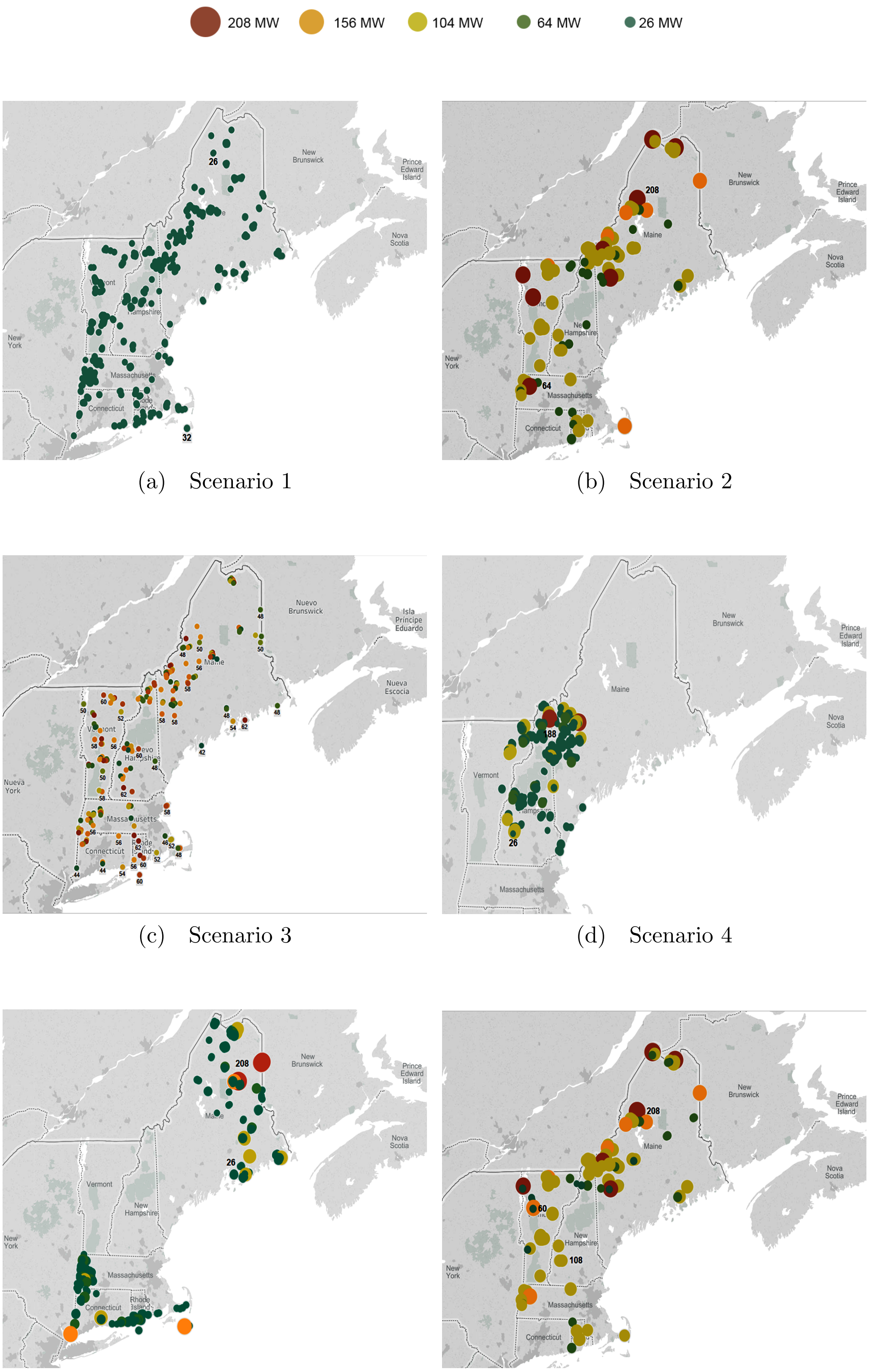
for having that many decision variables some of them as small as 2MW. Due to that, maintaining the Total Wind Capacity within the ISO of New-England (35,770 MW of wind resource), an aggregation of the wind sites has been proposed for simplification purposes.

New windfarm sizes (ISO-NE Model) are on a range from 26 to 208 MW, instead of the 2 to 16 MW of the ISO-NE Model proposed by (Brancucci and Hodge, 2014). The aggregation has been performed using the coordinates (latitude and longitude) of each 2,738 Wind Toolkit Data, evaluating the node and adjacent lines for avoiding creating any constrain to the network, the new 770 wind sites are calculated. Once the 770 new wind farms have been defined and located, as the installed capacity is 35,77GW, for our study purposes, six scenarios will be evaluated. Selecting wind sites among those 770, the maximum capacity to be installed was designed to be 10GW, which seems reasonable for the wind resource of New England and their 2030 renewable's commitment.

Table 4.4: WIND Toolkit Data Set for New England

State	Number of Sites	Total Wind Capacity (MW)
Connecticut	110	1,258
Maine	1,142	15,558
Massachusetts	512	5,810
New Hampshire	404	5,452
Rhode Island	126	1,492
Vermont	444	6,200
ISO-NE Data	2,738	35,770
ISO-NE Model	770	35,770

The mean distance value and number of sites for each scenario to the centre of New England is presented in Table 4.3. Scenario 1 represents the aggregation of smallest capacity installed on the sites, therefore 345 wind sites are needed to accomplish the 10GW wind commitment. Scenario 2, on the contrary, comprises the largest wind sites by capacity installed (89 wind sites), while Scenario 3 is a trade-off between scenarios one and two, seeking for the average sizes of the 770 windfarms, minimising the distances to the centre of NE. In terms of distances, two scenarios have been created, scenarios 4 and 5, represent the less and the most dispersion possible among those 770 windfarms. Scenario 6 is the one that accomplish the 10GW threshold with the wind-sites with largest capacity factors. Scenario 7 presents a visualisation of the six scenarios.



(a) Scenario 1

(b) Scenario 2

(c) Scenario 3

(d) Scenario 4

(e) Scenario 5

(f) Scenario 6

Figure 4.1: ISO-NE wind scenarios with high penetration of wind

4.3 Results ISO-NE High Wind penetration model

The integration of distributed wind in ISO-NE impacts the electricity generation mix in several ways. In absolute terms, the two largest changes are observed for gas- and coal-fired generation. Both sources decrease their electricity output with large amounts of wind power compare to actual real data available from the ISO-NE. Wind power forecasts reduce gas-fired electricity generation to a larger extent. If wind power forecasts are not considered, the over-commitment of gas power plants results in higher gas supply. In relative terms, noticeable changes in the generation mix caused by high wind penetration correspond to a very large increase in the electricity output of oil-fired, gas turbine, and gas internal combustion generators when simulated DA and 4HA operational wind forecasts are used. These power plants are used during few hours in the year and are characterized by their fast start-up and ramping capabilities. The uncertainty of wind increases their electricity output. The shares of nuclear and hydro in the electricity generation mix are not affected by wind power penetration.

They are both committed in the DA market; and in the case of hydro, the ISO-NE model does not allow redispatching in the 4HA and RT simulations. On the other hand, increasing wind power penetration might increase hydro pumping and decreases biomass electricity generation, however hydro pumping and imports and exports have not been model in this study for computational reasons.

Within this study, the ISO-NE PLEXOS model has been designed to simulate the DA, 4HA, and real-time (RT) markets, however, must be said that ISO-NE does not have a 4HA market in place (Woo et al., 2011). Due to early testing runs and high dispatch volatility, it has been useful introducing an intra-day market as the 4HA to commit gas combined-cycle (CC) power plants as well as gas and oil steam turbines, improving dramatically unserved energy events and volatility on prices(Borggrefe and Neuhoff, 2011). The DA and 4HA markets are modelled with 1-hour time steps; the RT market was modelled with 5 minutes resolution. This section is structured as follows. The next three subsections provide details about the different elements compounding the results section: prices, total generation cost and energy mix and finally, validation.

4.3.1 Electricity prices

Table 4.5 shows the pricing characterisation for ISO-NE in 2010, comparing the ISO-NE published data and the six scenarios evaluated.

Table 4.5: Electricity prices in the ISO-NE in 2010 vs PLEXOS Model

ISO-NE	Data	1	2	3	4	5	6
RT mean price ($/MWh)	49.56	51.99	51.67	54.37	47.06	47.94	50.97
Standard deviation RT price	24.78	36.82	36.30	38.95	32.32	28.16	34.97

As displayed on Table 4.5, ISO-NE 2010 mean RT price and the simulated by the ISO-NE PLEXOS scenarios are in the same range with a difference gap between 5% cheaper (Scenario 4) to 10% more expensive (Scenario 3) compared to the published data. In addition, we can say that simulated scenarios increases volatility of electricity prices between 13% (Scenario 5) and 57% (Scenario 3) Volatility is measured as the hour to hour changes in electricity prices. The increase on price volatility is due to the amount of wind in the system. Among the different scenarios the volatility is noticeable being the difference between Scenario 3 and Scenario 5 up to 28%.

Figures 4.2 to 4.7 present descriptive statistics of the six scenarios and will be the base to choose (along with Total Generation Costs in Figure 4.9) from which high wind penetration scenario start the optimisation in section 4.4.

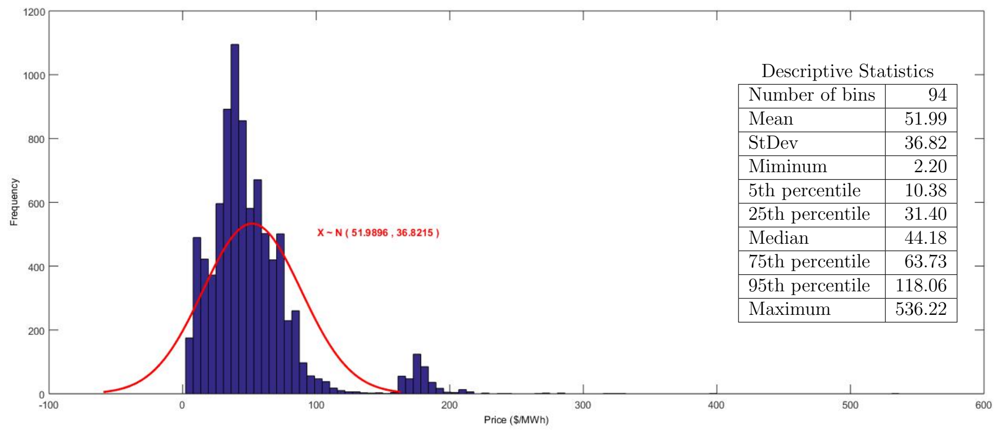


Figure 4.2: Histogram and statistics characterisation for Scenario 1

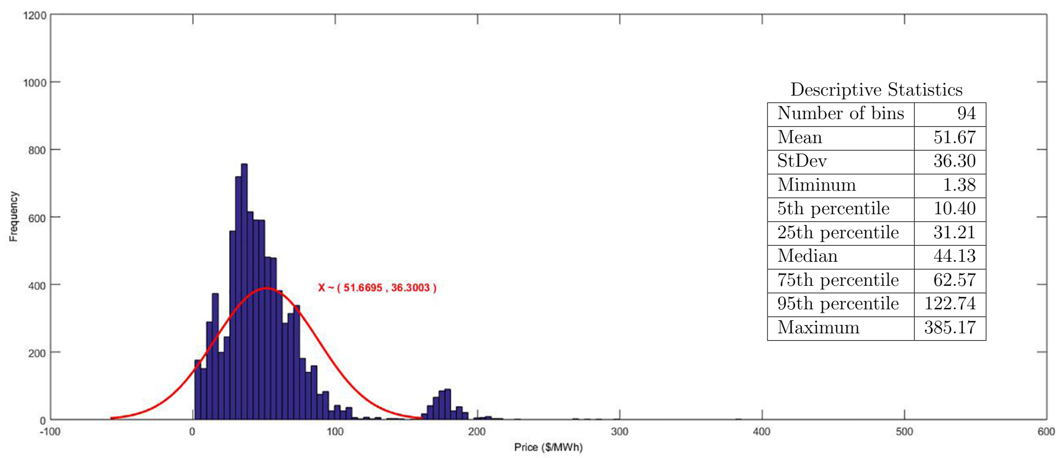
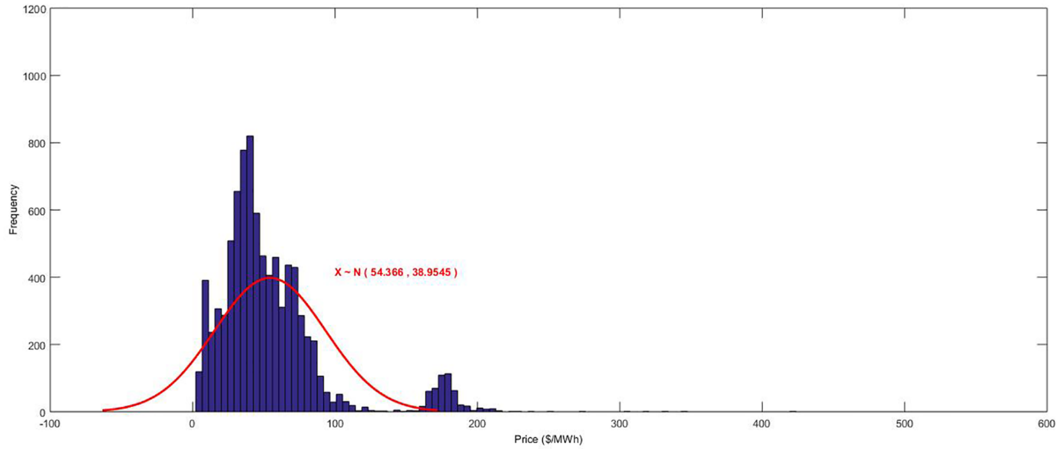
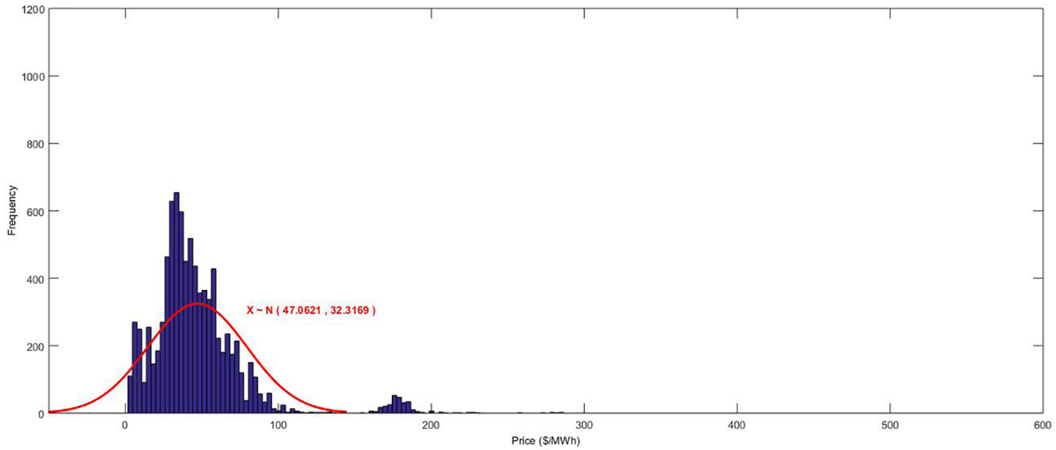


Figure 4.3: Histogram and statistics characterisation for Scenario 2



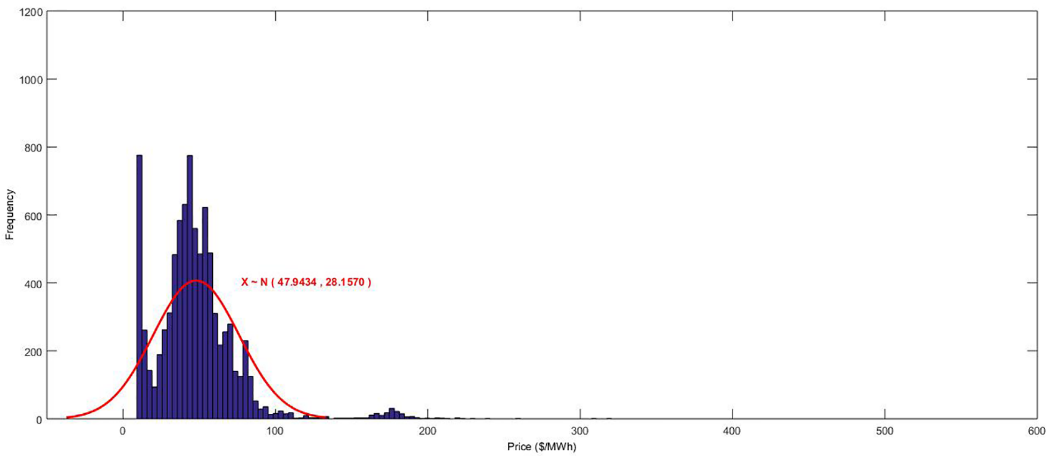
Descriptive Statistics	
Number of bins	94
Mean	54.37
StDev	38.95
Miminum	2.23
5th percentile	10.41
25th percentile	31.54
Median	44.71
75th percentile	67.25
95th percentile	166.43
Maximum	423.62

Figure 4.4: Histogram and statistics characterisation for Scenario 3



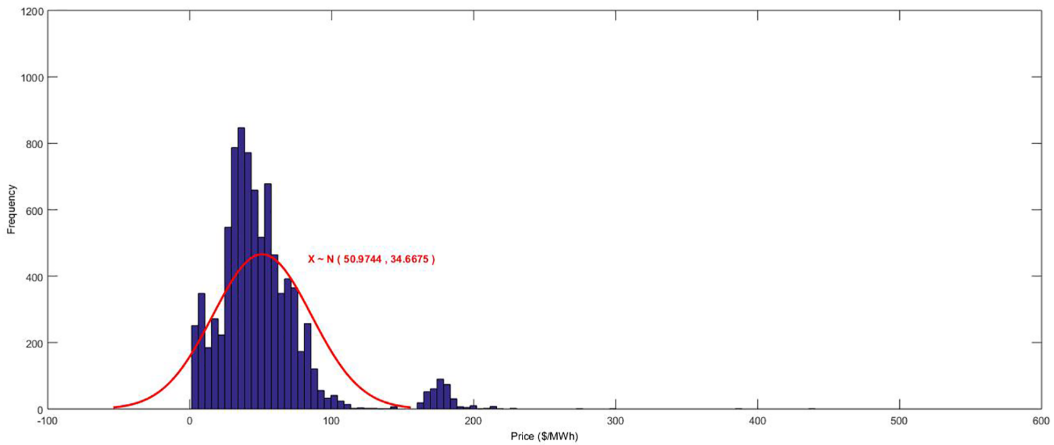
Descriptive Statistics	
Number of bins	94
Mean	47.06
StDev	32.32
Miminum	1.60
5th percentile	8.41
25th percentile	29.63
Median	41.13
75th percentile	57.41
95th percentile	91.41
Maximum	286.60

Figure 4.5: Histogram and statistics characterisation for Scenario 4



Descriptive Statistics	
Number of bins	94
Mean	47,94
StDev	28,16
Miminum	9,06
5th percentile	9,36
25th percentile	33,54
Median	45,18
75th percentile	57,86
95th percentile	84,15
Maximum	320,50

Figure 4.6: Histogram and statistics characterisation for Scenario 5



Descriptive Statistics	
Number of bins	94
Mean	50,97
StDev	34,67
Miminum	1,30
5th percentile	10,28
25th percentile	31,51
Median	44,38
75th percentile	62,20
95th percentile	103,24
Maximum	440,39

Figure 4.7: Histogram and statistics characterisation for Scenario 6

4.3.2 Total Generation Costs and Generation Mix

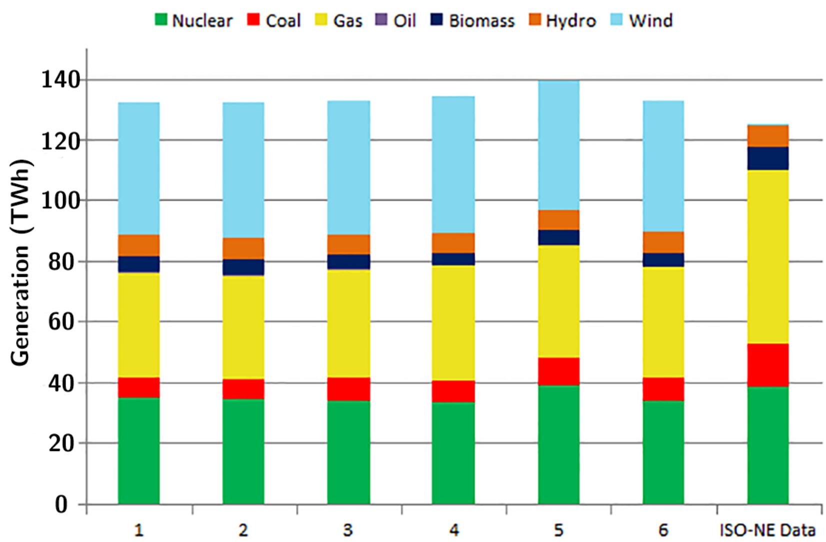


Figure 4.8: ISO-NE PLEXOS Model Scenarios Generation Mix

Figure 4.8 shows the energy mixes of the ISO-NE PLEXOS scenarios are very similar in relative terms to the one observed in ISO-NE in 2010. Beside wind, noticeable differences arose in oil, coal-powered and gas. Largest difference between scenario happens in Scenario 5.

Due to wind topology, and generation dispatch, that scenario presented the largest amount of generation required leading to be the most expensive option for the total generation cost (Figure 4.9).

Scenario 6 computed almost four more times more oil generation consumption compared with the ISO-NE 2010 (Table 4.6), while reducing up to 50% the generation coming coal power plants, and 40% from gas.

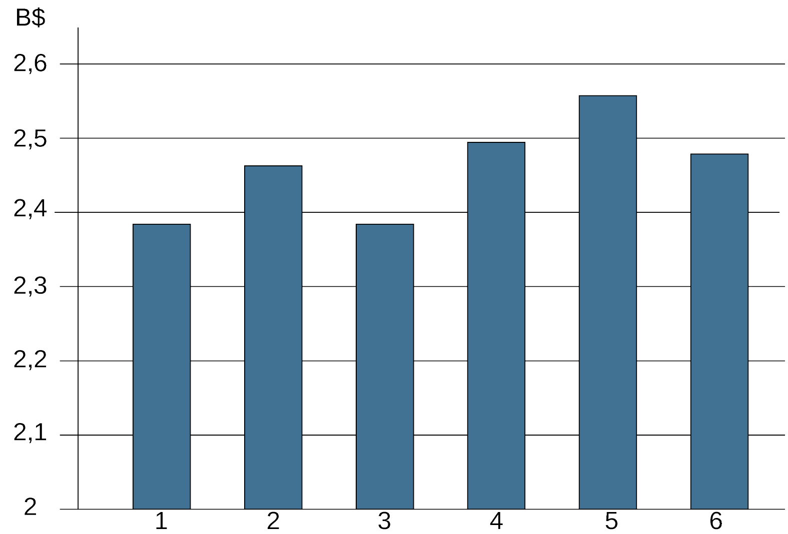


Figure 4.9: ISO-NE PLEXOS Model Scenarios Total Generation Costs

That increase of oil, occurs on the RT market where it is used to balance the wind, where the reduction of coal and gas consumption is it across all of the scenarios, being the generation sources being pushed out of the mix when 10GW of wind are forced into the system.

The ISO-NE model calculates the total generation cost as the sum of all the variable electricity generation costs of the electricity generators that are connected to the ISO-NE power system. These costs include fuel costs, variable operation and maintenance costs, and start-up and shut-down costs. Figure 4.9 shows the annual electricity generation cost for the six scenarios.

The ISO-NE model calculates the total generation cost as the sum of all the variable electricity generation costs of the electricity generators that are connected to the ISO-NE power system. These costs include fuel costs, variable

operation and maintenance costs, and start-up and shut-down costs. Figure 4.9 shows the annual electricity generation cost for the six scenarios.

Having into consideration the different wind topologies presented in Figure 4.1, there are significant differences in the total generation costs depending on locations described in Table 4.3. It has to be noticeable that this differences in prices and total generations can be even greater because within these scenarios study it has been consider that we have perfect wind power forecasts. However, these potential differences will be reduced if exchanges with neighbouring regions of the ISO-NE are allowed. Therefore, the results of electricity generation cost shown in Figure 4.9 should be considered to certify that even installing the same amount of wind power (10GW), depending on how the topology of wind is installed, it can have a difference up to 7%, 171 million dollars between the cheapest and most expensive wind topology configuration, Scenario 3 and Scenario 5 respectively.

The impact of high penetration of distributed wind on the annual electricity generation mix in ISO-NE using a modelling approach that included simulated DA and 4HA operational wind power forecasts allowing wind curtailment will lead to being able to evaluate the amount of energy that is yearly curtailed in each scenario. Table 4.6 displays how "unrealistic" wind topology configurations, such as scenarios 4 and 5, led to noticeable amount of wind curtailment in the system. Curtailment events, while allowed for all of the generators, are penalised in the scenarios with -30$/MWh, being wind curtailment of the causes that made scenarios 4 and 5 the most expensive ones.

Table 4.6: Dump Energy by ISO-NE PLEXOS scenarios

ISO-NE Scenarios	1	2	3	4	5	6
Dump Energy (GWh)	1,146.13	1,708.03	1,202.52	3,241.36	8,461.13	1,966.42

4.3.3 Model Validation and Summary

The high increase of wind power in the ISO-NE will lead to a decrease of the conventional sources share as it is displayed in Figure 4.8. The two largest changes are observed for gas- and coal-fired electricity generation; gas is the energy source displaced the most. Differences among scenario's results and ISO-NE published data reflect how the impact wind high penetration on transmission-level system operations affects the generation mix of the system. The goal for developing the ISO-NE model is not to recreate a perfect representation of the ISO-NE power system in 2010, but to have a model that realistically represents the operational characteristics of the ISO-NE power system. The six RT scenarios of the ISO-NE model have very similar outcomes, demonstrating that the model is robust and will present valuable insights for the study and further optimisation.

The ISO-NE PLEXOS Scenarios were validated against the 2010 data published by ISO-NE (ISO-NE, 2014). The ISO-NE model is run as described in the previous sections for the DA, 4HA, and RT markets with 1-hour time steps. The difference by generation source, table 4.7, is notorious on the wind generation, due to the relatively small installed wind capacity present in the ISO-NE power system in 2010.

Table 4.7: ISO-NE Model vs ISO-NE, Energy Mix in 2010

		ISO-NE Data	1	2	3	4	5	6
Generation	Nuclear	38.364	38.820	33.818	34.829	33.804	33.147	34.432
	Coal	14.131	9.262	7.653	6.706	7.536	7.408	6.593
	Gas	57.584	36.735	36.548	34.576	35.775	37.733	34.137
	Oil	0.57	0.54	1.71	1.818	1.94	1.66	2.32
	Biomass	7.194	5.255	4.497	5.067	4.561	3.986	4.936
	Hydro	7.227	6.738	6.841	7.083	6.899	6.601	7.188
	Wind	0.491	42.367	43.206	43.473	43.706	44.963	44.453
Demand	Load	130.773	130.772	130.772	130.772	130.772	130.772	130.772

Some of the limitations and reason for having slightly higher RT prices and noticeable Standard deviation of RT prices may come from discrepancies such as scenarios assumptions, the absence of bilateral contracts, fuel prices, power plant maintenance schedules, transmission interconnection capacities (Imports and Exports), and hourly electricity prices in the neighbouring regions. The displacement of coal and gas power plants from the generation mix due to the integration of the 10GW of wind, led to an increase of oil commitments in the RT market to cover wind intermittency motivates the next section: What about placing storage for co-optimising variability in prices, total generation costs and Unserved/Dump energy?

4.4 Multi-Objective Optimisation for addressing Massachusetts Storage Mandate

High penetration of distribution generation, integration of low carbon technologies, and ageing non-flexible power networks designed to operate coal and gas plants, are starting to experience congestion and peaking prices. Transmission and distribution networks investment uncertainty is a complex problem, where traditional deterministic models are in need to be revised to overcome present and future decision-making challenges. Proliferation of large amount of distributed renewable generation are creating new challenges for Transmission and Distribution Network Operators, increasing alternatives to conventional reinforcement in order to reduce network operation costs, increase security of supply and allows a more reliable renewable generation to be connected to the grid. Selecting the most optimal combination of generation mix portfolios in regards to long-term cost and performance of the system in a fast evolving environment do require innovative modelling and decision-making approaches.

In 2013, CAISO published the "duck chart", which shows a significant drop in mid-day net load on a spring day as solar photovoltaic are added to the system. The chart raises concerns that the conventional power system will be unable to accommodate the ramp rate and range needed to fully utilise solar energy, particularly on days characterized by the duck shape (Figure 4.10). This could result in "overgeneration" and curtailed renewable energy, increasing its costs and reducing its environmental benefits (Denholm et al., 2015). However, by allowing distributed resource, in our current case, wind and storage to provide grid services, system flexibility could be greatly enhanced (WECC, 2015) (Malekpour et al., 2013). In CAISO has been proven that storage plus renewable (solar in their case) could significantly reduce curtailment and allow much greater penetration of variable generation resources in achieving ambitious renewable targets. Fully integration of storage into planning and operations will allow maximum use of the wind resource.

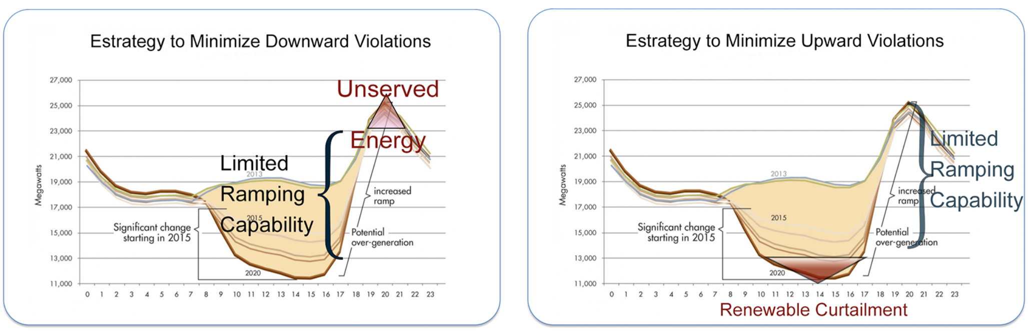


Figure 4.10: Downward and Upward Ramping violations in CAISO

Table 4.8: Cumulative Energy Storage Capacity Procurement Targets (MW) for California (California Public Utilities Commission, 2014)

Storage Grid Domain Point of Interconnection	2014	2016	2018	2020	Total by 2024
Southern California Edison					
Transmission	50	65	85	110	310
Distribution	30	40	50	65	185
Customer	10	15	25	35	85
Cumulative Subtotal SCE	90	120	160	210	580
Pacific Gas & Electric					
Transmission	50	65	85	110	310
Distribution	30	40	50	65	185
Customer	10	15	25	35	85
Cumulative Subtotal PG&E	90	120	160	210	580
San Diego Gas & Electric					
Transmission	10	15	22	33	80
Distribution	7	10	15	23	55
Customer	3	5	8	14	30
Cumulative Subtotal SDG&E	20	30	45	70	165
Total - all 3 utilities	200	270	365	490	1,325

Table 4.8 represents the CAISO Storage mandate and it is classified by utilities, years, domains namely, transmission, distribution, and customer. Massachusetts is aiming to have approved their own storage mandate by spring 2017 (Massachusetts Department of Energy, 2016). There is an ongoing debate regarding how ambitious this should be or the benefit that will bring across the value chain. Undoubtedly, it will enhance renewables integration and, in combination with ambitious energy efficiency programs, will contribute to manage a more flexible system with growing peak demand. Benefits of storage has been addressed in chapter 2 and beside that, just worth mentioning that T&D sector has been calculated in (Massachusetts Department of Energy, 2016) to the largest one for future savings. Total system benefits of: Energy Costs, Reduced Peak Capacity, Ancillary Services Costs, Wholesale Market Costs, Integrating Renewables, and T&D, are calculated to be up to

\$2.28B. The motivation of this sub-chapter is not dispute but to demonstrate how bottom-up nodal techno-economic modelling can contribute with locational insights to decision makers on where to accommodate the 600MW of storage that this stylised case study assumes as Massachusetts Storage Mandate. Starting from Scenario 6 of the previous section, the one that represent the configuration of turbines with higher capacity factor, storage locations for the optimisation problem will be selected among 512 locations of WIND (Table 4.4). Among the 512 locations, Figure 4.11, 85 will be selected as solution candidates depending on the distance to closest wind farm (0-1km^2, 1-5km^2, more than 5km^2).

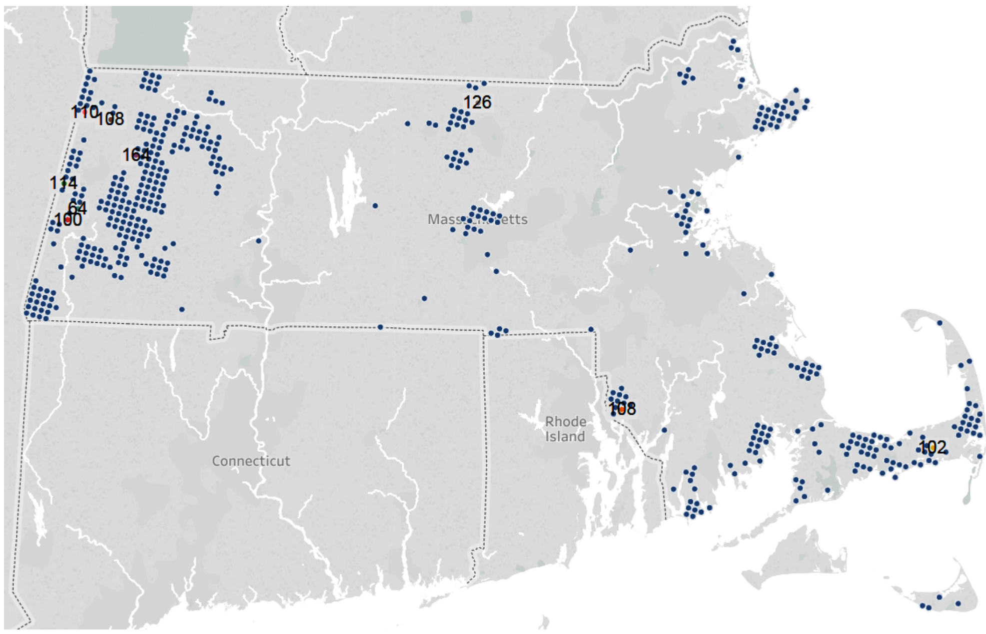


Figure 4.11: Scenario 6 Massachusetts wind locations and 512 storage potential locations

The goal of this section is to investigate how different storage topologies within Massachusetts can aid to reduce volatility and uncertainty for high wind penetration generation mixes. Optimising the standard deviation of RT prices, total generation costs, and dump energy and the consequent impact on

ISO-NE of the Massachusetts storage mandate is addressed within the next subsections.

4.4.1 Characterising the Optimisation

The optimisation problem is defined at a high level as a process to characterise the solution space for finding the set of potential storage locations, in which node will be connected, enabling the ISO-NE to operate a more flexible portfolio. The optimisation characterisation is non-linear and multi-dimensional, in both its variables vector and its objective functions.

The idea of using utility-scale storage for frequency control or system support it is not a novel idea, with some large pilot projects been operated as early as 1986 (Knisch et al., 1986). The operation of that project, despite decommissioned in 1993 by newer network design provided valuable insights of the roles that storage can have for enhancing grid operation (Wagner, 1997).

The storage units are defined as in Table 4.9 and for the optimisation purpose, each unit can take 0 value, meaning that at that location in that configuration the unit is not present, or 1, which means that its maximum capacity is accounted for accomplishing the 600MW constraint. Each PLEXOS simulation has an horizon of one calendar year (2010), as 365 steps of 1 day increments with 5 minutes resolution.

Table 4.9: Regulation Storage Operation Characteristics

Generic Storage Unit Operating Characteristics	
Max Power	10/15/20 MW
Charge Efficiency	100%
Discharge Efficiency	100%
Minimum State of Charge	30%
Maximum State of Charge	100%

The number of active storage units amended in the PLEXOS Xml model file which are sent to PLEXOS by Ganesh optimiser for each solution run, as detailed in Figure 3.11. As there are 85 candidate locations at which the storage units can be located, and 3 objective functions, the parameters vector of each candidate solution therefore consists of 88 variables: $v = (x_1, x_2, \ldots, x_n), n = 88$. This configuration allows a solution to have from 0 storage units up to a theoretical 88 installed units which is not possible in our case due to it will violate our hard constraint of 600MW of storage installed.

The candidate solutions chosen by Ganesh, once having been informed by PLEXOS results, are selected because they optimise the ISO-NE network operating characteristics with a set of storage topologies among the possible locations.

Ganesh evolutionary algorithm starts each new experiment with a random initial population of candidate solutions within their defined ranges, in our case [0,1] which accomplish the hard constraint, in this case, *Total Storage Installed Capacity* = 600MW.

In following generations, there might solutions that will break the hard constraint, due to the intrinsic mutation and recombination of parent solutions selected for breeding. If that happens, Ganesh will repair it, meaning in this context that will randomly choose one of the variables within the parameters vector and changing its value until the total capacity installed falls within the 600MW constraint.

Table 4.10: Run characterisations for each PLEXOS evaluation run

	DA	4HA	RT
Horizon	1 year	1 year	1 year
Time-step	1 hour	1 hour	5minutes
Optimitazion Windows	1 day	4 hours	5minutes
Look Ahead (Resolution)	1 day (6 hours)	5 intervals (4 hours)	(1 hour)
Time elapsed in HPC	5 hours	8 hours	2 hours
Time elapsed in PC	11 hours	32 hours	7 hours

In this study, there is a fixed population of size 12, allowing 0 duplicate solutions in any single generation, with initial crossover and mutation probabilities of 0.9 and 0.01176 (1/(85)) respectively. Each evaluation of a solution is an independent PLEXOS run (which is computational expensive) feeding the data which Ganesh optimiser uses as objective functions. For this stylised case study, Ganesh was allowed to run for 36 function evaluations (3 generations), with each evaluation taking approximately 50 hours elapsed time (on a 32GB RAM with quad-core), while took a third of that on a HPC, see Table 4.10. The population size needs to be a compromise between the minimum size which the optimisation would be useful, based on (Grefenstette, 1986) and the elapsed time per generation. Due to computational expensive PLEXOS runs, the three generations in this case study took 10 weeks to perform.

4.4.2 Results

The storage units are defined by locations taking 10, 15 or 20MW as values. The algorithm allows storage units just to be located at 230 or 345kV transmission nodes within Massachusetts as plotted in Figure 4.12. The long-term procurement plan (LTPP) modelled within PLEXOS has an horizon of one calendar year, representing the DA, 4HA and RT markets with a hour resolution.

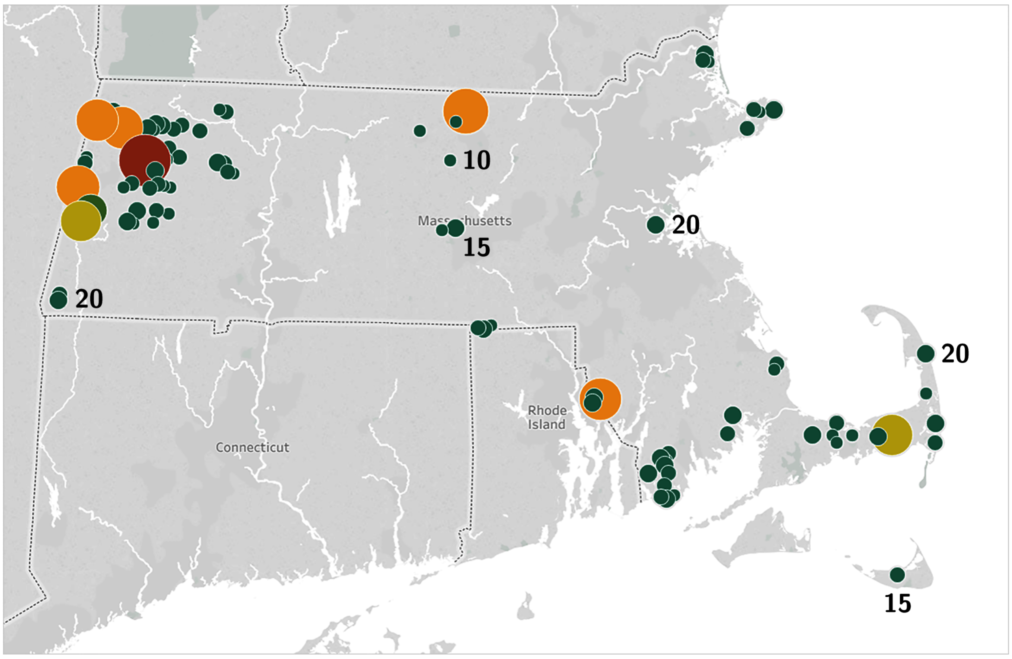


Figure 4.12: In green, feasible 85 feasible locations for 10, 15 or 20MW storage deployment. Yellow and Brown bubbles represent wind locations in the evaluated scenario.

Table 4.11: Optimisation parameter variable, Storage capacity installed, Distance to wind and the connection node

	Storage installed (MW)	Lat-Long to wind (m^2)	Node (kV)		Storage installed (MW)	Lat-Long to wind (m^2)	Node (kV)		Storage installed (MW)	Lat-Long to wind (m^2)	Node (kV)
v1	15	58	345	v31	20	1,230	345	v61	20	19,436	345
v2	20	568	345	v32	15	2903	345	v62	20	26,499	345
v3	10	534	345	v33	20	3,962	345	v63	15	15,551	345
v4	10	545	345	v34	10	3,444	345	v64	20	35646	345
v5	10	605	345	v35	10	2,964	345	v65	10	10,356	345
v6	20	22	345	v36	10	3,398	345	v66	10	41,507	345
v7	10	278	345	v37	15	1,762	345	v67	10	21,526	345
v8	10	50	345	v38	10	3,062	345	v68	10	32,988	345
v9	20	244	230	v39	20	4,286	345	v69	10	29,036	345
v10	15	305	345	v40	15	2,763	345	v70	15	33,645	345
v11	15	0	230	v41	10	4,686	345	v71	15	39,640	345
v12	20	486	345	v42	20	4,029	345	v72	20	6,350	345
v13	20	959	230	v43	10	2,565	345	v73	10	25,871	345
v14	15	459	345	v44	15	1,019	345	v74	20	11,468	345
v15	10	553	345	v45	15	3,796	345	v75	15	33,727	345
v16	10	764	230	v46	20	2,958	345	v76	15	39,363	345
v17	15	2	345	v47	15	4,224	345	v77	15	44,887	345
v18	20	921	345	v48	10	2,139	345	v78	15	42,140	345
v19	20	656	345	v49	20	3051	345	v79	10	23,415	345
v20	10	341	345	v50	15	2,875	345	v80	10	48,222	345
v21	15	50	345	v51	10	1,236	345	v81	15	37,948	345
v22	20	624	345	v52	15	3,211	345	v82	15	12,206	345
v23	10	883	345	v53	15	2,071	345	v83	10	47,190	345
v24	15	622	345	v54	20	2,323	345	v84	20	5,614	345
v25	20	580	345	v55	10	2,673	345	v85	20	6,014	345
v26	20	524	345	v56	15	1,549					
v27	10	397	345	v57	20	1,963					
v28	15	285	230	v58	15	2,107					
v29	15	138	345	v59	20	2,499					
v30	20	860	345	v60	20	4252					

Table 4.11 displays the 85 possible storage locations at which storage units can be located, the design vector of each candidate solution therefore consists of 85 variables: $v = (x_1, x_2, \ldots, x_n), n = 85$. The 3 objective functions defined for this optimisation have been largely used since 1999 when MIT defined them for evaluating the reliability of power systems (MIT, 1999). All of which are to be minimised simultaneously and the values for all of which come from PLEXOS, these being:

$$minF(TotalGenerationCost) = TGC \tag{4.1}$$

$$minF(\sigma RTPrice) = |\sigma RTPrice| \tag{4.2}$$

$$minF(UseDump) = |UseDump| \tag{4.3}$$

in which the values represent respectively:

1. The Total Generation Cost (\$000)

2. Hourly σRT Prices (\$/MWh)

3. The Unserved Energy/DUMP energy (GWh)

UseDump is going to represent brown areas in Figure 4.10, which are desired to be minimised for limiting ramping events during operations. Minimising the 5 minutes standard deviation of prices aims to minimise high volatility in prices appreciated in previous sections of this chapter.

A hard constraint on the total number of storage capacity installed, CAP, is applied in Equation (4.4), in order to accomplish the 600MW storage target for the evaluation region.

$$\sum_{i=1}^{85} CAP_i = 600 \tag{4.4}$$

Result plots are given as 2D scatter plots and with a high dimensional plot using parallel coordinates (||-coords) as technique (Inselberg, 1997).

The ||-coords technique enables multidimensional results to be plotted uniquely and without loss of information, together in one plot. The results shown in the ||-coords plots and related scatter plots contain all of the results from all of the generations, the dominated and the non-dominated ones.

In Figure 4.16 a query for visualising in a ||-coords plot the non-dominated solutions (in blue) has been made. They are the combinations of the 85 variables that after having been ran in PLEXOS, populated a Pareto front of non-dominated solutions. For a clearer view and further insights three 2D scatter plots were produced, Figures 4.13, 4.14, 4.15.

Figure 4.13 presents the three generations run for the optimisation, in light green, at the top-right corner, it is plotted the first generation. In the centre of the plot, in black, the second generation, which outperforms the previous, is presented. As for the third one, in blue, they are differentiated between light and dark blue, being the dark solutions those that in the third generation populate the Pareto frontier.

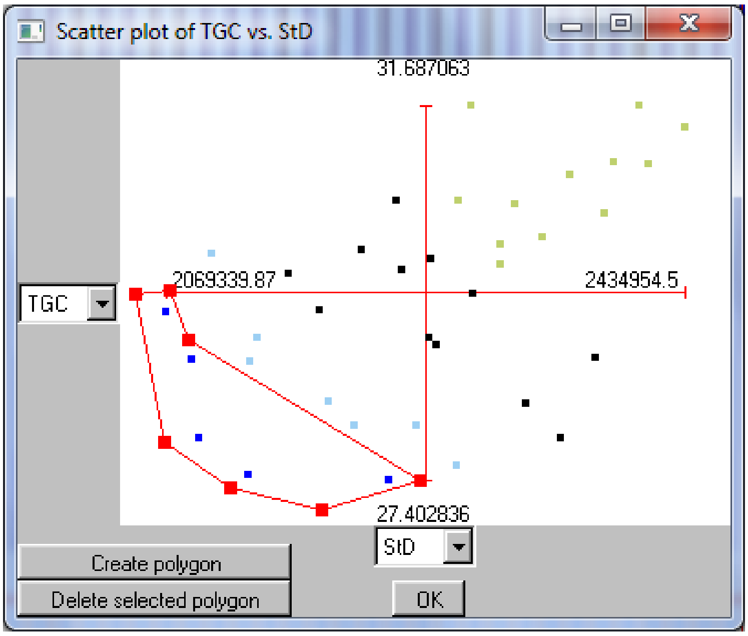


Figure 4.13: Scatter plot showing StDevPrice on x-axis against TGC on y-axis, with the most convergent solutions in blue forming the front of non-dominated solutions

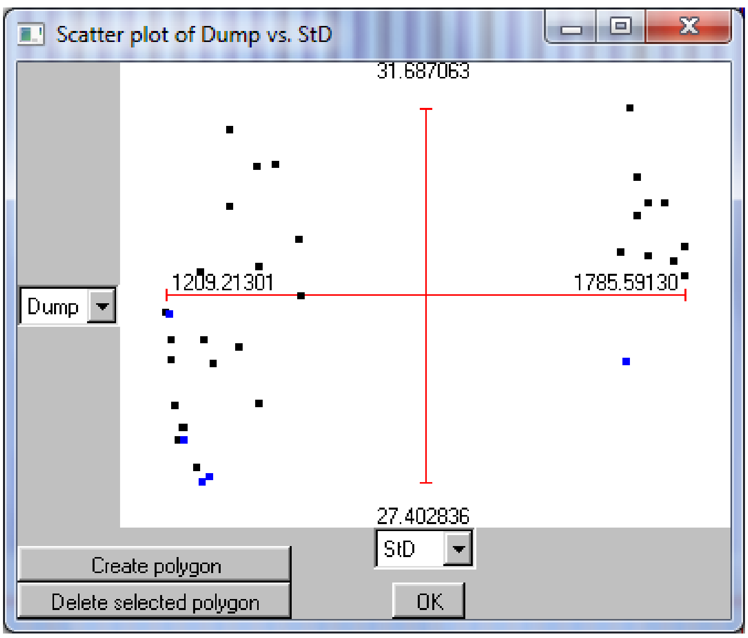


Figure 4.14: Scatter plot showing StDevPrice on x-axis against Dump on y-axis, with the non-dominated solutions from Figures 4.13 and 4.14 highlighted in blue

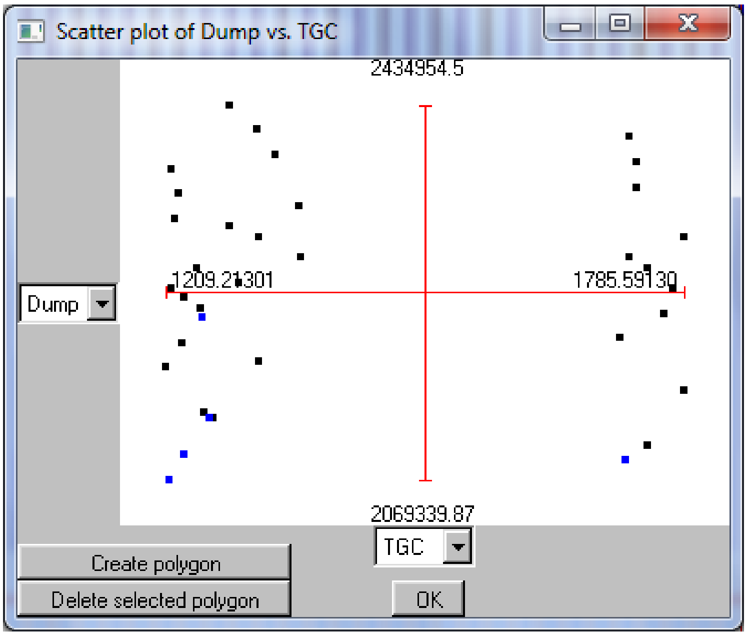


Figure 4.15: Scatter plot showing TGC on x-axis against Dump on y-axis, with the non-dominated solutions from Figures 4.13 and 4.14 highlighted in blue

The scatter plots of Figure 4.16 show the evolution from the random population on generation 1, situated on the top right corner of the plot, down to the bottom-left corner where in generation 3, five non-dominated solutions are highlighted in blue forming the Pareto front. Within the Pareto set in Figure 4.14 the second point from the left-side it is not dominated (but narrow to be) for the TGC OF. The particularity of that solution is studied on Figures 4.14 and 4.15, since it is the same point highlighted in blue on the bottom right.

In future generations, despite being non-dominated for generation 3, this solution might become dominated, eliminating off-spring solutions on the right side of Figures 4.14 and 4.15. With a closer look to Figure 4.16, this commented solution line (in blue) is the one that scores high on the OF3 (DumpE) axis. Table 4.12 compares the non-dominated solutions contained in the Pareto front for OF3 versus the ISO-NE PLEXOS Scenario 6 with no storage. The discussed

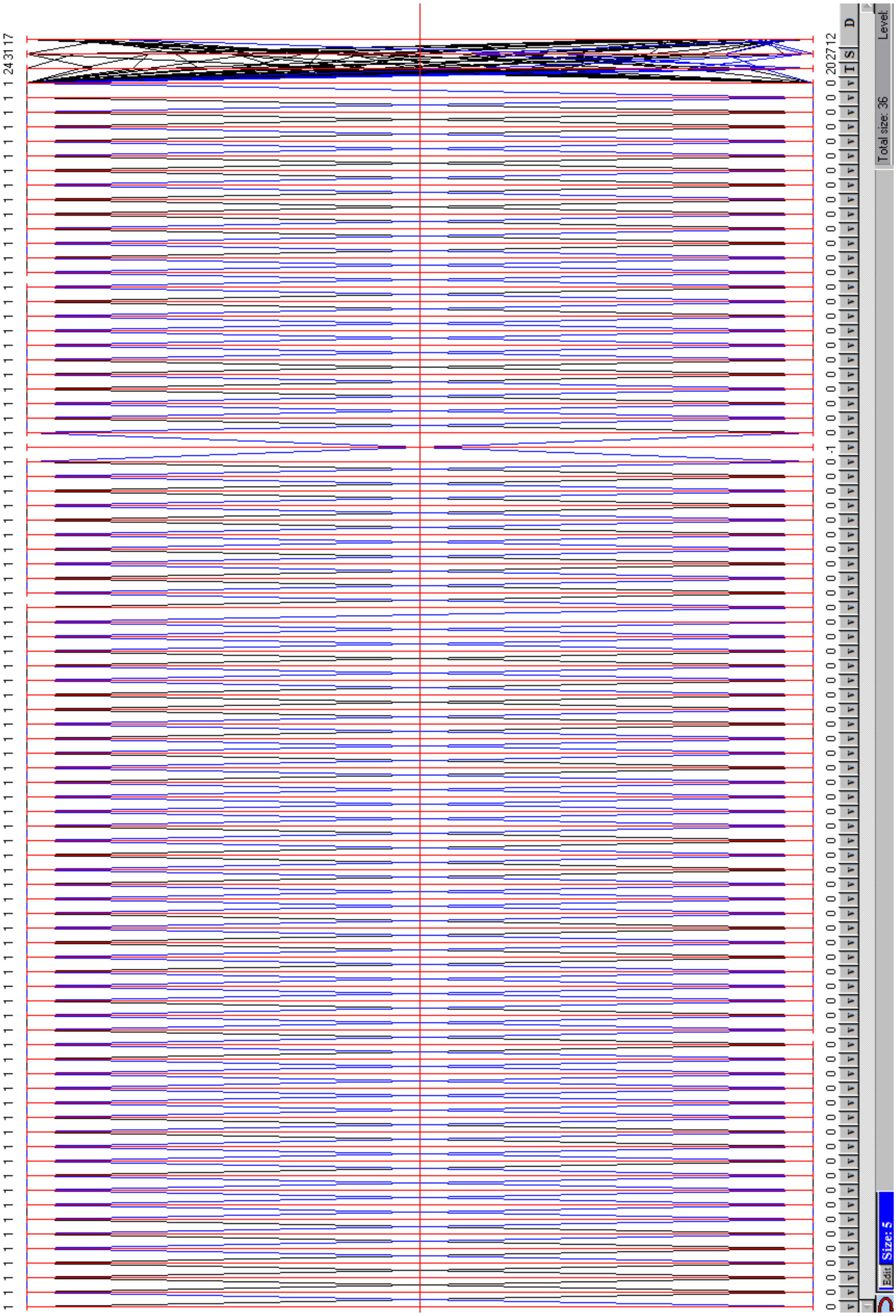


Figure 4.16: || -coord plot of the entire generation population, 36 results, showing the 85 varibles and the 3 OFs namely, TGC, StDevPrice, DumpE. The 5 non-dominated results are highlighted in blue

solution point is named 1, and improves no-storage scenario but not as much as its peers.

Table 4.12: Dump Energy comparing ISO-NE scenarios. No storage vs the five Pareto optimal storage solutions

ISO-NE + Storage	No Storage	1	2	3	4	5
Dump Energy (GWh)	1,966.42	1,722.13	1,250.11	1,224.53	1,258.32	1,213.59

4.5 Conclusions

It has been discussed the impact of high wind penetration topologies will have on prices, generation costs and dispatch shortcomings for a simulated year (2010) in ISO-NE and validated against the real 2010 ISO-NE data, (ISO-NE, 2014) (ISO-NE, 2014).

Combining PLEXOS modelled scenarios with evolutionary multi-objective optimisation we have gained insights not only the amount of storage that will aid system operators, but also their location and the impact that will have to provide extra flexibility within the network.

As there are not any interconnections with neighbouring regions, would be valuable for future work analysing how electricity prices in ISO-NE and its neighbouring regions in detail and design a methodology to incorporate electricity exchange revenues in the cost analysis of different wind power forecasts. (Brancucci and Hodge, 2014) study shows that at low penetration levels distributed wind does not have major impacts on transmission-level system operations, even if a system operator does not have any visibility or control of the individual utility-scale wind power plants connected throughout the different distribution networks in ISO-NE. Nonetheless, as distributed wind power penetration increases, the impact on system operations increases as well.

This meta-heuristic method can be used to aid in the planning design and future reinforcement investments across different network voltage levels. Further studies could assess lines capacity for enhancing flexibility in a localised congested area or region.

In an ISO-NE power system with a 30% of wind, coal and gas are the sources displaced for accommodating the 10GW of wind. The high integration of wind leads to a noticeable increase of oil in the RT market commitment for covering the intrinsic source intermittency.

Despite having modelled the power system with perfect wind forecast in the DA and 4HA, due to the lack of interconnections or bilateral agreements, the standard deviation and dump energy are higher and motivates a locational optimisation using storage to diminish those model limitations.

Dump energy can be reduced up to 30% when addressing Massachusetts storage target with high penetration of wind power in ISO-NE.

This reduction of curtailment leads to a reduction of price volatility which has been optimised through the standard deviation of RT prices.

Within this chapter has been shown that combining MOEA with Plexos as a market and operation solver, rapid solutions, as fast as Plexos model can be solved, are achieved. Moreover, the combination of a MOEA as an optimiser with Plexos, populated a Pareto-set of feasible solutions where further insights on locations can be discussed with decision-makers determining connections of high wind penetration and storage across a network topology.

Debugging the granularity of locations among the solutions contained in the Pareto-set, it seems that most of the storage is connected to a node that is close to wind. Continuing populating the Pareto-set will drive to more robust results on storage deployment.

Chapter 5

Evolutionary Planning for 11kV Distribution Smart Networks

The transition to a secure low-carbon system is raising a set of uncertainties when planning the path to a reliable decarbonised supply. The electricity sector is committing large investments on the transmission and distribution sector for 2050 in order to ensure grid resilience. The cost and limited flexibility of traditional approaches to 11 kV network reinforcement threaten to constrain the uptake of low carbon technologies. The aim of this paper is to assess the suitability and cost-effectiveness of smart grid techniques along with traditional reinforcements for the 11 kV electricity distribution network, in order to analyse expected investments up to 2050 under different DECC scenarios. The evaluation of assets planning is based on the Low Carbon Network Fund (LCNF) Tier 2 FALCON (Flexible Approaches for Low Carbon Optimised Networks) project network. To undertake the analysis in this chapter is used a revolutionary new model tool for electricity distribution network planning, called Scenario Investment Model (SIM). Comprehensive comparisons of short and long-term evolutionary investment planning strategies are presented.

Currently electricity distribution networks have been planned with typically linear load growths of up to 1% per annum. The expected increase in low carbon technologies will have a significant effect on the electricity demands on the network which may have significant rapid sporadic increases in the electricity demand on the 11kV networks (UK Power Networks, 2014). In addition, the daily electricity load shapes may also alter significantly. The networks will need to be upgraded, and systems being able to evolve and cope with new demand profiles.

The rising number of stakeholders in the electricity value chain increases the complexity for assets planning. Beside the number of decision makers, the energy sector is facing a data revolution and therefore, Utilities of the future must include in their planning capabilities the implementation of Information and Communication Technologies (ICTs). Most Network Modelling Tools, such as IPSA, GROND or DINIS perform power flow analysis and look after overloads and stress points of the network. Their approach can be consider static, in the sense that they evaluate an instantaneous view of the network at certain given time. However, dynamic modelling like the ones implemented within the SIM (Western Power Distribution, 2015) extends those static approaches making a series of evaluation runs, adjusting future network states (configuration of the network) to previous fixed states where the grid needed an intervention across its topology.

This chapter uses data from the FALCON project, using a section of Western Power Distribution (WPD), the DNO who operates the Midlands and Wales, in the Milton Keynes area. In contrast with the parametric top-down representation embedded in TRANSFORM model (EA Technology, 2016) the SIM aims to create long-term strategic investment plans. This study will deliver insights and scalability of these novel interventions for asset planning of the UK distribution power networks.

The research objective was settled to proof of the suitability of the six novel smart intervention trials presented in Chapter 1, and along with the traditional reinforcements, provide an evolutionary planning insight for future power networks. To undertake this study, specific experiments were selected for a certain power trial network under different demand scenarios and evaluation periods, assessing smart techniques along with traditional reinforcements. The approach, involved running a set of experiments using the SIM for the six 11kV primaries in the FALCON trial area.

5.1 Introduction

Sustainable energy production from renewable sources not only will increase energy security, but also deliver the 80-95% reductions of greenhouse gas emissions expected by the Energy Roadmap 2050, (European Commission, 2011) . To meet such ambitious targets, the networks is going to change significantly by 2050. Increased adoption of heat pumps, electric vehicles, deployment of renewable solar and wind generation alongside with combined heat and power(CHP) units will place new demands on the distribution network. To cope with these demands and achieve cost reduction in comparison with conventional network reinforcement, the grid needs to adopt advanced electricity networks and storage (EN&S) technologies. In fact, some of the low carbon technologies, e.g., wind and solar generation are critically dependant on EN&S technologies to leverage their full potential (Low Carbon Innovation Coordination Group, 2012).

At the moment, the innovation in EN&S technologies is riddled with uncertainty regarding which technologies to choose, which investment to support and how the choices would evolve in the long term (Moselle et al., 2010). With many alternatives to conventional network reinforcement available and being developed, e.g., distributed generation, various forms of energy storage (Kondoh et al., 2000), demand response (Poudineh and Jamasb, 2014), mesh networks (Behnke et al., 2005), dynamic asset rating (Yang et al., 2015), etc., it becomes difficult for the distribution network operators (DNOs), regulators and policy makers to find an optimal network investment roadmap, pick the right mix of EN&S technologies to create local network development plans and forecasts the costs of optimal electricity distribution.

There are a number of previous notable projects that address the uncertainty around integration of low carbon and EN&S technologies into the distribution grid. The Smart Distribution Network Operation for Maximising the Integration of Renewable Generation project performs optimisation of network operation modes and reinforcement planning in the presence of renewable generation. Smart Grid Forum Work Stream 3, which later became EA Technology Transform model (EA Technology, 2016), is a parametric representation of the electricity distribution network that is aimed to create long-term strategic investment plans.

It is important to note that there are certain limitations in Transform that are characteristic to all parametric models. The operating characteristics of devices and their relationship to other technologies require extensive calibration to produce a qualified answer. To some extent the limitations of Transform were addressed by Smart Grid Forum Work Stream 7 (Smart Grid Forum, 2015), which took four of Transform's parametric representations of typical distribution networks and converted them into nodal network models in order to understand how the Transform solutions function. Other examples include Energy Technology Institute (ETI) EnergyPath model, which targets local energy systems (ETI, 2016), and Comillas University Reference Network Model (RNM) (Domingo et al., 2011), (Comillas, 2009), which is a large scale distribution network planning tools that can create optimal networks. The RNM can be used by regulators and policy makers to estimate network development and operation costs.

Despite the differences in their respective approaches, the aforementioned models and software tools share some common limitations. They have limited ability to capture emerging behaviour arising from simultaneous application of multiple EN&S technologies to the electricity distribution network. Likewise, it is difficult to add new EN&S technologies into the mix, either due to lack of automatic application of smart techniques or, as is the case with Transform, the parametric approach needs information about the way different technologies compete with each other, which is difficult to obtain. And finally, no decision support for a particular piece of distribution network can be provided either because of lack of automation or the parametric nature of the model. The following sections introduce and describe a novel techno-economic modelling tool for the distribution network that performs dynamic network modelling and analysis in the presence of multiple EN&S technologies. It uses nodal network modelling to capture the emerging behaviour and create localised network development plans.

5.2 Overview of Techniques

5.2.1 Technique 1 - Dynamic Asset Rating

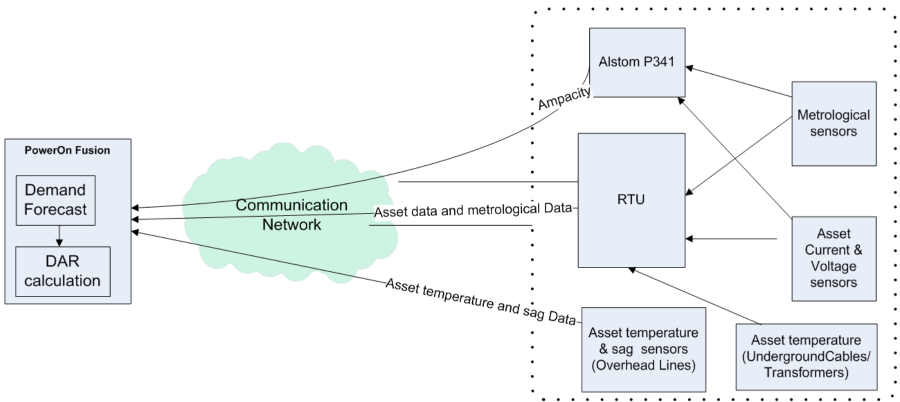


Figure 5.1: DAR trial schematic

The heating effect of current passing through a metal restricts the capacity of all transformers, overhead conductors and cables on a distribution network. This restriction is based on the maximum temperature on a critical component within the asset. Therefore each asset will have a finite current carrying capacity rating based on assumed values of external conditions which affect thermal build up - i.e. wind speed, ambient temperature, soil humidity etc. As the assets in general do not have temperature monitoring, the assumed values of the external conditions used in these calculations have as a basis a statistically low level of risk of the asset exceeding its critical temperature.

By more accurately monitoring metrological conditions and modelling asset ratings in real-time, capacity of the asset can be increased whilst keeping the risk of exceeding the critical temperature to a minimum. Further models and algorithms will be developed as part of this second implementation to cater for the increased information available.

In addition in many assets have a thermal capacity, such that it takes time for the asset to raise its temperature (i.e. an increase in the current passing through the asset will not cause a step change in the temperature of the asset). Such assets typically have short term current ratings which are significantly greater than their continuous current rating. These short term ratings are based on specific current carrying curves. By being able to forecast the actual current carrying curves the asset ratings can be further refined such that an even greater short term current can be supported. Transformers and underground cables have significant thermal capacity that can utilise this method whereas Overhead Line circuits do not have significant thermal capacity.

5.2.2 Technique 2 - Automated Load Transfer

As described on trial summary section in Chapter 2, (Western Power Distribution, 2015), consumers of electricity on the network use energy at different rates at different times of the day and by actively managing the network connectivity, the loads across connected feeders can be evenly balanced. Rather than the position of normal switching open points being determined for average network conditions, the positions can be changed automatically by the Network Management System to a more optimum location based on a number of factors such as security, voltage drop, capacity utilisation and load forecasts.

5.2.3 Technique 3 - Meshed Networks

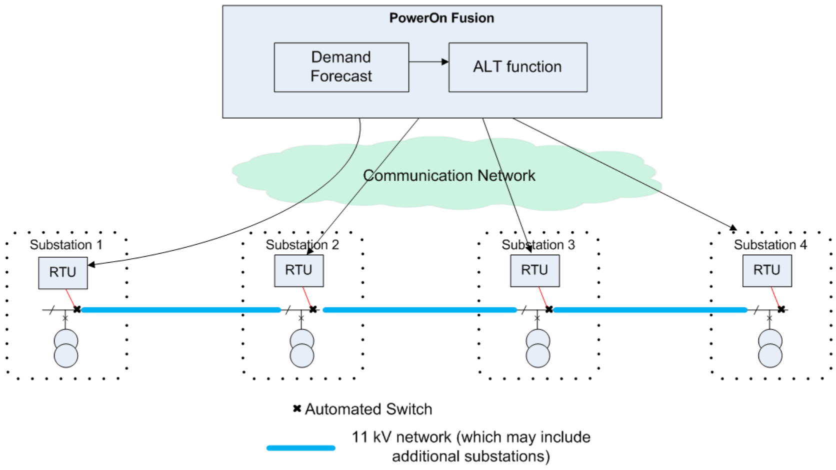


Figure 5.2: ALT trial schematic

This technique involves increasing the level of protection employed on the network in order to close all switches on a circuit, paralleling them together and feeding down from both ends. Similar to the way 11kV automatic load transfer changes where the normal open point separating two radial feeders is placed, meshing a network will allow the effective zero current point to move depending on the load around the circuit. Customer security is not reduced due to an increased level of protection and fault breaking capability. Customer security can also be increased with each additional circuit breaker and protection device installed.

5.2.4 Technique 4 - Storage

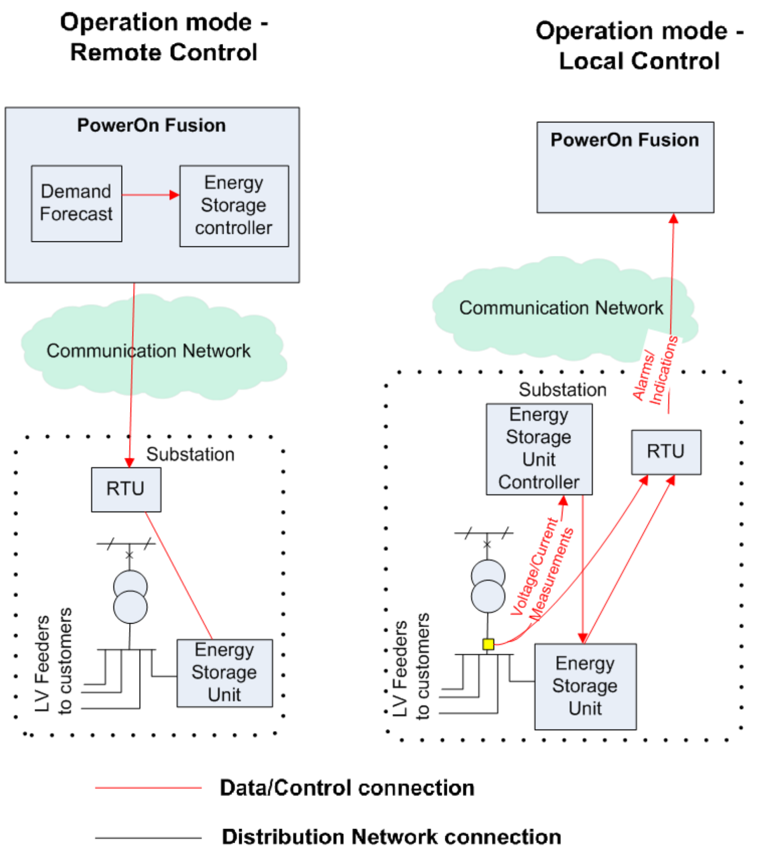


Figure 5.3: Storage trial representation

Energy demand in an 11kV feeder tends to occur in peaks and troughs throughout a 24 hour cycle. The current supplying capacity of a feeder is limited to the current carrying capability of the smallest cable or conductor in the circuit and these usually decrease in cross-sectional area size the further away from the Primary they are located. This is acceptable when the load is spread evenly across a circuit, but when the load occurs unevenly then the utilisation factor of the assets will also be uneven. By introducing energy storage devices on the network, they can feed out onto the system at peak demands and recharge during times of low demand, thus deferring the need to replace existing assets.

5.2.5 Technique 5 - Distributed Generation

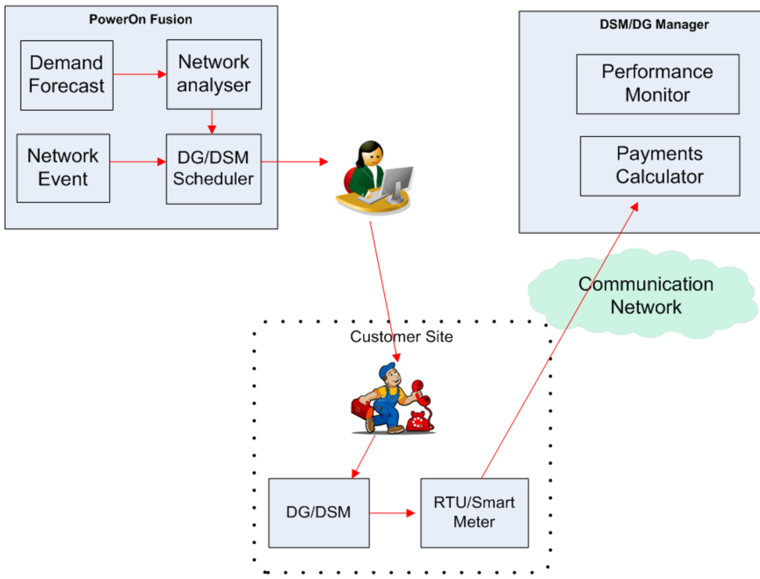


Figure 5.4: Commercial trials representation: DG/DSM

A number of industrial and commercial customers have their own, on-site generation and this number is likely to increase with the transition to a low carbon economy. In some cases, this may be uncontrollable renewable generation (wind or solar) but the majority is in the form of either standby generators or controllable plants such as biomass, refuse incinerators or combined heat and power (CHP) plants. If customers with controllable distributed generation can be incentivised to accept instruction from a DNO to increase or decrease generation, this can be used to reduce or increase site demand and/or provide/remove supply from the grid as a means of rectifying network problems.

5.2.6 Technique 6 - Demand Side Management

Similar to distributed generation, DSM involves putting in place commercial agreements between the DNO and industrial and commercial customers who have the ability to control appreciable amounts of load in relatively short periods of time. We expect demand side response to be in two forms

- To reduce the impact of predicted peak loads
- In response to an unplanned event, such as a fault

Demand side response can be used to enable the connection of low carbon technologies without carrying out the full extent of reinforcement work that would be required without demand side response.

5.3 Scenario Investment Model

The graph search algorithm embedded in the SIM was described in Chapter 3 and conceived as a new generation network planning tool to address the uncertainty around integration of low carbon and EN&S technologies into the distribution grid. Like the conventional network modelling tools, e.g., PSS SINCAL (Siemens, 2016) or Ipsa 2 (Tnei, 2016),the SIM uses nodal network models of actual networks. The nodal network model works in tandem with a state-of-the-art load prediction engine, which can produce substation load profiles showing annual changes in demand and distributed generation that comprise daily load curves for a number of characteristic days in a year. Pluggable models of novel EN&S technologies along with models of various modes of conventional reinforcement allow the SIM to perform automatic resolution of network issues and consequently create dynamic network evolution and investment plans.

The SIM initially supports six different EN&S technologies (Dynamic rating of underground Cables and Transformers, Automatic Load Transfer, Battery storage, Meshed Networks, Distributed Generation and Demand Side

Management) alongside six types of conventional reinforcement (Transformer, Cable, Busbar and Overhead line upgrade and replacement, creating new feeder, transferring load to adjacent feeder) trailed by Western Power Distribution during the FALCON project, where each of the techniques implemented within the SIM are fully detailed in (Western Power Distribution, 2015).

There had been identified two main streams of work to consider the use of the innovative techniques, namely: Strategic and Tactical Planning, and Design, Build and Operation. The Strategic and tactical Planning stream will consider the Network Planning roles whilst the Design and Operation stream will consider Design, Build and Operation roles. Figure 5.5, the Smart Gird Planning Framework Diagram presents key elements of each stream is displayed with their main interactions.

In order to leverage the capability of existing network analysis tools which are already extensively used by electricity network operators, the SIM is separated into two main packages a Network Modelling Tool which primarily performs the technical assessment of the application of the techniques and the SIM Harness which manages the overall process and perform the economic assessment and reporting functions.

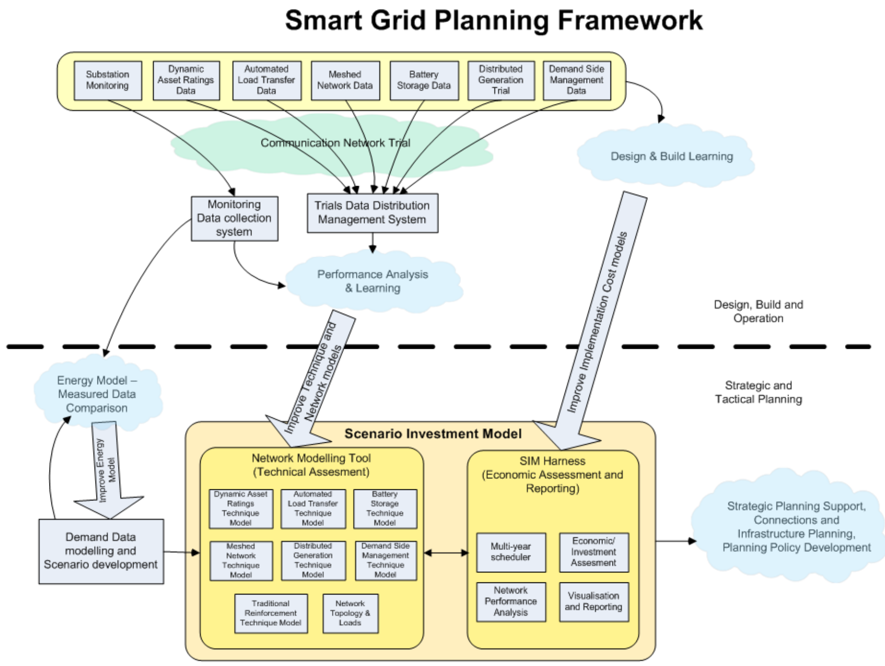


Figure 5.5: Commercial trials representation: DG/DSM

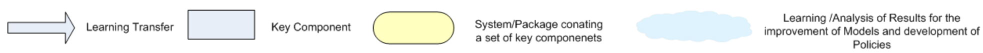


Figure 5.6: Smart Grid Planning Framework Diagram

Referring to Figure 5.7, the SIM includes use cases for three primary actors, namely, strategic planner, local planner and policy user. The local planner has three primary uses of the system, to plan asset replacement or diversion, connect new load or new local generation or to explore the dynamic network model. The strategic planner has just a single use of the software to prepare a long term investment plan for a larger segment of the network. Meanwhile, the policy user has access to the same use cases as both planners, but for a different purpose to produce rules of thumb for planning manuals. All user-oriented use cases map to three system use cases that allow to a) set up experiment, run simulation and save results to results store, b) browse and compare individual results and c) browse and compare aggregated results.

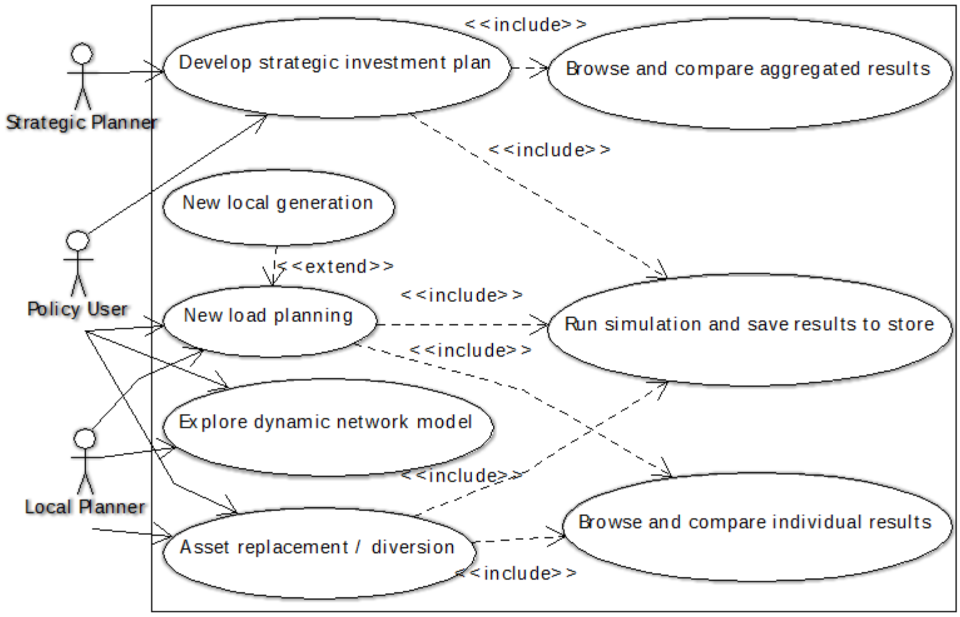


Figure 5.7: SIM use cases

5.3.1 SIM Architecture

To support the use cases, the SIM implements a multi-tier architecture with separate presentation, application processing and data management layers. Referring to Figure 5.8, there are 12 main component subsystems, among which components 1-4 are responsible for storage and management of load scenarios, network patches, which represent planned changes to the grid, nodal network model and costing models respectively. The experiment planner allows to set up an experiment by selecting network area, demand scenario, cost model and other run parameters such as start and end years of the evaluation period.

This creates a set of inputs, consisting of a nodal network model of the selected network area, annual load profiles for every substation in the selected network for each year of the experiment, network patches that represent planned modifications of the network at specific time points, a set of allowed intervention techniques with time series costs of applying them, and failure model that specifies what triggers an application of an intervention technique. The nodal network model includes various asset parameters, such as connectivity, electrical and fault ratings, location and auxiliary parameters such as soil type and duct information for cables and heat convection data for indoor transformers.

Annual load profiles include daily load data for 18 characteristic days, each day comprising 48 half-hourly load values.

Components 6 and 7 perform the actual experiment processing by performing heuristic expansion of the initial network state.

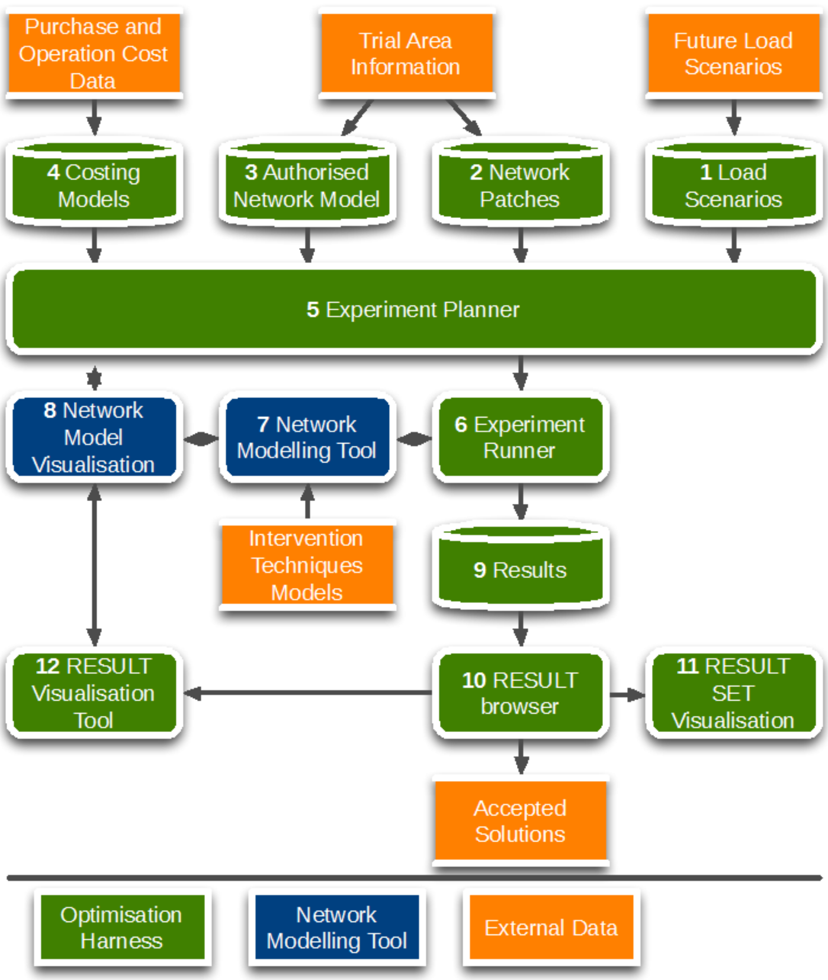


Figure 5.8: SIM component subsystem structure.

The experiment runner is an optimisation framework that performs heuristic exploration of the search space in order to find the best sequences of reinforcements to keep the network compliant. The framework is built around a network modelling tool (NMT) that performs power flow and reliability analysis of individual network states. The NMT is a commercial off the shelf software Ipsa2, produced by TNEI (Tnei, 2016). Ipsa 2 was selected for having an extensive application programming interface (API) for Python language, performance of power flow analysis and network model change management support.

The network modelling tool performs power flow analysis, reliability studies and also applies intervention technique models to resolve network issues, while the optimal combinations of techniques are selected by the experiment runner. Once the network development plans that keep the network compliant throughout the evaluation period are found, they are saved to the results store. The user can browse results either as individual solutions or aggregations using the result browser and view them using the result visualisation or result set visualisation tools, respectively. The result visualisation tool relies on the network model visualisation tool to render the dynamic network diagram either in single line or geographic layout.

5.3.2 SIM Search Algorithm

The essence of the SIM approach is its ability to take a network configuration and corresponding load profiles in a particular year (termed as initial network state), perform power flow and reliability analysis, and create derivative network states in a process known as network state expansion. The expansion happens either by transitioning to the following year for network states without any failures or by applying intervention techniques to resolve network issues. With each new network state created, the SIM, therefore, is faced with a decision as to which network state from the execution history to expand next. The expansion can be guided by simple depth first or breadth first algorithms, which are implemented in the SIM for verification purposes. The depth first algorithm always selects the newest, i.e., the most recently created network state that is not fully expanded for expansion, while the breadth first algorithm always selects the oldest network state. However, those simple heuristics are inadequate for any practical use beyond simple test cases due to the size of the search space obtained by permuting all possible interventions over a number of years.

To perform intelligent exploration of the search space, the SIM uses a heuristic approach that is based on a customised graph search A* algorithm (Hart et al., 1968) presented in subsection 3.4 of this thesis. Baseline A* algorithm aims to find the least-cost path through the search space. As A* traverses the search space, it builds a tree of partial paths. The leaf nodes of this tree (failed network states) are stored in a priority queue that is ordered using a cost function (equation (5.1))

$$f(x) = g(x) + h(x) \tag{5.1}$$

where $h(x)$ is the heuristic estimate of the path cost to reach the goal $h(x)$ and $g(x)$ is the distance travelled from the initial node.

Referring to Figure 5.9, the SIM selects network states from the priority queue to apply intervention techniques, one application at a time. Deployment of a technique produces a new network state, for which a power flow analysis is performed in intact and all $n-1$ (contingency) network operation modes.

If all the failures are resolved, a reliability analysis comprising Costumer Minutes Lost (CML)/Costumer Interruptions (CI), losses and fault level studies is performed. A new network state is subsequently created in the next year of evaluation, or, if it is already the last year of evaluation, the costs of interventions are calculated and the network state together with all its expansion history is saved to the results store as a new result. The evaluation terminates when criteria such as the number of results, number of network state evaluations or run time are reached.

As for the cost structure of the patches, they will be defined as: Initial costs (the cost in the first year that reflect the installation); Running costs (the fixed annual costs for all years); and Usage costs (representing the cost associated with the usage of a patch in a year). For a detailed parametric breakdown of CAPEX and OPEX among Direct Cost Labour, Direct Cost Pensions, Direct Cost Material, Direct Cost Civil Works, Disturbance Factor, Safety Costs and Other costs, do refer to the FALCON project technical note which may be requested from Western Power Distribution.

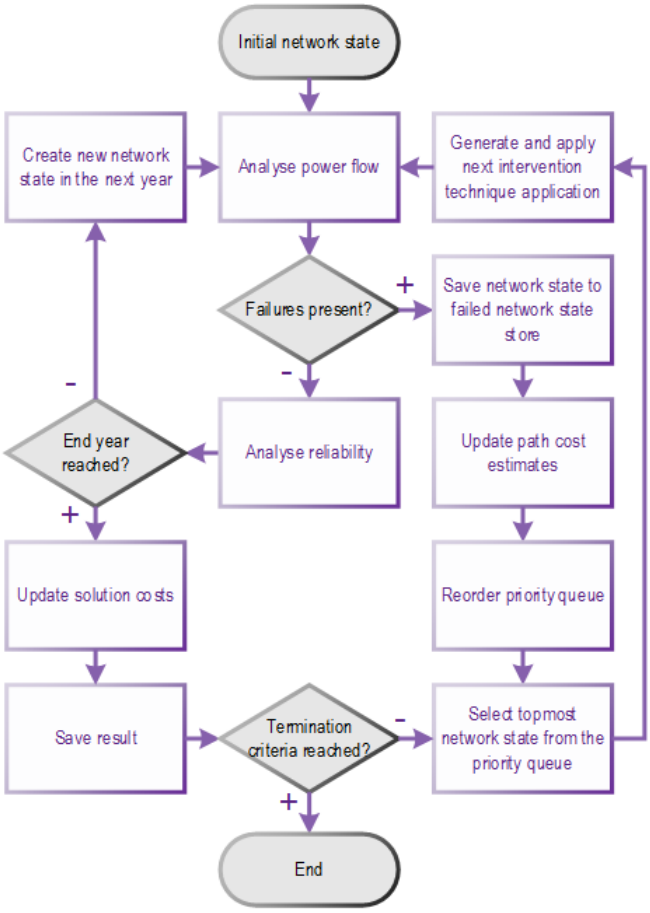


Figure 5.9: SIM search algorithm flowchart.

5.4 Setting an Experiment

5.4.1 Start of an Experiment

Figure 5.10 is an example expansion tree of the first year of an experiment. It is evident that the SIM Harness generates and tests a large number of patches and corresponding network states most of which are not expanded further thanks to the heuristic selection process. In Figure 5.10, each ellipse represents a network state. The numbers displayed within an ellipse are network state ID and total number of failures for each network state in the graph. For a detailed description of what is captured in a network state, refer to section 3.3.

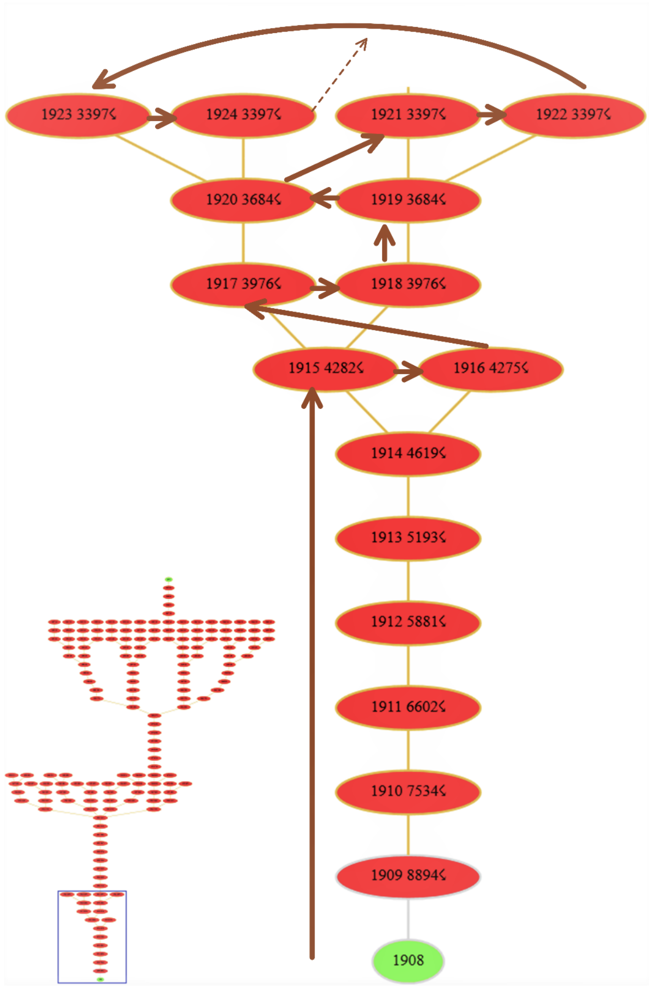


Figure 5.10: Initial expansion of the SIM scenario tree in the first year of an experiment.

Knowing the network state ID allows to restore the order of tree expansion as each network state gets its ID at the moment when it is saved to the SIM database. The reconstructed order of the tree expansion is shown with arrows. One of major findings for the partnering DNO was the lack of compliance of the current network. This had never been discovered while using the manual simulation tools as it is considered impractical for network planners to run the complete power flow study that is required to check the network compliance. The planners usually run power flow studies with a single fixed load pattern. In contrast, the SIM checks each network state for compliance under 18 characteristic day load scenarios each comprising of 48 half-hour settlement periods. All studies are performed under intact and n-1 contingency network operation modes. In the referred example this results in the SIM harness performing 864*12 evaluations for each network state, with 12 being the number of protection zones in the network.

The network state ID 1908 is a special case of the first network state in experiment. It does not have any assigned load profiles and so is always being displayed as a compliant network state. The next network state ID 1909 is the first one which has load profiles and having a full set of power flow studies performed. The large number of identified failures (8894) is normal due to the comprehensive nature of the compliancy check. As an example, a single asset with a thermal constraint may be overloaded during multiple half-hour settlement periods a day several characteristic days per year, thus showing as multiple failures.

In fact, the network state ID 1909 has 44 distinct assets experiencing thermal constraints with maximum p/u overload reaching 2.14 on a ring main unit under n-1 contingency. To resolve these issues, the SIM has to apply 46 patches with an associated total cost.

The metrics cost refers to incentive payments associated with reliability metrics comprising CML, customer interruptions CI, fault levels (FL) and losses. Negative OPEX is the result of undergrounding of some overhead lines with the resulting cables not requiring periodic inspection. Additional corrective maintenance savings are accounted for indirectly through reduced fault level costs.

5.4.2 End of an Experiment

Figure 5.11 shows an example of the expansion tree from a different experiment reaching the final year (2050) of an experiment. Different edge colours represent the type of the EN&S technology that was applied to the network to create a new network state. Yellow corresponds to traditional reinforcement while purple to dynamic asset rating. In main SIM results visualisation, the results, which are sequences of network state from the first to the last year of evaluation period are ranked and arranged by cost and performance criteria. This example, however, illustrates the different paths an expansion of the network state could take. Consider the network state ID 1862 in year 2047, which corresponds to a network with 3 assets having thermal issues. The left branch on the diagrams shows a traditional reinforcement option that keeps the network compliant for the following 3 years until the end of the evaluation period.

Meanwhile, the right branch shows an alternative route of resolving the issues with three successive applications of dynamic asset rating, which result in a network state which is going to have an additional issue in year 2049 (ID 1872).

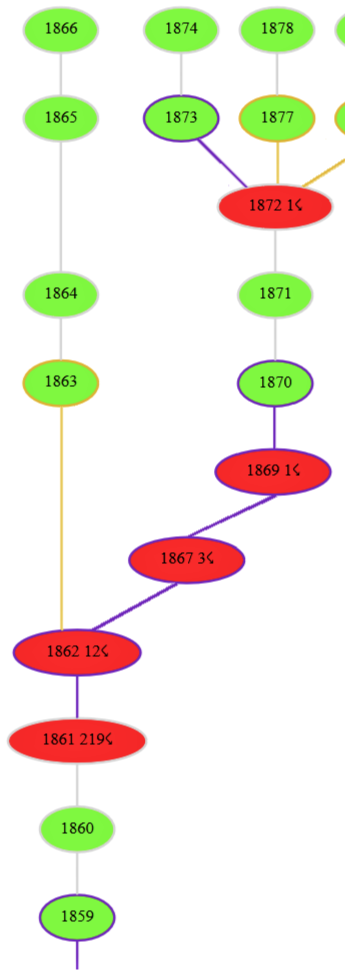


Figure 5.11: Last years of a SIM experiment.

The accumulated costs of corresponding network state in last year of evaluation are shown in Table 5.1.

Table 5.1: Network state costs

Net. state ID	CAPEX	OPEX	Metrics
1866	1124026.92	96180.10	4319641.98
1874	1118500.84	98549.95	4318533.51
1878	1123214.89	98230.39	4313531.82
1880	1122783.20	98230.39	4315346.95

Despite the lower overall number of interventions, for network state ID 1862 the traditional reinforcement is actually a more expensive reinforcement option compared to dynamic asset rating. Also it is interesting to see the spread of different costs in the total network-related expenditure. For the given network, the incentive costs of losses, CMLs, Cis and fault levels over 35 years from 2015 to 2050 constitute approximately 3.8 times the capital investment costs. In comparison, the operating expenditure is relatively minor 100k, despite the applied smart EN&S techniques.

5.4.3 Network State details

Figure 5.12 displays on the left in yellow and red, the number of issues faced on that network before the SIM implementation. On the right, 2050 scenario after the SIM having applied patches techniques to solve them.

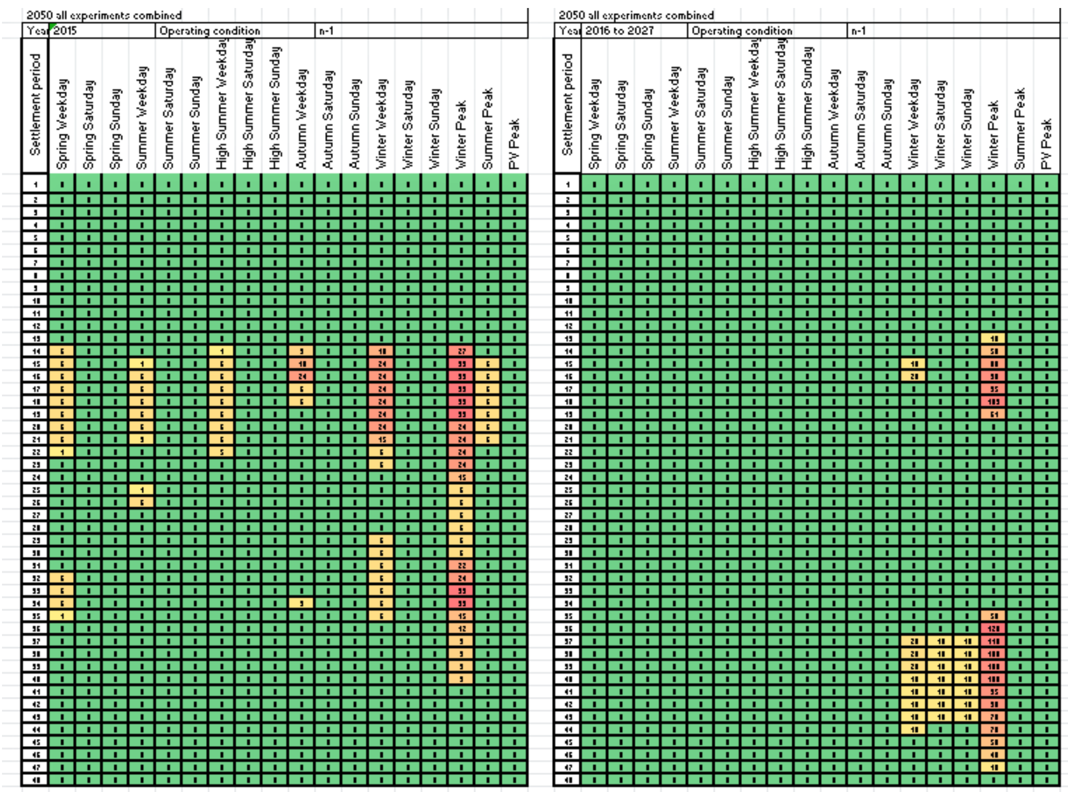
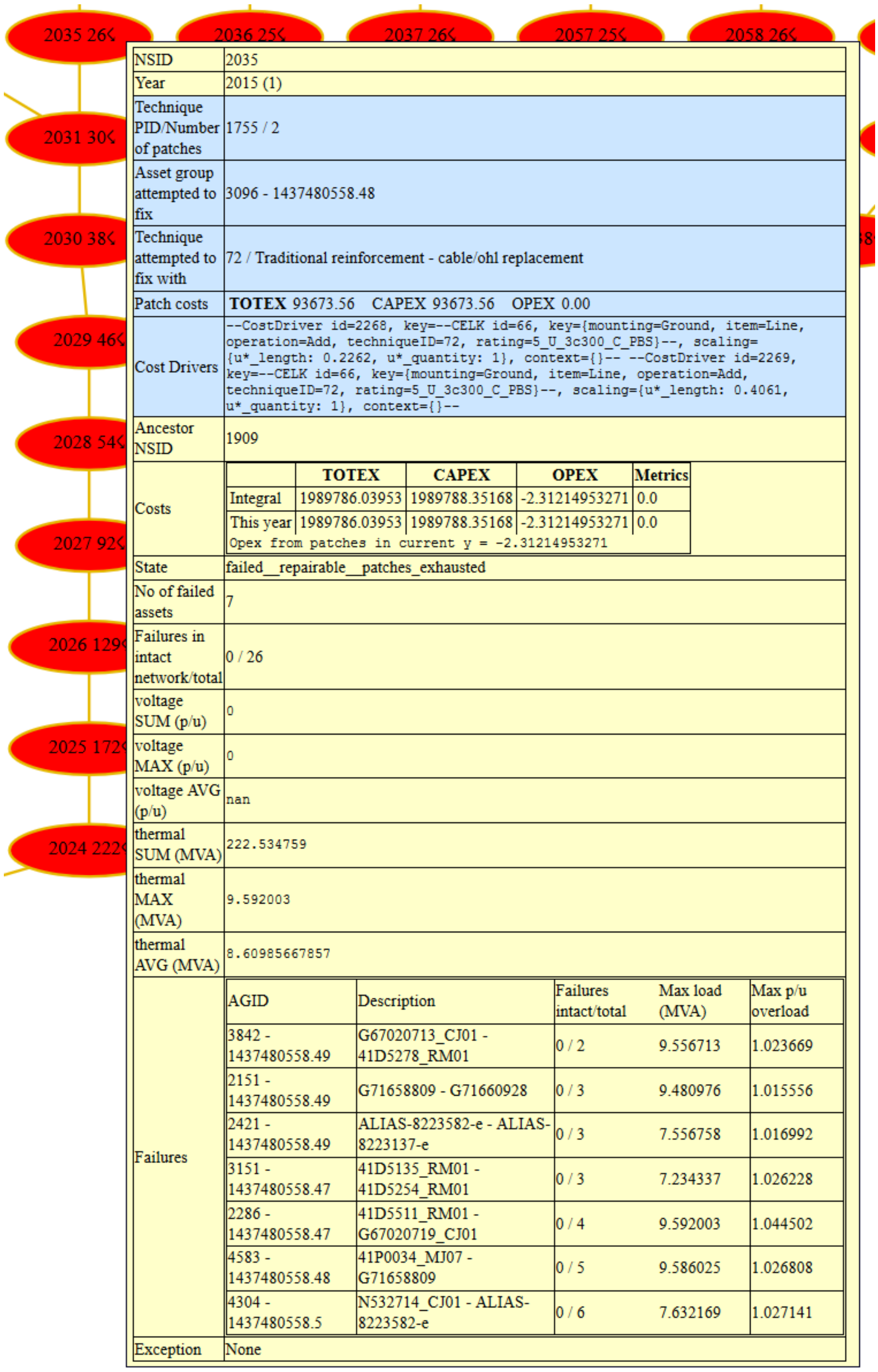


Figure 5.12: Visual representation of number of issues per representative day.



NSID	2035
Year	2015 (1)
Technique PID/Number of patches	1755 / 2
Asset group attempted to fix	3096 - 1437480558.48
Technique attempted to fix with	72 / Traditional reinforcement - cable/ohl replacement
Patch costs	**TOTEX** 93673.56 CAPEX 93673.56 OPEX 0.00
Cost Drivers	--CostDriver id=2268, key=--CELK id=66, key={mounting=Ground, item=Line, operation=Add, techniqueID=72, rating=5_U_3c300_C_PBS}--, scaling={u*_length: 0.2262, u*_quantity: 1}, context={}-- --CostDriver id=2269, key=--CELK id=66, key={mounting=Ground, item=Line, operation=Add, techniqueID=72, rating=5_U_3c300_C_PBS}--, scaling={u*_length: 0.4061, u*_quantity: 1}, context={}--
Ancestor NSID	1909
Costs	(see below)
State	failed__repairable__patches_exhausted
No of failed assets	7
Failures in intact network/total	0 / 26
voltage SUM (p/u)	0
voltage MAX (p/u)	0
voltage AVG (p/u)	nan
thermal SUM (MVA)	222.534759
thermal MAX (MVA)	9.592003
thermal AVG (MVA)	8.60985667857
Failures	(see below)
Exception	None

Costs:

	TOTEX	CAPEX	OPEX	Metrics
Integral	1989786.03953	1989788.35168	-2.31214953271	0.0
This year	1989786.03953	1989788.35168	-2.31214953271	0.0

Opex from patches in current y = -2.31214953271

Failures:

AGID	Description	Failures intact/total	Max load (MVA)	Max p/u overload
3842 - 1437480558.49	G67020713_CJ01 - 41D5278_RM01	0 / 2	9.556713	1.023669
2151 - 1437480558.49	G71658809 - G71660928	0 / 3	9.480976	1.015556
2421 - 1437480558.49	ALIAS-8223582-e - ALIAS-8223137-e	0 / 3	7.556758	1.016992
3151 - 1437480558.47	41D5135_RM01 - 41D5254_RM01	0 / 3	7.234337	1.026228
2286 - 1437480558.47	41D5511_RM01 - G67020719_CJ01	0 / 4	9.592003	1.044502
4583 - 1437480558.48	41P0034_MJ07 - G71658809	0 / 5	9.586025	1.026808
4304 - 1437480558.5	N532714_CJ01 - ALIAS-8223582-e	0 / 6	7.632169	1.027141

Figure 5.13: Network State Details

Figure 5.13 details an individual network state which are available in the ancillary visualisation of an experiment expansion tree. This includes network state ID, expansion year, ID of the parent network state, state status (e.g., failed_repairable _patches_exhausted), information about the last applied patch (traditional reinforcement cable replacement), including the application details that correspond to the modification of a network diagram and patch costs, number of assets that remain failed in the network state and a summary of remaining failures-average, total and maximum values for thermal and voltage failures.

At the bottom of the list is the detailed list of failures by asset. It was identified by planners as an indispensable tool to help validate the system and correlate the expansion trees to the actual assets on the network diagram. The failure details table contains asset id and description alongside information about the number of failures in intact and n-1 operating modes as well as absolute and per unit thermal and voltage failure magnitude.

The SIM calculates patch costs using cost drivers returned by the network modelling tool. The cost driver describes a network intervention and consists of two parts, namely, patch key and the scaling. The patch key identifies the nature of the modification of the network performed (removal or addition of an asset and the type of the asset). Scaling data is relevant only to patches that can be installed in multiples of one, such as cable upgrades and additional transformer installation. Scaling data structure provides a list of multipliers to the base cost data available in the SIM database. In case of cable upgrade or replacement, it enables the SIM to correctly estimate full installation costs from per unit of length values. For each network state the SIM works out the total cost comprised of CAPEX or one time installation cost, OPEX or recurring operating cost and Metrics cost which is equal to the sum of incentive payments. The interface, as depicted in Figure 5.13, provides two sets of costing data: the cost incurred in the current year and the overall costs that is spent to reach the current state of the network. All reinforcement costs are subject to net present value normalisation.

5.5 2015-2023 & 2015-2047 Experiments under DECC2 and DECC4

Two set of experiments were performed for this study, one for comparing short-term evaluation period for RIIO-ED1 (2015-2023) where the RIIO-ED1 investment planning has been stylised, and a longer planning period for RIIO-ED1 to RIIO-ED4, from 2015 up to 2047. The other set aimed to evaluate different DECC demand scenarios.

Demand data modelling has been based on a bottom-up approach. The methods used provide an estimate of demand for each half-hour at each secondary substation for 18 different season-day types (Western Power Distribution, 2015).

Table 5.2: Demand scenarios

Demand scenarios	Fuel efficiency	Low Carbon heat	Wall insulation
DECC 1	Medium	High	High
DECC 2	High	Medium	High
DECC 3	High	High	Low
DECC 4	Low	Low	Medium

Experiments evaluated two demand scenarios: DECC2 and DECC4. DECC4 represents, as displayed in Table 5.2, the slow-progression scenario and DECC2 is with DECC3 the most challenging scenario in terms of electrification and low carbon technologies integration.

The procedure to run the experiments in the SIM is shown in Figure 5.9 and the data flow throughout an experiment can be seen in Appendix B on this thesis. The inputs to be send to the SIM are detailed in Figure 5.5, the selected network, techniques, evaluation period, demand scenario and cost model. Whereas as outputs of the SIM we obtain, techniques used, failures solved, assets fixed and electrical performance indicators.

The SIM address mentioned outputs for long-term planning reinforcements, to optimise investment assets planning resolving network constraints. The performance criteria evaluated were Capital Expenditures (CAPEX), Operating Expenditures (OPEX), Utilisation of assets, CMLs, CIs and Losses. These parameter values are delivered by the SIM after each simulation. In order to look for the set of feasible solutions among the expansion tree pathways, the SIM allows a granularity study of each network state.

5.6 Results

This section presents the assessment of the six smart grid interventions along with traditional reinforcements in the FALCON trial area, compounded by six 11kV primary in Milton Keynes, for two different evaluation periods, DECC2 and DECC4. Subsection 5.6.1 introduces the results for 2015-2023 period as short-term planning, and 5.6.2 presents the results for a long-term evaluation period, 2015-2047.

Table 5.3: Number of interventions and CAPEX involved, DECC4 & DECC2, 2015-2023

	DECC4		DECC2	
Technique	Proportion of interventions %	CAPEX %	Proportion of interventions %	CAPEX %
DAR - Cable	15%	2%	14%	2%
DAR - Transformer	7%	1%	5%	1%
ALT	0%	0%	0%	0%
Mesh	3%	1%	4%	1%
Batteries	0%	0%	0%	0%
DSM	0%	0%	0%	0%
DG	0%	0%	0%	0%
TRAD - Transformer	8%	3%	7%	2%
TRAD - Cable	60%	89%	65%	91%
TRAD - Transfer Load	6%	2%	4%	1%
TRAD - New feeder	1%	2%	1%	2%

This section presents the assessment of the six smart grid interventions along with traditional reinforcements in the FALCON trial area, compounded by six 11kV primary in Milton Keynes, for two different evaluation periods, DECC2 and DECC4. Subsection 3.1 introduces the results for 2015-2023 period as short-term planning, and 3.2 presents the results for a long-term evaluation period, 2015-2047.

5.6.1 Short-term planning

In this subsection are introduced the results for the evaluation period 2015-2023 (RIIO-ED1). For each load demand scenario considered (DECC2 and DECC4) are presented the expected investments disaggregating CAPEX and OPEX, the number of techniques applied with the corresponding CAPEX and the relationship between techniques applied, failures solved, and assets fixed by type. This section concludes with a comparison between the solutions obtained for each demand scenario and a brief summary of the findings.

5.6.1.0.1 DECC4, 2015-2023 Figure 5.14 shows the trends of CAPEX and OPEX. Note that in the year 2015, there is a CAPEX's peak due to the application of more techniques. OPEX increments over time from 2017 to 2023.

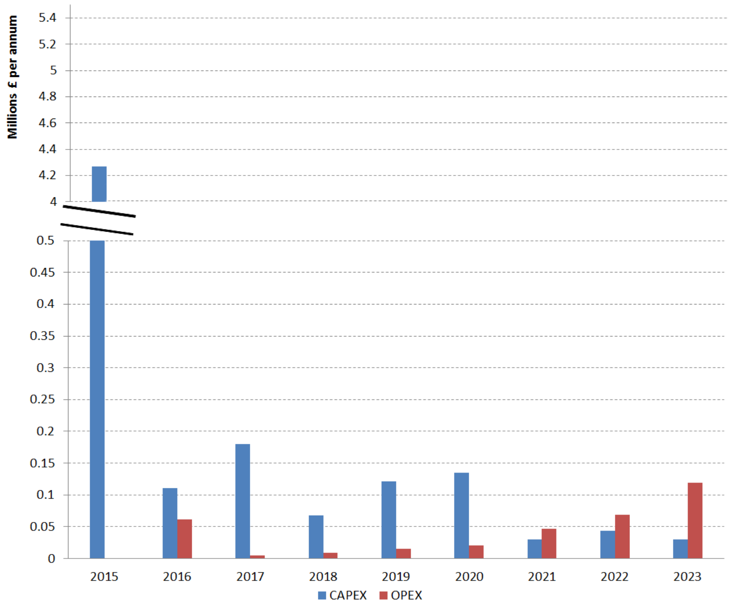


Figure 5.14: CAPEX & OPEX, DECC4, 2015-2023

Despite investment increase is compensated by a benefit in the electricity distribution network, with a reduction in CML, CI as shown in Figure 5.15.

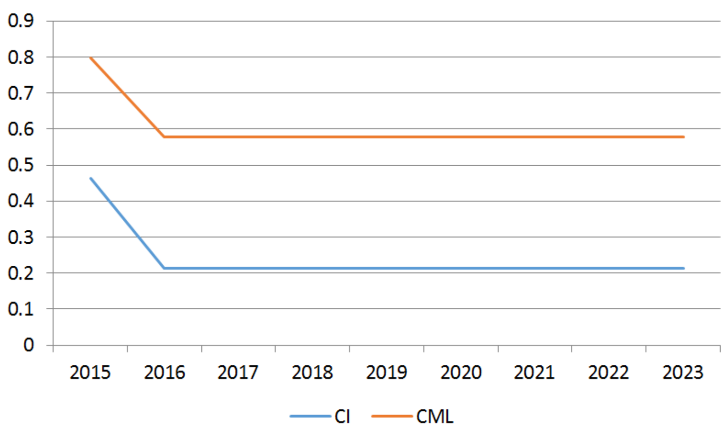


Figure 5.15: CML & CI, DECC4, 2015-2023

The summary of the proportion of installations required during this evaluation period and by capital expenditures per technique are presented in Table 5.4 for both DECC scenarios.

The average yearly price of each technique implemented to fix a network state is key for future decision-making considerations. Figure 5.16 displays the average price of each technique disaggregated by CAPEX and OPEX.

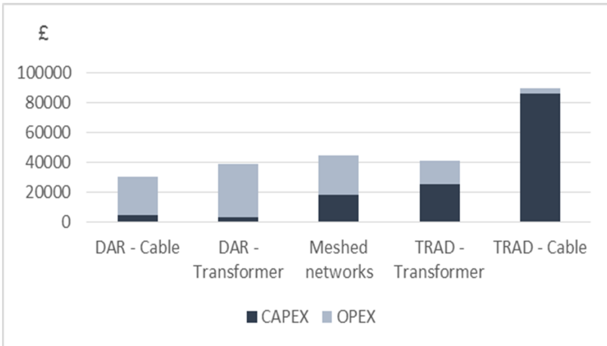


Figure 5.16: Average cost disaggregation per technique, DECC4, 2015-2023

Performance indicators are key parameters for future decision making within electricity distribution planning as quantifiers due to their influence on quality of service.

Therefore, as shown in Figure 5.17, the only technique that is able to improve CML and CI is Meshed networks.

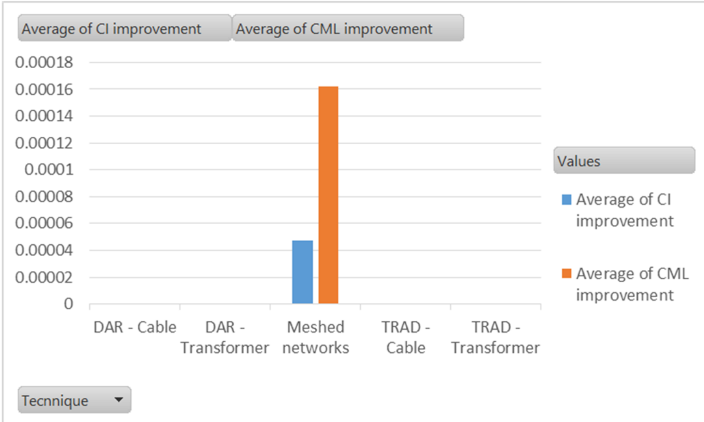


Figure 5.17: Average CML & CI improvement per technique, DECC4, 2015-2023

5.6.1.0.2 DECC2, 2015-2023 Figure 5.18 plots the trend of CAPEX and OPEX over the evaluation period. It is important to highlight that there is a CAPEX peak in 2015, due to an increase of techniques applied in this period. This CAPEX increment produces a benefit in terms of CML and CI, as observed in Figure 5.19. The distribution of techniques applied and capital expenditures per technique are shown in Table 5.3. The average price of each technique implementation in this demand scenario for this evaluation period, is shown in Figure 5.20.

As displayed in Figure 5.17 for DECC4's simulation, the only smart grid technique that improve power quality is Meshed network. In Figure 5.21, it is captured the average improvement of CML and CI for DECC2 scenario evaluation.

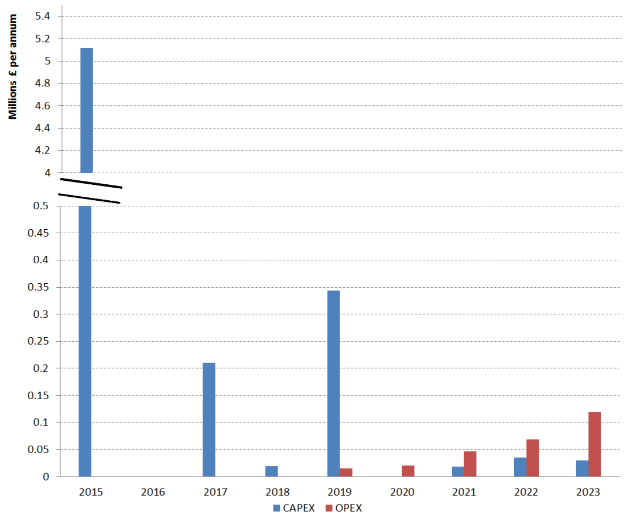


Figure 5.18: CAPEX & OPEX, DECC2, 2015-2023

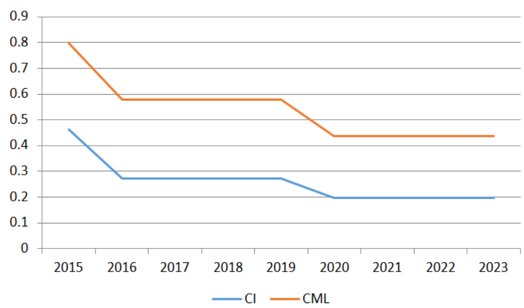


Figure 5.19: CML & CI, DECC2, 2015-2023

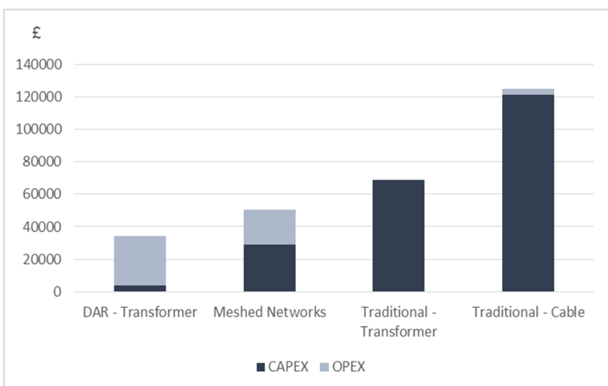


Figure 5.20: Average cost disaggregation per technique, DECC2, 2015-2023

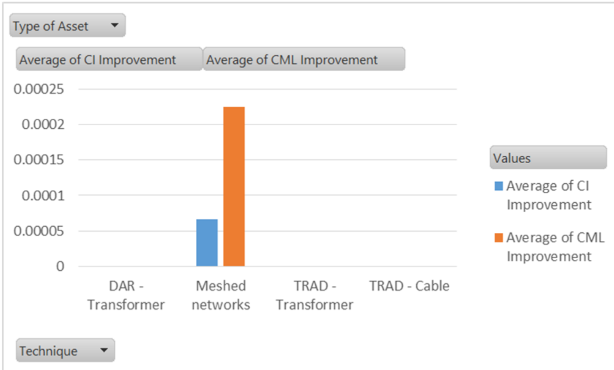


Figure 5.21: Average CML & CI improvement per technique, DECC2, 2015-2023

5.6.1.0.3 Comparison between DECC2 and DECC4 for 2015-2023

The results presented may facilitate improvements in electricity distribution networks operations and planning resulting on better informed decision making when upgrading current electricity distribution networks. The assessment of the six smart grid techniques discovered that only three of them were selected as part of optimal solutions for DECC4 and two in DECC2, as described in Table 5.3. These three techniques applied, are DAR for cables and transformers, and Meshed networks.

For DECC 4 are applied the three mentioned techniques along with traditional cable and transformer replacement (Table 5.3), whereas for DECC2 are applied two of them, DAR for cables and Meshed networks (Table 5.3). Comparing the cost trends of the two assessed scenarios, it is notable that in DECC4 the CAPEX peak occurs in 2015 (Figure 5.18), whereas in DECC2, beside the 2015s peak, there is also one in 2019 (Figure 5.18), reflecting the more difficult nature of network states to be fixed in a demanding scenario. Whereas, DECC2 shows a higher improvement of electrical performance indicators as can be seen in Figure 5.19.

The techniques applied are the key consideration to be assessed. It is necessary to analyse the number of interventions applied by type, the effect of these techniques in the electric grid solving failures and fixing assets. Figures 5.16 and 5.20 show average prices of techniques used in each demand scenario. Smart techniques have a lower TOTEX than analogous traditional reinforcements, however these novel techniques are not frequently able to fix failures and therefore produce feasible network states.

The only technique able to reduce CML and CI values is meshed networks as showed in Figures 5.17 and 5.21. Results attribute the majority of fixes to traditional reinforcements with a comparatively smaller number of failures being solved by smart techniques. In addition, traditional cable replacement, DAR for cables and meshed networks are able to fix cable, whereas traditional transformer replacement and DAR for transformers are able to fix transformer issues. The results obtained in terms of traditional reinforcements share for 2015-2023, show a 60% for DECC4 and a 65% for DECC2, which is close to the 59% forecasted by the Transform model for this evaluation period.

5.6.1.1 Long-term planning

This section evaluates two experiments namely characterising the DECC2 and DECC4 scenarios for 2015-2047 evaluation period. For each demand scenario are presented, expected investments disaggregating CAPEX and OPEX, the evolution of electrical performance indicators and the number of techniques applied.

5.6.1.1.1 DECC4, 2015-2047 In this experiment, are presented the most significant results to analyse the suitability of each technique. Figure 5.24 shows the trend of CAPEX and OPEX from 2015 to 2047. There are CAPEX peaks in year 2018 and during the beginning of RIIO-ED2 in years 2025 to 2026, due to the application of more techniques to fulfil low carbon targets. Figure 5.23 indicates that upgrades on the network are directly related to technical performance indicators, CML and CI.

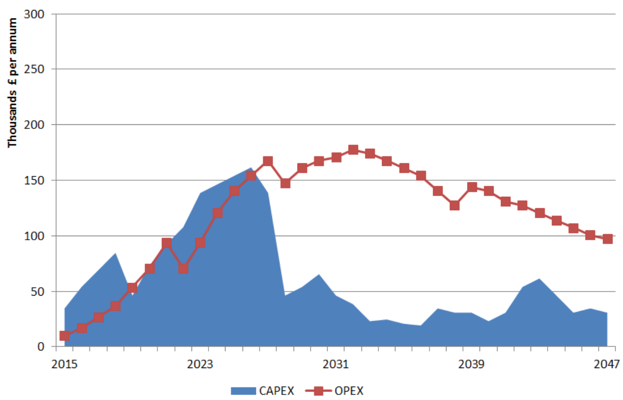


Figure 5.22: CAPEX & OPEX, DECC4, 2015-2047

In Table 5.4 are shown the techniques applied and its contribution to CAPEX during the evaluation period 2015 to 2047 by demand scenario.

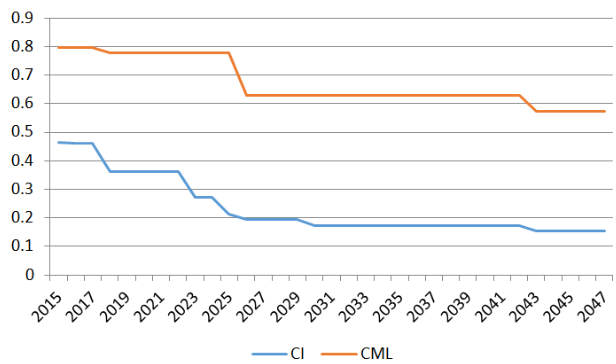


Figure 5.23: CML & CI, DECC4, 2015-2047

5.6.1.1.2 DECC2, 2015-2047 Within this experiment are presented the most relevant results to analyse the evolutionary network states. In figure 17 is shown the trend of CAPEX and OPEX from 2015 to 2023. There is

Table 5.4: Number of interventions and CAPEX involved, DECC4 & DECC2, 2015-2047

	DECC4		DECC2	
Technique	Proportion of interventions %	CAPEX %	Proportion of interventions %	CAPEX %
DAR - Cable	18%	5%	31%	6%
DAR - Transformer	32%	16%	32%	6%
ALT	0%	0%	0%	0%
Mesh	8%	3%	6%	3%
Batteries	0%	0%	0%	0%
DSM	0%	0%	0%	0%
DG	0%	0%	0%	0%
TRAD - Transformer	25%	44%	9%	16%
TRAD - Cable	15%	29%	20%	66%
TRAD - Transfer Load	1%	1%	1%	1%
TRAD - New feeder	1%	2%	1%	2%

a significant increase of CAPEX in years 2024 to 2026 at the beginning of RIIO-ED2, due to the necessary implementation of new techniques to reach low carbon targets. Evolution of CML and CI are presented in Figure 5.25, linking larger investment years when mayor reductions are found.

Contribution of each solution technique is presented in Table 5.4.

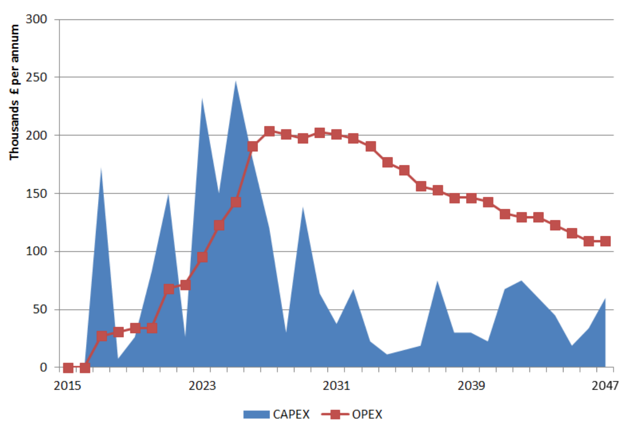


Figure 5.24: CAPEX & OPEX, DECC2, 2015-2047

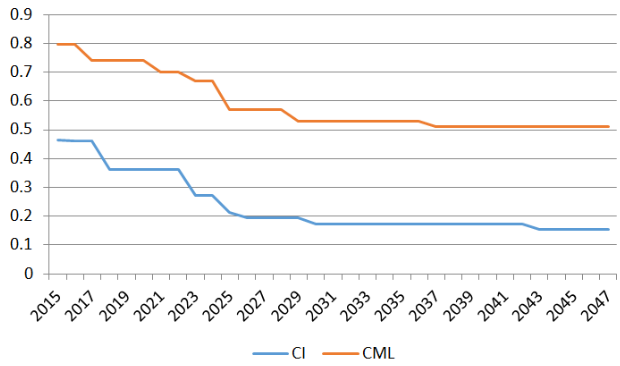


Figure 5.25: CML & CI, DECC2, 2015-2047

5.6.1.1.3 Comparison between DECC2 and DECC4 for 2015-2047

Figure 5.26 presents a multi-dimensional parallel coordinates representation of the feasible network state's combinations that produced a 2015-2047 investment pathway for the evaluated area.

Table 5.5: Summary of Network States and Results for demand scenario DECC4 & DECC2

Primary 11kV substation	Feeders	Year	Techniques	Results DECC4	NS DECC4	Results DECC2	NS DECC2
Fox Milne	13	2047	Smart and Traditional	54	276	47	259
Newport Pagnell	9	2047	Smart and Traditional	48	317	31	318
Secklow Gate	9	2047	Smart and Traditional	27	29	15	16
Bletchley	19	2047	Smart and Traditional	32	40	21	48
Marlborough Street	11	2047	Smart and Traditional	31	52	19	37
Childs Way	17	2047	Smart and Traditional	67	398	54	181

It bundles economic indicators, i.e. CAPEX and OPEX, with technical performance indicators providing valuable insights on the amount of traditional reinforcements utilised to heal falling network states. Results are also clustered by the two demand scenario assessed during the experiments.

Solutions of DECC 2 (represented in red and green) and DECC4' solutions (in black and blue) are clustered by the percentage of traditional reinforcements utilised as well as the utilisation factor. Solutions in green and in black represents those where smart grids were more used. Whereas orange and blue

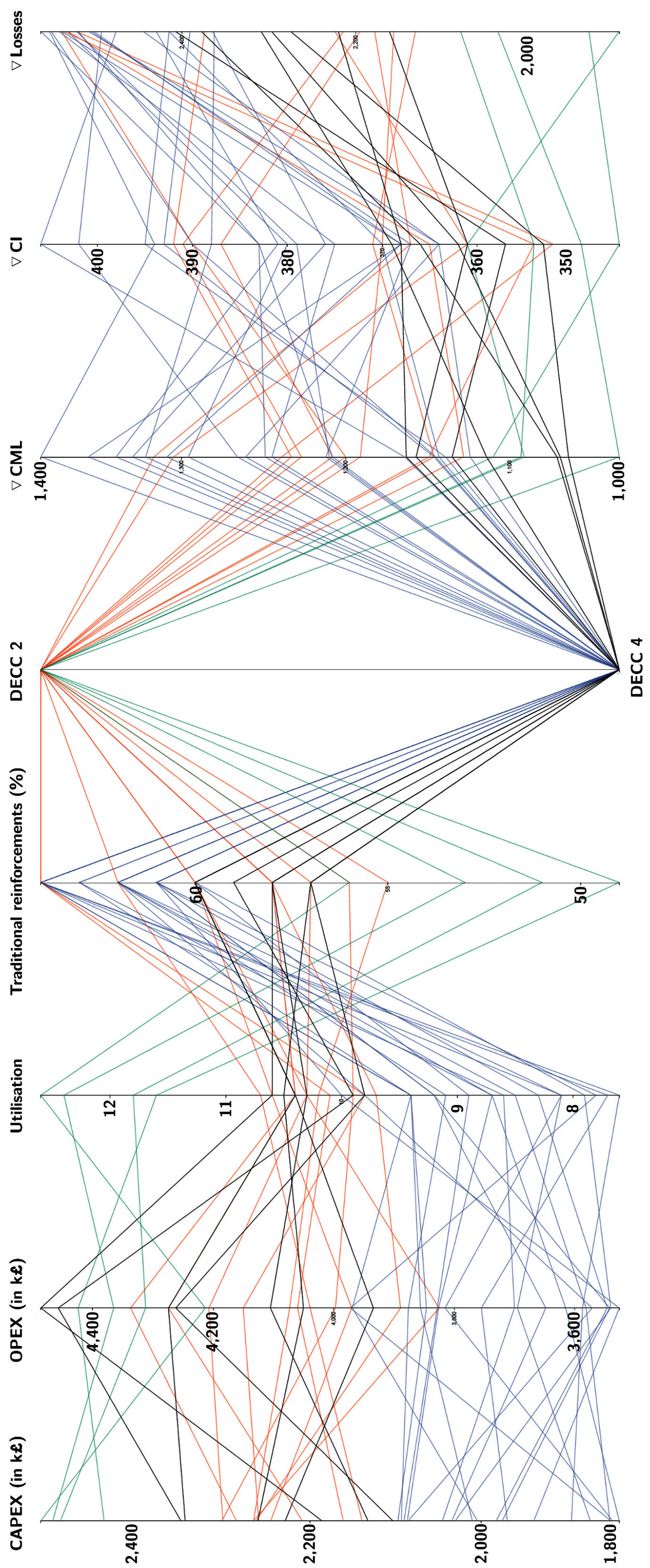


Figure 5.26: ||-coordinates visualisation of techno-economic performance indicators under DECC4 & DECC2

represent the cheapest (CAPEX and OPEX), less utilised, worst responding to decrease of CML, CI and losses, and the ones using more traditional reinforcement to fix network states.

Beside of the facts that DECC2 smart solutions are between a 16% and 38% more expensive than DECC4 traditional reinforcement solutions, and DECC2 traditional solutions are in the range of costs of smart solutions of DECC4, can it also be concluded that investment pathways using more smart techniques, are better suited to respond to technical performance evaluators such as assets utilisation, CML, CI and losses.

5.6.2 Summary

Experiment evaluation runs from period 2015-2047 show lower investment rates for the period 2015-2023 than if the evaluation is just performed with a 2015-2023 time-frame. This occurs as a result of the challenging low carbon targets up to 2047 and a myopic planning when planning with short-term lookahead. For a four times larger evaluation period, the CAPEX and TOTEX increased just 18% compared to 2015-2023, concluding that between £5.2M and £6.8M is required on the evaluation area regardless the time horizon for the investment or the demand scenario considered.

Furthermore, it can be inferred comparing Tables 5.3 and 5.4 that for the shorter term planning less smart interventions are used compared to the long-term horizon planning. DAR-Cable and Transformer replacement experienced a significant implementation variation between DECC4 and DECC2, as well as, CAPEX allocated in Cable upgrades. Both technical performance evaluators, CML and CI, respond to their respective CAPEX curve shape. Due to more incentivised smart grids technique during RIIO-ED2 and ED3, percentage of smart techniques implemented varied notably. For DECC4 in 2023's outlook the share of techniques is 25% for smart grid interventions whereas for 2050's outlook the share is increased up to 58%. In the same way for DECC2 in 2023's outlook the share of smart interventions is 23% whereas in 2050's outlook the share increases up to 69%.

Feasible solutions characterising the solution space (Figure 5.26) differ in the degree of investment required and technical performance evaluators. Disaggregating results by network states the six 11kV primaries, and by feeder if necessary for further granular debugging, can be discern locational capacity. Under both demand scenarios, Secklow Gate was seen the one with greater capacity, being necessary to apply less techniques over the evaluation period, 2015-2047. On the other hand, Newport Pagnell exceed capacity as soon as 2015, requiring a high number of network states evaluation to be fixed and that happens for each subsequent year, hence the large number of NS presented in Table 5.5.

5.7 Conclusions

Power flow analysis using a nodal network model is essential when determining the benefits of trailed smart interventions because these are highly specific to a particular location and scenario. This suggests that while the bottom-up approach is onerous in terms of data handling and manipulation, this is worthwhile for strategic planning and policy evaluation. Comparing both investment strategies, investment strategy adjustments will be necessary in future regulation periods if an over-invested network behaves as displayed in the short-term section of this study.

The model has demonstrated that using currently available hardware and off the shelf power flow analysis module it is possible to perform computationally and data intensive simulation comprising hundreds of thousands of power flows in a reasonable amount of time. The rigour of automated network analysis performed by the SIM provides the needed rationale for investment decisions for a DNO in the challenging regulated market. The network development plans consider long-term asset performance and costs and its effect on the entire network in deciding which interventions are the most optimal. This contrasts with the current practice of choosing the option that is cheapest in the short term.

The architecture of the model provides an interface for pluggable EN&S technology models. This means that new intervention techniques can be added later to the SIM, once the respective technology becomes available. Because the technologies are applied automatically, existing studies can be readily updated to include the latest EN&S technologies. The tree-based based expansion approach allows the SIM with no prior knowledge to dynamically learn the costs pertaining to keeping a particular piece of the network compliant. This expansion architecture also allows the SIM to backtrack on the decisions it had taken earlier should the recently expanded branch turn out to be suboptimal.

While traditional reinforcement will continue to be the main method by which network issues are mostly resolved, followed by dynamic asset rating and meshed networks. Batteries only tend to be selected once other options are exhausted and the relative scarcity of demand side management options limits its use.

The assessment of the six novel smart interventions in the FALCON 11kV primary test area in Milton Keynes, have proved the suitability of three techniques able to fix failures, improving the quality of service and ready to be deployed in the near future. These techniques are DAR for cables, DAR transformers, and Meshed networks. Meshed networks have been repeatedly selected as a feasible because using it will reduce CML, CI and power losses, improving the quality of service, the efficiency, while being a cost-effective solution.

The initial capacity at primary substations differed significantly and this affected the number and complexity of interventions required by the SIM. Due to the load scenarios showing significant peak load increases, DAR was often a temporary measure that would delay but not remove the eventual need for traditional reinforcement.

Implementing DAR for cables and transformers the monitoring of assets when their peak capacity is increased was analysed. In addition, it was found that smart techniques are applied in more onerous conditions, such as when failures are caused in winter peak days and within peak hours. On the other hand, it was observed that traditional reinforcements still play a key role in keeping the electricity distribution networks free of constraints. TRAD techniques such as transformer and cable replacements are able to fix majority of failures and will be essential also in the future.

The comparison between traditional reinforcements and novel smart techniques, have provided a new knowledge about the suitability of each technique to be applied, in terms of costs, electrical performance, failures fixed and asset replaced. Cables replacement is the most costly technique; however its use is unavoidable in a number of cases. Furthermore, the applicability of each technique regarding to costs involved, improvements on power quality and efficiency, and failures solved lead to new questions to be analysed, such as the lack of these techniques to provide flexible capacity within the trailed area.

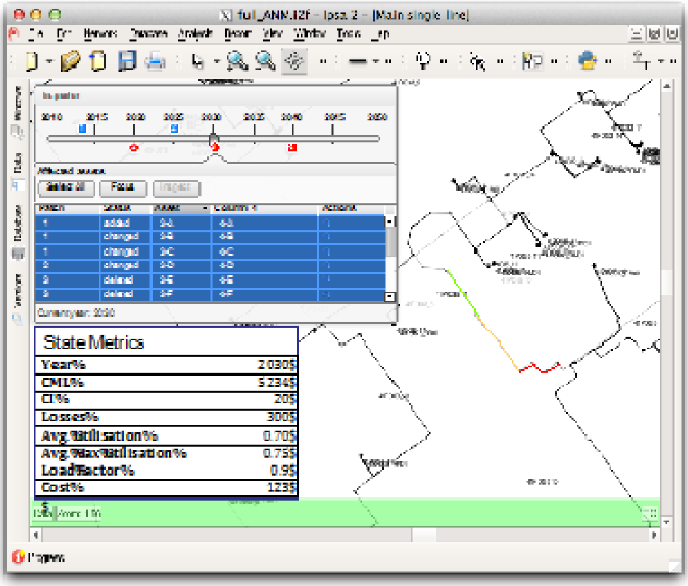


Figure 5.27: Disaggregation of results visualised by distribution feeder

DG and DSM, were a success and prove that they can be made to work and lead to a change of the current industry structural paradigm, moving towards a end-customer-centric market design to support DSM type of services. Locational implementations can be disaggregated down to substation level as presented in figure 5.27 and proposed for further analysis as future work.

The main contribution of the SIM towards the network process is due to the tree-based approach to the network reinforcement process. This makes this approach the main target of future research and development. The modified A* algorithm that is used in the model had been chosen for its relative simplicity. However, our experiments demonstrated that a form of learning feedback loop is required due to inconsistent number of patches and costs that are required to resolve all failures in a particular network state. This defines the main area of future research aimed toward enhanced heuristic search algorithms which may be based on approaches other than graph search, for example Evolutionary Algorithms as stated in Chapter 3.

To sum up, this research has performed a comparative analysis of novel smart intervention techniques, providing insights for future investments in electricity distribution planning. Further work can focus on scaling up the analysis to include a larger section of the network, or a constrained area to evaluate national applicability of current findings.

Chapter 6

Dynamic Investments in Flexibility Services for Electricity Distribution with Multi-Utility Synergies

Low Carbon technologies implementation are challenging current paradigms and requiring a significant shift on how distribution planning of power systems is conceived. Benefits for an adequate transitioning to a more flexible energy system is an ongoing debate where three options are proposed by innovators - interconnections, energy storage and demand side management. Selecting the optimal combination of those options and the pathway for electricity network upgrading, together with investments in flexible and resilient services to cope with local intermittent energy production, would urge to prompt changes on distribution utilities business models and their economic value in the supply chain (Bahramirad et al., 2015) (De Moraes and Carpio, 2006) (Conejo et al., 2016).

DNOs are seeking more active alternatives to conventional reinforcement in order to reduce network operation costs while increasing security of supply in the face of greater uncertainty in patterns of future load flows. The transition to Distribution System Operators (DSOs) would be accompanied by a change in system operations, moving from a centralised system to a detailed local bottom-up approach Ruester et al. (2013). This research develops a bottom-up methodology to evaluate the contribution of four flexibility services, namely smart contracts, aggregation, demand response and peer-to-peer trading. The application is to large scale British distribution area using a detailed network topology, national scenarios for power system demand, and a computationally-intensive, multi-stage optimisation methodology. This chapter highlights the potential of Multi-Utility options to create flexibility business models that may compete with traditional reinforcement and smart grid techniques to optimise where and when flexible capacity in the grid will be required.

6.1 Introduction

Distribution networks investment uncertainty is a complex problem, where traditional deterministic models are in need to be revised to overcome present and future decision-making challenges. Proliferation of distributed renewable generation and other low carbon technologies are creating new challenges for DNOs, increasing alternatives to conventional reinforcement in order to reduce network operation costs, increase security of supply and allows a more reliable renewable generation to be connected to the grid (Teng et al., 2016). Selecting the optimal combination of interventions in regards to long-term cost and performance of the network is something that the current tools and approaches used by the industry cannot adequately do. This study tackles these challenges in order to aid quantifying the value of a resilient and flexible robust power network.

Historically, electricity distribution networks have been designed to provide reliable connections to the customers by virtue of asset ratings sufficient to cope with peak demand. With the proliferation of low carbon technologies such as electric vehicles, heat pumps and distributed generation, the network is starting to experience congestion both, load and generation driven . The congestion restricts further deployment of distributed energy generation, making it more difficult to meet the emission reduction targets (Aguero et al., 2016).

Around two-thirds of current coal, nuclear and gas power stations are expected to be decommissioned by 2030 as they are reaching the end of their lives. The near term where new capacity has to be built, and the consideration of alternative more flexible sources lead to a paradigm change on how networks are operated. For 20 years since early 80s electricity distribution networks in the United Kingdom were experiencing steady and slow load growth of around 2 percent per year (Lakervi and Holmes, 1995). The growth was quantitative rather than qualitative, it did not change the demand structure and power flow direction within the network. Therefore, planning of changes in the network to accommodate the load growth was a relatively straightforward process (Koch, 2015).

Energy storage (ES) as well as interconnections and demand side response will provide an alternative approach to relieve network congestion by balancing periods of low and peak demand. ES is charged during periods of low demand and high generation and discharge during periods of high demand and low generation, therefore solving both types of congestion. Flexibility is defined here as the ability of a system to deploy its resources to respond to changes in net load, where net load is defined as the remaining system load not served by variable generation. Hence, an isolated power system containing mostly generation units with long start up times and low ramp rates will find it more difficult to successfully integrate variable generation than a well interconnected power system, containing many generation units which can start up and ramp quickly (Lannoye et al., 2012). One of the emerging challenges in whole systems planning is to quantify the resilience of a system to successfully respond to ramping events, and thus to include that flexibility reserve in their business portfolios (Sioshansi, 2015) (Schachter et al., 2016).

Electricity is distributed around the UK by DNOs, licensed by the regulator, Ofgem. They own and run the distribution network of pylons and cables that carry electricity from the national transmission network (owned and managed by National Grid) to homes and businesses (Bolton and Foxon, 2015), (Buchholz and Styczynski, 2014). DNOs do not sell electricity, they only distribute it. DNOs are regional monopolies, so Ofgem set price controls to manage the cost of electricity distribution to customers. Ofgem have recently introduced a new performance based price control model for DNOs. The RIIO model is designed to drive the innovation needed to tackle the challenges above. This incentive-based regulatory framework will run from 2015 to 2047, with 8 years evaluation period is still to be finalised (Ofgem, 2014). At the moment, each DNO has its own cost structure and it is expected the charges will vary with each RIIO period.

Connecting more small-scale renewable generation projects located throughout the UK to the network, including solar photovoltaic (PV) panels, wind turbines, hydroelectricity, anaerobic digester and micro combined heat and power (CHP), matching the electricity demand for new technologies, including electric cars, lead to an integration of multiple agents across the energy value chain beyond electricity (e.g., water, thermal and transport) requiring a shift of market designs (Bichler et al., 2010). The raising need for more flexible systems could lead to a re-emergence of multi-utility companies to contribute proposing new flexibility business propositions as demand response or acting as aggregators (Varga et al., 2015).

6.1.1 Evolutionary planning for addressing uncertainties

At the moment, the innovation in Electricity Networks and Storage (EN&S) technologies is riddled with uncertainty regarding which technologies to choose, which investment to support and how the choices would evolve in the long term (Moslehi and Kumar, 2010). With many alternatives to conventional network reinforcement available and being developed, e.g., distributed generation, various forms of energy storage (Kondoh et al., 2000), demand response (Poudineh and Jamasb, 2014), mesh networks (Behnke et al., 2005), dynamic asset rating (Yang et al., 2015), it becomes difficult for DNOs, regulators and policy makers to find an optimal network investment roadmap, pick the right mix of EN&S technologies to create local network development plans and forecasts the costs of optimal electricity distribution.

Despite the differences in their respective approaches, current models and software tools share some common limitations. They have limited ability to capture emerging behaviour arising from simultaneous application of multiple EN&S technologies to the electricity distribution network. Likewise, it is difficult to add new EN&S technologies into the mix, either due to lack of automatic application of smart techniques or, as is the case with TRANSFORM model (EA Technology, 2016), the parametric approach needs information about the way different technologies compete with each other, which is difficult to obtain. And finally, no decision support for a particular piece of distribution network can be provided either because of lack of automation or the parametric nature of the model.

The SIM represents a step change in the modelling, optimisation, and decision support of distribution planning and investment modelling of electricity distribution networks. Unlike conventional network modelling tools, that are designed for network state assessment in static load conditions, the SIM performs network state assessment under variable load conditions. More importantly, it performs network state expansion using models of EN&S technologies and optimisation of resulting dynamic network development scenarios.

Evolutionary networks will require a change of how flexibility business propositions are conceived nowadays. The following section presents four flexibility options with different levels of uncertainty from a DNO perspective as stated in Figure 6.1. Those uncertainties will be quantified in an evolutionary manner for each year Real Option Valuation (ROV) to quantify the risk that each business proposition have attached (Housel and Mun , 2006).

6.1.2 Business models for Flexibility Services

Traditional business models cannot cope with an increasingly demanding EN&S request to have a more active management role of local distribution networks. Increasing penetration of distributed energy resources (DERs) such as renewables, electrical transportation, smart appliances, or electrification of heat pumps, are augmenting the necessity of new business options for providing regulated and non-regulated energy agents new revenue streams.

Bussines Options	Comments
DSO	The DNO builds, owns and operates assets.DNO has full operational control. DNO is becoming a DSO coordinating portfolios of flexibility for both distribution and wider system benefit through a centralised control mechanism.
DNO contracting	DNO builds, owns and operates assets. DNO has full operational control. Prior to construction and during RIIO business investment commitments planning occurs, long term contracts (e.g 8 years) for commercial control of assets outside specified windows are signed.
Third-party servicing	DNO offers long term contracts (e.g 8 years) during RIIO investment commitments planning for services at specific locations with commercial control during certain agreed periods. Third party is responsible for building, owning and operating the asset, offering new additional revenue streams when assets performance is optimised.
Peer-to-peer incentive	DNO sets DUoS to create signals for peak shaving that reflect the value of reinforcement. As a drawback, DNO has no operational control so cannot schedule investments ahead due to end-users behaviour uncertainties.

Increasing uncertainty for DNO

Figure 6.1: Business Options proposition and description

There have been selected a range of business models propositions to represent coming disruptive options and the impact that will have on regulation, planning and operations. The four chosen business propositions comprises from a DSO with total operational control and no third party involved, to a Peer-to-peer incentive proposition where customers react to DUoS (Distribution Use of System) reduction incentives but has no commercial relationship with the DNO. In the middle, there are agreements or contracts between the DNO and a Third-party to provide a service as displayed in Figure 6.1.

Relationships among different domains, agents, transactions and contracts are presented in an schematic way in Figure 6.2.

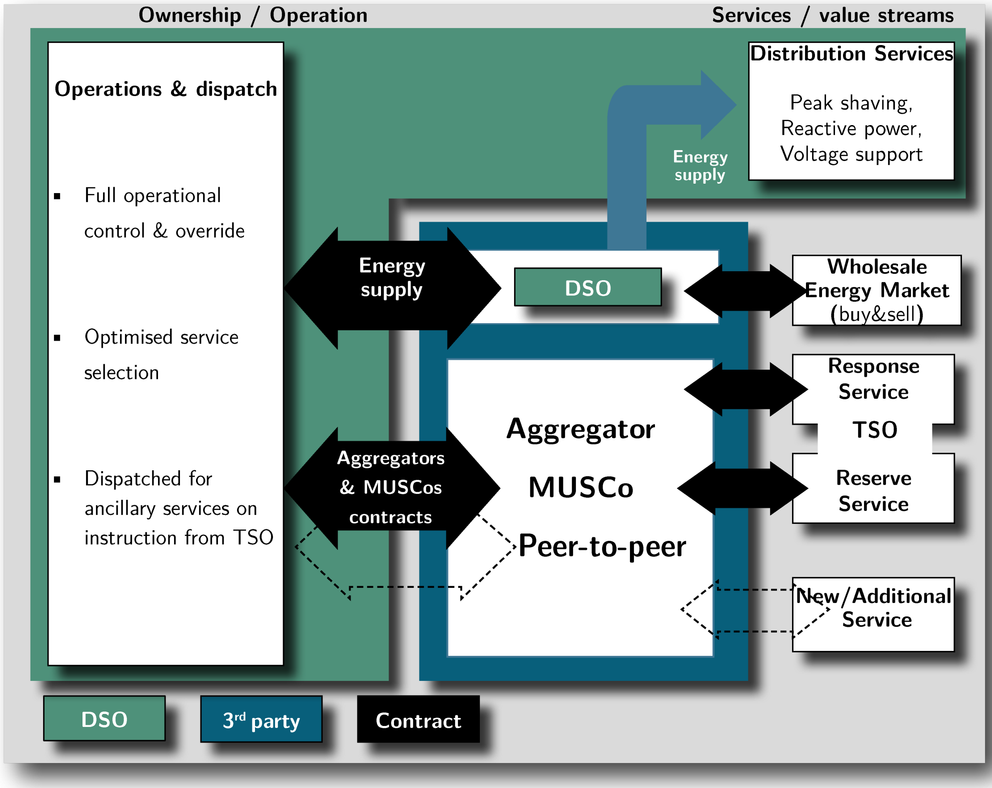


Figure 6.2: Business Domain interactions visualisation

6.1.2.1 Distribution System Operator

In this first Option, DSO proposition, despite it conflicts with current regulation, represents a business model where the DNO will take full ownership, operation and maintenance of the storage portfolio as part of their assumed role managing its licensed distribution area. It challenges the unbundling principle followed by many countries where DSO business splits off from DNO leading to the emergence of DSO as a potential new business entity in the value chin. This might allow the DSO to manage the risk and uncertainties of the value and operation of their assets. With this proposition the DSO will take some of the current roles from the TSO, adding some new ones such as owning and operating storage, which currently does not happen in the GB system (McGranaghan et al., 2016), however the Council of European Energy Regulators has recently characterised mechanisms to promote this transition, opening a consultation in 2017 (CEER, 2017).

This business model allow a futuristic DSO to manage a portfolio of storage, variable distributed generation and demand response services providing the capability to build, own and operate a more flexible grid where loads could be controlled.

6.1.2.2 DNO contracting

This Option involves a third-party for managing the capacity of storage assets portfolio when are not required by the DNO. As the previous Option, the DNO will build, maintain, and operate the storage, and when agreed with a third-party dispatch these assets for ancillary services.

The third-party will sign long term capacity contract, in our planning scenario, 8 years, a complete RIIO period but ideally these agreements in which an availability payment will be paid to the DNO, would be until the end of the operational life of the asset.

The DNO can compare investment decisions by comparing the Real Net Present Option for the availability payments for a long term capacity agreements with traditional reinforcements and other Smart Grid techniques implemented by the SIM.

6.1.2.3 Third-party servicing

If there is an Option where location planning matters for the DNO, since the DNO locate where the Third-party builds, owns and operates a storage portfolio for mitigating constraints on the network. In this business model, the DNO and the Third-party through an agreement establish the capacity security and storage requirements that have to be met.

The agreement to be signed will assure both parties a revenue stream. First, the Aggregator or Third-party, will be assured in that way a return over the lifetime of the asset from the DNO, but also, as they retain full commercial control can create additional revenues streams during periods where assets are not committed with the DNO.

6.1.2.4 Peer-to-peer incentives

A growing interest in Peer-to-peer energy trading raises questions over whether storage could help consumers gain extra benefit from distributed power generation and challenge current regulatory frameworks to provide non-traditional business options allowing, securing and promoting this type of decentralised competence. Under this business model, when planning at medium and long-term the DNO offers the right incentives for Peers for reducing their demand or even creating extra capacity within the network where required (Hall and Foxon, 2014) (Helms et al., 2016).

The DNO cannot rely when planning how much capacity is available when needed for operation and security purposes. In this case, the DNO would not hold operational control of the storage, since it is built, owned, maintained and operated by the Peer-to-peer third-party. This is an extra uncertain and have to be measured when DNO is planning a guaranteed security capacity.

6.2 Extending SIM for Flexible Real Options Valuation

The SIM software is a scenario-dependent, optimal-seeking feed-forward heuristic. For an exogenously defined scenario, each year is specified as a network state. The SIM search always starts with an unevaluated network state in the first year of the experiment (initial network state). Following a power flow study, the search either moves on to the following year, or, if the network state has failures, saves it into failed network states store. Evaluation then moves to the next year, so that the failed network states store accumulates all failed states contingent upon the scenario to its end date, before seeking to remedy any of them. Smart techniques implemented within the SIM (Nieto-Martin et al., 2017) are combined with traditional reinforcements (cables and substations upgrade, feeders upgrade or new installation) to overcome failed network states, defined by (Butans et al., 2017) and named as: Automated Load Transfer, Dynamic Asset Rating, Meshed Networks, Batteries, Demand Side Management and Distributed Generation. The SIM also evaluates traditional reinforcement techniques to solve network states namely, transformer and cable upgrades, new feeder installation or feeder upgrade.

Electricity bill contains an element of charge to cover electricity distribution costs (Rosado and Alba, 2014). Typically this distribution charge accounts for about 15% of the overall 29% of the electricity bill (Ofgem, 2016). The distribution charge covers the cost of operating and maintaining a safe and reliable electricity infrastructure between the transmission system and end users such as homes and businesses (Kind, 2013).

Distribution Network Operators are set an *allowed revenue* to cover a price control period. The allowed revenue is set at a level to cover most aspects of the DNOs on-going business including maintaining, repairing and replacing network assets (Du and Lu, 2014).

It also includes the costs of reinforcing some network assets (Hansen et al., 2009). The allowed revenue is mainly recovered from the electricity suppliers who use the electricity networks to distribute energy to their customers. A change on how allowed revenues are collected and its impact on DUoS tariffs will opening new revenue streams (Ochoa et al., 2016) (Connor et al., 2014). A patch for the SIM for integrating a customised ROV presented in Section 6.3, MURRA, has been produced to integrate business options discussed in subsection 6.1.2 within the SIM architecture, broadening SIM original methodology scope as displayed in Figure 6.3, increasing system resilience with a portfolio of flexibility value propositions.

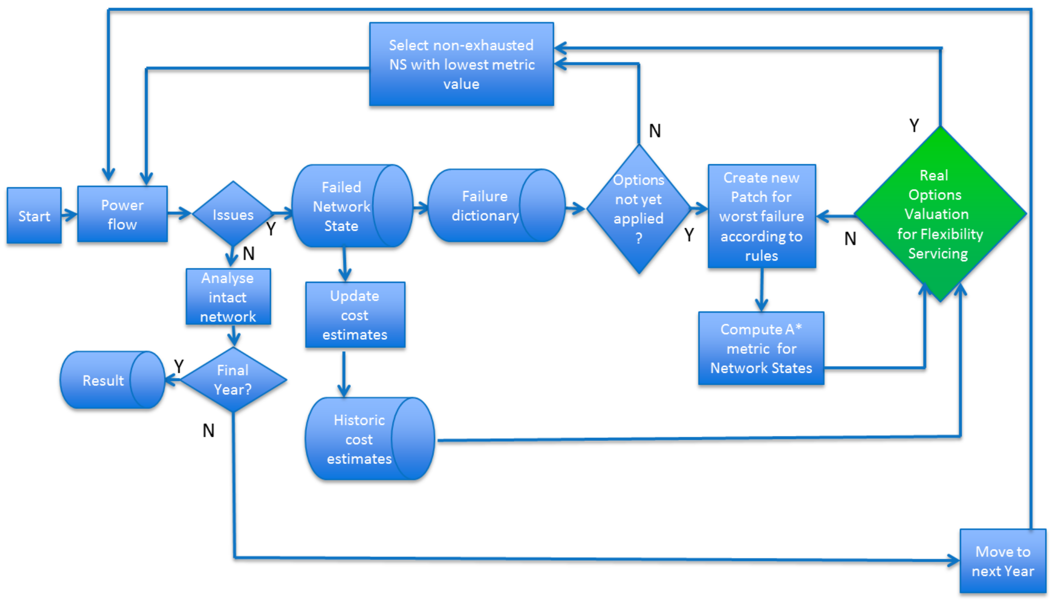


Figure 6.3: Integration of Real Options Valuation methodology within the SIM architecture

6.3 MURRA: Multi-Utility Resilience Rating Assessment

MURRA framework is proposed to be a customised Real Options Valuation (Bunn and Oliveira, 2007) (Chronopoulos et al., 2014) to compare short and long-term planning strategies that will complement the SIM software with the set of business propositions presented in subsection 6.1.2. As described in the metacode, Algorithm 1 (Figure 6.4), MURRA compares locational flexibility required at substation level with locational nodal prices from the SIM.

```
Algorithm 1: MURRA Business Options evaluation:
begin
    Initialise candidate population of yearly SIM solutions
    while stopping criteria not met do
        Solution population := update evolution year
        for each year in SIM solution do
            if (bOpt_t,i < SIM_t,i)
                bOpt pop_t,i : = bOpt_t,i
            else
                bOpt pop_t,i : = SIM_t,i
                bOpt pop_t,i ++
        Evaluate (bOpt pop)
        MURRA population := Extract (min bOption, bOption population)
        output solution MURRA population
```

Figure 6.4: MURRA metacode

6.3.1 Indices

i distribution nodes.

EA existing assets in the evaluation network.

MB multi-business Options propositions to be implemented.

t discrete time periods considered for business Options.

The first period (the *decision* period) and the last period in the analysis will be represented, respectively, as D and T.

The time elapsed between two periods will be referred to as Et_{t_1,t_2}.

mt multi-business propositions (Options). Each Option has different values and length of duration.

6.3.2 Parameters

$SIM_{t,i}$ SIM software value proposition for investment in node i in time t [£].

H_t horizon planning considered [y].

Vp_{im} value proposition for a particular multi-business Option [£/MWh].

$C_{t,i}$ capacity required in each node [kW].

Df_{t_2,t_1} discount factor to evaluate future Option value corresponding to date t_2 in value terms of a closer date t_1. It is calculated as:

$Df_{t_1,t_2} = e^{-\rho E_{t_1,t_2}}$.

ρ discount rate [p.u.].

6.3.3 Variables

$bOpt^{m_t}_{t,i}$ cumulative value of a candidate business Option m, proposition node i at time t. For clarification purposes, business Options m, will be represented within the solution visualisation as: *SIM, DSO, Outs, Agg, P2P.*

6.3.4 Objective function

The objective function evaluates locational business propositions against SIM traditional reinforcements and smart grid interventions:

$$min(\sum_{t=H}^{t}\sum_{i} Df_{t,H}(flexOpt^{m_t}_{t}) - \sum_{t=H}^{t}\sum_{i} SIM_{t,i}) \tag{6.1}$$

6.3.5 Constraints

Value proposition constraints:

$$flexOpt^{m_t}\sum_{im\in MB} Vp_{im}(bOpt^{m_t}_{t,i} - bOpt^{m_{t-1}}_{(t-1),i}) \tag{6.2}$$

$$bOpt_{t,i}^{m_t} \geq bOpt_{(t-1),i}^{m_{t-1}} \tag{6.3}$$

6.3.6 Calculation of Option values

D is the decision period. The decision to request a business service. The decision will be based on potential optimal business decision making (option value).

A is time duration when the contract agreement is granted (assumed to be up to 8 years, depending on the Option). Once the contract proposition has been made, the decision to pursue this agreement is not automatic. Service Options with an Option Value greater than $SIM_{t,i}$ will be pursued at that location.

S the period when businesses is already providing a service. This is assumed to happen 1 year after the service proposition is taken and services portfolio agreed between parts.

H final Horizon planning period in the analysis.

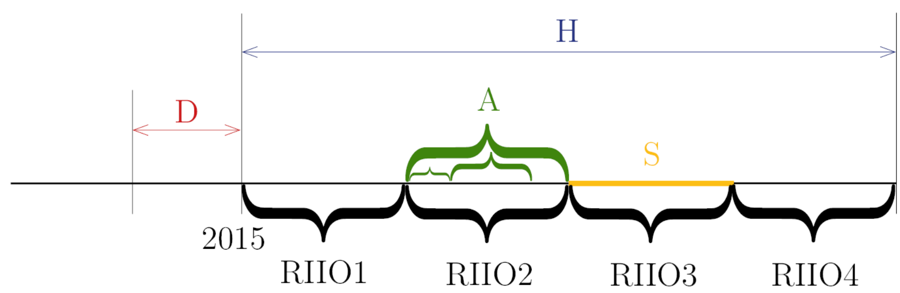


Figure 6.5: Visualisation of the planning Horizon, Agreement, Service and Decision time lines

Figure 6.5 visualise different planning and options periods while equation (6.4), present the scenarios where choosing the *SIM* option represents a potential loss, and therefore a quantifiable regret of not signing for alternative flexibility service.

$$
\begin{aligned}
OV(bOpt_{D,i}) = R\Bigg[\sum_{t=S}^{H}\sum_{m} Df_{t,D}flexOpt_t^{\frac{m_t}{bOpt_{t,i}^{m_t}}=0} - \\
-\sum_{t=B}^{H}\sum_{m} Df_{t,D}flexOpt_t^{\frac{m_t}{bOpt_{t,i}^{m_t}}=1} - \\
-\sum_{t=B}^{H}\sum_{m} Vp_{im}Df_{t,D} - \sum_{t=B}^{H}\sum_{m} SIM_{t,i}\Bigg]^{-}
\end{aligned}
\tag{6.4}
$$

It should be noted that our definition of option value is consistent with a European option, which implicitly assumes that the planner can decide to pursue the Option or not once the permit has been granted at the end of time D, as displayed in figure 6.5, but not later. The planner will normally have further opportunities to start requesting the service before the agreement expires.

However, due to locational network constraints agreement expiration dates are case dependent, so we assume that the permit can be used at the beginning of each RIIO period or abandoned, with no further actions taken. It is important to note that, given the investment is discrete, the differences in operation costs are based on increments rather than marginal information. If an investment plan has already been agreed, a service proposition can be cancelled if it is not considered profitable once the agreement has been granted and before service period starts. Following Option value reflects the possibility of cancelling or deferring the project. This case inverts the calculation of expected savings:

$$
\begin{aligned}
OV(bOpt_{D,i}) = R\Bigg[& \sum_{t=S}^{H}\sum_{m} Df_{t,D}\, flexOpt_t^{\frac{m_t}{bOpt_{t,i}^{m_t}}=1} - \\
& \sum_{t=B}^{H}\sum_{m} Df_{t,D}\, flexOpt_t^{\frac{m_t}{bOpt_{t,i}^{m_t}}=0} - \\
& -\sum_{t=B}^{H}\sum_{m} Vp_{im} Df_{t,D} - \sum_{t=S}^{H}\sum_{m} SIM_{t,i}\Bigg]^{-}
\end{aligned}
\tag{6.5}
$$

this expression will guide the rest of this section.

6.3.7 Description of the uncertainties

For a given scenario, the value of uncertain parameters at the time when S is assumed to follow a normal distribution centred on its forecast $\widehat{m}^0_{yt}$, where the expected cost for $\widehat{m}^0_{yt}$ is $\widehat{flexOpt_t}^{m_t} = flexOpt_t{}^{m_t}(\ \widehat{m}^0_{yt})$. Its standard deviation σ^y must be adjusted for time:

$$
\sigma^{*y} = \sigma^y \sqrt{Rt_{t,D}} \tag{6.6}
$$

Fitting a normal distribution to the uncertainties is arguably good for sources of uncertainty such as fuel prices, peak demand growth or generation capacities where increments can be very small (i.e., as wind or solar) (Shimko, 1994), (Lumbreras et al., 2016). In many cases, these uncertainties are usually represented by means of log normal distributions, so that the difference between the actual realization and the forecast can be reasonably approximated with a normal distribution (Hull, 2006).

$$m_{yt}^{0} - \widehat{m}_{yt}^{0} \approx N\left(0, \sigma^{*y}\right) \tag{6.7}$$

In a real-sized system, there will be many uncertain factors involved, so the central limit theorem supports the approximation of normality. This assumption allows calculating closed-form solutions for option value, which would otherwise be intractable for real-sized systems. Substituting in the option value expression, we obtain:

$$\begin{aligned} OV(bOpt_{D,i}) \approx R\Bigg[& \sum_{t=S}^{H}\sum_{m_t} Df_{t,D}\left(\widehat{flexOpt}_t^{\frac{m_t}{bOpt_{t,i}^{m_t}}=0} - \widehat{flexOpt}_t^{\frac{m_t}{bOpt_{t,i}^{m_t}}=1}\right) + \\ & + \sum_{t=S}^{H}\sum_{m_t} Df_{t,D}\left(\sum_{y}\left(\delta^{m_t,bOpt_{t,i}^{m_t}=0} - \delta^{m_t,bOpt_{t,i}^{m_t}=1}\right) N\left(0,\sigma^{*y}\right)\right) - \\ & - Vp_i Df_{A,D} - \sum_{t=S}^{H}\sum_{m_t} SIM_{t,i}\Bigg] = R\left[N\left(\mu_{Total}, \sigma_{Total}\right)\right]^{+} \end{aligned} \tag{6.8}$$

Once the parameters for the total normal distribution have been calculated, the option value can be derived as:

$$OV(bOpt_{D,ijc}) = R\left[N\mu_{Total}, \sigma_{Total}\right]^{+} = \left[\mu_{Total} + \sigma_{Total}\frac{\phi\frac{-\mu_{Total}}{\sigma_{Total}}}{1-\Phi\frac{-\mu_{Total}}{\sigma_{Total}}}\right] \tag{6.9}$$

where ϕ and Φ denote the standard normal probability density function and the standard cumulative distribution, respectively. This result is used to approximate option value in a closed form and is applied in the case study described in Section 6.4. Another useful result is the probability that a given investment will be carried out at a future date. This is referred to as the in-the-moneyness or in-the-money probability (ITMP) of the option, and can be calculated as:

$$ITMP\left(bOpt_{D,im}\right) = R\left[N\mu_{Total}, \sigma_{Total} \geq 0\right] = 1 - \Phi\left(\frac{-\mu_{Total}}{\sigma_{Total}}\right) \quad (6.10)$$

6.4 Locational flexibility case study

A bespoke case study is presented based on the integration proposed of the MURRA methodology, presented in Section 6.3, with the SIM software. The case, illustrated in Figure 6.6, receive as inputs: the trial area, which is the core 11kV FALCON area around Milton Keynes, East Midlands, in the UK, technique costs and the load data. It compromises 6 primaries and 1,155 secondary substations located on adjacent boundaries feeders of the FALCON trial area.

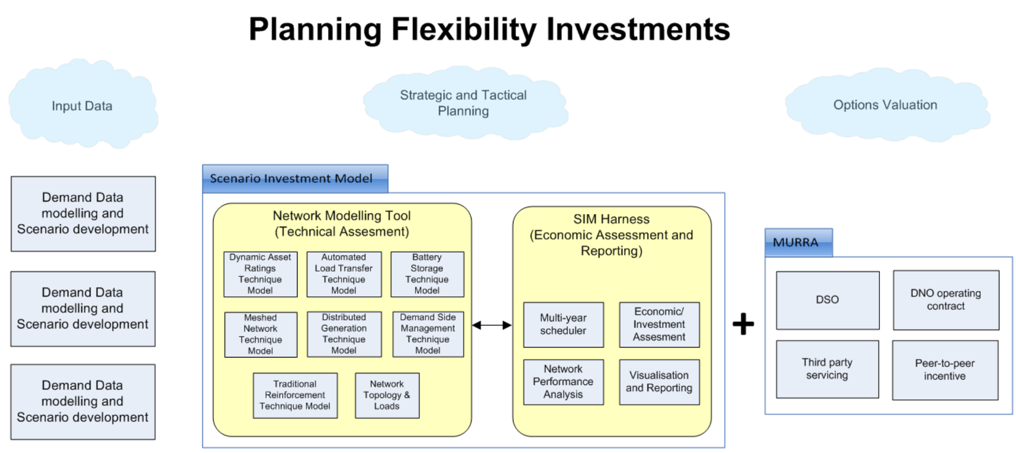


Figure 6.6: Domain representation of the Planning Flexibility Investment approach

The design of the SIM envisioned different types of users, from 11 kV Planners, Strategic Planners, to Policy users who would be interested on a variety of approaches such as planning specific localised network improvements, evaluating large parts of the grid over a period of time or providing insights of the underlined implications of business models regulation.

This multi-stage approach was designed to combine the planning of traditional reinforcements, smart grid interventions and combine them with innovative business propositions.

6.4.1 Scenario description

The MURRA implementation considers a deterministic demand scenario, named by the Department of Energy and Climate Change as "Gone Green Scenario", or DECC 2 (Department of Energy, 2011) and characterised in Table 5.2. Modelled scenario assumes that fuel efficiency and wall insulation will have a high impact on the electricity demand, where low carbon heat will have a medium impact. Matching against nodal points in the network are customer loads, these are implemented as Load Profiles, being arrays of load values arranged on a daily basis at 30 minute intervals (so that 48 load points make up a diurnal load profile for a given site and day type). The SIM evaluates the network against the loads on an annual basis, moving through the years specified in the evaluation interval and carrying out each new analysis using these evolving loads. A SIM year consists of just eighteen "characteristic days" which provide a pragmatic way to handle modelling of the intra-year time dimension as these cover the main types and extremes of load that would be expected to be encountered in a given year. Essentially, each day in a real year can be assigned to one of the 18 characteristic days and by using the number of each representative days in a real year annual metrics can be calculated for items such as losses or network utilisation. The SIM thus performs load flow analysis for the network for the 48 half-hourly periods during the day for different days of the week and different seasons of the year.

When power flow analysis within the SIM detects a voltage or thermal issue, the SIM will select from the supported remedial techniques that could help resolve the problem and determine how they could be applied to the network. The best solution can be selected using a weighted metric that combines elements such as installation, per use and operating costs, network performance, losses and disruption to customers. While some aspects of the various solutions can be assessed at the time an issue is reported, the longer term value for money of the options is determined by how they contribute to the overall performance of the network over a number of years. So for example a solution that is initially expensive may be value for money if this results in many years of issue-free operation. Therefore the SIM does not use a merit order approach to resolving network issues i.e. applying the technique which is expected to provide best value for money based on initial costs, but rather the SIM allows for the long term value to become apparent by allowing the simulation to branch. This creates a large number of potential options for the evolution of the network which requires a search mechanism to guide the search through the solution space.

The guided search mechanism for the SIM is the learning algorithm detailed in Chapter 3, providing feedback from the analysis carried out to refine the view of expected costs in a particular year.

The SIM exports results to the report outcome file (.CSV file) which is received by the MURRA algorithm and extract how much capacity is needed to be allocated at locational feeder and 11 KV primary level.

The Real Option Valuation analysis considers deterministic uncertainty in load profiles, lines capacity, and service price proposition. Business options are discounted as described in Table 6.1 depending on the duration A of each service business contract proposition. It might be said that the model is biased towards the SIM, as $bOpt_1$ SIM is discounted on a yearly basis, and the rest of the options every 2, 4 or 8 years. However, as DNOs have to get approved their business plans for a whole regulatory period, 8 years, these yearly discounts are known beforehand and therefore, multi-utility companies willing to become marginal, can customise their service prices within a regulatory period. To quantify the uncertainty in Figure 6.1, from a DNO perspective, business options ITMP are calculated and displayed as in Table 6.1.

Table 6.1: Flexibility contract proposition duration (A) and ITMP options value

	$bOpt_2$ DSO	$bOpt_3$ Out	$bOpt_4$ Agg	$bOpt_5$ $P2P$
A	8 years	4 years	8 years	2 years
ITMP	1	0.9	0.8	0.75

OV, μ, σ are not disclosed due to data privacy. Historical data were analysed in order to extract values for the uncertainty. For the discount factor, and pricing the business options, data are obtained from one UK DNO, aggregators and the future value of storage presented by McKinsey (McKinsey, 2016). A data series was created for each of the business option displayed in Table 6.1 and for further evaluation against SIM results.

6.4.2 SIM results

The model described in Section 6.4.1 was coded in Python for the SIM and solved using IPSA Power on 4 core 4 GB RAM virtual machines. A single SIM experiment used for calculations from 18-24 hours. Each experiment solution presented several tree branches (Butans et al., 2017) that can serve as an optimised investment pathway. Figure 6.7, presents using Parallel Coordinates

(Kipouros et al., 2013), the 27 solutions of non-failed network states clustered by the percentage of smart solutions implemented to solve hurdles within the 2015-2023 evaluation period. It can be noted that solutions that implements more smart techniques (represented in orange) are more expensive in CAPEX and OPEX required, although outperformed its peers that used higher percentage of traditional reinforcements in utilisation of assets, and higher reduction of Costumer Minutes Lost (CML), Customer Interruptions (CI) and Losses (in annual kWh).

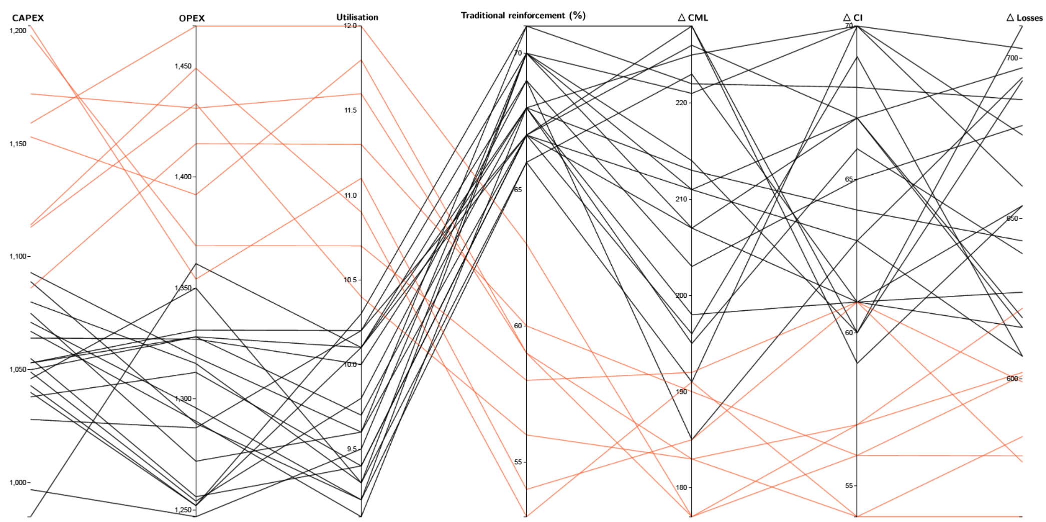


Figure 6.7: ∥ -coord solutions plot for DECC2 scenario. 2015-2023 planning horizon

Long-term look ahead results predominately follow short-term trends when clustered solutions by the percentage of traditional reinforcements implemented to solve a failed network state. In figure 8, fewer solutions are completed as feasible solutions, 15 instead of the 27 that we had in the short-term evaluation. Comparing indicators and having in mind that long-term scenario includes 24 more years after 2023, it can be concluded that OPEX, and the reduction of CML, CI and Losses perform better with a long-term look. Also percentage of smart grid techniques implemented is higher for the 2015-2047 solutions. SIM results are not likely to be in a situation where large capital spend is demanded, but extra flexible capacity will be necessary.

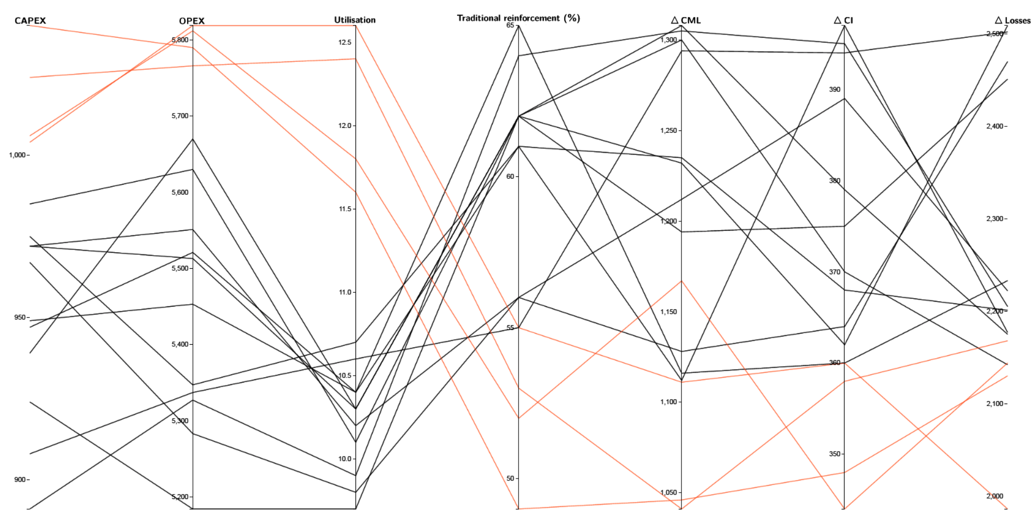


Figure 6.8: ∥ -coord solutions plot for DECC2 scenario. 2015-2047 planning horizon

6.4.3 MURRA results

From a DNO perspective, one of the major benefits for a service based method of managing a constraint issue through commercial techniques means that it will typically only incur costs to the business when it is being used. In that sense, the Commercial Trials of the FALCON project allocated 10 MW of flexible capacity (Western Power Distribution, 2015).

Once identified potential feeders and substations in need for flexible peak loads at certain periods, the DNO may look for alternatives to traditional reinforcements or smart grids techniques. The four business options proposed have an option service value attached. Those flexibility propositions described in subsection 6.1.2 and 6.4 are computed and coded in Python on a PC 2.20 GHz with 16-GB RAM running on Microsoft 7 Enterprise. The CPU time used for the longest set of calculations (Figure 6.11) was of 983 s (16 min).

A short-term evaluation using MURRA (2015-2023) is performed for the whole trial area. Results are presented normalised in Figure 6.9. SIM business proposition are selected in 6 years, whereas Aggregator (Agg) is the optimal option for 2021 and 2022. That is related that from 2015-2020, the DNO has been building capacity with traditional reinforcements and allows a competitive contract proposed by Agg to become competitive and thus, the option selected. As for the other options, Outs and P2P are close in value proposition to Agg and the DNO option becoming DSO and owning and operation assets, proposed services between (18% and 34%) more expensive than the optimal service option.

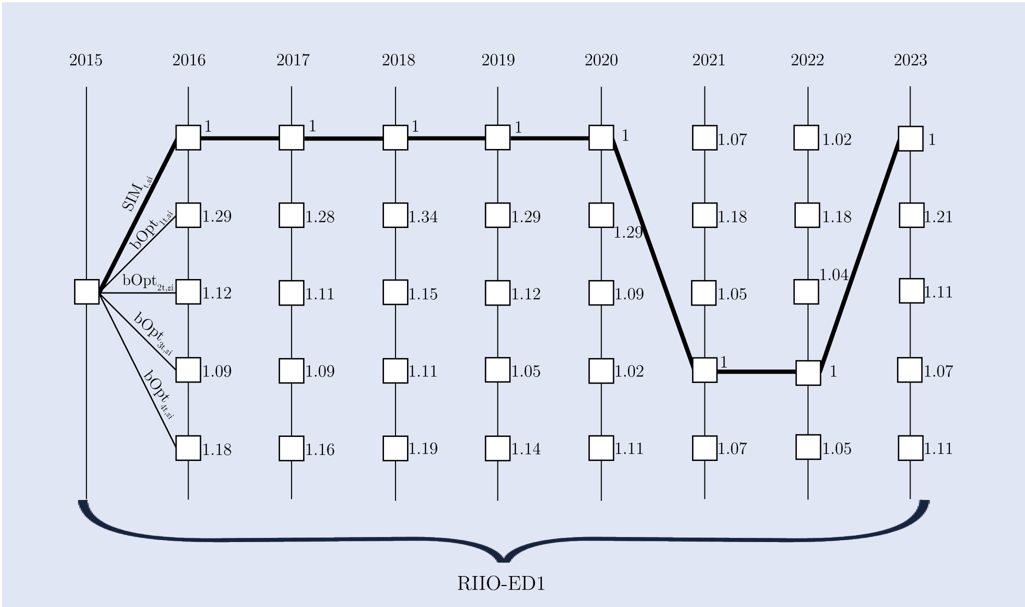
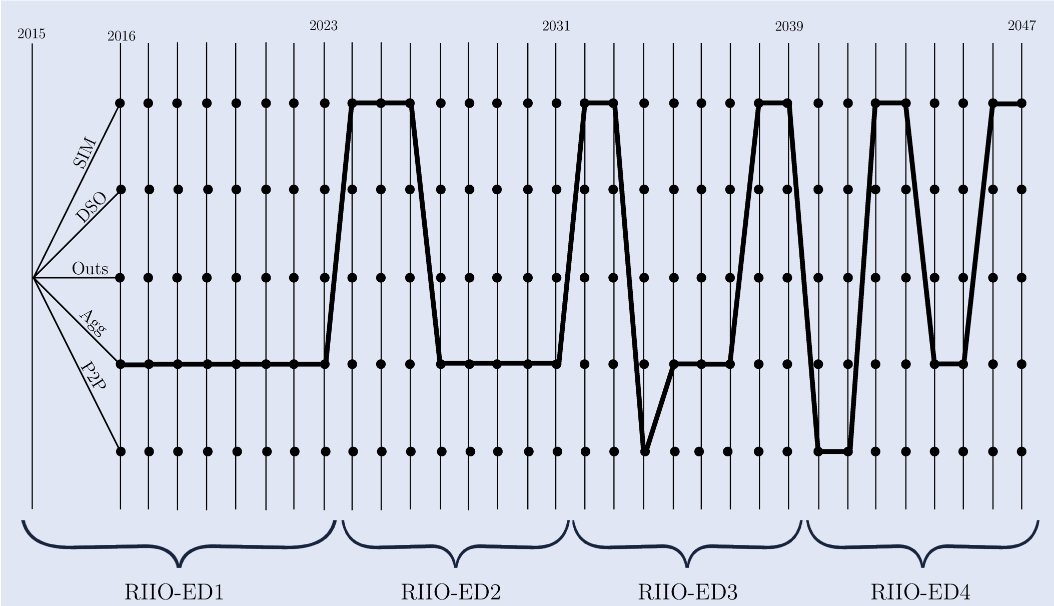


Figure 6.9: Investment Strategy comparing Real Option for the trial area for RIIO ED-1: 2015-2023

Two long-term scenarios from 2015 to 2047 are presented in Figure 6.10 and Figure 6.11. First one is the optimal investment solution path for contracting the 10 MW capacity requested. RIIO-ED1 period is radically different from the one presented for short-term (Figure 6.9). For a long-term optimising investment look-ahead, Agg options are the chosen ones, and extra capacity is just built (SIM option) when needed during the evaluation period. That extra capacity built at the beginning of RIIO-ED2, RIIO-ED3 and at the end of RIIO-ED3, allows to options with limited capital expenditure (Agg and P2P) to become the service solution provider.



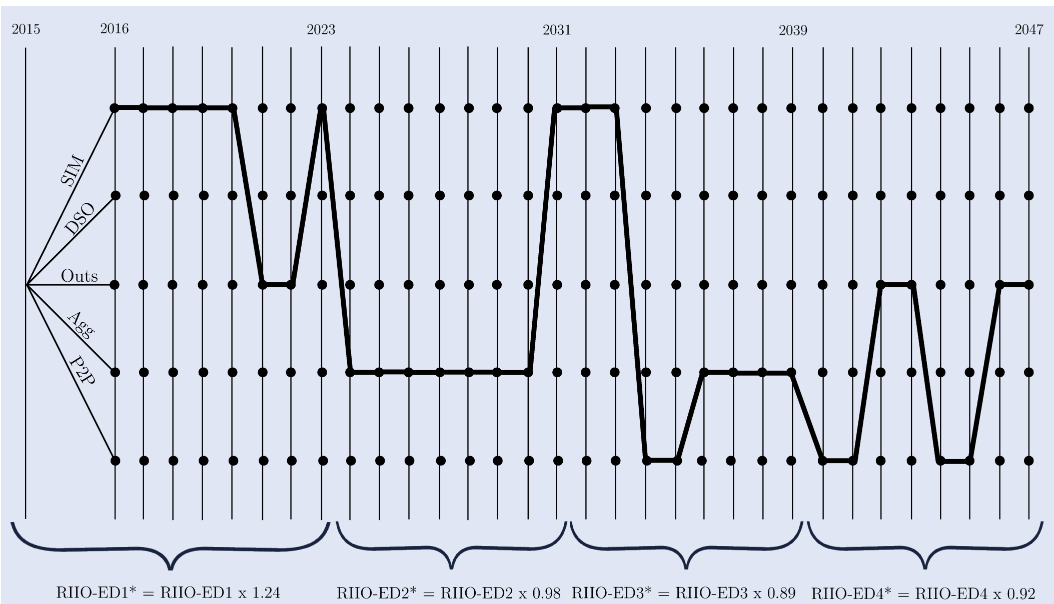
Optimal Path	All SIM	All DSO	All Outs	All Agg	All P2P
1	1.17	1.92	1.47	1.38	1.52

Figure 6.10: Investment Strategy for RIIO ED-1: 2015-2047

A normalised solution is calculated to compare the optimal path aforementioned described and a case where every year is used the same option, e.g., all of the years, DSO option is selected. The table in Figure 6.10 is displayed how much extra will it cost if that is the selected approach. From an extra 17% if only the SIM solutions are contracted, to a 92% if the batteries operated by the DSO are contracted as flexibility provider.

This last simulation of the MURRA ROV aims to quantify the value of regret (Bunn and Oliveira , 2001) if just planning for one RIIO-ED. Adopting the short-term investment pathway from Figure 6.9 for the RIIO-ED1 period in the Figure 6.11, the solution space completely varied when compared with the un-constrained option in Figure 6.10.

Over-investing in the network during the first RIIO period (24% more than the optimal solution) leads to have spare capacity in the system and therefore SIM option is only required at the beginning of RIIO-ED3. That leads options such as P2P double the number of years selected as the chosen solution, Aggs solutions are delayed on time from RIIO-ED1 to RIIO-ED2 and Outs are present for the first time as feasible solutions. Adopting this sub-optimal investment path will lead to a value of regret of an over-investment of 19%. Normalised values for the table in Figure 6.11 have been calculated with the optimal path from Figure 6.10. Comparing values in Figure 6.11 with the ones in Figure 6.10, leads to conclude that despite having chosen a sub-optimal, more expensive path, that makes all of the business propositions more attractive but for the SIM options.



Sub-Optimal Path	All SIM	All DSO	All Outs	All Agg	All P2P
1.19	1.33	1.81	1.39	1.36	1.41

Figure 6.11: Investment Strategy for RIIO ED-1: 2015-2047

6.5 Conclusions and policy implications

In this chapter is presented a two-stage service valuation methodology that can be used for assessing a portfolio of flexibility services for distribution power networks. A network state selector is presented in the form of the algorithms embedded within the SIM software, selecting those network states which outperform their peers and therefore advancing with a long-term investment strategy using traditional reinforcements and smart grid techniques.

The Real Options valuation of Flexibility services proposed within the MURRA methodology, parallelised and compared SIM flexibility requirements with those multi-utility service propositions, solve in an acceptable time frame the aforementioned model.

6.5.1 Locational planning

The key distinguishing factor for this stylised case study was to the way in which solutions were evaluated, with techniques being applied and simulated with reference to a nodal model of a real network, rather than assessing networks in terms of percentage headroom for representative network types. Being able to use the SIM, as a detailed bottom up model based on microscopic level analysis while other existing models can be characterised as top down macroscopic simulations based on summary views of the network. These two very different views ought to be complementary and there may even be expected to be some overlap in the middle ground when applied to the same network. However it can be hard to find representative networks to check this aspect, and using average networks could potentially miscalculate the levels of investment required.

Trial area used in this study only covers Milton Keynes which accounts for only 1.5% of East Midlands customers. Therefore scaling investment plans for the studied 11kV network from Milton Keynes to DNO or nation level for comparison is likely to provide only a very general test that the results are in the right order. Given the differences between flexibility models, the comparisons will be quite general. However, some areas of comparison can be considered for future studies:

- Load Profiles
- Proportions of investment type (Smart techniques vs Traditional reinforcements, Opex, Capex, losses)
- Impact on losses and interruptions
- Investment Triggers (Voltage vs Thermal issues)
- Locational Multi-Utility flexibility service propositions

There are various extensions of the present model that are intended in future research, such as disaggregation of results at feeder level. In practice, digitalisation of cyber-physical network assets will provide a more accurate system forecast of flexibility required. The fact that some evaluated service propositions here, such as storage, peer-to-peer or demand aggregation are not mature in their learning curves, along with regulatory variations, can represent a shift on optimal investment pathway using proposed methodology.

6.5.2 Consequences of periodic incentive-based regulation inducing short-termism

This chapter makes key contributions with a ROV applied to flexibility business models for long-term investment planning in distribution networks. Motivated by a real-world application a novel integration of the heuristics integrated within the SIM nodal investment planning software to evaluate myopic empirical ROV strategies. Short-term myopic evaluation planning periods have been proving more expensive in the long-term for the system. Forcing long-term planning (2015-2047) to adopt during the first years (2015-2023) a sub-optimal investment strategy will lead to:

- In the short term, an over-investment in flexibility will be of 24%, being defined as the value of regret.

- Adopting this sub-optimal business as usual look-ahead investment strategy, would lead to over-paying 19% for flexibility services compared to unconstrained portfolio investment strategy for the 2015-2047 period.

- By comparing long-term investment strategies, short-term myopic and unconstrained, it can be concluded that with an over-invested grid during the first regulatory period, less capacity investment is required in subsequent years.

- Competition among flexibility options is enhanced in the sub-optimal path due to the excess of investment early years, always traditional reinforcements, which will permit that with promoting policies, flexibility options such as peer-to-peer or demand aggregation will become marginal more often and therefore, the option selected.

In summary, this chapter concludes that resilience of power systems could be also ensured by outsourcing flexibility services, although how much you pay for that is sensible to the chosen investment path. It also suggests the potential scope for promote and develop multi-utility business models to enhance competition in the power sector. In future research, the author looks forward to quantify the implications of the simplified assumptions, and the integration of MURRA within the SIM software for reducing computational effort. To investigate non-myopic investment strategies, Monte-carlo planning techniques will be evaluated. Nonetheless, this study also suggests further research should be pursued to assess nation wide potential for the flexibility business services markets from a bottom-up modelling perspective.

Chapter 7

Discussion and conclusions

In the continuance of this work, after having completed the 3 years of the Doctorate degree, conclusions of the thesis have to be settled. Having now a broader view of how challenging this topic can be, findings and contributions, limitations, future research, and concluding remarks are to be covered in this chapter.

7.1 Findings & Contributions

The aim of this thesis was to characterise evolutionary planning techniques for real-world size problems that are capable of:

- Quantifying performance system indicators.
- Identifying set of optimal solutions using meta-heuristics.
- Proposing novel methodology to evaluate non-traditional flexibility business models for distribution supply networks.
- Validating and evaluating performance metrics for power systems optimisation.

The literature review characterised the uncertainties that power systems planning are facing towards the three decarbonisation of the electric sector by 2050. Chapter 2 presents an state-of-the-art review of barriers that the power value chain is facing while raising questions regarding modelling future power networks. To analyse current regulatory framework implications during case studies' chapters, a brief review of RIIO regulation framework and US Independent System Operators relevance for this research is discussed within the literature, positioning this thesis on the planning-operations domain (Appendix C).

Many controversies have been identified on the technology that will prevail or inaccurate price forecast for many of them (particularly solar) (U. S. Energy Information Administration , EIA). This thesis provides a set of methodology options that enables an efficient modelling of bottom-up power systems regardless on which technologies, incentives or regulation are chosen, leaving that to future modellers.

The rapid integration of solar photovoltaic triggered the debate for defining a more flexible power system. Storage mandates have been pursued in some States of the US, as presented in Chapter 2, and combined with high penetration of intermittent renewable sources have motivated the impact evaluation in Chapter 4. That stylised study models in a first stage the Independent System Operator of New England in the presence of high wind penetration (30% generation mix), evaluating on a second stage the impact contribution of the Massachusetts' Storage target on New England's volatility of prices, curtailment and total generation costs.

Within Chapter 5, a novel evolutionary approach is presented for evolving network states over many evaluation periods. Smart techniques and traditional reinforcements leveraged the optimal combination for planning new digital energy systems to provide resilient 11 kV networks. Experiments' solutions providing bespoke local network requirements under different demand and time evaluation period scenarios are performed.

The performance of techno-economic indicators combined with bottom-up meta-heuristic modelling on benchmarks problems were designed to identify significant variations on cost and technical indicators. The data revolution is leading to three transformative Ds for the energy sector: Decarbonise, Decentralise and Deregulated. IoT technologies and advanced metering are key enablers of this transformative revolution providing dynamic responses for costs, charges, and services, and therefore resulting new business models. In that sense, Chapter 6 proposed a Real Options valuation of flexible resilient service propositions.

Following detailed contributions have been made with the work presented in this thesis:

- *Two-step optimisation approach to bottom-up power networks modelling.* Having looked for a source that provide both, evolutionary planning and techno-economics modelling of power systems, the author concluded that a two-step approach where first, the objective functions, decision variables and constraints are defined and then, a real-life size power system in need to be evaluated, are required. The complexity associated with power networks have required to focus on optimising multiple-objectives at each evaluation, so meta-heuristic algorithms Ganesh (Genetic Algorithm) and customised SIM A* (Graph Search algorithm) are selected for the experiments within this thesis.

- *Customisation of a novel optimiser for real-life size studies.* The capabilities of Ganesh optimiser, as an improved Non-Sorted Genetic Algorithm-II, have been extended to handle not just scalars as it used to do but also now, can handle large lists of inputs (such as 5 minutes resolution yearly time-series) coming from a .csv file and calculates, for example the hourly standard deviation of electricity prices, using it as Objective Function in an optimisation. For the near future, integration between Ganesh and High Performance Computing is planned using, Nimrod toolkit (MeSsAGE, 2000). From there, will be easier to run real-life size parallelised models reducing computational time.

- *High penetration wind in New England & Massachusetts' Storage stylised case studies.* Starting with the WIND tool-kit produced by the National Renewable Energy Laboratory, a case study modelled in PLEXOS and combined with Ganesh optimiser is presented in Chapter 4. It contains an empirical evaluation of all of the onshore wind resource in New England, US. 6 different topologies are produced and evaluated for further study the total generation cost and standard deviation of prices for a year with a 30% of wind installed. This generation mix is compared and tested against the actual ISO-NE real-system. On the second half of the chapter, a multi-objective optimisation is presented accomplishing Massachusetts Storage target locating the most suitable locations for the storage devices installation, aiming to optimise maximum operational in New England as a whole-system.

- *Distribution networks evolutionary optimisation.* Chapter 5 presents bespoke scenarios of the FALCON 11 kV trial area. Aggregated at area level and highlighted locational feeder insights, the study shows feasibility of using meta-heuristics for evolutionary planning. Bottom-up evolving network states modelling has an applicability in real-world distribution networks design. The methodology and scenarios of this chapter have motivated independent pieces of work across the energy value chain and different impact domains (Appendix C), such as public and private electrical transportation, (Peláez et al., 2015), (Zafred et al., 2016).

- *Multi-Utility Flexibility Options.* A learning from chapter 5 is the need to create greater flexible capacity within the network. Chapter 6 tackles that need proposing a Real Options methodology, MURRA (Multi-Utility Resilience Rating Assessment), and future integration within the SIM provides extra capability for evaluating flexibility service portfolios. The myopic consequence of short-term vs long-term service agreements has been tested and used in the study to validate the methodology.

- *Multi-dimensional visualisation technique.* Case studies chapters 4, 5 and 6 have used parallel coordinates to debug multi-dimensional analysis when optimising conflicting objectives. It is a feasible solution to link both, parameters of the optimisation with objective functions, enabling a better understanding of system dynamics and correlation among results.

7.2 Limitations

The limitations of this work are divided into two domains, namely, methodological, and validation.

A major limitation that falls under methodology is that there are no software available to integrate studies in chapters 4 and 5 within it.

Therefore, the lack of common case-independent metrics to evaluate end-to-end future power networks and interdependencies and conflicting objectives among transmission and distribution modelling. This issue is not specific to evolutionary planning networks, but also to static problems and future research might want to extend the knowledge of frontiers between Transmission System Operator and Distribution Network Operator, their conflicting roles and market interactions. The other methodology limitation is due to the selection of chosen meta-heuristics and therefore being limited by their intrinsic features. Graph search algorithms and Genetic algorithms helped to characterise the solution space but were not able to find a global optimum.

Linking previous limitation with one on the validation domain is necessary to highlight that non-other meta-heuristics were tested thoroughly. Consequently, comparison with other evolutionary approaches would be recommended. Only parallel coordinates and Pareto fronts were used to compare many-dimensional decision spaces and, although correlations were discussed, other feasible solutions might remain hidden.

As a final limitation and when addressing technical limitations (computing running resources, parallel computation, High Performance Computing...), would be meaningful to study a modelling limitation such as in which decision variables and objective functions change over time.

7.3 Future research

The merging of the energy sector with Information Technologies will enable a new era of distributed, low-carbon, and digital energy. Within this in mind I am seeking to evaluate different emergent fields (domains) in terms of their innovative directions, potential impact and pace of change in order to prioritise achievable research themes resulted from this thesis for future study.

Key finding from chapters 4, 5, and 6 have built the first steps to setting out the domains that can be the base ground to extend this current research to a future digitalisation of the energy sector. These are: Cyber-physical asset systems, Agent-centric modelling and design, Distributed Ledger Technologies, Real-time decision-making and visualization techniques, High-Frequency trading and Data-centric engineering using Machine Learning Techniques. Together these technologies have the potential for wide-ranging and transformational change in whole energy systems.

As a system of systems, these digital technologies represent the highly adventurous integrated whole. Each of these areas are emerging research domains. How these can work together to solve energy transitions is not all clear. Bringing them together is highly speculative but has transformational potential.

Intelligent integration of local low-carbon energy, the use of Internet of Things to operate power networks, or the powering of electrical transportation, are challenges that the UK and many countries across the world are facing in our digital 21st century, first steps have been settled in chapters 4 and 5, and proposed meta-heuristics can be adopted for pilot tests as has been done within this thesis. Furthermore, proposed micro-Genatic Algorithms (Coello and Pulido, 2001), as well as other meta-heuristics might be explored for further consideration depending on case study application. Also, due to their parallelisation feature, it is recommended to pursue the combination of Ganesh with Nimrod, to explore the impact on computational time. As mentioned in the Limitations section, that should be done in a High Performance Computing with multiple PLEXOS licenses.

Planning energy sector is shifting over to create a step change in our understanding of how consumer-centric decision-making enabled by digital technologies will impact on the digital energy transition. The potential for digitalisation of the UK's energy operations, at all scales, aiding the integration of Smart appliances with variable and fixed loads, Smart gas and electricity contracts, or Electrical Vehicles, will raise uncertainties that need to be addressed with architectural solutions. Traditional methods would not allow real-time propositions to emerge as these methods require data collection and computational time for searching the problem-space. Distributed Ledger Technologies (i.e., Blockchain) as enabler technologies hand have the necessary information and processing capability distributed locally and in parallel, overcoming some of the computing limitations aforementioned.

Combining decentralised decision-making using Distributed Ledger Technologies and bottom-up analysis of interactions occurring among agents, i.e., lines, cables, substations, would allow us to create a step change in our understanding of how to unlock some of the value streams that digital energy transition will bring, as well as identifying novel risks and uncertainties that will emerge when moving quickly toward decentralised low-carbon systems.

This future research aims to improve the design of Complex Systems, by reviewing stochastic agent-based modelling with Distributed Ledger Technologies. Optimising local solutions (e.g. households, districts and cities) may lead to sub-optimal consequences for nation-wide objectives; therefore, a procurement is needed where consumers can be aggregated as communities, in a landscape of heterogeneous actors, in order to understand local and global effects. Thus, future strategic data-driven planning needs a holistic approach to ensure that the energy trilemma - security, equity, and sustainability - is resolved at local levels while contributing to a national increase of population welfare.

Addressing the engineering-driven actions necessary to develop more defensible and resilient systems - including services that depend on those systems, are another domain where digitalisation of energy is having an impact. The ultimate objective is to address security issues from a stakeholder requirements and protection needs perspective and to use established engineering processes to ensure that such requirements and needs are addressed with appropriate fidelity and rigour, early and in a sustainable manner throughout the life cycle of the assets increasing reliability of the system.

More transparent systems will cope with consumers need of more information and knowledge in order to be able to engage in the market. Consumer engagement should, however, be considered also in light of the potential costs. Further, a strong focus should be given to demand-side flexibility in the retail market. Developing further MURRA, presented in Chapter 6, may led to better service flexibility propositions where self-generation and self-consumption would be crucial in future energy systems. Regulators could analyse the regulatory framework proposing new and innovative offers should be enabling retail market to propose choices to consumers.

The current energy market environment is characterised by high systemic risk and not transparent transactions, leading end-consumer to be reluctant to engage with the system. In these markets, regulated and non-regulated any competitive advantage is highly sought after. Outlining how technological, market and regulatory considerations will lead to the importance to the evolution of High-Frequency Trading and the innovation it brings to digital markets. The digital revolution allows combining distributed decision-making with Generalised autoregressive conditional heteroscedasticity (GARCH) to price, measure, and explain how volatility of cyber-physical assets can largely impact on prices. The move to digital decentralised planning and the real-time decision making can lead to debug correlation between markets, assets, or consumers, providing a more robust and transparent system.

7.4 Concluding remarks

This research concludes that evolutionary approaches can be used to address real-life complexity in power networks planning problems. The proposed solutions are able to aid decision-makers improving their current insights on planning power networks. Meta-heuristics implemented are suitable to characterise the solution space offering a range of trade-off to select from with feasible solutions.

Using novel off-the-shelf software such as the SIM, Ganesh or MURRA, and a combination of them, provide satisfactory results that validates early-project assumptions of the necessity of responsive bespoke solutions depending on the real-world problem tackling. To conclude this research, the research objectives formulated in Chapter 1 are analysed against the findings and accomplishments of this thesis:

1. *To develop problem detailed quantitative representation of real-world power systems suitable for being optimised.* Chapters 4 and 5 characterises two power systems, one at transmission and the other at distribution level. Chapter 6 defines a methodology to be integrated as part of new modelling options portfolio in Chapter 5 power system. Eventually, a Common Information Model could link transmission and distribution optimisation objectives.

2. *To fit existing algorithms and heuristics evolutionary techniques to real-world size problems.* Chapter 3 debugs dynamics and modifications needed of state-of-the-art meta-heuristics for real-world size case studies. Bespoke optimisation frameworks are presented in that chapter and implemented in Chapters 4 and 5.

3. *To visualise performance criteria for case studies decision making.* Each of the case studies in chapters 4, 5, and 6 outline and define their own evaluation performance metrics for many-dimension decision making based on parallel coordinates.

4. *To propose non-traditional flexibility services for creating capacity within distribution networks.* Characterisation, performance and associated volatility risks to increase network capacity resilience are addressed on Chapter 6 by MURRA methodology providing Multi-Utility flexibility service proposition valuation. It presents an opportunity for a proactive reform where, like in RIIO, innovation is incentivised across the value chain.

5. *To validate and evaluate performance metrics for power systems optimisation and customising optimisation frameworks for measuring their performance.* Proposed evolutionary meta-heuristics, its constraints and evaluation metrics (objective functions) were analysed using chapters 4 and 5 transmission and distribution power systems and validated using aforementioned chapters' case studies.

The aim of this research is to gain a set of evolutionary techniques for rapidly modelling evolving power network systems. The data revolution is shifting on how power systems have been traditionally designed. Smart new techniques, untested technologies, digitalisation or uncertain impact on systems integration are some of the challenges the sector is facing. The impact on power networks of restructured systems operators, their roles, and foreseeable decentralised markets arrangements looking for transparent mechanisms, are critical functions that will define future research. With this thesis the author has contributed providing a portfolio of insights on how to model, analyse and visualise those future impacts on power network systems.

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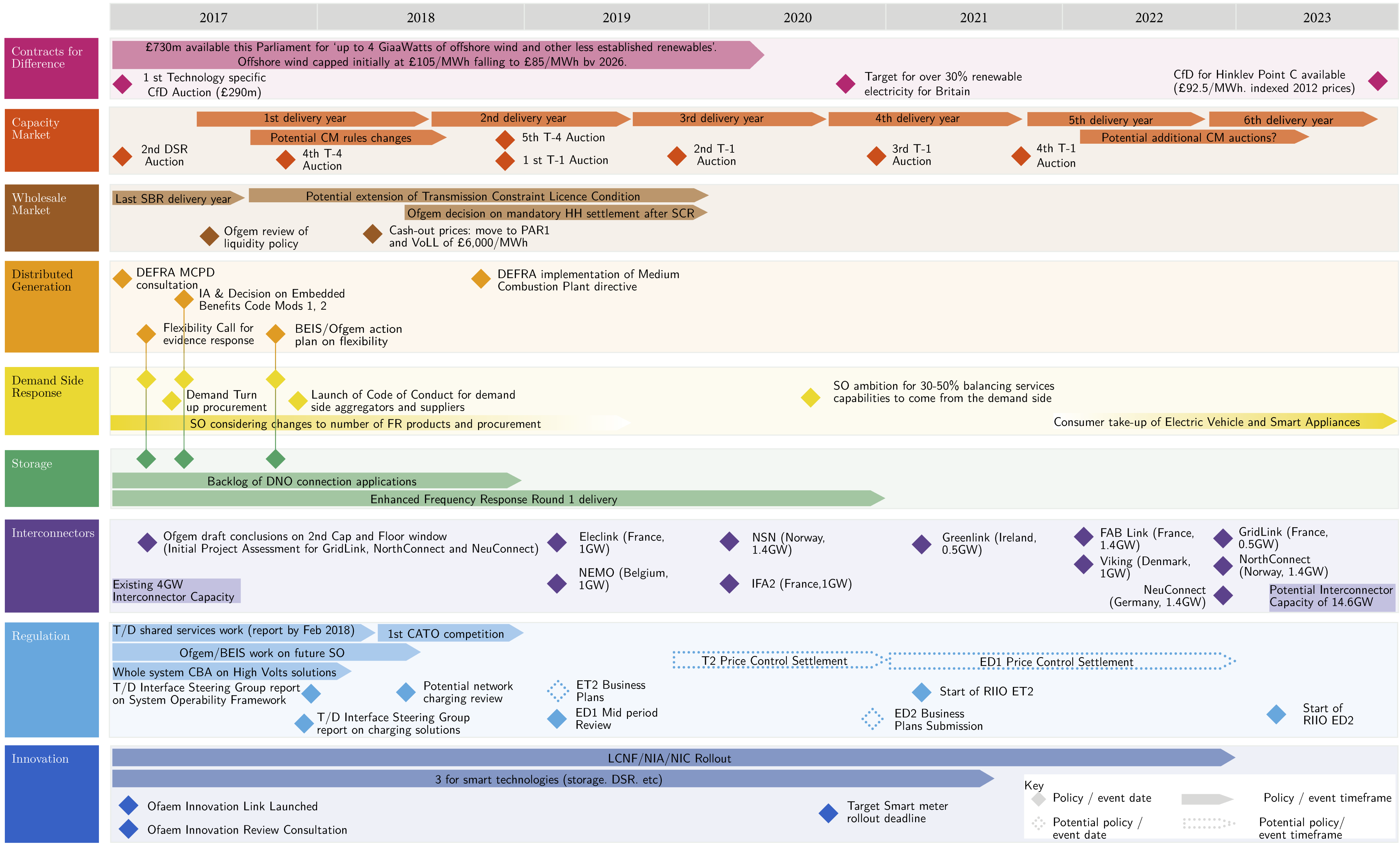
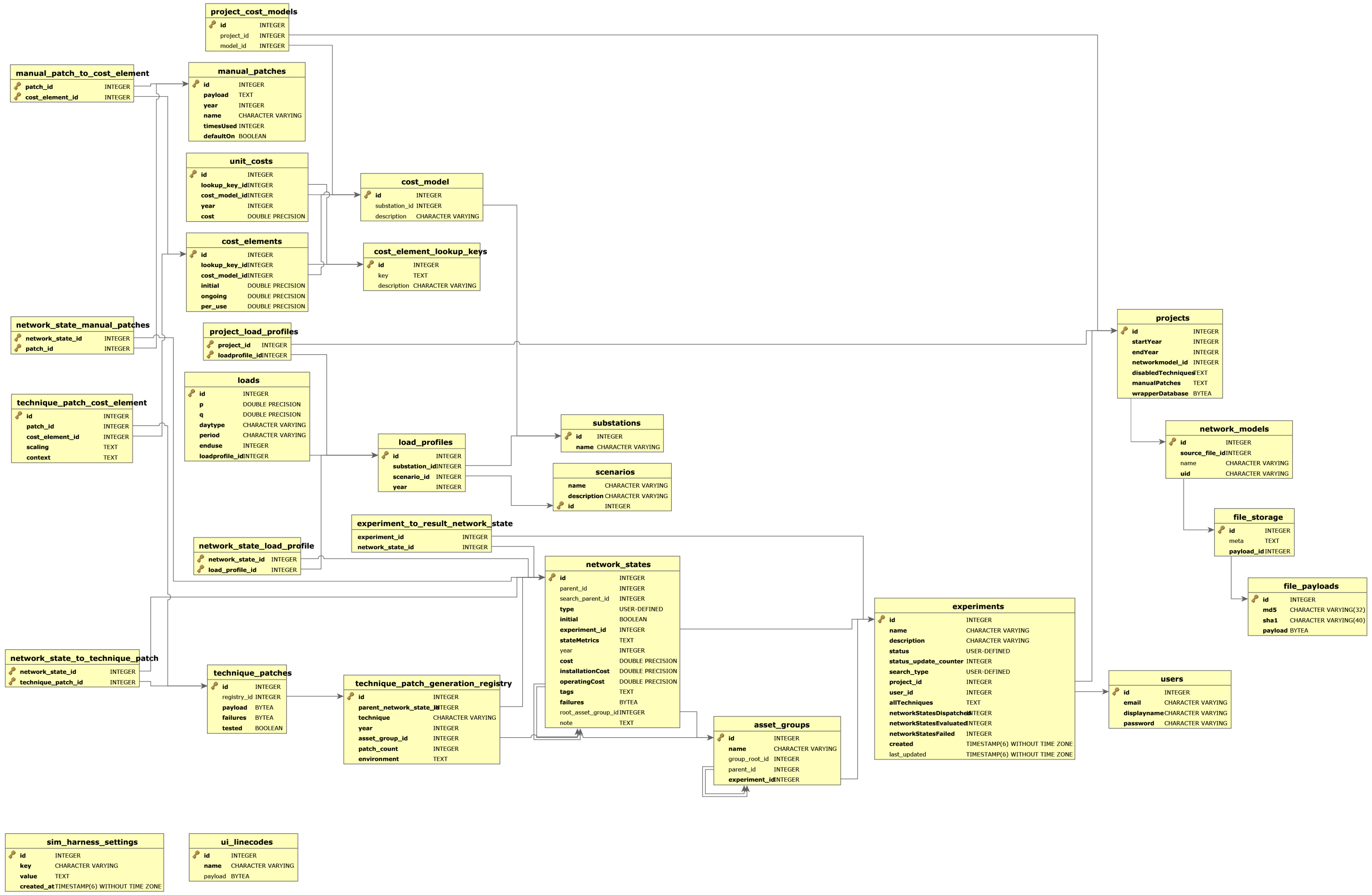
Appendices

Appendix A - UK Electricity Timeline

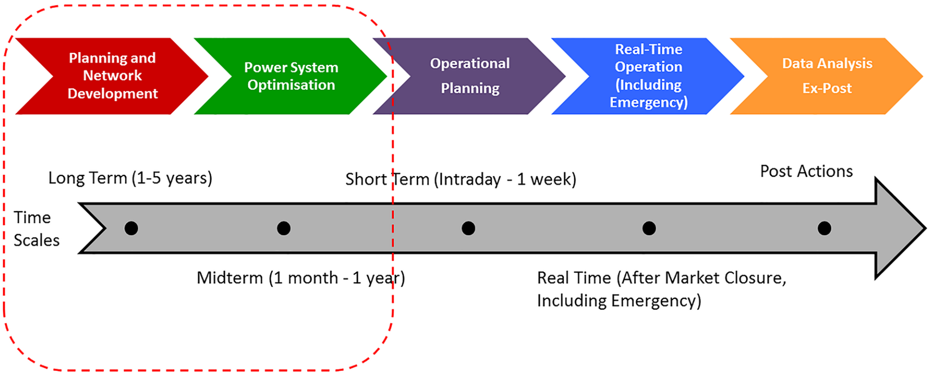


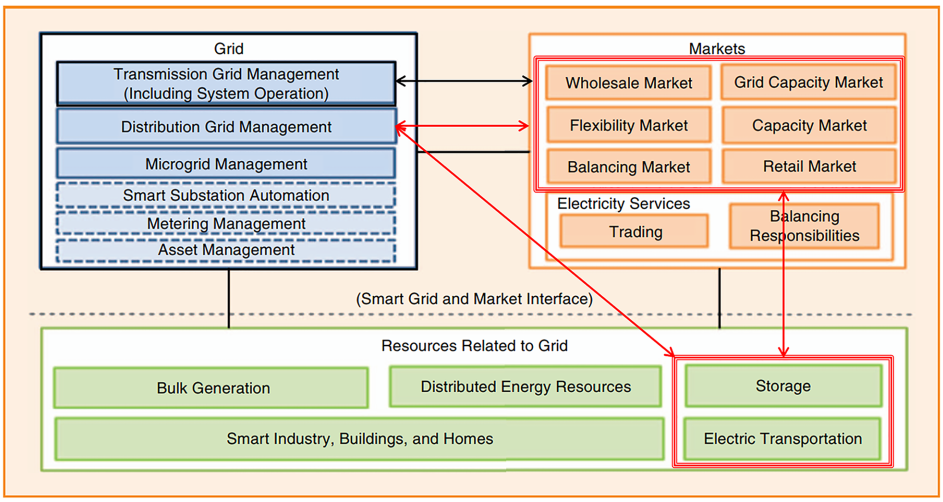
Source: Arup (2017) http://publications.arup.com/publications/u/uk_electricity_flexibility_timeline

Appendix B - SIM experiments data flow



Appendix C - Thesis operation impact and impacts





Adapted from source: McGranaghan, M., Houseman, D., Schmitt, L., Cleveland, F. & Lambert, E. (2016). "Enabling the integrated grid: Leveraging data to integrate distributed resources and customers". *IEEE Power and Energy Magazine*, 14(1), 83-93.