A multi-objective optimisation approach to the network arrangement of flexible heat demand

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Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed:

Date:

Acknowledgements

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Abbreviations

AC	Alternating Current
ANM	Active Network Management
BRE	Building Research Establishment
CHP	Combined Heat and Power
CO_2	Carbon Dioxide
DC	Direct Current
DEFRA	Department for Energy, Food and Rural Affairs
DG	Distributed Generation
DECC	Department for Energy and Climate Change
DER	Distributed Energy Resource
DNO	Distribution Network Operator
DSO	Distribution System Operator
ETS	Electrical Thermal Storage
EU	European Union
GHG	Green House Gas
HLGA	Hajela and Lin's Genetic Algorithm
MODERNE	Multi-objective Distributed Energy Resources and Network Evaluation
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Fast Non-dominated Sorting Genetic Algorithm
PESA	Pareto Envelope-based Selection Algorithm
SPEA	Strength Pareto Evolutionary Algorithm
SPEA2	Improved SPEA
UK	United Kingdom
US	United States
VEGA	Vector Evaluated Genetic Algorithm

Abstract

The electricity network in the UK is facing a challenging future where environmental and efficiency goals to be met require significant changes in the industry. The rethinking of how distribution networks are arranged and operated is essential due to increasing connections of generation at this level. This also gives significance to the issue of arranging and operating these assets in the most optimal manner. The saturated state of the transmission network has led to the popularity of connecting generation to distribution networks. It becomes evident that, when increasing generation from renewable sources, a means of storing energy is required. One area of storage being investigated for this aim is Electrical Thermal Storage (ETS), which is a form of flexible heating demand. This type of energy storage is cost effective, however it is limited in its application due to the natural dissipation of heat. It is preferable that this heat loss be of use and therefore ETS devices are used in the domestic setting. These devices can be in the form of space storage heaters or hot water storage tanks, which are able to store heat or hot water for up to several days, until the user wishes to make use of the resource.

Although decentralised generation and energy storage (Distributed Energy Resources - DER) at first glance appear to be an attractive means for the energy and carbon targets to be met, it can introduce further problems to the electricity network. It is possible for the addition of DER to lead to voltage rise or voltage drop, negatively impact on the protection systems and affect power quality. In order for distribution networks to successfully operate it is important that any new network assets are connected in an optimal manner.

This research has modified and used a multi-objective network planning framework to determine the optimal arrangement of ETS devices in distribution networks. The framework is built around the Strength Pareto Evolutionary Algorithm 2 (SPEA2), which takes its inspiration from evolution in nature, and is able to take into consideration the constraints of the network and multiple, conflicting objectives. The framework has been adapted to optimise the number of ETS devices, their location and operation, whilst ensuring that the network will operate within its constraints. The results generated by the planning framework illustrate the potential benefits offered by the inclusion of ETS in distribution networks, as well as demonstrate that the method and tools used are valuable and appropriate.

Chapter 1 - Introduction

Sustainability has been a popular political topic for some years now and in recent years in particular it has been widely publicised that the EU Directive calls for the UK to produce 15% of all energy from renewable sources by 2020 [1]. Alongside this commitment, the UK is working to reduce carbon emissions by 80% by 2050 [2]. Wind farms will play a significant role in helping the UK reach these targets as Scotland in particular has a vast natural wind resource. However the inherent issue with having so much energy coming from wind is that it is a naturally variable and intermittent source. The unpredictability of wind as an energy source brings about the requirement for effective storage in the network as compensation. As well as this requirement for renewable generation, as part of the pursuit of a low carbon future, the electrification of the heating load could be beneficial, especially with the introduction of effective thermal storage devices. It is possible that domestic heating could become a responsive demand.

The electricity network in the UK has been experiencing growing demands over the last few years, which has compelled an intensification of the interest and research into methods to maximise efficiency and to minimise energy loss. In order for the increase in wind energy deployment and carbon reductions to be realised, the electricity network must undergo significant change. In order to avoid costly upgrades to an already saturated transmission network, a move towards decentralised energy has been proposed. This will see different types of generation connected, locally, to distribution networks. Local generation supplying local load will help to improve efficiency, and alleviate strains on the saturated transmission network. However it is not as simple as merely connecting generation at distribution level. Currently distribution networks are passive networks and assets have previously been connected with a fit and forget technique. With adding more renewable generation, distribution networks will be required to become active, with more responsive and controllable demands. Aside from this, other technical issues include overcoming voltage rise from the connection of generators and reverse power flows which could cause violation of network limits.

Research into different forms of energy storage has also received growing attention as the inclusion of this type of technology could also help to mitigate the issues surrounding the intermittency and variability of wind energy. With the interest in electrification of the heating demand for the reduction of carbon emissions, it is possible that Electrical Thermal Storage (ETS) in the form of flexible heat demand could be a means of helping to compensate for the issues raised by renewable generation. The aggregated effect of installing ETS at a residential level as a responsive demand could aid with the variability and intermittency in renewable energy. By allowing the ETS devices to charge at times when there is an abundance of power from renewable sources, the ETS devices could be switched off from the network at times when generation does not meet demand, without leaving the consumers without adequate heating.

In order to successfully integrate ETS devices into the distribution network and to manage their operation, whilst considering the operational limits of the network, environmental concerns, network operator and consumer interests, a multi-objective optimisation approach is suggested as an appropriate method to use. A multi-objective approach will allow for these considerations to be included within the decision process.

It is the intrinsic requirement for effective storage and the pursuit of a low carbon future that is driving this research project. The aim of this research project is to investigate the limitations of the distribution network with regard to the prerequisite for increasing the penetration of renewable generation at this voltage level. Aside from this requirement to increase connections of these technologies, an adequate means of storage is also necessary. In order to achieve these aims a multi-objective optimisation approach is required. This is to ensure that the various different stakeholder points of view are taken into account in the network analysis and planning process. As such, the title of this research is: "*A multi-objective optimisation approach to the network arrangement of flexible heat demand.*"

1.1 Thesis Objectives

The research presented in this thesis is based around a multi-objective approach to network planning and asset operation. The main objective is to determine if integration of Electrical Thermal Storage into distribution networks can compensate for the intermittent and variable nature of renewable generation.

In order to achieve this key objective the completion of further, secondary objectives is necessary. These objectives have been identified as:

- Investigation of how storage can help to meet the renewable energy and carbon targets in the UK;
- Investigation of available storage media and network planning techniques;
- Investigation of available multi-objective optimisation techniques;
- Development of an appropriate ETS model;
- Modification of a multi-objective optimisation framework to incorporate ETS;
- Generation of results pertaining to architecture and management of ETS in distribution networks.

The final outcome will be a network analysis tool that will present the optimal number and arrangement of ETS devices in the distribution network. It will also illustrate how ETS can be responsive in order to aid the operation of the distribution network.

1.2 Contribution to Knowledge

To date there has been little research conducted [2-4] into the uses of heat storage for power distribution networks. The most recent studies carried out have been at Queen's University in Belfast. Fox et al [2], first propose using heating load control to manage the variability of wind energy in Ireland in 2007. They propose using wind power to supply water and space heating. The main focus is on electricity markets and how a greater penetration of wind and greater heat load will affect pricing. The system that they propose does not require any special equipment and although wind energy is variable, it can still maintain a suitable level of comfort for the customer.

The ideas that are first presented in [2] are developed further in [4] where Kennedy et al propose using the price of electricity to match heat loads to power generated from wind resources. They discuss the effect that wind generation has on the price of electricity in Ireland and presented a decreasing price for increasing wind generation. They propose using a price based controller for the heat demand so that peaks are avoided and times of high wind generation are taken advantage of. The study they conducted using a thermal model of a typical house showed that the thermal inertia of the heating system was sufficient to cope with high pricing periods whilst maintaining a satisfactory level of comfort to the customer.

This course of research, although sharing the same fundamental direction of using heat storage to compensate for the variability in wind energy, will focus on the optimisation of connecting the devices as well as scheduling and system operation; and the electricity market not playing a significant role. The techniques that will be used as part of this research programme, although having been applied to power systems engineering problems previously, are not currently associated with heat storage in power networks. This research programme aims to take advantage of this current gap in active research.

The contributions to knowledge from this course of research are:

- A comprehensive literature review in the area of ETS integration into electrical distribution networks;
- A formulated multi-objective optimisation problem for the optimal integration of ETS into distribution networks;
- A model of an ETS device for use in electricity system simulation and planning studies that demonstrates flexible response depending on power available from wind generation;
- Development and analysis of case studies of ETS integration and conclusions on parameters for successful arrangements in networks.

1.3 Thesis Overview

Chapter 1 presents the research area and question, identifies the area of novelty and details the associated publications. Chapter 2 provides a detailed review of Distributed Energy Resources, their benefits and their disadvantages. The reasons as to why optimal integration of various network assets is required is also outlined. Chapter 3 provides a review of the various multi-objective optimisation techniques that are available and how various techniques have been applied to the field of power systems planning. Chapter 4 introduces the Electrical Thermal Storage technologies in more detail and describes the model that was further developed of the domestic, electric hot water storage tank. Chapter 5 provides information on the multi-objective optimisation approach taken in the research project and how the network planning framework has been created around it. Chapter 6 presents case studies applied to the framework and the results that have been generated. The results are analysed and discussed in this section as well. Chapter 7 summarises the work that has been carried out in this research project as well as the findings from the results, and discusses possible avenues of future work.

1.4 Associated Publications

The following titles have been presented and published at conferences:

- **Microgen 2011:** S. Inglis, R. L. Storry, G. W. Ault and S. J. Galloway, "Methodology for Optimal Integration of Electric Vehicles as Microgeneration and Electrical Heat Storage as Responsive Demand", *MicrogenII 2nd International Conference on Microgeneration and Related Technologies,* Glasgow, April 2011
- **UPEC 2011:** R. L. Storry, G. Ault and S. Galloway, "The Use of Electrical Thermal Storage to Balance the Variability and Intermittency of Renewable Energy", *Universities Power Engineering Conference (UPEC), 2011 46th International*, Soest, 2011
- **CIRED 2013:** R. L. Storry, G. Ault and S. Galloway, "The Multiple Objective Optimisation of Electrical Thermal Storage To Compensate for the Intermittency and Variability in Renewable Generation in Distribution Networks", CIRED 2013, 22nd International Conference on Electricity Distribution, Stockholm, 2013

The following has been submitted for publication in the IEEE Power & Energy Society Transactions:

- R. L. Storry, G. Ault, "A multi-objective optimization approach to network arrangement of Electrical Thermal Storage"

1.5 References for Chapter 1

[1] Department for Energy and Climate Change, "Climate Change Act 2008 Impact Assessment," 2009.

[2] B. Fox, D. Flynn, H. Savage, and J. Kennedy, "Managing the variability of wind energy with heating load control," in *Information and Communication Technology in Electrical Sciences (ICTES 2007), 2007. ICTES. IET-UK International Conference on*, 2007, pp. 1-6.

[3] M. Akmal, D. Flynn, J. Kennedy, and B. Fox, "Flexible heat load for managing wind variability in the Irish power system," in *Universities Power Engineering Conference (UPEC), 2009 Proceedings of the 44th International*, 2009, pp. 1-5.

[4] J. Kennedy, B. Fox, and D. Flynn, "Use of electricity price to match heat load with wind power generation," in *Sustainable Power Generation and Supply, 2009. SUPERGEN '09. International Conference on*, 2009, pp. 1-6.

Chapter 2 – The Development of Distributed Energy Resources

Distributed generation (DG) can be loosely defined as "an electric power source connected directly to the distribution network or on the customer side of the meter" [1] and has become an attractive solution to renewable generation targets. Distributed Energy Resources (DER) are classified as being small, decentralised, grid-connected or off-grid connected systems that are in the locale of where the energy is used. DER encompasses generation technologies (typically referring to renewable generation), energy storage technologies and flexible demand at distribution level [2]. DER as a whole are able to provide support for intermittent generation and larger scale renewable generation. It is through the widespread deployment of DER that it is envisaged where the future of the power system lies.

2.1 The requirement for Distributed Energy Resources

Traditionally deployment of DER was the rule, not the exception, as the very first DC electricity networks, at the end of the 1800s, saw locally generated electricity supplied to local loads. These early electricity networks also employed local storage (typically batteries) to aid the balancing of supply and demand. As technologies developed and evolved the new AC grids, that appeared in the early 1900s, allowed for electricity to be transmitted over much larger distances and therefore generating plants increased their power outputs, and thus the electricity grid grew [2]. However the emergence of environmental concerns, the ambition to reduce carbon emissions and now binding targets for renewable generation sees the UK revisiting the concept of DER.

In a discussion by Pepermans et al in [2] five main drivers behind the growing, renewed interest in DER are stated as being: the development of DER technologies, the inability to develop or extend transmission lines, the consumers' demand for secure, reliable generation, the liberalisation of electricity markets and the issues relating to climate change. Overall, these five drivers can be split into two categories which are environmental issues and the liberalised electricity markets. This report does not, however, reflect the importance of security of supply. It is possible that security of supply could improve with greater diversity in the generation mix as reliance on one type of technology is reduced; but if all additional generation connecting to the grid is intermittent, such as wind, then security of supply can suffer. Whilst there are methods to help determine the contribution that DG technologies make to security of supply, such as those outlined in Engineering Technical Recommendation 130, it is still difficult to properly define.

Strbac et al in [5] also discuss why there has been renewed interest in DER and why it is required. Existing transmission and distribution infrastructure are now reaching the end of their operational life, and the current network arrangement has been designed to optimise the operation of assets in a more traditional network, with large generation sites connected at transmission level. As upgrading the transmission networks will incur considerable costs, the opportunity to redesign the networks, certainly at distribution level, is present and includes localised DER to relieve strains on transmission lines. This develops the concept of decentralised networks that will incorporate more DG technologies at distribution level, rather than continuing to add generation at transmission level.

Pecas Lopez et al [3] also describe the issues behind why incorporating DER is an appropriate path for the electricity network to take and are split into three categories of environmental concerns, commercial drivers and regulatory issues. Using DER and also incorporating Combined Heat and Power (CHP) plants into distribution networks to reduce greenhouse gas (GHG) emissions is a very significant driver, alongside the ambition to avoid the construction of more transmission lines and large scale power plants. Public resistance to new construction, visual and chemical pollution is the main issue and therefore DER are an appropriate solution as it avoids producing GHG whilst generating power.

In terms of commercial drivers, these stem from the uncertainties faced by all participating members of the electricity markets. DER are an attractive option in the markets as their comparative financial risk is less than that for the larger, conventional generating plants. Electricity markets aside, DER may also help to improve the reliability and power quality for the consumer as local generation will be supplying local loads [3].

Moving on to the regulatory issues that Pecas Lopez et al discuss, it is stated that by increasing the diversity of the energy generation profile, the security of supply can be better protected. For example, a local generator going offline will have less of an impact on the overall network than if a huge conventional plant were to fail. Furthermore, by changing the energy generation profile now and increasing the diversity of resources available, it is possible to be more in control of the future of the electricity network and the resources that will be available [4].

2.2 Benefits of Distributed Energy Resources

Distributed energy resources have the potential to benefit distribution networks in many different ways. Jenkins et al [4] outlined the main issues for pushing DER in various countries and the results included:

- Reduction of carbon emissions;
- Increasing energy efficiency;
- Introducing more competition to the markets;
- Diversifying the generation mix.

In general, the benefits that DER can bring can be categorised into economic, technical and environmental benefits. The main benefits associated with each are [2-6]:

1. Economic Benefits
    - Reduction in operating costs for the Distribution System Operator
    - Deferral of network investment costs
    - Increased reliability of the system
    - Increased revenues for DER developers due to lower initial capital costs and financial risk
2. Environmental Benefits
    - Reduction in carbon emissions
    - Increased operating efficiency of the network
3. Technical Benefits
    - Voltage profile improvement
    - Losses at distribution level are reduced
    - Losses at transmission level are reduced
    - Increased reliability of the system
    - Peak loads are reduced

The potential to provide the above benefits make DG an attractive solution for the UK's renewable energy and carbon emissions targets. Some benefits will depend on the physical location of the DG such as line losses; the nearer the generator is to the demand, the lower the line losses will be. Also, if DG, and storage technologies if they are incorporated into distribution networks, are able to output at peak times and meet high demands locally, the transmission network will experience less strain on its resources as it is transporting less power nationally, which results in a deferral of the upgrade costs for the transmission network. The issue that occurs here, is that with intermittent DG technologies it can be difficult to specifically target peak times, but the role of storage technologies that are able to export to the grid could be beneficial.

Table 2-1 presents a summary of the benefits brought about DG, with respect to ancillary services that are also provided.

Table 2-1 - Benefits & Services from DG [7]

		Benefit Categories							
		Energy Cost Savings	Savings in T&D Losses and Congestion Costs	Deferred Generation Capacity	Deferred T&D Capacity	System Reliability Benefits	Power Quality Benefits	Land Use Effects	Reduced Vulnerability to Terrorism
DG Services	Reduction in Peak Power Requirements	✓	✓	✓	✓	✓	✓	✓	✓
	Provision of Ancillary Services –Operating Reserves – Regulation – Blackstart –Reactive Power	✓	✓	✓	✓	✓	✓	✓	✓
	Emergency Power Supply	✓	✓			✓	✓		

T&D= transmission and distribution.

2.3 Issues raised by Distributed Energy Resources

The introduction of DER into distribution networks does also raise many issues. Pecas Lopez [8] discusses the issues surrounding increased penetrations of renewable generation at distribution network level. In terms of technical issues that are raised, voltage rise effect, protection, power quality and system stability are discussed. The available reserve for the grid is another important issue to be considered with the uptake in DG and DER technologies. Whilst charged storage technologies, such as fuel cells and batteries, can be classed as a form of reserve, the reliance on other forms of DG will impact on the whole system. There is no guarantee that wind farms and PV plants will be operational, or have a suitable natural resource at the time when reserve generation is required.

The voltage rise effect is a limiting factor when connecting generation to rural distribution networks. The problem lies in the fact that the distribution networks were designed to be passive and to pass power from the transmission network down to the low voltage levels to the consumers. However, connecting DER will introduce power flows in both directions, and the voltage profiles that the distribution networks have experienced previously will change. Voltage rise is produced by generators operating at higher voltages than the primary substations in order to export their energy [8].

The issues surrounding protection when connecting DER consider protecting both the network and the DER itself. Kauhaniemi et al [9] state that the most common protection issues concerning the connection of DER are:

- False tripping;
- Blinding of protection;
- Prevention of automatic reclosing;
- Unsynchronised reclosing;
- Islanding issues.

Also, introducing DER to distribution networks will add to fault currents and make the identification of disturbances more difficult, however the severity of the problem depends on the type of DER and its connection [10, 11].

It is also possible for the connection of DER to impact negatively on the power quality [3]. Voltage flicker and harmonics impact on power quality, or are indicative of power quality. Voltage flicker occurs when large loads vary, or are switched on and off, in a distribution network that is weak. This is visible as flicker in lights that is perceivable by the human eye. Considering a wind generator as an example, in a weak network the starting and stopping of the generation could present power quality problems [12]. Harmonics are caused by loads that are non-linear and can affect the voltage waveform. DER units that are connected through inverters could cause high-voltage distortion at the point of connection and impact on the distribution network [12, 13].

If the DER generation units are not connected to the distribution network in the most effective way then it is possible that system stability is compromised. Loss of stability can be associated with generators losing synchronism, and the impact on the overall system is greater with larger generation units [14].

Table 2-2 presents an overall summary of the potential benefits and impacts of DER on the distribution network [15]. The benefits described, which are also shown in Table 2-2, although are for DER in general, have more of a bias on the generation technologies encompassed by DER. The energy storage technologies and ETS in particular, are unable to offer as many benefits as the generation technologies. ETS is able to offer smoothing of loads, peak load clipping and the ability to aid the network at times where there is either an abundance in renewable generation or a shortage. In each instance the ETS devices are able to either charge up or be switched off from the network.

The possible benefits that could arise from more connections of DG are becoming more widely accepted, however the issues associated with the technologies must also be recognised. Table 2-2 shows the possible benefits and negative impacts. Whilst, improvement of the voltage profile and reduction in line losses are presented as benefits, the opposite is presented as a negative impact. It is through non-optimal integration with the grid that prompts increase in losses and voltage rise (significant demand and storage technologies could result in voltage drop). If the behaviour of the new DG connecting has not been properly investigated, there is also the risk of reverse power flows occurring in the distribution network that may put network assets at risk by exceeding thermal limits.

Similar statements can also be made for the economic benefits and negative impacts. Whilst DG technologies may result in lower costs for the Distribution System Operator (DSO), non-optimal integration and operation could also increase costs as losses in the network increase. This conflict between benefits and negative impacts helps to illustrate how important optimal integration of network assets is, particularly DG technologies.

Table 2-2 - Benefits and Impacts of DER [15]

	Possible Benefits	Possible Negative Impacts
Technical	• Improvement of voltage profile through connection of generation/load • Reduction of distribution losses • Reduction of transmission losses • Increased reliability • Reduction of peak loads	• Voltage rise/drop due to non-optimal integration of generation/load • Increase of line losses • Reverse power flows, which may exceed thermal limits of equipment • Increase of network fault levels • Unbalance • Transient voltage variations • Injection of harmonics • Network instability
Environmental	• Reduction of aggregate carbon emissions • High overall efficiencies (e.g. micro-CHP)	• Noise and visual pollution (e.g. wind farms) • Effect on the ecosystem and fisheries (e.g. micro-hydro) • Increment of localised emissions due to connection of generation (e.g. micro CHP)
Economic	• Reduction of DSO operating costs (through line losses reduction) • Investment deferral • Increased reliability • DER developer revenues, less up-front capital costs and reduced financial risk of investment	• Need for grid reinforcements • Increased DSO costs, (through increasing losses and fault levels) • Increased uncertainty in demand prediction

2.4 The requirement for effective Energy Storage

Due to the envisaged increase in penetration of DER, and with a significant increase in energy coming from wind generation in particular, the level of generation at specific times becomes more unpredictable. The intermittency and variability that is inherent in wind generation presents problems to the network operator such as system balancing. It is this variability and intermittency that provides the requirement for effective energy storage [16, 17]. It is also this ability to aid in balancing fluctuations in supply and demand that energy storage is able to provide benefits at both the generator end and the consumer end. At the generator end, it is possible that efficiency could be increased and at the consumer end it is possible power quality could be increased and for peak loads to be reduced [17].

The other main drivers for including energy storage into the electricity network include the requirement to keep an adequate spinning reserve available in order to suitably meet dramatic changes in supply and demand; there is also the unwillingness of the public to see the extension of the transmission network. Benefits that can arise from installing energy storage to avoid network upgrading at both transmission and distribution levels can include enhanced reliability, load shifting and avoiding losses by using local generation to supply local loads.

2.5 Types of Energy Storage

Foote et al [17] present a comprehensive summary of energy storage systems that are available. The possible energy storage media they identify are:

- Pumped hydro;
- Battery storage;
- Electrochemical fuel cells;
- Hydrogen fuel cells;
- Compressed air energy storage;
- Flywheel storage;
- Superconducting energy storage;
- Electrical thermal storage.

Connolly [18] also presents an extensive review of the storage technologies available and adds super capacitor energy storage and electric vehicles to this list.

A pumped hydro facility essentially involves two reservoirs, one upper and one lower, and a pipe connecting them allowing the flow of water between the reservoirs. Figure 2-1 shows an example of the hydroelectric plant at Cruachan in Scotland [19]. Pumped hydro storage allows for electricity to be stored in the form of potential energy in the upper reservoir, and at times of peak demand it is released and allowed to flow down to the lower reservoir through the turbines. At times of low demand the water is pumped to the upper reservoir. Pumped hydro is able to supply electricity to meet fluctuating demand within seconds [19]. The most significant disadvantage with this type of storage is the geographical requirement for reservoirs at certain elevations, although it is not uncommon for the second reservoir to be constructed if there is one suitable body of water that is naturally occurring [20, 21].

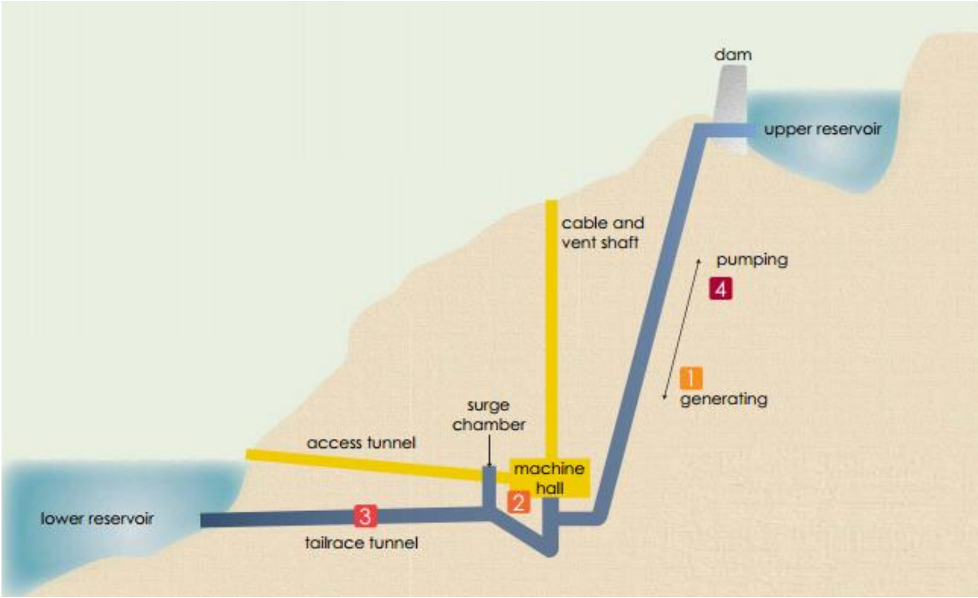

Figure 2-1 - Representation of the Ben Cruachan Hydro Plant [18]

Battery storage is a well-established technology that stores electricity in the form of chemical energy. A battery consists of electrochemical cells that contain an electrolyte in the form of a liquid or paste or solid and positive and negative electrodes. The technology has developed over recent years and moved from the traditional lead acid combination to sodium nickel chloride combinations. Currently these technologies are well established for small scale storage and running of electronic devices, however interest is growing in their possible application for large storage [21, 22]. These devices are able to supply electricity instantly as it is required; however in a large scale application the cost associated with battery storage systems becomes very large. Also in such a large scale application as to assist the power network, the lifetime of these devices, maintenance and disposal of chemicals all become very important issues to be considered [16].

Electrochemical fuel cells use an electrochemical reaction to convert electrical energy into chemical energy. The cells use two liquid electrolytes to carry out the reversible reaction. Figure 2-2 shows a simplified diagram of the electrochemical fuel cell.

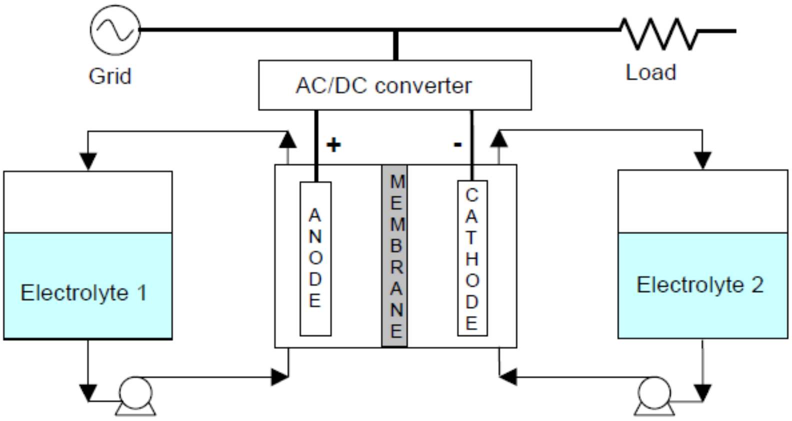

Figure 2-2 - Representation of an Electrochemical Fuel Cell [23]

The difference between these cells and traditional batteries is that instead of storing energy in a solid generated through the conversion process, energy is stored in the liquid electrolyte [19]. Although this technology is still undergoing significant technical development and is very costly, it has the capability to eliminate self-discharge and degradation [16, 21].

Hydrogen fuel cells utilise the electrolysis process to convert water into hydrogen. The application of this type of storage can include the transport industry. Energy is stored as hydrogen, and electricity is released once the hydrogen recombines with oxygen. The storage system itself will incorporate the electrolyser, the fuel cell and a tank to store hydrogen to ensure there is reserve if the grid requires it. The advantages that this technology boasts are a high efficiency and zero emissions as water is the by-product of the recombination process, especially in comparison to the internal combustion engine. The conversion process results in efficiencies ranging from 50% to 80%, which can be up to double the efficiency of the internal combustion engine which has an average efficiency of approximately 20%. There has also been significant interest in tying in hydrogen storage with renewable energy in networks; however the technology is still in development, issues relating to the life time of the system exist and it is expensive [19, 24].

Compressed air energy storage utilises disused salt mines and naturally occurring caverns to have air pumped into them at high pressure. When electricity is required at peak times, the air is heated and released through a turbine; Figure 2-3 shows the components involved in the system. On average compressed air storage systems can offer a larger capacity over other storage media, with the exception of pumped hydro, however the environmental requirements present a limitation to the locations that this technology could be applied to.

Typically capacities for compressed air energy storage sites can range from 50 MW to 300 MW. To overcome the geographical restrictions for this technology, studies are being conducted to pursue the possibility of compressed air being stored in manmade tanks or pipes [19, 21].

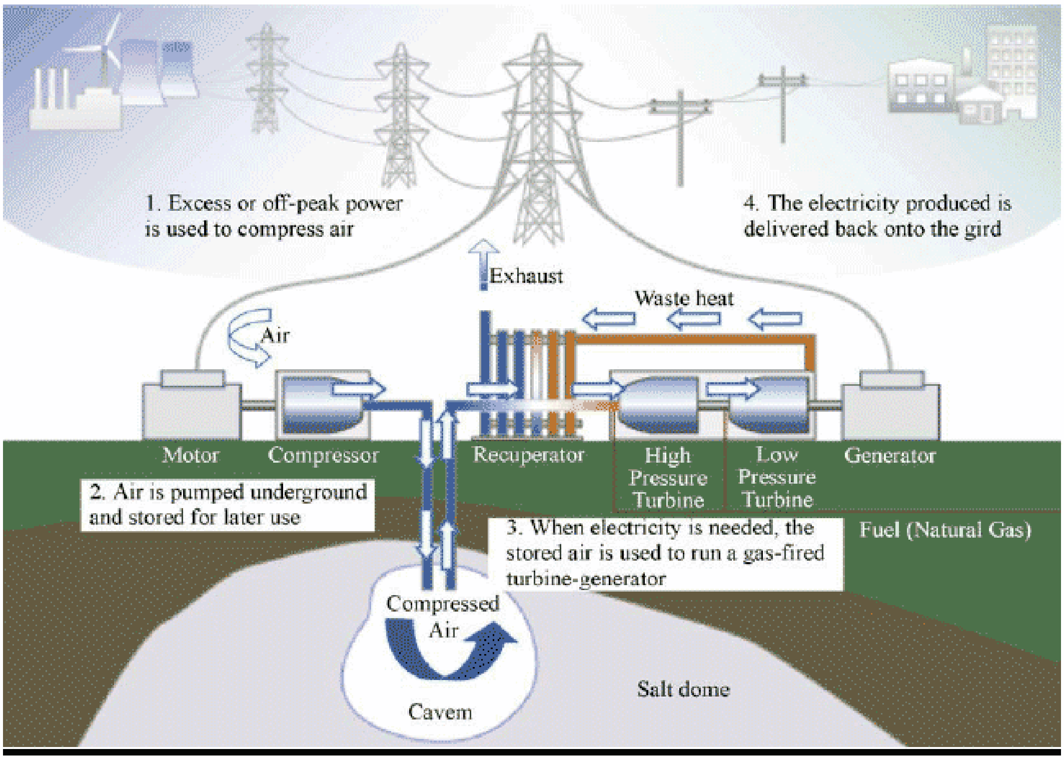

Figure 2-3 - Illustration of a Compressed Air Energy Storage System [25]

Flywheel energy storage systems store electrical energy as kinetic energy. The system involves a motor-generator and a rotating mass to convert electrical energy. The speed at which the flywheel is rotating and the moment of inertia determine the energy it can store. Flywheel systems fall into two categories. The first is a conventional steel rotor, low speed flywheel, and the second uses composite materials and operate at higher speeds. The advantages of flywheel energy storage systems are that they offer good charging and discharging rates and are able to respond to demand requirements very quickly. The technology experiences losses due to friction in the system and it is hypothesised that the instantaneous efficiency is at approximately 85%. This means that should the stored energy be released, it would be 85% of the input. It is estimated that this efficiency decreases over time, with an approximation that after 24 hours efficiency would be 45%. The degrading efficiency limits its application to short term storage, and much longer term application, from a practical point of view, unforeseeable [19, 21, 26].

Superconducting energy storage systems incorporate a conducting coil at a cryogenic temperature. The materials used have a very low resistance, and with the temperature being so low the losses are minimal. The arrangement also involves a power conditioning system to convert current between AC and DC. This system allows energy to be stored in the magnetic field, and is able to charge and discharge very quickly. This technology is incredibly expensive, however it can offer a life time that can experience tens of thousands of charging cycles [19, 26-28].

Electrical Thermal Storage is typically considered on a smaller scale, with the effect of operational devices being aggregated. This type of storage does present a cost effective means of storage, however the application itself is limited to an environment where the natural dissipation of heat is not wasted energy. Devices such as storage heaters and hot water storage tanks allow for energy to be stored in the form of heat which can be stored for a matter of a couple of days, until the user wishes to heat their home or use hot water [17].

Super capacitor energy storage differs from standard capacitor storage by using an extremely thin layer of electrolyte that separates the charge plates; and they offer a very high capacitance without requiring a large size. Super capacitors fall into various categories which are displayed in Figure 2-4. This technology is capable of very fast charging and discharging which offers an advantage over conventional capacitors and battery technologies. Maintenance for super capacitors is minimal and they boast a long lifetime, however the cost is extremely high when compared to established storage media, and a reduction would be required for super capacitor storage to become viable [21, 29].

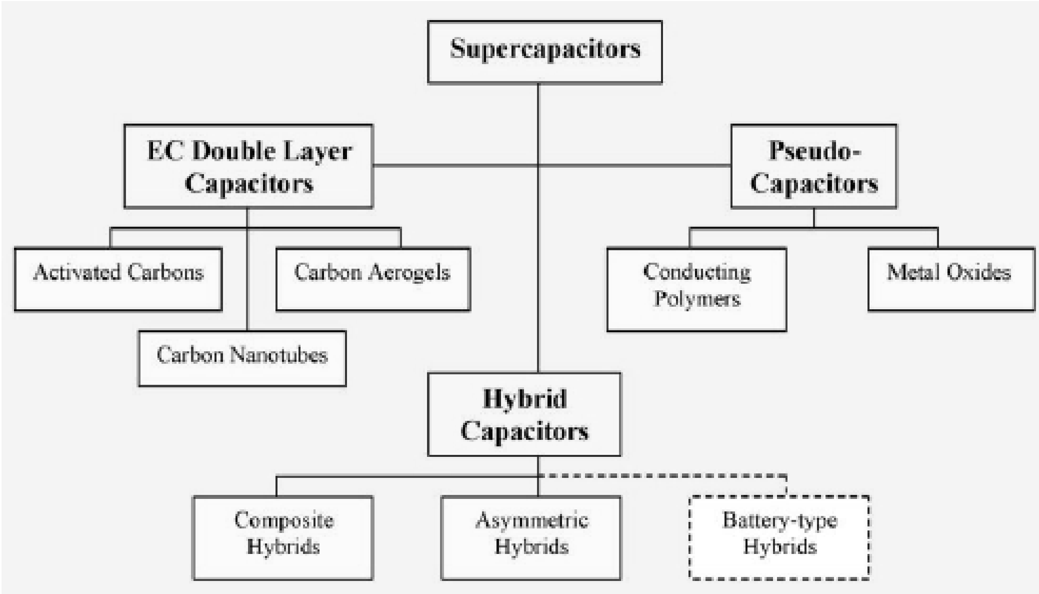

Figure 2-4 - Types of super capacitor [21]

The concept of using electric vehicle batteries as a form of storage has been gaining increased interest in recent years for the potential to offer grid support. The aggregated use of electric vehicle batteries is known as Vehicle-to-Grid power [30-32]. As transportation begins to shift towards electric-drive vehicles, and electricity generation is shifting towards renewable sources, the opportunity to use electric vehicle batteries as dispatchable storage is presented. There are a number of issues with this technology, which surround the batteries for the vehicles. They have a long charge time, and should battery switching stations be used instead of charging stations, the issue moves from being that of a longer charging time, to the owner of the vehicle not owning the battery. Also, if electric vehicles are going to be used as an aggregated demand or source, then benefits or incentives would need to be put in place to appease the electric vehicle owner as their vehicle is to be unavailable to them in the event that the vehicle must supply its stored energy to the grid. Aside from this, electric vehicles would also require active network management in order to optimally dispatch the stored energy and also ensure that a minimum state of charge is left in batteries should the owner wish to use the vehicle before it is charged again.

2.6 Benefits to the Network from Energy Storage

There are many possible benefits arising from the connection of energy storage to distribution networks. In a report for the US Department of Energy [32], a comprehensive list of the benefits brought about by the inclusion of energy storage technologies. The benefits are:

- *Electric energy time shift:*

  Using energy storage allows for demand to be shifted. Available storage will charge when there is an abundance of generation and discharge when supply does not meet demand. In the case of thermal storage, it is the electric heat demand that is shifted.

- *Increase capacity:*

  In areas where there is a limit to how much generation capacity can be connected, such as rural areas, connecting storage devices will allow for the cost of connecting new generation and upgrading to be offset.

- *Load following:*

  Incorporating storage into the network may make load following more easily achievable as technologies such as pumped hydro can be brought online very quickly; however it is essential to also realise the uncertainty that some renewable technologies, such as wind, introduce and will in fact make load following more difficult to achieve.

- *Frequency regulation:*

  Energy storage devices are able to provide a regulation service whilst both charging and discharging to aid in the regulation of the system's frequency and compensate for the differences between supply and demand.

- *Reserve capacity:*

  When the network requires more energy than is being generated, storage technologies are able to discharge their stored electricity back into the grid, providing support.

- *Voltage support:*

  Using storage to provide voltage support offsets the need to use the generating plant and reduces the costs associated.

- *Transmission support, Transmission congestion relief & Deferral of network upgrade costs:*

  The addition of energy storage will relieve the strain on the transmission network as the storage devices and other DER will be able to support their local distribution networks.

- *Time of Use Energy Cost management:*

  Time of use tariffs would aim to encourage end users to charge storage devices during off-peak, or cheap energy, prices. This would reduce the cost to the consumer by having stored energy priced at a lower rate; however such a scheme would rely heavily on appropriate policy and commercial structures, and ultimately the possible cost savings are debateable.

- *Demand charge management:*

  This will oversee when storage devices charge and discharge by using price signals, and aim to reduce the overall cost of energy to the consumer.

- *Reliability:*

  The inclusion of energy storage could reduce the occurrence of outages.

- *Power quality:*

  Improvement of power quality is possible, with a reduction in fluctuations and flicker.

- *Renewable energy time shift:*

  Energy devices will be able to charge when there is an abundance of renewable generation and discharge when there is not.

- *Renewable capacity firming & Wind generation grid integration:*

  Energy storage can help to increase the connections of renewable generation and ensure that they can connect to the network with a firm connection.

In summary, Table 2-3 presents an outline of various energy storage technologies and their applications.

Table 2-3 - Energy Storage Technologies and their Applications [33]

Full Power Duration of Storage	Applications of Storage and Feasible Replacement of Conventional Technologies	Biomass	Hydrogen Fuel Cell	Large Hydro	Compressed Air Energy Storage	Thermal Storage	Pumped Hydro	Redox Flow Cells	New and Old Battery Technologies	Flywheel	Superconducting Magnetic Energy Storage	Super Capacitor	Conventional Capacitor or Inductor
4 months	Annual smoothing of loads, PV, wind and small hydro	✓	✓	✓									
3 weeks	Smoothing weather effects: load, PV, wind, small hydro	✓	✓	✓									
3 days	Weekly smoothing of loads and most weather variations	✓	✓	✓	✓	✓	✓	✓					
8 hours	Daily load cycle, PV, wind, transmission line repair	✓	✓	✓	✓	✓	✓	✓	✓				
2 hours	Peak load lopping, standing reserve, wind power smoothing	✓	✓	✓	✓	✓	✓	✓	✓				
20 minutes	Spinning reserve, wind power smoothing, clouds on PV		✓	✓	✓	✓	✓	✓	✓	✓			
3 minutes	Spinning reserve, wind power smoothing of gusts		✓				✓	✓	✓	✓			
20 seconds	Line or local faults, voltage and frequency control							✓	✓	✓	✓	✓	✓

In Table 2-3 it can be seen that thermal storage technologies are able to aid in the weekly smoothing of loads and most weather variations. It is also able to aid during the shorter term – 20 minutes to 8 hours – by ensuring customers still have heat at times of low generation from renewable sources, or if portions of the network are experiencing outages for repairs, and making up demand when there is an abundance of renewable generation. Thermal storage does have some areas that it is not able to be of assistance. It is not able to assist in longer term goals of smoothing weather effects and loads. It is also unable to provide assistance in network deviations that happen in a matter of seconds and a few minutes. These instances include gusting for wind turbines and dealing with voltage and frequency variations.

2.7 The Need for Optimal Integration of Network Assets

It is possible that the non-optimal connection of DER will affect the quality of supply and damage equipment. There is also the potential for violation of the network's operating limits. In particular, in rural areas where wind farms are typically located, the sudden connection of generation can lead to voltage rise and violation of voltage constraints. Also, in urban areas where combined heat and power plants are being connected, it is the thermal limits and fault levels that can be readily exceeded [5, 34].

Various difficulties relating to the connection of DER are a result of the current fit and forget approach to distribution networks, which focuses more on connection rather than integration [35]. Under this approach, any new generation is connected under a worst-case scenario assessment which is usually one of maximum generation at minimum demand. This is referred to as a firm connection, and dictates that generation connected to the network may generate to its full capacity regardless of the demand. In this scheme generation is able to supply local loads and reduce the electricity transported through transmission lines; however without active network management it is unable to offer system support. On the other hand it is possible to provide generators with non-firm connections to the grid where the network operator is able to curtail the generation when required. With this arrangement active network management would benefit the network by determining the optimal and most efficient use of assets [5, 34, 36].

Determining the optimal integration of DER is essential for them to have the desired positive impact. Two areas of optimisation, from the DNO perspective, could be the location and number of devices to ensure that network assets are being utilised in the best possible way. However, there are also various stakeholder points of view to consider in the optimisation process. The network operator will be concerned with issues such as minimising outgoing cost, which could include network upgrading, and maximising revenue. The consumer will be concerned with quality and security of supply. Aside from this there are also network constraints (thermal limits, voltage limits) and environmental concerns (minimise carbon emissions, maximise penetration of renewable energy) to be considered when optimising the connection of DER. The different stakeholder points of view also illustrate the different perspectives from which optimisation can be achieved.

This problem requires a multi-objective approach to optimisation as there are many different and conflicting objectives to be taken into account as well the network constraints [34, 37]. By using multi-objective optimisation, the integration and operation of ETS devices can be achieved from the distribution network planning perspective, whilst also insuring that other stakeholder points of view are considered.

2.8 Summary

This chapter has provided an introduction to DER, which encompasses all network assets at a distribution network level. The reasons as to why there is now a renewed interested in a decentralised approach to generation have been highlighted with some of the main drivers being both environmental and technical. The desire to reduce carbon emissions and still ensure that the growing energy demand in the UK can be met has prompted this renewed interested. Aside from the main drivers behind this shift in interest, evidence has been emerging that details the potential benefits that both a decentralised approach to generation can bring, and that the inclusion of energy storage and responsive demands can bring.

It is important however that the issues raised by installing generation, storage and responsive demands are taken hand in hand with the benefits. It is possible that when connecting these devices to the distribution network, protection systems are adversely affected, as well as introducing voltage rise and negatively impacting on power quality.

This chapter also introduces the different types of energy storage that are currently available and being researched; the benefits that can be achieved specifically from energy storage are also highlighted

In taking into consideration the effects, both positive and negative, that arise from decentralised generation and energy storage, the requirement for optimal integration of these devices becomes apparent. The next chapter investigates the different methods that are available for assessing how network assets can be optimally integrated into distribution networks.

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Chapter 3 – Multi-objective Optimisation for Power Distribution Network Planning

It is possible to achieve multi-objective optimisation through a number of methods. In the fields of electrical engineering and power engineering, a popular approach to take is that of a Genetic or Evolutionary Algorithm which is based on evolutionary principles that are evident in nature.

The main driver for using a multi-objective optimisation approach is the ability to consider multiple and conflicting objectives, and problem constraints, simultaneously. The concept of evolutionary, or genetic, algorithms is introduced in this chapter, along with other multi-objective optimisation techniques. The reasons behind the choice of genetic algorithm are presented and the specific characteristics are further discussed in Chapter 5 when it is discussed in the context of the multi-objective optimisation network planning framework used in this research.

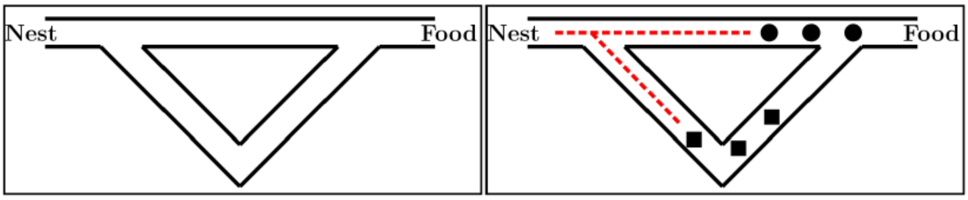
3.1 Methods for Multi-objective Optimisation

The move to heuristic approaches to optimisation was the result of the inability to apply the methods used in single objective optimisation to the more complex multi-objective optimisation problems. There are several approaches available which include: simulated annealing, tabu search, ant colony search, neural networks, fuzzy programming, hybrid techniques and evolutionary algorithms [1].

Simulated annealing is an optimisation technique based on the controlled heating and cooling used in metallurgy to increase the size of crystals in the material and reduce defects. If the cooling process is permitted to occur slowly, the kinetic energy in the material allows for a reduction in the occurrence of local optima and global optima are encouraged; producing a strong metal as opposed to being brittle. Kirkpatrick et al used this approach to determine optimal layouts of printed circuit boards. The simulated annealing approach conducts a search that allows changes between solutions, including to lesser solutions but the ability to do this reduces as the search continues and only moves to more optimal solutions are permitted. The main advantage of simulated annealing is its ability to be applied to any problem with relatively simple implementation, however it is unable to recognise when an optimal solution has been reached [1, 2].

The tabu search makes use of an adaptive memory and responsive exploration. This method starts with an initial solution and searches to find a better solution. Local optima are avoided by making use of the memory capabilities which store information relating to search strategies and recently visited solutions. While the search space is being explored, a subset of the search space is generated which the next solution is chosen from. The tabu search modifies the subset by labelling some of the solutions as 'tabu' or infeasible. An aspiration criterion can also be applied which determines if a solution that is marked as tabu can be reclassified as feasible, as it may lead to a more optimal result. The tabu search holds the advantage of being simpler to implement than simulated annealing and genetic algorithms, however it is possible for the method to overlook solutions in the search space [1].

The ant colony search is based on the ability that ants display in being able to find the shortest paths between food sources and the colony, and adapting to find a new shortest route should the first path become obstructed or infeasible. Real ants deposit pheromones along the path they are taking and this helps them to determine which path to follow. In the ant colony search this is mimicked by randomly exploring the search space, when the ants find a food source they leave a pheromone trail. How strong the trail is may depend on the quality and quantity of the food source, but they guide other ants to the site. The pheromone trail is strengthened as each ant that visits the site will leave a trail. Figure 3-1 illustrates this concept. The ant colony search has positive feedback which allows for solutions to be found quickly, and is also capable of handling dynamic problems. The disadvantages associated with this method are that the process is dependent on random events that are not independent and the convergence time is unknown [1, 3].



(a) All ants are in the nest. There is no pheromone in the environment.

(b) The foraging starts. In probability, 50% of the ants take the short path (symbolized by circles), and 50% take the long path to the food source (symbolized by rhombs).

(c) The ants that have taken the short path have arrived earlier at the food source. Therefore, when returning, the probability to take again the short path is higher.

(d) The pheromone trail on the short path receives, in probability, a stronger reinforcement, and the probability to take this path grows. Finally, due to the evaporation of the pheromone on the long path, the whole colony will, in probability, use the short path.

Figure 3-1 - Illustration of ant pheromone trails [3]

Neural networks for optimisation are based on biological neural networks. Neural networks process the information associated with a specific problem in the manner in which the brain would. Their performance is dependent on their architecture and their process techniques, and their ability to identify and classify patterns is one area in which this optimisation technique excels [1]. The Hopfield network is a recurrent network that stores information in a dynamically stable environment. Once a pattern has been identified it is stored in the energy landscape. When optimising, the energy function of the network is related to the objective function and therefore the search for minimum energy corresponds to the search to minimise the objective function [1, 4].

Fuzzy programming allows uncertainties and ambiguities in real world problems to be considered when simulating or optimising a specific problem. By using fuzzy programming, the input to the problem can be “fuzzy” itself, which is more indicative of a real world problem where not all components are defined or included. Due to the ability that fuzzy programming has to accommodate imprecise statements, the problem is represented accurately with reference to how the operators describe it. As well as the fuzzy input, there is a knowledge database and a rule-set which are used to make logical data manipulations [1, 5].

Hybrid techniques make use of the advantages of the differing methods in a bid to develop more powerful algorithms and processes for dealing with increasingly complex real world problems. The following hybrid techniques have emerged: simulated annealing and tabu search, simulated annealing and genetic algorithm, genetic algorithm and local search, fuzzy logic and genetic algorithm [1].

Evolutionary algorithms take their inspiration from the adaptability through the evolution of species in nature. The characteristics of the individual in the species are held in the chromosomes and through reproduction these characteristics are modified. Through years of reproduction these modifications result in a much stronger species that is more likely to survive in its environment. Modifications that will not be of benefit to the species typically die out so that only advantageous changes remain. Figure 3-2 illustrates the basic process including the initial population, fitness evaluation, crossover and mutation.

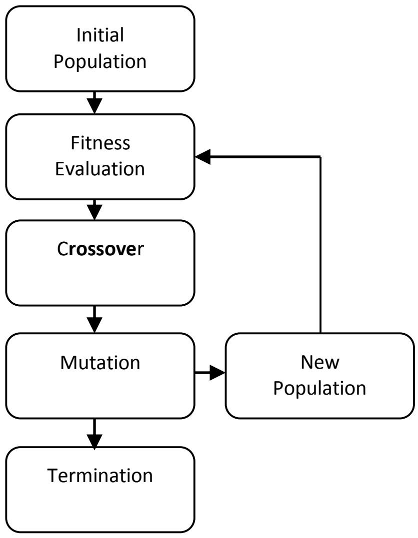


Figure 3-2 - Basic concept of an evolutionary algorithm

A suitable representation is chosen for the chromosomes, which correspond to feasible solutions to the optimisation problem. Chromosomes are typically coded in a binary representation. A number of solutions are required to form the initial population and this is usually achieved by randomly creating feasible solutions. The fitness evaluation ensures that chromosomes that are chosen to be "parents" for new solutions are good candidates. These chromosomes then undergo crossover which sees them generate offspring which are new solutions to the problem. The mutation operator is employed to generate a random change to some of the chromosomes to ensure that the population is kept diverse and the process does not run short of suitable solutions. Once this process is complete it is repeated with the new population made up of the offspring generated during the crossover stage and this continues until a predetermined termination criterion is reached or the user terminates the process [1, 6]

3.1.1 Pareto Optimality in Genetic Algorithms

A significant characteristic of genetic algorithms is Pareto optimality. In multi-objective optimisation this is achieved through dominance which determines if one solution is better than another. The optimal set of solutions is termed the Pareto front and solutions belong to this set if there is no other solution that can decrease in one objective without an increase in another. These solutions are also termed non-dominated solutions [6]. Figure 3-3 illustrates a Pareto Front.

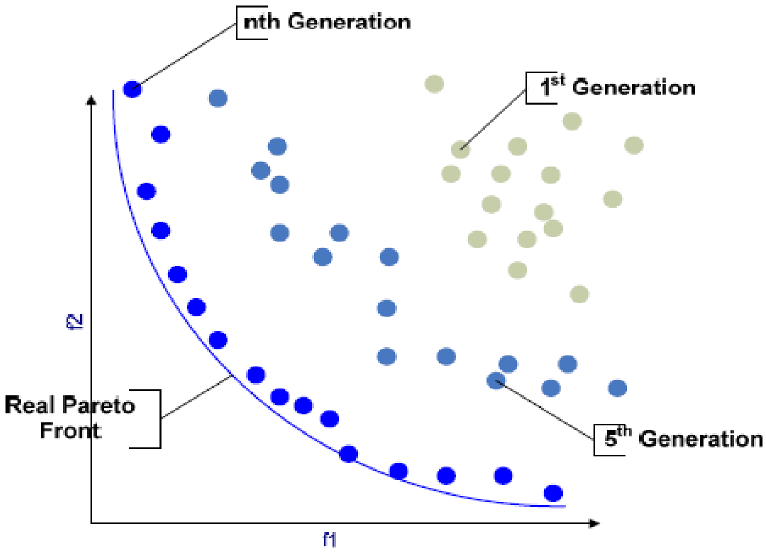


Figure 3-3 - Pareto Set for Multi-objective Evolutionary Algorithm [2]

As the genetic algorithm progresses through its processes, the solutions generated become fitter and stronger and they move towards the Pareto front. The solutions that populate the Pareto front illustrate the compromising nature of multi-objective optimisation as they demonstrate the trade-offs between the different objectives.

The concept of dominance is key in determining the Pareto front. This concept is illustrated in Figure 3-4. In this example five solutions are presented for the minimisation of objectives f1 and f2. Solution 2 dominates solutions 1, 3 and 5, solution 3 dominates solution 5 and solution 4 dominates solution 5. This means that solutions 2 and 4 are the non-dominated solutions as no other solutions dominate them. A solution that is non-dominated is part of the Pareto front, or set.

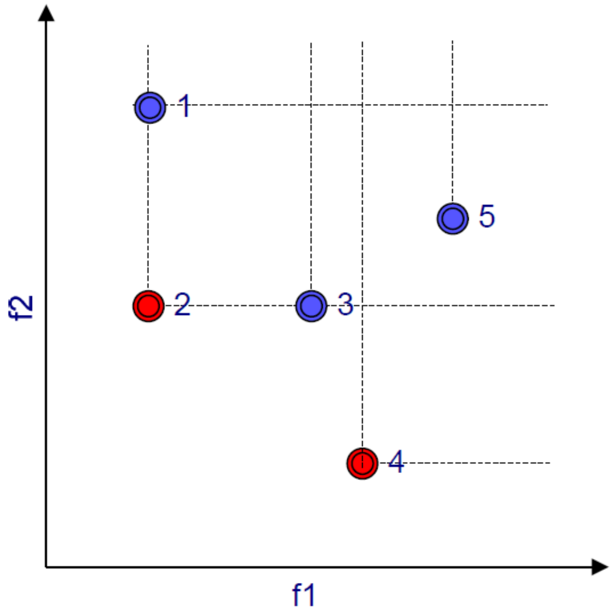


Figure 3-4 – Pareto Optimality Example [2]

As the concept of Pareto optimality is key to the multi-objective optimisation process, the results generated in the case studies laid out in Chapter 6 display the optimal solutions in the form of a chart, as illustrated in the example in Figure 3-4.

3.2 Multi-objective Optimisation with Genetic Algorithms

Since the initial concepts of the genetic algorithm were formed in the 1960s and 1970s by Holland, many different variations have been developed. Since the first genetic algorithm, the Vector Evaluated Genetic Algorithm, there has been continuous development in the field to generate more diverse algorithms that are able to more effectively evaluate the objectives to be optimised. The main differences between genetic algorithms are determined by their diversity, elitism and fitness assignment. Some of the better known genetic algorithm approaches are listed below [7].

- Vector Evaluated Genetic Algorithm (VEGA)

The first of the multiple objective evolutionary algorithms, proposed by Schaffer [8]. Compared to the more recent genetic algorithms, this is a straightforward genetic algorithm to implement. However, there is little in the way of diversity or elitism and frequently converges towards the extremes of the objectives

- Pareto Envelope-based Selection Algorithm (PESA)

  This genetic algorithm has no fitness assignment but uses a cell-based density function for its diversity. It is an elitist algorithm and is both easy to implement and efficient in reaching convergence, however its performance is dependent on the size of the cells.

- Non-dominated Sorting Genetic Algorithm (NSGA)

  The NSGA uses a ranking system based on non-domination sorting as its fitness assignment and diversity is achieved by using niching for fitness sharing. This particular genetic algorithm is particularly fast at converging, but again has issues pertaining to the niching parameter size.

- Fast Non-dominated Sorting Genetic Algorithm (NSGA-II)

  NSGA-II is a continuation of NSGA. The fitness assignment is achieved by the same means; however diversity is achieved through evaluating crowding distance. This new development of NSGA is elitist and is an efficient genetic algorithm; however the crowding distance to ensure diversity is only effective in the objective space.

- Strength Pareto Evolutionary Algorithm (SPEA)

  SPEA incorporates a separate archive to store non-dominated solutions and uses a ranking system for fitness assignment. In order to truncate the external population to meet a specified size, a complex clustering algorithm is used.

- Improved SPEA (SPEA2)

  SPEA2 is a continuation of SPEA. The fitness assignment is determined by the strength of solutions which is established by the number of solutions the individual dominates and the number of solutions it is dominated by. This improved SPEA ensures that extreme solutions are preserved; however the downfall of this particular genetic algorithm is that is computationally very time-consuming.

Like any other method of optimisation, genetic algorithms have their advantages and disadvantages. It is evident that the most significant advantage to the genetic algorithm approach is that it is able to cope with variables that are integers and functions that are both non-convex and non-differentiable. This ability results in the genetic algorithm approach being able to solve complex problems [8, 9]. Aside from this, genetic algorithms are implemented modularly, which is the basis of their adaptability to different problems. It is the ability to separate the search procedure from the rest of the functions in the genetic algorithm that facilitates the modularity [10]. The actual implementation of the genetic algorithm is relatively simple, which allows users without a strong mathematical background to still be able to put a sensible method into operation. One could argue that by having a more in depth knowledge of the problem being analysed rather than the method by which it is being analysed is more advantageous; meaning that the genetic algorithm can be better suited to the problem it faces [7, 11, 12]. Another important advantage for using genetic algorithms is that they are less likely to get stuck at local optima. This is achieved due to the ability to run searches in various, different sections of the search simultaneously [10, 13]. Their capability for assessing numerous solutions concurrently also allows for computation time to be reduced compared to other optimisation techniques [10].

As well as highlighting the advantages for genetic algorithms, they must be taken hand in hand with their limitations. When using the genetic algorithm approach it is never certain that a specific result, or global optima, will be reached in a limited time. Due to the large computational time that evolutionary optimisation approaches require, they are ruled out from being applied to “real-time” problems. However the trade-off for this can be identified in that genetic algorithms are able to find solutions otherwise deemed too difficult to obtain [9-11]. It is also important to consider how the parameters for the genetic algorithm are set. Parameters that require definition before starting the optimisation process include size of population and the rates of both crossover and mutation and the number of generations to be carried out. These all have an effect on how the genetic algorithm performs and without proper consideration of these parameters it is possible for the search to move towards local optima. This effect is called genetic drift [11]. It can occur when the population is either too small or not diverse enough, however if the population is too large then the computation time is greatly increased. This is an example of the trade-off that has to be made and the importance of considering the parameters for the genetic algorithm.

Zitzler and Thiele in [14] present a comparative study of the performance of the original SPEA against other genetic algorithms. SPEA is compared against VEGA, NPGA, NSGA and a method of aggregation by variable objective weighting, termed Hajela and Lin’s Genetic Algorithm

(HLGA). The case study applied to the genetic algorithms was the Multiobjective 0/1 Knapsack Problem, with the performance criteria defined as: the effectiveness in finding multiple Pareto optimal solutions. The problem has a number of items and each item has a weight and profit associated with it. The knapsack also has a constraint on it which limits its capacity. The aim is to find a selection of items that maximises the profit, but is also within the constraint of the knapsack. It was found that the solutions generated by SPEA included all solutions found by the other methods, and that SPEA was able to find solutions closer to the Pareto Front. It was determined that SPEA could comfortably outperform the other methods used. In [15] Zitzler et al detail improvements made to SPEA. In an effort to address weaknesses in SPEA, and ensure that SPEA2 would be an effective, state-of-the-art technique in solving multi-objective optimisation problems, Zitzler et al performed the following modifications to SPEA:

- The fitness assignment process was updated to include the number of individuals a particular solution both dominates and is dominated by;
- A density estimation technique was incorporated to determine the nearest neighbours in an effort to more effectively guide the search;
- An archive truncation method was applied in order to preserve boundary solutions.

In testing the new SPEA2 against the original SPEA and against new rival algorithms NSGA-II and PESA it was found that SPEA2 was capable of outperforming its predecessor and compared well to the new rival algorithms. Both combinatorial and continuous problems were applied, including the previously mentioned knapsack problem. It was found that PESA had difficulty in preserving outer solutions while NSGA-II and SPEA2 seemed to behave in a similar manner. In some cases NSGA-II would reach a broader spread of solutions while SPEA2 would provide a better distribution of solutions, especially as the objectives increased in number.

In this research project it is SPEA2 that is used to achieve the multi-objective optimisation and this genetic algorithm is described in more detail in Chapter 5.

3.3 Multi-objective Optimisation Approaches in Distribution Network Planning

The issue of distribution network planning, and planning with DER, lends itself perfectly to the multi-objective optimisation approach. The benefits from taking this approach can be summarised as:

- Provides a more realistic representation of the problem being addressed, which in turn helps to generate more realistic solutions [16].
- Many different points of view can be incorporated into the problem, so solutions that are generated represent the trade-offs that are essential when choosing which solution to implement [17].
- The Pareto fronts that are generated aid the decision making process by illustrating the relationships between objectives.

Various research has been carried out using a multi-objective optimisation approach. Celli et al presented research using the ε-constrained optimisation method [18]. This method was applied to optimising the size and location of embedded generation with the aim of minimising a range of objectives including cost of power losses and cost of reinforcements. It is also important to note that this analysis was carried out from the perspective of a Distribution Network Operator (DNO) that has no say in the investment in embedded generation. This approach is further developed in [19] where the main difference sees a probabilistic load flow used. Due to this there are linear relationships between the embedded generation and loads and as such it does not consider controllable DER. This was further developed by Carpinelli et al in [20] which saw the incorporation of the ε-constrained method into a double trade-off approach which is based on a method developed by Burke et al in [21]. The solutions that are part of the Pareto front are those with the greatest robustness. The specific problems that this approach was applied to are the minimisation of harmonic distortion, voltage profile and the cost of energy losses and to optimise the size and location of power electronics interfaced controllable embedded generation [20, 22]. It is important to recognise that this research has been based around the ε-constrained method. Technically this is a single objective method of optimisation that is able to achieve multi-objective solutions through iterations and requires thorough knowledge of the problem before implementation.

Ochoa et al have also performed research investigating using multi-objective optimisation for network planning [23]. They propose the use of a multi-objective performance index to determine the best locations for distributed generation. The index was used to establish the effects of distributed generation on various technical aspects of the network including short circuit currents, voltage profile and the network losses. This is then applied to a problem further investigating the issues of installing distributed generation and weighting factors are introduced in order to determine the multi-objective performance index and associate the various technical issues being investigated [24]. The aspects investigated include voltage profile, real and reactive power losses, capacitor current capacity and various possible short circuits. The outcomes of this stated that the relevance factors used to equate the various impacts were flexible which is advantageous in multi-objective optimisation as it allows for the decision process to be adaptable to different points of view. This approach was also applied to time-varying generation [25]. This study takes in to account the more variable characteristics, particularly relating to renewable generation. A time-varying approach is applied to both the generation and the load and weighting factors are applied to the various technical issues associated with installing such generation. The outcome of the research identifies that the multi-objective performance index is a powerful tool and their formulation of the problem still allows for inclusion of environmental and financial considerations, should they be required. The main drawback with the approach used, however, is in the determination of a suitable weighting factor for the technical issues being investigated.

Haesen et al presented a view of the changing distribution networks and a possible way in which planning could be modified to cope with those changes. In [26] they present a multi-objective optimisation approach that is based around a genetic algorithm. The specific algorithm they use is SPEA and the objectives for minimisation were line losses, main grid energy flow, DER installation cost and gas distribution grid investment costs. Haesen et al then went on to present a comparison of both traditional optimisation and evolutionary algorithm approaches for DER planning [27]. They compare a Mixed Integer Quadratic Programming approach to the Monte-Carlo simulation characteristic in genetic algorithms. The conclusion presented that the traditional optimisation approach is not as suitable for DER planning as the genetic algorithm technique is. The traditional optimisation method requires objectives to be mathematically formulated and so is not suitable for the more random aspects of generation and load. The genetic algorithm technique allows for the objectives that are not easily represented mathematically to still be considered. This view is further developed in [28] where the authors state the limitations of a traditional analytical method and that an evolutionary algorithm process is more able to cope with the stochastic nature of generation and load data and is much more adaptable to the distribution network planning problem.

In the same year as [28], Haesen et al also presented [29] detailing a multi-objective planning approach for energy storage technologies. In this research they considered both technical objectives and economic objectives. The objectives chosen for optimisation are voltage supply, power quality and economic advantages with the imbalance market and the Strength Pareto Evolutionary Algorithm is the genetic algorithm used in this case. The realisation made is that the multi-objective optimisation approach is appropriate and effectively provides a Pareto front of suitable arrangements of storage technologies. It is also clearly stated that the information given to the algorithm process is important and impacts on the results, however the results that are generated offer the user a varied choice in which solution is implemented.

In the last few years more distribution planning problems have had a multi-objective optimisation approach applied to them. For example, Yongmei et al in [30] discuss the placement of distributed generators in distribution networks. In this case the linear, weighted sum method is used and the goal was to determine the maximum, optimal size of the DG and minimise the network's line losses. Kothari et al in [31] present a review of the different multi-objective optimisation techniques available for power systems planning problems. They discuss genetic algorithms and evolutionary programming, simulated annealing, tabu search and the ant colony search method; which have been described previously. The popularity of using such methods is highlighted along with the disadvantages associated with some techniques and that it is possible for some methods to be more prone to converging at local optima than others. Pokharel et al [32] present a planning framework based around SPEA2 for the optimal integration of DG. In this research the suitability of SPEA2 is highlighted due to "its suitability for optimising different types of stochastic and controllable DG simultaneously". The attributes considered in this case are the minimisation of real power generation, line losses, CO_2 emissions and benefits seen to come from DG. The operational constraints of the networks are the constraints the planning framework must adhere to. The authors highlight that the main benefit to using a SPEA2 based approach is that it allows all stakeholders to view the trade-offs between the different objectives.

In following the work that has applied multi-objective optimisation techniques, it is clear that genetic algorithms and SPEA/SPEA2 in particular, are an attractive option. The fact that the issues associated with each problem are varied shows their adaptability. While disadvantages include the large computation time and the requirement for proper consideration of parameters before implementation must be taken into account; the very adaptability that these methods have shown still renders them a popular and appropriate method to employ.

3.4 Summary

It has already been stated that this research project is aiming to modify a network planning framework to determine the optimal arrangement, number and operation of electrical thermal storage devices. This chapter has introduced the concepts of multi-objective optimisation and described many different approaches that are available. Genetic algorithms have been a popular method to implement for distribution network planning and an emphasis has been made on their presence and the development of research relating to multi-objective optimisation in distribution networks. A brief description of the different genetic algorithms, as they have been developed since their introduction, is presented with the distinction that SPEA2 will be the method used in this research project.

This chapter has introduced the key concepts concerned with multi-objective optimisation; particularly Pareto optimality, which can be observed in the results presented in Chapter 6. The next chapter introduces the ETS device model that has been developed for inclusion in the network planning framework, before going on to discuss the framework used in this research in Chapter 5.

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Chapter 4 - Electrical Thermal Storage Modelling for Power System Optimisation

The main driver behind the possible reintroduction of ETS devices, and research into the possible benefits to the network, is the pursuit of a low carbon future. By using electricity as the fuel for heating and hot water as opposed to burning gas, there is the possibility that carbon emissions related to both could be reduced – especially if the electricity is produced by clean, renewable sources. As previously stated, in a domestic setting ETS can be in the form of storage heaters or hot water storage tanks. This chapter will describe more about the reason for the electrification of the heat demand, ETS in more detail and the modelling undertaken to ensure that an accurate a model as possible was created to represent the ETS functionality. The model presented in this chapter has been further developed in order to introduce power consumption that is dependent on the available generation from wind.

4.1 The Electrification of Heat Demand

In the "Meeting the Energy Challenge" white paper from the Department of Energy and Climate Change (DECC), it is outlined that both CO_2 emissions and energy losses could be reduced by focusing on supplying local heat and electricity demands from decentralised, renewable generation [1]. Further pursuit of decarbonisation in the endeavour to achieve a low carbon future will require significant change, and not just within the scope of domestic space and water heating. The three main areas that require attention are power generation, heating and transport [2]. Electricity generation will be required to move away from reliance on fossil fuels and harness the renewable resources available. Transportation will also require change to reduce CO_2 emissions. There are a number of options available when considering possible courses of action for decarbonising space and water heating. With the continuing interest in a decentralised approach to generation, CHP is becoming a popular method in supplying both electricity and heat to the immediate locale. However CHP is not always easily installed and connected to the surrounding properties and businesses. Therefore, space storage heaters and hot water storage tanks are another appropriate heat technology in the pursuit of a low carbon future. As they are powered by electricity and not a gas supply, there is an immediate reduction in CO_2 emissions, however it must not be forgotten that the electricity supplying the devices may still be from conventional sources. An increasing use of electricity for providing heat and hot water will also reduce dependency on gas supplies from abroad.

The importance of decarbonising the heat demand in the UK is highlighted in the “Meeting the Energy Challenge” from DECC [1]. It is stated that, in 2007 when the paper was published, heat is accountable for 47% of the total carbon emissions in the UK. Figure 4-1 illustrates the CO_2 emissions by sector and how heat is used.

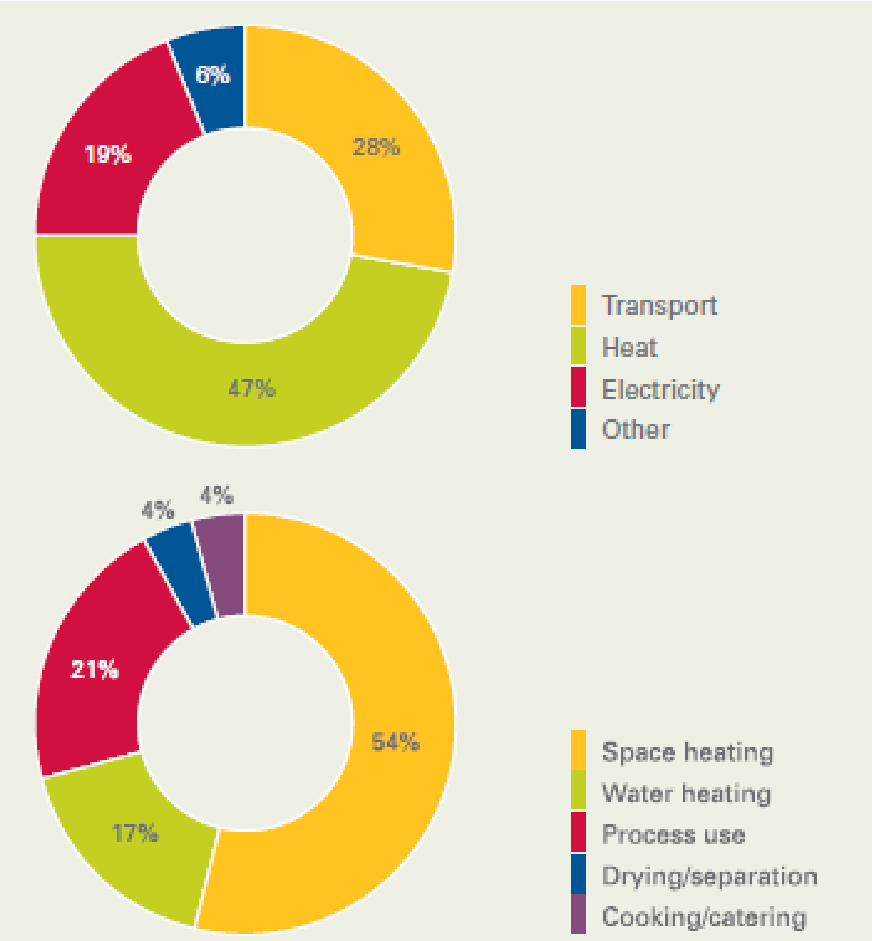

Figure 4-1 - TOP: CO_2 Emissions by Sector; BOTTOM: How Heat is used [1]

In order to achieve a reduction in emissions resulting from the heat demand, certain changes throughout the building sector are also required. New homes and other buildings that are to be constructed would need to embrace new technologies in order to help achieve the CO_2 reduction. Buildings would need to be geared towards incorporating heat and water heating either from CHP and district heating schemes or by including new electric space and hot water storage systems [3].

4.2 Electrical Thermal Storage

4.2.1 Storage Heating

Storage heaters in Britain started development in the 1940s and 1950s due to the ideology that if a new product was electric it was considered to be efficient and modern. As well as this, it was cheaper and more efficient for the power companies to keep the generators running rather than turning them off at night due to the decrease in demand. In their view, creating an electrical demand at night would help to realise their desire to keep the generators running.

The first commercial storage heater was available in 1961, and coupled with the Economy 7 tariff, they became a popular heating solution. These units were typically large and bulky as large ceramic blocks were used to store heat. Modern day storage heaters are much more slim line as a result of advances with the materials that can be used [4, 5].

Figure 4-2 is a diagram of a typical space storage heater. At the centre of the storage heater are ceramic bricks that hold the heat from the elements. On the Economy 7 tariff these heaters charge up overnight and their heat is dissipated over the course of the day. The output controls determine how much heat is released through the valve, however more modern models are now incorporating thermostat controls.

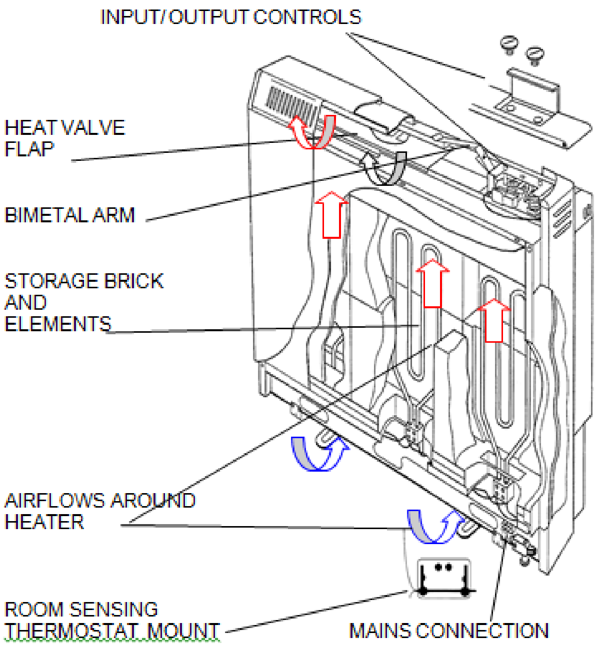

Figure 4-2 - Diagram of space storage heater [6]

There are various benefits and disadvantages to electric storage heaters. It is far cheaper to run the storage heater on the night tariff in Economy 7 rather than running at regular rates. Furthermore, due to the natural dissipation of heat from storage heaters the home will receive heat throughout the night as opposed to central heating users that typically switch off heating overnight. The installation and initial, capital cost of storage heaters is much cheaper than that of a gas central heating system and maintenance is seldom required, which keeps running costs down. As well as these advantages there is also the benefit that by using storage heating it is possible to situate homes in areas where gas supplies are not available.

However, there are associated disadvantages to an electric heating system. The most significant issue with using electric storage heating is the natural dissipation of the stored heat. The heat is released without consideration of requirement as this release is uncontrollable. If the home is left unoccupied it is needlessly heated. Also, if the storage control setting has not been correctly set for the day ahead it is possible that not enough heat will be stored during the night for the coming day. Finding the appropriate capacity of a storage heater for a particular room can be difficult. If the heater is too small, the result will be that the user has to buy additional electric heating during the day. If the heater is too large, again the cost will be high. As well as finding the appropriate capacity, the physical size of the storage heaters can be off-putting. They are much bulkier than their gas central heating counterparts and occupy more space [7].

4.2.2 Hot Water Storage

In the domestic environment, hot water heating is typically combined with another heat source. This could be a domestic fire place, a heat pump or boiler. Whatever the method adopted in the home, the method is required to be efficient and well controlled [8].

If a home has storage heaters then it is likely that hot water is generated through an immersion tank. This set up typically involves a tank, with suitable insulation to retain heat, two immersion heaters, a cold water inlet and a hot water outlet. This is illustrated in Figure 4-3.

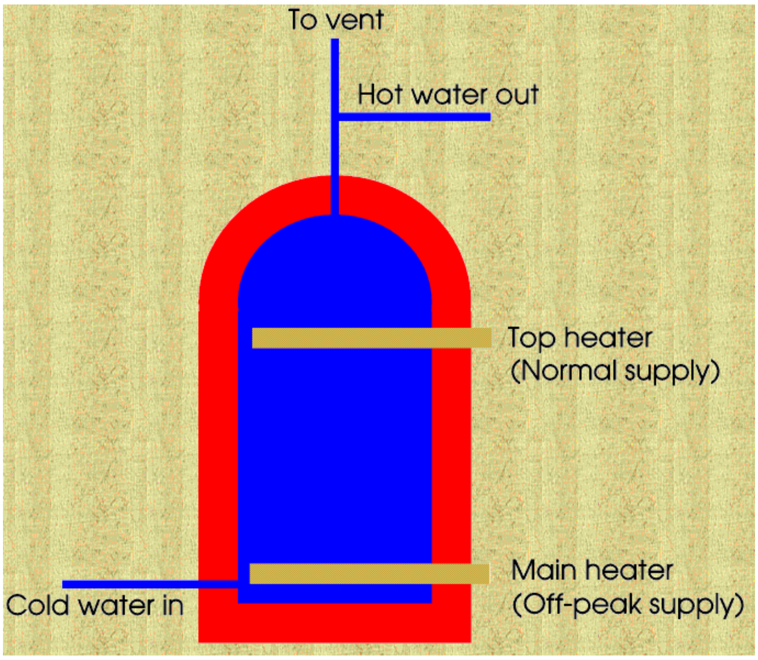

Figure 4-3 - Diagram of hot water storage tank [5]

Electricity is an effective and efficient way to heat water, and due to effective insulation in the hot water storage tanks it is possible to heat water during off-peak times, when electricity is cheaper, and store it until it is needed during the day. As mentioned before, there are typically two immersion heaters within the tank. The heater at the base of the tank heats all the water present in the tank. A second heater is placed nearer the top of the tank to provide heat to cold water that is replacing used, hot water [9].

As well as providing an effective source of water heating and storage, electric hot water storage tanks provide many benefits. Installation of the tanks is relatively simple and depending on the geographical situation of properties, there is the possibility of incorporating solar heated water into the tanks [9]. This would result in hot water tanks having input from both electric and solar sources.

Electric hot water tanks can be found alongside domestic space heaters in the home. Although there are individual variations in water draw, on aggregate a group of people produce a stable operation and demand profile. Electric hot water heating is also still popular. A study carried out in 2005 by DEFRA, BRE and the Energy Saving Trust highlighted that in 2001, approximately 58% of English homes had immersion heating for their hot water [10, 11].

4.3 Modelling Electrical Thermal Storage

This research project models a domestic electric hot water storage tank as an ETS device for optimisation in a distribution system planning context. Their capacity for thermal energy storage makes them an ideal aggregated, controllable load, therefore meaning that they can benefit the electricity network [12]. The argument for modelling this type of thermal storage came from the fact that a large proportion of homes have electric hot water storage tanks, and that information on modelling them is much more widely available than for space storage heaters. The characteristics of hot water tanks have been modelled frequently in recent years for varying research interests. One area in particular is that of solar heated water. Research has been conducted to determine various features of electric hot water storage, for example, Kerkeni et al investigate the thermal stratification in solar water heaters [13]. The study was aimed at determining the extent of the effect of thermal stratification that occurred in solar hot water heaters in an effort to determine at what time of the day the first draw of hot water should occur.

Another area in which electric hot water storage features is in load aggregation for network benefits. Vrettos et al investigated the aggregation of electric hot water storage for load frequency control [14]. The main aim of the research was to quantify the detrimental effect to the end user should external controls be introduced to domestic electric hot water storage.

Aside from this there is extensive research into varying designs, materials and implementations to determine their impact on solar water heating. For example in [15], Yang and Shue investigate the effect of storage tank design on performance of the solar water heater. In [16], Murthy et al investigate replacing the traditional solar collector with a concrete panel and an array of copper tubing in an effort to make solar water heating more affordable in India. In [17], Ennaceri et al investigate the effect of the collector angle on the performance of the solar water heater. This is an investigation that is also carried out by Kezhi et al in [18].

Domestic, electric hot water tanks are still popular in homes, and as such is modelled in this research. The following sections illustrate the approach and parameters used to achieve a model of an electric hot water storage tank, and the further development to ensure wind dependent power consumption.

4.3.1 Water Draw Profile

In order to develop an accurate hot water tank model, an idea of the average domestic water draw for a day is required as a starting point. The hot water draw profile in Figure 4-4 illustrates the usage for a typical dwelling. This profile indicates that the largest draw in water on a day to day basis occurs between 0800 and 1000 in the morning, with another spike in water draw occurring at 1800.

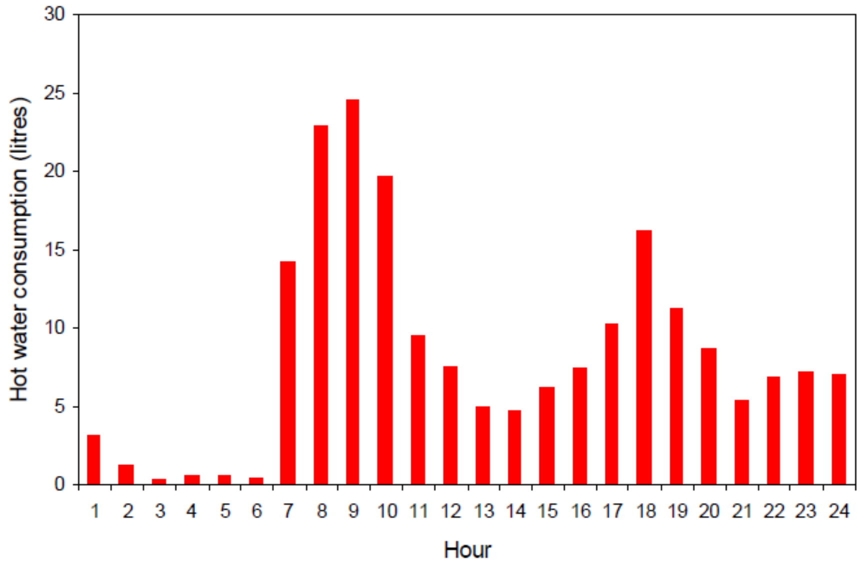

Figure 4-4 - Average domestic daily water usage [11]

This was tabulated into litres per half hour to be compatible with the MODERNE framework. Table 4-1 displays the data.

Table 4-1 - Average domestic hot water usage

Time (h)	Hot Water Draw (L)	Time (h)	Hot Water Draw (L)
0	3.2	12.5	5.9
0.5	3.2	13	5.3
1	2.2	13.5	5.3
1.5	2.2	14	4.4
2	1.4	14.5	4.4
2.5	1.4	15	3.7
3	1.1	15.5	3.7
3.5	1.1	16	3.8
4	0.9	16.5	3.8
4.5	0.9	17	4.5
5	1.6	17.5	4.5
5.5	1.6	18	6.3
6	2.1	18.5	6.3
6.5	2.1	19	9
7	5.5	19.5	9
7.5	5.5	20	7.6
8	10.8	20.5	7.6
8.5	10.8	21	7.2
9	9.2	21.5	7.2
9.5	9.2	22	5.9
10	7.3	22.5	5.9
10.5	7.3	23	5.2
11	6.9	23.5	5.2
11.5	6.9	24	5
12	5.9		

4.3.2 Hot Water Tank Model

The ETS model developed in this research is a representation of the electric hot water heater model presented at the World Renewable Energy Congress in Sweden in 2011 in [19] and subsequently at Electrical and Computer Engineering Conference in Montreal, Canada in 2012 by Elamari et al in [20]. The model was built in Matlab, in order to integrate its data into the multi-objective power network optimisation framework, and further developed in order to achieve a power consumption that is dependent the availability of wind generation. This particular approach was used primarily because it does not incorporate a solar heating element. Using such a method would require work to extract all solar heating properties. Modelling an electric hot water tank in the chosen method also comprehensively includes all influencing factors. Results are changeable depending on the ambient temperature, inlet water temperature, tank size and energy input rate to name a few influencing variables. The method outlined in the following provides a thorough view of the internal power consumption characteristics of a domestic electric hot water tank, which is the most significant characteristic for this research as ultimately, it is the changing of the power consumption that can benefit networks with renewable generation.

The power rating and volume for the model tank were set at 5.5 kW and 200 litres respectively as this is a suitable representative of the average [19]. These values are suitable for a home with 3-4 bedrooms and 2-3 bathrooms, assuming an average hot water draw per day of 30-50 litres per person. The ambient temperature is set at 20˚C which is representative of a typical room temperature. The incoming water temperature is taken as 10˚C to represent the average cold water temperature from the mains between the summer and winter extremes. These extremes are 20˚C and 4˚C respectively [20]. The reference temperature range for the hot water tank was set at 55-65 ^{o}C in order to ensure that the water from the tank is at an adequate temperature for use. Also, aiming for a temperature between 55^{o}C and 65^{o}C will ensure that dangerous bacteria, such as Legionella, cannot multiply or survive [26].

The model is based on a typical domestic, electric hot water tank with two internal elements, such as that in the diagram in Figure 4-3. The tank's water capacity is 200 litres and is rated at 5.5 kW [21]. Equation 4.1 (including equations 4.2-4.5) was implemented to capture the effects of variation in the temperature of the water within the tank over time [19].

$$T_H(t) = T_H(t_0)e^{-\left(\frac{1}{\tau}\right)(t-t_0)} + (R'GT_a + R'BT_{in} + R'Q)\left(1 - e^{-\left(\frac{1}{\tau}\right)(t-t_0)}\right) \tag{4.1}$$

Where:

$$G = U.SA \tag{4.2}$$

$$B = W_d \rho C \tag{4.3}$$

$$R' = \frac{1}{G + B} \tag{4.4}$$

$$\tau = R'C \tag{4.5}$$

T_H Temperature of the water in the tank, *°C*

T_a Ambient temperature outside the tank, *°C*, set at 20°C

W_d Average water draw per hour, *l/h*

ρ Density of water, *kg/m³*, set at 1000 kgm^{-3}

C Thermal capacity of water in the tank, *J/°C*, set at 417 J/°C

T_{in} Incoming water temperature, *°C*, set at 10°C

Q Energy input rate, *J/h*, set at 19 MJ/h

U Stand-by heat loss coefficient, *$J/°Chm^2$*, in WK^{-1} or $Btu/^oF.h.ft^2$. This is a parameter that is dependent on the type of heat exchanger used [22]. As this model does not have information pertaining to a heat exchanger, the assumption is made to use G value from the article by Goh and Apt [23] as Elamari et al did. G=U.SA, G= 3.6 $Btu/^oF.h$. Further information on finding the stand-by heat loss coefficient can be found in [24].

SA Surface area of tank, *m^2*, assuming the surface area of the tank is equal to that of the cylinder then surface area is equal to $2\pi rh+2\pi r^2$.

The graph in Figure 4-5 demonstrates the changing internal tank temperature over time for the given average water draw profile.

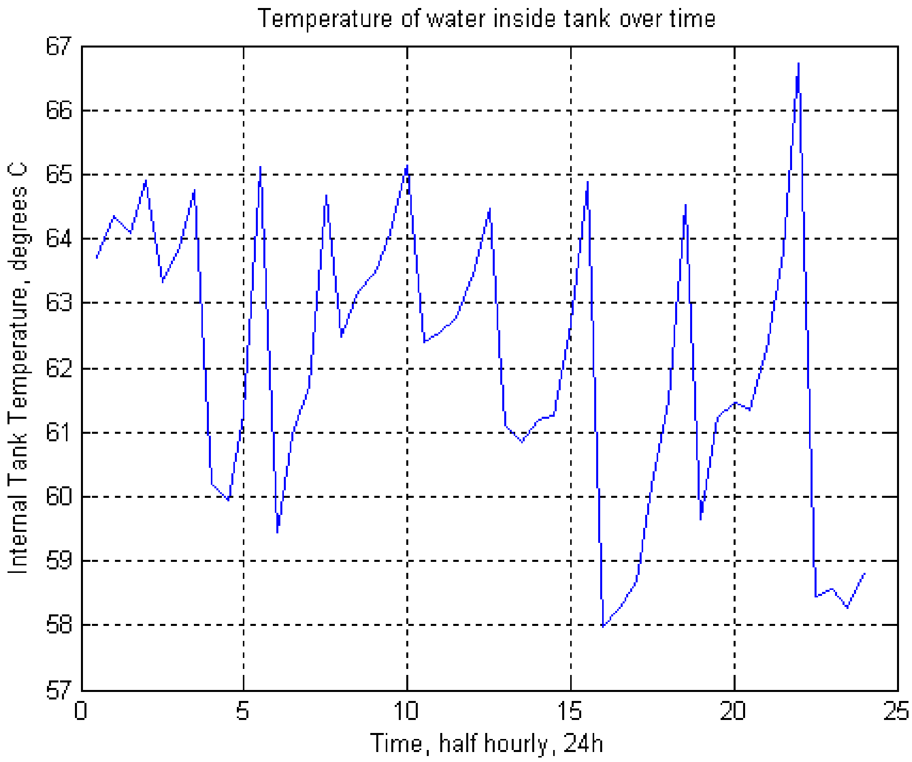

Figure 4-5 - Internal tank temperature over time

In order to successfully incorporate the hot water tank model into the multi-objective optimisation framework, it is necessary to realise the power consumed by the hot water tank. Once its behaviour is established, its ability to be a responsive demand can be determined.

The amount of time that the tank is heating and not heating is calculated using equations 4.6 and 4.7 in order to then calculate the power consumed [20].

$$t_{on} = \frac{C(T_{high} - T_{low})}{G(T_a - T_d) + \rho C_p W_d (T_{in} - T_d) + Q} \tag{4.6}$$

$$t_{off} = \frac{C(T_{high} - T_{low})}{G(T_a - T_d) + \rho C_p W_d (T_d - T_{ind})} \tag{4.7}$$

Where:

t_{on} Time that the tank is on, *h*

t_{off} Time that the tank is off, *h*

T_{high} Maximum temperature in tank, *°C*

T_{low} Minimum temperature in tank, *°C*

C_p Specific heat of water, *J/kg°C,* set at 4.181 j/g°C

T_d Reference temperature for tank, *°C*, between 55 and 65°C

From these two equations the power consumed by the tank is calculated with equation 4.8, where P_{HWT} is the power consumed by tank in kW [20].

$$\Delta P_{HWT} = \frac{G + W_d \rho C_p}{Q} \Delta T_d + \frac{(T_d - T_{in}) \rho C_p}{Q} \Delta W_d \tag{4.8}$$

The ΔT_d and the ΔW_d in equation 4.8 are included as the power consumption of the tank is affected by both the water draw and reference temperature and the change in these values from one sample to the next.

Figure 4-6 shows the graph outputted, displaying the power consumed by the tank over time. The hot water tank model is also able to determine what the operation of the tank should be given data pertaining to generation from wind resource. This is achieved by analysing the wind profile that will be used in multi-objective power network optimisation framework that is described in the following chapter. During occasions where wind generation is between 0 and 0.2 p.u., the energy input rate, Q, to the hot water tank is turned off completely. When the power available from wind is between 0.8 and 1 p.u., the hot water tank receives its maximum input. A sliding scale is applied to the hot water tank's input when wind generation is between 0.2 and 0.8 p.u.; the input is increased by 8.3% for every 0.05 p.u. increase in wind generation between 0.2 and 0.8 p.u. An index, $W_{(t)}$, is assigned to each possible step increase in wind; for example 0.25 p.u. has an index of 1, 0.3 p.u. has an index of 2. This is illustrated in equation 4.9.

$$Q = W_{(T)} \times 0.83 \times Q_{max} \tag{4.9}$$

Figure 4-7 illustrates the difference that can occur when considering generation from renewable sources.

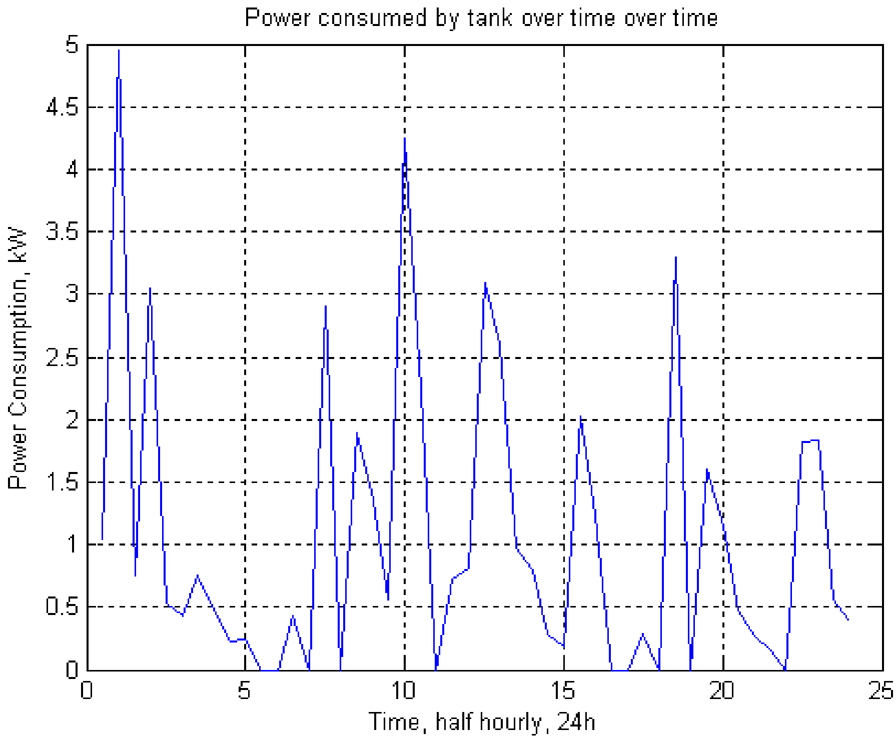

Figure 4-6 - Tank power consumption over time

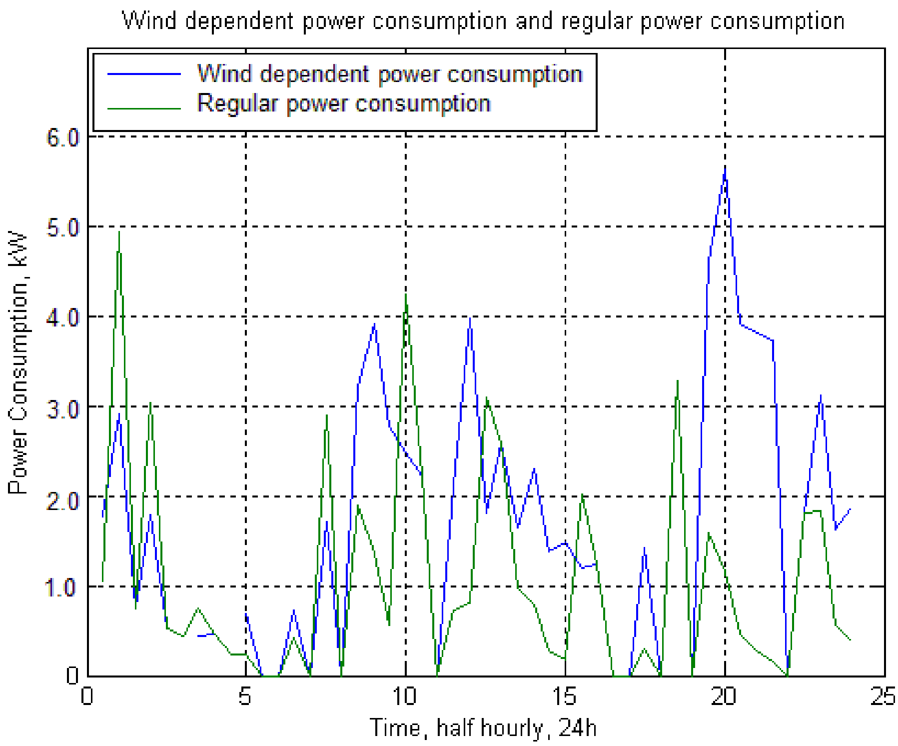

Figure 4-7 - Regular and wind dependant operation of tank

In Figure 4-7, the regular power consumption is shown in green and when compared with the average water draw profile in Figure 4-4, there is a correlation between power consumption and water draw. Power consumption is high in the lead up to the highest water draw of the day between 0800 and 1000. Electricity is cheaper overnight for Economy 7 users, and charging overnight allows that tank to fully recover its volume and temperature from the use the previous day. Power consumption increases in Figure 4-7 between 07:00 and 11:00 in order to heat new water coming in to the tank. A similar effect can be seen between 17:00 and 21:00 for the evening rise in water demand.

The wind data used to generate the blue profile in Figure 4-7 is shown in Table 4-2. On looking at the blue profile, the most noticeable spike in power consumption occurs between 19:00 and 22:00. Looking at the wind data in Table 4-2 for these times, the wind being generated at this time is adequate to allow an increased input to the tank. Similarly, the decrease in power consumed by the tank between 12:00 and 15:00 is due to the decreasing wind availability at the corresponding times.

Table 4-2 - Wind data

Time	Wind	Time	Wind
0	0.1451	12	0.5367
0.5	0.3091	12.5	0.5336
1	0.8791	13	0.548
1.5	0.672	13.5	0.582
2	0.5578	14	0.8216
2.5	0.26	14.5	0.6085
3	0.3522	15	0.3288
3.5	0.3787	15.5	0.7475
4	0.2101	16	0.6289
4.5	0.5064	16.5	0.7453
5	0.5661	17	0.61
5.5	0.616	17.5	0.6009
6	0.6213	18	0.2041
6.5	0.6115	18.5	0.1277
7	0.542	19	0.1202
7.5	0.4225	19.5	0.1421
8	0.4981	20	0.155
8.5	0.4452	20.5	0.1572
9	0.5457	21	0.1602
9.5	0.5488	21.5	0.1572
10	0.548	22	0.3197
10.5	0.5865	22.5	0.3794
11	0.7339	23	0.5215
11.5	0.613	23.5	0.4263

4.4 Summary

In this chapter the driver behind the possible reintroduction of ETS devices is outlined. The UK has a commitment to reduce its CO_2 emissions by 80% by 2050 and a lot of change is required if this target is to be met [25]. Power generation, transportation and space and hot water heating all require significant change, especially the heating as it accounts for 47% of the total carbon emissions. Installing ETS devices in residences is one way to aid in reaching the emissions target.

ETS devices are stated as being storage heaters or hot water tanks and are typically in a domestic setting, where the natural dissipation of heat can be of use. The technology for both devices has been briefly outlined before stating that a hot water storage tank would be modelled. The parameters for the hot water storage tank have been detailed as well as graphical evidence of the model's internal tank temperature and power consumption over time, and details of the model's implementation.

The next chapter will introduce the Multi-objective Distributed Energy and Network Evaluation (MODERNE) framework. The specific genetic algorithm that it employs will be described, as will the structure of the MODERNE framework and the objectives available for optimisation.

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Chapter 5 - Integration of an Electrical Thermal Storage Module into a Multi-objective Distribution Network Planning Approach

The Multi-objective Distributed Energy Resources and Network Evaluation, or MODERNE, Framework is a network planning tool based around the Strength Pareto Evolutionary Algorithm 2 (SPEA2) and was the result of recent research [1].

In its original incarnation the MODERNE framework was able to accept different distribution network models and analyse them. The framework used multi-objective optimisation to determine the optimal size, type and location of DER in the network depending on the objectives that were set. The MODERNE framework has been further developed in order to optimise the type, location and number of ETS devices to be installed. The framework is able to optimise four different types of ETS devices, however this analysis only considers one type, the hot water tank described in Chapter 4. This approach was adopted as, to include four different types of ETS device more modelling of ETS devices would be required.

The reason a multi-objective optimisation approach was used in this case was to ensure that as many points of view as possible were included in the optimisation process. For example, when optimising the connections of DER as MODERNE did in its original state, the network operator will be concerned with issues such as minimising cost, which could include network upgrading, and maximising revenue. The consumer will be concerned with quality and security of supply. Aside from this there are also network constraints, such as thermal limits and voltage limits and environmental concerns, such as minimising carbon emissions. Using a multi-objective optimisation approach such as SPEA2 allows for these different points of view to be considered, as well as incorporating the operational constraints of the network.

SPEA2 was chosen as the means of achieving the multi-objective optimisation for a number of reasons. SPEA, the predecessor to SPEA2, has been seen to outperform other multi-objective optimisation approaches. Zitzler et al showed that SPEA2 outperformed both its predecessor and other multi-objective evolutionary algorithms in terms of the ability in reaching closer to the Pareto front, the distribution of solutions found and the effectiveness in dealing with problems with a large number of objectives [2-4].

This chapter explains both the MODERNE framework and the Strength Pareto Evolutionary Algorithm 2 in greater detail. The aim is to illustrate the trade-off between different solutions when incorporating ETS devices into distribution networks and as such the MODERNE framework has been modified to achieve this aim. The MODERNE framework is described with reference to the optimisation of ETS devices, which encapsulates the modifications made to the original incarnation of MODERNE. Most importantly, the way in which the objectives are optimised has been updated so that they relate to the installation of ETS and the gene encoding and decoding processes have been modified to allow for ETS devices instead of DER as in the original case.

5.1 MODERNE Structure

Originally the MODERNE framework was able to optimise the size, type and location of DERs, specifically distributed generation, to be connected to a distribution network. It utilised SPEA2 and has been modified to optimise the location and number of ETS devices for connection. The flowchart in Figure 5-1 illustrates how the framework operates.

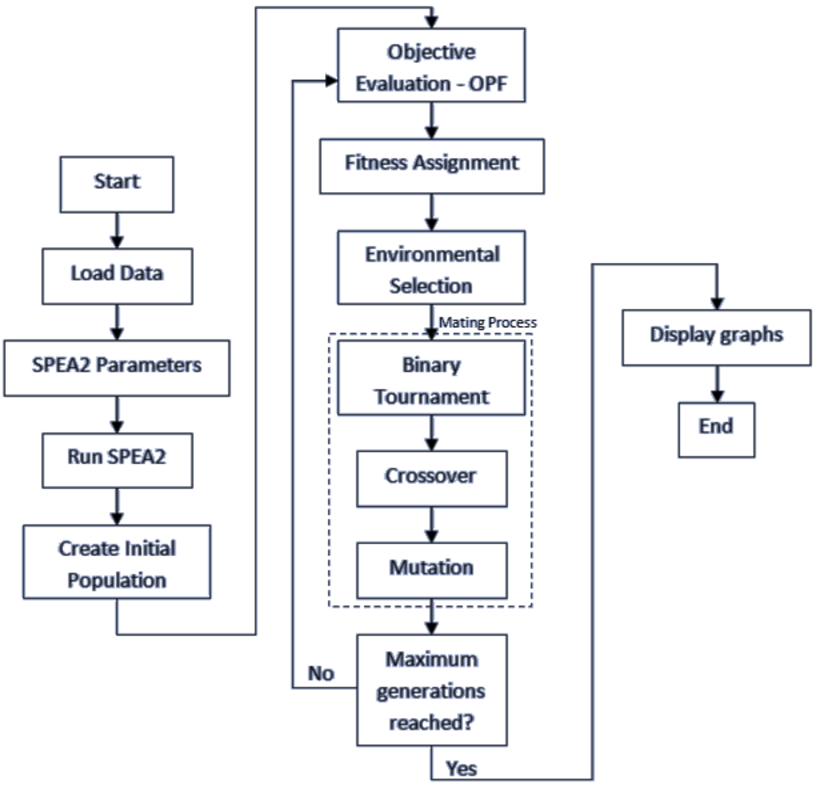

Figure 5-1 - Flowchart of the MODERNE framework process

The framework loads the relevant power network, generation and demand data as well as the information pertaining to SPEA2, such as the number of generations and archive size. The performance of solutions is determined by the application of an optimal power flow before continuing to the fitness assignment, and the process continues as previously stated for SPEA2. When a maximum number of generations is reached then the results are diaplayed by means of graphs displaying the optimal arrangements of solutions.

5.1.1 MODERNE Objectives and Constraints

Objectives to be considered in this problem can be classified as environmental, technical and economic objectives and this classification helps to incorporate the different stakeholder points of view that need to be considered in multi-objective optimisation. Table 5-1 presents the objectives that can be considered when optimising the number and location of ETS devices in the distribution network. Whilst Table 5-1 presents all the objectives that the framework is currently able to optimise, the case studies outlined in the following chapter will work with a subset.

Table 5-1 - Objectives available in the MODERNE framework for consideration in optimisation

Objective
Minimise Line Losses (MWh/year)
Minimise Overload Probability (%)
Minimise Imported Energy (MWh/year)
Minimise Exported Energy (MWh/year)
Maximise Exported Energy (MWh/year)
Minimise Grid dependency (Net flow to and from the grid)
Minimise Emissions Factor (Kgr CO2/Kwh)
Maximise CO2 Emissions Reduction (%, compared with grid)
Minimise Dispatched energy
Minimise Maximum Thermal Loading in Lines (%)
Minimise Penetration Level (% of Load)
Minimise Curtailed energy

A brief explanation of the objectives from Table 5-1.

- Line Losses

  As the minimisation of line losses is a significant goal in power network planning it is included in the MODERNE framework. The total line losses in the system can be represented by Equation 5.1 [1]:

$$Losses_t = 3|I_{line}|^2 \times R \tag{5.1}$$

where I_{line} represents the magnitude of the line current and *R* represents the line resistance in a three phase system. *t* represents the simulation iteration. Yearly losses can then be calculated by Equation 5.2 [1]:

$$YearLosses = \frac{8760}{n}\sum_{t}^{n} Losses_t \tag{5.2}$$

where *n* is the number of simulations run and 8760 is the value used to convert average power losses to annual energy losses. These calculations are representative of variable line losses or copper line losses which means that only active energy losses are calculated. In distribution network planning, the real energy losses are of most concern [1, 7].

- Imported and Exported Energy

  In order to calculate the energy imported and exported through the connection to the main grid, the energy flow through the grid power connection is calculated at each simulation iteration and summed. This gives Equations 5.3 and 5.4 [1]:

$$ImportedEnergy = \frac{8760}{n}\sum_{t}^{n} GridPower_t \qquad \forall GridPower_t > 0 \tag{5.3}$$

$$ExportedEnergy = \frac{-8760}{n}\sum_{t}^{n} GridPower_t \qquad \forall GridPower_t < 0 \tag{5.4}$$

The imported energy is characterised by a minimisation which sees local resources utilised at a maximum. The exported energy is characterised by a maximisation as in this case, the utilization of local DER is desired.

To determine the gird power, Equation 5.5 is used [1]:

$$GridPower_t = 3R(V_{grid}(I_{grid})^*) \tag{5.5}$$

where I_{grid} and V_{grid} are the network current and voltage respectively. I_{grid} is then calculated by Equation 5.6 [1]:

$$I_{grid} = \sum_{node} I_{node} \tag{5.6}$$

where I_{node} is calculated by a backwards, forwards sweep power flow. If I_{node} is positive after summation over the simulations, then power is being imported from the grid and conversely, a negative value of I_{node} shows power is being exported to the grid.

- Grid dependency

  Grid dependency is calculated to provide an indication of the extent of independence from the grid that a network has. Minimisation of grid dependency can be achieved by minimising the sum of imported and exported energy as shown in Equation 5.7 [1]:

$$\begin{aligned} GridDependency &= ImportedEnergy + ExportedEnergy \\ &= \frac{8760}{n}\sum_{t}^{n} |GridPower_t| \end{aligned} \tag{5.7}$$

- Overload Probability

  To determine the probability of the occurrence of an overload event, a ratio of the number of simulations run where there could be an overload to the total number of simulations run is used. This can be expressed as Equations 5.8 and 5.9 [1]:

$$Tloading_{prob} = \frac{\sum_t Ibreak_t}{n} \times 100 \tag{5.8}$$

$$Ibreak_t = \begin{cases} 1 & if\ (any(I_{line_t} > I_{max}) \\ 0 & otherwise \end{cases} \tag{5.9}$$

  This allows for measurement of the probability of any of the lines in the network overloading and exceeding their limits. This provides a worst case scenario in terms of performance for the network and this objective should be minimised.

- Emissions Factor

  The following expression in Equation 5.10 [1] can be used to represent the total carbon emissions in the network; this includes emissions from imported and exported energy and generated from the DER in the network.

$$Total_{CO_2} = \frac{ImportedEnergy \times grid_{CO_2} + TotalDEREnergy \times DER_{CO_2}}{ExportedEnergy + TotalLoad + YearLosses} \tag{5.10}$$

To provide an insight into the carbon emissions associated with the load and losses in the network, the following expression in Equation 5.11 [1] uses the energy that is imported and the remaining energy that was generated from DER and not exported.

$$Load_{CO_2} = \frac{ImportedEnergy \times grid_{CO_2} + (TotalDEREnergy - ExportedEnergy) \times DER_{CO_2}}{TotalLoad + yearLosses} \quad (5.11)$$

In minimising this value MODERNE determines the best arrangement of the ETS devices for low carbon operation in the network. The calculation of carbon emissions is an important objective for network planning as environmental impacts from energy use is important for government targets [1, 8].

- Dispatched Energy

  A vector is produced to represent the dispatched energy when the OPF has been run. When this vector, P_{disp}, is summed over the whole year, the yearly dispatched energy can be determined. This is achieved by using Equation 5.12 [1]:

$$DispatchedEnergy = \frac{8760}{n} \sum_{t}^{n} \sum_{node} P_{disp_t} \quad (5.12)$$

  This objective is treated as a minimisation function, and in doing so the aim is to reduce the use of energy generated from fossil fuels.

- Thermal Loading in Lines

  The thermal loading for the lines is calculated for all of the simulation iterations and is expressed as a percentage. Equation 5.13 gives [1]:

$$TLoading_{max} = max_t \left[max_{line} \left(\frac{|I_{line_t}|}{I_{max}} \right) \right] \times 100 \quad (5.13)$$

  This presents the worst, most likely event that could happen with respect to the data available and simulations performed.

- Penetration Level

The penetration level of the ETS devices is defined as a percentage of the overall sites where they can be placed in the network. For example, if a distribution network has 200 homes then a 10% penetration of ETS devices will mean that 20 homes will have them installed. The penetration level is used in a minimisation process; this is so the best arrangement and operation of ETS devices can be found whilst installing the fewest devices.

- Curtailed Energy

  A vector is produced to represent the curtailed energy when the OPF has been run. When this vector, P_{curt}, is summed over the whole year, the yearly dispatched energy can be determined. This is achieved by Equation 5.14 [1]:

$$CurtailedEnergy = \frac{8760}{n}\sum_{t}^{n}\sum_{node} P_{curt_t} \tag{5.14}$$

  In minimising the curtailed energy, the aim is to maximise the energy from renewable generation.

5.1.2 Generation of Initial Population

To start the genetic algorithm process it is important to have an initial population that is very diverse in order to ensure that the search space will be extensively searched. The MODERNE framework employs a user defined method to generate solutions for part of the initial population. ETS devices are added to solutions and are limited to a maximum penetration level. The restriction is dependent on a maximum number of ETS devices, the size of the network and feeder loading levels. The remainder of the initial population is generated by adding ETS devices to all eligible nodes at increasing penetration levels until the maximum is reached.

This approach to generating the initial population aims to avoid the creation of solutions that are not feasible and provide a good spread in the search space [1, 9].

5.1.3 Gene Encoding and Decoding

In order to achieve optimisation of the number and location of the ETS devices, the MODERNE framework needs the problem to be presented in the form of an array. Each possible solution in the population can also be described as a chromosome. ETS devices installed in a network node are encoded as a gene in the chromosome. The chromosome can be represented by a vector, or array, with elements equal to the number of nodes in the network, as illustrated in Figure 5-2.

Network Node	Node 1	Node 2	Node 3	Node i	Node n
Chromosome Genes	$G_{1j}G_{12}G_{11}$	$G_{2j}G_{22}G_{21}$	$G_{3j}G_{32}G_{31}$	GijGi2Gi1	$GnjGn2G_{j1}$

Figure 5-2 - Decision variable encoding

Each network node can be represented by a series of integer values, as illustrated in Figure 5-2, and it is assumed that every load node in the network is able to have ETS devices installed there. Within the gene structure, the integer number G_{ij} can be interpreted as the j^{th} type of ETS device installed at the i^{th} node, where *G* represents the number of ETS devices. As an example, a chromosome may be illustrated as:

- $4_{11}9_{12}3_{2,2}6_{33}$.

This chromosome states:

- 4 ETS devices of type 1 at node 1;
- 9 ETS devices of type 2 at node 1;
- 3 ETS devices of type 2 at node 2;
- 6 ETS devices of type 3 at node 3.

As stated previously, in this project and analysis there is one type of ETS device, which is the modelled hot water tank described in Chapter 4. There does, however, remain the option of including different types of ETS devices at a later date if suitable models are developed. In this research project, even though there is the possibility of four different types of ETS device, they are all identical. In real world installations, there are hot water tanks of varying power ratings and capacities, and space storage heaters are also considered as ETS devices. It is possible for 4 different hot water tanks, with different power ratings and capacities to be considered in the optimisation; likewise space storage heaters of varying capacities and ratings may also be considered should a suitable model be developed.

Figure 5-3 illustrates the encoding for the MODERNE framework [1].

Analysis Type	**Gij**	**Decoding**	**Example**
Optimisation of the location and number of ETS installations	**0, 1, 2,.......,99**	**The number represents the amount of the ETS devices of type *i* installed in node *j***	**Find the best number and location for a set number of ETS devices. Each node may have up to a specific limit.**

Figure 5-3 - Gene Encoding Example

The decoding process translates the vector into a matrix, Equation 5.15, which illustrates the number, type and location of ETS devices for the analysed network. Each element X_{ij}, shown in the matrix below, in the i^{th} row and j^{th} column directly relates to the number of ETS devices of type *i* at node *j*. The MODERNE framework then outputs separate results detailing the numbers and types of ETS device at each node.

$$Decoding\ Matrix = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1j} & X_{1Node} \\ X_{21} & \cdots & \cdots & \cdots & \cdots \\ X_{i1} & \cdots & \cdots & X_{ij} & X_{iNode} \\ X_{Type1} & \cdots & \cdots & X_{Typej} & X_{TypeNode} \end{bmatrix} \tag{5.15}$$

Table 5-2 below illustrates the decoded output from the MODERNE framework.

Table 5-2 - Example of decoded solutions from MODERNE

49	53 00 00	At node 49 place 53 units of type 3
50	56 23 00	At node 50 place 56 units of type 3 and 23 units of type 2
5	46 00 00 00	At node 5 place 46 units of type 4
7	44 00 00	At node 7 place 44 units of type 3
14	42 00 14 00	At node 14 place 42 units of type 4 and 14 units of type 2

5.1.4 Objective Evaluation

A list of the objectives, or attributes, that are available to be optimised can be seen in Table 5-1. In order to evaluate the objectives and constraints for the problem, the MODERNE framework generates a matrix to represent the attributes. Each possible attribute is represented in the matrix by a column and each row represents a possible solution, or chromosome.

Before the SPEA2 process starts, the objectives and constraints that are chosen for the problem are defined in a separate data file and are read into MODERNE. The constraints that have been identified for the problem are then incorporated into a total constraint violation calculation for every j^{th} chromosome as a sum of the relative constraint violations as shown in Equation 5.16.

$$C_j = \sum_i \left| \frac{a_{ij} - c_i}{c_i} \right| \tag{5.16}$$

Where a_{ij} is the i^{th} objective of the j^{th} chromosome and c_i is the constraint value. Figure 5-4 helps to illustrate this arrangement.

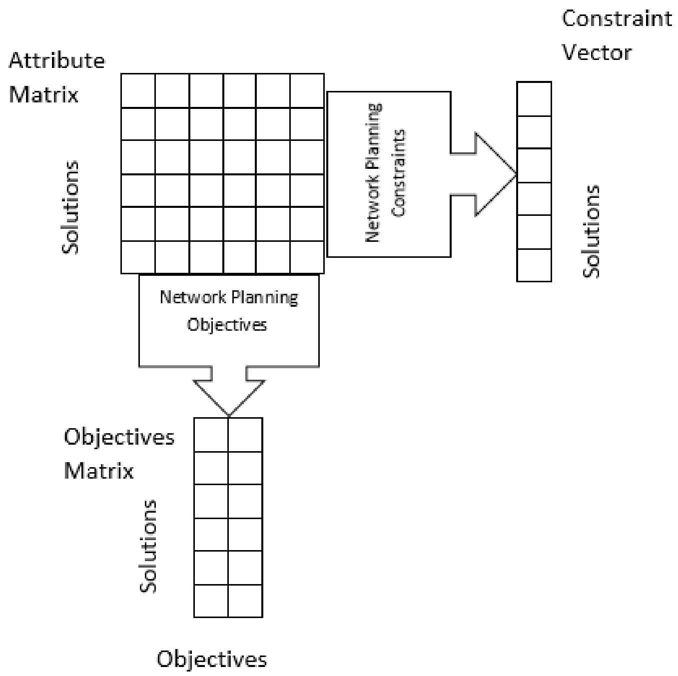

Figure 5-4 - Illustration of the matrix structure

Once this has been performed, the algorithm then determines the dominance relationships between the different solutions which then allows for the fitness assignment for each solution.

5.1.5 Environmental Selection or Mating Selection

The process that is used to ensure that the best solutions are chosen for the mating pool is binary tournaments. It is outlined in [10] that the binary tournament, as a method of producing offspring in a genetic algorithm, has equivalent or superior convergence and computational properties [1]. Figure 5-5 displays a flow chart of the binary tournament process.

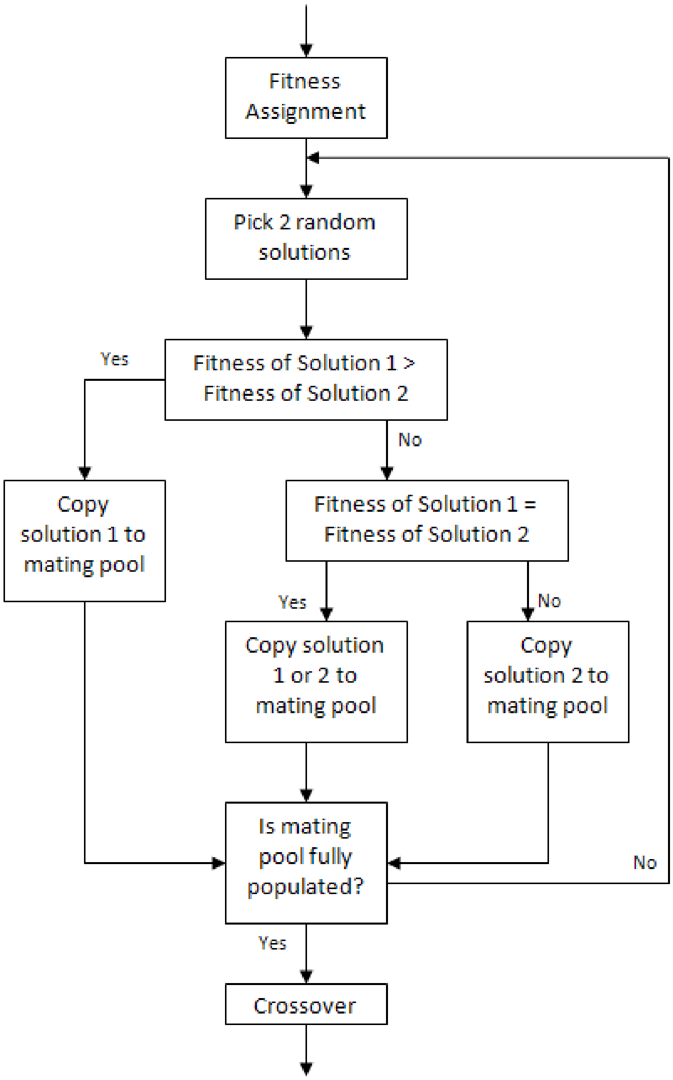

Figure 5-5 - Flow chart of binary tournament process

Two solutions are randomly chosen and their fitness values are compared. If one is greater than the other then it is copied to the mating pool. If the two solutions have identical fitness values then just one of them is chosen for the mating pool. This process continues until the mating pool is fully populated; the mating pool is typically of the same size as the general algorithm population.

5.1.6 Crossover Probability Operation

There are a number of crossover algorithms widely available for implementation in genetic algorithms including uniform crossover, single point crossover and two point crossover. The crossover operator is one of the most important parts of the algorithm as it ensures that information is passed between two adult solutions to produce offspring. In [9] these three crossover methods are outlined and it is stated that whilst the two point crossover method outperforms the single point crossover method; the uniform crossover method outperforms them both.

In the MODERNE framework the crossover method used is the uniform crossover. It swaps different arrangements of ETS devices between two solutions in an attempt to find more optimal numbers, types and locations of ETS devices. How the crossover method is implemented differently depends on whether or not the ETS devices are limited in installation. When the number of ETS devices is not limited, the crossover implementation is as follows, and as illustrated in Figure 5-6:

- By using a uniform probability distribution a crossover mask can be created
- The mask determines which parts of each parent are inherited by the offspring

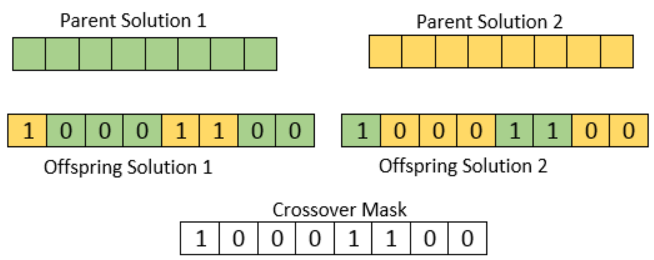

Figure 5-6 - Uniform crossover implementation

The uniform crossover is sometimes seen as being weaker than the single or double point crossovers as it is a method that relies solely on the mutation operator for introducing new information, and can be seen as being more disruptive as potential contributing parent sections can be lost; however it has been shown that uniform crossover outperforms both alternatives as it favours exploration of the search space [9, 11].

When the number of ETS devices that can be added to the network is limited it is possible that the application of the standard uniform crossover mask can produce results that exceed the set limit. It could be possible that the installation of ETS devices is restricted to only a certain proportion of the network: for example, half of the network. It is possible for one parent solution to have ETS devices installed at every even node location and for another parent solution to have ETS devices installed at every odd node location. In this scenario it is possible that the resulting offspring could exceed the restriction of installation in half the network.

In order to avoid such an occurrence some additional features are added to the uniform crossover. Two vectors are created so that the numbers of ETS devices are stored in one, and the locations of the installations are stored in the other. The length of the vectors is determined by the maximum number of ETS devices of a particular type. Both the ETS numbers and the locations are exchanged between the parent solutions using an identical mask. It is this technique that ensures solutions do not exceed the limit imposed on the number of ETS devices. Figure 5-7 illustrates the implementation for crossover with a limit on ETS devices [1].

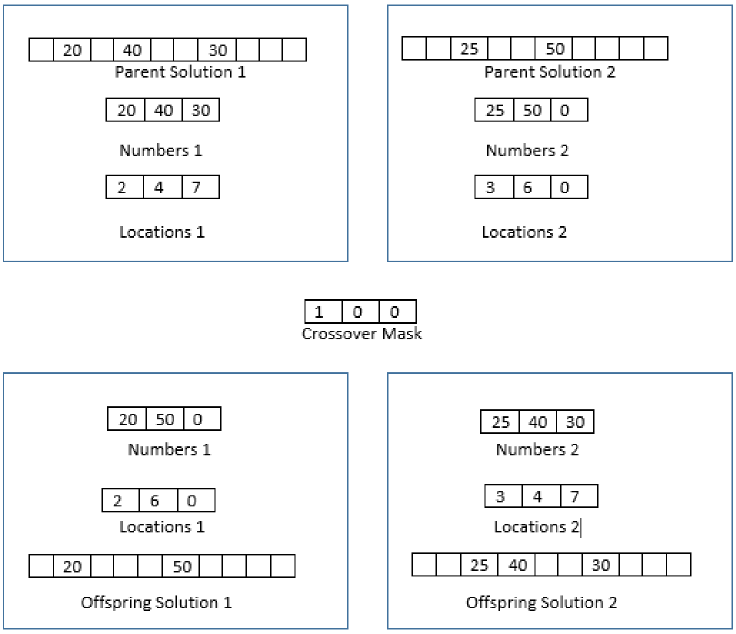

Figure 5-7 - Uniform crossover implementation for limited ETS devices

The example in Figure 5-7 is restricted to three types of ETS device (however in the implementation of MODERNE in this research all ETS types are identical). One parent solution has three ETS units and the other has two ETS units. The crossover mask applied indicates which data will be exchanged; in this example 0 denotes what will be exchanged.

It is also important to note that this implementation is able to support a crossover between solutions that have different numbers of ETS devices. There is also a built in checking routine that ensures an offspring solution does not have two units assigned in the same node. By referring to Figure 5-7, if the second unit in “Parent 1” – 30 in node 4 – was in fact in node 3, then with the crossover mask that is being used, the offspring would be allocated both 30 and 15 at the same time. The built in checking routine ensures that this issue does not occur [1].

5.1.7 Mutation Probability Operation

The mutation operator is included in the genetic algorithm to introduce new solutions randomly to promote investigation of the whole search space. As with the crossover implementation, the mutation operator is applied differently depending on whether the number of ETS devices is limited or not.

If the number of ETS devices is not limited, the mutation is implemented by flipping the binary value of the gene that is being mutated. The probability of mutation (*p*) is typically set between 0.1 and 0.2. The process is as follows:

- If ETS devices of type *j* is in a node *i* (G_{ij}>0):
    - There is a low probability (*p*) that the ETS device will be removed;
    - There is a high probability (1-*p*) that the number of ETS devices will be changed to a random number.
- If there are no ETS devices of type *j* at node *i*:
    - A random number of ETS devices are added to node *i.*

A probability is applied to the implemented mutation operator which is designed to allow the deletion of ETS devices. If there is no possibility for deletion it is possible that the ETS device penetrations can increase rapidly. The introduction of a 0 gene helps to ensure diversity is maintained [1]. An example of this process is shown in Figure 5-8. In this example, if there are ETS devices at node *i* then they are either removed (which is an event with a low probability) or the number of devices is changed (which is an event with a high probability). The changes are shown by the green sections denoting node 1. If there are no ETS devices at node *i* then a random number of devices is added. This change is shown by the green section denoting node 7.

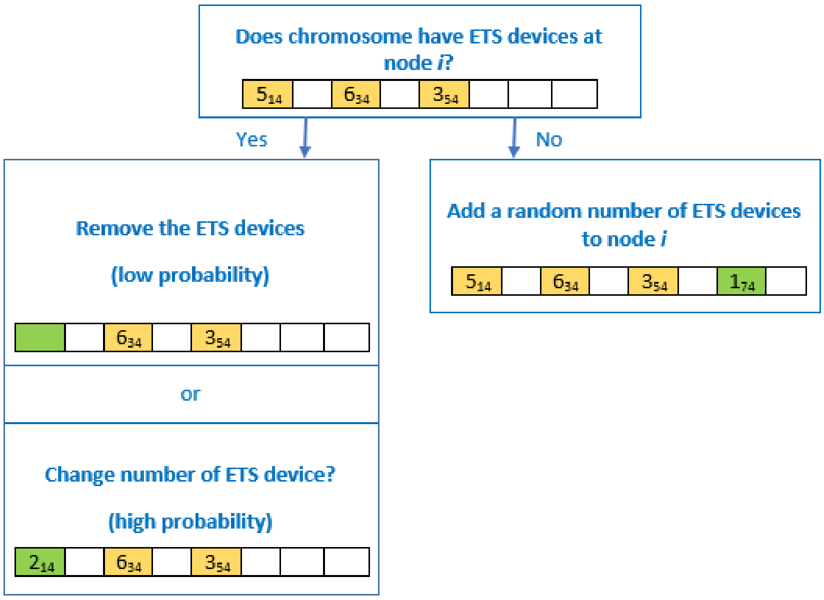

Figure 5-8 – Mutation operator example

If the number of ETS devices is limited, two vectors are created for both the ETS type and chromosome, as illustrated for the crossover implementation, as shown in Figure 5-7. If a gene is to be mutated then the process is as follows:

- If an ETS device of type *j* is in a node *i* (G_{ij}>0) either:
  - The location is changed and the number of devices remains unchanged, with 50% of probability
  - The number of devices is changed and the location remains unchanged, with 50% of probability
- If there is not an ETS device of type *j* at node *i* (G_{ij}=0):
  - A random number of ETS devices is added to a random location [1].

5.2 Strength Pareto Evolutionary Algorithm 2

The original SPEA was found to have potential weaknesses, and in order to address this SPEA 2 was developed. There are three significant upgrades that were made in SPEA2 and these were [5]:

- The fitness assignment that was used in the original SPEA2 was upgraded in order to include the number of individual solutions that a specific solution is dominated by.
- A density estimation function was included in order to ensure that the overall search process is more effectively guided.

- A truncation function was included to truncate the external archive and ensure the preservation of boudary solutions.

5.2.1 The SPEA2 Process

SPEA2 uses a population, *P*, of size *N* and an external archive, *A*, of size $\overline{N}$. The archive stores the non-dominated solutions. The process for SPEA2 is as follows for *T* generations [1, 6]:

- **Initialisation:** The initial population is created, P_t, and an empty archive is created, A_t.
- **Fitness Assignment:** The initial population is evaluated and the fitness values of P_t and A_t are determined.
- **Environmental Selection:** The non-dominated solutions from P_t and A_t are copied to A_{t+1}. If A_{t+1} exceeds $\overline{N}$, then A_{t+1} will be reduced by application of a truncation method. If A_{t+1} is less than $\overline{N}$ then the fittest of the dominated solutions are added to A_{t+1}.
- **Termination:** If the number of iterations has reached a pre-determined value, the process is terminated.
- **Mating Selection:** Binary tournaments are applied to A_{t+1} to fill the mating pool.
- **Variation:** The new population P_{t+1} is created by applying crossover and mutation operators to the mating pool. The counter is incremented and the process continues at Fitness Assignment.

When approaching a multi-objective optimisation problem, any technique that is to be applied to the problem must be able to achieve accuracy, diversity and spread in its search for optimal solutions. For SPEA2, the incorporation of a fitness assignment allows for successful exploration of less dense areas of the search space; and the use of a truncation method means that a diverse selection of solutions is available. Moreover, only the best solutions in the external archive participate in the crossover to produce new solutions, so the next generation of solutions should be stronger than the previous generation.

5.2.2 Fitness Assignment

In SPEA is it was found that individuals that were dominated by the same archive members had the same fitness values. Considering the case where the archive contains one solution, all members of the population are ranked the same, regardless of whether they dominate each other or not. This leads to a reduction in functionality in SPEA, and in a case like the one described, it acts as a random search function. To circumvent this SPEA2 takes into account the number of individuals a solution dominates and is dominated by. To begin with each individual is assigned a strength value, which represents how many solutions the individual dominates. A raw fitness value is then determined by the fitness of the individual's dominators in both the population and the external archive. For raw fitness, the aim is to have a minimal value; a high value indicates that the solution is dominated by many other individuals [3, 4]. Figure 5-9 illustrates the fitness assignment process [1].

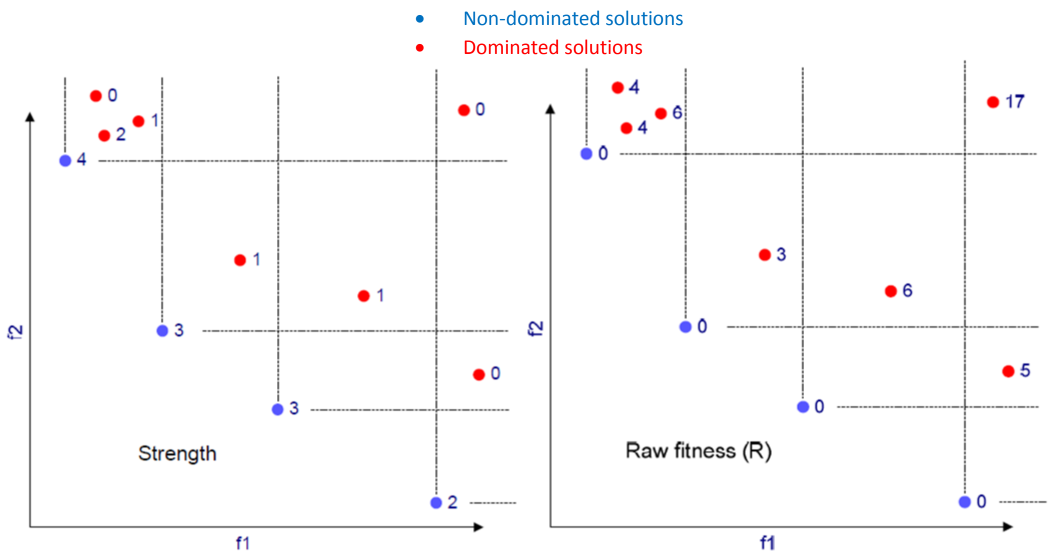

Figure 5-9 - Illustration of SPEA2 fitness assignment

Each solution is assigned a strength value (Figure 5-9, Left) which represents how many solutions are dominated by the individual. The number associated with each point illustrates how many solutions it dominates. For example, the blue point represented by the number 4 dominates four solutions. There are two blue points which each dominate three solutions, and one blue point dominating 2 solutions.

A raw fitness value (Figure 5-9, Right) is then assigned to each solution. This is calculated as the sum of the strength of the solutions dominating an individual. For example the red point in top right of Figure 5-9 has a raw fitness of 17. This is arrived at my summing the strength values (from the left hand diagram) of all the solutions that dominate it. This process of fitness assignment leads to solutions being assigned a worse fitness if they dominated by solutions that dominate many other solutions, and the non-dominate solutions are assigned a fitness of 0 [4].

5.2.3 Density Estimation

A density estimation technique is employed to differentiate between individuals that have matching raw fitness values. In order to do this, SPEA2 utilises the inverse of the distance to the k^{th} nearest neighbour. Equation 5.17 gives [4]:

$$D(i) = \frac{1}{\sigma_i^k + 2} \tag{5.17}$$

where σ_i^k is the distance to the k^{th} nearest neighbour. The presence of the two in the denominator is to ensure that the value is greater than zero. The resulting fitness is an addition of the density and raw fitness, and fitness is further enhanced if a solution has no near neighbours [1, 5].

5.2.4 Archive Truncation

An improvement in SPEA2 sees the size of the archive being kept constant, and the employment of a truncation operator ensures that boundary solutions are not lost to keep the spread of the search wide. During the environmental selection individuals that are non-dominated are copied from both the population and the archive to the external archive of the next iteration of the algorithm, A_{t+1}. When this occurs it is possible that:

- The number of non-dominated solutions being copied from the population and archive to A_{t+1} exactly matches the size of the archive. In this case the environmental selection part of SPEA2 is complete.
- The number of non-dominated solutions being copied is smaller than the size of the archive. In this case the archive is filled with solutions from the population and archive that are the best, although dominated by others.
- The number of non-dominated solutions being copied exceeds the size of the archive and a truncation operator is applied.

The truncation operator functions by iterations, therefore in each iteration an individual is chosen for deletion. The individual that is chosen has the shortest distance to a neighbour. If there are a number of individuals with a minimum distance, then the second minimum distance is used [5, 6]. Figure 5-10 helps to illustrate how the truncation is applied.

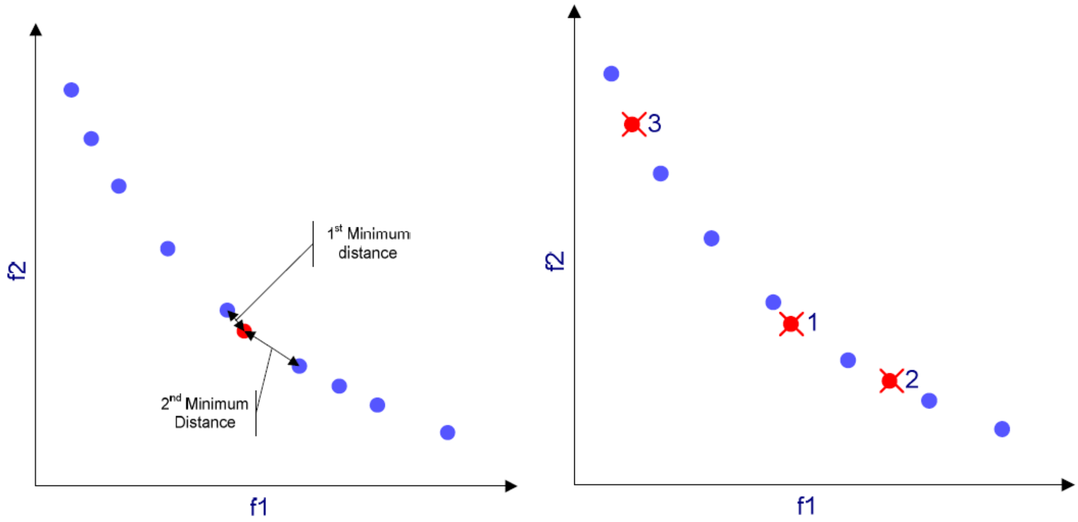

Figure 5-10 - Illustration of SPEA2 truncation operator [1]

5.3 Differences between methodologies

It is important to emphasise the differences between the methodologies for MODERNE in its original incarnation, and in its new form of being able to optimise the number and location of ETS devices.

Perhaps the most significant difference between the two versions of MODERNE is that in its original format it was capable of optimising generation being connected to the distribution network. In order for this research to proceed, the framework had to be modified so that demand was being optimised. This involved changing the way in which MODERNE analysed the inputs it received and how it constructed the various matrices that have been outlined.

The original MODERNE framework was able to optimise the size and location of four different types of DG. Although the modified MODERNE also has the capability of optimising four different types of ETS devices, however to achieve this more modelling of ETS devices would be required. Instead, the modified MODERNE optimises the number and location of one type of ETS device. The way in which the modifications were carried out also leave the possibility open for different kinds of controllable demand to added for optimisation in the future.

The modified MODERNE can also more easily analyse different distribution networks. If a network model is presented in the correct format, then the modified MODERNE can easily apply its multi-objective optimisation process. The original incarnation of the framework struggled with some different networks and had a specified few that could be analysed.

5.4 Summary

This chapter has provided a detailed insight into the MODERNE framework. SPEA2 is the genetic algorithm that MODERNE is built around and a comprehensive review of its characteristics and processes is provided. The MODERNE framework is then broken down into its component parts, including the objectives and constraints available to the user, details about creating the initial population for the genetic algorithm, how MODERNE encodes and decodes the data, the evaluation of the objectives, how the environmental selection is implemented, and the application of both the crossover and mutation operators. Throughout the presentation of the MODERNE framework in this chapter and its internal, necessary processes it has been demonstrated how the optimisation of ETS has been implemented. The most significant differences between the original incarnation and the new, modified MODERNE have also been stated. The following chapter will describe different case studies applied to MODERNE and the results generated.

5.5 References for Chapter 5

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Chapter 6 – ETS Integration Case Studies and Analysis

This chapter lays out the case studies, network models and data that the MODERNE framework was applied to and the results generated. The MODERNE framework has been used to optimise the number and location of ETS devices in two different distrbution networks. The genetic algorithm, SPEA2, determines various, feasible, solutions to find the optimal number and location of the ETS devices and iterates through its processes, producing better solutions, until the maximum numer of generations is reached. The aim of these studies is to illustrate the output from MODERNE, show its adaptability to different scenarios and present the trade off between solutions that the user must make when determining which solution should be implemented.

6.1 Distribution Networks

The distribution networks that are used for analysis in this research are the Orkney distribution network and the Shetland distribution network. These networks were chosen to provide sets of results for each case study applied to the MODERNE framework. The Orkney Isles and the Shetland Isles are sets of islands off the north east coast of Scotland. Figure 6-1 shows their geographical location to the Scottish mainland.

Figure 6-1 - Location of Orkney and Shetland Islands

These two distribution networks were chosen for a number of reasons. First of all the Orkney Isles are electrically interconnected to mainland Scotland, whereas the Shetland Isles operate an isolated network. By using two networks that differ in this way, the effect on the results of the optimisation process can be observed. Both networks have a good energy mix with a representation of renewable generation. On Orkney there is a mix of wind, wave and gas as sources of power and on Shetland there is generation from diesel, gas and wind. Not only that, Orkney is host the UK's first, fully operational, Active Network Management (ANM) system which was installed in 2009 and controls the output of generators on the islands to ensure the network stays within operational limits [1]. Shetland is currently involved in a similar endeavour. Currently no further connections for generation (mostly from wind) are being accepted on Shetland as, by being an isolated network, there cannot be more generation than demand or vice versa. By employing an ANM scheme that also incorporates demand response and energy storage, connections of generation can be accepted [2]. Also, by using these networks, as they are of a limited size, computation time is reduced than if larger, more complex networks were being analysed. ETS is an example of demand response and is the type of device that could be controlled in an effort to provide benefit to the network by moving space heating and hot water demand away from peak times. The Orkney and Shetland distribution networks are ideal examples of networks with renewable generation and where a controllable demand could be of benefit. By using these networks in case studies applied to MODERNE, a real world situation is being analysed as opposed to analysing fictitious networks; results can be seen in the context of a physical network. Network diagrams for Orkney and Shetland are provided in Figure 6-2 and Figure 6-3 respectively. The profiles applied in the case studies have a maximum generation and demand of 33.35 MW and 32.56 MW respectively, and every node is capable of having ETS installed, however this is limited to 100 units per node. As the Orkney and Shetland islands are typically made up of smaller towns and villages, the assumption was made that there would be approximately 100 homes per node, and thus 100 ETS devices could be installed. Appendix A contains more information pertaining to the two networks.

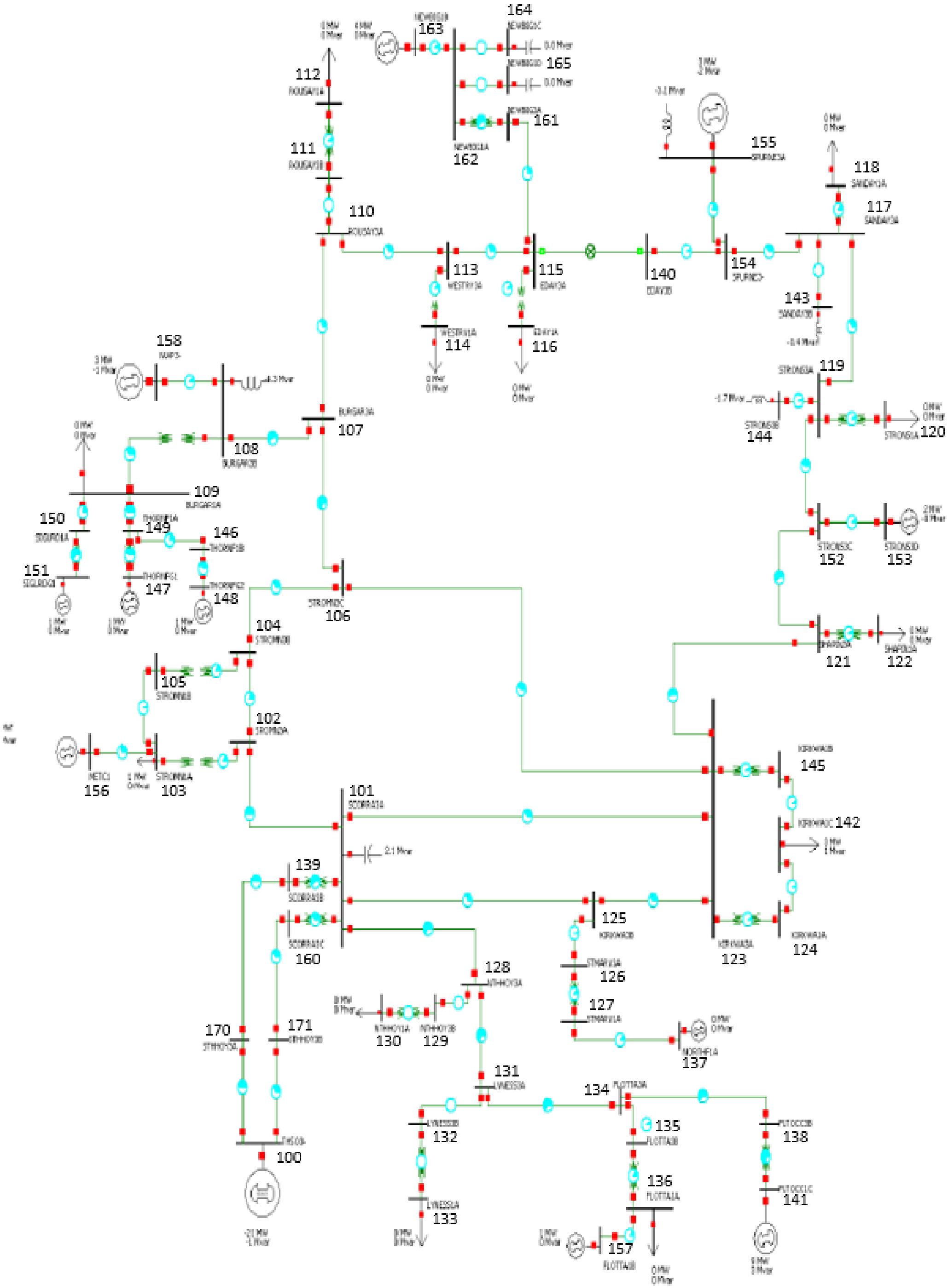

Figure 6-2 - Orkney distribution network

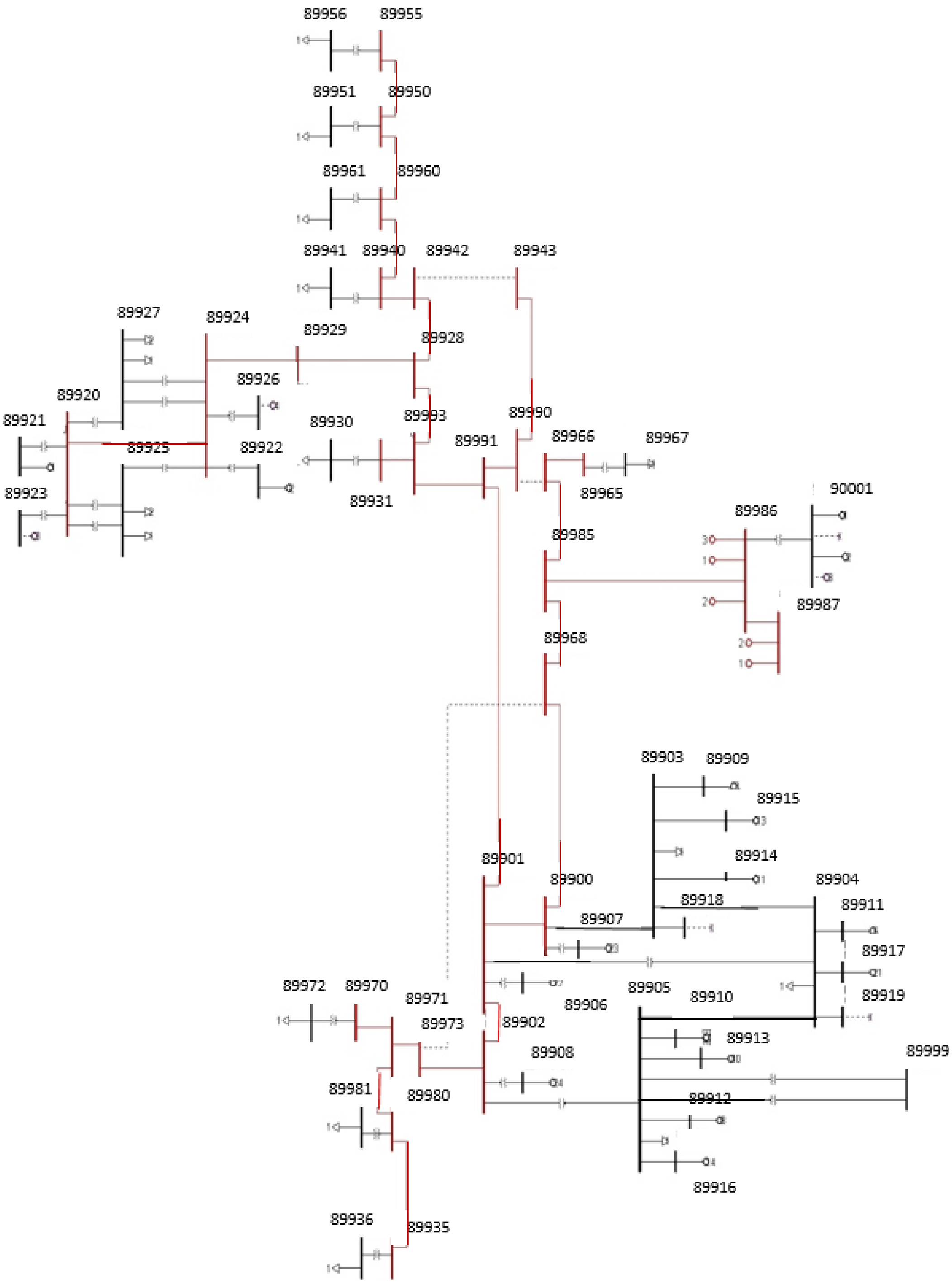

Figure 6-3 - Shetland distribution network

For both networks, it is hard to present all the relevant information in the network diagram due to the size and number of elements, however they are useful to illustrate the overall network topology. Both networks can be represented by simplified models, in which it is easier to view network assets. Figure 6-4 and Figure 6-5 present the simplified network diagrams for Orkney and Shetland respectively.

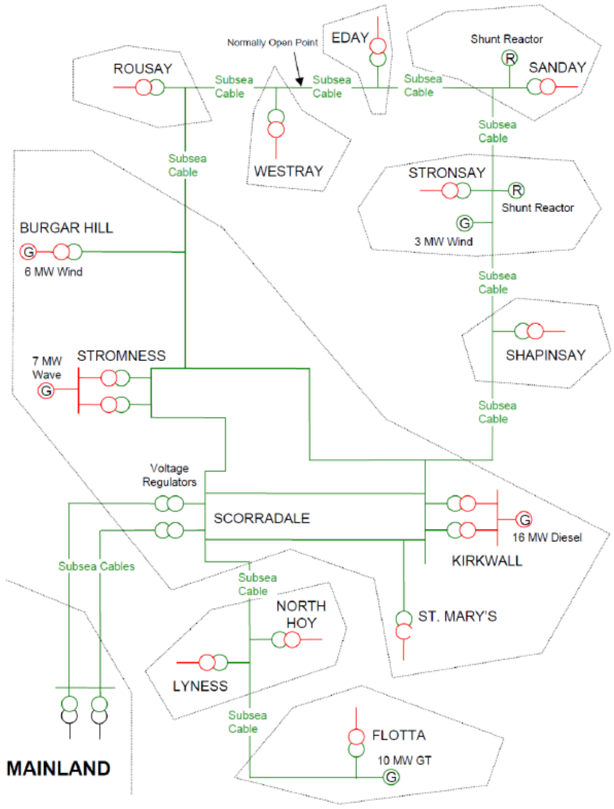

Figure 6-4 – Simplified Orkney network diagram

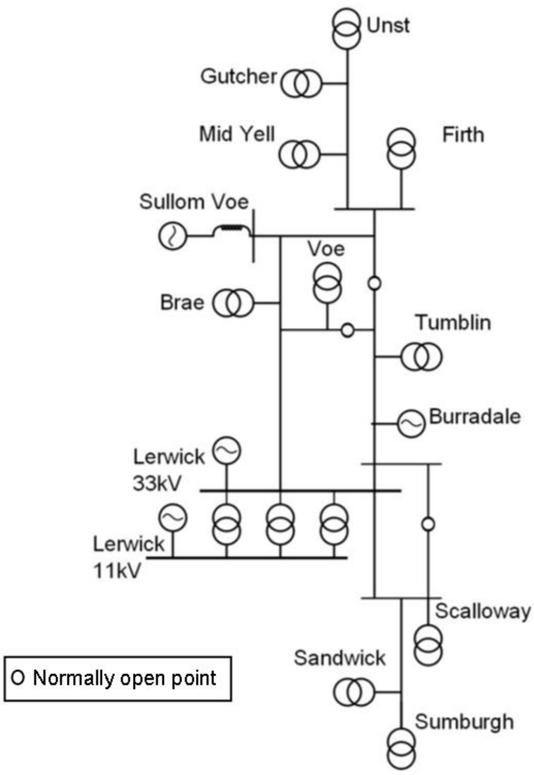

Figure 6-5 – Simplified Shetland network diagram

6.2 Case Study 1: Integrating ETS - minimising emissions, exported energy and penetration level

To evaluate MODERNE with a real world environment and to allow for direct comparisons to be made between the two distribution networks, each case study is applied to both the Orkney and Shetland networks. This case study will see the installation of ETS optimised for both distribution networks while considering environmental, operation and investment objectives. Additionally the optimisation process is bound by the operational constraints of the network and an additional operational constraint which sets an overload probability. The main for the case study is to highlight the optimised deployment and operation of ETS.

6.2.1 Objectives, Constraints and SPEA2 Parameters

The defining characteristics for this case study are the following chosen objectives:

- Minimise the emissions factor;
- Minimise exported energy;
- Minimise penetration level.

These objectives were chosen to represent an environmental concern (the carbon emissions), a network operating concern (exporting energy, balancing the network) and an investment concern (controlling the number of devices installed). The additional constraint that is set to be considered alongside the normal operating limits of the networks is to restrict an overload probability to 6%. This value is exaggerated to show the effect and would normally be set by power system planners; as a result it would be expected to be a lower number, as it is typical for no overloads to be planned. The parameters that were set for SPEA2 are shown in Table 6-1.

Table 6-1 - SPEA2 Parameters

Total Size	**50**
Archive Size	**50**
Crossover Probability	**0.8**
Mutation Probability	**0.01**
Minimum Number of Generations	**50**
Maximum Number of Generations	**50**

The main driving factor for setting the population, archive and number of generations at 50 was computation time. Running the optimisation, along with an OPF for every possible solution was very time consuming so restricting these sizes allowed for a greater number of simulations to be carried out in the given computation time.

6.2.2 MODERNE Output

Figure 6-6 to Figure 6-11 illustrate the results for the Orkney network, and Figure 6-12 to Figure 6-17 illustrate the results for the Shetland network. The results from the framework are presented in graph form and a number of different displays are presented. Using a graphical approach allows for the Pareto front, described in Section 3.1.1, for this optimisation problem to be easily illustrated. These graphs present the optimal solutions for the multi-objective optimisation problem and show exported energy against emissions factor, overload probability against emissions factor, overload probability against exported energy, overload probability against penetration level, penetration level against emissions factor and penetration level against exported energy.

6.2.3 Observations

In the results for Orkney, the most evident results are that the overload probability is zero. This is regardless of the other objectives for optimisation. Thermal overloading is caused by excessive current through cables. It is likely that, for the Orkney network, the overload probability is zero due to the ability of the Orkney network to be balanced as it is interconnected to the mainland grid. This is the first significant difference between the results for the two networks. In the results for Shetland, it is clear that overloading is likely to occur as optimal solutions are shown. In Figure 6-13, the graph illustrates that the emissions factor should remain at a value between 100 and 200 $KgCO_2/kWh$ in order to stay within the constraint set to limit the overload probability to 6%. The graph showing overload probability against exported energy, Figure 6-14, shows a general trend where, as exported energy is decreased, the overload probability is also decreased. The graph that presents overload probability against penetration level, Figure 6-15, shows that the optimal results cluster around an ETS penetration level of 90-110%.

In the Orkney results, looking at Figure 6-10, as the penetration level increases the emissions factor decreases, as would be expected. The ETS devices are able to store energy and therefore the power from wind sources can be exploited. The graph of penetration level against exported energy, Figure 6-11, shows that there is an increase in exported energy as the penetration of ETS devices increases. This is due to the possibility that all ETS devices could be fully charged whilst the network is experiencing an abundance of generation from wind generators and the surplus generation still needs to be exported to elsewhere in the grid that is experiencing a higher demand. The equivalent graphs for the Shetland network show that, again, as penetration of the ETS devices increases the emissions factor will decrease; this can be seen in Figure 6-16. The graph that shows penetration level against exported energy, Figure 6-17, displays results that cluster around a penetration level of approximately 100% in order to minimise exported energy. The difference between the results for the networks here, is that the Shetland network is islanded and therefore exporting energy is impossible. The framework therefore attempts to find the optimal level of penetration for ETS devices that allows for optimum balancing, as well as considering the other objectives.

The remaining graph to be compared between the networks is that of exported energy against the emissions factor; Figure 6-6 for the Orkney network and Figure 6-12 for the Shetland network. In the Orkney network, the emissions factor actually increases as energy that is exported decreases. This could be the result of exported energy in these cases coming purely from generation that is heavy in carbon emissions, and as exported energy increases there could be more of that energy coming from renewable sources and therefore lowering the associated emissions factor. For the Shetland case, results are clustered between an emissions factor if 150-200 $KgCO_2/kWh$, and as the framework attempts to optimally balance the network, there are results for exported energy that are very close to zero, however it also illustrates that, should Shetland ever be interconnected, there is the capability to export energy.

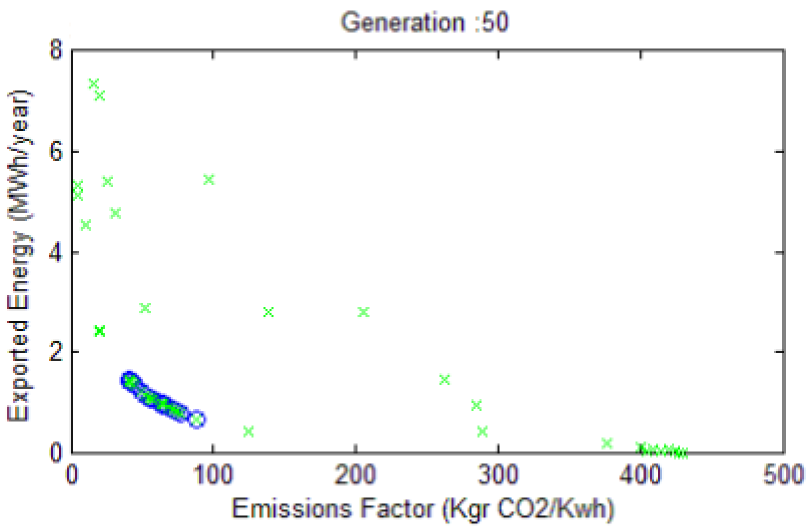

Figure 6-6 - Case Study 1, Orkney Exported Energy against Emissions Factor

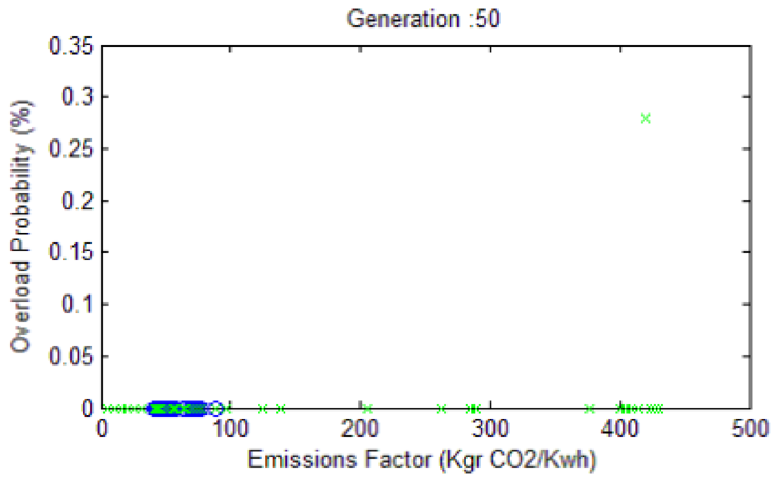

Figure 6-7 - Case Study 1, Orkney Overload Probability against Emissions Factor

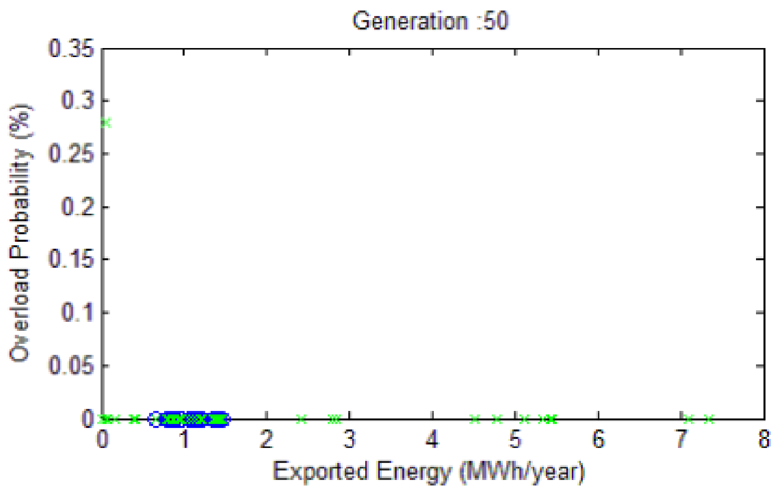

Figure 6-8 - Case Study 1, Orkney Overload Probability against Exported Energy

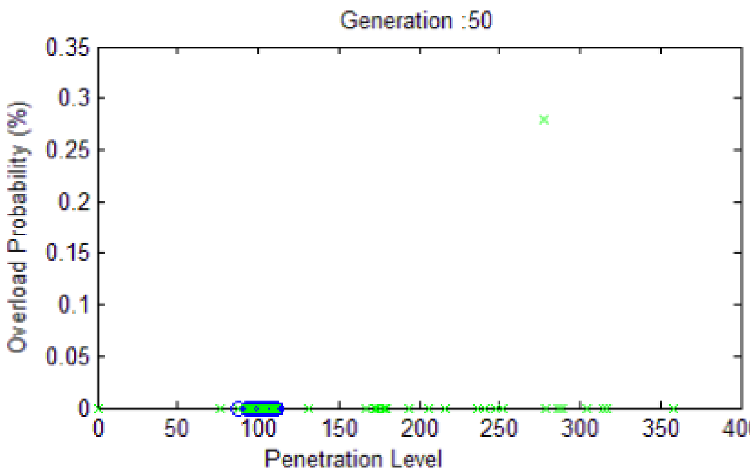

Figure 6-9 - Case Study 1, Orkney Overload Probability against Penetration Level

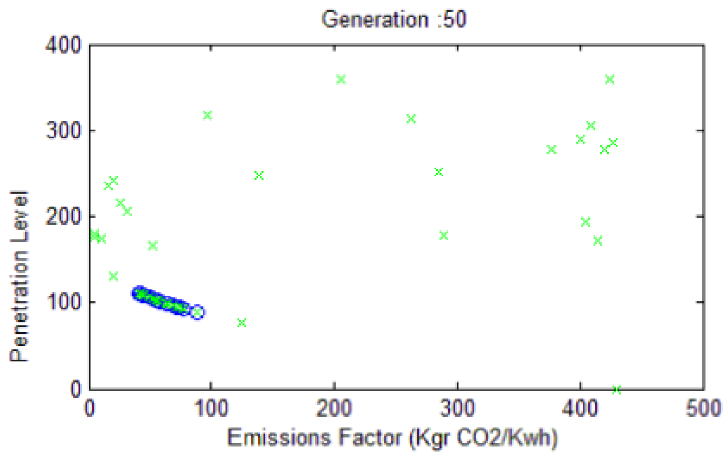

Figure 6-10 - Case Study 1, Orkney Penetration Level against Emissions Factor

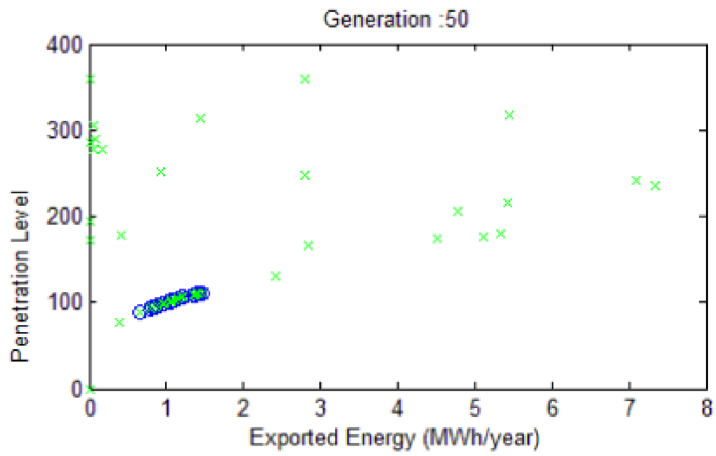

Figure 6-11 - Case Study 1, Orkney Penetration Level against Exported Energy

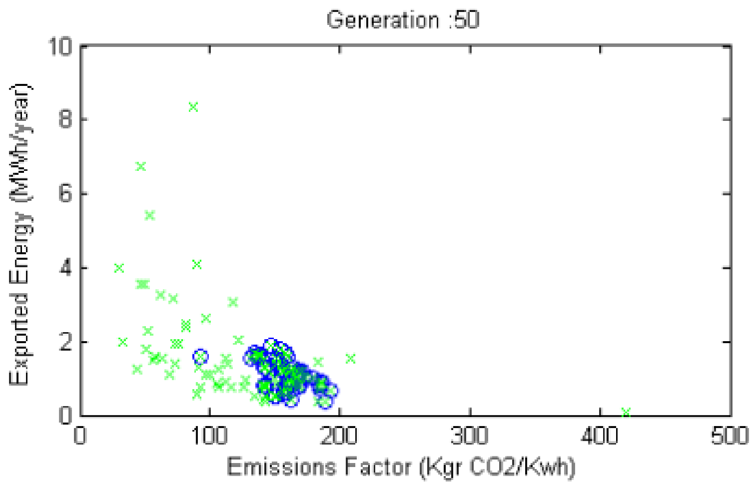

Figure 6-12 - Case Study 1, Shetland Exported Energy against Emissions Factor

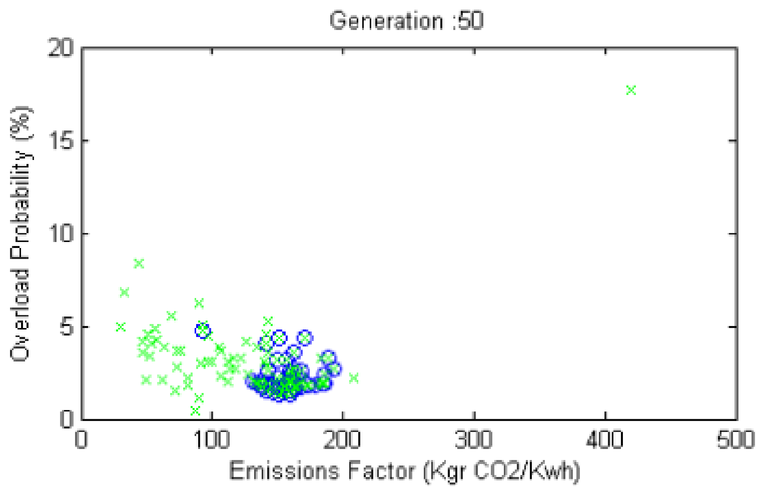

Figure 6-13 - Case Study 1, Shetland Overload Probability against Emissions Factor

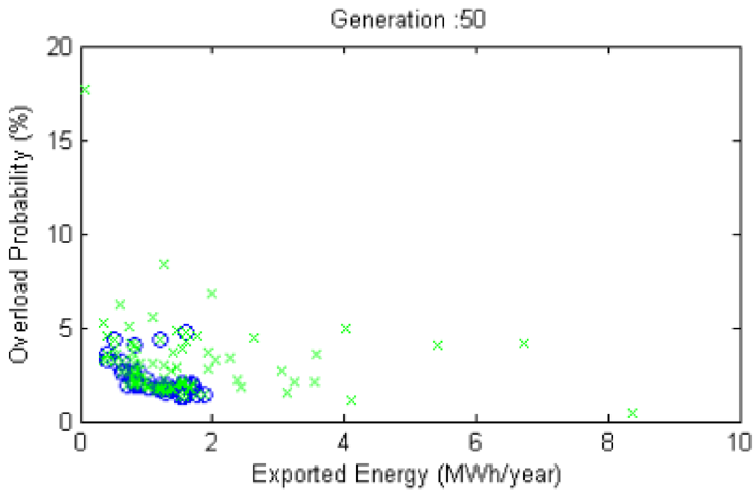

Figure 6-14 - Case Study 1, Shetland Overload Probability against Exported Energy

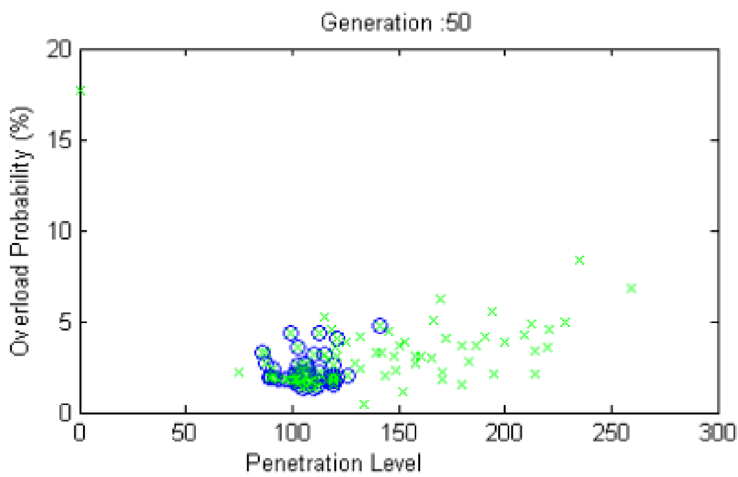

Figure 6-15 - Case Study 1, Shetland Overload Probability against Penetration Level

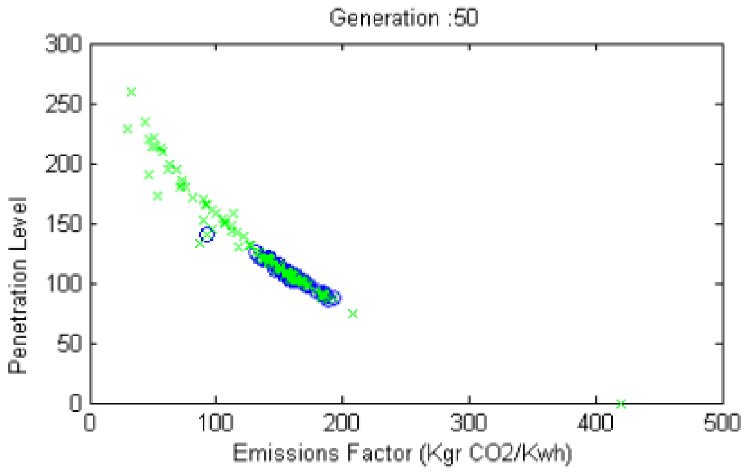

Figure 6-16 - Case Study 1, Shetland Penetration Level against Emissions Factor

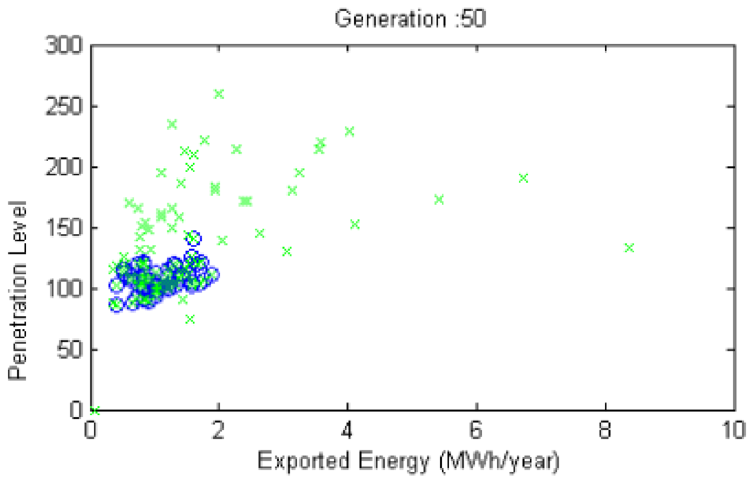

Figure 6-17 - Case Study 1, Shetland Penetration Level against Exported Energy

6.2.4 Illustrating the Trade-Off between Solutions

A very important factor in the selection of which solution to implement is the compromise that must be made between objectives. To illustrate this, Figure 6-18 to Figure 6-23 present the solutions for Orkney and Figure 6-24 to Figure 6-29 present the solutions for Shetland with three solutions identified. The aim is to analyse the extremes of the Pareto Front as much as possible and a solution from the centre of the front. Table 6-2 presents the data for each solution and objective.

Table 6-2 – Case Study 1: Individual solution data for Orkney and Shetland

Orkney Results			
	A	B	C
Emissions Factor (Kg CO_2/kWh)	35.63	49.74	97.32
Exported Energy (MWh/year)	1.81	0.98	0.65
Penetration Level (% of load)	116.02	97.85	91.16
Overload Probability (%)	0	0	0
Shetland Results			
	A	B	C
Emissions Factor (Kg CO_2/kWh)	96.24	148.52	198.77
Exported Energy (MWh/year)	1.78	0.72	0.48
Penetration Level (% of load)	148.82	112.61	88.42
Overload Probability (%)	5.02	1.89	3.87

In Figure 6-18 to Figure 6-29 solutions A, B and C have been denoted by arrows with their values displayed in Table 6-2. It can be seen from the table that the values for each objective are different, with exception to Overload Probability in Orkney. Solutions A and C have been chosen to represent the extremes of the range of solutions, and Solution B represents a mid-range solution. The range of values for the various objectives is broad. For the emissions factor, the range is from 35.63 to 97.32 KgCO_2/kWh with the associated range for exported energy being from 0.65 to 1.81 MWh/year and the penetration level of ETS devices reducing from 116.02% to 91.16%. This data helps to illustrate the compromise the planner must make when choosing which solution should be implemented. In this case, should minimising the penetration level be deemed more important than other objectives, solution C gives a penetration level of 91.16%, which is the lowest value but with the highest value for emissions factor. However if minimising exported energy is deemed to be the most important objective, solution A provides the lowest value of 35.63 MWh/year.

Similarly for the Shetland network, the solutions aim to represent both extremes of the Pareto Front. The emissions factor ranges from 96.24 to 198.77 KgCO_2/kWh, exported energy ranges from 0.48 to 1.78 MWh/year, the penetration level ranges from 88.42 to 148.52% and the overload probability ranges from 1.89 to 5.02%. As in the results for Orkney, the result for Shetland with the highest penetration level of ETS devices experiences the lowest emissions factor. In this case it is solution A. This also results in the largest amount of energy available for export, so minimising the exported energy is compromised, and in this case there is a probability of overload which, for solution A is 5.02%. If the planner wished to implement solution A to achieve a high penetration of ETS devices, they would be compromising on minimising the exported energy and would experience a greater probability of overloads. By contrast, choosing solution C with the lowest penetration of ETS devices results in the highest emissions factor and a value of exported energy that lies between solutions A and B.

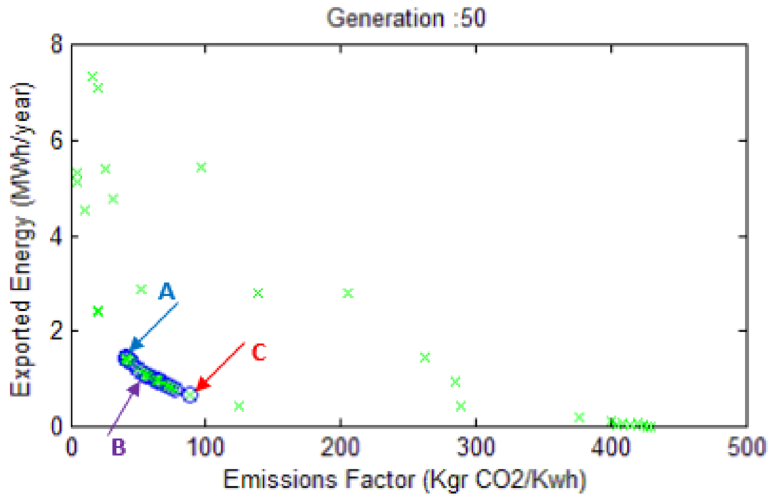

Figure 6-18 - Orkney, Comparison of Results, Exported Energy against Emissions Factor

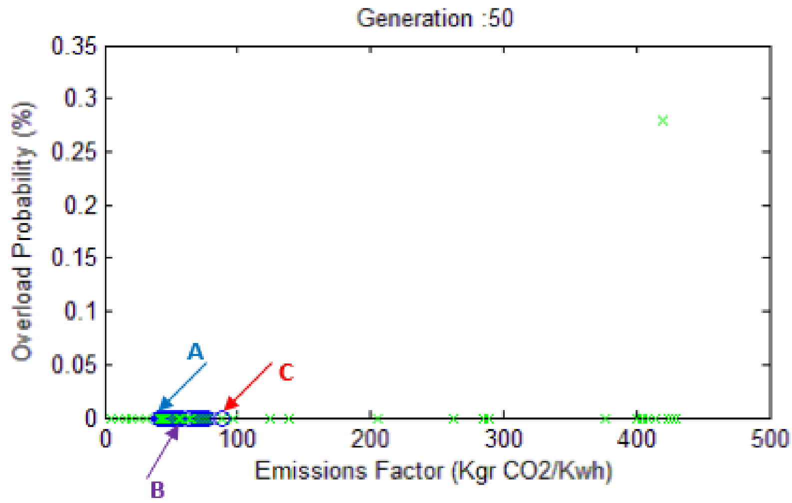

Figure 6-19 - Orkney, Comparison of Results, Overload Probability against Emissions Factor

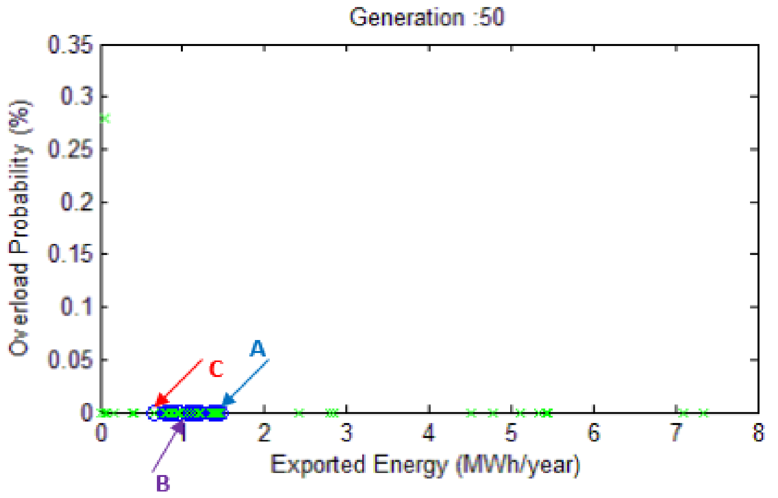

Figure 6-20 - Orkney, Comparison of Results, Overload Probability against Exported Energy

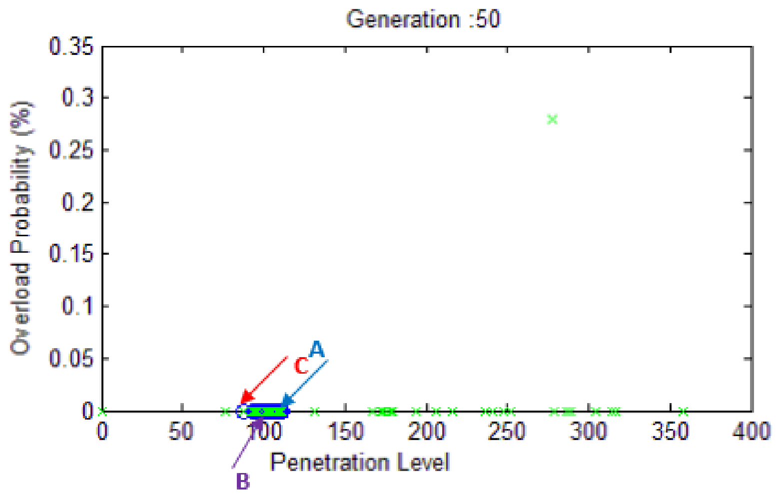

Figure 6-21 - Orkney, Comparison of Results, Overload Probability against Penetration Level

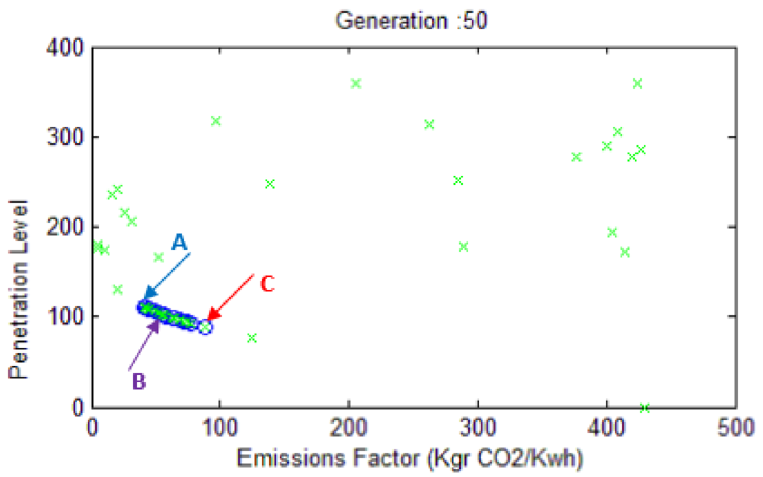

Figure 6-22 - Orkney, Comparison of Results, Penetration Level against Emissions Factor

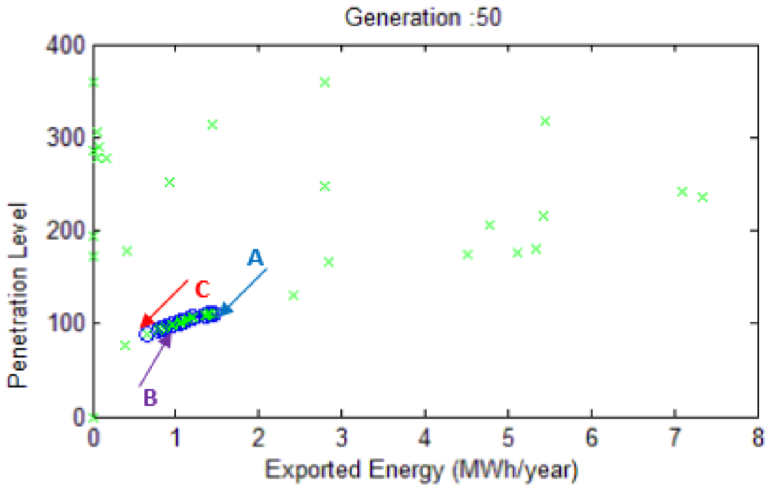

Figure 6-23 - Orkney, Comparison of Results, Penetration Level against Exported Energy

It is also possible to represent solutions A, B and C in terms of the number and location of ETS devices in the corresponding network, as these are key decision variables in the multi-objective optimisation problem. The numerical results for Orkney are displayed in Table 6-3.

Table 6-3 – Case Study 1, Orkney numerical results for Solutions A, B and C

Solution	Node	ETS Type	Number of Devices
A	2	1	4
	14	2	27
	28	3	10
	36	1	24
	43	4	30
	51	3	20
	61	2	1
	67	3	14
B	2	1	4
	14	2	27
	28	3	10
	36	1	24
	67	2	14
C	2	1	4
	11	4	10
	14	2	27
	23	1	3
	28	3	1
	36	1	24
	58	3	11
	62	3	2
	67	3	14

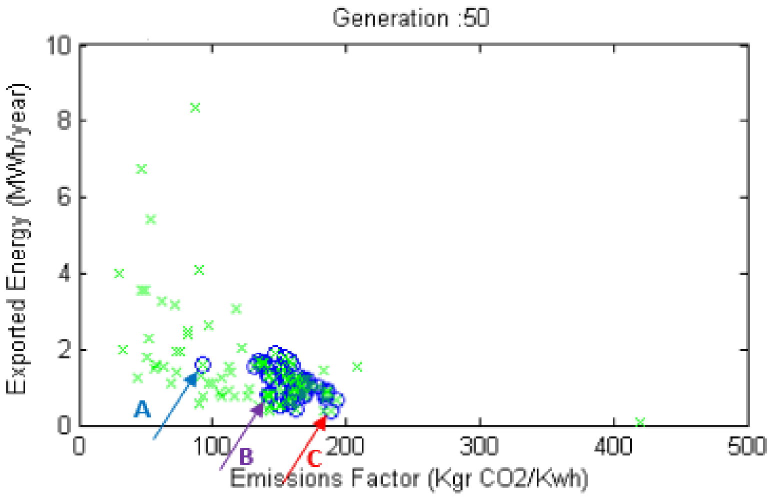

Figure 6-24 - Shetland, Comparison of Results, Exported Energy against Emissions Factor

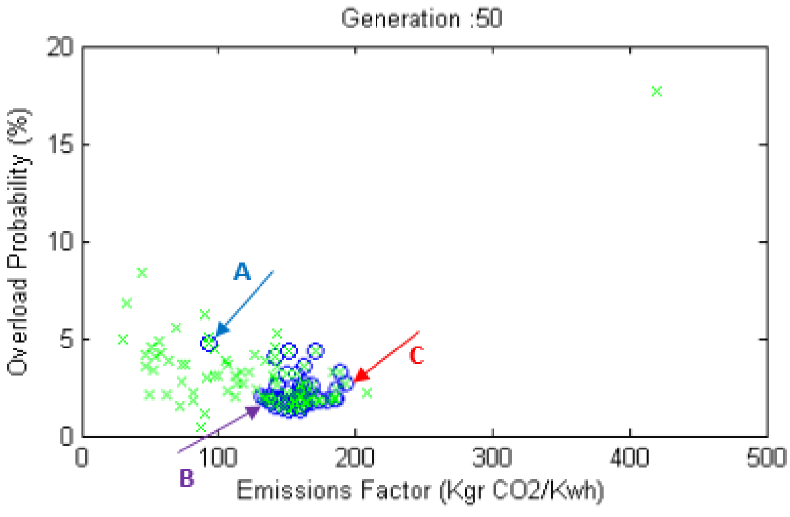

Figure 6-25 - Shetland, Comparison of Results, Overload Probability against Emissions Factor

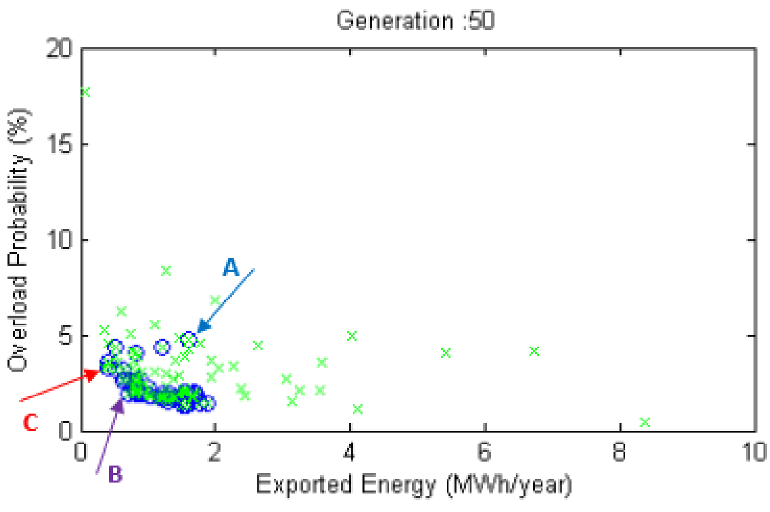

Figure 6-26 - Shetland, Comparison of Results, Overload Probability against Exported Energy

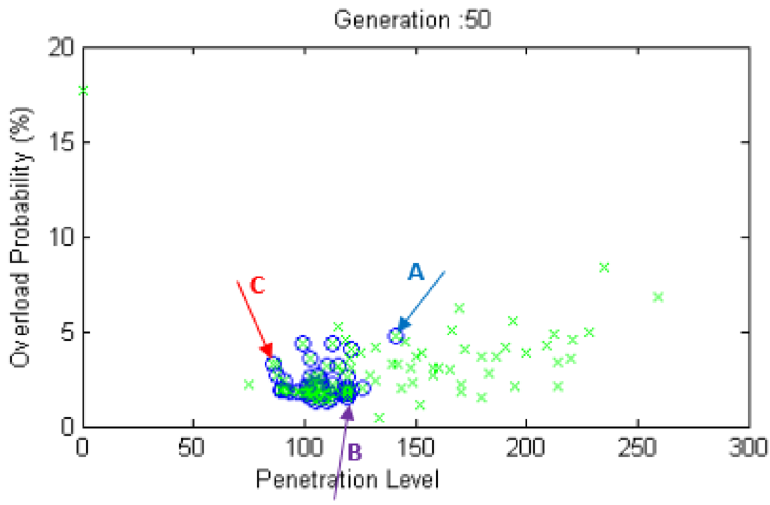

Figure 6-27 - Shetland, Comparison of Results, Overload Probability against Penetration Level

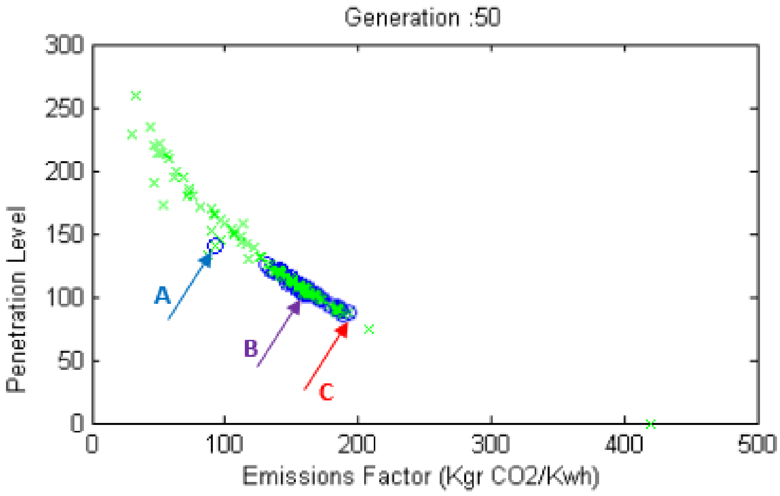

Figure 6-28 - Shetland, Comparison of Results, Penetration Level against Emissions Factor

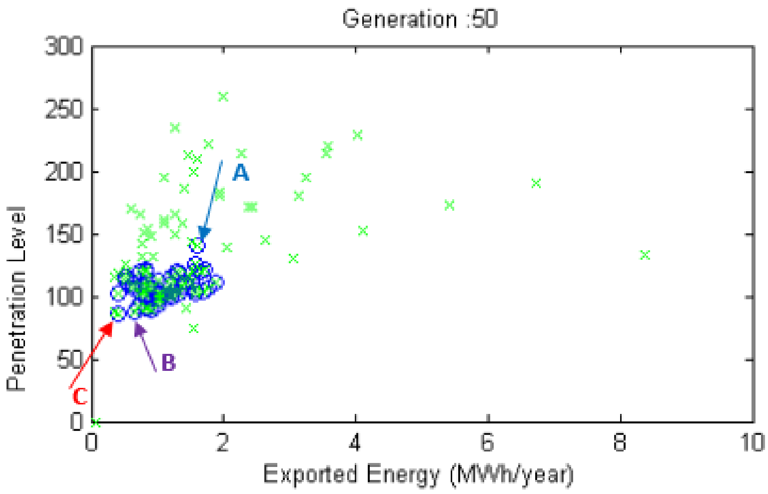

Figure 6-29 - Shetland, Comparison of Results, Penetration Level against Exported Energy

The numerical results corresponding to Solutions A, B and C for Shetland are presented in Table 6-4.

Table 6-4 – Case Study 1, Shetland numerical results for Solutions A, B and C

Solution	Node	ETS Type	Number of Devices
A	11	2	58
	11	4	3
	13	2	30
	13	3	45
	16	1	52
	22	2	49
	24	4	7
B	2	2	27
	6	1	7
	10	1	25
	11	2	58
	11	4	3
	13	3	45
	16	1	17
	22	1	7
C	5	4	14
	6	1	5
	6	3	16
	7	3	37
	11	2	15
	11	4	6
	13	2	58
	13	3	36
	16	1	52
	21	1	25

6.2.5 Summary of Case Study 1

This case study had three objectives, minimise the emissions factor, minimise exported energy and minimise penetration level, and one additional constraint, an overload probability of 6%, as well as the operational constraints of the network. The main observations from the results are:

- For Orkney the overload probability is zero whilst for Shetland overloading still occurs for the optimal solutions.
- On Orkney and Shetland while the penetration of ETS increases the emission factor decreases, and as the penetration level increases so does the exported energy.

- For Orkney as exported energy decreases the emissions factor increases whereas on Shetland exported energy does not reduce to zero, but the results do show that Shetland could export energy should the islands be interconnected.

This case study, however, does not consider objectives for maximisation. The next case study contains more objectives for optimisation, some of which are for maximisation, to show the adaptability of MODERNE to different problem arrangements.

6.3 Case Study 2: Integrating ETS - minimising exported energy, grid dependency and emissions factor, maximising CO_2 reduction

As in the previous case study, the same optimisation problem is applied to both the Orkney and Shetland distribution networks for comparison. This is again to evaluate MODERNE with a real world environment and to allow for direct comparisons to be made between the two networks. In this case study the objectives are set to cover both minimisation and maximisation of objectives, as well as consider operational and environmental objectives while abiding by the operational constraints of the networks. The main aim for the case study is to highlight the optimised deployment and operation of ETS.

6.3.1 Objectives, Constraints and SPEA2 Parameters

In this case study four objectives were chosen for optimisation. This is to illustrate that the framework is able to both handle a larger number of objectives for optimisation and the ability to work with both minimisation and maximisation objectives. As this method of multi-objective optimisation is proposed for the deployment of ETS devices, it is important to show that the method is adaptable to different problems. The defining characteristics for this case study are the following chosen objectives:

- minimisation of exported energy;
- minimisation of grid dependency;
- minimisation of emissions factor;
- maximisation of CO_2 reduction.

The minimisation of exported energy objective has been chosen in order for the solutions generated to strive towards the most efficient operation of the network. By choosing to minimise grid dependency, the solutions that are generated aim to ensure the network is as self-balancing and as self-sufficient as possible. It is important to again note, as stated in Case

Study 1, that as the Shetland network is islanded the solutions generated handle the exported energy and grid dependency objectives by ensuring the network is as balanced as possible, and the difference between generation and demand is kept to a minimum. The minimisation of emissions factor is included in this optimisation problem in order to represent an environmental objective. CO_2 emissions reduction is also included to reflect the maximisation of objectives that can be achieved by the framework. It also reflects an environmental objective, and presents the emissions factor in another form. In this case study no additional operational constraint was set, and the SPEA2 parameters are as in Table 6-1.

6.3.2 MODERNE Output

Figure 6-30 to Figure 6-34 present the results for the Orkney network and Figure 6-35 to Figure 6-39 present the results for the Shetland network. These graphs illustrate the optimal solutions for the problem set and present graphs for CO_2 emissions reduction against emissions factor, CO_2 emissions reduction against exported energy, CO_2 emissions reduction against grid dependency, emissions factor against exported energy, emissions factor against grid dependency and grid dependency against exported energy.

6.3.3 Observations

Figure 6-30 displays grid dependency against exported energy. As one objective decreases, so does the other. However, independence from the grid cannot be fully achieved as the minimum value is at 2 MWh/year. However, this is less than the average energy used in a household so the result is within a very small margin. To analyse the equivalent graphs for Shetland, Figure 6-35, is difficult as Shetland is an islanded network, and therefore does not have an interconnected grid to import and export with. As in the previous case study, the framework attempts to find the optimal results where system balancing is the concern, and the generated solutions aim to minimise the difference between generation and demand.

Figure 6-31 shows emissions factor against exported energy for the Orkney network; as exported energy is decreased the emissions increase. This was seen in the previous case study as well. It is possible that the energy being exported is from purely conventional generation which would have a higher emissions factor associated with it. It is also possible that a lower output from wind could lead to the lesser export, so the higher emissions could be associated with the lower level of wind power. The equivalent graph for the Shetland network, Figure 6-36, illustrates that as the system moves towards a more balanced state, the emissions factor will decrease. Figure 6-32 shows that, in the Orkney network, as grid dependency decreases, so does the emissions factor. For Shetland, Figure 6-37 shows that the emissions factor will decrease as the network becomes more balanced. Figure 6-33 shows CO_2 emissions factor against exported energy. These graphs show that as exported energy reduces, the CO_2 emissions reduction reduces. This implies that the Orkney network is capable of supplying some of its load from low carbon generation, it is not able to completely reduce the energy exported and there are times when conventional generation is required to meet demand. Figure 6-34 shows that CO_2 reduction can improve as grid dependency is minimised to its lowest value. In the case of Shetland, CO_2 reduction against grid dependency, Figure 6-39, shows the CO_2 reduction decreases as the network improves its balancing. This would be possible if the network had to rely on conventional plant in order to achieve balancing.

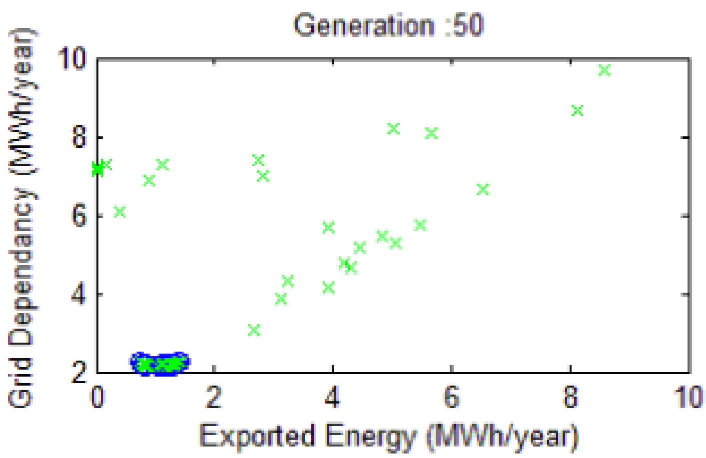

Figure 6-30 - Case Study 2, Orkney Grid Dependency against Exported Energy

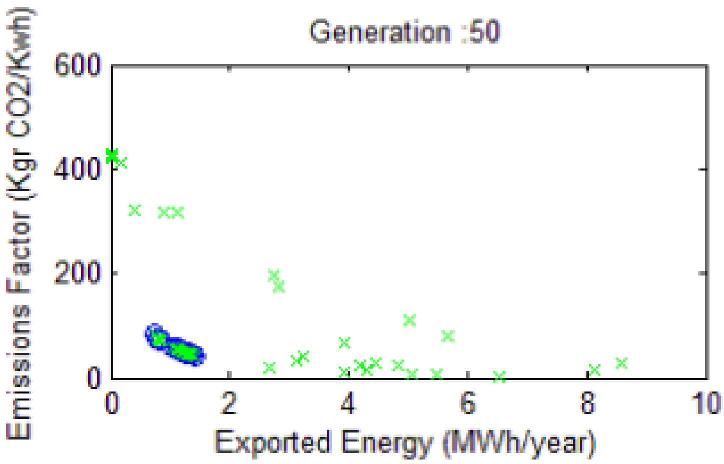

Figure 6-31 - Case Study 2, Orkney Emissions Factor against Exported Energy

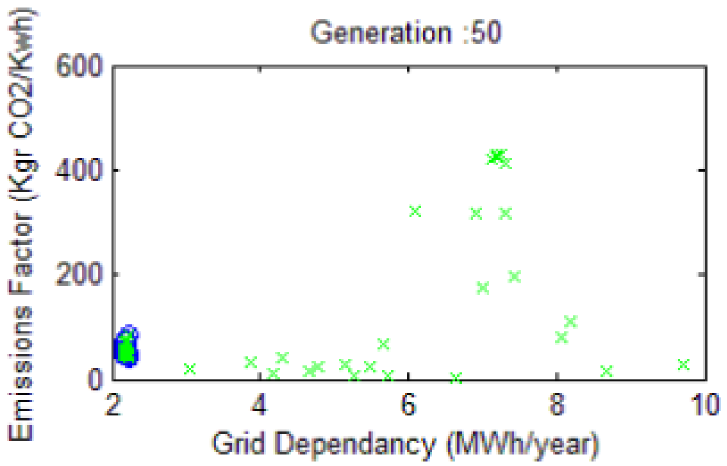

Figure 6-32 - Case Study 2, Orkney Emissions Factor against Grid Dependency

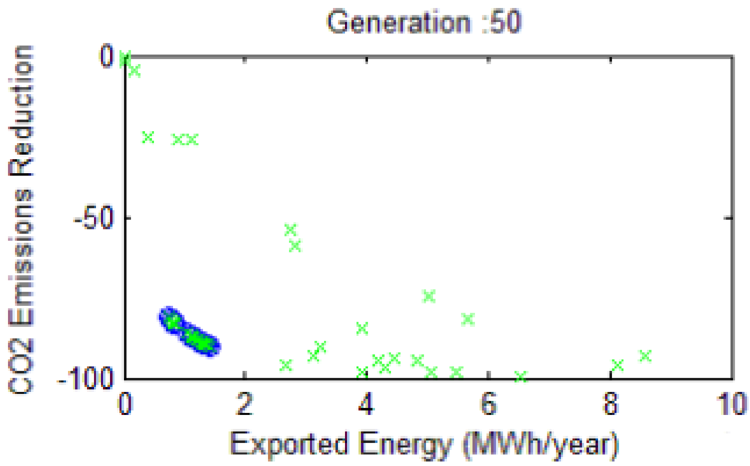

Figure 6-33 - Case Study 2, Orkney CO2 Emissions Reduction against Exported Energy

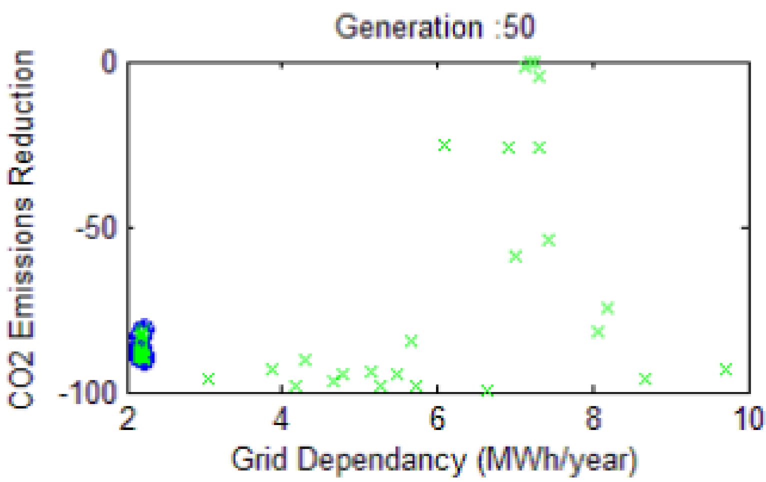

Figure 6-34 - Case Study 2, Orkney CO2 Emissions Reduction against Grid Dependency

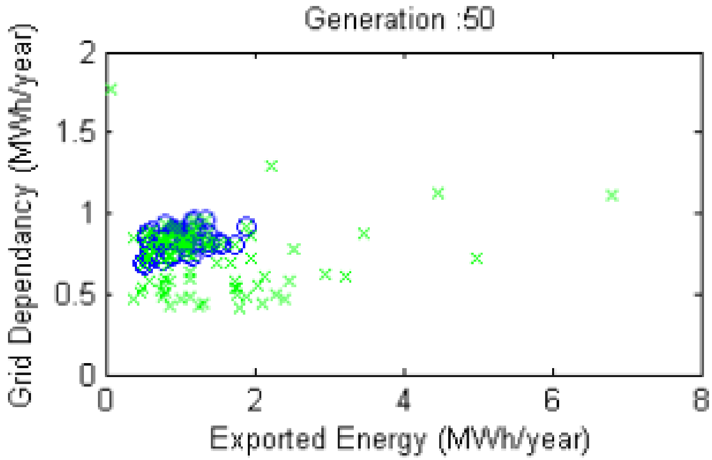

Figure 6-35 - Case Study 2, Shetland Grid Dependency against Exported Energy

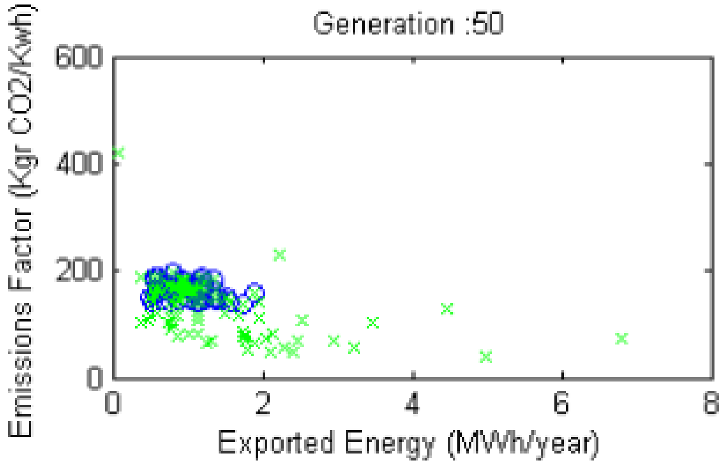

Figure 6-36 - Case Study 2, Shetland Emissions Factor against Exported Energy

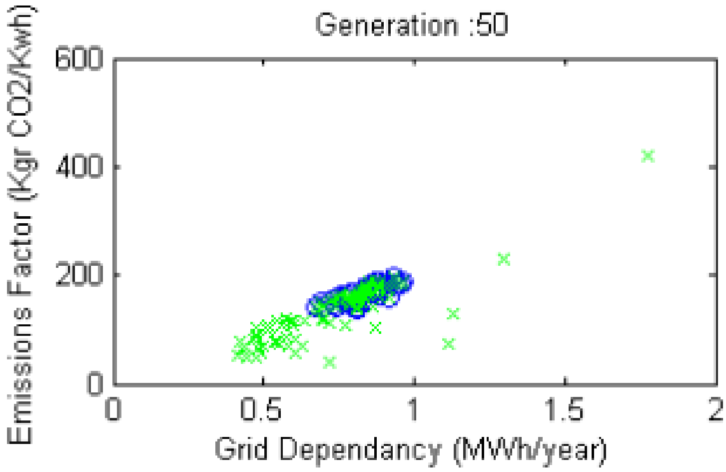

Figure 6-37 - Case Study 2, Shetland Emissions Factor against Grid Dependency

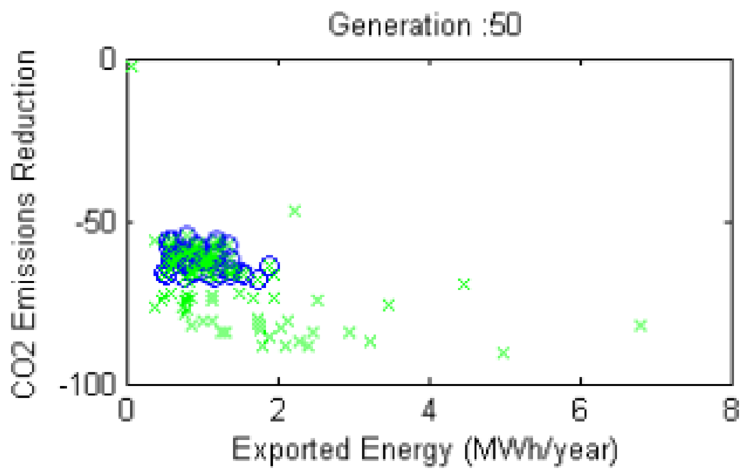

Figure 6-38 - Case Study 2, Shetland CO2 Emissions Reduction against Exported Energy

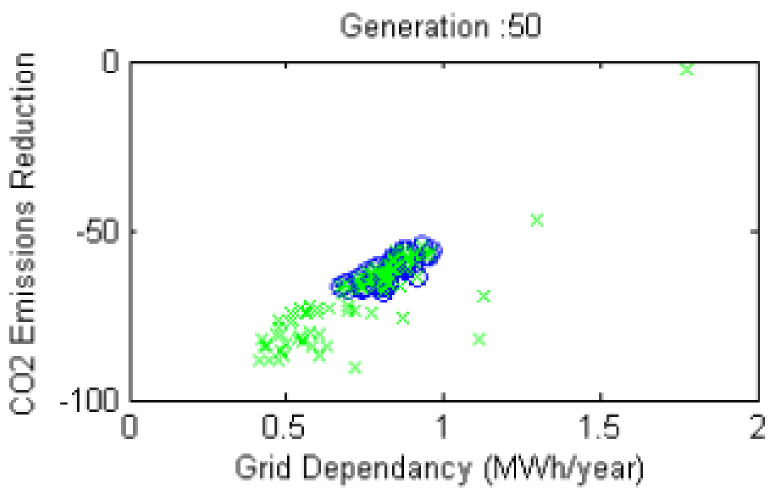

Figure 6-39 - Case Study 2, Shetland CO2 Emissions Reduction against Grid Dependency

6.3.4 Illustrating the Trade-Off between Solutions

As in the previous case study, Figure 6-40 to Figure 6-45 present the solutions for Orkney and Figure 6-46 to Figure 6-51 present the results for Shetland, with three solutions identified. Table 6-5 presents the data for each solution and objective.

Table 6-5 – Case Study 2: Individual solution data for Orkney and Shetland

Orkney Results			
	A	B	C
Exported Energy (MWh/year)	0.56	1.14	1.72
Grid Dependency (MWh/year)	2.22	2.20	2.23
Emissions Factor (kg CO_2/kWh)	110.04	78.82	51.16
CO_2 Emissions Reduction (%)	-64.65	-83.41	-92.27

Shetland Results			
	A	B	C
Exported Energy (MWh/year)	0.53	0.98	1.97
Grid Dependency (MWh/year)	0.64	0.97	0.96
Emissions Factor (kg CO_2/kWh)	162.21	201.86	186.47
CO_2 Emissions Reduction (%)	-71.29	-54.71	-66.75

As with the results in Case Study 1, the solutions chosen in this case study aim to illustrate the two extremes on the Pareto Front and a solution that lies between them. Solutions A and C represent the extremes while solution B represents the remaining example. For the Orkney network the value for exported energy ranges from 0.56 to 1.72 MWh/year, grid dependency remains at approximately 2.2 MWh/year in the Pareto Front, the emissions factor ranges from 51.16 to 110.04 kgCO_2/kWh and the reduction of CO_2 emissions ranges from -64.65 to -92.27%. The negative polarity indicates that CO_2 is still being produced for each solution, however the framework aims to minimise that production. In this case, if the user were to decide that achieving the lowest emissions factor was key, this would be solution C. In choosing this solutions, the minimisation of exported energy is heavily compromised as this solution has the highest energy export associated with it. The production of CO_2 is also only limited at 92.27%. If it was decided that minimising exported energy was the most important factor, this would be solution A. This compromises the minimisation of the emissions factor which increases to 110.04 kgCO_2/kWh.

Again in the case for Shetland, solutions A and C aim to represent the extremes while solutions B lies in between them. In this case the value for exported energy ranges from 0.53 to 1.97 MWh/year, grid dependency ranges from 0.64 to 0.97 MWh/year, the emissions factor ranges from 162.21 to 201.86 kgCO_2/kWh and the value for CO_2 emissions reduction ranges from -54.71 to -71.29%. If the planner decided that solution A should be implemented then the minimum exported energy is realised as well as the minimum grid dependency and minimum emissions factor, however the CO_2 emissions reduction is limited to 71.29% which is the maximum value. If it was decided that solution C was the best to implement, then exported energy, grid dependency and the emissions factor would all experience a compromise as solution C has the highest values for these objectives. The CO_2 emissions reduction is not at its minimum, however, with a value between the two extremes at 66.75%.

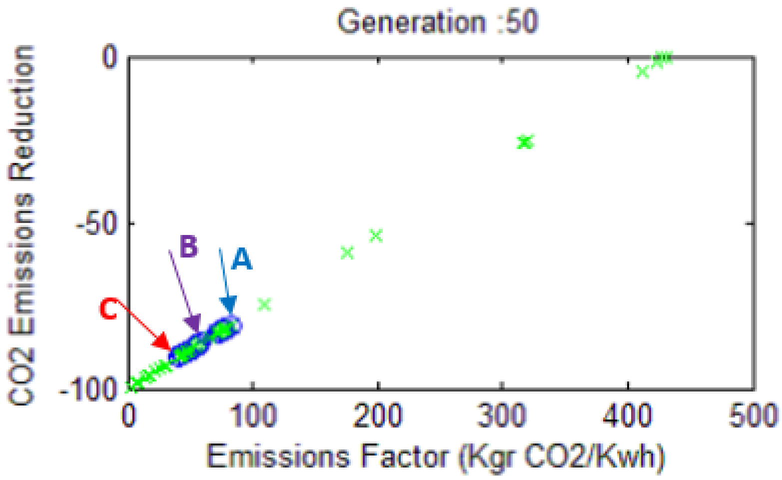

Figure 6-40 - Orkney, Comparison of Results, CO2 Emissions Reduction against Emissions Factor

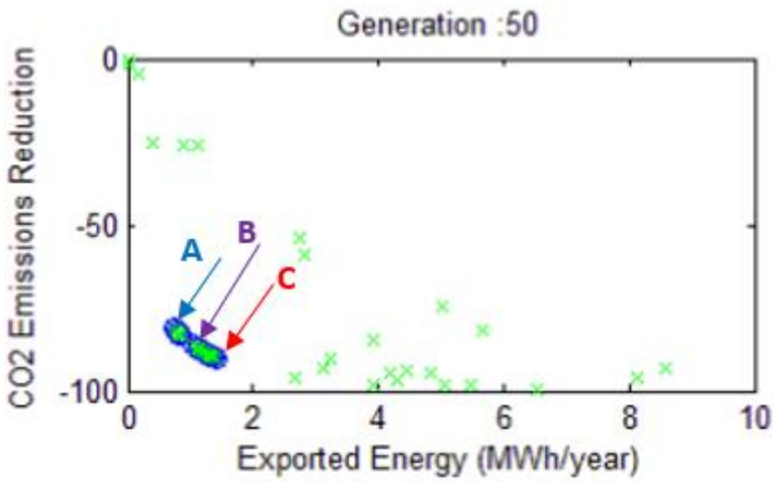

Figure 6-41 - Orkney, Comparison of Results, CO2 Emissions Reduction against Exported Energy

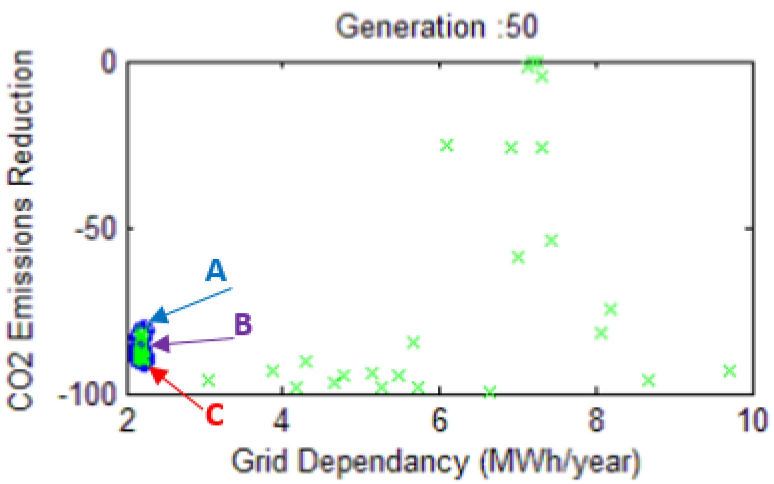

Figure 6-42 - Orkney, Comparison of Results, CO2 Emissions Reduction against Grid Dependency

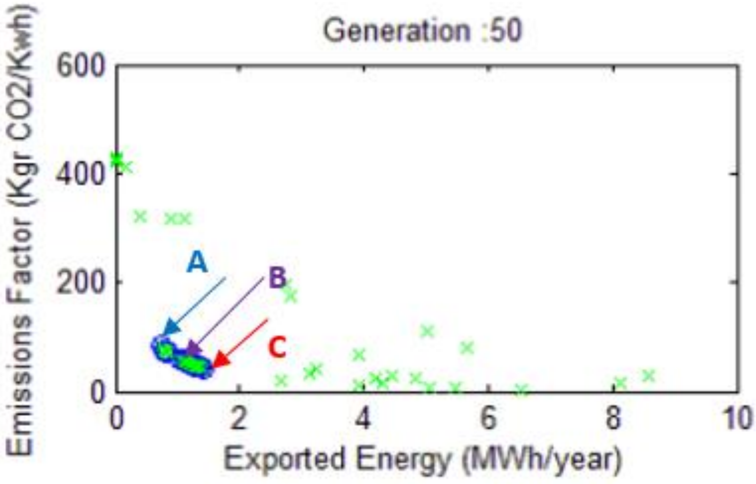

Figure 6-43 - Orkney, Comparison of Results, Emissions Factor against Exported Energy

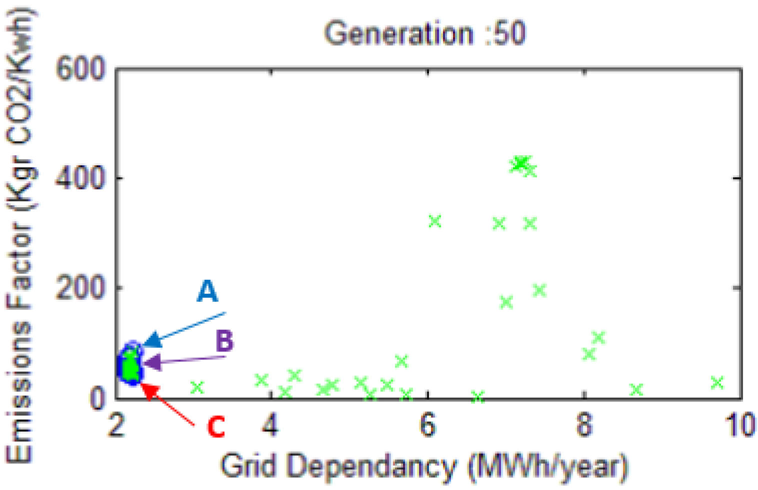

Figure 6-44 - Orkney, Comparison of Results, Emissions Factor against Grid Dependency

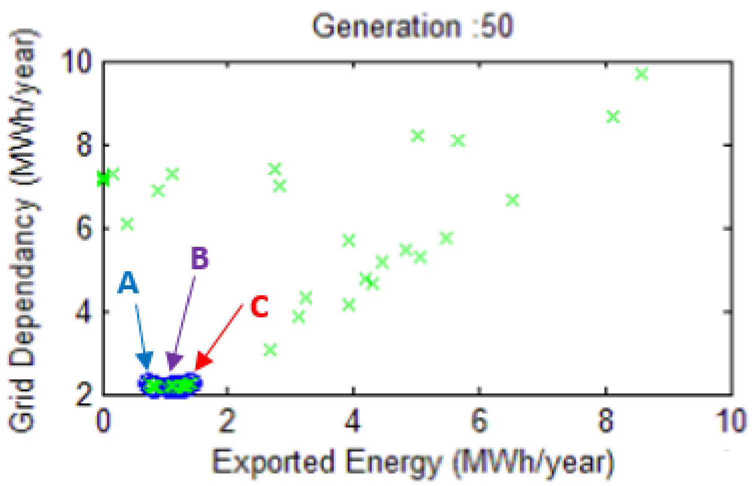

Figure 6-45 - Orkney, Comparison of Results, Grid Dependency against Exported Energy

The numerical results relating to Solutions A, B and C, for the Orkney network, are presented in Table 6-6.

Table 6-6 - Case Study 2, Orkney numerical results for Solutions A, B and C

Solution	Node	ETS Type	Number of Devices
A	7	1	7
	11	2	14
	25	1	23
	29	3	40
	32	1	14
	48	4	8
	54	1	9
	65	4	1
B	25	1	23
	32	4	28
	48	4	8
	55	1	1
C	7	1	7
	11	2	14
	27	4	14
	29	3	4
	41	2	1
	43	1	17
	46	3	13
	54	1	9
	55	4	15
	65	4	1

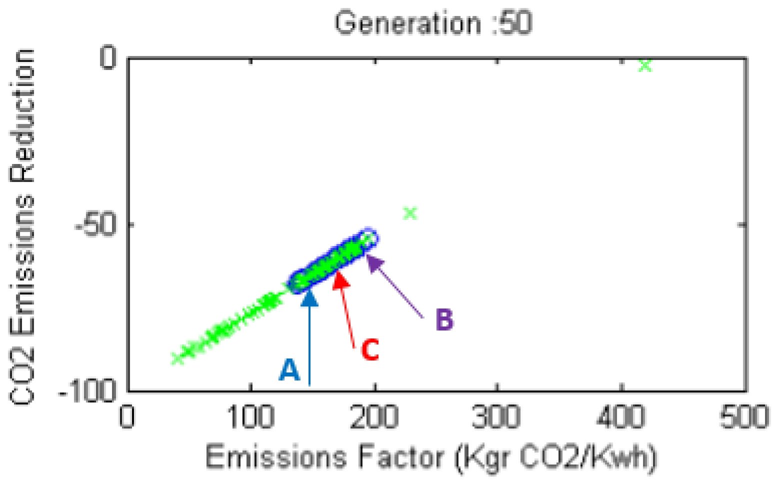

Figure 6-46 - Shetland, Comparison of Results, CO2 Emissions Reduction against Emissions Factor

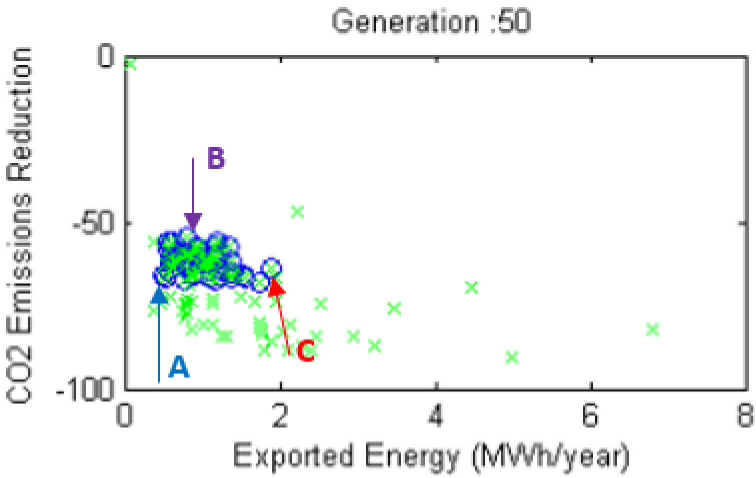

Figure 6-47 - Shetland, Comparison of Results, CO2 Emissions Reduction against Exported Energy

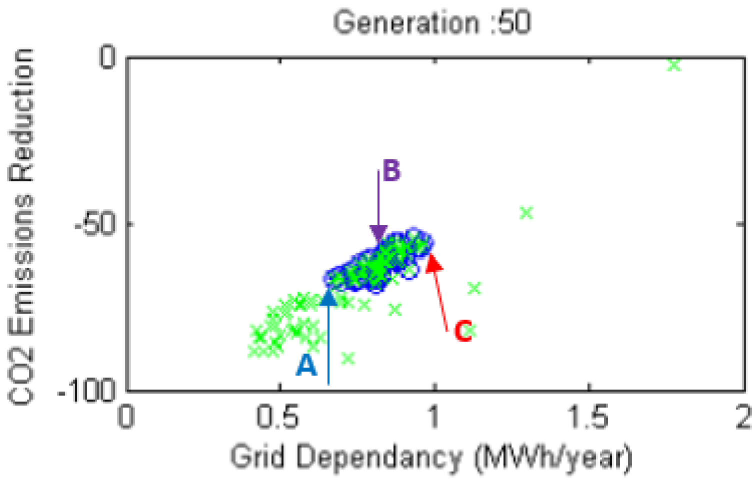

Figure 6-48 - Shetland, Comparison of Results, CO2 Emissions Reduction against Grid Dependency

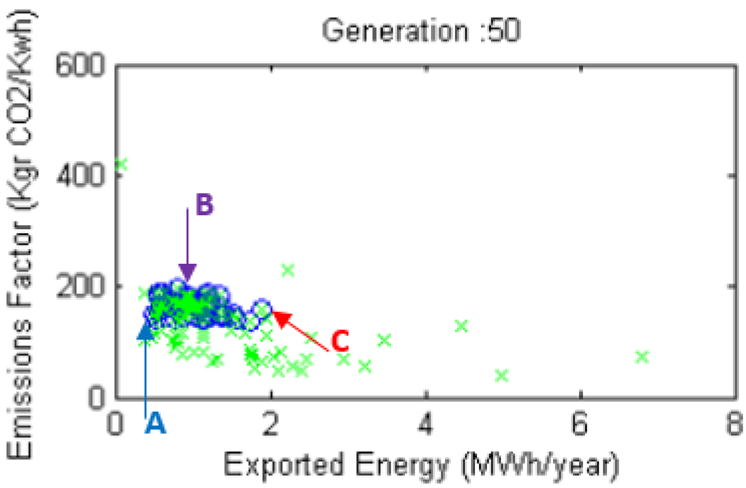

Figure 6-49 - Shetland, Comparison of Results, Emissions Factor against Exported Energy

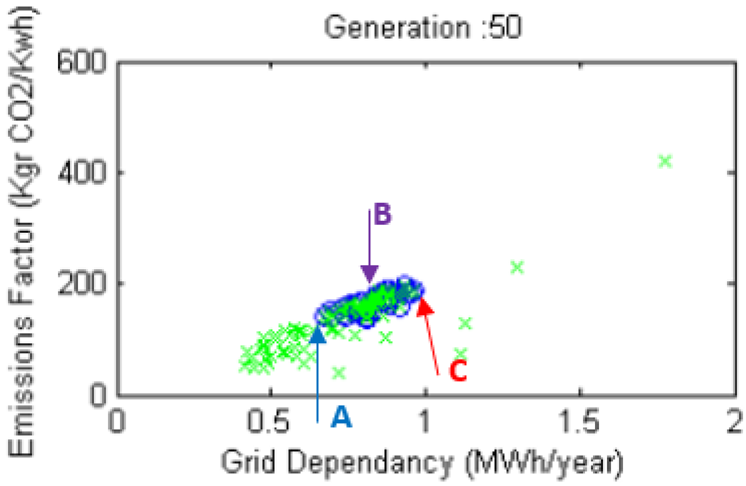

Figure 6-50 - Shetland, Comparison of Results, Emissions Factor against Grid Dependency

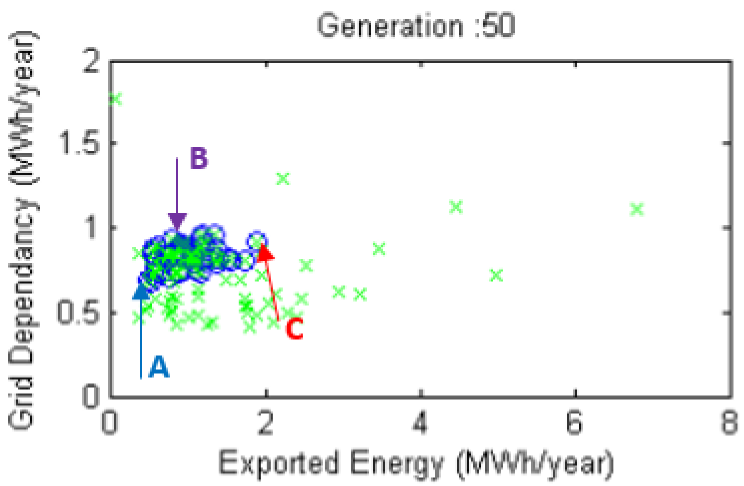

Figure 6-51 - Shetland, Comparison of Results, Grid Dependency against Exported Energy

The numerical results corresponding to Solutions A, B and C for the Shetland network are presented in Table 6-7.

Table 6-7 - Case Study 2, Shetland numerical results for Solutions A, B and C

Solution	Node	ETS Type	Number of Devices
A	2	3	38
	5	4	3
	6	4	3
	8	3	2
	10	1	5
	11	2	13
	11	4	16
	13	2	58
	13	3	32
	16	1	34
	22	1	6
	23	4	3
B	5	4	1
	6	1	15
	8	4	39
	12	4	4
	13	2	58
	13	3	32
	16	1	34
	16	4	35
	17	3	1
C	2	1	23
	6	1	15
	11	2	13
	13	2	58
	13	3	32
	16	1	34
	16	4	35
	17	3	2
	20	2	5
	26	3	29

6.3.5 Summary of Case Study 2

In this case study five objectives were considered for optimisation. These objectives were to minimise exported energy, maximise exported energy, minimise gird dependency, minimise emissions factor and maximise the reduction of CO_2. This case study was not bound by any constraints additional to those of network operation. The main observations from the results are:

- In Orkney grid dependency is not fully achieved, however the results are within a very small margin. In Shetland as the system is very well balanced.
- In Orkney as exported energy decreases the emissions factor increases while on Shetland as the system becomes more balanced, the emissions factor decreases.
- Orkney sees an increase in CO_2 reduction as grid dependency is reduced and as the Shetland system become more balanced, the CO_2 reduction decreases.

This study and Case Study 1 both consider the same ETS parameters. The next case study will see a change in the maximum number of ETS devices allowed for installation. Again, this is to show the adaptability of the framework and that such parameters can be altered.

6.4 Case Study 3: Integrating ETS – increasing the maximum of ETS devices for installation

This case study is applied to both the Orkney and the Shetland networks, with the same objectives for optimisation, but without an additional constraint, as in Case Study 1 to allow for a comparison to be made between results. In this case study the maximum installation of ETS devices across the network has been increased, by 100% to 200 per node, in order to observe the effect on the optimisation results.

Figure 6-52 to Figure 6-57 and Figure 6-58 to Figure 6-63 present the results from the MODERNE framework for the Orkney and Shetland networks respectively. In comparison to Figure 6-6 to Figure 6-11 from Case Study 1, it is evident that the results are very similar. By increasing the maximum number of ETS devices that can be connected to each node, the optimisation process is less constrained as it possible that by increasing that restriction more optimal solutions may be found. However, in the comparison with Case Study 1 results for Orkney it can be seen that the increase made to the limit on ETS devices for installation has had an effect on the results. In the graph for exported energy against emissions factor, Figure 6-52, it can be seen that the Pareto Front ranges from 0 at the very lowest to 2.7 MWh/year. In Figure 6-6 the values range from 0.65 to 1.81 MWh/year. This change in result comes from the increase in the installed devices. The new results show that exported energy can be reduced down to close to 0 MWh/year, as there are now more ETS devices to operate optimally and balance supply and demand. The exported energy has also been able to increase in the new results to reflect the exported energy when no ETS devices can be charged from available generation. Looking at Figure 6-52, the solution with the lowest emissions factor results in the greatest export of energy, and the solution with the highest emissions factor gives the lowest in exported energy. This illustrates that it is possible for the Orkney network to balance itself and not export energy, however it is possible that this will be met with use of resources that are higher in carbon emissions

Looking at the graph for penetration level against emissions factor, Figure 6-56, the results for the emissions factor range from 7.89 to 181KgrCO_2/KWh, and the results for penetration level range from 55.14 to 169.23%. In comparison, the values for this graph in Figure 6-10 range from 91.16 to 116.02% for penetration level and from 35.63 to 97.32 KgrCO_2/KWh for emissions factor. This shows that by increasing the maximum installation limit for ETS devices, the optimal solutions for objectives chosen do change to reflect the new limit. The maximum result for penetration level of ETS devices has increased in the new results and the new results for emissions factor show that the minimum value has increased from the original results, however the maximum value has remained the same. The graph for penetration level against emissions factor, Figure 6-56, shows that the solution with the greatest penetration level of ETS devices gives the lowest emissions factor, while the solution with the largest emissions factor has the lowest penetration level. This shows that the network can be operated with a very low emissions factor should there be a large penetration of ETS devices. However, having the lowest emissions factor also results in having the greatest exported energy.

One characteristic that is the same in both the Case Study 1 results and in the Case Study 3 results is that the overload probability is zero. The increase in the maximum of ETS devices for installation has had no effect on this additional constraint.

The results for Shetland in this case study are very similar to those shown in Case Study 1. The main difference between the Orkney network and the Shetland network is that Shetland is completed islanded, whereas Orkney is interconnected to mainland UK. As the Shetland network is islanded, and therefore must balance itself without any wider grid support, there would only be a change in the results from Case Study 1 if the increase in the number of ETS devices that could be installed resulted in there being more optimal solutions than those already found. When comparing Figure 6-58 - Figure 6-63 to Figure 6-12 - Figure 6-17 it can be seen that the results are identical. This means that the solutions found in Case Study 1 for Shetland are optimal, and allowing a greater installation of ETS devices does not impact this.

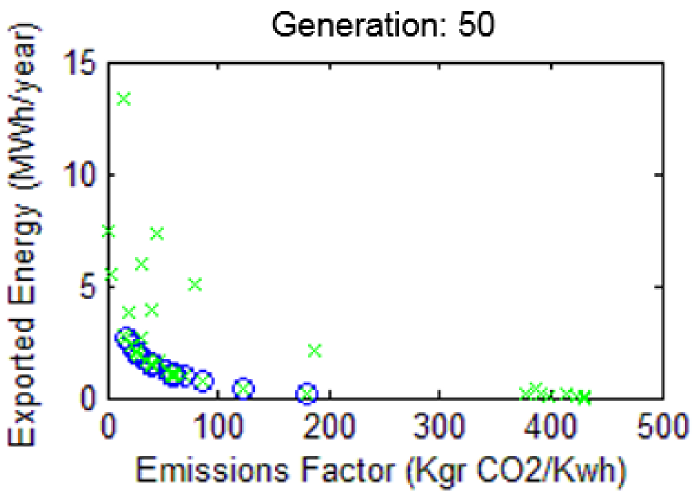

Figure 6-52 - Case Study 3, Orkney Exported Energy against Emissions Factor

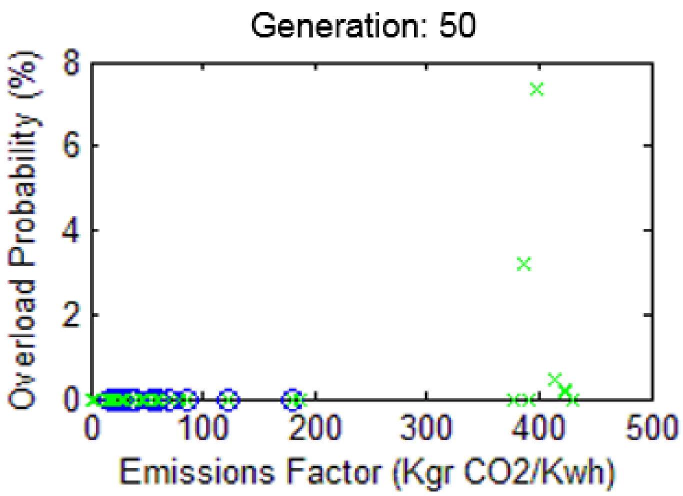

Figure 6-53 - Case Study 3, Orkney, Overload Probability against Emissions Factor

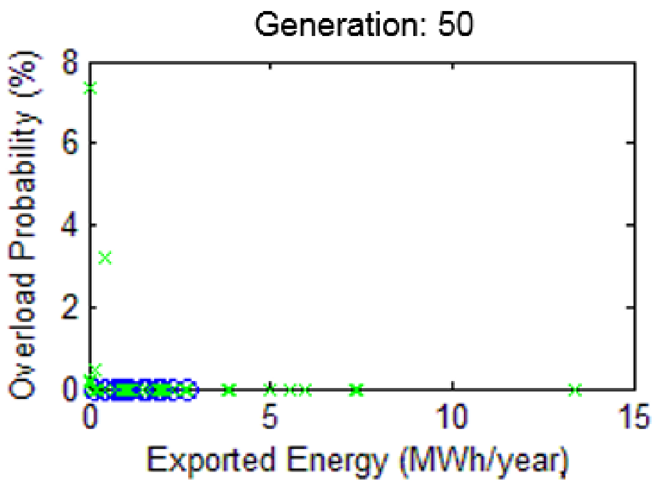

Figure 6-54 - Case Study 3, Orkney Overload Probability against Exported Energy

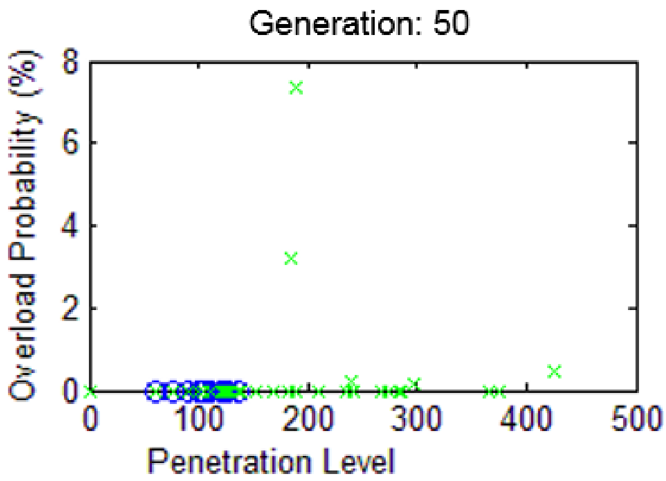

Figure 6-55 - Case Study 3, Orkney Overload Probability against Penetration Level

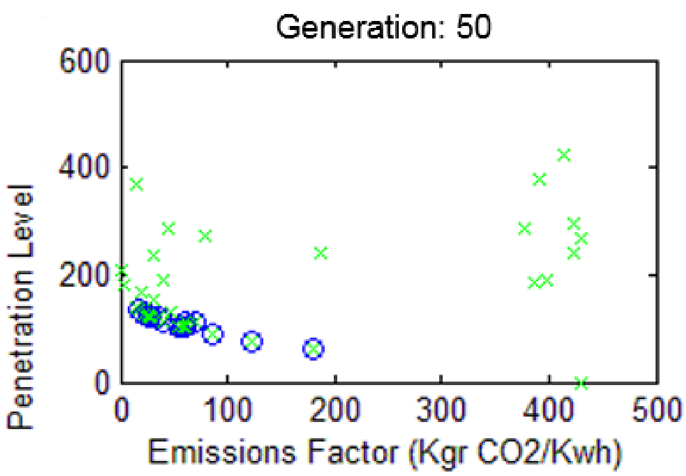

Figure 6-56 - Case Study 3, Orkney Penetration Level against Emissions Factor

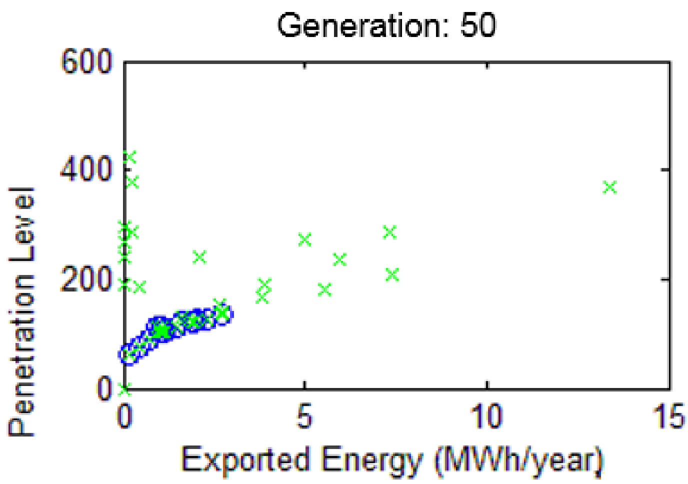

Figure 6-57 - Case Study 3, Orkney Penetration Level against Exported Energy

As another comparison between the results for Case Study 1 and Case Study 3, the numerical results for the equivalent A, B and C solutions in the Orkney network for Case Study 3 are presented in Table 6-8. The numerical results relating to the arrangement of ETS devices in the Orkney network are very different from those in

Table 6-3.

Table 6-8 - Case Study 3, Orkney numerical results

Solution	Node	ETS Type	Number of Devices
A	30	3	5
	38	3	14
	40	4	6
	41	2	1
	47	3	8
	49	3	5
	65	4	1
	67	2	29
B	7	1	7
	27	3	107
	30	3	5
	41	1	100
	42	4	47
	50	3	28
C	22	4	10
	30	3	5
	41	1	100
	43	1	17

	67	3	100

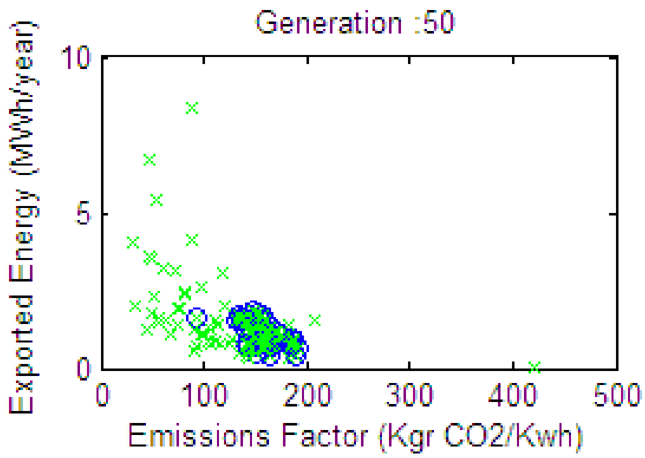

Figure 6-58 - Case Study 3, Shetland Exported Energy against Emissions Factor

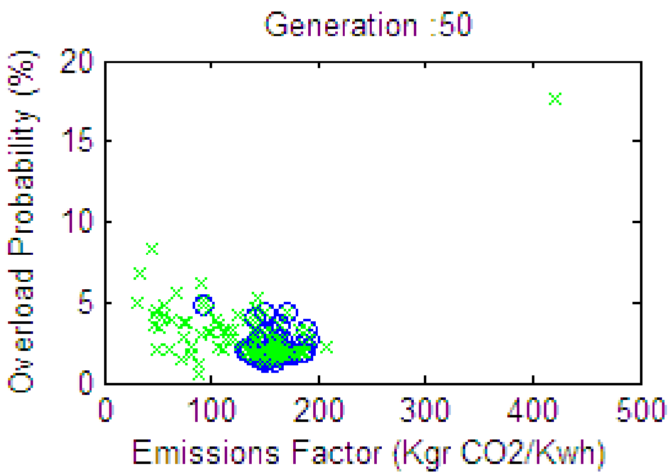

Figure 6-59 - Case Study 3, Shetland Overload Probability against Emissions Factor

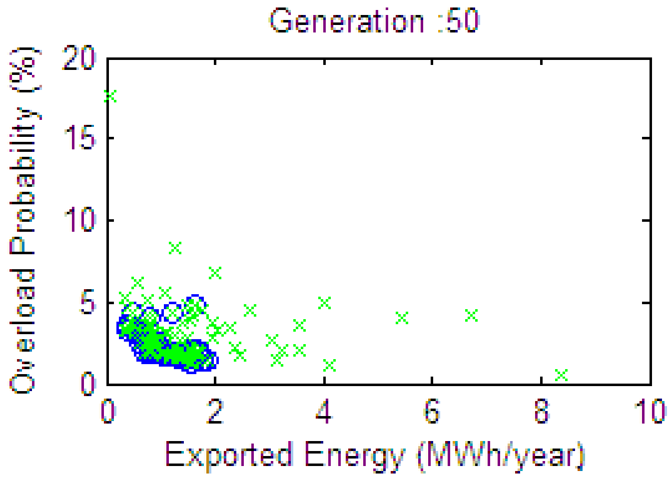

Figure 6-60 - Case Study 3, Shetland Overload Probability against Exported Energy

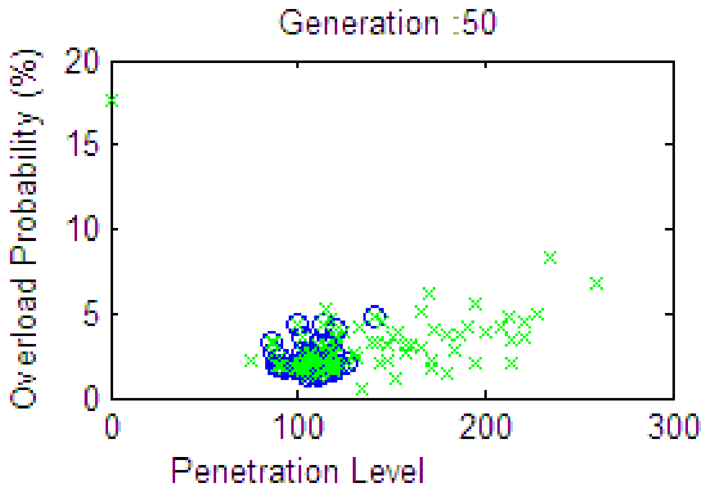

Figure 6-61 - Case Study 3, Shetland Overload Probability against Penetration Level

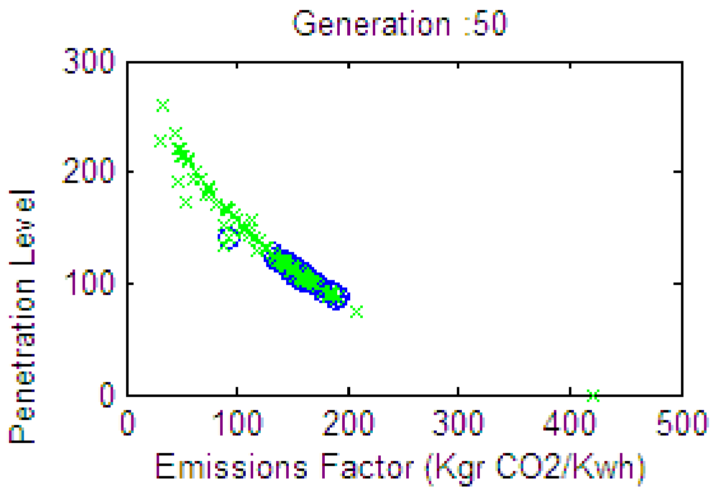

Figure 6-62 - Case Study 3, Shetland Penetration Level against Emissions Factor

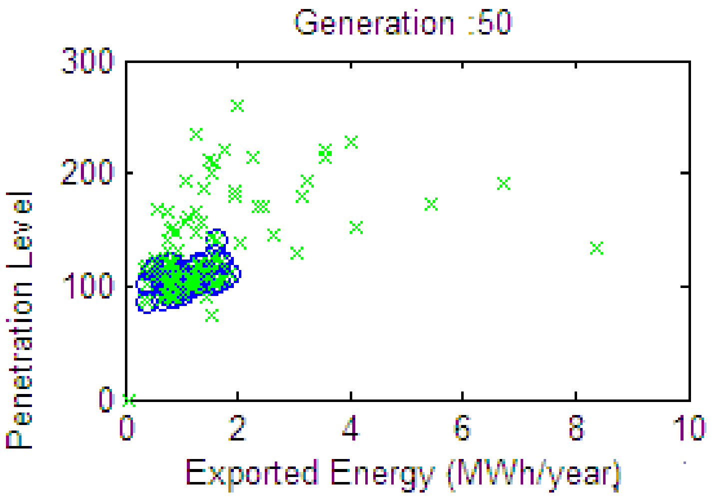

Figure 6-63 - Case Study 3, Shetland Penetration Level against Exported Energy

The numerical results for the equivalent A, B and C solutions for the Shetland network in Case Study 3 are presented in Table 6-9. These results are identical to those shown in Table 6-4, which confirms that the optimal results for Shetland do not change when the maximum number of ETS devices able to connect to a node is increased.

Table 6-9 - Case Study 3, Shetland numerical results

Solution	Node	ETS Type	Number of Devices
A	11	2	58
	11	4	3
	13	2	30
	13	3	45
	16	1	52
	22	2	49
	24	4	7
B	2	2	27
	6	1	7
	10	1	25
	11	2	58
	11	4	3
	13	3	45
	16	1	17
	22	1	7
	5	4	14
	6	1	5
C	6	3	16
	7	3	37

	11	2	15
	11	4	6
	13	2	58
	13	3	36
	16	1	52
	21	1	25

6.4.1 Summary of Case Study 3

In this case study the maximum limit on the number of ETS devices that can be installed was increased to double that in Case Study 1. The results generated showed that by changing this parameter, a visible effect was seen on the results for the Orkney network. In the Shetland network however, there was no change in the optimisation results. The Orkney network is much more flexible in terms of the importing and exporting of energy and accepting a greater penetration of ETS devices. The Shetland network is much more constrained in its operation. Being a completely islanded network means that demand and generation must be balanced within the group of islands as there is no wider grid support, therefore the fact that there is no change in the optimal solutions is expected. The next Case Study will illustrate the effect of increasing the wind generation available.

6.5 Case Study 4: Integrating ETS – increasing wind generation

This case study is applied to both the Orkney network and the Shetland network, with the same objectives for optimisation, but without an additional constraint, as in Case Study 1 to allow for direct comparison to be made between results. In this case study the generation available from wind has been increased, by 50%, in order to observe the effect on the optimisation results.

Figure 6-64 to Figure 6-69 show the new results generated for the Orkney network under the conditions with 50% more generation from wind. In comparing the Case Study 1 results to the results generated under these new conditions, the two sets of results look similar, however there are differences between them. The most notable similarity in this case is that, as in Case Study 3, the overload probability remains at 0%. Looking at the graph for exported energy against emissions factor, Figure 6-64, the results for exported energy range from 0.23 to 2.65 MWh/year, whereas the original results in Figure 6-6 range from 0.65 to 1.81MWh/year. The optimal solutions have changed in the new results to reflect the increase in generation from wind. These new results take account for when much more energy needs to be exported from the Orkney Isles in the situations where ETS devices are already charged and there is an abundance of generation from wind. The values for the emissions factor in Figure 6-64 range from 9.86 to 193.41 KgrCO_2/KWh with the values from the Case Study 1 results ranging from 35.63 to 97.32 KgrCO_2/KWh. The new results reflect that the emissions factor can be greatly reduced due to 50% increase in generation from wind. However, it is also possible for the situation to arise where there is no wind available to generate energy, and the Orkney network must be supplied by other generation resources. This accounts for the higher values seen in the new results. The graph for exported energy against emissions factor shows that the solutions with the maximum value for emissions factor also has the minimum value for exported energy. This illustrates that it is possible for the Orkney network to balance itself and not export energy, however it is possible that this will be met with use of resources that are higher in carbon emissions.

Looking at the graph showing penetration level against emissions factor, Figure 6-68, the results for penetration level vary from 55.74 to 145.92%. This in an increase in range from the original results in Figure 6-10 where the range for penetration level is 91.16 to 116.02%. This shows that the results have taken in to account a greater amount of generation from wind as more ETS devices can be optimally integrated into the network.

The graph for penetration level against emissions factor shows that the solution with the lowest penetration of ETS devices has the lowest exported energy, whereas the solution with the highest penetration level has the most exported energy.

The results for the Shetland network for this Case Study are shown in Figure 6-70 to Figure 6-75. The most obvious difference between the results in Case Study 1 and in the new results, is that the overload probability for the Shetland network has significantly increased in the new results. In the results in Case Study 1, the overload probability lies between 0 and 5%, whereas in the new results this is now between 10 and 20%. This illustrates how MODERNE is able to stay within additional constraints, as in Case Study 1 the limit for overload probability is set at 6%, and in this case study it is not limited. However this presents the opportunity for other methods of addressing overloads, such as dynamic line rating technology, if meeting the optimisation objectives is most important.

Looking at the graph for exported energy against emissions factor, Figure 6-70, the results generated are much more tightly packed than the original results for Shetland in Case Study 1. For exported energy the results range from 0.48 to 2.07MWh/year and for emissions factor the results range from 137.41 to 193.64 KgrCO_2/KWh. The results from Figure 6-12 have exported energy varying from 0.48 to 1.78 MWh/year, and ranging from 96.24 to 198.77 KgrCO_2/KWh for emissions factor. By increasing the wind generation on Shetland by 50%, the balancing of the network becomes more difficult, and therefore the operation of the network may become more restricted.

Looking at the graph of penetration level against emissions factor, Figure 6-74, penetration level varies from 96.27 to 132.77%. The results from Figure 6-16 show penetration level ranging from 88.42 to 148.82%. As with the graph of exported energy against emission factor, the increase in the generation available from wind has reduced the range of values for optimal solutions. As with the results in Case Study 1, the higher the penetration of ETS, the lower the emissions factor.

The graph that shows penetration level against exported energy, Figure 6-75, displays results that cluster around a penetration level of approximately 100% in order to minimise exported energy, which is similar to the results from Case Study 1 for Shetland. The difference between the results again comes from the reduced range in penetration level.

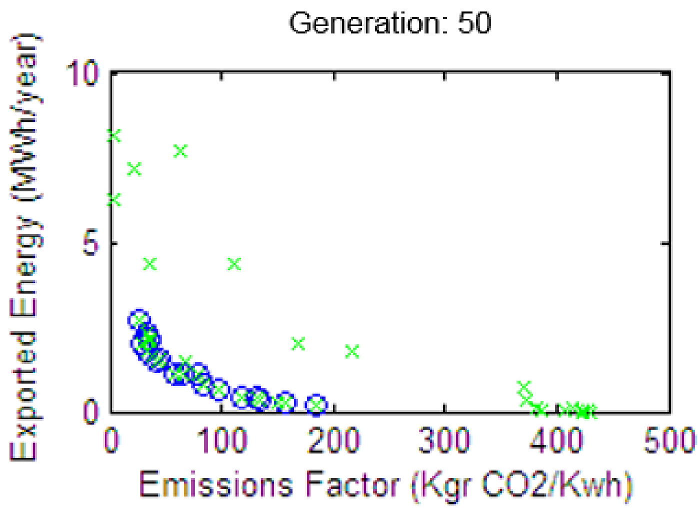

Figure 6-64 - Case Study 4, Orkney Exported Energy against Emissions Factor

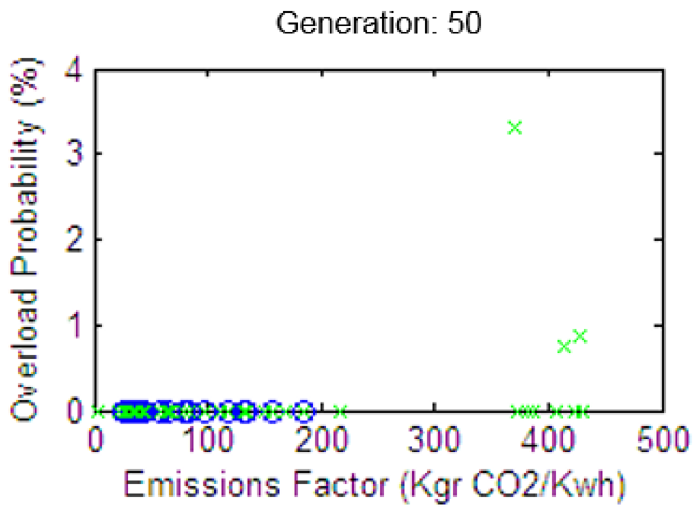

Figure 6-65 - Case Study 4, Orkney Overload Probability against Emissions Factor

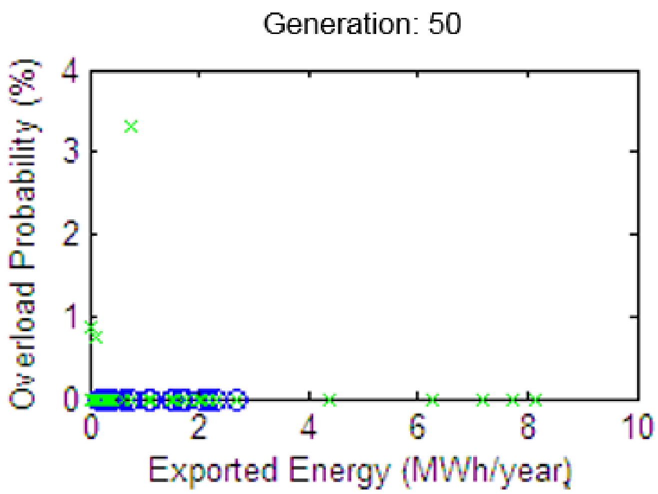

Figure 6-66 - Case Study 4, Orkney Overload Probability against Exported Energy

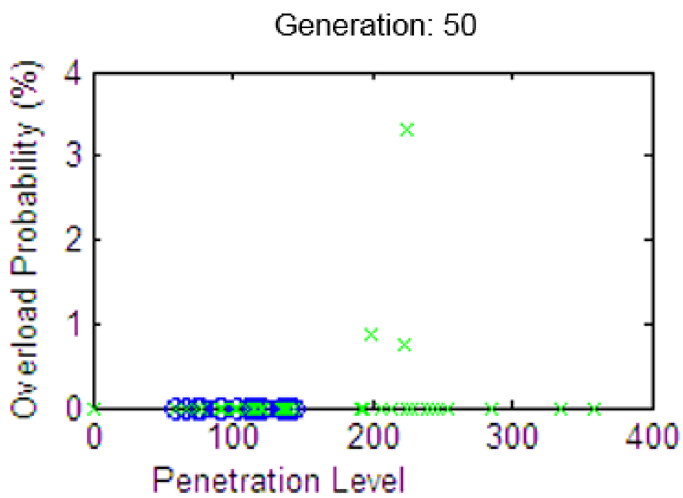

Figure 6-67 - Case Study 4, Orkney Overload Probability against Penetration Level

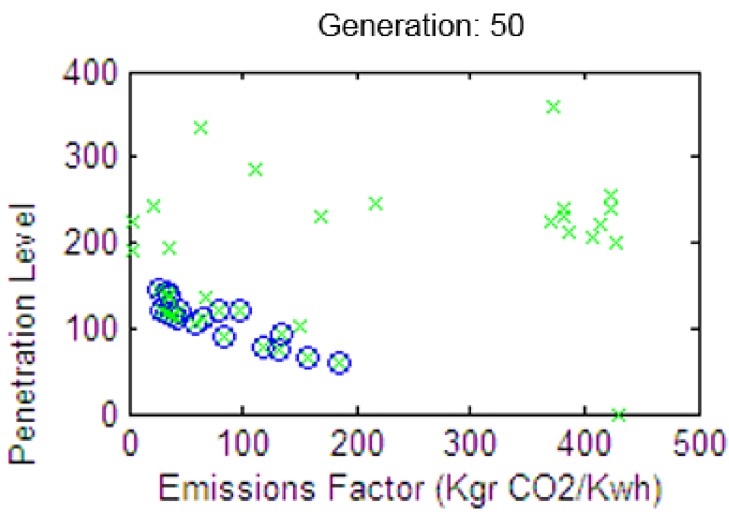

Figure 6-68 - Case Study 4, Orkney Penetration Level against Emissions Factor

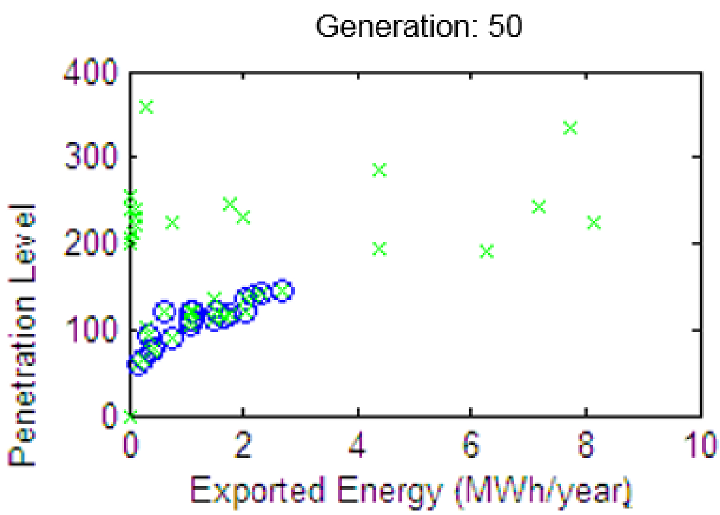

Figure 6-69 - Case Study 4, Orkney Penetration Level against Exported Energy

Another comparison that can be made between the results in this case study, and with the results in Case Study 1, is to show the change in network arrangement brought about by allowing an increase in generation from wind. The equivalent A, B and C Solutions for Case Study 4 are presented in Table 6-10. These results, when compared with

Table 6-3, show a very different network arrangement for ETS device installation.

Table 6-10 - Case Study 4 Orkney numerical results

Solution	Node	ETS Type	Number of Devices
A	16	4	8
	28	1	1
	32	1	3
	33	1	32
	34	1	2
	38	3	14
	43	2	17
	45	4	6
	48	2	3
	66	3	7
B	7	1	11
	38	3	14
	49	2	20
	56	1	3
	67	4	35
C	6	1	8
	41	1	47
	43	1	4
	44	4	8
	54	3	39
	57	2	2

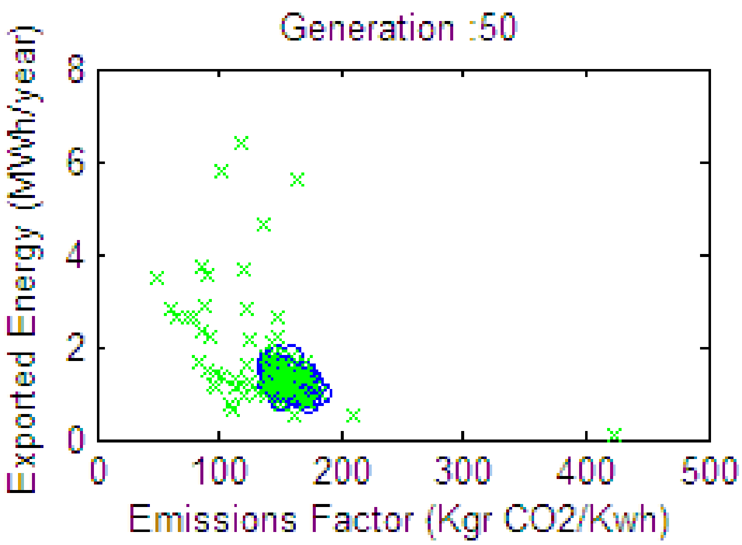

Figure 6-70 - Case Study 4, Shetland Exported Energy against Emissions Factor

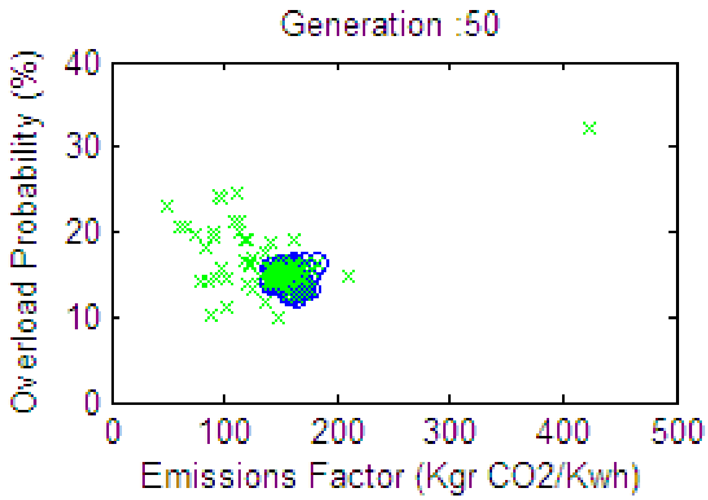

Figure 6-71 - Case Study 4, Shetland Overload Probability against Emissions Factor

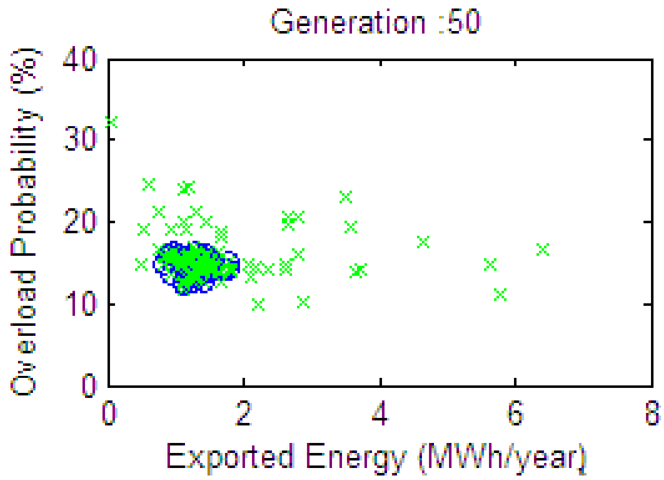

Figure 6-72 - Case Study 4, Shetland Overload Probability against Exported Energy

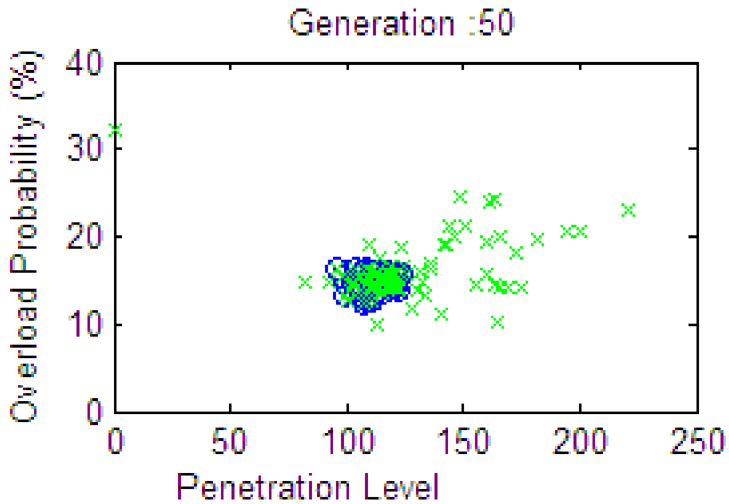

Figure 6-73 - Case Study 4, Shetland Overload Probability against Penetration Level

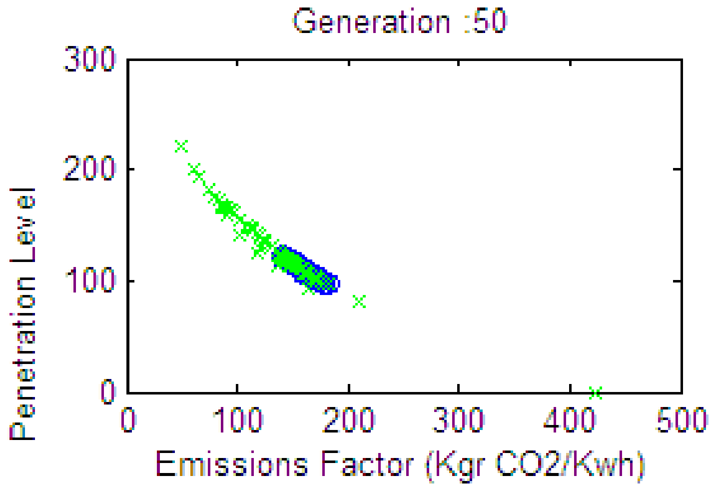

Figure 6-74 - Case Study 4, Shetland Penetration Level against Emissions Factor

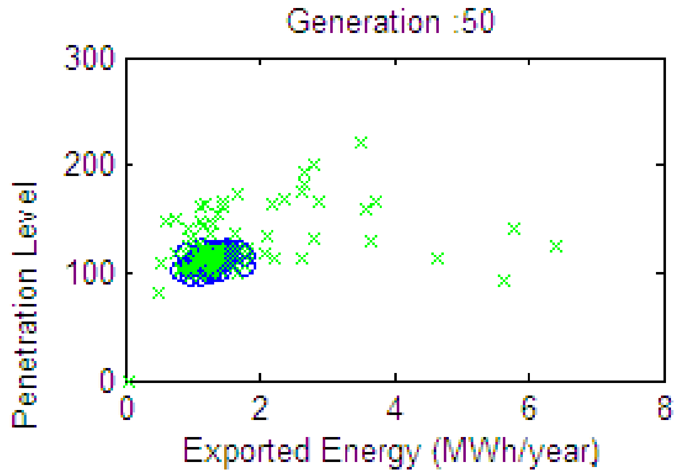

Figure 6-75 - Case Study 4, Shetland Penetration Level against Exported Energy

The equivalent numerical results for the Shetland network are presented in Table 6-11. When compared with

Table 6-3, a change in network arrangement is observed. This illustrates that different optimal results are required to facilitate an increase in generation from wind; and there is an increase in the number of locations for each solution in order to optimise for the increase in wind.

Table 6-11 - Case Study 4, Shetland numerical results

Solution	Node	ETS Type	Number of Devices
A	2	1	4
	2	2	49
	2	3	11
	2	4	17

Solution	Node	ETS Type	Number of Devices
	4	3	1
	5	4	40
	7	4	50
	11	4	16
	12	1	16
	13	1	1
	13	2	41
	13	4	39
	15	1	53
	16	2	28
	22	1	1
	24	3	3
	25	2	14
B	2	2	49
	2	4	34
	4	4	8
	11	4	49
	12	1	54
	13	1	1
	13	4	39
	26	3	14
	26	4	6
C	3	4	27
	6	1	31
	7	3	29
	11	4	59
	12	1	54
	12	3	1
	13	1	1
	13	4	33
	14	4	12
	16	2	57
	19	2	19
	21	2	30
	24	3	3
	26	3	27

6.5.1 Summary of Case Study 4

In this case study the generation available from wind is increased by 50% from that set in Case Study 1. The results generated showed that by changing this parameter, a visible effect was seen in the results for both of the networks. As with Case Study 3, the Orkney network is much more flexible in terms of the importing and exporting of energy and accepting a greater penetration of ETS devices. The Shetland network is much more constrained in its operation. Being a completely islanded network means that demand and generation must be balanced within the group of islands as there is no wider grid support, therefore the fact that the optimal solutions have a reduced range in values, such as for exported energy and emissions factor, is expected.

6.6 Hot Water Tank Power Consumption

To illustrate the capability of the hot water tank model to alter its power consumption depending on the generation available from wind, four sets of 24 hours were chosen at random and their associated wind generation was used to produce Figure 6-76 to Figure 6-79. These graphs display the power consumption of the hot water tank for each, that is now dependent on the generation available from wind, and the wind generation is also displayed graphically. The wind generation profile is applied to the hot water tank model in order to produce these results.

In the graph for Day 1, Figure 6-76, at 11:00 a significant drop in power consumption can be seen. This occurs due to the lack of wind availability at 11:00. Power consumption remains at a low level between 01:00 and 06:00, and then a large increase occurs between 07:00 and 08:00. The initial power draw occurs in line with the low wind availability early in the morning, but the large spike in power consumption occurs in line with hot water draw in the morning. As power consumption is also dependent on the water draw profile, the tank will consume power, if it is required, in order to maintain end user comfort, as mentioned in Section 4.3. Power consumption then decreases until 18:00. Wind generation then increases, and power consumption increases as well. The increase is not as large as that seen earlier in the day, however this will be due to the tank requiring much less power in order to maintain the availability of hot water for the end user.

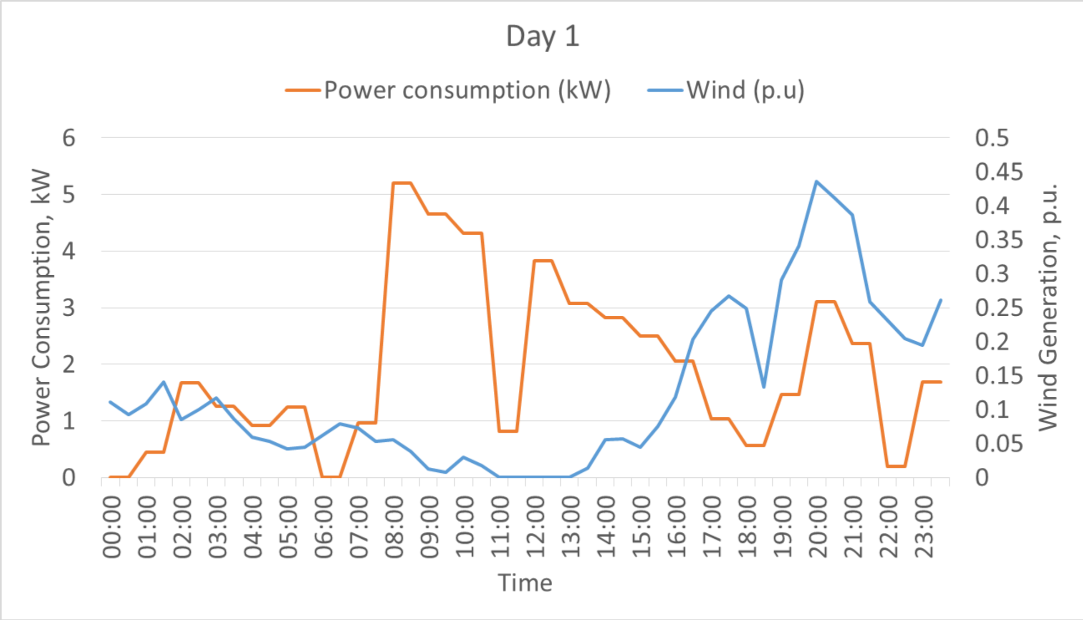

Figure 6-76 - Day 1 Wind Generation and Power Consumption

In the graph for Day 2, Figure 6-77, between 08:00 and 13:00 the tank consumes more power. Looking at the wind generation, between these times there is greater wind availability to allow for this increase in power consumption. The power consumption decreases as the tank reaches its capacity for storage. However, there is a short period of increased power consumption between 19:00 and 21:00 as, due to evening water draw, the tank is able to draw more power as there is available capacity.

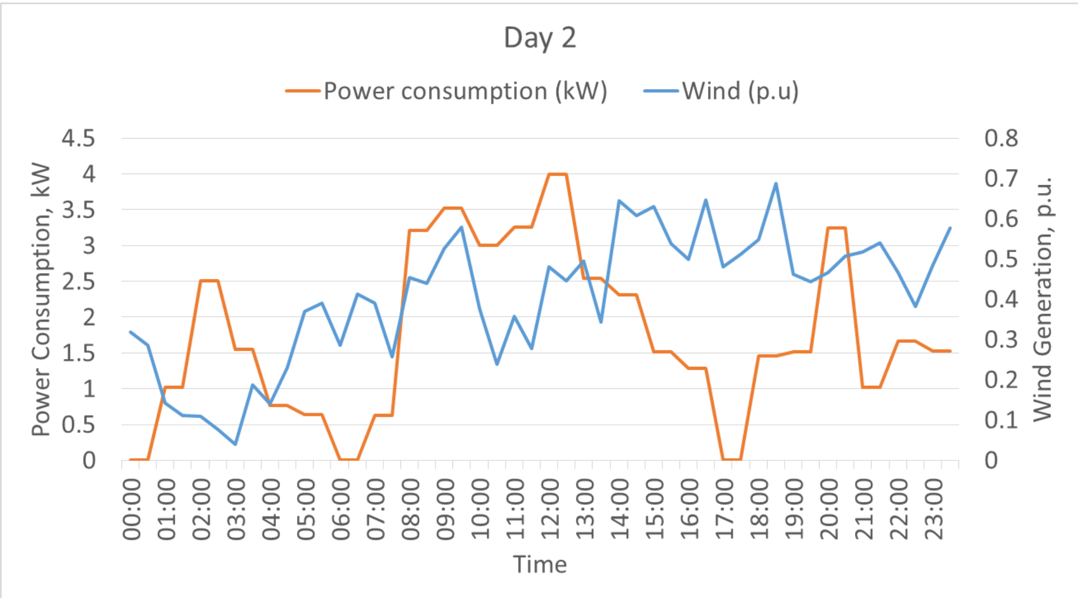

Figure 6-77 - Day 2 Wind Generation and Power Consumption

The wind generation in Day 3, Figure 6-78, is never at a zero value. As a result the graph for Day 3 in Figure 7 does not experience vast increases or decreases in power consumption, apart from the initial consumption at 01:00 to ensure there is hot water available for the morning demand. At the points where consumption does go to zero, in this case it is due to the tank being full, with all internal water at a suitable temperature. When this occurs, power is no longer required.

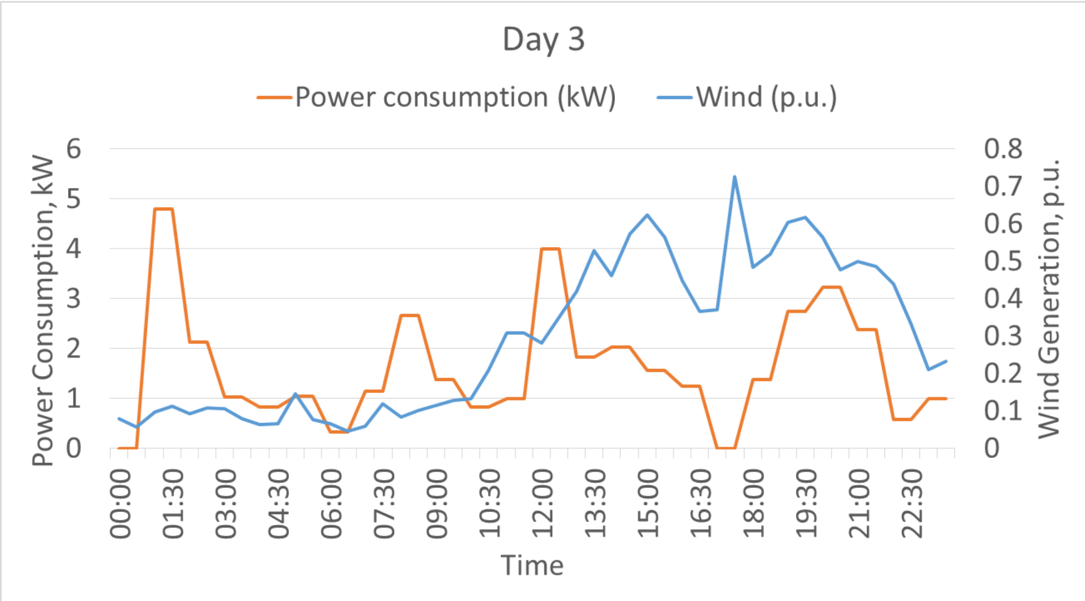

Figure 6-78 - Day 3 Wind Generation and Power Consumption

It can be seen that for Day 4, Figure 6-79, there is no wind availability for the first five hours of the day. In this case the hot water tank requires power even though it cannot receive power from wind generation. The power consumption is also dependent on water draw which ensure the end user's requirements are a priority. The tank must receive power in order to reach an acceptable internal temperature in time for the user requiring water in the morning. For the remainder of Day 4, the power consumption for the hot water tank follows the trend in wind availability.

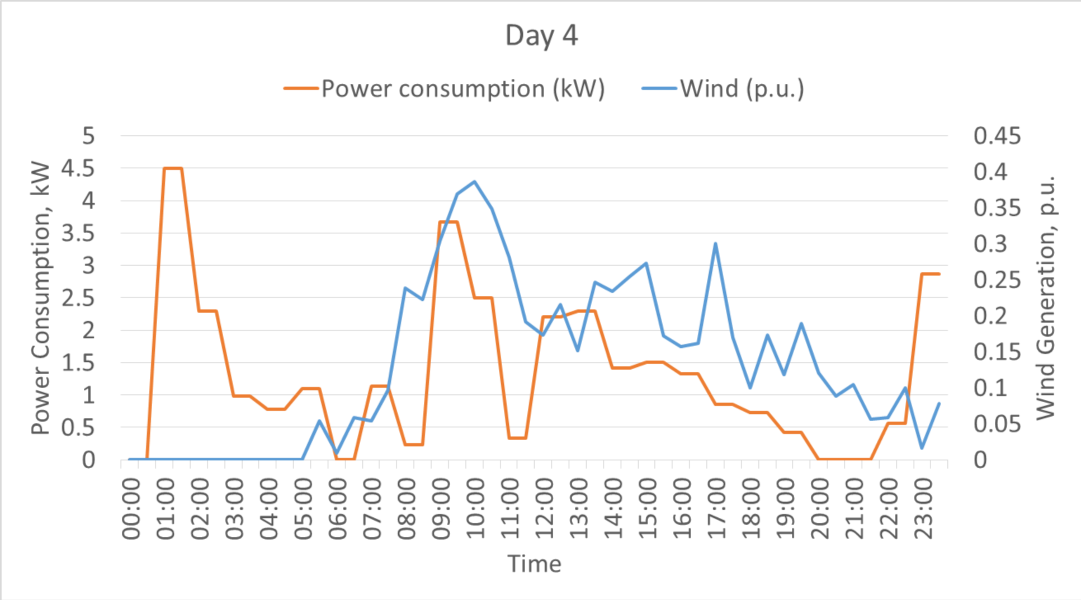

Figure 6-79 - Day 4 Wind Generation and Power Consumption

6.7 Summary

This chapter has outlined the case studies that were set up for the network planning framework to analyse and has presented the results produced. For each case study both the Orkney and Shetland distribution networks were analysed to show the comparison between two different networks. The most significant difference between the two networks is due to Orkney being an interconnected distribution network, and Shetland being islanded.

The results displayed for both the distribution networks in each case study have shown that the Pareto Fronts produced are different for different networks. Not only that, the importance of analysing the Pareto Front has been discussed for each case as whichever solution is chosen by the user for implementation will lead to a compromise between solutions. From looking at the results in Table 6-2 and Table 6-5 it is evident that choosing solutions that are not at the extreme edges of the Pareto Front results in a smaller compromise between solutions because, choosing a solution that is at an extreme edge can, in a most circumstances, hold the optimal minimum value for one objective whilst holding the maximum value for another.

Case Studies 3 and 4 illustrate the ability of the framework to adapt to varying conditions. In these two case studies the surrounding parameters have been changed, which are increasing the maximum number of ETS devices that can be installed at each node and increasing generation from wind by 50%, rather than the optimisation problem and objectives that the MODERNE framework has been applied to. In Case Study 3 the maximum limit of ETS devices for installation was increased while keeping the same optimisation problem as in Case Study 1, which produced a visible change in results for the Orkney network, but no change in the results for Shetland. The Shetland Isles are isolated from the mainland UK network and therefore operation is much more limited, and the lack of change in results is expected. In Case Study 4 the generation available from wind was increased whilst keeping the optimisation problem the same as in Case Study 1. In this case study a visible change, specifically the reduced range of solutions found for the emissions factor, exported energy and penetration level, was seen in the results for both networks, which illustrates the adaptability and suitability of the framework.

Analysis of the hot water tank model charging characteristics has also been shown. Four days of the year were chosen at random to illustrate how the charging of the device can be altered depending on the wind resources available. In each case the profiles are different, which illustrates the variable nature of wind generation. However, the hot water tank operates within its limits and the results illustrate that wind dependent charging is possible and that optimised energy system operation can be achieved with response ETS.

The next chapter will discuss the outcomes of the research project as a whole with reference to the initial aims and title that were proposed, as well as discussion opportunities of future development for the network planning framework.

6.8 References for Chapter 6

[1] D. MacLeman, "The Orkney Smart Grid," *SSEPD, SSE Power Distribution,* 2009.

[2] Ofgem, "Shetland Northern Isles New Energy Solution Project Consulation," *Office of Gas and Electtricity Markets https://www.ofgem.gov.uk/ofgem-publications/43538/shepdninesconsultation.pdf,* 2011.

Chapter 7 - Conclusion

This chapter outlines the conclusions and outcomes that can be made from this research, as well as highlight specific conclusions from the case studies and contributions to knowledge. The objectives for this research are:

- Investigation of energy storage techniques and their ability to aid distribution networks;
- Investigation of multi-objective optimisation techniques;
- Further development of an electric hot water storage tank which includes wind dependent power consumption;
- Modification and further development of a multi-objective optimisation network planning framework;
- Generation of results that illustrate the functionality of the framework.

These objectives are met through the literature review presented in Chapter 2 and Chapter 3. In Chapter 4 a model of a domestic, electric hot water tank is presented and further developed in order to incorporate it into the multi-objective optimisation framework and so that the power consumption for the model was depending on the available generation from wind. Chapter 5 introduces the MODERNE framework, which is then applied to the Orkney and Shetland networks with various optimisation problems in Chapter 6.

7.1 Conclusions from Case Studies

The main conclusions that can be drawn from looking at the results of all the case studies are:

- Different networks generate different results and trends;
- The Shetland network still has overloads in its optimal solutions;
- The Orkney network does not fully achieve independence from the mainland;
- The Orkney network can support an increase in the maximum allowance of ETS devices;
- Introducing more wind generation in Shetland increases overload probability and network imbalance, despite storage technologies;

The change in parameters for the multi-objective optimisation problem leads to different network arrangement solutions. These are general conclusions that can be drawn. However, it is also useful to look at each case study, and draw conclusions from the scenarios. In Case Study 1, the MODERNE framework is applied to an optimisation problem requiring the minimisation of emissions factor, minimisation of exported energy and minimisation of ETS penetration level, while adhering to the additional constraint limiting overload probability to 6%. The main observations from this case study are that the Shetland network experiences overloading in the optimal solutions found, whereas the Orkney network has optimal solutions without overloading. For both networks, as the penetration level of ETS devices increases, the emissions factor decreases and the exported energy increases. The results for penetration level against overload probability for the Shetland network illustrate that the optimal penetration level ranges between 90-110%, with the lowest overload probability at approximately 1% for a penetration level of 105%. These results show that the MODERNE framework is able to find optimal solutions whilst ensuring the overload probability constraint is met.

The results that illustrate the trade-off between solutions demonstrate the compromises that the system planner has to make. For both networks, should the minimisation of the ETS penetration level be the binding objective for the planner, then the emissions factor suffers; the corresponding values for minimum ETS deployment are the maximum values for emissions factor with 97.32 $KgCO_2/kWh$ and 198.77 $KgCO_2/kWh$ for Orkney and Shetland respectively. Government and utilities could look for ways to incentivise ETS in order to aid the integration of lower carbon technologies, and thus reducing the carbon intensity of electricity supplied.

In Case Study 2, the framework is applied to a problem with four objectives for optimisation. This optimisation problem requires the minimisation of exported energy, minimisation of grid dependency, minimisation of emissions factor and maximisation of CO_2 reduction. The main observations from this optimisation problem are that firstly, the Orkney network is not able to be fully independent of the grid, whereas the Shetland network manages to balance itself very well. In the Orkney network as exported energy decreases the emissions factor increases, whereas in the Shetland network the emissions factor decreases as the system becomes more balanced. A similar trend can be seen for the reduction of CO_2. As grid dependency is reduced for Orkney, the reduction in CO_2 increases, whereas the opposite effect is seen in Shetland as the system becomes more balanced.

Looking to the results that reflect the compromise between solutions, it becomes clear that the same optimisation problem, when applied to two different networks, does not return the same relationships between objectives. For example, in the results for Case Study 2, the Orkney network has a minimum value of exported energy at 0.56 MWh/year which corresponds to the maximum value for emissions factor which is 110.04 $kgCO_2/kWh$. However, for the Shetland network the results that minimises exported energy (0.53 MWh/year) corresponds to the minimum emissions factor (162.21 $kgCO_2/kWh$). It should be noted that this emissions factor, even as the minimum value for Shetland, is still greater than the maximum for Orkney. This is due to the fact that Orkney is interconnected and therefore is able to import energy from the mainland that is low carbon. This highlights the requirement for effective planning for the integration of low carbon technologies, and the fact that each network analysed will have different characteristics. The planner responsible for the choice of solution to implement will have to determine the priority of objectives.

The results from Case Studies 3 and 4 are able to provide an insight into how changing outside parameters for the framework affects the optimisation process. For example, in Case Study 3 the optimisation problem that MODERNE is applied to is the same as that in Case Study 1 without the additional constraint which limits the overload probability. The change in outside parameter is related to increasing the maximum number of ETS devices for deployment by 100%, from 100 per node to 200. In Case Study 4 the power available from wind generation is increased by 50%. There is no change in overload probability for Orkney in Case Studies 3 and 4; this is due to the interconnection to the mainland. For the Shetland network, in Case Study 3 the overload probability remains as it was in Case Study 1, which was limited to 6%. In Case Study 4, with the 50% increase in generation from wind, the overload probability now lies between 10 and 20%. This shows that without the additional constraint, the optimal solutions disregard overload probability and optimise ETS installations to cope with the increase in generation from wind.

In Case Study 3 a visible change can be seen in the results generated for the Orkney network. As Orkney is interconnected to the mainland it is much more flexible in its ability to import and export energy, and more flexible in its ability to support greater penetrations of ETS devices. The Shetland network has less capacity available to support increased ETS deployment due the requirement to balance the network, and so the results do not change in Case Study 3. Notable differences between the results in Case Study 1 and Case Study 3 are, for Orkney:

- Maximum export energy has increased to 2.7 MWh/year from 1.81 MWh/year.
- Exported energy can be reduced to zero with the increase in ETS devices.
- The results for both emissions factor and penetration level cover a larger range in Case Study 3; from 35.63-97.32 $KgCO_2$/kWh to 7.89-181 $KgCO_2$/kWh for emission factor and from 91.16-116.02% to 55.14-169.23% for penetration level..

These results in particular highlight that Orkney can reduce its energy export to zero, and support the increased demand from ETS. Government and utilities could look to incentivising a roll out of ETS technologies in a move to make distribution networks more efficient and self-sufficient.

In Case Study 4, for the Orkney network the range in values for emissions factor is from 9.86-193.41 $KgCO_2$/kWh, which is an increase on the range in Case Study 1. The values for penetration level range from 55.74-145.92% in the Case Study 4 results. For the Shetland network, the most obvious change is that overload probability now lies between 10 and 20% as the additional constraint that limits overload probability to 6% has not been applied. This illustrates the ability for MODERNE to stay within constraints during the optimisation process. The other main differences between results for Shetland in Case Study 4 are:

- Maximum exported energy has increased to 2.07 MWh/year from 1.78 MWh/year. As Shetland cannot export due to being an isolated network, this shows the change in imbalance. This shows that it is more difficult to balance the network with a 50% increase in generation from wind.
- The range of values for emissions factor has reduced from that in Case Study 1. In Case Study 4 the emissions factor ranges from 137.41 $KgCO_2$/kWh to 193.64 $KgCO_2$/kWh, and in Case Study 1, 96.24 $KgCO_2$/kWh to 198.77 $KgCO_2$/kWh. This shows that by allowing a 50% increase in generation from wind, and with the optimal integration of ETS devices, the CO_2 emissions in the network can be reduced, which will aid in meeting government targets.
- The range of values for penetration level has also reduced with the increase in generation from wind. The Case study 4 results are 96.27-132.77% and those for Case Study 1 are 88.42-148.82%. With the increase in generation from wind, there is a

more defined window for ETS device penetration level. As the Shetland network is responsible for its system balancing, having as defined a requirement for ETS installation as possible is essential as it ensures the network will be able to operate with both the increase in generation and in demand. Should having the minimum possible penetration level be the binding decision for implementing a solution, then this shows that an increase in the minimum value from Case Study 1 is required in order to help cope with the now increased generation from wind. Should the maximum penetration level be the binding decision, this can be achieved more efficiently as the maximum required has decreased from the value in Case Study 1.

Case Studies 3 and 4 illustrate the adaptable nature of the MODERNE framework and its ability to handle different optimisation problems, additional constraints and further changes to the network data surrounding the optimisation process.

7.2 Contributions to Knowledge

The following contributions from this research and thesis are:

1. A literature review covering the different storage technologies and various optimisation techniques available has been conducted. The literature review also covers optimisation techniques in power systems, and the novelty in this work is identified: a multi-objective optimisation approach has not been used in conjunction with thermal storage devices in the field of power systems.
2. An ETS model has been developed in the power systems context. This model has been developed to interact with the MODERNE framework and have its characteristics utilised in the optimisation process to determine the optimal locations and numbers of ETS devices that should be installed.
3. A network planning optimisation framework has been modified and extended in order to optimise the number and location of ETS devices. The modular nature of SPEA2, and the MODERNE framework, allow for the adaptations and extensions to functionality to be made and it has been possible to integrate the optimisation of network arrangements with ETS as well as explore a number of different parameters in this planning problem.
4. A formulated multi-objective optimisation problem for the optimal integration of ETS into distribution networks has been developed. This sees both maximisation and

minimisation objectives applied to MODERNE, as well as objectives that show the consideration of operational, environmental and economic objectives.

5. From the case studies that the MODERNE framework is applied to it is evident that the framework is able to adapt to a number of different optimisation scenarios. The framework is able to optimise objectives for both minimisation and maximisation problems, it is able to conduct the optimisation process whilst keeping optimal solutions within additional constraints and shows that different optimal results can be generated when network parameters are changed. Another significant point from the results is that correlations between objectives in one network may not apply in another. For example, in Case Study 1, the results with the minimum value for exported energy corresponds to the maximum value for emissions factor for the Orkney network. For the Shetland network, the result that provides the minimum value for exported energy results in a mid-range value for emissions factor.
6. From the results generated in this research, it is clear that ETS is able to aid in the expansion of renewable generation in distribution networks, and depending on the solutions chosen ETS integration can also reduce emissions. This would aid the meeting of targets for both increasing renewable generation and decreasing CO_2 emissions, as well as reduce reliance on traditional fossil fuels. ETS devices can positively benefit distribution networks, can operate as a responsive demand that can help to compensate for the variable nature of renewable generation and can help to meet UK Government targets.

7.3 Further work

As stated already, this research has the main objective of illustrating that ETS devices are capable of assisting distribution networks in coping with the intermittency and variability in wind generation. Whilst this research has shown that ETS can assist the operation of the network, there are various avenues that have not been investigated; these include practical implementation, policy and pricing and efficiency of analysis.

From a practical implementation point of view, this research has not looked into the required communications and control technology for implementing such a scheme or the extent of installation that would be required. Research would need to be conducted to determine whether existing ETS devices could be retrofitted with communications and control equipment, or whether devices would need to be replaced with new generation technology. The level of communications and control required would also need to be defined.

In terms of policy and pricing, any possible policy that would need to be formed to back such a scheme, or possible changes in electricity pricing have also not been researched. Detailed research and analysis is also necessary to determine the intricacies of a payment structure to the end user, if their appliances are going to be used without their input. However, in the future, these issues could be analysed and applied to a scheme involving the aggregated effect of ETS for a greater understanding of the problems surrounding implementation and rollout.

There are also aspects of further development to the MODERNE framework that could be explored, in particular the efficiency of the analysis. One issue with the MODERNE framework is the computational time required in order to reach optimal solutions. This could be improved upon by exporting the MODERNE framework to another programming language such as Java for a much faster implementation. Currently, the MODERNE framework operates in Matlab, with the optimal power flow analysis exported to another application. By avoiding this arrangement it is anticipated that the computation time could be reduced.

In this research the operation of the MODERNE framework has been modified from its original format which optimised the size, type and location of DER, in order to optimise the number and location of ETS devices in a distribution network. In future the full integration and modularisation of MODERNE, as required for incorporating these two operations into the one framework and include other avenues of optimisation such as the charging of electric vehicles, would be necessary to realise the full potential of such a powerful and adaptable tool. Also, any future advancements in multi-objective optimisation techniques should be incorporated into MODERNE to ensure it remains as efficient and up to date as possible.

This research explores a small, but significant, range of optimisation issues. Future work could also include the application of MODERNE to more and more optimisation problems and determine the implication of ETS devices on a wider range of objectives. The framework is capable of having more objectives for optimisation programmed into it, and further analysis could determine, more extensively, the effect of ETS devices on operational, environmental and economic factors.

7.4 Final Summary

This thesis has presented a multi-objective optimisation based network planning framework that has been modified to optimise the inclusion of ETS devices into distribution networks. This thesis has also presented the model used to represent a hot water storage tank to realise the operation of such a device. Through the application of the case studies, the framework is shown to be a powerful tool for network planning and optimising the incorporation of ETS devices. The results for the case studies show that ETS can be successfully incorporated into distribution networks, and can assist in promoting greater connections of wind generation. The analysis of the hot water tank has also illustrated the capability for demand response.

Appendix A: Network Model Information

This appendix presents the network data for both the Orkney and the Shetland networks. These representations of the networks are used in conjuntion with the MODERNE framework to achieve the optimisation of ETS devices in network models.

Table A-1 to Table A-10 in the following sections present the data used to represent the distribution networks used with the multi-objective optimisation framework. The networks are represented by various assets and parameters. The assets and parameters are summarised as follows:

- Buses
  - Number: each bus is identified by a unique number.
  - Name: each bus may also be assigned a name.
  - X and Y Coordinates: some power systems software require co-ordinates for mapping networks, and associating objects with each other. These are not required in this analysis.
  - Base Voltage: the base voltage for the bus in kV.
  - Bus Type: this indicated the type of bus, PQ, PV or swing bus. These are denoted with 1, 2 and 3.
  - Status: whether the bus is in or out of service. This is represented by a 1 for in service, and 0 for out of service.
  - Target Voltage: target value for voltage at the bus, in per unit.
  - Minimum and Maximum Voltage: the maximum and minimum allowed voltages at the bus, in per unt.
  - Voltage Angle: target voltage angle for the bus. This is usually not required and can be set to 0. This is in degrees.
- Loads
  - Load Bus: identifies which bus the load is connected to.
  - Load ID: a number which identifies a load if there is more than one object connected at a bus.
  - Real Power: the real power output of the load in MW.
  - Reactive Power: the reactive power output of the load in MVAr.
- Generators
  - Bus Number: identifies which bus the generator is connected to.

    - Generator ID: identifies the generator if there is more than one object connected to a bus.
    - Real Power, Maximum Power and Minimum Real Power: the real power output of the generators, and maximum and minimum capabilities in MW.
    - Reactive Power, Maximum and Minimum Reactive Power: the reactive power output of the generators, and maximum and minimum capabilites in MVAr.
    - Generator MVA Base: the base used for the generator in MVA.
- Branches
    - From Bus, To Bus: identifies which buses are connected by the branch.
    - Branch ID: a number to identify individual branches if there is more than one at a bus.
    - Positive and Negative Sequence Resistance: resistance in the lines in per unit.
    - Positive and Negative Sequence Reactance: reactance in the lines in per unit.
    - Zero Sequence Resistance: resistance in the lines in per unit.
    - Zero Sequence Reactance: reactance in the lines in per unit.
    - Winter, Standard and Summer Rating: the thermal ratings of the line, which can be variable depending on season, in MVA.
    - Length: length of the lines in km.
    - Status: indicates if the line is in or out of service, 1 for in service and 0 for out of service.
- Transformers
    - From Bus, To Bus: identifies which buses are connected by the transformer.
    - Transformer ID: a number to identify individual transformera if there is more than one at a bus.
    - Positive and Negative Sequence Resistance: resistance of the transformer in per unit.
    - Positive and Negative Sequence Reactance: reactance of the transformer in per unit.
    - Zero Sequence Resistance: resistance of the transformer in per unit.
    - Zero Sequence Reactance: reactance of the transformer in per unit.
    - Winter, Standard and Summer Rating: the thermal ratings of the transformer in MVA.

- Status: indicates if the transformer is in or out of service, 1 for in service and 0 for out of service.
- Starting Tap Ratio: a starting point for the transformer tap, in per unit of nominal ratio.
- Minimum and Maximum Position: maximum and minimum tap positions in per unit.
- Tap Positions: the number of tap positions.
- Winding Connection: YY, YD, DY or DD.
- Phase Shift Angle: the transformer phase shift angle in degrees.

A.1 Orkney Network Model

A.1.1 Buses

Table A-1 - Bus Data for Orkney

Number	Name	X Co-ordinate	Y Co-ordinate	Base Voltage	Bus Type	Status	Target Voltage Magnitude	Minimum Voltage	Maximum Voltage	Voltage Angle
				kV			p.u.	p.u.	p.u.	
100	THSO3-	10	0	33	3	1	1	0.94	1.1	0
101	SCORRA3A	60	0	33	2	1	1	0.94	1.1	0
102	STROMN3A	10	40	33	1	1	1	0.94	1.1	0
103	STROMN1A	30	40	33	1	1	1	0.94	1.1	0
104	STROMN3B	30	40	33	1	1	1	0.94	1.1	0
105	STROMN1B	30	40	11	1	1	1	0.94	1.1	0
106	STROMN3C	40	40	33	1	1	1	0.94	1.1	0
107	BURGAR3A	50	40	33	1	1	1	0.94	1.1	0
108	BURGAR3B	60	40	33	2	1	1	0.94	1.1	0
109	BURGAR1A	80	40	11	1	1	1	0.94	1.1	0
110	ROUSAY3A	60	50	33	1	1	1	0.94	1.1	0
111	ROUSAY3B	70	50	33	1	1	1	0.94	1.1	0
112	ROUSAY1A	80	50	11	1	1	1	0.94	1.1	0
113	WESTRY3A	90	50	33	1	1	1	0.94	1.1	0
114	WESTRY1A	10	60	11	1	1	1	0.94	1.1	0
115	EDAY3A	20	60	33	1	1	1	0.94	1.1	0
116	EDAY1A	30	60	11	1	1	1	0.94	1.1	0
117	SANDAY3A	30	70	33	1	1	1	0.94	1.1	0
118	SANDAY1A	40	70	11	1	1	1	0.94	1.1	0
119	STRONS3A	10	70	33	1	1	1	0.94	1.1	0
120	STRONS1A	20	70	11	1	1	1	0.94	1.1	0
121	SHAPIN3A	60	60	33	1	1	1	0.94	1.1	0
122	SHAPIN1A	70	60	11	1	1	1	0.94	1.1	0
123	KIRKWA3A	50	30	33	1	1	1	0.94	1.1	0
124	KIRKWA1A	60	30	11	1	1	1	0.94	1.1	0
125	KIRKWA1B	80	30	11	1	1	1	0.94	1.1	0
126	STMARY3A	20	30	33	1	1	1	0.94	1.1	0
127	STMARY1A	30	30	11	1	1	1	0.94	1.1	0
128	NTHHOY3A	10	10	33	1	1	1	0.94	1.1	0
129	NTHHOY3B	20	10	33	1	1	1	0.94	1.1	0
130	NTHHOY1A	30	10	11	1	1	1	0.94	1.1	0
131	LYNESS3A	40	10	33	1	1	1	0.94	1.1	0
132	LYNESS3B	50	10	33	1	1	1	0.94	1.1	0
133	LYNESS1A	60	10	11	1	1	1	0.94	1.1	0
134	FLOTTA3A	70	10	33	1	1	1	0.94	1.1	0
135	FLOTTA3B	80	10	33	1	1	1	0.94	1.1	0
136	FLOTTA1A	90	10	11	1	1	1	0.94	1.1	0
137	NORTHF1A	40	30	11	1	1	1	0.94	1.1	0
138	FLTOCC3B	20	20	33	1	1	1	0.94	1.1	0
139	SCORRA3B	40	0	33	1	1	1	0.94	1.1	0
140	EDAY3B	70	70	33	1	1	1	0.94	1.1	0
141	FLTOCC1C	30	20	11	1	1	1	0.94	1.1	0
142	KIRKWA1C	70	30	11	1	1	1	0.94	1.1	0
143	SANDAY3B	50	70	33	2	1	1	0.94	1.1	0
144	STRONS3B	70	70	33	2	1	1	0.94	1.1	0
145	KIRKWA3B	10	30	33	1	1	1	0.94	1.1	0
146	THORNF1B	40	50	11	1	1	1	0.94	1.1	0
147	THORNFG1	30	50	11	1	1	1	0.94	1.1	0
148	THORNFG2	50	50	11	1	1	1	0.94	1.1	0
149	THORNF1A	20	50	11	1	1	1	0.94	1.1	0
150	SIGURD1A	90	40	11	1	1	1	0.94	1.1	0
151	SIGURDG1	10	50	11	1	1	1	0.94	1.1	0
152	STRONS3C	80	60	33	1	1	1	0.94	1.1	0
153	STRONS3D	90	60	33	1	1	1	0.94	1.1	0
154	SPURNE3-	60	70	33	1	1	1	0.94	1.1	0
155	SPURNE3A	80	70	33	2	1	1	0.94	1.1	0
156	METC1	20	40	11	1	1	1	0.94	1.1	0
157	FLOTTA1B	10	20	11	1	1	1	0.94	1.1	0
158	NWP3-	70	40	33	1	1	1	0.94	1.1	0
160	SCORRA3C	50	0	33	1	1	1	0.94	1.1	0
161	NEWBIG3A	40	60	33	1	1	1	0.94	1.1	0
162	NEWBIG1A	50	60	11	1	1	1	0.94	1.1	0
163	NEWBIG1B	50	60	11	1	1	1	0.94	1.1	0
164	NEWBIG1C	50	60	11	1	1	1	0.94	1.1	0
165	NEWBIG1D	50	60	11	1	1	1	0.94	1.1	0
170	STHHOY3A	20	0	33	1	1	1	0.94	1.1	0
171	STHHOY3B	30	0	33	1	1	1	0.94	1.1	0

A.1.2 Loads

Table A-2 - Load Data for Orkney

Load Bus Number	Load ID	Real Power	Reactive Power
		MW	MVAr
103	1	1.9625	0.39
109	1	1.9625	0.39
112	1	0.24525	0.0485
114	1	0.24525	0.0485
116	1	0.24525	0.0485
118	1	0.24525	0.0485
120	1	0.24525	0.0485
122	1	0.24525	0.00485
130	1	0.024525	0.00485
133	1	0.24525	0.00485
136	1	1.9625	0.39
142	1	5.885	1.165

A.1.3 Generators

Table A-3 - Generator Data for Orkney

Bus Number	Generator ID	Real Power	Maximum Real Power	Minimum Real Power	Reactive Power	Maximum Reactive Power	Minimum Reactive Power	Generator MVA Base
		MW	MW	MW	MVAr	MVAr	MVAr	MVA
100	1	30	150	-150	30	150	-150	100
108	1	0	0	0	0	0	-8	100
101	1	0	0	0	0	0	-2	100
143	1	0	0	0	-0.4	0	-0.5	100
144	1	0	0	0	-1.6	0	-1.7	100
155	1	0	0	0	0	0	-3	100

A.1.5 Branches

Table A-4 - Branch Data for Orkney

From Bus	To Bus	Branch ID	Positive and Negative Sequence Resistance	Positive and Negative Sequence Reactance	Zero Sequence Resistance	Zero Sequence Reactance	Winter Rating	Standard Rating	Summer Rating	Length	Status
			p.u.	p.u.	p.u.	p.u.	MVA	MVA	MVA	km	
101	123	1	0.343800	0.457100	0.000001	0.000001	16.9	15.7	13.5	15.3000	1
101	128	1	0.141800	0.123200	0.000001	0.000001	14.0	14.0	14.0	6.4000	1
101	145	1	0.343200	0.479200	0.000001	0.000001	17.4	16.1	13.9	14.0000	1
101	102	1	0.223742	0.297806	0.000001	0.000001	17.1	16.3	13.7	9.1100	1
103	105	1	0.000010	0.000010	0.000001	0.000001	50.0	50.0	50.0	1.0000	1
102	104	1	0.000010	0.000010	0.000001	0.000001	30.0	30.0	30.0	0.0000	1
104	106	1	0.272616	0.362859	0.000001	0.000001	17.1	16.3	13.7	14.0000	1
106	107	1	0.300860	0.400453	0.000001	0.000001	17.1	16.3	13.7	12.2500	1
106	123	1	0.216200	0.287300	0.000001	0.000001	16.9	15.7	13.5	10.0000	1
107	108	1	0.142939	0.190256	0.000001	0.000001	17.1	16.3	13.7	5.8200	1
107	110	1	0.277200	0.318500	0.000001	0.000001	12.0	12.0	12.0	10.9000	1
110	111	1	0.000010	0.000010	0.000001	0.000001	50.0	50.0	50.0	1.0000	1
110	113	1	0.374000	0.251200	0.000001	0.000001	12.0	12.0	12.0	13.3000	1
113	115	1	0.318000	0.208400	0.000001	0.000001	12.0	12.0	12.0	11.2000	1
115	161	1	0.105600	0.035000	0.000001	0.000001	14.3	14.3	14.3	2.8000	1
117	143	1	0.000010	0.001000	0.000001	0.000001	50.0	50.0	50.0	1.0000	1
117	154	1	0.019600	0.026200	0.000001	0.000001	17.4	16.1	13.9	0.8000	1
117	119	1	0.200100	0.167800	0.000001	0.000001	16.0	16.0	13.9	9.8000	1
119	144	1	0.000001	0.001000	0.000001	0.000001	50.0	50.0	50.0	1.0000	1
121	123	1	0.197600	0.183600	0.000001	0.000001	12.0	12.0	12.0	8.1000	1
125	142	1	0.000010	0.001000	0.000001	0.000001	50.0	50.0	50.0	0.0000	1
127	137	1	1.408200	0.250200	0.000001	0.000001	3.9	3.5	3.5	3.0000	1
128	129	1	0.011106	0.014855	0.000001	0.000001	17.1	16.3	13.7	0.5000	1
128	131	1	0.242111	0.323828	0.000001	0.000001	17.1	16.3	13.7	9.8000	1
131	132	1	0.000010	0.000010	0.000001	0.000001	50.0	50.0	50.0	0.0000	1
131	134	1	0.140500	0.153600	0.000001	0.000001	14.0	14.0	14.0	6.0000	1
134	135	1	0.000982	0.001308	0.000001	0.000001	17.1	16.3	13.7	0.0400	1
134	138	1	0.011543	0.015364	0.000001	0.000001	17.1	16.3	13.7	0.4700	1
136	157	1	0.199650	0.105450	0.000001	0.000001	7.5	7.5	7.5	1.5000	1
124	142	1	0.000010	0.001000	0.000001	0.000001	50.0	50.0	50.0	0.0000	1
123	145	1	0.048000	0.018500	0.000001	0.000001	12.3	11.1	11.1	1.1000	1
126	145	1	0.108900	0.218200	0.000001	0.000001	24.1	22.3	19.3	6.6000	1
146	149	1	0.170000	0.043400	0.000001	0.000001	4.4	4.4	4.4	0.5000	1
109	149	1	0.170000	0.043400	0.000001	0.000001	4.4	4.4	4.4	0.5000	1
109	150	1	0.119000	0.029000	0.000001	0.000001	4.4	4.4	4.4	0.2000	1
119	152	1	0.167000	0.222300	0.000001	0.000001	17.4	16.1	13.9	6.8000	1
121	152	1	0.568300	0.411900	0.000001	0.000001	12.0	12.0	12.0	20.5000	1
153	152	1	0.001100	0.000900	0.000001	0.000001	22.7	20.6	20.6	0.1000	1
140	154	1	0.159600	0.101600	0.000001	0.000001	12.0	12.0	12.0	5.7000	1
154	155	1	0.005900	0.005600	0.000001	0.000001	27.4	24.9	24.9	0.5000	1
103	156	1	0.320800	0.169400	0.000001	0.000001	12.0	12.0	12.0	4.8000	1
108	158	1	0.003480	0.002370	0.000001	0.000001	26.9	26.9	26.9	0.3000	1
162	163	1	0.000001	0.000010	0.000001	0.000001	50.0	50.0	50.0	1.0000	1
162	164	1	0.000001	0.001000	0.000001	0.000001	50.0	50.0	50.0	1.0000	1
162	165	1	0.004000	0.001000	0.000001	0.000001	8.0	7.1	7.1	1.0000	1
100	170	1	0.381600	0.606800	0.000001	0.000001	23.4	23.4	23.4	44.0000	1
139	170	1	0.155700	0.379900	0.000001	0.000001	23.4	23.4	23.4	15.5000	1
100	171	1	0.351000	0.606800	0.000001	0.000001	30.0	30.0	30.0	44.0000	1
160	171	1	0.151900	0.379900	0.000001	0.000001	30.0	30.0	30.0	15.5000	1

A.1.6 Transformers

Table A-5 - Transformer Data for Orkney

From Bus	To Bus	Transformer ID	Positive and Negative Sequence Resistance	Positive and Negative Sequence Reactance	Zero Sequence Resistance	Zero Sequence Reactance	Winter Rating	Standard Rating	Summer Rating	Status	Starting Tap Ratio	Maximum Tap Position	Minimum Tap Position	Tap Positions	Winding Connection	Phase Shift Angle	Controlled Bus
			p.u.	p.u.	p.u.	p.u.	MVA	MVA	MVA		p.u.	p.u.	p.u.				
101	139	1	0.01	0.05	0	0.0425	20	20	20	1	1	1.0429	0.8141	17	YY	0	139
101	160	1	0.01	0.0413	0	0.035105	30	30	30	1	1	1.0429	0.8141	17	YY	0	160
103	102	1	0.0704	1	0	0.85	8	8	8	1	1	1.0429	0.8141	17	YY	0	102
105	104	1	0.0704	1	0	0.85	8	8	8	1	1	1.0429	0.8141	17	YY	0	104
109	108	1	0.0704	1	0	0.85	8	8	8	1	1	1.0429	0.8141	17	YY	0	108
111	112	1	0.7722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	112
113	114	1	0.7722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	114
115	116	1	0.7722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	116
117	118	1	0.7722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	118
120	119	1	0.7722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	119
121	122	1	0.7722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	122
123	124	1	0.0365	1	0	0.85	24	24	24	1	1	1.09	0.86	17	YY	0	124
123	125	1	0.0365	1	0	0.85	24	24	24	1	1	1.09	0.86	17	YY	0	125
126	127	1	0.2247	1.75	0	1.4875	4	4	4	1	1	1.0429	0.8141	17	YY	0	127
129	130	1	7.8939	60	0	51	0.1	0.1	0.1	1	1	1.05	0.75	17	YY	0	130
132	133	1	0.07722	6	0	5.1	1	1	1	1	1	1.0429	0.8141	17	YY	0	133
135	136	1	0.0704	1	0	0.85	8	8	8	1	1	1.0429	0.8141	17	YY	0	136
138	141	1	0.0668	1	0	0.85	12.5	12.5	12.5	1	1	1.125	0.0875	17	YY	0	141
147	149	1	0.3609	2.8	0	2.38	2.5	2.5	2.5	1	1	1.0429	0.8141	17	YY	0	149
148	146	1	0.3609	2.8	0	2.38	2.5	2.5	2.5	1	1	1.0429	0.8141	17	YY	0	146
151	150	1	0.5154	4	0	3.4	1.6	1.6	1.6	1	1	1.0429	0.8141	17	YY	0	150
161	162	1	0.1107	1.2	0	1.02	6.25	6.25	6.25	1	1	1.0429	0.8141	17	YY	0	162

A.2 Shetland Network Model

A.2.1 Buses

Table A-6 - Bus Data for Shetland

Number	Name	X Co-ordinate	Y Co-ordinate	Base Voltage	Bus Type	Status	Target Voltage Magnitude	Minimum Voltage	Maximum Voltage	Voltage Angle
				kV			p.u.	p.u.	p.u.	
89900	LERWCK3A	0	20	33	1	1	1	0.9	1.1	0
89901	LERWCK3B	10	20	33	1	1	1	0.9	1.1	0
89902	LERWCK3C	20	20	33	1	1	1	0.9	1.1	0
89903	LERWCK5J	30	10	11	1	1	1	0.9	1.1	0
89904	LERWCK5K	40	10	11	1	1	1	0.9	1.1	0
89905	LERWCK5L	50	10	11	1	1	1	0.9	1.1	0
89906	LERWCK5S	60	10	11	1	1	1	0.9	1.1	0
89907	LERWCK5T	70	10	11	1	1	1	0.9	1.1	0
89908	LERWCK5R	80	10	11	2	1	1	0.9	1.1	0
89909	MAC3	90	10	11	1	1	1	0.9	1.1	0
89910	MAC4	100	10	11	1	1	1	0.9	1.1	0
89911	MAC5	110	10	11	1	1	1	0.9	1.1	0
89912	MAC8	120	10	11	1	1	1	0.9	1.1	0
89913	MAC10	130	10	11	1	1	1	0.9	1.1	0
89914	MAC11	140	10	11	1	1	1	0.9	1.1	0
89915	MAC13	150	10	11	1	1	1	0.9	1.1	0
89916	MAC14	160	10	11	1	1	1	0.9	1.1	0
89917	MAC21	170	10	11	1	1	1	0.9	1.1	0
89918	CAPBANK1	180	10	11	1	1	1	0.9	1.1	0
89919	CAPBANK2	190	10	11	1	1	1	0.9	1.1	0
89920	SVOETM3K	200	20	33	1	1	1	0.9	1.1	0
89921	SVOETM5J	210	10	11	1	1	1	0.9	1.1	0
89922	SVOETM5K	220	10	11	2	1	1	0.9	1.1	0
89923	SVOETM5L	230	10	11	1	1	1	0.9	1.1	0
89924	SVOETM3J	240	20	33	1	1	1	0.9	1.1	0
89925	SVT51	250	10	11	1	1	1	0.9	1.1	0
89926	SVOETM5M	260	10	11	1	1	1	0.9	1.1	0
89927	SVT53	270	10	11	1	1	1	0.9	1.1	0
89928	REACTOR	280	20	33	1	1	1	0.9	1.1	0
89929	REACTOR_	290	20	33	1	1	1	0.9	1.1	0
89930	BRAE5-	300	10	11	1	1	1	0.9	1.1	0
89931	BRAE5J	310	20	33	1	1	1	0.9	1.1	0
89935	SUMBRG3-	350	20	33	1	1	1	0.9	1.1	0
89936	SUMBRG5-	360	10	11	1	1	1	0.9	1.1	0
89940	FIRTH3-	400	20	33	1	1	1	0.9	1.1	0
89941	FIRTH5-	410	10	11	1	1	1	0.9	1.1	0
89942	FIRTH3T	420	20	33	1	1	1	0.9	1.1	0
89943	FIRTH3S	430	20	33	1	1	1	0.9	1.1	0
89950	GUTCHR3-	500	20	33	1	1	1	0.9	1.1	0
89951	GUTCHR5-	510	10	11	1	1	1	0.9	1.1	0
89955	UNST3-	550	20	33	1	1	1	0.9	1.1	0
89956	UNST5-	560	10	11	1	1	1	0.9	1.1	0
89960	MIDYEL3-	600	20	33	1	1	1	0.9	1.1	0
89961	MIDYEL5-	610	10	11	1	1	1	0.9	1.1	0
89965	TUMLIN3-	650	20	33	1	1	1	0.9	1.1	0
89966	TUMLIN3T	660	20	33	1	1	1	0.9	1.1	0
89967	TUMLIN5-	670	10	11	1	1	1	0.9	1.1	0
89968	TUMLIN3U	680	20	33	1	1	1	0.9	1.1	0
89970	SCALWY3-	700	20	33	1	1	1	0.9	1.1	0
89971	SCALWY3T	710	20	33	1	1	1	0.9	1.1	0
89972	SCALWY5-	720	10	11	1	1	1	0.9	1.1	0
89973	SCALWY3U	730	20	33	1	1	1	0.9	1.1	0
89980	SNDWCK3-	800	20	33	1	1	1	0.9	1.1	0
89981	SNDWCK5-	810	10	11	1	1	1	0.9	1.1	0
89985	BURRAT-	850	20	33	1	1	1	0.9	1.1	0
89986	BURRA3A	860	20	33	1	1	1	0.9	1.1	0
89987	BURRA3B	870	20	33	1	1	1	0.9	1.1	0
89990	VOE3J	900	20	33	1	1	1	0.9	1.1	0
89991	VOE3K	910	20	33	1	1	1	0.9	1.1	0
89992	VOE5L	920	10	11	1	1	1	0.9	1.1	0
89993	VOE5M	930	20	33	1	1	1	0.9	1.1	0
89999	EARTH	990	10	11	1	1	1	0.9	1.1	0
90001	TESTWFARM	10	0	0.6	1	1	1	0.9	1.1	0

A.2.2 Loads

Table A-7 - Load Data for Shetland

Load Bus Number	Load ID	Real Power	Reactive Power
		MW	MVAr
89903	1	9.4	1.91
89904	1	9.4	1.91
89905	1	9.4	1.91
89925	1	8	0.98
89925	2	5	2.5
89927	1	8	0.98
89927	2	5	2.5
89930	1	2.42	0.49
89936	1	2.15	0.44
89941	1	1.19	0.24
89951	1	0.83	0.17
89956	1	1.59	0.32
89961	1	0.97	0.2
89967	1	0.5	0
89972	1	5	1.02
89981	1	2.85	0.58
89992	1	3.71	0.75

A.2.3 Generators

Table A-8 - Generator Data for Shetland

Bus Number	Generator ID	Real Power	Maximum Real Power	Minimum Real Power	Reactive Power	Maximum Reactive Power	Minimum Reactive Power	Generator MVA Base
		MW	MVAr	MW	MVAr	MVAr	MVAr	MVA
10000	BATTERY 0.4800	1	1	0	0	0	0	1.25
89906	LERWCK5S 11.000	22	8.1	0	0.3824	5.02	-2.98	9.54
89907	LERWCK5T 11.000	23	8.1	0	0.3824	5.02	-2.98	9.54
89908	LERWCK5R 11.000	24	12	0	0.3824	7.5	-4.5	14
89909	MAC3 11.000	3	4.59	0	0.3824	2.84	-1.69	5.4
89910	MAC4 11.000	4	4.59	0	0.3824	2.84	-1.69	5.11
89911	MAC5 11.000	5	4.59	0	0.3824	2.84	-1.69	5.11
89912	MAC8 11.000	8	3.52	0	0.3824	2.18	-1.29	4.14
89913	MAC10 11.000	10	4.59	0	0.3824	2.84	-1.69	5.4
89914	MAC11 11.000	11	4.59	0	0.3824	2.84	-1.69	5.4
89915	MAC13 11.000	13	3.6	0	0.3824	2.23	-1.32	4.24
89916	MAC14 11.000	14	3.6	0	0.3824	2.23	-1.32	4.24
89917	MAC21 11.000	21	2	0	0.3824	0.56	-0.33	2
89921	SVOETM5J 11.000	1	25	0	9.6563	6	-5	27
89922	SVOETM5K 11.000	2	25	0	6	6	-5	27
89923	SVOETM5L 11.000	3	25	0	0	6	-5	27
89926	SVOETM5M 11.000	4	25	0	0	6	-5	27
89986	BURRA3A 33.000	1	0.66	0	-0.2169	-0.2169	-0.2169	0.81
89986	BURRA3A 33.000	2	0.66	0	-0.2169	-0.2169	-0.2169	0.81
89986	BURRA3A 33.000	3	0.66	0	-0.2169	-0.2169	-0.2169	0.81
89987	BURRA3B 33.000	1	0.85	0	0	0	0	0.94
89987	BURRA3B 33.000	2	0.85	0	0	0	0	0.94
90001	TESTWFARM 0.6000	1	0.66	0	0	0	0	0.81
90001	TESTWFARM 0.6000	2	0.66	0	-0.2169	-0.2169	-0.2169	0.81
90001	TESTWFARM 0.6000	3	0.66	0	-0.34	-0.34	-0.34	0.81

A.2.5 Branches

Table A-9 - Branch Data for Shetland

From Bus	To Bus	Branch ID	Positive and Negative Sequence Resistance	Positive and Negative Sequence Reactance	Zero Sequence Resistance	Zero Sequence Reactance	Winter Rating	Standard Rating	Summer Rating	Length	Status
			p.u.	p.u.	p.u.	p.u.	MVA	MVA	MVA	km	
89900	89901	1	0	0.001	0.0685	0.026	50	50	50	1	1
89900	89968	1	0	0.001	0.0064	0.0208	50	50	50	1	1
89901	89902	1	0	0.001	0.0581	0.187	50	50	50	1	1
89901	89991	1	0.4009	0.8074	0.0309	0.0997	22.3	20.7	17.8	24.34	1
89902	89973	1	0	0.001	0.0446	0.1437	50	50	50	1	1
89903	89904	1	0	0.001	0.0128	0.0412	50	50	50	1	1
89903	89909	1	0.0039	0.0003	0.0128	0.0413	7.5	6.8	6.8	0.04	1
89903	89914	1	0.0083	0.0006	0.0179	0.0576	7.5	6.8	6.8	0.09	1
89903	89915	1	0.0245	0.0017	0.0409	0.1319	7.5	6.8	6.8	0.25	1
89903	89918	1	0.0039	0.0003	0.0189	0.0608	7.5	6.8	6.8	0.04	1
89904	89905	1	0	0.001	0.0644	0.2074	50	50	50	1	1
89904	89911	1	0.0039	0.0003	0.0191	0.0617	7.5	6.8	6.8	0.04	1
89904	89917	1	0.0078	0.0005	0.0327	0.1054	7.5	6.8	6.8	0.08	1
89904	89919	1	0.0039	0.0003	0.0314	0.0949	7.5	6.8	6.8	0.04	1
89905	89910	1	0.0039	0.0003	0.0228	0.063	7.5	6.8	6.8	0.04	1
89905	89912	1	0.0059	0.0004	0.0224	0.0621	7.5	6.8	6.8	0.06	1
89905	89913	1	0.0083	0.0006	0.0418	0.1158	7.5	6.8	6.8	0.09	1
89905	89916	1	0.0245	0.0017	0.0197	0.0547	7.5	6.8	6.8	0.25	1
89920	89924	1	0	0.001	0.0232	0.0398	50	50	50	1	1
89924	89929	1	0	0.258	0.0264	0.0453	25	25	25	1	1
89928	89929	1	0.0276	0.0568	0.0048	0.0081	22.3	20.7	17.8	1.6	1
89928	89942	1	0.0346	0.0697	0.0761	0.1307	22.3	20.7	17.8	2.1	1
89928	89993	1	0.1329	0.2543	0.0501	0.0859	22.3	20.7	17.8	8.1	1
89931	89993	1	0	0.001	0.0127	0.0218	50	50	50	1	1
89935	89980	1	0.7565	0.5499	0.0196	0.0335	11	10.2	8.8	15.43	1
89940	89942	1	0.0348	0.0253	0.0746	0.1281	11	10.2	8.8	0.71	1
89940	89960	1	0.5079	0.6196	0.0284	0.0915	12	12	12	20.04	1
89942	89943	1	0	0.001	0.034	0.1094	50	50	50	1	1
89943	89990	1	1.1884	0.864	0.0028	0.0048	11.1	10.3	9.1	12.6	1
89950	89955	1	0.869	0.6525	0.0496	0.1374	11	10.2	8.8	19.15	1
89950	89960	1	0.3244	0.4534	0.0137	0.038	17.4	16.1	13.9	13.21	1
89965	89966	1	0.4584	0.3332	0.0142	0.0395	11	10.2	8.8	9.35	1
89966	89985	1	0.2014	0.3709	0.01	0.01	23.3	21.1	19.3	11.22	1
89966	89990	1	0.1885	0.3503	0.0685	0.026	24.1	22.3	19.3	10.44	1
89968	89973	1	0	0.001	0.0064	0.0208	50	50	50	1	1
89968	89985	1	0.0632	0.1174	0.0581	0.187	24.1	22.3	19.3	3.5	1
89970	89971	1	0.1035	0.0752	0.0309	0.0997	11	10.2	8.8	2.11	1
89971	89973	1	0.1117	0.1562	0.0446	0.1437	17.4	16.1	13.9	4.55	1
89971	89980	1	0.3571	0.499	0.0128	0.0412	17.4	16.1	13.9	14.54	1
89985	89986	1	0.058	0.03	0.0128	0.0413	14.9	14.9	14.9	2	1
89986	89987	1	0	0.001	0.0179	0.0576	50	50	50	1	1
89990	89991	1	0	0.001	0.0409	0.1319	50	50	50	1	1
89991	89993	1	0.1466	0.3016	0.0189	0.0608	22.3	20.7	17.8	8.5	1

A.2.6 A.2.6 Transformers

Table A-10 - Transformer Data for Shetland

From Bus	To Bus	Transformer ID	Positive and Negative Sequence Resistance	Positive and Negative Sequence Reactance	Zero Sequence Resistance	Zero Sequence Reactance	Winter Rating	Standard Rating	Summer Rating	Status	Starting Tap Ratio	Maximum Tap Position	Minimum Tap Position	Tap Positions	Winding Connection	Phase Shift Angle	Controlled Bus
			p.u.	p.u.	p.u.	p.u.	MVA	MVA	MVA		p.u.	p.u.	p.u.				
10000	89908	1	1	1	0	0.85	1.3	1.3	1.3	1	1	1.05	0.86	17	YY	0	0
89900	89903	1	1	1	0	0.85	18	18	18	1	1	1.05	0.86	17	YY	0	0
89900	89907	2	1	1	0	0.85	10	10	10	1	1	1.05	0.86	17	YY	0	0
89901	89904	2	1	1	0	0.85	18	18	18	1	1	1.05	0.86	17	YY	0	0
89901	89906	1	1	1	0	0.85	10	10	10	1	1	1.05	0.86	17	YY	0	0
89902	89905	3	1	1	0	0.85	18	18	18	1	1	1.05	0.86	17	YY	0	0
89902	89908	3	1	1	0	0.85	15	15	15	1	1	1.05	0.86	17	YY	0	0
89905	89999	1	1	1	0	0.85	0.2	0.2	0.2	1	1	1.05	0.86	33	YY	0	0
89905	89999	2	1	1	0	0.85	0.2	0.2	0.2	1	1	1.05	0.86	33	YY	0	0
89920	89921	1	1	1	0	0.85	30	30	30	1	1	1.05	0.86	17	YY	0	0
89920	89923	1	1	1	0	0.85	30	30	30	1	1	1.05	0.86	17	YY	0	0
89920	89925	1	1	1	0	0.85	32	32	32	1	1	1.05	0.86	17	YY	0	0
89920	89925	2	1	1	0	0.85	32	32	32	1	1	1.05	0.86	17	YY	0	0
89920	89927	1	1	1	0	0.85	32	32	32	1	1	1.05	0.86	17	YY	0	0
89922	89924	1	1	1	0	0.85	30	30	30	1	1	1.05	0.86	17	YY	0	0
89924	89925	1	1	1	0	0.85	32	32	32	1	1	1.05	0.86	17	YY	0	0
89924	89926	1	1	1	0	0.85	30	30	30	1	1	1.05	0.86	17	YY	0	0
89924	89927	1	1	1	0	0.85	32	32	32	1	1	1.05	0.86	17	YY	0	0
89924	89927	2	1	1	0	0.85	32	32	32	1	1	1.05	0.86	17	YY	0	0
89930	89931	1	1	1	0	0.85	6	6	6	1	1	1.05	0.86	17	YY	0	0
89935	89936	1	1	1	0	0.85	4	4	4	1	1	1.05	0.86	17	YY	0	0
89940	89941	1	1	1	0	0.85	6	6	6	1	1	1.05	0.86	17	YY	0	0
89950	89951	1	1	1	0	0.85	4	4	4	1	1	1.05	0.86	17	YY	0	0
89955	89956	1	1	1	0	0.85	4	4	4	1	1	1.05	0.86	17	YY	0	0
89960	89961	1	1	1	0	0.85	1	1	1	1	1	1.05	0.86	17	YY	0	0
89965	89967	1	1	1	0	0.85	2.5	2.5	2.5	1	1	1.05	0.86	17	YY	0	0
89970	89972	1	1	1	0	0.85	8	8	8	1	1	1.05	0.86	17	YY	0	0
89980	89981	1	1	1	0	0.85	2.5	2.5	2.5	1	1	1.05	0.86	17	YY	0	0
89986	90001	1	1	1	0	0.85	2.5	2.5	2.5	1	1	1.05	0.86	17	YY	0	0
89990	89992	1	1	1	0	0.85	6.3	6.3	6.3	1	1	1.05	0.86	17	YY	0	0