Modelling the transition to a low-carbon energy supply

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I would like to dedicate this thesis to my family and my loving parents…

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Alexander John Michael Kell
July 2020

Acknowledgements

And I would like to acknowledge ...

Abstract

This is where you write your abstract ...

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Glossary

agent-based model A simulation technique made up of individual agents.

artificial neural network A machine learning algorithm that is modelled on the brain and made up of multiple layers of neurons and weights.

dispatched A power plant can be dispatched if the time and amount of electricity that can be controlled by a human operator. Examples are gas, coal and oil power plants..

generation company A company which owns power plants and sells electricity to the grid.

market power Market power refers to the ability of a firm, or group of firms, to raise and maintain prices above the level that would prevail under competition.

online learning Online learning is a machine learning or statistical method which data which is made available in sequential order is used to update the predictor for future data at each step.

peaker plant A peaker power plant is one which which is used in times of high demand and low supply. Due to their expense they are only used when necessary and can not compete with other sources of energy during the majority of market operation.

short run marginal cost The cost it takes to produce an additional MWh of electricity, excluding capital costs.

simulation A computer program which models real world phenomena.

smart meter A small digital meter which records electricity consumption within a household or business premises.

weighted average cost of capital The rate at which a company is expected to pay on average for its loans and in stock dividends/buybacks.

Acronyms

ABM Agent Based Model.

ABMs Agent Based Models.

GenCos Generation Companies.

IRES Intermittent Renewable Energy Sources.

SVR Support Vector Regression.

WACC Weighted Average Cost of Capital.

Chapter 1

Introduction

1.1 Motivation

The impacts of global warming on the earth may have profound effects on land and ocean ecosystems [113]. The release of carbon emissions into the atmosphere increases the likelihood of the most severe of impacts, and increases the likelihood that tipping points are reached, where runaway carbon emissions, and average temperature rises are likely. Examples of these tipping points include the irreversible melting of Greenland and Antarctic ice sheets, which could happen with a rise of 1.5°C or 2°C. A tipping point is an irreversible change in the climate system.

Some of the consequences of climate change include increases in mean temperature in most land and ocean regions, hot extremes in most inhabited regions, heavy precipitation in several regions and the probability of drought in some regions [113]. Sea level rise will continue beyond 2100 even if global warming is limited to 1.5°C. Land based impacts on biodiversity and ecosystems include species loss and extinction. These are projected to be lower at 1.5°C of global warming compare to 2°C. Limiting global warming to 1.5°C compared to 2°C is projected to lower the impacts on terrestrial, freshwater and coastal ecosystems and enable that more of their services are available to humans [113].

A study by Cook *et al.* demonstrated that 97% of scientific literature concurred that recent global warming was anthropogenic [38]. Limiting global warming requires limiting the total cumulative global anthropogenic emissions of CO_2 [150].

Global carbon emissions from fossil fuels, however, have significantly increased since 1900 [23]. Fossil-fuel based electricity generation sources such as coal and natural gas currently provide 65% of global electricity. Low-carbon sources such as solar, wind, hydro and nuclear provide 35% [26].

Global energy consumption, however, has an even higher proportion of fossil-fuel based electricity generation. Oil accounts for 34% of global energy consumption, coal accounts for 27%, natural gas accounts for 24%, hydro and nuclear account for 7% and 4% respectively, with renewables slightly behind at 4% [27].

It can be seen, therefore, that a transition to a low-carbon electricity supply is not enough. A transition from fossil-fuel powered transport and heating to electricity must occur to halt the emissions of CO_2. This would require a significant increase in electricity demand, a move towards Intermittent Renewable Energy Sources (IRES), such as wind and solar, and storage to fill the gaps in supply when the wind is not blowing or the sun is hidden by clouds.

However, such a transition needs to be performed in a gradual and non-disruptive manner. This ensures that there are no electricity shortages or power cuts that would cause damage to businesses, consumers and the economy. Due to the large uncertainties and difficult choices related to energy and environment policy, as well as energy technology investment, quantitative analysis can be used in the form of models [46]. These models can provide an intuition and outlook on the consequences of certain decisions on the energy market.

These models can be used to assess scenarios under different variants of government policy, future electricity generation costs and energy demand. These energy modelling tools aim to mimic the behaviour of energy systems through different sets of equations and data sets to determine the energy interactions between different actors and the economy [146].

With the increase in decentralised energy markets and renewable energy, a paradigm shift is required from large centralised models with yearly time-steps to models based upon many actors and high resolution time steps [171, 165]. For this purpose, in this PhD, we have developed a generalisable long-term agent-based simulation of decentralised electricity markets with hourly time steps. Using this agent-based model, we have used various machine learning and statistical models to assess what may happen in the future, what the optimal carbon tax strategies could be, and how to prevent market power within a decentralised electricity market. In addition, I have explored the impact of poor forecasting models on the utilisation and investment of the electricity mix.

Much of the work of this PhD focuses on the electricity market in the United Kingdom. However the techniques extend to decentralized electricity markets around the world with similar characteristics.

1.2 Research questions

In order to understand how the transition to a low-carbon energy supply can be optimised, understood and modelled, a number of research questions must be investigated:

- **Electricity market modelling** Traditional electricity market models model centralised actors with perfect foresight and information. Other models which model actors as having imperfect foresight and information lack the ability to model multiple time-steps over a long time horizon. In addition, the generalisability of such a model is critical, to enable policy makers from around the world to utilise a common model and approach.

- **Modelling the variability of intermittent renewable energy supplies** Intermittent renewable energy can produce electricity at both maximum capacity and at a capacity of zero within the same hour period. It, therefore, becomes important to model these variations in power output over a long-term horizon. Otherwise, the model may overestimate the production of energy from renewables, and underestimate the variability of such technologies.

- **Validating the accuracy of electricity market models** Whilst long-term energy models can provide quantitative advice to experts, policy makers and stakeholders, the veracity of these models are rarely validated. The validation of long-term electricity models can highlight problems with the dynamics of the model, important components, and provide confidence in the outputs.

- **Understanding the long-term impact of poor forecasts on electricity markets** Forecasting of electricity demand within electricity markets is critical. The settlement of markets occurs prior to the time in which the demand must be supplied. However, the long-term effect on the markets of poor forecasts has not been investigated.

- **Finding optimal strategies for decision makers** Setting carbon taxes has been proposed as a solution to reduce our reliance on fossil fuels. However, the impact of such carbon taxes are unknown, as are the optimal strategies. Such a problem can be solved using optimisation based techniques.

- **Limiting the impact of collusion and market power** It is known that oligopolies have a negative effect on markets for consumers. However, what has been explored to a lesser degree, is the proportion of capacity that generation company must own before they have market power. In addition, what would the effect be of a market cap on such electricity markets? Would a market cap reduce the ability for Generation Companies (GenCos) to artificially inflate electricity prices?

1.3 Methodology

Primarily, in this work, simulation is used as a tool to better understand and make projections for electricity markets. Specifically, in this thesis, the agent-based modelling paradigm is used. This enables us to model generator companies as individual agents, with heterogeneous strategies and characteristics. These agents have access to imperfect information and imperfect foresight. This methodology differentiates us from the traditional centralised optimisation approach.

Machine learning and statistical techniques are used to make short-term forecasts of electricity demand. We use both deep learning and online learning to further improve our methods. Online learning is a machine learning approach which utilises new data to update model weights, and does not require the model to be completely retrained. Whereas deep learning utilises neural networks with many different layers.

Once our simulation model is built we are able to answer different questions using several approaches. For example, we perturb the exogenous electricity demand by the error distribution generated by the aforementioned electricity demand forecasting methods. This provides an insight into how small errors can have large impacts on the long-term electricity markets in terms of both investments made and generator utilisation.

Multi-objective genetic algorithms are used to explore carbon tax policies which will reduce both carbon emissions and average electricity price. We find that we are able to achieve both of these goals by setting a median carbon tax of $\sim$£200.

Finally, we explore the ability for deep reinforcement learning to make strategic bidding decisions within a day-ahead electricity market. We short run marginal cost. This work enables us to see the proportion of capacity that must be controlled to artificially inflate the electricity price in the market using market power.

1.4 Contributions

The work in this thesis makes a number of key contributions:

1. Development of the open-source, generalised long-term agent based model for decentralised electricity markets, ElecSim [122].
2. Validation of the aforementioned model through the use of cross-validation through five years and comparison with the established UK Government model until 2035 [127].
3. Optimisation of a carbon tax policy for the UK electricity market using multi-objective genetic algorithm [129].
4. Forecasting of electricity demand using machine learning models and exploration of the impact of these errors on the long-term electricity market [124].
5. Exploration of the long-term impact of strategic bidding and collusion on decentralized electricity markets.

1.5 Thesis organisation and structure

Chapter 1 describes the motivations behind this thesis and highlights the main contributions of the research. Finally we state the peer-reviewed publications produced during this PhD.

Chapter 2 describes the technical background material that relates to the rest of this work.

Chapter 3 investigates the different types of solutions that have been used in the current literature and differentiates our work.

Chapter 4 introduces the simulation developed within this work. This includes the technical details of the simulation tool, how we validated this model, and the difficulties of validating such models. Finally, we display a sensitivity analysis to show the impact of various variables, and produce some example future scenarios.

Chapter 5 explores the literature on electricity demand forecasting, how this can be improved with online learning, and what the long-term impact of errors are on decentralised electricity markets.

Chapter 6 demonstrates the ability for the model to come up with optimal strategies and scenarios through the use f machine learning techniques. Specifically, we optimise a carbon tax strategy between 2018 and 2035 to reduce both electricity cost and carbon emissions.

Chapter 7 demonstrates the ability for large or colluding generator companies to influence the price of electricity in their favour using deep reinforcement learning.

Chapter 8 summarises the conclusion of the work and motivates future directions for work in this area.

1.6 Related publications

During the course of my PhD I have contributed to the following peer-reviewed publications:

[122] Kell, A., Forshaw, M., & McGough, A. S. (2019). ElecSim : Monte-Carlo Open-Source Agent-Based Model to Inform Policy for Long-Term Electricity Planning. The Tenth ACM International Conference on Future Energy Systems (ACM e-Energy), 556–565.

In this work we introduce the agent-based model, ElecSim. We review the current state-of-the art of agent-based models, and detail the technical foundations of how ElecSim works. We use an initial validation method of comparing the price duration curve of our model to that observed in real life. Finally, we present some example scenarios. This work forms the basis for Chapter 4.

[123] Kell, A., Forshaw, M., & McGough, A. S. (2019). Modelling carbon tax in the UK electricity market using an agent-based model. E-Energy 2019 - Proceedings of the 10th ACM International Conference on Future Energy Systems, Ldc, 425–427.

In this paper, we explore further scenarios with varying the carbon tax level. We demonstrate the effect of carbon tax on investments in the electricity market. This work augments the work done in Chapter 4.

[128] Kell, A. J. M., Forshaw, M., & McGough, A. S. (2020). Long-Term Electricity Market Agent Based Model Validation using Genetic Algorithm based Optimization. The Eleventh ACM International Conference on Future Energy Systems (e-Energy'20).

In this paper, we make further modifications to further improve our simulation. Through the addition of representative days we are able to validate our model between 2013 through 2018 by optimising for long-term predicted electricity price. We compare our results to those of the UK Government, for both the a long-term and short-term validation. Our results are comparable to those of the UK Government. This work further extends Chapter 4.

[124] Kell, A., McGough, A. S., & Forshaw, M. (2018). Segmenting residential smart meter data for short-Term load forecasting. E-Energy 2018 - Proceedings of the 9th ACM International Conference on Future Energy Systems.

In this work we use various machine learning and deep learning techniques to predict electricity demand 30 minutes ahead using smart meter data. We cluster various households using a k-means clustering technique to further improve our accuracy. This paper forms the basis for Chapter 5.

[126] Kell, A. J. M., Forshaw, M., & Stephen McGough, A. (2019). Optimising energy and overhead for large parameter space simulations. 2019 10th International Green and Sustainable Computing Conference, IGSC 2019.

In this work, we use a multi-objective genetic algorithm to reduce both overhead and energy consumption of a cluster of computers at Newcastle University. We achieve this by varying different parameters of a reinforcement learning algorithm. The methods used in this paper influence much of the work presented in Chapters 4, 5 and 7.

[129] Kell, A. J. M., McGough, A. S., & Forshaw, M. (2020). Optimizing carbon tax for decentralized electricity markets using an agent-based model. The Eleventh ACM International Conference on Future Energy Systems (e-Energy'20), 454–460.

In this paper, we trial different carbon tax strategies using a multi-objective genetic algorithm. We aim to minimise both electricity price and carbon emissions. We find that we are able to achieve both of these goals through different carbon tax strategies.

Chapter 2

Background

Prologue

This chapter provides an overview of the relevant material which motivates and underpins the work carried out in this thesis. Section 2.1, introduces electricity markets and how they are regulated. In Section 2.2, an introduction into how electricity markets are modelled is shown. We provide an introduction in Section 2.3 to simulation and machine learning. Finally, we conclude this chapter in Section 2.4.

2.1 Introduction to Electricity Markets

Electricity markets are complex. One of the principal reasons for this is the expense and difficulty of storing electricity. Additionally, as electricity travels over high voltage transmission lines, electricity doesn't always follow simple or unique paths, especially when the transmission lines become congested. Finally, electricity markets require technical overseers to ensure that the entire transmission system operates safely and reliably.

Another aspect to consider is the fact that electricity is homogeneous. A single unit of electricity produced by a wind turbine is equivalent to a unit of electricity produced by a gas turbine. However, the functioning of different electricity producers, or generators, are not homogenous. Coal, gas and oil power plants can be dispatched at the will of a human operator. Their ramp rates are well understood, as is the amount of fuel that is available. IRES, however, such as solar, wind and tidal are dependent on the supply of solar irradiance, wind speed and the tide at any moment. Whilst these can be predicted, predictions are often wrong, and perfect knowledge is impossible. Therefore, at times where there is too much supply from Intermittent Renewable Energy Sources (IRES) generators must be curtailed. In the opposite case, where there is too little supply from IRES, supply must be made up from other sources, such as coal, gas or hydro.

The environmental impact from different electricity generators differs significantly between generators. Whilst gas and coal can be dispatched at a time convenient to the grid operators, they emit CO_2 along with other toxic substances. Wind and solar do not dispatch such substances or gases, but can not be controlled as easily. Storage technologies can be used to fill these gaps, however, large-scale storage depends on large pumped reservoirs that can move water to a higher position when demand for electricity is low, and supply is high. Not all geographies have access to such reservoirs, and therefore would rely on battery technology made from chemicals. However, reaching such high storage capabilities are expensive, and are yet to have been done in the real world. Another option is converting electricity to hydrogen. However, this technology is also expensive and uncompetitive with traditional fossil fuels such as coal, gas and oil. Currently, peaker plant are used to fill these gaps, however these plants are expensive to operate, highly polluting and use fossil fuels. It is expected that these peaker plants will be used increasingly due to the intermittent nature of renewable technologies.

The electricity grid must match supply with demand at all times. Failure to do so results in an imbalance of supply and demand, and affects the frequency of the electricity network. Large differences between supply and demand can lead to blackouts or oversupply and damage equipment. A number of different markets exist to regulate the supply and demand, running from within seconds, to days-ahead and bilateral contracts which settle electricity for years ahead.

There are a number of different market mechanisms that can be used to balance the supply and demand of electricity. Largely these can be divided between ancillary services and wholesale transactions. Wholesale transactions can occur as bilateral trades or on a day-ahead market. Bilateral trades can occur between two electricity suppliers and those that have an electricity demand. In this case, suppliers and customers create contracts for electricity in advance. Typically, these agents must let the market operator know of their trades. In a day-ahead market, the system price is, in principle, determined by matching offers from generators to bids from consumers at each node to develop a supply and demand equilibrium price.

Ancillary markets, on the other hand, provide a method to facilitate and support the continuous flow of electricity so that supply continually meets demand. These include markets to regulate power and voltage control as well as frequency control. These markets make use of increasing supply or reducing demand at the times where this is required.

2.2 Introduction to Electricity Market Modelling

Energy models are useful tools for insight into the functioning of electricity markets. For example, modellers and analysts can develop an intuition how such a system works, and through modelling, they can challenge untested hypothesise. The argument that these models are used for insight and not just numbers is as old as the models themselves [108, 165], and is true for models in many different disciplines [73]. We argue that energy models should not be taken as truth, as, as previously mentioned, no model can perfectly model the real world. However, the intuition that can be learned can prove to be a valuable resource.

Energy modelling and energy policy as a distinct field began after the oil crisis in the 1970s, where long-term planning was deemed as important in the electricity field. Models which make use of optimisation techniques have been used since these times for diverse applications, from the global energy market to small off-grid systems.

The utilisation of energy models has lately been redirected to ensuring that there exists a security of supply, resilience of the energy system, affordability and that there is a transition to a low-carbon supply. These models can also be used to investigate the impact that different technologies have on investments made in the future.

However, since the traditional models have been established, various changes in the energy industry have occurred. Originally, electricity systems were built upon large-scale centralized electricity production based on fossil fuels. Since then there has been a transition towards decentralised, distributed, intermittent renewable energy sources, such as solar and wind. In addition there has been an advent in flexible demand driven by new technologies such as smart meters. This paradigm shift requires models which can work with higher temporal and spatial detail to account for fluctuations in demand, supply and distributed electricity generators.

Modelling electricity markets is a complex task. There exist many variables, actors, services and behaviours within electricity markets which make it impossible to perfectly model the system. Often simplifications must be made, where models are designed for a specific task [165]. Large established models exist which model every possible detail, however, with the increase in temporal and spatial resolution required, the computer tractability of these models can be negatively impacted. Many of the large models used today have existed for a long time, before the advent of the internet [165]. Therefore, these models and modellers risk being left behind.

Energy and electricity models generally follow two approaches: top-down or a bottom-up approach [171]. Bottom-up models are often referred to as the engineering approach and are based on detailed technological representations of the energy system. Top-down models, on the other hand, follow an economic approach and consider the long-term changes and macroeconomic relationships [148]. It is possible to combine both the technological properties and long-term changes by creating a hybrid approach [66].

2.3 Introduction to Simulation and Machine Learning

Computer simulation is a virtual model of a real-world system which is programmed into computer software. These models can be used to study how such a system works. One is able to change parameters in the system and make predictions as to how a system might behave. These simulations are particularly beneficial when the system one is analysing is difficult to experiment with. For example, the system exhibits a high financial costs of experimentation or negative consequences may have large impacts. Additionally, for systems that operate on long timescales, such as energy markets, one may not have the ability to repeat experiments in a controlled environment.

Digital twins are a particular instance of a simulation. Digital twins often have been instantiated to a particular system, as opposed to a general system. For example, a digital twin can be made of the UK electricity market, whilst a simulation can be generalised to any decentralised market. By having a digital twin of a particular system, we are able to remove the risks associated with interacting with a system and iterate many experiments within a short time to find an optimal set of parameters.

Whilst simulations must be built with expert knowledge and through a thorough understanding of the system that one would like to model, machine learning is a data-driven approach. Data-driven approaches do not require an understanding of the system in which they are trying to model. Rather, they infer properties of the system entirely from data. These models are desirable in cases where a system is too complicated to have a full understanding of how the system works. These models have been shown to generate accurate results in many different disciplines [202, 208, 40].

Machine learning methods can be split into three different categories: (1) supervised learning, (2) unsupervised learning and (3) reinforcement learning. Each of these methods can be used in the following cases:

1. Supervised learning is used where the data used has labelled data. That is, the true value that one is trying to predict is available in the data.

2. Unsupervised learning is where the true value is unknown. The model must therefore infer from distinct clusters in the data where the divides in the values may lie.

3. Reinforcement learning is concerned with how software agents must take actions in an environment in order to maximize a cumulative reward.

In addition to the aforementioned machine learning methods, there exists an additional paradigm: optimisation methods. These methods explore a mathematical or software function to find a minimum or maximum value. These can be used to minimise an expected error, minimise total cost or maximise total return from a system for example.

2.4 Conclusion

In this chapter we have introduced key concepts that have been used as part of this thesis: electricity markets and their modelling, simulation and digital twins, machine learning methods such as supervised learning and reinforcement learning as well as optimisation techniques. All of the mentioned methods have been used in this thesis for the purpose of increasing our understanding of electricity markets over both a long, and short time period.

We have motivated the need for novel approaches to be used when understanding and modelling energy systems due to the fundamental changes that have undertaken since the 1970s. From a system with a centralised actor and power stations which run on fossil fuels to one built on prosumers with decentralised generation capacity and many heterogeneous actors. A prosumer in this context is a person who both consumes and produces a product.

Additionally, we have discussed the complexity of modelling a system such as electricity markets. However, the insight that can be gained is invaluable and can provide further understanding to those who need to make decisions under large uncertainties. The ramifications of such decisions go far beyond the energy sector, and therefore any help that can be given to decision makers is of utmost importance.

Chapter 3

Literature review

Prologue

In this chapter we give an introduction to the relevant energy modelling literature. We review the three major types of quantitative models: (1) optimisation models, (2) simulation models, and (3) equilibrium models. Section 3.1 gives an introduction to the field of energy modelling. In Section 3.2 we introduce optimisation based models. Section 3.3 introduces equilibrium models and Section 3.4 introduces simulation models. We present a table in Section 3.5 which displays a high-level overview of the major models in the literature. We conclude this chapter in Section 3.6, where we discuss the limitations and benefits of different types of models.

3.1 Energy Modelling

In this thesis, we define energy systems as the entire energy system; from the extraction of primary energy to the final use of energy to produce and supply services and goods [165]. Energy systems models can often be modelled by different submodules. These submodules can model technical, environmental and social elements.

Energy modelling is a broad field, and so, there have been multiple reviews which attempt to separate these models into different classifications. Examples of the metrics for classification are the mathematical underpinning, the underlying methodology, analytical approach or data requirements. Table 3.1 shows the various reviews that were used to inform part of this literature review. Many of these reviews attempt to provide a classification schema to classify models [84, 177] and provide future research direction [165, 177].

Energy models can typically be classified as top-down macro-economic models or bottom-up techno-economic models [24]. Top-down models typically focus on behavioural realism with a focus on macro-economic metrics. They are useful for studying economy-wide responses to policies [85]. Examples of these types of model are MARKAL-MACRO [61] and LEAP [89]. Bottom-up models represent the energy sector in detail, and are written as mathematical programming problems [72]. They detail technology explicitly, and can include cost and emissions implications [85].

Table 3.1 Reviews of energy system models

Publication	Focus
The gap between energy policy challenges and model capabilities [177]	Assesses the ability of energy systems models to answer major energy policy questions.
Agent-based simulation of electricity markets: a literature review [183]	An overview of the work applying agent-based models to the analysis of electricity markets.
A review of modelling tools for energy and electricity systems with large shares of variable renewables [171]	An aid for modellers to choose an appropriate model which can cater for large shares of variable renewables.
Energy systems modeling for twenty-first century energy challenges [165]	The issues of using existing models for twenty-first century challenges in energy.
A review of energy systems models in the UK: Prevalent usage and categorisation [84]	Provide a classification schema for energy models.
A survey of stochastic modelling approaches for liberalised electricity markets [152]	Overview and classification of stochastic models dealing with price risks in electricity markets.

Within these two classifications, there exist four further paradigms of models within the literature: (1) energy systems optimisation models, (2) energy system simulation models, (3) power system and electricity market models and (4) economic models [165]. These four paradigms can be described as follows:

Energy systems optimisation These models cover the entire energy system and use optimisation methods. The primary aim of these is to provide scenarios of how the system can involve.

Energy system simulation Models which cover the entire energy system using simulation techniques. These models have a primary purpose of providing forecasts of how the system may evolve.

Power system and electricity market These models are focused exclusively on the electricity system. They have a diverse set of methods and aims. Some can be based on optimisation whilst others are based on simulation.

Economic models These models focus on long-term growth paths and study the complete economic system.

In practice, it is possible for models to lie between any of these paradigms and within a top-down or bottom-up approach. Table 3.2 displays the model families, examples of such models and their primary focus.

Within the models previously presented, there is a dichotomy between planning models and operational models. Operational models allow for a high-resolution analysis of dispatch within an energy grid. In contrast, planning models allow for long-term analysis of systems. Traditionally these planning models have used a coarse-grained temporal and spatial resolution. However, with the increase in IRES there has been an amalgamation of these two approaches. This is due to the fact that long-term planning models must model the intermittency of IRES to capture the variance of supply of renewable energy.

Table 3.2 Four different model types [165]

Model family	Examples	Primary focus
Energy system optimisation models	MARKAL [62], TIMES [75], MESSAGE [181], OSeMOSYS [102]	Normative scenarios
Energy system simulation models	LEAP[182], NEMS [81], PRIMES[55]	Forecasts, predictions
Power system and electricity market models	WASP [109], PLEXOS [110], EMCAS [37], ElecSim[122]	Operational decisions
Economic models	MARKAL-MACRO, E3MG, POLES	Operational decisions

With IRES, such as wind and solar power, the output can vary temporally on many time scales. For example, there may be a gust of wind which lasts a number of seconds, or cloud cover which lasts for less than a minute. In an electricity grid, where supply must meet demand at all times, this can lead to challenges. Currently, conventional technologies provide a spinning reserve. Where a spinning reserve can increase or decrease capacity rapidly by increasing or decreasing the torque applied to a generator. However, if IRES is to reduce the size of this spinning reserve, then battery technologies will be required. It is for reasons such as this, that long-term energy models require an increase in temporal granularity.

3.2 Optimisation models

Large, detailed bottom-up optimisation models have long been used for energy system modelling. These optimisation models are typically based upon a detailed description of the technical components of the energy system. However, due to this fine granularity, simplifications must often be made to ensure tractability of the model. Often the time-steps are seasonally averaged, the models are limited to nationally aggregated technology builds [164].

The ultimate goal of optimisation models is to optimise a given quantity. For example, the minimisation of cost or the maximisation of welfare. In this context, welfare can be designed as the material and physical well-being of people [121]. Two examples of optimisation models are MARKAL/TIMES [61] and MESSAGE [181]. MARKAL is possibly the most widely used general-purpose energy systems model [164]. Optimisation models are able to provide prescriptive, policy-relevant insight and relate near-term actions to long-term outcomes [46].

A linear programming (LP) approach is often used for optimisation. For example, a formulation can be made to minimise the total system cost subject to certain constraints. A constraint could be that of having certain carbon emissions within the model run time, or that supply must meet demand at all times. Mixed-integer linear programming (MILP) approaches force certain variables to be integers. This can be useful when the optimisation of discrete variables is required. For example, the number of power plants or solar panels one should invest in [171]. It is possible to have non-linear optimisation models. These models use heuristic-based optimisation. Heuristic optimisation differs from traditional optimisation modelling in that they do not necessarily find the global optimum [15].

The MARKAL/TIMES model developed into TIAM (TIMES Integrated Assessment Model). TIAM is a global version of TIMES which also allows for climate response modelling. The

MARKAL/TIMES family of models is developed by the IEA ETSAP. IEA ETSAP are a consortium of researchers from IEA member countries.

Both MARKAL/TIMES and MESSAGE represent possible scenarios of how the energy system may develop on a national, regional or global scale over a number of decades. However, these models do not state how likely each of these scenarios are to develop. These are both linear optimisation models which minimise the total energy system cost. Recent versions also allow for non-linear and mixed-integer linear optimisations.

Hybrid models were developed in the 1990s [100]. Hybrid models link bottom-up models with top-down general equilibrium economic models. General equilibrium economic models attempt to characterise economy-wide movements in response to energy system changes. An example of such a model is the MESSAGE-MACRO model [151] which soft-links two separate models. MESSAGE is a linear model which links to the non-linear MACRO model macroeconomic model.

MESSAGE-MACRO soft-links these two models. This means that the two models are iteratively solved. In this case, the output from one is used as an input into the other. Over time this will hopefully lead to convergence. MARKAL-MACRO, however, hard-links the two models into one solution, which solves in a single iteration [3].

Even though these models have been the established approach for many decades, other examples of optimisation models are being developed. An open-source version of a similar style to MARKAL has been developed, known as OSeMOSYS [101].

There are, however, limitations to optimisation based models: traditional centralised optimisation models are not designed to describe a system which is out of equilibrium. Optimisation models assume perfect foresight and risk-neutral investments with no regulatory uncertainty. The core dynamics which emerge from equilibrium remain a black-box. For example, the model assumes a target will be reached, and does not provide information for which this is not the case. Reasons for this could be investment cycles which move the model away from equilibrium [32].

3.3 Equilibrium models

Equilibrium models take an economic approach. They model the energy sector as a part of the whole economy and study how it relates to the rest of the economy [171]. There exist two types of equilibrium models: general equilibrium models or computable general equilibrium models (CGE). Both of these consider the whole economy, determine the equilibrium across all markets and determine important economic parameters such as the gross domestic product (GDP) endogenously. Partial equilibrium models (PE) focus on balancing one market. In this case, the market which is modelled is the electricity or energy market. They do not model the rest of the economy [171, 84].

POLES is a global detailed econometric model developed by the European Commission. POLES is able to evaluate long-term global energy outlooks with demand, supply and price projections by each main region. In addition, CO_2 emissions are recorded, and technological change can be both endogenous and exogenous. The time step of POLES is yearly.

E3MG is an econometric simulation developed by Cambridge Econometrics. It models the global energy-environment-economy system [43]. It represents each technology by 21 characteristics, and has a horizon up to 2100. It runs on a yearly time-step until 2030, and then every 10 years until 2100. The demand is calculated endogenously using econometrics.

MARKAL-MACRO is a hybrid model. Were MARKAL is bottom-up, and MACRO is top-down. MACRO is a macro-economic model and uses partial equilibrium through optimisation for matching demand and supply in MARKAL. MARKAL MACRO uses a non-linear dynamic programming approach as the mathematical underpinning [84].

3.4 Simulation models

Simulation models simulate an energy system based upon specified equations, characteristics and rules. These are often bottom-up models, and are designed with a high level of technological description [171]. Agent-based models are a specific case of simulation models, where actors are modelled explicitly as agents with heterogeneous strategies and behaviours.

Whilst energy optimisation models are built open mathematical formulations; simulation models can be built modularly and incorporate a range of methods. These simulation methods can also incorporate optimisation based methods as submodules. Examples of these models are NEMS and PRIMES. NEMS is the US Energy Information Administration's National Energy Modelling System, whereas PRIMES covers the EU. These models have been used since the 1990s.

The Annual Energy Outlook is produced by NEMS and is used to inform policy decisions by the US Government. NEMS is made up of a number of submodules that are iteratively solved [71]. Whilst each of the submodules can be implemented in different ways; the model can become complex, and therefore difficult to understand.

PRIMES is also a modular system. An integrating module finds an equilibrium solution for energy supply, demand, cross-border energy trade, and emissions for all European countries [55]. The analysis that PRIMES has provided has formed the basis of the EU's Energy Roadmap 2050 [56].

LEAP (Long-range Energy Alternatives Planning System) is another simulation model and was developed by the Stockholm Environment Institute [182]. LEAP provides an accounting system for supply with annual time-steps, but can also represent demand with a macroeconomic model.

Additionally, there exist a set of power system models which can help with decisions such as investment planning or decisions about generator dispatch. Power system models typically have greater temporal detail, so that supply and demand is always matched. Examples of large power systems models include WASP and PLEXOS.

WASP (Wien Automatic System Planner) is maintained by the International Atomic Energy Agency (IAEA). It is used primarily for generation expansion planning. WASP uses a custom dynamic programming algorithm, and has a horizon of several decades into the future.

PLEXOS is a mixed-integer linear programming model which contains detailed modules for power plants, the transmission grid and for capacity expansion. PLEXOS is able to perform analysis at up to 1-minute resolution, which is good for modelling the balancing of IRES at all times. WASP and PLEXOS are both commercial models, which is a similar case for most commonly used large-scale power system models [164].

ELMOD is a bottom-up electricity market model. It considers the engineering and economic data of the European electricity market, and considers 24-hour windows with an hourly resolution. It is formulated as a non-linear mathematical programming problem, and can be used for applications such as market design or investment decisions.

Agent-based models

In this subsection, we give an outline of current agent-based models available and motivate why the model, ElecSim, is required. Part of the literature review outlined here has been previously published in [122].

Electricity market liberalisation in many western democracies has changed the framework conditions. Centralised, monopolistic, decision making entities have given way to multiple heterogeneous agents acting for their own best interest [152]. Policy options must therefore, be used to encourage changes to attain a desired outcome. It has been proposed that these complex agents are modelled using ABMs due to their non-deterministic nature [122].

A number of ABM tools have emerged over the years to model electricity markets: SEPIA [86], EMCAS [37], NEMSIM [19], AMES [190], GAPEX [35], PowerACE [175], EMLab [32] and MACSEM [169]. Table 3.3 shows, however, that these do not suit the needs of an open source, long-term market model.

There have been a number of recent studies using ABMs which focus on electricity markets. However, they often utilise ad-hoc tools which are designed for a particular application [178, 83, 135]. In our work, we develop the model ElecSim, which has been built for re-use and reproducibility. The survey [204] cites that many of these tools do not release source code or parameters, which is a problem that ElecSim seeks to address by being open source.

Table 3.3 contains six columns: tool name, whether the tool is open source or not, whether they model long-term investment in electricity infrastructure and the markets they model. We determine how the stochasticity of real life is modelled and determine whether the model is generalisable to different countries.

An open-source toolkit is important for reproducibility, transparency and lowering barriers to entry. It enables users to expand the model to their requirements and respective country. The modelling of long-term investment enables scenarios to emerge and enable users to model investment behaviour.

SEPIA [86] is a discrete event ABM which utilises Q-learning to model the bids made by GenCos. SEPIA models plants as being always on and does not have an independent system operator (ISO), which in an electricity market, is an independent non-profit organisation for coordinating and controlling of regular operations of the electric power system and market [216]. SEPIA does not model a spot market, instead focusing on bilateral contracts. As opposed to this, ElecSim has been designed with a merit-order, spot market in mind. As shown in Table 3.3, SEPIA does not include a long-term investment mechanism.

EMCAS [37] is a closed source ABM. EMCAS investigates the interactions between physical infrastructures and economic behaviour of agents. However, ElecSim focuses on the dynamics of the market, and provides a simplified, transparent model of market operation, whilst maintaining the robustness of results.

NEMSIM [82] is an ABM that represents Australia's National Electricity Market (NEM). Participants are able to grow and change over time using learning algorithms. NEMSIM is non-generalisable to other electricity markets, unlike ElecSim.

AMES [190] is an ABM specific to the US Wholesale Power Market Platform and therefore not generalisable for other countries. GAPEX [35] is an ABM framework for modelling and simulating power exchanges. GAPEX utilises an enhanced version of the reinforcement technique Roth-Erev [174] to consider the presence of affine total cost functions. However, neither of these model the long-term dynamics for which ElecSim is designed.

PowerACE [175] is a closed source ABM of electricity markets that integrates short-term daily electricity trading and long-term investment decisions. PowerACE models the spot market, forward market and a carbon market. Similarly to ElecSim, PowerACE initialises GenCos with each of their power plants. However, as can be seen in Table 3.3, unlike ElecSim, PowerACE does not take into account stochasticity of price risks in electricity markets [152].

EMLab [32] is an open-source ABM toolkit for the electricity market. Like PowerACE, EMLab models an endogenous carbon market; however, they both differ from ElecSim by not taking into account stochasticity in the electricity markets, such as in outages, fuel prices and operating costs. After correspondence with the authors, however, we were unable to run the current version.

MACSEM [169] has been used to probe the effects of market rules and conditions by testing different bidding strategies. MACSEM does not model long term investments or stochastic inputs.

As can be seen from Table 3.3, none of the tools fill each of the characteristics we have defined. We therefore propose ElecSim to contribute an open-source, long-term, stochastic investment model.

3.5 Energy models classification

In this Section, we present a high-level overview of the various models that are in existence, which fall into various categories as presented by table 3.2. Table 3.4 shows the various models and their analytical approach, underlying methodology, mathematical approach and other information such as sectoral coverage, time horizon and number of time-steps. This list is not exhaustive, however, as we have focused on the major models.

3.6 Conclusion

In this Chapter, we have introduced various electricity market models and the categories that they fall into. However, it can prove to be challenging to place models within a clear boundary,

Tool name	**Open Source**	**Long-Term Investment**	**Market**	**Stochastic Inputs**	**Country Generalisability**
SEPIA [86]	✓	×	✓	Demand	✓
EMCAS [37]	×	✓	✓	Outages	✓
NEMSIM [19]	?	✓	✓	×	×
AMES [190]	✓	×	Day-ahead	×	×
GAPEX [35]	?	×	Day-ahead	×	✓
PowerACE [175]	×	✓	✓	Outages Demand	✓
EMLab [32]	✓	✓	Futures	×	✓
MACSEM [169]	?	×	✓	×	✓
ElecSim [122]	✓	✓	Futures	✓	✓

Table 3.3 Features of electricity market agent-based models.

Model	Analytical approach	Underlying methodology	Mathematical approach	Sectoral coverage	Time horizon	Time step
E3MG	Hybrid	Non-equilibrium	Unknown	Energy-environment-economy	2100	Annually until 2030 and then each decade until 2100
LEAP	Hybrid	Accounting model	Not available	All sectors	Medium and long-term	Annual
MARKAL	Bottom-up	Optimisation	Linear programming, dynamic programming	Energy sector only	Medium and long-term	User-defined
MARKAL-MACRO	Hybrid	Macro-economic for MACRO, optimisation for MARKAL	Non-linear dynamic programming	All sectors	Medium and long-term	User-defined
NEMS	Hybrid	Optimisation, agent-based, simulation	Partial equilibrium and linear programming	Energy system	Medium (25 years)	Yearly
OSeMOSYS	Bottom-up	Optimisation	Linear programming and mixed integer programming	Energy sector	Medium and long-term (2010-2050)	5-year
PRIMES	Hybrid	Agent-based	Equilibrium model	All energy sectors	Medium to long-term	Yearly
POLES	Hybrid	Optimisation and simulation	Partial equilibrium	15 energy demand sectors	Long-term (up to 2050)	Yearly
TIMES	Bottom-up	Optimisation	Linear programming and dynamic programming	Whole energy sector	Medium and long-term	User-chosen time-slices
WASP	Bottom-up	Optimisation, simulation	Linear programming and dynamic programming	Power sector	Medium and long-term	12 load duration curves per year
MESSAGE	Bottom-up	Optimisation	Dynamic programming	Energy sector	Short, medium and long-term	User-defined (Multiple of number of years)
PLEXOS	Bottom-up	Optimisation	Linear programming	Electricity sector	Short-term	1-minute
ELMOD	Bottom-up	Optimisation	Non-linear programming	Electricity sector	Short-term	Hourly
ElecSim	Bottom-up	Agent-based model	Simulation	Electricity market	Short, medium and long-term	Hourly

Table 3.4 Model schema and presentation of various energy models [84]

as many models fall within a continuous spectrum. We introduced the concept that traditional models may not have the ability to detail every single component of an electricity market without losing tractability.

The need for a new paradigm in which decentralised agents act within an environment was discussed. So was the need for a model with high temporal resolution to more accurately model the intermittency of renewable energy. Traditional optimisation models work in a normative, prescriptive way. However, it is not possible to describe a system which is out of equilibrium. Another limitation of the traditional optimisation models is that they assume perfect foresight, with risk-neutral investments and no regulatory uncertainty. It assumes that certain scenarios are possible, but does not highlight the way a target may not be reached.

It is for these reasons that in this thesis, we focus on agent-based models, which move away from the traditional optimisation approach, and allow for a more dynamic solution without rigid mathematical expressions.

Additionally, we found that there was a gap in the literature for an open-source agent-based model that could model long-term investments, was generalisable to many countries ad modelled stochastic inputs. It is for this reason that we developed the model ElecSim.

Chapter 4

ElecSim model

Prologue

In this Chapter we motivate and introduce the agent-based model, ElecSim. The majority of the work presented here was published in [122] and [127]. The contribution of this Chapter is a new open-source framework for the long-term modelling of electricity markets. We provide curated data, improve realism with Monte-Carlo sampling, and validate our model using genetic algorithm based optimisation. We validate our model between 2013 and 2018, as well as compare our model using the UK Government's baseline scenario. We provide a sensitivity analysis of important variables.

We introduce our work in Section 4.1, including why a simulation model is required to aid in a low carbon transition. We provide a literature review of work done to validate energy models in Section 4.2. The architecture of the model is presented in 4.3. The model is validated in Section 4.4. Various scenarios are presented in Section 4.5, where we vary demand until 2035. A sensitivity analysis is provided in 4.6, where we vary the weighted average cost of capital, as well as the down payment required for investments. Finally, we present the limitations of our model in Section 4.7 and conclude our work in Section 4.8.

4.1 Introduction and Motivation

4.1.1 Transition to a low-carbon energy supply

Global carbon emissions from fossil fuels have significantly increased since 1900 [23]. Fossil-fuel based electricity generation sources such as coal and natural gas currently provide 65% of global electricity. Low-carbon sources such as solar, wind, hydro and nuclear provide 35% [26]. To halt this increase in CO_2 emissions, a transition of the energy system towards a renewable energy system is required.

Such a transition needs to be performed in a safe and non-disruptive manner – it may be possible to close down all fossil fuel plants in the next year, though if this leads to electricity shortages and power cuts then this is likely to cause significant problems both for industry and consumers. Therefore a stepped approach which allows seamless transfer is desirable. This may seem a simple process to achieve – slowly phase out existing fossil fuel generators and replace these by renewable sources – however, there are many risks and uncertainties in this process. Existing power plants have an expected lifetime and their owners wish to maximise this and the profits which can be made from them, renewable sources are still developing – meaning that their efficiency and reliability will change in years to come.

Due to the long construction times, operating periods and high costs of power plants, investment decisions can have long term impacts on future electricity supply [32]. Governments and society, therefore, have a role in ensuring that the negative externalities of emissions are priced into electricity generation. This is most likely to be achieved via a carbon tax and regulation to influence electricity market players such as Generation Companies (GenCos).

Decisions made in an electricity markets may have unintended consequences due to their complexity. A method to test hypothesise before they are implemented would therefore be useful.

To aid in such a transition, energy modelling can be used by governments, industry and agencies to explore possible scenarios under different variants of government policy, future electricity generation costs and energy demand. These energy modelling tools aim to mimic the behaviour of energy systems through different sets of equations and data sets to determine the energy interactions between different actors and the economy [146].

4.1.2 ElecSim: Modelling and simulation

Live experimentation of physical processes is not often practical. The costs of real life experimentation can be prohibitively high, and can require a significant amount of time in order to fully ascertain the long-term trends. There is also a risk that changes can have detrimental impacts and lead to risk-averse behaviour. These factors are true for electricity markets, where decisions can have long term impacts. Simulation, however, can be used for rapidly prototyping ideas. The simulation is parametrised by real world data and phenomena. Through simulation, the user is able to assess the likelihoods of outcomes under certain scenarios and parameters [136].

Simulation is often used to increase understanding as well as to reduce risk and reduce uncertainty. Simulation allows practitioners to realise a physical system in a virtual model. In this context, a model is defined as an approximation of a system through the use of mathematical formulas and algorithms. Through simulation, it is possible to test a system where real life experimentation would not be practical due to reasons such as prohibitively high costs, time constraints or risk of detrimental impacts. This has the dual benefit of minimising the risk of real decisions in the physical system, as well as allowing practitioners to test less risk-averse strategies.

Agent Based Models (ABMs) are a class of computational simulation models composed of autonomous, interacting agents and model the dynamics of a system. Due to the numerous and diverse actors involved in electricity markets, ABMs have been utilised in this field to address phenomena such as market power [173].

The work presented in this Chapter develops ElecSim, an open-source ABM that simulates GenCos in a wholesale electricity market. ElecSim models each GenCo as an independent agent and electricity demand. An electricity market facilitates trades between the two.

GenCos make bids for each of their power plants. Their bids are based on the generators short run marginal cost [163], which excludes capital and fixed costs. The electricity market accepts bids in cost order, also known as merit-order dispatch. GenCos invest in power plants based on expected profitability.

ElecSim is designed to provide quantitative advice to policy makers, allowing them to test policy outcomes under different scenarios. They are able to modify a scenario file to realise a scenario of their choice. It can also be used by energy market developers who can test new electricity sources or policy types, enabling the modelling of changing market conditions.

This model can be used by the following players:

- **Policy experts** to test policy outcomes under different scenarios and provide quantitative advice to policy makers. They can provide a simple script defining the policies they wish to use along with the parameters for these polices.

- **Energy market developers** who can use the extensible framework to add such things as new energy sources, policy types, consumer profiles and storage types. Thus allowing ElecSim to adapt to a changing ecosystem.

Optimization based solutions are the dominant approach for analysing energy policy [32]. However, the results of these models should be interpreted in a normative manner. For example, how investment and policy choices should be carried out, under certain assumptions and scenarios. The processes which emerge from an equilibrium model remain a black-box, making it difficult to fully understand the underlying dynamics of the model [32].

In addition to this, optimization models do not allow for endogenous behaviour to emerge from typical market movements, such as investment cycles [32, 79]. By modelling these naturally occurring behaviours, policy can be designed that is robust against movements away from the optimum/equilibrium. Thus, helping policy to become more effective in the real world.

Agent-based models differ from optimization models by the fact that they are able to explore '*what-if*' questions regarding how a sector could develop under different prospective policies, as opposed to determining optimal trajectories. ABMs are particularly pertinent in decentralised electricity markets, where a centralised actor does not dictate investments made within the electricity sector. ABMs have the ability to closely mimic the real world by, for example, modelling irrational agents, in this case Generation Companies (GenCos) with incomplete information in uncertain situations [74].

To further enhance the perfomance of ElecSim, we use representative days to model a year time period. Similarly to Nahmmacher *et al.* we demonstrate how clustering of multiple relevant time series such as electricity demand, solar irradiance and wind speed can reduce computational time by selecting representative days [154]. In this context, representative days are a subset of days that have been chosen due to their ability to approximate the weather and electricity demand in an entire year. Similarly to Nahmacher *et al.* we use a Ward hierarchical clustering algorithm [120], However, we also try a *k*-means clustering approach [65]. We chose the *k*-means clustering approach due to previous success of this technique in clustering time series [124].

4.1.3 Validation of long-term models

There is a desire to validate the ability of energy-models to make long-term predictions. Validation increases confidence in the outputs of a model and leads to an increase in trust amongst the public and policy makers. Energy models, however, are frequently criticised for being insufficiently validated, with the performance of models rarely checked against historical outcomes [20].

In answer to this, we postulate that ABMs can provide accurate information to decision makers in the context of electricity markets. We increase the temporal granularity of the work by Kell *et al.* [122] and use genetic algorithms to tune the model to observed data enabling us to perform validation. This enables us to understand the parameters required to observe certain phenomena, as well as use these fitted parameters to make inferences about the future.

We use a genetic algorithm approach to find an optimal set of price curves predicted by generation companies (GenCos) that adequately model observed investment behaviour in the real-life electricity market in the United Kingdom. Similar techniques can be employed for other countries of various sizes [122].

We measure the accuracy of projections for our improved ABM with those of the UK Government's Department for Business, Energy and Industrial Strategy (BEIS) for the UK electricity market between 2013 and 2018. In addition to this, we compare our projections from 2018 to 2035 to those made by BEIS in 2018 [50].

4.1.4 Results

Through this validation process, we are able to adequately model the transitional dynamics of the electricity mix in the United Kingdom between 2013 and 2018. During this time there was an $\sim$88% drop in coal use, $\sim$44% increase in Combined Cycle Gas Turbines (CCGT), $\sim$111% increase in wind energy and increase in solar from near zero to $\sim$1250MW. We are therefore able to test our model in a transition of sufficient magnitude.

We show in this Chapter, that agent-based models are able to mimic the behaviour of the UK electricity market under the same specific scenario conditions. Concretely, we show that under an observed carbon tax strategy, fuel price and electricity demand scenario, the model, ElecSim, closely matches the observed electricity mix between 2013 and 2018. We achieve this by determining an exogenous predicted price duration curve using a genetic algorithm to minimise error between observed and simulated electricity mix in 2018. The predicted price curve is an arrangement of all price levels in descending order of magnitude. The predicted price duration curve achieved is similar to that of the simulated price duration curve in 2018, increasing confidence in the underlying dynamics of our model.

In addition, we compare our projections to those of the BEIS reference scenario from 2018 to 2035 [50]. To achieve this, we use the same genetic algorithm optimisation technique as during our validation stage, optimising for predicted price duration curves. Our model demonstrates that we are able to closely match the projections of BEIS by finding a set of realistic price duration curves which are subject to investment cycles. Our model, however, exhibits a more realistic step change in nuclear output than that of BEIS. This is because, whilst BEIS projects a gradual increase in nuclear output, our model projects that nuclear output will grow instantaneously at a single point in time as a new nuclear power plant comes online.

This allows us to verify the scenarios of other models, in this case BEIS' reference scenario, by ascertaining whether the optimal parameters required to achieve such scenarios are realistic. In addition to this, we are able to use these parameters to analyse '*what-if*' questions with further accuracy.

4.1.5 Contributions of this Chapter

As part of this work we contribute a validated open-source agent-based model called ElecSim. Whilst we have used the United Kingdom as a use-case for this thesis, ElecSim is able to model decentralised markets of various sizes.

To improve our results, we increased the temporal granularity of the model using a *k*-means clustering approach to select a subset of representative days for wind speed, solar irradiance and electricity demand. This subset of representative days enabled us to approximate an entire year and only required a fraction of the total time-steps that would be necessary to model each day of a year independently. This enabled us to decrease execution time. We show that we are able to provide an accurate framework, through this addition, to allow policy makers, decision makers and the public to explore the effects of policy on investment in electricity generators.

We demonstrate that with a genetic algorithm approach we are able to optimise parameters to improve the accuracy of our model. Namely, we optimise the predicted electricity price, the uncertainty of this electricity price and nuclear subsidy. We validate our model using the observed electricity mix between 2013-2018.

A major contribution of this work is to demonstrate that it is possible for agent-based models to accurately model transitions in the UK electricity market. This was achieved by comparing our simulated electricity mix to the observed electricity mix between 2013 and 2018. In this time a transition from coal to natural gas was observed. We demonstrate that a high temporal granularity is required to accurately model fluctuations in wind and solar irradiance for intermittent renewable energy sources.

4.2 Literature Review

Whilst Chapter 3 provided a review of the literature of models, this section covers the difficulties inherent in validating energy models and the approaches taken in the literature to validate these models..

4.2.1 Limits of Validating Energy Models

Beckman *et al.* state that questions frequently arise as to how much faith one can put in energy model results. This is due to the fact that the performance of these models as a whole are rarely checked against historical outcomes [20].

Under the definition by Hodges *et al.* [95] long-range energy forecasts are not validatable [41]. Under this definition, validatable models must be observable, exhibit constancy of structure in time, exhibit constancy across variations in conditions not specified in the model and it must be possible to collect ample data [95].

Whilst it is possible to collect data for energy models, the data covering important characteristics of energy markets are not always measured. Furthermore, the behaviour of the human population and innovation are neither constant nor entirely predictable. This leads to the fact that static models cannot keep pace with global long-term evolution. Assumptions made by the modeller may be challenged in the form of unpredictable events, such as the oil shock of 1973 [41].

This, however, does not mean that energy-modelling is not useful for providing advice in the present. A model may fail at predicting the long-term future because it has forecast an undesirable event, which led to a pre-emptive change in human behaviour. Thus avoiding the original scenario that was predicted. This could, therefore, be viewed as a success of the model.

Schurr *et al.* argued against predicting too far ahead in energy modelling due to the uncertainties involved [197]. However, they specify that long-term energy forecasting is useful to provide basic information on energy consumption and availability which is helpful in public debate and in guiding policy makers.

Ascher concurs with this view and states that the most significant factor in model accuracy is the time horizon of the forecast; the more distant the forecast target the less accurate the model. This can be due to unforeseen changes in society as a whole [76].

It is for these reasons that we focus on a shorter-term (5-year) horizon window when validating our model. This enables us to have an increased confidence that the dynamics of the model work without external shocks and can provide descriptive advice to stakeholders. However, it must be noted that the UK electricity market exhibited a fundamental transition from natural gas to coal electricity generation during this period, meaning that a simple data-driven modelling approach would not work.

In addition to this short-term cross-validation, we compare our long-term projections to those of BEIS from 2018 to 2035. It is possible that our projections and those of BEIS could be wrong, however, this allows us to thoroughly test a particular scenario with different modelling approaches, and allow for the possibility to identify potential flaws in the models.

4.2.2 Validation Examples

In this section we explore a variety of approaches used in the literature for energy model validation.

The model OSeMOSYS [101] is validated against the similar model MARKAL/TIMES through the use of a case study named UTOPIA. UTOPIA is a simple test energy system bundled with ANSWER, a graphical user interface packaged with the MARKAL model generator [107, 157]. Hunter *et al.* use the same case study to validate their model Temoa [107]. In these cases, MARKAL/TIMES is seen as the "gold standard". In this paper, however, we argue that the ultimate gold standard should be real-world observations, as opposed to a hypothetical scenario.

The model PowerACE demonstrates that realistic prices are achieved by their modelling approach, however, they do not indicate success in modelling GenCo investment over a prolonged time period [172].

Barazza *et al.* validate their model, BRAIN-Energy, by comparing their results with a few years of historical data, however, they do not compare the simulated and observed electricity mix [18].

Work by Koomey *et al.* expresses the importance of conducting retrospective studies to help improve models [133]. In this case, a model can be rerun using historical data in order to determine how much of the error in the original forecast resulted from structural problems in the model itself, or how much of the error was due to incorrect specification of the fundamental drivers of the forecast [133].

A retrospective study published in 2002 by Craig *et al.* focused on the ability of forecasters to accurately predict electricity demand from the 1970s [41]. They found that actual energy usage in 2000 was at the very lowest end of the forecasts, with only a single exception. They found that these forecasts underestimated unmodelled shocks such as the oil crises which led to an increase in energy efficiency.

Hoffman *et al.* also developed a retrospective validation of a predecessor of the current MARKAL/TIMES model, named Reference Energy System [97], and the Brookhaven Energy System Optimization Model [2]. These were studies applied in the 70s and 80s to develop projections to the year 2000. This study found that the models had the ability to be descriptive, but were not entirely accurate in terms of predictive ability. They found that emergent behaviours in response to policy had a strong impact on forecasting accuracy. The study concluded that forecasts must be expressed in highly conditioned terms [96].

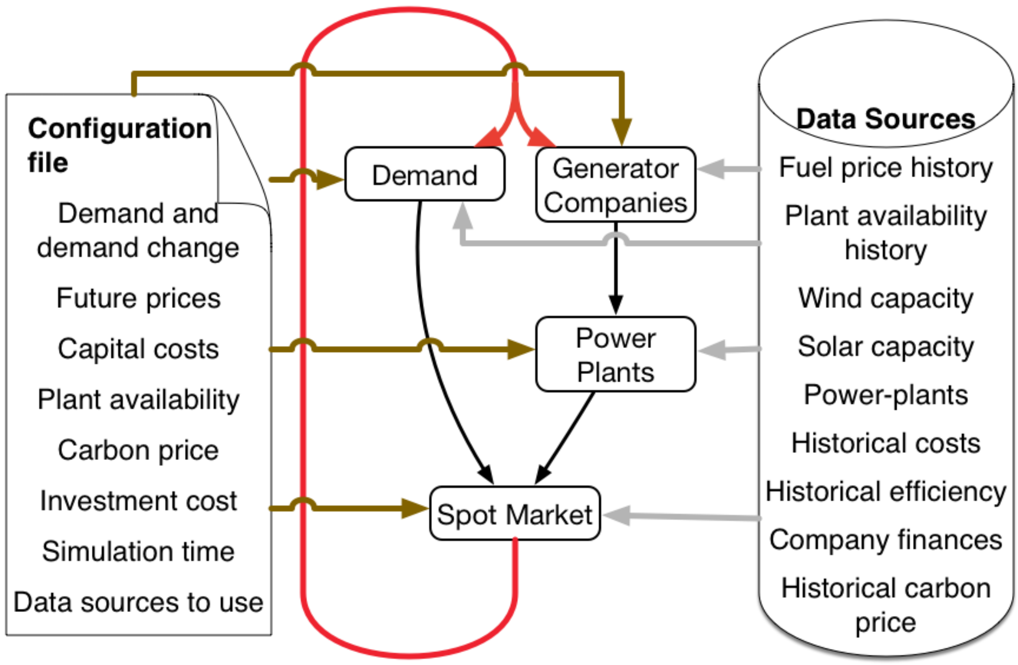


Fig. 4.1 High level overview.

4.3 Architecture

In this section we detail the architecture of how ElecSim has been designed.

ElecSim is made up of six parts: the agents, which are split up into demand and GenCos; power plants; a Power Exchange, which controls an electricity spot market; the time-steps ;and the data for parametrisation. A schematic of ElecSim is displayed in Figure 4.1.

Data parametrisation. ElecSim contains a configuration file and a collection of data sources for parametrisation. These data sources contain information such as historical fuel prices, historical plant availability, wind and solar capacity.

The configuration file allows for rapid changes to test different hypothesis and scenarios, and points to the different data sources. The configuration file enables one to change the demand growth and shape, future fuel and carbon prices, capital costs, plant availability, investment costs and simulation time.

Demand Agent. The demand agent is a simplified representation of aggregated demand in a country. The demand is represented as a load duration curve (LDC). An example load duration curve for a year is demonstrated in Figure 4.2. An LDC is an arrangement of all load levels in descending order of magnitude. where the lowest segment demand demonstrates baseload, and the highest segment represents peak demand. Each year, the demand agent changes each of the LDC segments proportionally.

Generation Company Agents. The GenCos have two main functions. Investing in power plants and making bids to sell their generation capacity. We will first focus on the buying and selling of electricity, and then cover the investment algorithm.

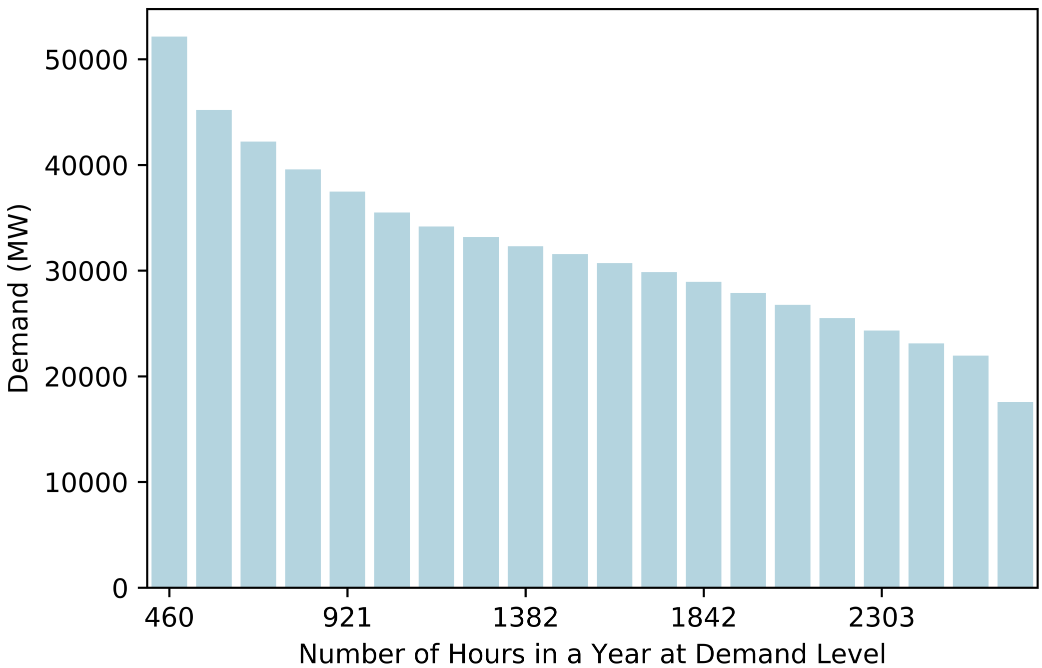


Fig. 4.2 Example load duration curve in a single year.

The power exchange runs every year, accepting the lowest bids until supply meets demand. Once this condition is met, the spot price or system marginal price (SMP) is paid to all generators regardless of their initial bid. Generators are motivated to bid their SRMC, to ensure that their generator is being utilised, and reduce the risk of overbidding.

Investment. Investment in power plants is made based upon a net present value (NPV) calculation. NPV is a summation of the present value of a series of present and future cash flow. NPV provides a method for evaluating and comparing investments with cash flows spread over many years, making it suited for evaluating power plants which have a long lifetime.

Equation 4.1 is the calculation of NPV, where t is the year of the cash flow, i is the discount rate, N is total number of periods, or lifetime of power plant, and R_t is the net cash flow at time t.

$$NPV(t,N) = \sum_{t=0}^{N} \frac{R_t}{(1+t)^t} \tag{4.1}$$

A discount rate set by a GenCo's weighted average cost of capital (WACC) is often used [131]. WACC is the rate that a company is expected to pay on average for its stock and debt. Therefore to achieve a positive NPV, an income larger than the WACC is required. However, a higher WACC is often selected to adjust for varying risk profiles, opportunity costs and rates of return. To account for these differences we sample from a Gaussian distribution, giving us sufficient variance whilst deviating from the expected price.

To calculate the NPV, future market conditions must be considered. For this, each GenCo forecasts N years into the future, which we assume is representative of the lifetime of the plant.

As in the real world, GenCos have imperfect information, and therefore must forecast expected demand, fuel prices, carbon price and electricity sale price. This is achieved by fitting functions to historical data. Each GenCo is different in that they will use differing historical time periods of data for forecasting.

Fuel and carbon price are forecast using linear regression. Demand, however, is forecast using an exponential function, which considers compounded growth. Linear regression is used if an exponential function is found to be sub-optimal.

The forecasted electricity price N years ahead is difficult to ascertain accurately. We therefore use two methods for forecasting these. The first is to simulate a market N years ahead. The second is to optimise for the predicted PDC using a genetic algorithm. We describe this optimisation in Section **??**.

For the simulated market, the forecasted data is used to simulate a market N years into the future using the electricity market algorithm. We simulate a market based on the expected bids – based on SRMC – that every operating power plant will make. This includes the removal of plants that will be past their operating period, and the introduction of plants that are in construction or pre-development stages.

There may be scenarios where demand is forecast to grow significantly, and limited investments have yet been made to meet that demand. The expected price, would be that of lost load. Lost load is defined as the price customers would be willing to pay to avoid disruption in their electricity supply. To avoid GenCos from estimating large profits, and under the assumption that further power plant investments will be made, the lost load price is replaced with a predicted electricity price using linear regression based on prices at lower points of the demand curve. If zero segments of demand are met, then the lost load price is used to encourage investment.

Once this data has been forecasted, the NPV can be calculated. GenCos must typically provide a certain percentage of upfront capital, with the rest coming from investors in the form of stock and shares or debt (WACC). The percentage of upfront capital can be customised by the user in the configuration file. The GenCos then invest in the power plants with the highest NPV.

Time-steps For the time-steps, two approaches were taken. For the first approach, as per Chappin *et al.* [32], we modelled the LDC of electricity demand with twenty segments. Twenty segments enabled us to capture the variation in demand throughout the year to a high degree of accuracy, whilst reducing computational complexity. However, as we show later in Section 4.5, this led to an overestimation of the supply of IRES.

For the second approach, we used representative days to model a year. Representative days in this context are a subset of days which have characteristics, that when scaled proportionally can accurately model an entire year. To select these representative days we used a k-means approach. We describe this in full detail in Section 4.3.1

Power Plant Parameters. Costs form an important element of markets and investment, and publicly available data for power plant costs for individual countries can be scarce. Thus, extrapolation and interpolation is required to estimate costs for power plants of differing sizes, types and years of construction.

Users are able to initialise costs relevant to their particular country by providing detailed cost parameters. They can also provide an average cost per MWh produced over the lifetime of a plant, known as levelised cost of electricity (LCOE).

The parameters used to initialise the power plants are detailed in this section. Periods have units of years and costs in £/MW unless otherwise stated: Efficiency (η) is defined as the percentage of energy from fuel that is converted into electrical energy (%). Operating period (OP) is the total period in which a power plant is in operation. Pre-development period (P_D) and pre-development costs (P_C) include the time and costs for pre-licensing, technical and design, as well as costs incurred due to regulatory, licensing and public enquiry. The construction period (C_D) and construction costs (C_C) are incurred during the development of the plant, excluding network connections. The infrastructure costs (I_C) are the costs incurred by the developer in connecting the plant to the electricity or gas grid (£). Fixed operation & maintenance costs (F_C) are costs incurred in operating the plant that do not vary based on output. Variable operation & maintenance (V_C) costs are incurred in operating the plant that depend on generator output [141].

Precise data is not available for every plant size. Linear interpolation is used to estimate individual prices between known points. When the plant to be estimated falls outside of the range of known data points, the closest power plant is used. We experimented with extrapolation but this would often lead to unrealistic costs.

If specific parameters are not known, the LCOE can be used for parameter estimation, through the use of linear optimisation. Constraints can be set by the user, enabling, for example, varying operation and maintenance costs per country as a fraction of LCOE.

To fully parametrise power plants, availability and capacity factors are required. Availability is the percentage of time that a power plant can produce electricity. This can be reduced by forced or planned outages. We integrate historical data to model improvements in reliability over time.

The capacity factor is the actual electrical energy produced over a given time period divided by the maximum possible electrical energy it could have produced. The capacity factor can be impacted by regulatory constraints, market forces and resource availability. For example, higher capacity factors are common for photovoltaics in the summer, and lower in winter.

To model the intermittency of wind and solar power we allow them to contribute only a certain percentage of their total capacity (nameplate capacity) for each load segment. This percentage is based upon empirical wind and solar capacity factors. In this calculation we consider the correlation between demand and renewable resources.

When initialised, V_C is selected from a uniform distribution, with the ability for the user to set maximum percentage increase or decrease. A uniform distribution was chosen to capture the large deviations that can occur in V_C, especially over a long time period.

Fuel price is controlled by the user, however, there is inherent volatility in fuel price. To take into account this variability, an ARIMA [207] model was fit to historical gas and coal price data. The standard deviation of the residuals was used to model the variance in price that a GenCo will buy fuel in a given year. This considers differences in chance and hedging strategies.

Figure 4.3 demonstrates the simulation and how it co-ordinates runs. The world contains data and brings together GenCos, the Power Exchange and demand. The investment decisions are based on future demand and costs, which in turn influence bids made.

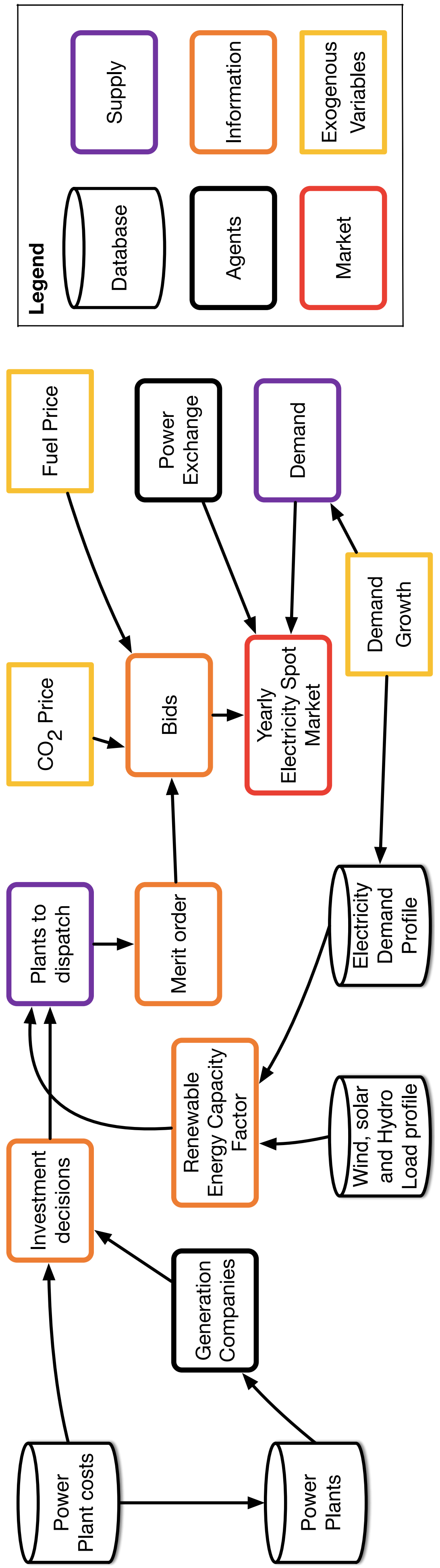


Fig. 4.3 ElecSim simulation overview

Exogenous variables include fuel and CO_2 prices as well as demand growth. Once the data is initialised, the world calls on the Power Exchange to operate the yearly electricity spot market. The world also settles the accounts of the GenCos, by paying bids, and removing operating and capital costs as well as loans and dividends.

We initialise the United Kingdom with our model with exemplar data from the UK. We model every single power plant in operation in the year 2018, which are owned by their respective generation companies. Individual historical power plant costs are estimated from levelized cost of electricity (LCOE) [44, 111, 115], whereas future and present power plant costs are taken from the department of business and industrial strategy [49]. The variable operation and maintenance cost was defined stochastically to model the varying costs per project. A uniform distribution was chosen to provide sufficient variance between projects.

The demand agent is modelled as a single aggregated demand, split up into 20 segments of a yearly load duration curve (LDC), enabling us to increase speed of computation whilst maintaining accuracy. An LDC is defined as load sorted in order of magnitude.

We model the influence of outages using availability data for gas, coal, photovoltaic, and wind power generators [141, 106, 30]. Historical availabilities are modelled for old gas, coal and hydro power plants [11]. Capacity factors per geographical location were taken as an average of the UK for solar and wind [166, 189]. Where a capacity factor is defined as the ratio of electrical output over a given time period over the maximum possible electrical energy output.

The generation companies make electricity bids each year for each of their power plants. The market operator then matches demand with supply in order of price, also known as merit-order dispatch. We model a uniform pricing market, where each of the companies are paid the highest accepted bid per load segment.

GenCos have the ability to invest every year in new power plants based on the expected net present value (NPV) of each type of power plant. NPV is a summation of the present value of a series of present and future cash flow. The NPV calculation is dependent on a stochastic representation of GenCos predictions of fuel, carbon and electricity price and demand.

Each GenCo has a separate weighted average cost of capital (WACC), which is the average rate that a company is expected to for its stock and debt. This is used as the discount rate in the NPV calculation [131]. The WACC is modelled as a stochastic variable, with a Gaussian distribution, with a $\pm 3\%$ standard deviation, with values of 5.9% for non-nuclear power plants, and 10% for nuclear power plants [134, 161].

Stochasticity of fuel price within a year was also modelled, to take into account difference in hedging strategies and chance. An ARIMA model [207] was fit to historic coal and natural gas prices.

4.3.1 Representative days

In this subsection we describe how we decide the granularity of time-steps. Specifically, we use representative days. Representative days, in this context, are a subset of days which when scaled up to 365 days can adequately represent a year.

In this paper, we initialised the model to a scenario of the United Kingdom as an example, however, the fundamental dynamics of the model remain the same for other decentralised electricity markets.

Similarly to findings of other authors, using a relatively low number of time-steps leads to an overestimation of the uptake of intermittent renewable energy resources (IRES) and an underestimation of flexible technologies [143, 87]. This is due to the fact that the full intermittent nature of renewable energy could not be accurately modelled in such a small number of time-steps.

To address this problem, whilst maintaining a tractable execution time, we approximated a single year as a subset of proportionally weighted, representative days. This enabled us to reduce computation time. Each representative day consisted of 24 equally separated time-steps, which model hours in a day. Hourly data was chosen, as this was the highest resolution of the dataset available for offshore and onshore wind and solar irradiance [166]. A lower resolution would allow us to model more days, however, we would lose accuracy in terms of the variability of the renewable energy sources.

Similarly to Nahmmacher *et al.* we used a clustering technique to split similar days of weather and electricity demand into separate groups. We then selected the historic day that was closest to the centre of the cluster, known as the medoid, as well as the average of the centre, known as the centroid [154]. Similarly to Nahmmacher, we used Ward's clustering algorithm and selected the centroid [120]. However, we also used the k-means clustering algorithm [65]. This was due to the ability for the k-means algorithm to cluster time-series into relevant groups [125]. These days were scaled proportionally to the number of days within their respective cluster to approximate a total of 365 days. The Ward's clustering algorithm is an extension of the work published in [127]

Equation 4.2 shows the series for a medoid or centroid, selected by the clustering algorithms:

$$P_h^{x,i} = \{P_1, P_2, \ldots, P_{24}\} \tag{4.2}$$

where $P_h^{x,i}$ is the medoid for series x, where $x \in X$ refers to offshore wind capacity factor, onshore wind capacity factor, solar capacity factor and electricity demand, h is the hour of the day and i is the respective cluster. $\{P_1, P_2, \ldots, P_{24}\}$ refers to the capacity values at each hour of the representative day.

We then calculated the weight of each cluster. This gave us a method of assigning the relative importance of each representative day when scaling the representative days up to a year. The weight is calculated by the proportion of days in each cluster. This gives us a method of determining how many days within a year are similar to the selected medoid or centroid. The calculation for the weight of each cluster is shown by Equation 4.3:

$$w_i = \frac{n_i}{||N||} \tag{4.3}$$

where w_i is the weight of cluster i, n_i is the number of days in cluster i, and $||N||$ is the total number of days that have been used for clustering.

The next step was to scale up the representative days to represent the duration curve of a full year. We achieved this by using the weight of each cluster, w_i, to increase the number of hours that each capacity factor contributed in a full year. Equation 4.4 details the scaling process to turn the medoid or centroid, shown in Equation 4.2, into a scaled day. Where $\widetilde{P}_h^{x,i}$ is the scaled day:

$$\widetilde{P}_h^{x,i} = \{P_{1w_i}, P_{2w_i}, \ldots, P_{24w_i}\} \tag{4.4}$$

Equation 4.4 effectively extends the length of the day proportional to the amount of days in the respective cluster.

Finally, each of the scaled representative days were concatenated to create the series used for the calculations which required the capacity factors and the respective number of hours that each capacity factor contributed to the year. Equation 4.5 displays the total time series for series x, where each scaled medoid is concatenated to produce an approximated time series, $\widetilde{P}^x$:

$$\widetilde{P}^x = \left(\widetilde{P}_h^{x,1}, \widetilde{P}_h^{x,2}, \ldots, \widetilde{P}_h^{x,||N||}\right) \tag{4.5}$$

the total number of hours in the approximated time series, $\widetilde{P}^x$, is equal to the number of hours in a day multiplied by the number of days in a year, which gives the total number of hours in a year ($24 \times 365 = 8760$), as shown by Equation **??**:

$$\sum_{w \in W} \sum_{t=1}^{T=24} (w_i t) = 24 \times 365 = 8760 \tag{4.6}$$

where $w \in W$ is the set of clusters.

4.3.2 Error Metrics

To measure the validity of our approximation using representative days and also compare the optimum number of days, or clusters, we used a technique similar to Poncelet *et al.* [52, 167]. We trialled the number of clusters against three different metrics: correlation (CE_{av}), normalised root mean squared error ($nRMSE$) and relative energy error (REE_{av}).

REE_{av} is the average value over all the considered time series $\widetilde{P}^x \in \widetilde{P}$ compared to the observed average value of the set $P^x \in P$. Where $P^x \in P$ are the observed time series and $\widetilde{P}^x \in \widetilde{P}$ are the scaled, approximated time series using representative days. REE_{av} is shown formally by Equation 4.7:

$$REE_{av} = \frac{\sum_{P^x \in P} \left(\left| \frac{\sum_{t \in T} DC_{P_t^x} - \sum_{t \in T} \widetilde{DC}_{\widetilde{P}_t^x}}{\sum_{t \in T} DC_{P_t^x}} \right| \right)}{||P||} \tag{4.7}$$

where $DC_{P_t^x}$ is the duration curve for P^x and $DC_{\widetilde{P}_t^x}$ is the duration curve for $\widetilde{P}^x$. In this context, the duration curve can be constructed by sorting the capacity factor and electrical load data from high to low. The $x-$axis for the DC exhibits the proportion of time that each capacity factor represents. The approximation of the duration curve is represented in this text as $\widetilde{DC}_{\widetilde{P}^x}$.

$t \in T$ refers to a specific time step of the original time series. $\widetilde{DC}$ refers to the approximated duration curve for $\widetilde{P}^x$. Note that in this text $|\cdot|$ refers to the absolute value, and $||\cdot||$ refers to the cardinality of a set and $||P||$ refers to the total number of of considered time series.

Specifically, the sum of the observed values, P^x, and approximated values, $\widetilde{P}^x$, for all of the time series are summed. The proportional difference is found, which is summed for each of the different series, x, and divided by the number of series, to give REE_{av}.

Another requirement is for the distribution of load and capacity factors for the approximated series to correspond to the observed time series. It is crucial that we can account for both high and low levels of demand and capacity factor for IRES generation. This enables us to model for times where flexible generation capacity is required.

The distribution of values can be represented by the duration curve (DC) of the time series. Therefore, the average normalised root-mean-square error ($NRMSE_{av}$) between each DC is used as an additional metric. The $NRMSE_{av}$ is shown formally by Equation 4.8:

$$NRMSE_{av} = \frac{\sum_{P^x \in P} \left(\frac{\sqrt{\frac{1}{||T||} \cdot \sum_{t \in T} (DC_{P^x_t} - \widetilde{DC}_{\widetilde{P}^x_t})^2}}{max(DC_{P^x}) - min(DC_{P^x})} \right)}{||P||}. \tag{4.8}$$

Specifically, the difference between the approximated and observed duration curves for each time-step t is calculated. The average value is then taken of these differences. This average value is then normalised for the respective time series P^x. The average of these average normalised values for each time series are then taken to provide a single metric, $NRMSE_{av}$.

The final metric used is the correlation between the different time series. This is used due to the fact that wind and solar output influences the load within a single region, solar and wind output are correlated, as well as offshore and onshore wind levels within the UK. This is referred to as the average correlation error (CE_{av}) and shown formally by Equation 4.9:

$$CE_{av} = \frac{2}{||P|| \cdot (||P|| - 1)} \cdot \left(\sum_{p_i \in P} \sum_{p_j \in P, j > i} \left| corr_{p_i, p_j} - \widetilde{corr}_{p_i, p_j} \right| \right) \tag{4.9}$$

where $corr_{p1,p2}$ is the Pearson correlation coefficient between two time series $p_1, p_2 \in P$, shown by Equation 4.10. Here, $V_{p1,t}$ represents the value of time series p_1 at time step t:

$$corr_{p1,p2} = \frac{\sum_{t \in T} \left(\left(V_{p1,t} - \overline{V}_{p1}\right) \cdot \left(V_{p2,t} - \overline{V}_{p2}\right) \right)}{\sqrt{\sum_{t \in T} \left(V_{p_1,t} - \overline{V}_{p1}\right)^2 \cdot \sum_{t \in T} \left(V_{p2,t} - \overline{V}_{p2}\right)^2}}. \tag{4.10}$$

Integrating higher temporal granularity

To integrate the additional temporal granularity of the model, extra time-steps were taken per year. The higher temporal granularity of the model enabled us to accurately model the hourly fluctuations in solar and wind which leads to more accurate expectations of the investment opportunities of these technologies [143, 87].

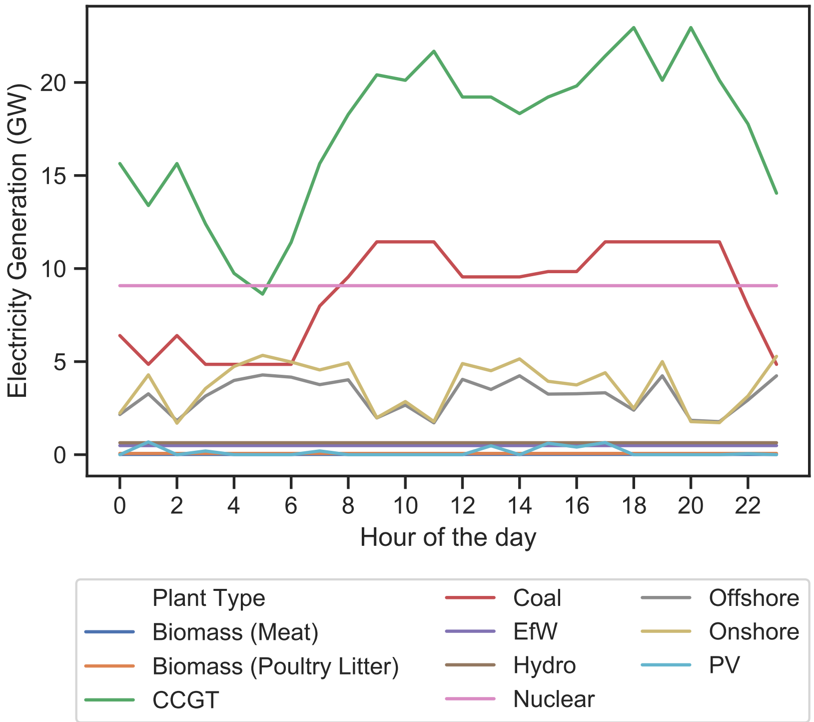


Fig. 4.4 Example of a single day of dispatched supply.

GenCos make bids at the beginning of every time-step and the Power Exchange matches demand with supply in merit-order dispatch using a uniform pricing market. An example of electricity mix in a single representative day is shown in Figure 4.4.

Figure 4.4 displays the high utilization of low marginal-cost generators such as nuclear, wind and photovoltaics. At hour 19, an increase in offshore wind leads to a direct decrease in CCGT. In contrast to this, a decrease in offshore and onshore between the hours of 8 and 12 lead to an increase in dispatch of coal and CCGT. One would expect this behaviour to prevent blackouts and meet demand at all times. This process has enabled us to more closely match fluctuations in IRES.

Evaluation of representative days

Figure 4.5 displays the error metrics versus number of clusters. Both CE_{av} and $NRMSE_{av}$ display similar behaviour for the k-means approach (centroids and medoids), namely the error improves significantly from a single cluster to eight clusters for both centroids and medoids. For the number of clusters greater than eight there are diminishing returns. For REE_{av}, however, the error metric is best at a single cluster, and gets worse with the number of clusters. The Wards approach, however, performs significantly worse for all metrics at every number of clusters.

We chose eight clusters, for centroids and medoids, as a compromise between accuracy of the three error metrics and compute time of the simulation. This is because, eight was the largest number of clusters that gave us the lowest score for CE_{av}, $NRMSE_{av}$ and REE_{av} without significantly increasing compute time. Whilst there was little significant difference between

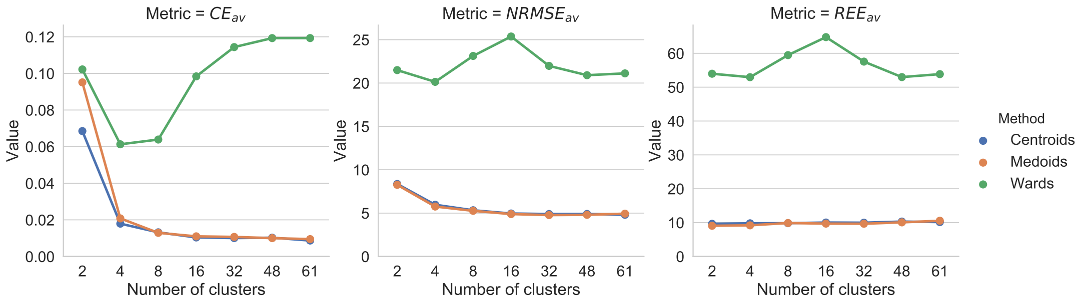


Fig. 4.5 Number of clusters compared to error metrics.

centroid and medoid, we chose to use the medoids due to the fact that the extreme high and low values would not be lost due to averaging [90].

4.4 Validation and performance

In this section we detail the validation approaches taken in our model. For this, we take two approaches. One is to compare the price duration curve of the actual vs. our simulated price duration curve in 2018 using the 20 time-steps per year approach. The other is to use cross-validation between the years 2013 and 2018, using our representative days approach.

4.4.1 Price Duration Curve Validation

Validation of models is important to ascertain that the output is accurate. However, it should be noted that these long-term simulations are not predictions of the future, rather possible outcomes based upon certain assumptions. Jager posits that a certain outcome or development path, captured by empirical data, might have developed in a completely different direction due to chance. However, the processes that emerge from a model should be realistic and in keeping with expected behaviour [117].

We begin by comparing the price duration curve in the year 2018. Figure 4.6 shows the N2EX Day Ahead Auction Prices of the UK [80], the Monte-Carlo simulated electricity prices, and the non Monte-Carlo electricity price throughout the year 2018. Fuel prices varying throughout a year, as does V_C and WACC. WACC is sampled from a Gaussian distribution with a standard deviation of $\pm 3\%$. V_C is sampled from a uniform distribution between 30% and 200% of the mean V_C price, whilst fuel price is sampled from the residuals of an ARIMA model fit on historical data. The N2EX Day Ahead Market is a day ahead market run by Nord Pool AS. Nord Pool AS runs the largest market for electrical energy in Europe, measured in volume traded and in market share [80].

We ran the initialisation of the model 40 times to capture the price variance. Outliers were removed as on a small number of occasions large jumps in prices at peak demand occurred which deviated from the mean. We did this, as although this does occur in real life, it occurs at a smaller fraction of the time than 5% of the year (twenty time-steps per year), therefore the results would be unreasonably skewed for the highest demand segment.

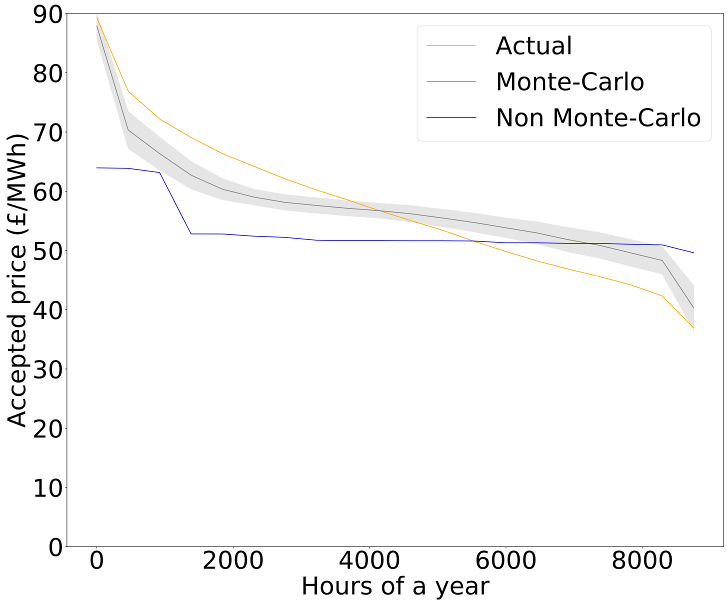


Fig. 4.6 Price duration curve which compares real electricity prices to those paid in ElecSim (2018).

Metric	N2EX Day Ahead	ElecSim	Non Monte-Carlo
Avg. Price (£/MWh)	57.49	57.52	53.39
Std. dev (£/MWh)	-	9.64	-
MAE (£/MWh)	-	3.97	8.35
RMSE (£/MWh)	-	4.41	10.2

Table 4.1 Validation performance metrics.

Figure 4.6 demonstrates very little variance in the non-stochastic case. This is due to the fact that combined cycle gas turbines (CCGTs) set the spot price. These CCGTs have little variance between one another as they were calibrated using the same dataset. By adding stochasticity of fuel prices and operation and maintenance prices, a curve that more closely resembles the actual data occurs. The stochastic curve, however, does not perfectly fit the real data, which may be due to higher variance in fuel prices and historical differences in operation and maintenance costs between power plants. One method of improving this would be fitting the data used to parametrise to the curve.

Table 4.1 shows performance metrics of the stochastic and non-stochastic runs versus the actual price duration curve . The stochastic implementation, improves the mean absolute error (MAE) of the non-stochastic case by 52.5%.

4.4.2 Representative days validation

In this section we detail the approach taken in this paper to validate our model using representative days as time-steps.

To achieve this, we use a genetic algorithm to find the predicted price duration curves which lead to the smallest error between our simulated electricity mix and the scenarios tested. The scenarios examined here are the observed electricity mix of the UK between 2013 and 2018 and the BEIS reference scenario projected in 2018 till 2035. When projecting the BEIS reference scenario we also optimise for nuclear subsidy and uncertainty in the price duration curves.

As mentioned in Section 4.3, GenCos make investments based upon the net present value. As shown in Equation 4.1, an expectation of the net cash flow, R_t is required.

The net cash flow, R_t, is calculated by subtracting both the operational and capital costs from revenue over the expected lifetime of the prospective plant. The revenue gained by each prospective plant is the expected price they will gain per expected quantity of MWh sold over the expected lifetime of the plant. This is shown formally in Equation 4.11:

$$R_t = \sum_{t=0}^{T} \sum_{h=0}^{H} \sum_{m=0}^{M} \left(m_{h,t} (PPDC_{h,t} - C_{var_{h,t}}) \right) - C_c \tag{4.11}$$

where $m_{h,t}$ is the expected quantity of megawatts sold in hour h of year t. $PPDC_{h,t}$ is the predicted price duration curve at year t and hour h. $C_{var_{h,t}}$ is the variable cost of the power plant, which is dependent on expected megawatts of electricity produced, C_c is the capital cost.

The predicted price duration curve ($PPDC_{h,t}$) is an expectation of future electricity prices over the lifetime of the plant. The $PPDC_{h,t}$ is a function of supply and demand. However, with renewable electricity generator costs falling, future prices are uncertain and largely dependent upon long-term scenarios of electricity generator costs, fuel prices, carbon taxes and investment decisions. [114]. Due to the uncertainty of future electricity prices over the horizon of the lifetime of a power plant we have set future electricity prices as an exogenous variable that can be set by the user in ElecSim.

To gain an understanding of expected electricity prices that lead to particular scenarios we use a genetic algorithm optimisation approach. This enables us to understand the range of future electricity prices that lead to certain scenarios developing. In addition, it allows us to understand whether the parameters required for certain scenarios to develop are realistic. This enables us to check the assumptions of our model and the likelihood of scenarios. Further, using these optimised parameters, we are better able to further explore '*what-if*' scenarios.

To verify the accuracy of the underlying dynamics of ElecSim, the model was initialised to data available in 2013 and allowed to develop until 2018. We used a genetic algorithm to find the optimum price duration curve predicted (*PPDC*) by the GenCos 10 years ahead of the year of the simulation. This *PPDC* was used to model expected rate of return of prospective generation types, as shown in Equations **??** and 4.11.

The genetic algorithm's objective was to reduce the error of simulated and observed electricity mix in the year 2018 by finding a suitable *PPDC* used by each of the GenCos for investment evaluation.

Scenario

For this experiment, we initialised ElecSim with parameters known in 2013 for the UK. ElecSim was initialised with every power plant and respective GenCo that was in operation in 2013 using the BEIS DUKES datatset [63]. The funds available to each of the GenCos was taken from publicly released official company accounts at the end of 2012 [48].

To ensure that the development of the electricity market from 2013 to 2018 was representative of the actual scenario between these years, we set the exogenous variables, such as carbon and fuel prices, to those that were observed during this time period. In other words, the scenario modelled equated to the observed scenario.

The data for the observed EU Emission Trading Scheme (ETS) price between 2013 and 2018 was taken from [176]. Fuel prices for each of the fuels were taken from [47]. The electricity load data was modelled using data from [5], offshore and onshore wind and solar irradiance data was taken from [166]. There were three known significant coal plant retirements in 2016. These were removed from the simulation at the beginning of 2016.

Optimisation problem

The price duration curve was modelled linearly in the form $y = mx + c$, where y is the cost of electricity, m is the gradient, x is the demand of the price duration curve and c is the intercept.

Equation 4.12 details the optimisation problem formally:

$$\min_{m,c} \sum_{o \in O} \left(\frac{|A_o - f_o(m,c)|}{||O||} \right) \tag{4.12}$$

where $o \in O$ refers to the average percentage electricity mix during 2018 for wind (both offshore and onshore generation), nuclear, solar, CCGT, and coal, where O refers to the set of these values. A_o refers to observed electricity mix percentage for the respective generation type in 2018. $f_o(m,c)$ refers to the simulated electricity mix percentage for the respective generation type, also in 2018. The input parameters to the simulation are m and c from the linear *PPDC*, previously discussed, ie. $y = mx + c$. $||O||$ refers to the cardinality of the set.

4.4.3 Long-Term Scenario Analysis

In addition to verifying the ability for ElecSim to mimic observed investment behaviour over 5 years, we compared ElecSim's long-term behaviour to that of the UK Government's Department for Business, Energy and Industrial Strategy (BEIS) [50]. This scenario shows the projections of generation by technology for all power producers from 2018 to 2035 for the BEIS reference scenario. This is the same scenario as discussed in the next section.

Scenario

We initialised the model to 2018 based on [122]. The scenario for development of fuel prices and carbon prices were matched to that of the BEIS reference scenario [50].

Optimisation problem

The optimisation approach taken was a similar process to that discussed in Sub-Section 4.4.2, namely using a genetic algorithm to find the optimum expected price duration curve. However, instead of using a single expected price duration curve for each of the agents for the entire simulation, we used a different expected price duration curve for each year, leading to 17 different curves. This enabled us to model the non-static dynamics of the electricity market over this extended time period.

In addition to optimising for multiple expected price duration curves, we optimised for a nuclear subsidy, S_n. Further, we optimised for the uncertainty in the expected price parameters m and c, named σ_m and σ_c respectively, where σ is the standard deviation in a normal distribution. m and c are the parameters for the predicted price duration curve, as previously defined, of the form $y = mx + c$.

This enabled us to model the different expectations of future price curves between the independent GenCos. The addition of a nuclear subsidy as a parameter is due to the likely requirement for Government to provide subsidies for new nuclear [191].

A modification was made to the reward algorithm for the long-term scenario case. Rather than using the discrepancy between observed and simulated electricity mix in the final year (2018) as the reward, a summation of the error metric for each simulated year was used. This is detailed formally in Equation 4.13:

$$\min_{m \in M, m \in C} \sum_{y \in Y} \sum_{o \in O} \left(\frac{|A_{y_o} - f_{y_o}(m_y, c_y)|}{||O||} \right) \tag{4.13}$$

where M and C are the sets of the 17 parameters of m_y and c_y respectively for each year, y. $y \in Y$ refers to each year between 2018 and 2035. m_y and c_y refer to the parameters for the predicted price duration curve, of the form $y = mx + c$ for the year y. A_{y_o} refers to the actual electricity mix percentage for the year y and generation type o. Finally, $f_{y_o}(m_y, c_y)$ refers to the simulated electricity mix percentage with the input parameters to the simulation of m and c for the year y.

4.4.4 Genetic Algorithms

Genetic Algorithms (GAs) are a type of evolutionary algorithm which can be used for optimisation. We chose the genetic algorithm for this application due to its ability to find good solutions with a limited number of simulation runs, ability for parallel computation and its ability to find global optima. These characteristics are useful for our application, as a single simulation can take up to 36 hours.

In this section we detail the genetic algorithm used in this paper. Initially, a population P_0 is generated for generation 0. This population of individuals is used for the parameters to the simulation. The output of the simulations for each of the individuals are then evaluated. A subset of these individuals $C_{t+1} \subset P_t$ are chosen for mating. This subset is selected proportional to their fitness. With 'fitter' individuals having a higher change of reproducing to create the offspring group C'_{t+1}. C'_{t+1} have characteristics dependent on the genetic operators: crossover and mutation. The genetic operators are an implementation decision [14].

Once the new population has been created, the new population P_{t+1} is created by merging individuals from C'_{t+1} and P_t. See Algorithm 1 for detailed pseudocode.

We used the DEAP evolutionary computation framework to create our genetic algorithm [67]. This framework gave us sufficient flexibility when designing our genetic algorithm. Specifically,

Algorithm 1 Genetic algorithm [14]

$t = 0$
initialize P_t
evaluate structures in P_t
while termination condition not satisfied **do**
    $t = t + 1$
    select reproduction C_t from P_{t-1}
    recombine and mutate structures in C_t forming C'_t
    evaluate structures in C'_t
    select each individual for P_t from C'_t or P_{t-1}
end while

it enabled us to persist the data of each generation after every iteration to allow us to verify and analyse our results in real-time.

Parameters for Validation with Observed Data

The parameters chosen for the problem explained in Section 4.4.3 was a population size of 120, a crossover probability of 50%, a mutation probability of 20% and the parameters, m and c, as per Equation 4.12, were given the bounds of $[0.0, 0.004]$ and $[-30, 100]$ respectively.

The bounds for m and c were calculated to ensure a positive price duration curve, with a maximum price of £300 for $50,000$MW. The population size was chosen to ensure a wide range of solutions could be explored, whilst limiting compute time to $\sim$1 day per generation to allow for sufficient verification of the results. The crossover and mutation probabilities were chosen due to suggestions from the DEAP evolutionary computation framework [67].

Parameters for Long-Term Scenario Analysis

The parameters chosen for the genetic algorithm for the problem discussed in Section 4.4.3 are displayed here. The population size was 127, a crossover probability of 50%, a mutation probability of 20%. The parameters m_y, c_y were given the bounds $[0.0, 0.003]$ and $[-30, 50]$ respectively, whilst σ_m and σ_c were both given the bounds of $[0, 0.001]$.

The population size was slightly increased, and the bounds reduced when compared to the parameters for Section 4.4.4. This was to increase the likelihood of convergence to a global optima, which was more challenging to achieve due to the significantly higher number of parameters.

4.4.5 Results

Here we present the results of the problem formulation of Section 4.4.3. Specifically, we compare the ability of our model to that of BEIS in the context of a historical validation between 2013 and 2018 of the UK electricity market. We also compare our ability to generate scenarios up to 2035 with that of BEIS.

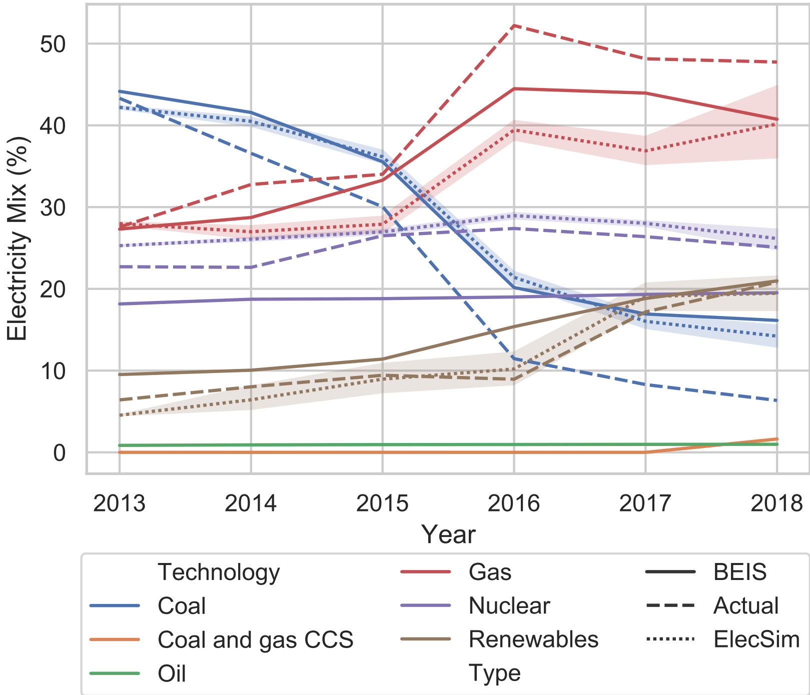


Fig. 4.7 Comparison of actual electricity mix vs. ElecSim vs. BEIS projections and taking three coal power plants out of service.

Validation with Observed Data

Figure 4.7 displays the output of ElecSim under the validation scenario, BEIS' projections and the observed electricity mix between 2013 and 2018, as explained in Section 4.4.2.

The observed electricity mix changed significantly between 2013 and 2018. A continuous decrease of electricity production from coal throughout this period was observed. 2015 and 2016 saw a marked decrease of coal, which can be explained by the retirement of 3 major coal power plants. The decrease in coal between 2013 and 2016 was largely replaced by an increase in gas. After 2016, renewables play an increasingly large role in the electricity mix and displace gas.

Both ElecSim and BEIS were able to model the fundamental dynamics of this shift from coal to gas as well as the increase in renewables. Both models, however, underestimated the magnitude of the shift from coal to gas. This could be due to unmodelled behaviours such as consumer sentiment towards highly polluting coal plants, a prediction from industry that gas would become more economically attractive in the future or a reaction to The Energy Act 2013 which aimed to close a number of coal power stations over the following two decades [158].

ElecSim was able to closely model the increase in renewables throughout the period in question, specifically predicting a dramatic increase in 2017. This is in contrast to BEIS who predicted that an increase in renewable energy would begin in 2016. However, both models were able to accurately predict the proportion of renewables in 2018.

ElecSim was able to better model the observed fluctuation in nuclear power in 2016. BEIS, on the other hand, projected a more consistent nuclear energy output. This small increase in nuclear power is likely due to the decrease in coal during that year. BEIS consistently underestimated the share of nuclear power.

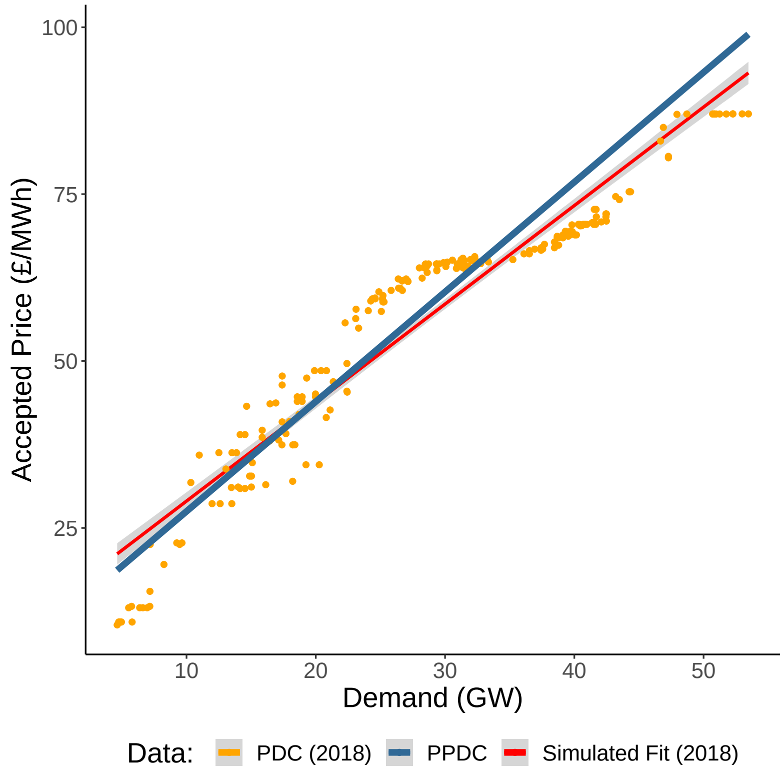


Fig. 4.8 Predicted price duration curve for investment for most accurate run against simulated run in 2018.

We display the error metrics to evaluate our models 5 year projections in Table 4.2. Where MAE is mean absolute squared error, MASE is mean absolute scaled error and RMSE is root mean squared error.

We are able to improve the projections for all generation types when compared to the naive forecasting approach using ElecSim, as shown by the MASE. Where the naive approach is simply predicting the next time-step by using the last known time-step. In this case the last known time-step is the electricity mix percentage for each generation type in 2013.

Technology	MAE	MASE	RMSE
CCGT	9.007	0.701	10.805
Coal	8.739	0.423	10.167
Nuclear	1.69	0.694	2.002
Solar	0.624	0.419	1.019
Wind	1.406	0.361	1.498

Table 4.2 Error metrics for time series forecast from 2013 to 2018.

Figure 4.8 displays the optimal predicted price duration curve (*PPDC*) found by the genetic algorithm. This price curve was used by the GenCos to achieve the results shown in Figure 5.9.

The yellow points show the simulated price duration curve for the first year of the simulation (2018). The red line (Simulated Fit (2018)) is a linear regression that approximates the simulated price duration curve (PDC (2018)). The blue line shows the price duration curve predicted (*PPDC*) by the GenCos to be representative of the expected prices over the lifetime of the plant.

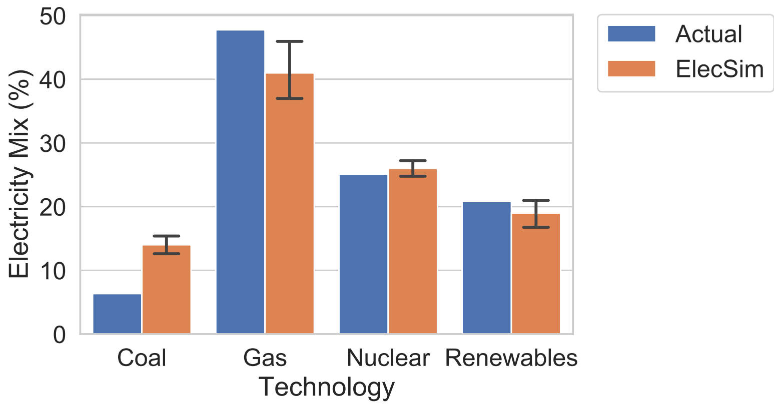


Fig. 4.9 Electricity generation mix simulated by ElecSim from 2013 to 2018 compared to observed electricity mix in 2018.

The optimal predicted price duration curve (*PPDC*) closely matches the simulated fit in 2018, shown by Figure 4.8. However, the *PPDC* has a slightly higher peak price and lower baseload price. This could be due to the fact that there is a predicted increase in the number of renewables with a low SRMC. However, due to the intermittency of renewables such as solar and wind, higher peak prices are required to generate in times of low wind and solar irradiance at the earth's surface.

To generate Figure 4.9, we ran 40 scenarios with the *PPDC* to observe the final, simulated electricity mix. The error bars are computed based on a Normal distribution 95% confidence interval.

ElecSim was able to model the increase in renewables and stability of nuclear energy in this time. ElecSim was also able to model the transition from coal to gas, however, underestimated the magnitude of the transition. This was similar to the projections BEIS made in 2013 as previously discussed.

Long-Term Scenario Analysis

In this section we discuss the results of the analysis of the BEIS reference scenario explained in Section 4.4.3. Specifically, we created a scenario that mimicked that of BEIS in ElecSim and optimised a number of parameters using a genetic algorithm to match this scenario. Through this we are able to gain confidence in the underlying dynamics of ElecSim to simulate long-term behaviours. Further, this enables us to verify the likelihood of the scenario by analysing whether the parameters required to make such a scenario are realistic.

Figure 4.10 displays the electricity mix projected by both ElecSim and BEIS. To generate this image we ran 60 scenarios under the optimal collection of predicted price duration curves, nuclear subsidy and uncertainty in predicted price duration curves.

The optimal parameters were chosen by choosing the parameter set with the lowest mean error per electricity generation type and per year throughout the simulation, as shown by Equation 4.13.

Figure 4.11 displays the optimal predicted price duration curves (*PPDC*s) per year of the simulation, shown in blue. These are compared to the price duration curve simulated in 2018, as per Figure 4.8. The optimal nuclear subsidy, S_n, was found to be $\sim$£120, the optimal σ_m and σ_c were found to be 0 and $\sim$0.0006 respectively.

The BEIS scenario demonstrates a progressive increase in nuclear energy from 2025 to 2035, a consistent decrease in electricity produced by natural gas, an increase in renewables and decrease to almost 0% by 2026 of coal.

ElecSim is largely able to mimic the scenario by BEIS. A large increase in renewables is projected, followed by a decrease in natural gas.

A significant difference, however, is the step-change in nuclear power in 2033. This led to an almost equal reduction in natural gas during the same year. In contrast, BEIS project a continuously increasing share of nuclear.

We argue that the ElecSim projection of nuclear power is more realistic than that of BEIS due to the instantaneous nature of large nuclear power plants coming on-line.

Figure 4.11 exhibits the price curves required to generate the scenario show in Figure 4.10. The majority of the price curves are similar to the simulated price duration curve of 2018 (Simulated Fit (2018)). However, there are some price curves which are significantly higher and significantly lower than the predicted price curve of 2018. These cycles in predicted price duration curves may be explained by investment cycles typically exhibited in electricity markets [79].

In this context, investment cycles reflect a boom and bust cycle over long timescales. When electricity supply becomes tight relative to demand, prices rise to create an incentive to invest in new capacity. Price behaviour in competitive markets can lead to periods of several years of low prices (close to short-run marginal cost) [205].

As plants retire or demand increases, the market becomes tighter until average prices increase to a level above the threshold for investment in new power generators. At this point investors may race to bring new plants on-line to make the most out of the higher prices. Once adequate investments have been made, the market returns to a period of low prices and low investment until the next price spike [79].

The nuclear subsidy, S_n, of $\sim$£120 in 2018 prices is high compared to similar subsidies, but this may reflect the difficulty of nuclear competing with renewable technology with a short-run marginal cost that tends to £0.

The low values of σ_m and σ_c demonstrates that the expectation of prices does not necessarily have to differ significantly between GenCos. This may be due to the fact that GenCos have access to the same market information.

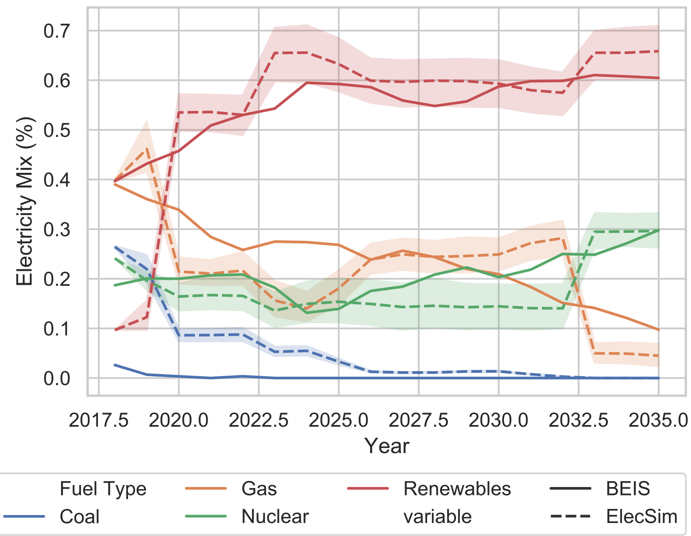


Fig. 4.10 Comparison of ElecSim and BEIS' reference scenario from 2018 to 2035.

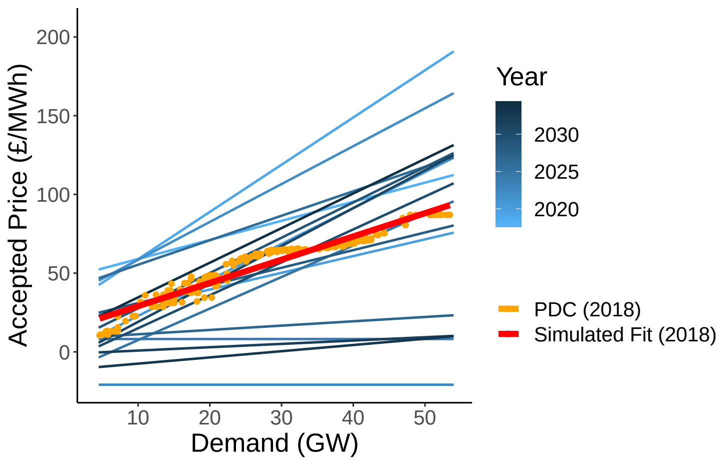


Fig. 4.11 Comparison between optimal price duration curves and simulated price duration curve in 2018.

4.5 Scenario Testing

In this Section we display scenario runs of ElecSim using 20 time-steps per year and using representative days

4.5.1 Scenarios for 20 time-steps

In this section we present example scenario runs using ElecSim with 20 time-steps. We vary the carbon tax and grow or reduce total electricity demand. This enables us to observe the effects of carbon tax on investment. In this paper, we have presented scenarios where electricity demand decreases 1% per year, due to the recent trend in the UK.

For the first scenario run displayed, we have approximated the predictions by the UK Government, where carbon tax increases linearly from £18 to £200 by 2050 [49]. Figure 4.12a demonstrates a significant increase in gas turbines in the first few years, followed by a decrease, with onshore wind increasing.

Figure 4.12b displays a run with a £40 carbon tax. This run demonstrates a higher share of onshore wind than in the previous scenario.

We experimented with the following levels of carbon tax: £10 ($13), £20 ($26) and £70 ($90) with demand decreasing 1% per year. This was chosen due to the increasing efficiency of homes, industry and technology, and due to the recent trend in the UK. We run each scenario 8 times to capture the stochastic nature of the process. Via the observation of the emergent investment behaviour until 2050, an understanding of how real life investors may behave emerges.

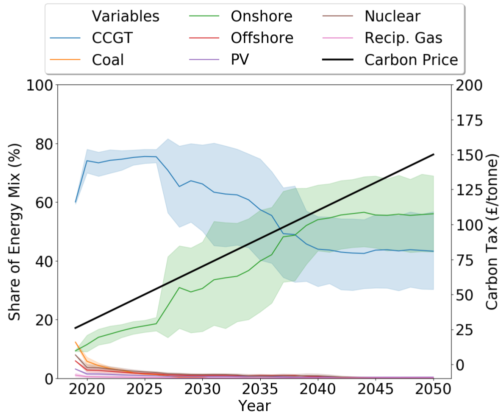
Figure 4.13a shows that with a carbon tax of £10, whilst renewable technology does grow, gas power plants provide the majority of supply in each year. However, at a level of £20 the increase in wind turbines is enough to match gas turbines. A carbon tax of £70, however, shows a near 100% uptake of wind turbines.

It is infeasible for the power supply to be provided solely by wind turbines today. This overestimation, however, is due to the low time granularity of the model [36]. This scenario therefore assumes perfect storage capabilities.

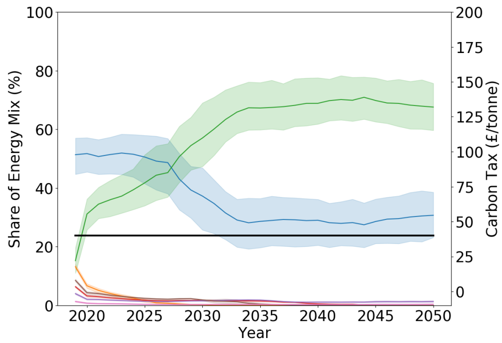
These runs demonstrate that a consistent, but relatively low carbon tax can have a larger impact in the uptake of renewable energy than increasing carbon tax over a long time frame. We hypothesise that an early carbon tax affects the long-term dynamics of the market for many years. We, therefore, suggest early action on carbon tax to transition to a low-carbon energy supply

4.5.2 Conclusion

Agent-based models provide a method of simulating investor behaviour in an electricity market. We observed that an increase in carbon tax had a significant impact on investment. These findings enable policy makers to better understand the impact that their decisions may have. For a high uptake of renewable energy technology, rapid results can be seen after 10 years with a carbon tax of £70 ($90).



(a) £26 to £150 linearly increasing carbon tax.



(b) £40 carbon tax

Fig. 4.12 Scenarios with varying carbon taxes and decreasing demand (-1%/year)

4.5.3 Scenarios for representative days

In this section we discuss various scenarios under the model which uses representative days as time-steps. This work builds upon the work in Section **??**; we used the same predicted price duration curves as modelled on BEIS' scenario. We selected an optimal carbon tax level which would reduce both electricity price and carbon emissions, as shown later in Chapter 6. The optimal carbon tax strategy found in Chapter 6 is shown by Figure 4.14. Each of the scenarios were run 10 times to display any variability in the results. We chose 10 runs to limit both computation time and cost.

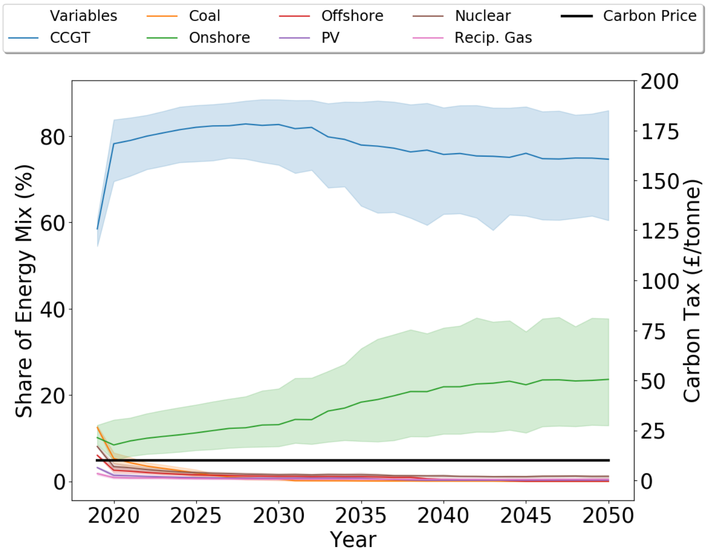
Figures 4.15 and 4.16 show the electricity mixes of various demand scenarios. Figure 4.15 displays the scenarios in which demand either stays flat, or decreases by 1% and 2%. For these scenarios it can be seen that solar is the dominant electricity supply, supplying $\sim$50%, with nuclear power in second supplying between 20% and 30%. With a decreasing demand scenario of 1% per year, as shown by Figure 4.15b, nuclear provides a higher proportion by the year 2034, of $\sim$30%, however before the year 2033, provides a similar proportion to the other scenarios as shown by Figures 4.15a and 4.15c.

For the scenarios shown in Figure 4.15, CCGT, coal and onshore provide around $\sim$10% each by 2034. Coal and CCGT, however, progress towards 0% whereas onshore wind increases. This is to be expected due to the high carbon price, as shown by Figure 4.14. Offshore does not exhibit a high amount of investment. We believe this is the case as offshore wind is more expensive than onshore wind, and in our scenario subsidies other than for nuclear are not modelled.

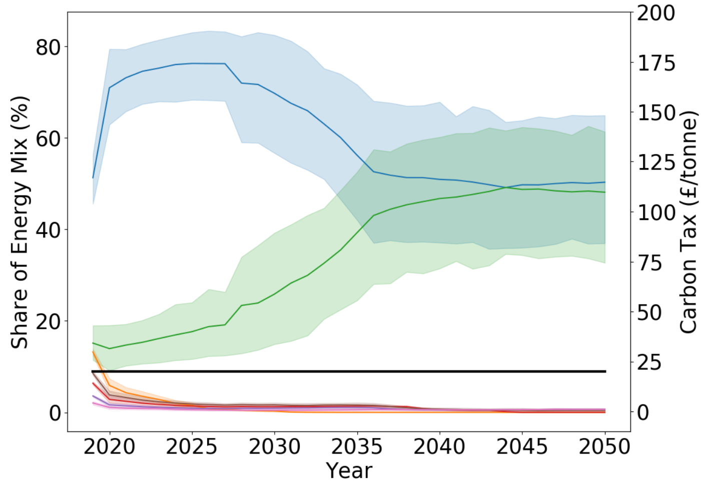
Figure 4.16 shows scenarios where demand increases per year. Whilst electricity mix distribution is similar to the scenarios shown in Figure 4.15, solar plays a significantly increased role than nuclear. This may be down to the large expense of nuclear, and the long time of deployment of this type of technology. Solar power, on the other hand, is able to be installed much more quickly to maintain the high demand. This is especially true for the scenarios shown in Figures 4.16b and 4.16c where demand rises by 2% and 2.5% per year respectively.

4.5.4 Performance

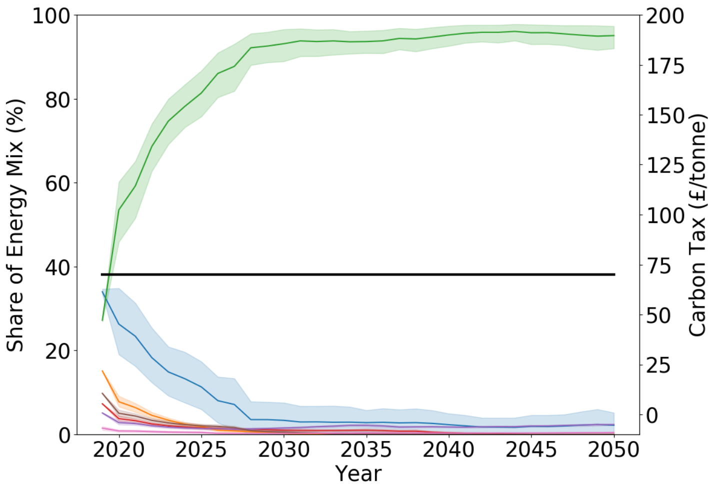
Figure 4.17 shows the running time for ElecSim with varying installed capacity. We varied demand between 2GW and 320GW to see the effect of different sized countries on running time. The makeup of the electricity mix was achieve through stratified sampling of the UK electricity mix. The results show a linear time complexity.



(a) £10 carbon tax.



(b) £20 carbon tax.



(c) £70 carbon tax.

Fig. 4.13 Scenarios from 2020 to 2050 with varying carbon tax.

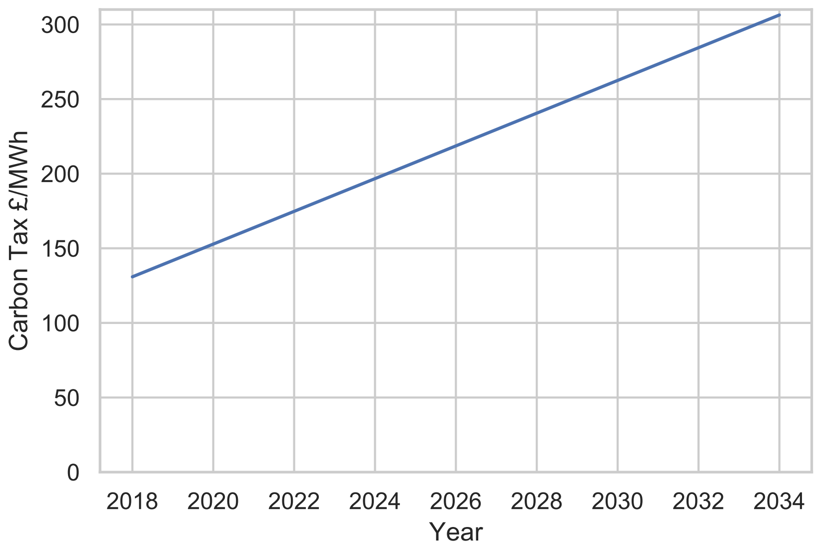
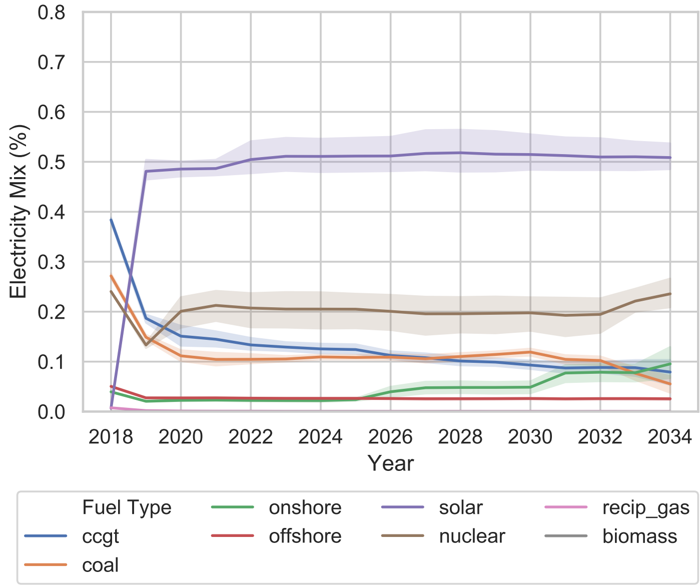
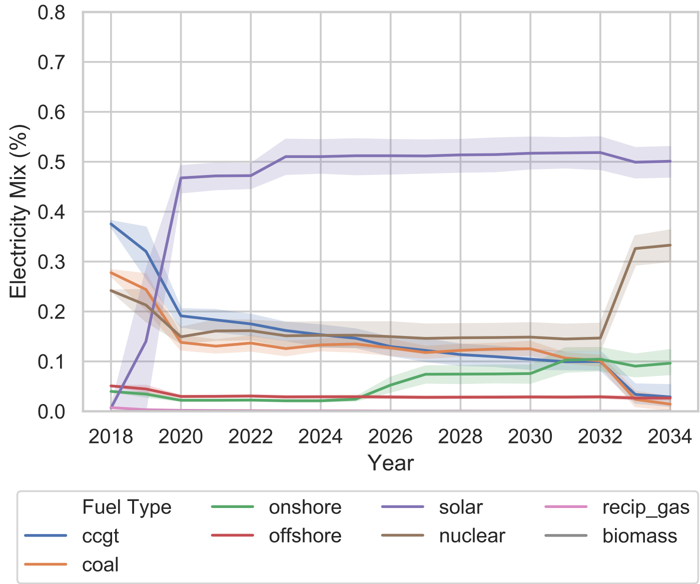


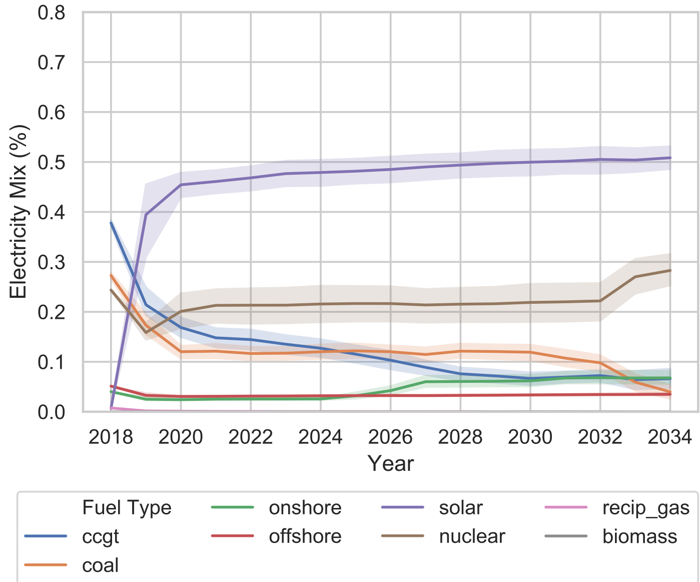
Fig. 4.14 Optimal carbon tax strategy to reduce both electricity cost and carbon emissions.



(a) Demand does not increase or decrease.

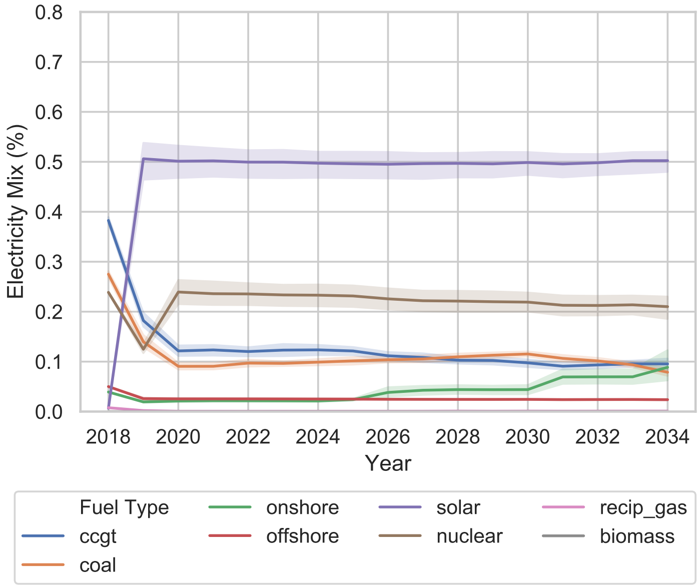


(b) Demand reduces by 1% per year.

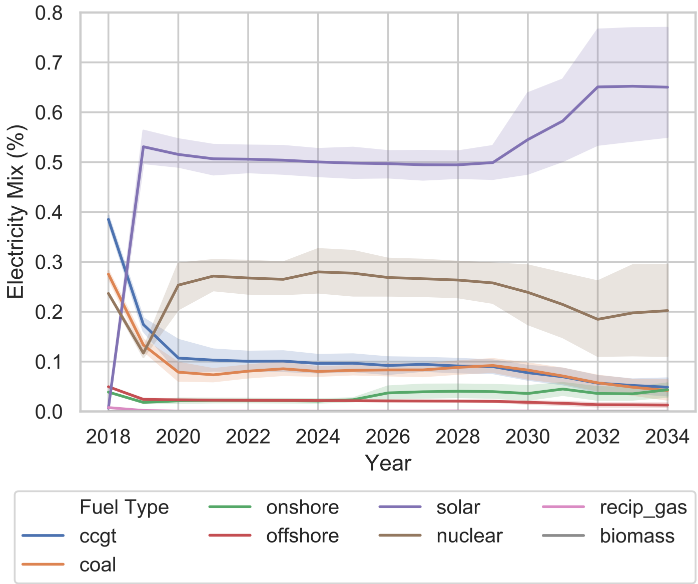


(c) Demand reduces by 2% per year

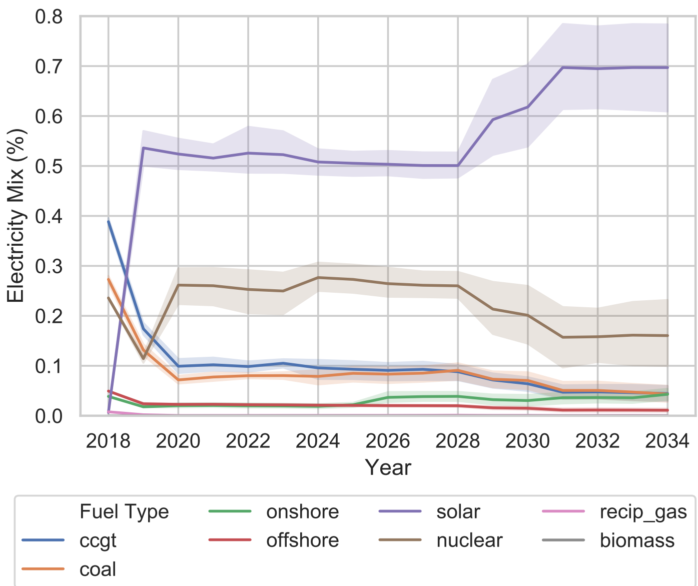
Fig. 4.15 Scenarios from 2018 to 2035 with varying demand.



(a) Demand increases by 1% per year.



(b) Demand increases by 2% per year.



(c) Demand increases by 2.5% per year

Fig. 4.16 Scenarios from 2018 to 2035 with varying demand.

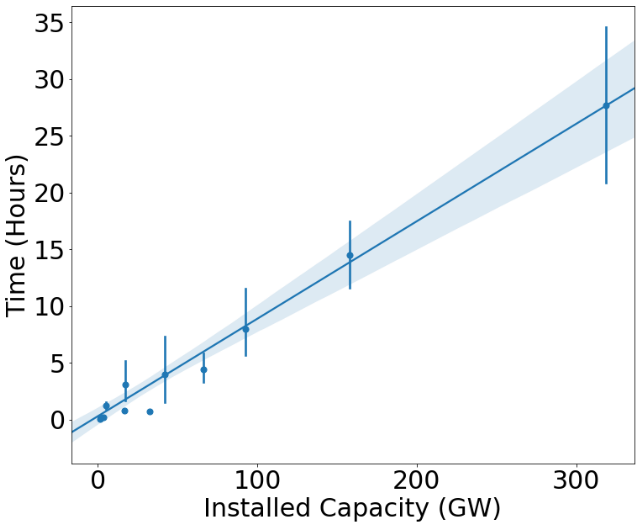


Fig. 4.17 Run times of different sized countries.

4.6 Sensitivity Analysis

In this section we investigate a sensitivity analysis of ElecSim, where we vary the weighted average cost of capital and the down payment required for investment. We used the reference scenario discussed in Section 4.5, with the optimal carbon tax to reduce both emissions and electricity price. The work done in this Section is in addition to the work published in [127].

We ran ten iterations per weighted average cost of capital and down payment element. We did this due to the monte-carlo nature of the simulation. We chose ten runs to give us sufficient variance in results, but reduce compute power, to reduce both time and cost of calculation.

4.6.1 Results

Figure 4.18 displays the results of the sensitivity analysis for the Weighted average cost of capital for non-nuclear power generators. For this, we trialled nine different Weighted Average Cost of Capital (WACC) values, where a value of 5.9% is the reference case [131].

It can be seen that the WACC has an effect on the total investment in solar, nuclear and CCGT. With a WACC equal to or greater than 7.4%, nuclear increases significantly, whilst solar decreases. Nuclear has a WACC of 10%, therefore 7.4% may be the point where nuclear becomes more competitive than solar in an environment where a low-carbon electricity supply is elicited from an optimal carbon tax.

Offshore and coal do not change significantly over different levels of WACC. This may be due to the fact that CCGT and onshore are more competitive than coal and offshore respectively, without external subsidies.

Onshore seems to play a larger role at the lowest WACC, 3.9%. This may be due to onshore wind's high competitiveness when compared to nuclear.

Figure 4.19 displays the relative carbon emissions in 2035. With a low WACC of 3.9%, the relative carbon emissions falls, on average, to zero. This seems to be due to the high levels of solar, onshore and nuclear.

As WACC increases, so does carbon emissions, until there is a WACC of 0.5, where it reduces slightly. This is seemingly due to the higher levels of CCGT and coal, which is able to displace solar. However, it must be noted, that in this scenario with the optimal carbon tax, the relative carbon emissions remains low.

Figure 4.20 displays the sensitivity analysis results for different levels of down payment required for all investments. We varied the down payment required between the values of 10% and 40%.

As down payment required increases, so does nuclear and onshore, whilst solar decreases. CCGT also shows an increase with down payment required. The increase in down payment may help nuclear, due to the high costs of WACC. With a higher down payment, the total costs of the project will fall when compared to other, cheaper, generators. It is likely that nuclear displaces solar in this case. CCGT increases up until a 35% down payment required. This may be due to the increased use of onshore wind, where CCGT and coal is required to fill for times of low wind speeds.

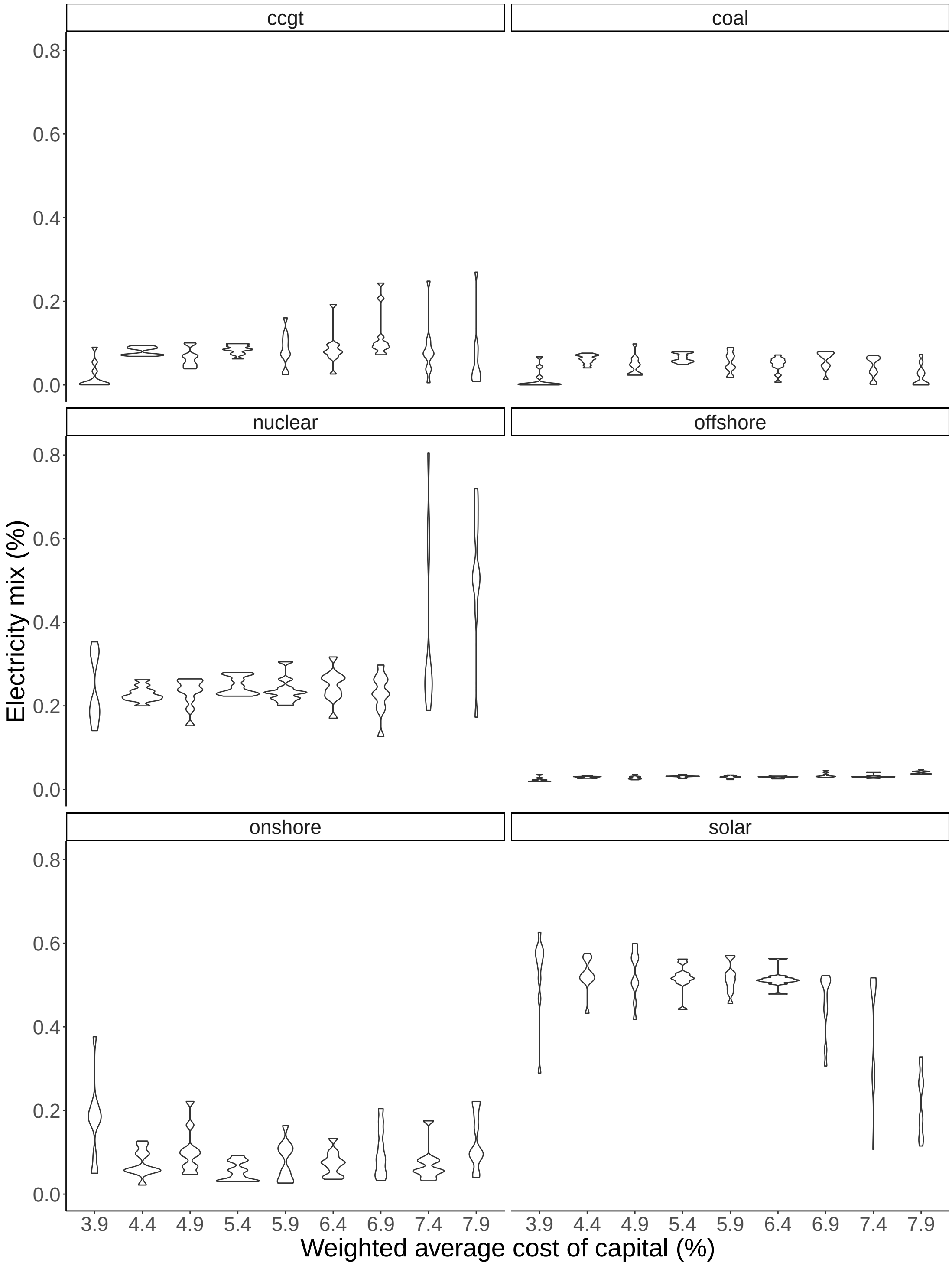


Fig. 4.18 Sensitivity analysis where Weighted Average Cost of Capital (WACC) was varied. Results compare electricity mix in 2035.

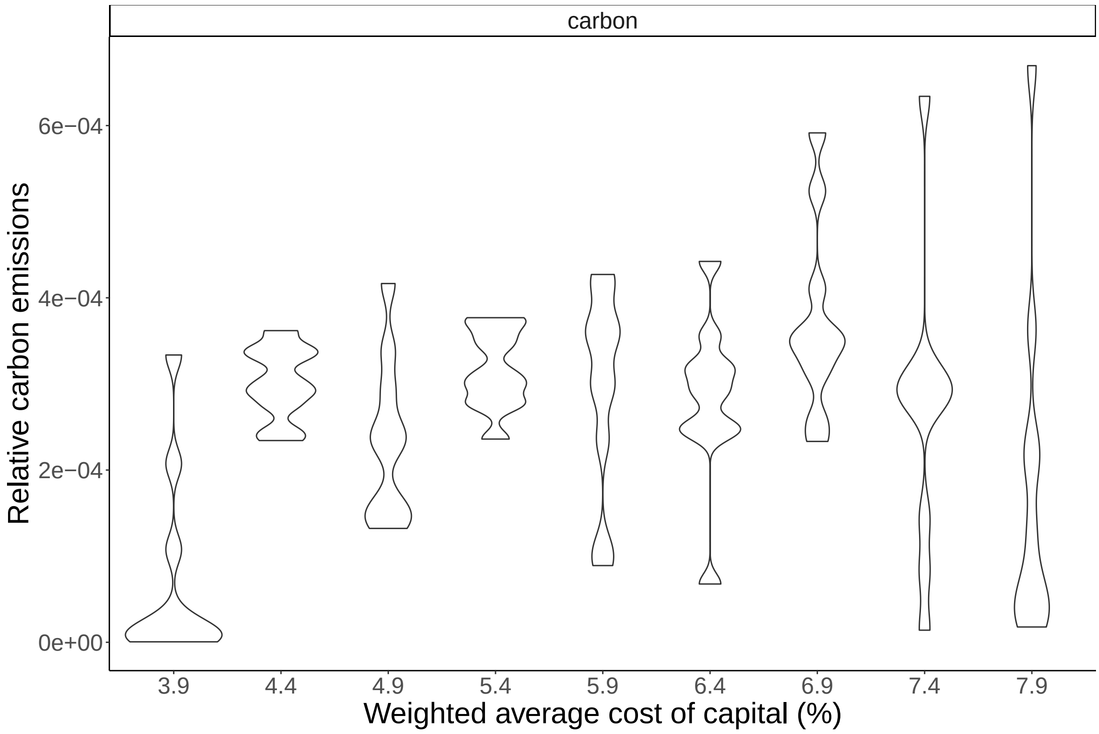


Fig. 4.19 Sensitivity analysis where weighted average cost of capital (WACC) was varied. Results compare relative carbon emissions in 2035.

Figure 4.21 displays the relative carbon emissions versus down payment required for investors. As down payment increases, so does relative carbon emissions. This is down to the increasing role that CCGT and coal play in the electricity mix, and decreasing solar capacity.

A down-payment of 10% seems to have the lowest carbon emissions. This is due to the high investment in solar, and low investment in CCGT and coal.

4.7 Limitations

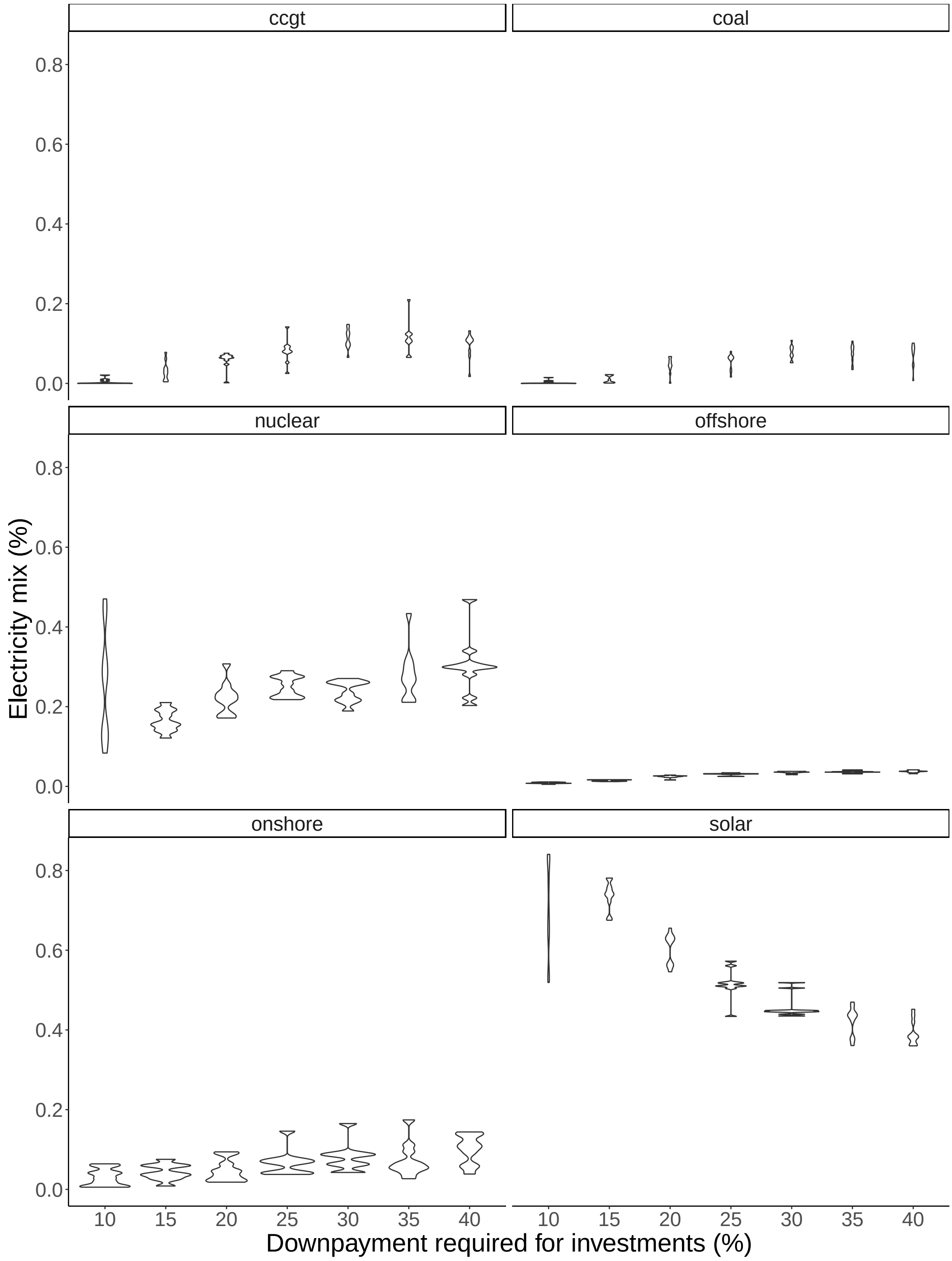


Fig. 4.20 Sensitivity analysis where percentage of down payment was varied. Results compare electricity mix in 2035.

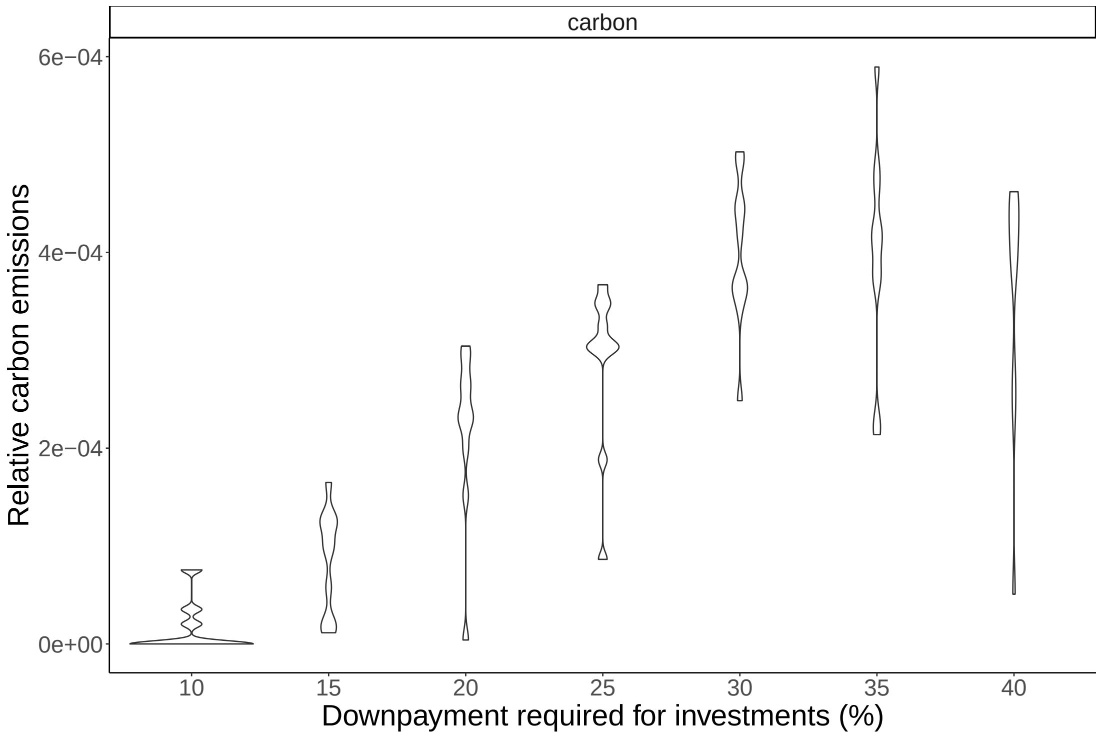


Fig. 4.21 Sensitivity analysis where percentage of down payment was varied. Results compare relative carbon emissions in 2035.

4.8 Conclusions

Liberalised electricity markets with many heterogeneous players are suited to be modelled with ABMs. ABMs incorporate imperfect information as well as heterogeneous actors. ElecSim models imperfect information through forecasting of electricity demand and future fuel and electricity prices. This leads to agents taking risk on their investments, and model market conditions more realistically.

In this Chapter we have demonstrated that it is possible to use ABM to simulate liberalised electricity markets. Through validation, we are able to show that our model, ElecSim, is able to accurately mimic the observed, real-life scenario in the UK between 2013 and 2018. This provides confidence in the underlying dynamics of ElecSim, especially as we are able to model the fundamental transition between coal and natural gas observed between 2013 and 2018 in the UK.

In addition to this, we were able to compare our long-term scenario to that of the UK Government, Department for Business, Energy & Industrial strategy. We show that we are able to mimic their reference scenario, however, demonstrate a more realistic increase in nuclear power. The parameters that were gained from optimisation show that the BEIS scenario is realistic, however a high nuclear subsidy may be required.

To improve the accuracy of our model, we used eight representative days of solar irradiance, offshore and onshore wind speed and demand to approximate an entire year. The particular days were chosen using a *k*-means clustering technique, and selecting the medoids. This enabled us to accurately model the daily fluctuations of demand and renewable energy resources.

In addition to this, a method of dealing with the non-validatable nature of electricity markets, as per the definition of Hodges *et al.* is to vary input parameters over many simulations and look for general trends [95]. This could be achieved using ElecSim through the analysis of a reference case, and a limited set of scenarios which include the most important uncertainties in the model structure, parameters, and data, i.e. alternative scenarios which have both high plausibility and major impacts on the outcomes.

Additionally, we showed a number of scenarios, and shows that total demand has an effect on electricity mix. An increasing demand, year-on-year, can lead to an increase in solar to accommodate for this demand. However, if demand reduces, there is a higher investment in nuclear, which contributes to the electricity mix by 2034.

We ran a sensitivity analysis of Weighted Average Cost of Capital (WACC) and down payment required. We showed that these two variables have a large effect on total electricity mix by the year 2035, which in turn effects the total carbon emissions. We therefore show that the input assumptions have an effect on the simulation, which must be considered when analysing model outputs.

Chapter 5

Electricity demand prediction

5.1 Prologue

In this Chapter we use several different machine learning and statistical methods to predict electricity demand 30 minutes ahead as well as a day ahead. The 30 minutes ahead methodology is used in the work on day-ahead work. We utilise the errors from the day ahead predictions to see what the impact of such errors are on the day-ahead market. The work looks specifically at the difference in electricity mix with prediction error, as well as carbon emitted. The work on 30-minute ahead forecasting was published in [125].

We introduce this work in Section 5.2. Section 5.3 provides a literature review on the topic of demand forecasting. We introduce the methods used in Section 5.4. Sections 5.5 and 5.6 look at 30-minute ahead predictions and day-ahead predictions respectively. Section 5.6 integrates these day ahead projections into the ElecSim model.

5.2 Introduction

The need for accurate load forecasting is essential for control and planning of electricity generation in electrical grids due to the fact that supply must meet demand [142]. Short-term electricity demand forecasting has become increasingly important due to the introduction of competitive energy markets. Accurate estimates of demand are required so that the correct amount of electricity is purchased on the wholesale market [53]. Electricity is unique to other commodities in that it must be either consumed the moment that it is generated or stored. The difficulties in storing electricity arise from high installation and maintenance costs, inefficiencies and low capacity [168]. It is therefore important to match demand to supply and thus regulate frequency. Failure to accurately forecast electricity demand can lead to financial loss and/or system-wide blackouts [92].

The integration of higher proportions of intermittent renewable energy sources (IRES) in the electricity grid will mean that the forecasting of electricity demand will become increasingly important and challenging. Examples of IRES are solar panels and wind turbines, which fluctuate in terms of power output based on localized wind speed and solar irradiance. However, as supply must meet demand at all times and the fact that IRES are less predictable than dispatchable energy sources such as coal and combined-cycle gas turbines (CCGTs) this means extra attention must be made in predicting future demand if we wish to keep, or better reduce, the current frequency of blackouts [142]. A dispatchable source is one that can be turned on and off by human control and therefore, able to adjust output just in time, at a moment convenient for the grid.

Typically, peaker plants, such as reciprocal gas engines, are used to fill fluctuations in demand that had not been previously planned for. Specifically, peaker plants meet the peaks in demand where other cheaper options are at full capacity. These peaker plants are typically expensive to run and have higher greenhouse gas emissions than their non-peaker counterparts [147]. Whilst peaker plants are also dispatchable plants, not all dispatchable plants are peaker plants. For example coal, which is a dispatchable plant, is run as a base load plant, due to its inability to deal with the fluctuating conditions required of a peaker plant.

To reduce reliance on peaker plants, it is helpful to know how much electricity demand there will be in the future so that more efficient plants can be used to meet this expected demand. This is so that these more efficient plants can be brought up to speed at a time suitable to match the demand. Forecasting a day into the future is especially useful in decentralized electricity markets which have day-ahead markets. Decentralized electricity markets are ones where electricity is provided by multiple generation companies, as opposed to a centralized source, such as a government. To aid in this prediction, machine learning and statistical techniques have been used to accurately predict demand based on several different factors and data sources [124], such as weather [99], day of the week [10] and holidays [200].

The introduction of smart meters in many countries (USA, Europe, Canada and South Korea) has led to an influx of high granularity electricity consumption data that can be used for load forecasting [51]. Smart meters are digital devices that measure electricity consumption of individual households at regular intervals (intervals of an hour or less) and offer two-way communication between the meter and utility company. Smart meters aid customers to understand precisely how much electricity they consume at different time intervals, and enable dynamic pricing [7]. Dynamic pricing allows utilities to charge varying prices at different times, for instance, charging a higher price when costly generation sources are used in times of peak demand, and lower prices at night time or weekends when demand is low [140, 116]. In this Chapter we forecast both 30-minutes ahead using smart meter data, as well as 24-hours ahead to simulate the process made for a day-ahead market.

Firstly, we explore short term load-forecasting at an interval of 30 minutes ahead and cluster similar users based on their electricity usage. A variety of different forecasting techniques were evaluated such as Random Forests [Tin Kam Ho], Long-Short Term Memory neural networks (LSTM) [94], Multilayer Perceptron neural networks [198] and Support Vector Regression (SVR) [54].

Random Forests are an ensemble based learning method for classification and regression, and are made up of many decision trees. LSTM networks are recurrent neural networks which remember values over arbitrary time intervals. Multilayer Perceptrons are a popular type of neural network which are made up of a minimum of three layers and can be used to make non-linear predictions. SVRs are supervised learning models which analyze data used for regression analysis.

To improve forecasting results, the clustering of smart meter data was evaluated. The technique used for this was k-means clustering. An average 24-hour electricity load profile was calculated, and the result used for clustering. The clustered sub-system is then aggregated and separate models trained on this aggregate. The yearly, weekly and daily periodicity of electricity load is accounted for by input variables into the models. Once forecasts for each cluster are made using the individual models, the results are aggregated for the final predictions. These predictions are compared to the actual results and the accuracy measured using mean absolute percentage error (MAPE).

Secondly, we introduce day-ahead forecasting and what impact errors have on the long-term dynamics of the market. Various studies have looked at predicting electricity demand at various horizons [186, 103, 12]. However, the impact of poor demand predictions on the long-term electricity mix has been studied to a lesser degree.

We compare several machine learning and statistical techniques to predict the energy demand for each hour over the next 24-hour horizon. We chose to predict over the next 24 hours to simulate a day-ahead market, which is often seen in decentralized electricity markets. However, our approach could be utilized for differing time horizons. In addition to this, we use our long-term agent-based model, ElecSim [122, 127], to simulate the impact of different forecasting methods on long-term investments, power plant usage and carbon emissions for the years 2018 through 2035 in the United Kingdom. Our approach, however, is generalizable to any country through parametrization of the ElecSim model.

As part of our work, we utilize online learning methods to improve the accuracy of our predictions. Online learning methods can learn from novel data while maintaining what was learnt from previous data. Online learning is useful for non-stationary datasets, and time-series data where recalculation of a model would take a prohibitive amount of time. Offline learning methods, however, must be retrained every time new data is added. Online approaches are constantly updated and do not require significant pauses while the offline training is being re-run. By training on data that has already been used for training, the computational load and time required increases.

We trial different algorithms and train different models for different times of the year. Specifically, we train different models for the different seasons. We also split weekdays and train both weekends and holidays together. This is due to the fact that holidays and weekend exhibit similar load profiles due to the reduction in industry electricity use and an increase in domestic. This enables a model to become good at a specific subset of the data which share similar patterns, as opposed to having to generalize to all of the data. Examples of the algorithms used are linear regression, lasso regression, random forests, support vector regression, multilayer perceptron neural network, box-cox transformation linear regression and the passive aggressive model.

We expect a-priori that online algorithms will outperform the offline approach. This is due to the fact that the demand time-series is non-stationary, and thus changes sufficiently over time. In terms of the models, we presume that the machine learning algorithms, such as neural networks, support vector regression and random forests will outperform the statistical methods such as linear regression, lasso regression and box-cox transformation regression. We expect this due to the fact that machine learning has been shown to be able to learn more complex feature representations than statistical methods [186].

However, it should be noted, that such a-priori intuiton, is no substitute for analytical evidence and can (and has) been shown to be wrong in the past, due to imperfect knowledge of the data and understanding of some of the black box models, such as neural networks.

Using online and offline methods, we take the error distributions, or residuals, and fit a variety of distributions to these residuals. We choose the distribution with the lowest sum of squared estimate of errors (SSE). SSE was chosen as the metric to ensure that both positive and negative errors were treated equally, as well as ensuring that large errors were penalized more than smaller errors. We fit over 80 different distributions, which include the Johnson Bounded distribution, the uniform distribution and the gamma distribution. The distribution that best fits the respective residuals is then used and sampled from to adjust the demand in the ElecSim model. We then observe the differences in carbon emissions, and which types of power plants were both invested in and utilized, with each of the different statistical and machine learning methods. To the best of our knowledge, this is the most comprehensive evaluation of online learning techniques to the application of day-ahead load forecasting as well as assessing the impacts of the errors that these models produce on the long-term electricity market dynamics.

We show that online learning has a significant impact on reducing the error for predicting electricity consumption a day ahead when compared to traditional offline learning techniques, such as multilayer artificial neural networks, linear regression, extra trees regression and support vector regression, which are models used in the literature [142, 8, 33]. For a full list of algorithms used in this work see Table 5.3.

We show that the forecasting algorithm has a non-negligible impact on carbon emissions and use of coal, onshore, photovoltaics, reciprocal gas engines and CCGT. Specifically, the amount of coal, photovoltaics, and reciprocal gas used from 2018 to 2035 was proportional to the median absolute error, while both onshore and offshore wind are inversely proportional to the median absolute error.

Total investments in coal, offshore and photovoltaics are proportional to the median absolute error, while investments in CCGT, onshore and reciprocal gas engines are inversely proportional.

The contributions of this work are:

1. A methodology to forecast smart-meter using a *k*-means clustering technique.
2. The evaluation of different online and offline learning models to forecast the electricity demand profile 24 hours ahead.
3. Evaluation of poor predictive ability on the long-term electricity market in the UK through the perturbation of demand in the ElecSim simulation.

5.3 Literature review

In this section we carry out a literature review on 30-minute ahead forecasting, day-ahead forecasting and online forecasting methods. In addition, we cover literature on the impact of forecasting on electricity markets.

5.3.1 30-minute ahead forecasting

The forecasting of aggregated and clustered electricity demand has been the focus of a considerable amount of research in recent years. The research can generally be classified into two classes, Artificial Intelligence (AI) methods [130, 153, 170] and classical time series approaches [103, 156]. We trial both approaches in this Chapter.

Singh *et al.* [186] produced a review of load forecasting techniques and methodologies and reported that hybrid methods, which combine two or more different techniques, are gaining traction, as well as soft computing approaches (AI) such as genetic algorithms. Our work presents a hybrid method which combines *k*-means clustering with multiple different learning algorithms.

Artificial Intelligence Methods

Dillon *et al.* presented a neural network for short term load forecasting. Their neural network consisted of three-layers and used adaptive learning for training [53]. They proposed the use of weather information to augment their electricity load data. They found better results with the adaptive neural network than with a linear model, or non-adaptive neural network. In contrast to Dillon our work focuses on a non-adaptive neural network and does not take into account weather information.

Chen *et al.* used an Artificial neural network to predict electricity demand of three substations in Taiwan. They integrated temperature data and reported that the best results when forecasting residential and commercial substations were during the week due to the influence of weather [34]. In contrast to the work done by Chen *et al.*, we focus on client-side prediction using smart meter data as opposed to substation data. We were, therefore, able to cluster the data based on load profile, as opposed to geographical location.

Time Series Methods

Al-Musaylh *et al.* proposed the use of Support Vector Regression (SVR), an autoregressive integrated moving average (ARIMA) model and a multivariate adaptive regression spline (MARS) in their short term electricity demand forecasting system [10]. They found that for a half, and one-hour forecasting horizons, that the MARS model outperformed both the ARIMA and SVR.

Taylor evaluates different statistical methods including ARIMA, an adaptation of Holt-Winters' exponential smoothing [98], and an exponential smoothing method which focuses on the evolution of the intra-day cycle [88]. He found that the double seasonal adaptation of the Holt-Winters' exponential smoothing method was the most accurate method for short lead times between 10 and 30 minutes.

In contrast to Taylor, Fard *et al.* proposed a novel hybrid forecasting method based on both artificial intelligence and classical time series approaches. They utilised the wavelet transform, ARIMA and ANNs for short term load forecasting [60]. The ARIMA model is created by finding the appropriate order using the Akaike information criterion [9]. The ARIMA model models the linear component of the load time series, and the residuals contain the non-linear components. These residuals are then decomposed by the discrete wavelet transform into its sub-frequencies. ANNs are then applied to these sub-frequencies and the outputs of both the ANN and ARIMA models are summed to make the final prediction. They found that this hybrid technique outperformed traditional methods. Our work does not integrate artificial intelligence and classical time series techniques.

Clustering

Multiple techniques have been proposed for the clustering of electricity load data prior to forecasting. Both Shu and Luonan, and Nagi *et al.* propose a hybrid approach in which self-organizing maps are used to cluster the data, and Support Vector Regression is used to make predictions [184, 153]. This technique proved robust for different data types, and was able to tackle the non-stationarity of the data. Shu showed that this hybrid approach out-performed a single SVR technique, whilst Nagi showed superior results to a traditional ANN system. In contrast to both Nagi *et al.* and Shu and Luonan our work utilises *k*-means as the clustering algorithm

Quilumba *et al.* also apply machine learning techniques to individual households' electricity consumption by aggregation [60]. To achieve this aggregation, they use *k*-means clustering to aggregate the households to improve their forecasting ability. The authors also use a neural network based model for forecasting, and show that the number of optimum clusters for forecasting is dependent on the data, with three clusters optimal for a particular dataset, and four for another.

Wijaya *et al.* demonstrated that implementing clusters improved load-forecasting accuracy up to a certain level [209]. Whilst, a study by Ilić *et al.* showed that increasing the number of clusters did not improve accuracy [112].

Humeau *et al.* compare MLPs, SVRs and linear regression at predicting smart meter data [104]. They aggregate different households and observe which models work the best at each aggregate level. They find that linear regression outperforms both MLP and SVR when forecasting individual households. However, after aggregating over 32 households, SVR outperforms linear regression.

5.3.2 Online learning

Whilst multiple papers have looked at demand-side forecasting [186], to the best of our knowledge, the impact of online learning has been discussed with less frequency. In addition to this, our research models the impact of the performance of different algorithms on investments made, electricity sources dispatched and carbon emissions over a 17 year period. To model this, we use the long-term electricity market agent-based model, ElecSim. In our work, we trial a different set of algorithms to our problem. Due to time and compute constraints, we do not trial the additional techniques discussed in this literature review within our work.

Johansson *et al.* apply online machine learning algorithms for heat demand forecasting [119]. They find that their demand predictions display robust behaviour within acceptable error margins. They find that artificial neural networks (ANNs) provide the best forecasting ability of the standard algorithms and can handle data outside of the training set. Johansson *et al.*, however, do not look at the long-term effects of different algorithms on their application.

Baram *et al.* combine an ensemble of active learners by developing an active-learning master algorithm [17]. To achieve this, they propose a simple maximum entropy criterion that provides effective estimates in realistic settings. Their active-learning master algorithm is empirically shown to, in some cases, outperform the best algorithm in the ensemble on a range of classification problems.

Schmitt *et al.* also extends on existing algorithms through an extension of the FLORA algorithm in [180, 206]. The FLORA algorithm generates a rule-based model, which has the ability to make binary decisions. Their FLORA-MC enhances the FLORA algorithm for multi-classification and numerical input values. They use this algorithm for an ambient computing application. Ambient computing is where computing and communication merges into everyday life. They find that their model outperforms traditional offline learners by orders of magnitude.

Similarly to us, Pindoriya *et al.* trial several different machine learning methods such as adaptive wavelet neural network (AWNN). They find that AWNN has good prediction properties when compared to other forecasting techniques such as wavelet-ARIMA, multilayer perceptron (MLP) and radial basis function (RBF) neural networks as well as the fuzzy neural network (FNN).

Goncalves Da Silva *et al.* show the effect of prediction accuracy on local electricity markets [77]. To this end, they compare forecasting of groups of consumers in comparison to single individuals. They trial the use of the Seasonal-Naïve and Holt-Winters algorithms and look at the effect that the errors have on trading in an intra-day electricity market of consumers and prosumers. They found that with a photovoltaic penetration of 50%, over 10% of the total generation capacity was uncapitalized and roughly 10, 25 and 28% of the total traded volume were unnecessary buys, demand imbalances and unnecessary sells respectively. This represents energy that the participant has no control. Uncapitalized generation capacity is where a participant could have produced energy, however, it was not sold on the market. Additionally, due to forecast errors, the participant might have sold less than it should have. Our work, however, focuses on a national electricity market, as opposed to a local market.

5.4 Methods

In this section, we explore the principles behind the methods used in this Chapter.

5.4.1 Error Metrics

Mean Absolute Percentage Error

The mean absolute percentage error (MAPE) is a measure of prediction accuracy which is used in this thesis. It can be defined as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{5.1}$$

where y_i is the actual value, $\hat{y}_i$ is the forecast value and n is the number of points forecast [139].

Root Mean Squared Error

The root mean squared error (RMSE) is a measure between the values predicted by a model and the observed values. The RMSE is the sample standard deviation of the differences between the predicted and observed values.

The RMSE is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_i - y_i)^2)}{n}} \tag{5.2}$$

where $\hat{y}_i$ are the predicted values, y_i are the observed values, and n is the number of observations.

Mean Absolute Scaled Error

The mean absolute scaled error (MASE) is a measure of accuracy of forecasts. It is defined as the mean absolute error of the forecast values, divided by the mean absolute error of the in-sample one-step naive forecast. MASE can be scaled across difference scales, has symmetry for both positive and negative errors, is interpretable and has predictable behaviour for a value of 0.

MASE can be defined as follows:

$$MASE = mean\left(\frac{|e_j|}{\frac{1}{T-1}\sum_{t=2}^{T}|Y_t - Y_{t-1}|}\right) = \frac{\frac{1}{J}\sum_j|e_j|}{\frac{1}{T-1}\sum_{t=2}^{T}|Y_t - Y_{t-1}|} \tag{5.3}$$

where e_j is the forecast error for a given period, J is the number of forecasts. Where e_j is defined as the actual value (Y_j) minus the forecast value (F_j) for that period. The denominator is the mean absolute error of the one-step naive forecast method on the training set. This naive forecast is the actual value from the prior period, or $F_t = Y_{t-1}$. T is the total number of forecasts.

5.4.2 Machine learning

Machine learning is a methodology for finding and describing structural patterns in data [210]. Offline learning models are trained with the data availalable at a single point in time. With non-stationary data where underlying distributions change, the model must be retrained at periodic intervals, determined by how quickly the model goes out of step with the true data. With online learning, the model is able to retrain every time a new data point becomes available, without having to retrain the entire model. This makes these models good for time-series data which exhibit moderate to significant non-stationary properties, such as electricity demand profiles.

5.4.3 Online learning

Examples of online learning algorithms are Passive Aggressive (PA) Regressor [42], Linear Regression, Box-Cox Regressor [25], K-Neighbors Regressor [65] and Multilayer perceptron regressor [93]. For our work, we trial the stated algorithms, in addition to a host of offline learning techniques. The offline techniques trialled were Lasso regression [195], ridge regression [**?**], Elastic Net [69], Least Angle Regression [57], Extra Trees Regressor [57], Random Forest Regressor [28], AdaBoost Regressor [68], Gradient Boosting Regressor [70] and Support vector regression [39]. We chose the boosting and random forest techniques due to our previous successes of these algorithms when applied to electricity demand forecasting [125]. We trialled the additional algorithms due to availability of these algorithms using the scikit-learn package and online learning package, Creme [**? ?**].

5.4.4 Linear regression models

Linear regression is a linear approach to modelling the relationship between a dependent variable and one or more independent variables. Linear regressions can be used for both online and offline learning. In this work, we used them for both online and offline learning. Linear regression models are often fitted using the least squares approach. The least squares approach minimizes the sum of the squares of the residuals.

Other methods for fitting linear regressions are by minimizing a penalized version of the least squares cost function, such as in ridge and lasso regression [195**?**]. Ridge regression is a useful approach for mitigating the problem of multicollinearity in linear regression. Multicollinearity is where one predictor variable can be linearly predicted from the others with a high degree of accuracy. This phenomenon often occurs in models with a large number of parameters.

In ridge regression, the OLS loss function is augmented so that we not only minimize the sum of squared residuals but also penalized the size of parameter estimates, in order to shrink them towards zero:

$$L_{ridge}(\hat{\beta}) = \sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2 + \lambda \sum_{j=1}^{m} \hat{\beta_j^2} = ||y - X\hat{\beta}||^2 + \lambda||\hat{\beta}||^2. \tag{5.4}$$

Where λ is the regularization penalty which can be chosen through cross-validation, or the value that minimizes the cross-validated sum of squared residuals, for instance. n is the number of observations of the response variable, Y, with a linear combination of m predictor variables, X, and we solve for $\hat{\beta}$, where $\hat{\beta}$ are the OLS parameter estimates.

Lasso is a linear regression technique which performs both variable selection and regularization. It is a type of regression that uses shrinkage. Shrinkage is where data values are shrunk towards a central point, such as the mean. The lasso model encourages models with fewer parameters. This enables the selection of models with fewer numbers of parameters, or automate the process of variable selection.

Under Lasso the loss is defined as:

$$L_{lasso}(\hat{\beta}) = \sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2 + \lambda \sum_{j=1}^{m} |\hat{\beta}_j|. \tag{5.5}$$

The only difference between lasso and ridge regression is the penalty term.

Elastic net is a regularization regression that linearly combines the penalties of the lasso and ridge methods. Specifically, Elastic Net aims to minimize the following loss function:

$$L_{enet}(\hat{\beta}) = \frac{\sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2}{2n} + \lambda(\frac{1-\alpha}{2}\sum_{j=1}^{m}\hat{\beta}_j^2 + \alpha\sum_{j=1}^{m}|\hat{\beta}_j|), \tag{5.6}$$

where α is the mixing parameter between ridge ($\alpha = 0$) and lasso ($\alpha = 1$). The two parameters λ and α can be tuned.

Least Angle Regression (LARS) provides a mean of producing an estimate of which variables to include in a linear regression, as well as their coefficients.

5.4.5 Decision tree-based algorithms

The decision tree is a model which goes from observations to output using simple decision rules inferred from data features [**?**]. To build a regression tree, recursive binary splitting is used on the training data. Recursive binary splitting is a greedy top-down algorithm used to minimize the residual sum of squares. The RSS, in the case of a partitioned feature space with M partitions, is given by:

$$RSS = \sum_{m=1}^{M}\sum_{i\in R_m}(y - \hat{y}_{R_m})^2. \tag{5.7}$$

Where y is the value to be predicted, $\hat{y}$ is the predicted value for partition R_m.

Beginning at the top of the tree, a split is made into two branches. This split is carried out multiple times and the split is chosen that minimizes the current RSS. To obtain the best sequence of subtrees cost complexity, pruning is used as a function of α. α is a tuning parameter that balances the depth of the tree and the fit to the training data. This parameter can be tuned using cross-validation.

The AdaBoost training process selects only the features of a model known to improve the predictive power of the model [68]. By doing this, the dimensionality of the model is reduced and can improve compute time. This can be used in conjunction with multiple different models. In our work, we utilized the decision tree based algorithm with AdaBoost.

Random Forests are an ensemble learning method for classification and regression [28]. Ensemble learning methods use multiple learning algorithms to obtain better predictive performance. They work by constructing multiple decision trees at training time, and outputting the predicted value that is the mode of the predictions of the individual trees.

To ensure that the individual decision trees within a Random Forest are not correlated, bagging is used to sample from the data. Bagging is the process of randomly sampling with replacement of the training set and fitting the trees. This has the benefit of reducing the variance of the model without increasing the bias.

Random Forests differ in one way from this bagging procedure. Namely, using a modified tree learning algorithm that selects, at each candidate split in the learning process, a random subset of the features, known as feature bagging. Feature bagging is undertaken due to the fact that some predictors with a high predictive ability may be selected many times by the individual trees, leading to a highly correlated Random Forest.

ExtraTrees adds one further step of randomization [57]. ExtraTrees stands for extremely randomized trees. There are two main differences between ExtraTrees and Random Forests. Namely, each tree is trained using the whole learning sample (And not a bootstrap sample), and the top-down splitting in the tree learner is randomized. That is, instead of computing an optimal cut-point for each feature, a random cut-point is selected from a uniform distribution. The split that yields the highest score is then chosen to split the node.

5.4.6 Gradient Boosting

Gradient boosting is also an ensemble model [70]. Gradient boosting optimizes a cost-function over function space by iteratively choosing a function that points in the negative gradient descent direction, known as a gradient descent method.

5.4.7 Support vector regression

Support vector regression is an algorithm which finds a hyperplane and decision boundary to map an input domain to an output [39]. The hyperplane is chosen by minimizing the error within a certain tolerance.

Suppose we have the training set: $(x_1, y_1), \dots, (x_i, y_i), \dots, (x_n, y_n)$, where x_i is the input, and y_i is the output value of x_i. Support Vector Regression solves an optimization problem [184, 33], under given parameters $C > 0$ and $\varepsilon > 0$, the form of support vector regression is [54]:

$$\min_{\omega, b, \xi, \xi^*} \frac{1}{2}\omega^T \omega + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{5.8}$$

subject to

$$\begin{aligned} y_i - (\omega^T \phi(x_i) + b) &\leq \varepsilon + \xi_i^*, \\ (\omega^T \phi(x_i) + b) - y_i &\leq \varepsilon + \xi_i, \\ \xi_i, \xi_i^* &\geq 0, i = 1, \dots, n \end{aligned} \tag{5.9}$$

x_i is mapped to a higher dimensional space using the function ϕ. The ε-insensitive tube $(\omega^T \phi(x_i) + b) - y_i \leq \varepsilon$ is a range in which errors are permitted. ξ_i and ξ_i^* are slack variables which allow errors for data points which fall outside of ε. This enables the optimization to take into account the fact that data does not always fall within the ε range [187].

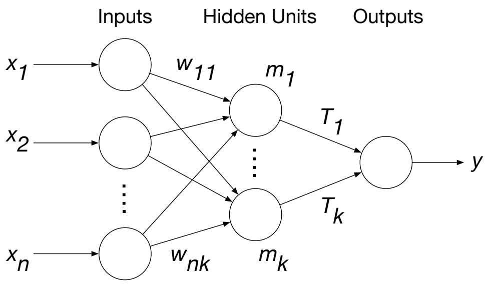


Fig. 5.1 A three-layer feed forward neural network.

The constant $C > 0$ determines the trade-off between the flatness of the support vector function. ω is the model fit by the SVR. The parameters which control regression quality are the cost of error C, the width of the tube ε, and the mapping function ϕ [184, 33].

5.4.8 K-Neighbors Regressor

K-Neighbors regression is a non-parametric method used for regression [65]. The input consists of a new data point, and the algorithm finds the k closest training examples in the feature space. The output is the average value of the k nearest neighbours.

A neural network can be used in both offline and online cases. In this work, we used them for both online and offline.

Artificial Neural Networks are a model which can model non-linear relationships between input and output data [9]. A popular neural network is a feed-forward multilayer perceptron. Fig. 5.1 shows a three-layer feed-forward neural network with a single output unit, k hidden units, n input units. w_{ij} is the connection weight from the i^{th} input unit to the j^{th} hidden unit, and T_j is the connecting weight from the j^{th} hidden unit to the output unit [160]. These weights transform the input variables in the first layer to the output variable in the final layer using the training data.

For a univariate time series forecasting problem, suppose we have N observations $y_1, y_2, \ldots, y_N$ in the training set, and m observations in the test set, $y_{N+1}, y_{N+2}, \ldots, y_{N+m}$. In the test set and we are required to predict m periods ahead [160].

The training patterns are as follows:

$$y_{p+m} = f_W(y_p, y_{p-1}, \ldots, y_1) \tag{5.10}$$
$$y_{p+m+1} = f_W(y_{p+1}, y_p, \ldots, y_2) \tag{5.11}$$
$$\vdots$$
$$y_N = f_W(y_{N-m}, y_{N-m-1}, \ldots, y_{N-m-p+1}) \tag{5.12}$$

where $f_W(\cdot)$ represents the MLP network and W are the weights. For brevity we omit W. The training patterns use previous time-series points, for example, $y_p, y_{p-1}, \ldots, y_1$ as the time series is univariate. That is, we only have the time series in which we can draw inferences from. In addition, these time series points are correlated, and therefore provide information that can be used to predict the next time point.

The m testing patterns are

$$y_{N+1} = f_W(y_{N+1-m}, y_{N-m}, \dots, y_{N-m-p+2}) \tag{5.13}$$

$$y_{N+2} = f_W(y_{N+2-m}, y_{N-m+1}, \dots, y_{N-m-p+3}) \tag{5.14}$$

$$\vdots$$

$$y_{N+m} = f_W(y_N, y_{N-1}, \dots, y_{N-p+1}). \tag{5.15}$$

The training objective is to minimize the overall predictive mean sum of squared estimate of errors (SSE) by adjusting the connection weights. For this network structure the SSE can be written as:

$$SSE = \sum_{i=p+m}^{N} (y_i - \hat{y}_i) \tag{5.16}$$

where $\hat{y}_i$ is the prediction from the network. The number of input nodes corresponds to the number of lagged observations. Having too few or too many input nodes can affect the predictive ability of the neural network [160].

It is also possible to vary the hyperparameter, the number of input units. Typically, various different configurations of units are trialled, with the best configuration being used in production. The weights W in f_W are trained using a process called backpropagation, which uses labelled data and gradient descent to update and optimize the weights.

5.4.9 Online Algorithms

In this Section we discuss the algorithms which were used exclusively for online learning in this work.

5.4.10 Box-Cox regressor

In this subsection, we discuss the Box-Cox regressor. Ordinary least square is a method for estimating the unknown parameters in a linear regression model. It estimates these unknown parameters by the principle of least squares. Specifically, it minimizes the sum of the squares of the differences between the observed variables and those predicted by the linear function.

The ordinary least squares regression assumes a normal distribution of residuals. However, when this is not the case, the Box-Cox Regression may be useful [25]. It transforms the dependent variable using the Box-Cox Transformation function and employs maximum likelihood estimation to determine the optimal level of the power parameter lambda. The Box-Cox Regression requires that no dependent variable has any negative values.

Variable selection and ordinary least squares output dialogues are identical to that of linear regression.

The Box-Cox regression will transform the dependent variable as follows:

$$y^{(\lambda)} = \frac{y^\lambda - 1}{\lambda} \, if \, \lambda \neq 0 \tag{5.17}$$

$$y^{(\lambda)} = Ln(y)\ if\ \lambda = 0 \tag{5.18}$$

Where λ is the power parameter, and the data vectors are $yi = (y_1, \ldots, y_n)$. The optimal value of (λ) is determined by maximising the following log-likelihood function:

$$L^{(\lambda)} = -\frac{n}{2} Ln(\hat{\sigma}^2_{(\lambda)} + (\lambda - 1) \sum_{i=1}^{n} Ln(y_i) \tag{5.19}$$

where $\hat{\sigma}^2_{(\lambda)}$ is the estimate of the least squares variance using the transformed y variable.

5.4.11 Passive-Aggressive regressor

The goal of the Passive-Aggressive (PA) algorithm is to change itself as little as possible to correct for any mistakes and low-confidence predictions it encounters [42]. Specifically, with each example PA solves the following optimisation [144]:

$$w_{t+1} \leftarrow argmin \frac{1}{2} ||w_t - w||^2 \tag{5.20}$$

$$s.t.\ \ y_i(w \cdot x_t) \geq 1. \tag{5.21}$$

Where x_t is the input data and y_i the output data, and w_t are the weights for the PA algorithm. Updates occur when the inner product does not exceed a fixed confidence margin - i.e., $y_i(w \cdot x_t) \geq 1$. The closed-form update for all examples is as follows:

$$w_{t+1} \leftarrow w_t + \alpha_t y_t x_t \tag{5.22}$$

where

$$\alpha_t = max \left\{ \frac{1 - y_t(w_t \cdot x_t)}{||x_t||^2}, 0 \right\}. \tag{5.23}$$

a_t is derived from a derivation process which uses the Lagrange multiplier. For full details of the derivation see [42].

5.5 Short-term demand forecasting

In this section we present the work undertaken for short-term demand forecasting. We forecast 30-minutes ahead using smart meter data.

5.5.1 Methodology

Data Collection

Smart meter data obtained from the Irish Social Science Data Archive (ISSDA) on the 28th of September 2017 was used in this study [64]. The Commission for Energy Regulation released a

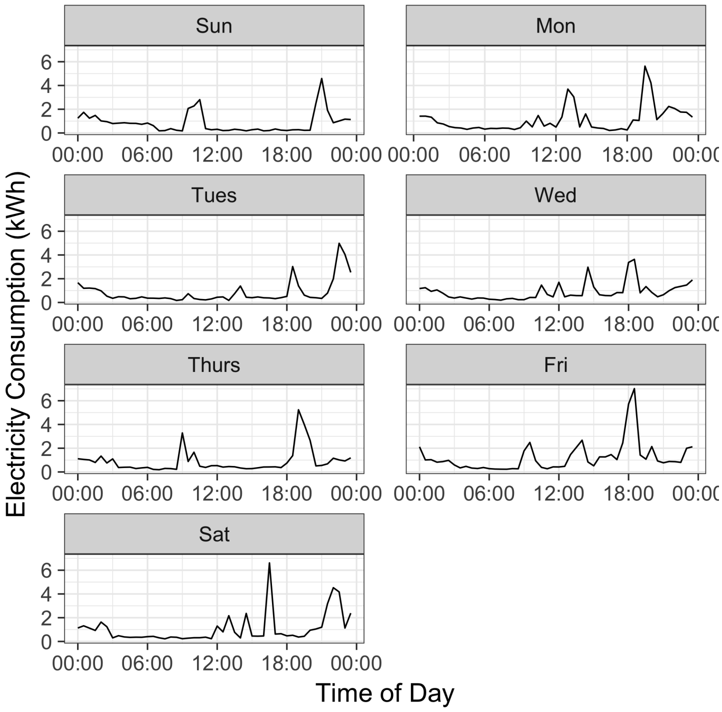


Fig. 5.2 Daily load profiles of a single customer over a week between 20th July 2009 and 27th July 2009.

public dataset of anonymised smart meter data from the "*Electricity Smart Metering Customer Behaviour Trials*" [4]. This dataset is made up of over 5000 Irish homes and businesses and is sampled at 30-minute intervals.

The data was recorded between the 14th July 2009 and 31st December 2010, providing 17 months worth of data. For the purposes of cross-validation the data was split into two partitions, the training set and the testing set. The training set made up the first 11 months of data and was used to parametrise the models, whereas the test set is made up of the remaining 6 months of data. This split was chosen to balance the amount of training data with the test data and to give the models a chance to learn the periodicity inherent in a one year period of electricity load. The test set was used for evaluation of the models proposed. Due to the long training times for these algorithms, we worked with a sub-sample of 709 individual Irish homes from the whole dataset. However, we believe that our results would hold over the full dataset.

Figure 5.2 demonstrates the electricity consumption profile of a single week for a single user. Whilst it can be seen that electricity usage changes significantly between days, a pattern of behaviour is exhibited. There is a large peak displayed each day in the evening, as well as a peak earlier during the day. It can, therefore, be assumed that this customer has some form of habitual behavioural pattern.

Figure 5.3 shows eight different residential customer load profiles on the 22nd June 2009. It can be seen that the daily load profile changes between each customer. The consumers use varying quantities of electricity and at different times.

These figures display that electricity consumption changes per person, per day. To capture this variability between customer types these customers are clustered and then aggregated. Each

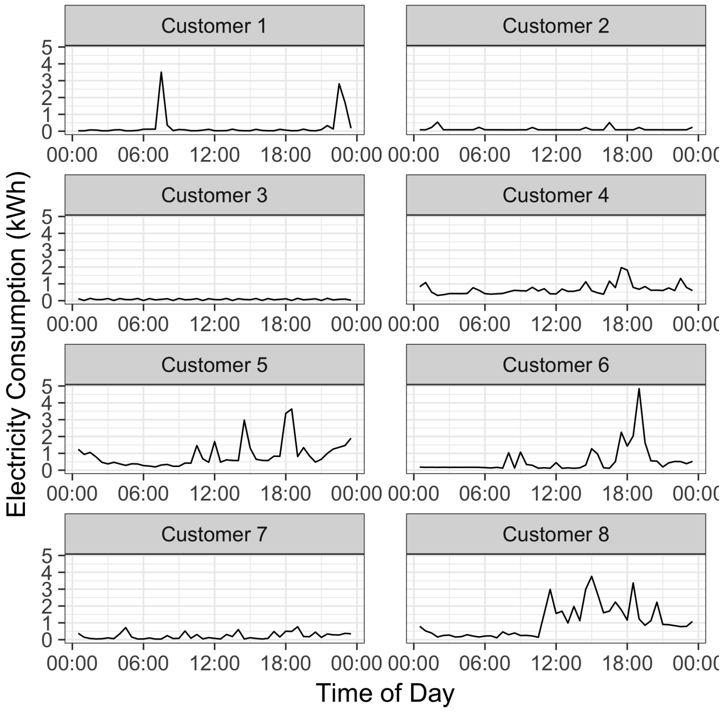


Fig. 5.3 Daily load profiles of different customers over a single day on the 22nd June 2009.

of the different aggregated electricity consumptions should provide a less stochastic load profile, and therefore increase the accuracy of the models.

Clustering

We propose that clustering similar customer load profiles and aggregating each cluster's electricity consumption improves the accuracy of the models.

Figure 5.4 displays four different customers with similar load profiles. Each of the users display a strong peak in electricity consumption during the evening and less consumption during the day. These customers may potentially be clustered together by the *k*-means clustering algorithm.

To cluster the load profiles different options were considered. Hierarchical clustering using metrics such as Euclidean and wavelet distance metrics were evaluated [149], as was *k*-means [**?**]. *K*-means demonstrated to be the most robust and best-performing clustering algorithm, and thus was chosen for use in this work.

To select the optimum number of clusters (k) cross-validation was explored. This allowed us to compare the results of each of the models and select k with the highest MAPE accuracy.

The cross-validation method proposed, worked by trying a different number of clusters per model, and testing for the resulting MAPE. The optimum number of clusters with a low MAPE is then chosen. In this work we varied k between 1 and 7, this range was chosen due to the fact that the error did not vary greatly past seven clusters. We fit multiple models per cluster and predicted 6 months of electricity consumption.

With *k*-means clustering, it is possible that with the same initialization number of clusters, different clusters are formed. This is due to the algorithm converging at a local minima. To

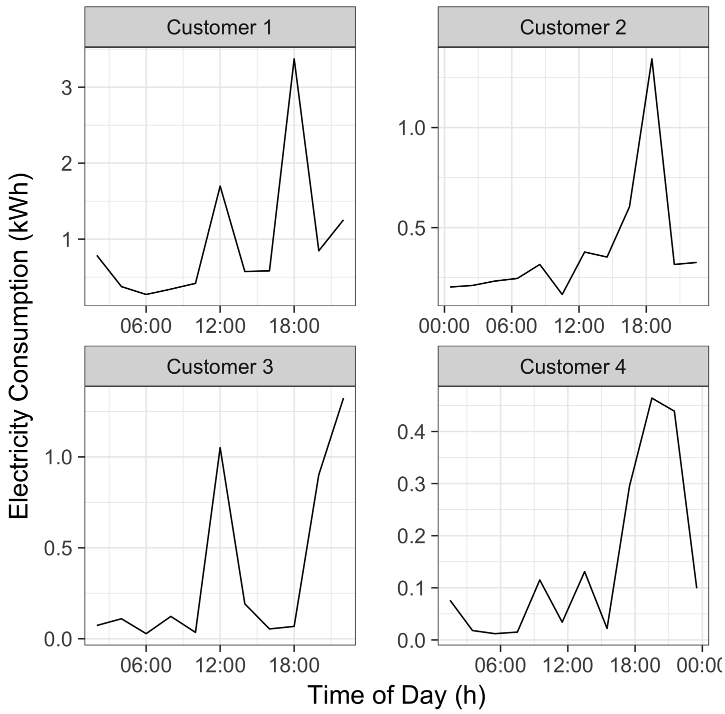


Fig. 5.4 Figure showing similar load profiles for four different customers on the 22nd July 2009.

overcome local minima the *k*-means algorithm is run multiple times and the partition with the smallest squared error is chosen [118]. In our case, the *k*-means clustering algorithm is run 1000 times to reduce the chance of finding a local minima.

The clustering technique utilised in our work was a scaled input approach. The daily load profile was averaged for each customer based on each day of the training data. The data was then scaled so that households of different sizes, but with similar usage profiles were clustered together. This data, which is made up of a *m-by-n* matrix, where *m* is equal to the total number of meters and *n* is equal to 48 (two readings for each hour in the day).

To find the optimum number of clusters it is recommended that the user selects a value of *k* that is high enough that distinct average load profiles are displayed, however, not so high that well-clustered customers are split. By doing this, the stochasticity of the load profiles in each of the clusters will be reduced, and thus lead to the best results.

Aggregating Demand

Once each customer is assigned to their respective cluster, the total electricity consumed per cluster is aggregated. This is achieved by summing the electricity consumed at each time interval per cluster. This creates a partial system load. A different model is trained on each of the different partial system loads, and the resultant forecasts are aggregated to generate the total system load forecast. The total system load forecast is then used to evaluate the accuracy of each of the different models using MAPE.

Random Forests, Support Vector Regression, Multilayer Perceptron neural networks and Long-Short Term Memory neural networks were evaluated, and a comparison between the different models were made.

These models were chosen due to their ability to model multivariate non-linear relationships. They are data-driven methods and therefore suited to this type of problem.

Feature Selection

Each component of the training data is known as a feature. Features encode information from the data that may be useful in predicting electricity consumption.

Calendar Attributes

Due to the daily, weekly and annual periodicity of the electricity consumption daily calendar attributes may be useful to model the problem. The calendar attributes included are as follows:

- Hour of day
- Day of the month
- Day of the week
- Month
- Public holidays

These attributes enable the daily, weekly and annual periodicity to be taken into account by the model.

It is noted that electricity consumption changes on a public holiday such as Christmas or New Year's Eve. It is therefore proposed that public holidays in Ireland are input into the model as features.

For testing purposes, two sets of models for Random Forests, Multilayer Perceptrons and Support Vector Regression were fit. One set omitted these calendar attributes whilst the other didn't. This is done to evaluate the importance of periodicity in electricity consumption prediction.

Time Series Data

As well as the calendar attributes it is important to consider the historical load demand. This allows the time-series element to be modelled.

To do this, a lagged input of the previous 3 hours, the equivalent three hours from the previous day, and the equivalent 3 hours from the previous week were used. For example, to predict the electricity consumed on the 21st December 2010 at 12:00 pm the electricity between 9:00 pm and 11:30 pm on the 21st of December are used as inputs, as are the times between 9:00 pm and 12:00 pm on the 20th and 14th of December.

Long-Short Term Memory neural networks remember values over arbitrary time intervals. They can remember short-term memory over a long period of time, for this reason, 5 lagged inputs of the previous two and a half hours were used as features to the Long-Short Term Memory network.

Table 5.1 List of Input Data for Models

Input	Variable	Detail description
1	Hour	Single numeric input representing hour of the day
2	Day of month	Single numeric input representing day of the month
3-9	Day of week	Six binary digits representing calendar information regarding day of the week
10-21	Month	Eleven binary digits representing calendar information regarding month
22-42	Lagged inputs	Twenty numeric inputs representing lagged inputs of previous 3 hours, previous 3 hours of previous day including hour to be predicted, and previous 3 hours of previous week including hour to be predicted
43	Holiday	One binary digit representing whether the day was a public holiday

Data Representation

Once useful information is selected we must encode the data for input into the models. To encode the day of the week seven binaries are utilised. Six of the binaries are for Monday through to Saturday. When all six binaries are equal to zero Sunday is encoded. A single binary for public holidays is included. Eleven binaries are used for month of the year, with the first eleven representing January to November, with December represented by all zeros in the calendar binaries. The current hour and date are input using a numerical attribute. The lagged data inputs, such as previous hour's electricity usage are also input using a numerical attribute for each entry, totaling 20 attributes (six half hourly entries for each 3 hour period multiplied by three days plus 2 entries for the time to be predicted on the previous day and week). Table 5.1 displays these features.

5.5.2 Experiments

This section explores the different methods used to select the model parameters, and the tests to evaluate our models. Once the parameters were chosen the models were trained on the different clusters of residential customers. Each model was run five times to explore the variance of the results.

Support Vector Regression

To implement a Support Vector Regression model a variety of parameters must be chosen. These parameters influence the performance of the model. The parameters were evaluated using cross-validation. To do this, the data was split 75% into training data, and the remaining 25% into test data. This split was chosen to balance the trade-off between having enough training data so that

Kernel Type	Kernel Parameters	RMSE
Linear	No values	0.02103
RBF	C=2, $\gamma = 0.016$	0.0245
Polynomial	C=2, $d = 2, r = 2$	0.0315

Table 5.2 Prediction Accuracy Based on Type of Kernel

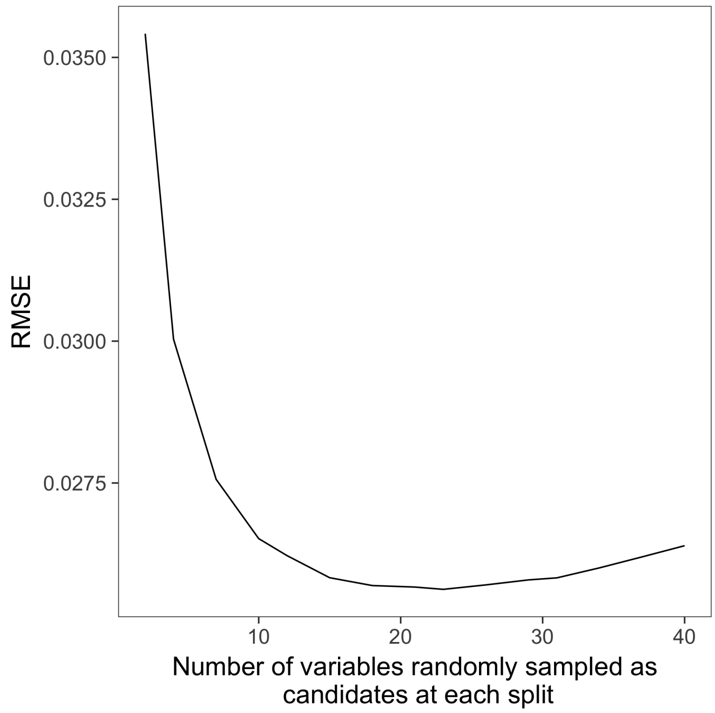


Fig. 5.5 RMSE vs Number of variables randomly sampled as candidates at each split in the Random Forest model.

the model can accurately learn the underlying form of the data, but also to have enough data to test each model.

To choose the optimum support vector machine kernel cross-validation was also used. Again, with 75% acting as the training data and 25% as the test. The kernels compared were polynomial, radial basis function (RBF) and the linear kernel [31, 194]. These were chosen due to their popularity, support and relative speed of computation.

The parameter values selected are shown in Table **??**. These parameter values were chosen from the results of cross-validation for each of the different kernels. From the cross-validation, the linear kernel was found to be the best performing. For this reason, the linear kernel was utilised for prediction of electricity consumption in this work.

Random Forest

To initialize the Random Forest algorithm with the number of variables randomly sampled as candidates at each split, cross-validation was used. Once again, 75% of the data was used for training and the remaining 25% for testing due to the trade-off between training and testing.

Figure 5.5 shows the results of tuning the parameter of the number of variables randomly sampled as candidates at each split. The optimum number was found to be 23. Either side of this value the RMSE increases. Therefore the value 23 was selected to be the number of variables randomly sampled as candidates at each split in the Random Forest model. It is proposed that the value 23 was found to be optimum due to the 20 lagged inputs, as this data is crucial for the Random Forest to learn the underlying nature of electricity load.

Multilayer Perceptron

A feed-forward Multilayer Perceptron is a common neural network architecture used for the prediction of time series data, which has comparable, and occasionally better results than statistical models [91].

The first step when designing a Multilayer Perceptron neural network is to design the architecture. For this case, the number of input neurons is set to 41 (see Table 5.1). Once an input for each neuron is entered, the output layer must be designed. Due to the fact that we are forecasting only one time step ahead (30 minutes ahead) one output neuron is required.

The next step is to design the architecture of the hidden layers. To accomplish this, cross-validation is utilised as per the previous models. A maximum of 3 hidden layers were tested and the results analysed. A similar method to Fan *et al.* was evaluated to choose the number of neurons and hidden layers, a technique known as the Levenberg-Marquardt technique [59]. The Levenberg-Marquardt is a technique suitable for training medium-sized Artificial Neural Networks with a low mean-squared error.

The fundamental rule is to select the minimum number of neurons in the hidden layer so as to capture the complexity of the model, but not too many as to introduce over-fitting, which results in a loss in generalization of the algorithm.

The method begins by choosing a small number of neurons and gradually increasing the number each time the model is trained and the forecast error obtained. The forecast error is monitored until an optimum value is found, to which no further improvement is noted. Once the optimum number of neurons in the layer is obtained an additional layer is added, and the same technique is used.

Using this technique an optimal architecture with three layers is obtained. The first layer contained two neurons, the second contained five, and the third contained four.

LSTM

To initialize the LSTM, cross-validation was used to select the number of stacked layers and memory units. Similarly to the technique used for the Multilayer Perceptron, the Levenberg-Marquardt was used. The optimum number of layers was found to be 2, with a total of 50 memory units. Different combinations of layers and memory units displayed worse results.

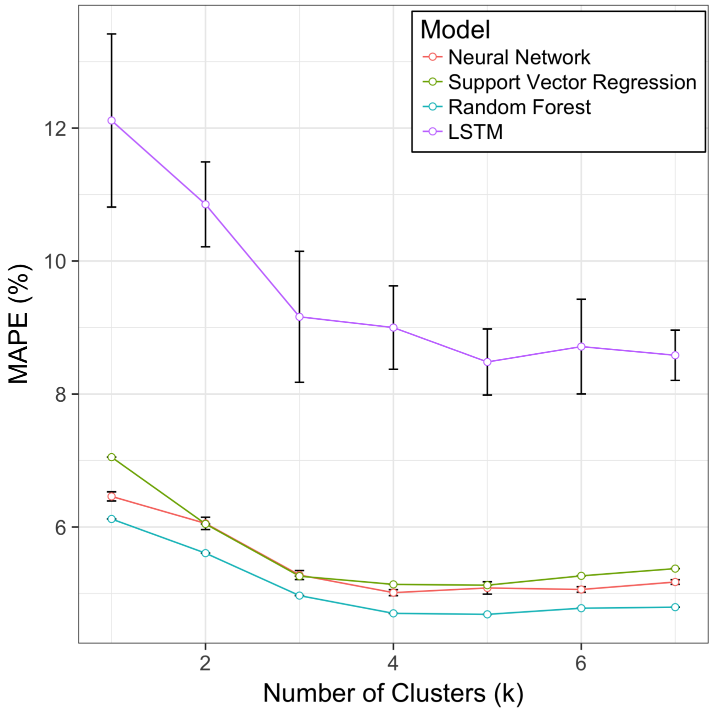


Fig. 5.6 Comparison of accuracy of models forecasting electricity with varying number of clusters.

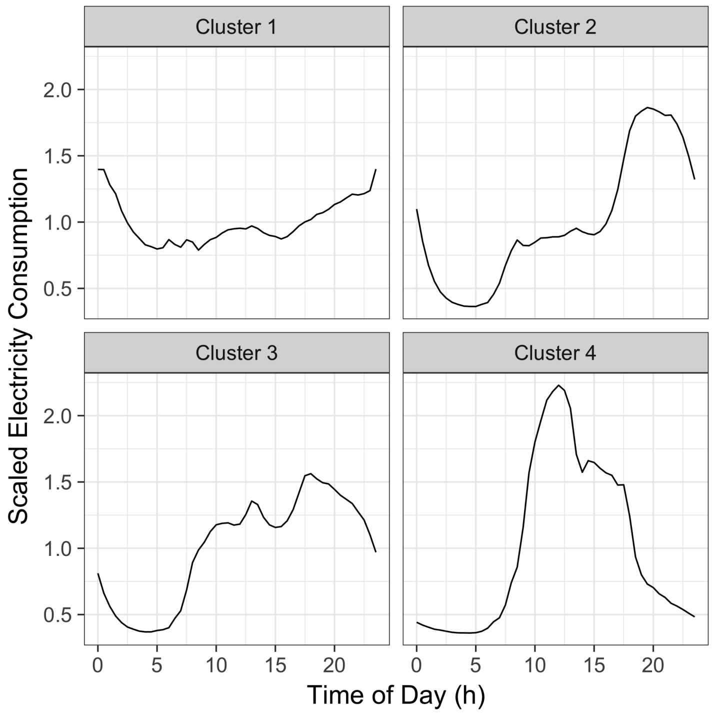


Fig. 5.7 Average load profile for each cluster.

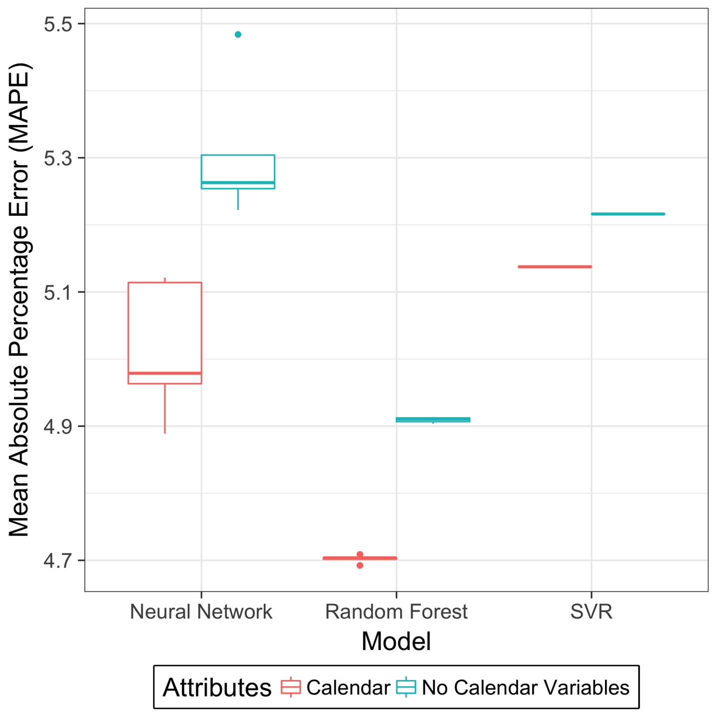


Fig. 5.8 Comparison of accuracy of models with or without calendar attributes.

5.5.3 Results

To test the accuracy of the trained model the data was split into a training and test set. The data between the 14th of July 2009 and the 15th of June 2010 was used as the training data, whilst the data between the 15th of June 2010 and 31st of December 2010 was used for testing purposes. The test set is separate from the training set and not used during training.

28 independent forecasting models are constructed for each of the Random Forests, Support Vector Regression, LSTMs and Multilayer Perceptron neural networks for each of the groups with k varying from 1 to 7. This was done to determine the optimal number of clusters. Each of the 28 models are trained independently, five times each so that the standard deviation results of MAPE for each cluster could be displayed. We evaluated the MAPE of the overall prediction.

Figure 5.6 displays the accuracy of the models trained at different numbers of clusters (k). The results demonstrate that introducing clusters to group similar customers improve results in all cases. The optimum value for k for Random Forests, Support Vector Regression and neural networks was shown to be four for our dataset. After this, the accuracy diminishes slightly. The error bars shown in Figure 5.6 show a small variance in MAPE in SVRs, ANNs and Random Forests. However, the MAPE of the LSTMs seem to vary by up to 11% in the five models run.

Figure 5.8 demonstrates the impact of using calendar attributes such as month, day of the month, and day of the week on prediction accuracy. The results show an increase in prediction accuracy of 6% for neural networks, 4% for Random Forests and 1% for support vector regression when taking into account these variables. It is proposed that the ability for the models to take into account the cyclic yearly, monthly and weekly behaviour improves the results.

Figure 5.7 shows the average load profiles of different clusters when $k = 4$. It is proposed that the optimum number of clusters is four due to the distinct load profiles that can be seen in

Figure 5.7. The four different distinct patterns seen are high night time use in cluster 1, a typical residential load profile is shown in cluster 2, a spread of usage in cluster 3, and high daytime usage in cluster 4. At $k = 3$ these distinct patterns are not adequately clustered, and at $k = 5$ one of the distinct clusters are split, leading to an increase in stochasticity.

It is true that the optimum number of clusters will vary for different datasets. Whilst residential smart meter datasets may be similar, it is entirely possible that different geographies display different usage characteristics based on factors such as culture, temperature and economical reasons. It is therefore important to choose an optimal number of clusters for each dataset.

The results demonstrate that SVR, Random Forests and the Multilayer Perceptrons have a similar overall accuracy. The LSTM shows a similar pattern in increasing accuracy with number of clusters. However, the Random Forest seems to outperform each of the models at every point. This may be due, in part, to the internal operation of the Random Forest which undertakes its own cross-validation using out-of-bag samples and only having a few tuning parameters.

It has been shown that neural networks, SVR and Random Forests all perform within an adequate range of predicting electricity consumption. Whilst LSTMs perform poorly. This may be due to the features given to the LSTM which only had previous two and a half hours of data as input.

However, it is well known that the best machine learning technique for predicting energy consumption cannot be chosen *a priori*. Therefore it is necessary to compare different techniques to find the best solution to a particular regression problem [8].

For this work, the training time was tested by timing how long the models would be fit to create one cluster (single model trained on the training set). The Support Vector Regression took much less time than all of the other methods, whereas the LSTM took the longest. The Artificial Neural Network required 9 minutes and 5 seconds to run. The Support Vector Regression model required 3 minutes and 32 seconds to run. The Random Forest, on the same data, required 9 minutes and 44 seconds to run, whilst the LSTM took 12 minutes 55 seconds.

5.5.4 Conclusion

The availability of high granularity data produced by the smart grid enables network operators to gain greater insights into their customer behaviour and electricity usage. This enables them to improve customer experience, utility operations and power management. We demonstrated that implementing the k-means clustering algorithm to group similar customers improved the accuracy of every one of the different models tested. Distinct models were trained for each of the clusters and the individual forecasts aggregated for the total aggregated forecast. It was found that Random Forests outperformed the other models at all levels of clustering and that the optimum number of clusters was 4. Whilst the dataset used focused on residential data it is expected that applying a similar clustering technique on commercial properties would have a similar effect.

In future work, we will look into the features that best aid in the forecasting of electricity consumption, try a wider variety of models in an ensemble manner and try different clustering techniques such as self-organizing maps (SOM) to obtain better accuracy measures. We will also compare different prediction error measures.

To utilize more of the data and increase the number of models trained these results could be run in parallel and on the cloud in future.

5.6 Day-ahead forecasting

In this section we expand on the work undertaken in Section 5.5 by utilising further time-series prediction algorithms, including online machine learning methods. We take the error distributions and perturb the exogenous electricity demand of ElecSim, and observe the long-term impacts of poor error forecasts on the UK electricity market. It should be noted that this could work for any decentralised electricity market.

5.6.1 Methods

Data preparation

Similarly to our previous work in Chapter 4 [124], we selected a number of calendar attributes and demand data from the GB National Grid Status dataset provided by the electricity market settlement company Elexon, and the University of Sheffield [5]. This dataset contained data between the years 2011-2018 for the United Kingdom. The calendar attributes used as predictors to the models were hour, month, day of the week, day of the month and year. These attributes allow us to account for the periodicity of the data within each day, month and year.

It is also the case that electricity demand on a public holiday which falls on a weekday is dissimilar to load behaviours of ordinary weekdays [130]. We, therefore, marked each holiday day to allow the model to account for this.

As demand data is highly correlated with historical demand, we lagged the input demand data. In this context, the lagged data is where we provide data of previous time steps at the input. For example, for predicting $t+1$, we use n inputs: $t, t-1, t-2, \ldots, t-n$. This enabled us to take into account correlations on previous days, weeks and the previous month. Specifically, we used the previous 28 hours before the time step to be predicted for the previous 1st, 2nd, 7th and 30th day. We chose this as we believe that the previous two days were the most relevant to the day to be predicted, as well as the weekday of the previous week and the previous month. We chose the previous 28 hours to account for a full day, plus an additional 4 hours to account for the previous day's correlation with the day to be predicted. We could have increased the number of days provided to the algorithm. However, due to time and computational constraints, we used our previously described intuition for lagged data selection. The number of lagged inputs to trial increases exponentially with each additional day added, therefore making the problem intractable when also trialling such a high number of algorithms and hyperparameters.

In addition to this, we marked each of the days with their respective seven seasons. These seasons were defined by the National Grid Short Term Operating Reserve (STOR) Market Information Report [155]. These differ from the traditional four seasons by splitting autumn into two further seasons, and winter into three seasons. Finally, to predict a full 24-hours ahead, we used 24 different models, 1 for each hour of the day.

The data is standardized and normalized using min-max scaling between -1 and 1 before training and predicting with the model. This is due to the fact that the inputs such as day of the week, hour of day are significantly smaller than that of demand. Therefore, the demand will influence the result more due to its larger value. However, this does not necessarily mean that demand has greater predictive power.

Algorithm Tuning

To find the optimum hyperparameters, cross-validation is used. As this time-series data was correlated in the time-domain, we took the first six years of data (2011-2017) for training and tested on the remaining year of data (2017-2018).

Each machine learning algorithm has a different set of parameters to tune. To tune the parameters in this work, we used a grid search method. Grid search is a brute force approach that trials each combination of parameters at our choosing; however, for our search space this was small enough to make other approaches not worth the additional effort.

Tables 5.3 and 5.4 display each of the models and respective parameters that were used in the grid search. Table 5.3 shows the offline machine learning methods, whereas Table 5.4 displays the online machine learning methods. Each of the parameters within the columns "Values" are trialled with every other parameter.

Whilst there is room to increase the total number of parameters, due to the exponential nature of grid-search, we chose a smaller subset of hyperparameters, and a larger number of regressor types. Specifically, with neural networks, there is a possibility to extend the number of layers as well as the number of neurons, to use a technique called deep learning. Deep learning is a class of neural networks that use multiple layers to extract higher levels of features from the input. For this work, however, we decided to trial a large number of different models, instead of a large number of different configurations for neural networks.

Prediction Residuals in ElecSim

Each of the previously mentioned models trialled will have a certain degree of error. Prediction residuals are the difference between the estimated and actual values. We collect the prediction residuals to form a distribution for each of the models. We then trial 80 different closed-form distributions to see which of the distributions best fits the residuals from each of the models. These 80 distributions were chosen due to their implementation in scikit-learn [**?**].

Once each of the prediction residual distributions are fit with a sensible closed-form distribution, we sample from this new distribution and perturb the demand for the electricity market at each time step within ElecSim.

By perturbing the market by the residuals, we can observe what the effects are of incorrect predictions of demand in an electricity market using the long-term electricity market model, ElecSim. We are able to understand the differences that prediction residuals have on long-term investment decisions as well as generators utilized.

Regressor Type	**Parameters**	**Values**	**Parameters**	**Values**	**Parameters**	**Values**
Linear	N/A	N/A				
Lasso	N/A	N/A				
Elastic Net	N/A	N/A				
Least-Angle	N/A	N/A				
Extra Trees	# Estimators	[16, 32]				
Random Forest	# Estimators	[16, 32]				
AdaBoost	# Estimators	[16, 32]				
Gradient Boosting	# Estimators	[16, 32]	learning rate	[0.8, 1.0]		
Support Vector	Kernel	[linear, rbf]	C	[1, 10]	Gamma	[0.001, 0.0001]
Multilayer Perceptron	Activation function	[tanh, relu]	hidden layer sizes	[1, 50]	Alpha	[0.00005, 0.0005]
K-Neighbours	# Neighbours	[5, 20, 50]				

Table 5.3 Hyperparameters for offline machine learning regression algorithms

Regressor Type	**Parameters**	**Values**	**Parameters**	**Values**	**Parameters**	**Values**
Linear	N/A	N/A				
Box-Cox	Power	[0.1, 0.05, 0.01]				
Multilayer Perceptron	Hidden layer sizes	[(10, 50, 100), (10), (20), (50), (10, 50)]				
Passive Aggressive	C	[0.1, 1, 2]	Fit intercept?	[True, False]	Max iterations	[1, 10, 100, 1000]

Table 5.4 Hyperparameters for online machine learning regression algorithms

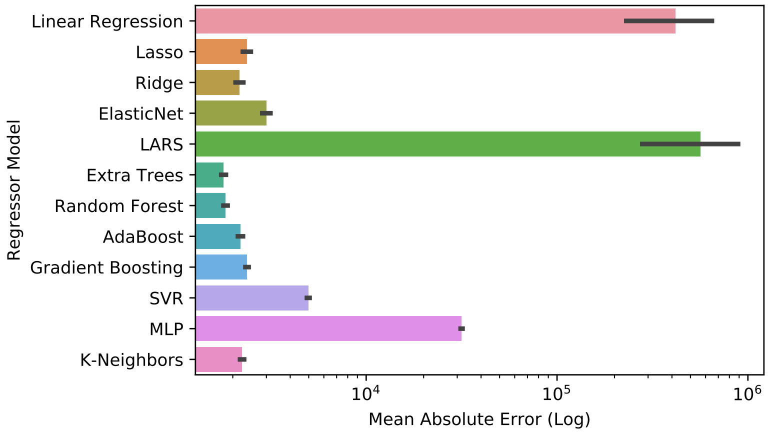


Fig. 5.9 Offline models mean absolute error comparison, with 95% confidence interval for 5 runs of each model.

5.6.2 Results

In this Section, we detail the accuracy of the algorithms and statistical models to predict 24 hours ahead for the day-ahead market. In addition to this, we display the impact of the errors on electricity generation investment and electricity mix from the years 2018 to 2035 using the agent-based model ElecSim.

Offline Machine Learning

To generate these results, we use a training set to train the data, and a test set to see how well each algorithm performs on the testing data. That is, how well the algorithm can predict data it is yet to see. In our case, the training data was from 2011 to 2017, and the testing data was from 2017 to 2018.

Figure 5.9 displays the mean absolute error of each of the offline statistical and machine learning models on a log scale. It can be seen that the different models have varying degrees of success. The least accurate models were linear regression, the multilayer perceptron (MLP) model and the Least Angle Regression (LARS). These all have mean absolute errors over 10,000MWh. This error would be prohibitively high in practice; the max tendered national grid reserve is 6,000MWh, while the average tendered national grid reserve is 2,000MWh [155].

A number of models perform well, with a low mean absolute error. These include the Lasso, gradient Boosting Regressor and K-neighbours regressor. The best model, similar to [124], was the decision tree-based model, Extra Trees Regressor, with a mean absolute error of $1,604$MWh. This level is well within the average national grid reserve of 2,000MWh.

Figure 5.10 displays the distribution of the best offline machine result (Extra Trees Regressor). It can be seen that the max tendered national grid reserve falls well above the 5% and 95% percentiles. However, there are occasions where the errors are greater than the maximum tendered national grid reserve. In addition, the majority of the time, the model's predictions fall within the average available tendered national grid reserve.

Figures 5.11 and 5.12 display the time taken to train the model and time taken to sample from the model versus the absolute error respectively for the offline algorithms. Multiple fits are

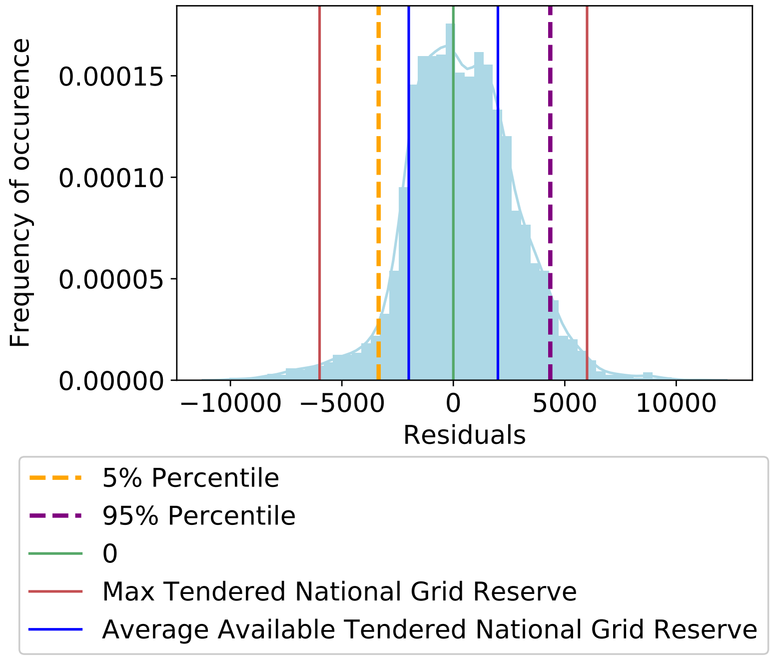


Fig. 5.10 Best offline machine learning algorithm (Extra Trees Regressor) distribution.

trialled for each parameter type for each model. The error bars indicate the results of multiple cross-validations.

It can be seen from Figure 5.11 that the time to fit varies significantly between algorithms and parameter choices. The multilayer perceptron consistently takes a long time to fit, when compared to the other algorithms and performs relatively poorly in terms of MAE. There are many models, such as the random forest regressor, and extra trees regressors which perform well, however, take a long time to fit, especially when compared to the K-Nearest neighbours.

For a small deterioration in MAE it is possible to decrease the time it takes to train the model significantly. For example, by using the K-Nearest neighbours or support vector regression (SVR).

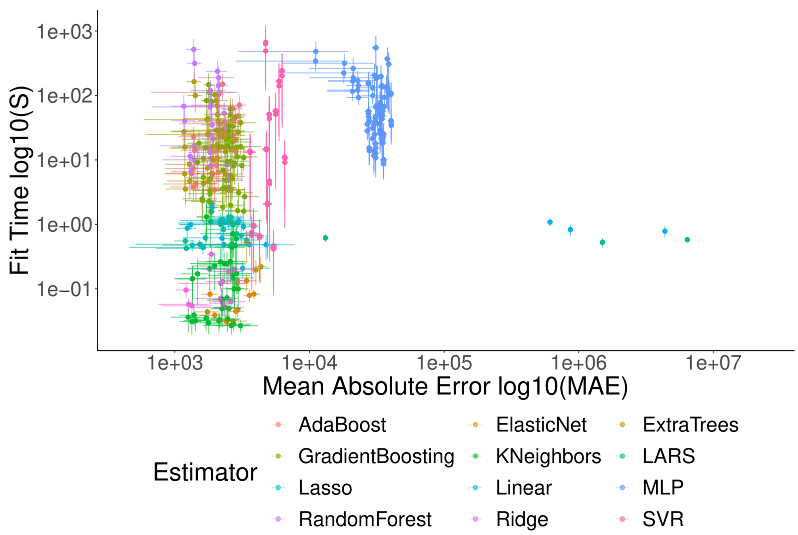


Fig. 5.11 Time taken to train the offline models versus mean absolute error. Error bars display standard deviation between points.

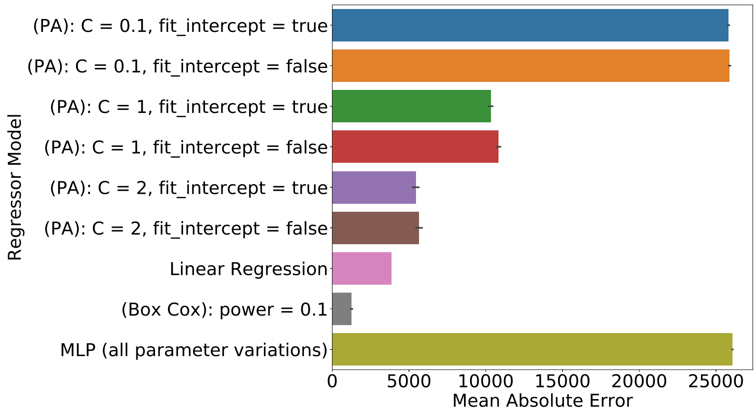


Fig. 5.13 Comparison of mean absolute errors (MAE) for different online regressor models. MLP results for all parameters are shown in a single barchart due to the very similar MAEs for the differing hyperparameters.

The scoring time, displayed in Figure 5.12, also displays a large variation between model types. For instance, the MLP regressor takes a shorter time to sample predictions when compared to the K-Neighbors algorithm and support vector regression. It is possible to have a cluster of algorithms with low sample times and low mean absolute errors. However, often a trade-off is required, with a fast prediction time requiring a longer training time and vice-versa.

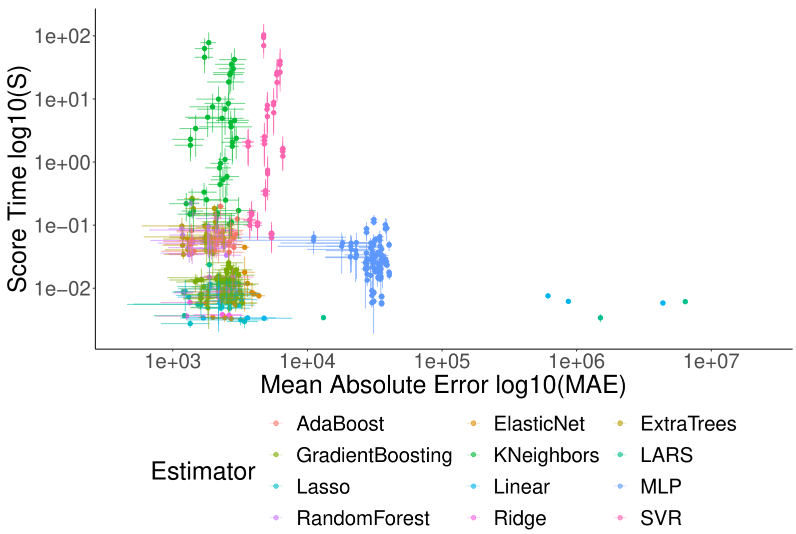


Fig. 5.12 Time taken to score the offline models versus mean absolute error. Error bars display standard deviation between points.

Online Machine Learning

To see if we can improve on the predictions, we utilize an online machine learning approach. If we are successful, we should be able to reduce the national grid reserves, reducing cost and emissions.

Figure 5.13 displays the comparison of mean absolute errors for the different trialled online regressor models. To produce this graph, we showed various hyperparameter trials. Where the

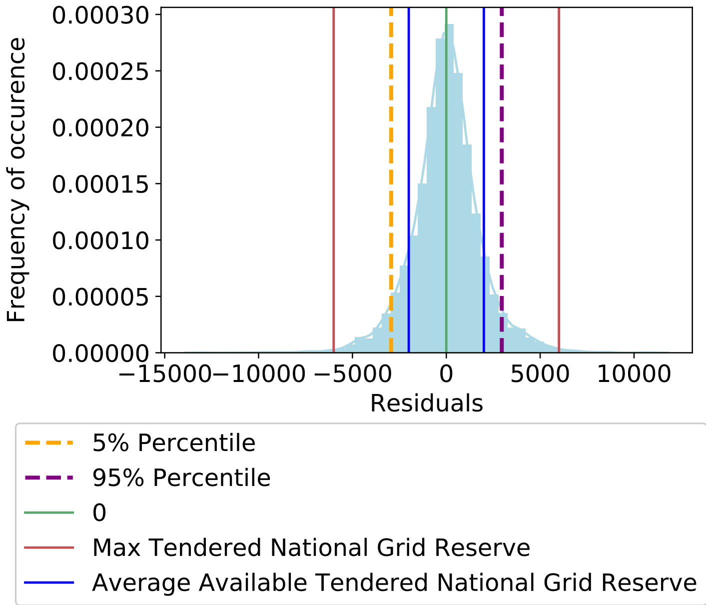


Fig. 5.14 Best online model (Box-Cox Regressor) distribution.

hyperparameters had the same results, we removed them. For the multilayer perceptron (MLP), we aggregated all hyperparameters, due to the similar nature of the predictions.

It can be seen that the best performing model was the Box-Cox regressor, with an MAE of 1100. This is an improvement of over 30% on the best offline model. The other models perform less well. However, it can be seen that the linear regression model improves significantly for the online case when compared to the offline case. The passive aggressive (PA) model improve significantly with the varying parameters, and the MLP performs poorly in all cases.

Figure 5.14 displays the best online model. We can see a significant improvement over the best online model distribution, shown in Figure 5.10. We remain within the max tendered national grid reserve for 98.9% of the time, and the average available tendered national grid reserve is close to the 5% and 95% percentiles.

Figure 5.15 displays the residuals for a model with poor predictive ability, the passive aggressive regressor. It displays a large period of time of prediction errors at -20,000MWh, and often falls outside of the national grid reserve. These results demonstrate the importance of trying a multitude of different models and parameters to improve prediction accuracy.

Figure 5.16 displays a comparison between the actual electricity consumption compared to the predictions. It can be seen that the Box-Cox model better predicts the actual electricity demand in most cases when compared to the best offline model, the Extra Trees regressor. The Extra Trees regressor often overestimates the demand, particularly during weekdays. Whilst the Box-Cox regressor more closely matches the actual results. During the weekend (between the hours of 120 and 168), the Extra Trees regressor performs better, particularly on the Saturday (between hours of 144 and 168).

Figures 5.17 and 5.18 display the mean absolute error versus test and training time respectively. In these graphs, a selection of models and parameter combinations are chosen.

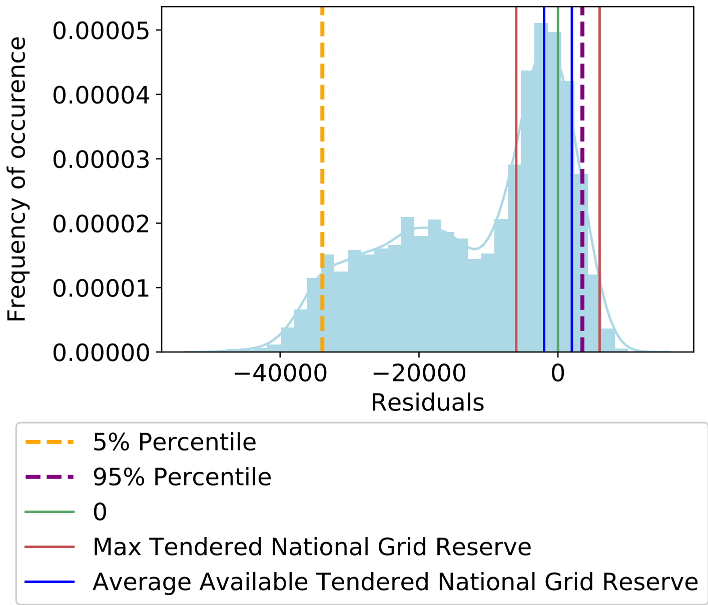


Fig. 5.15 Online machine learning algorithm distribution. (Passive Aggressive Regressor (C=0.1, fit intercept = true, maximum iterations = 1000, shuffle = false, tolerance = 0.001), chosen as it was the worst result for the passive aggressive model.

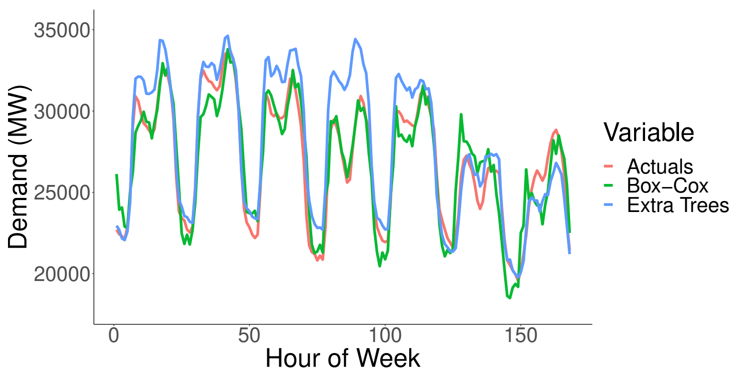


Fig. 5.16 Best offline model compared to the best online model over a one week period.

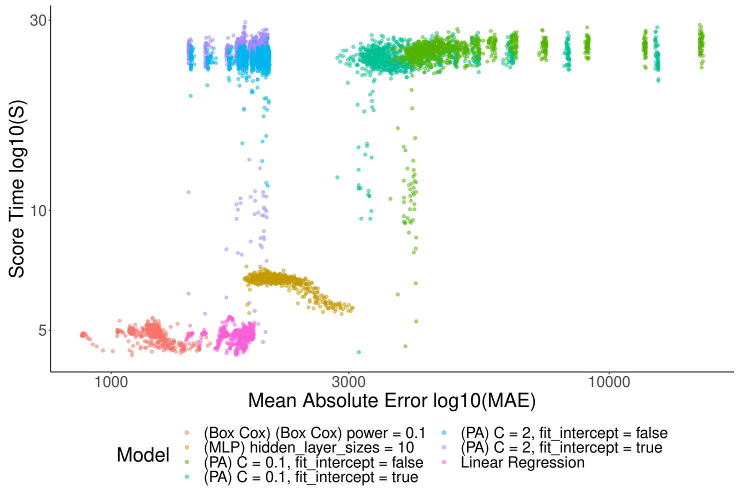


Fig. 5.17 Time taken to test the online models versus mean absolute error.

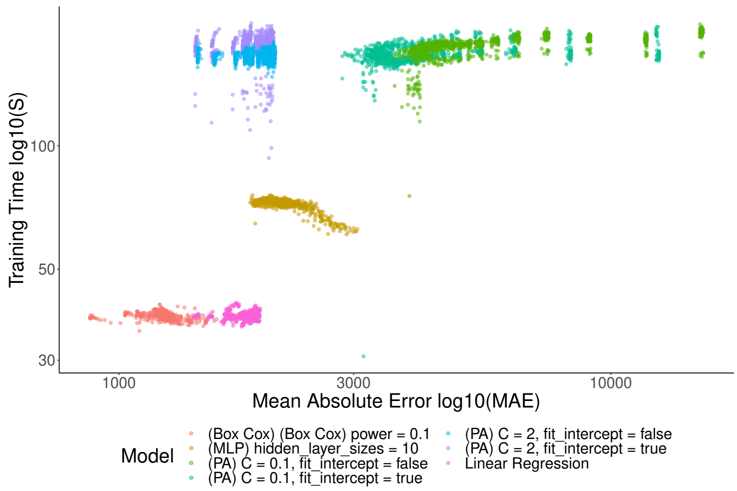


Fig. 5.18 Time taken to train the online models versus mean absolute error.

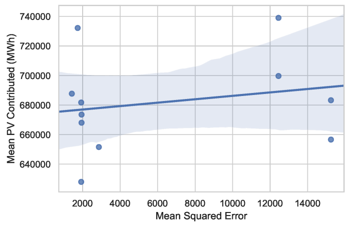
Clear clusters can be seen between different types of models and parameter types. With the passive aggressive (PA) model performing the slowest for both training and testing. Different parameter combinations show different results in terms of mean absolute error.

The best performing model is the Box-Cox model, which is also the fastest to both train and test. The linear regression, which performs worse in terms of predictive performance, is as quick to train and test as the Box-Cox model. Additionally, the multilayer perceptron (MLP) is relatively quick to train and test when compared to the PA models.

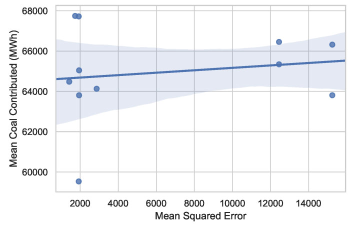
It is noted that when compared to the offline models, the training time is a good indicator to the testing time. In other words, models that are fast to train are also fast to test and vice-versa.

5.6.3 Scenario Comparison

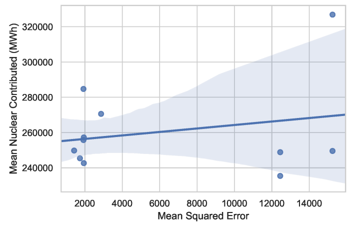
In this Section we explore the effect of these residuals on investments made and the electricity generation mix. To generate these graphs, we perturbed the exogenous demand in ElecSim by sampling from the best-fitting distributions for the respective residuals of each of the online methods. We did this for all of the online learning algorithms displayed in Figure 5.13. We let the simulation run for 17 years from 2018 to 2035.



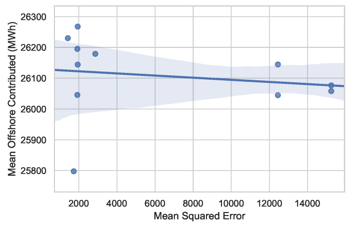
(a) Photovoltaic output.



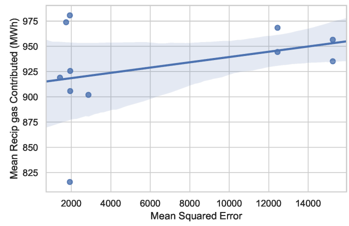
(b) Coal output.



(c) Nuclear output.



(d) Offshore output.



(e) Reciprocal gas engine output.

Fig. 5.19 Mean outputs of various technologies vs. mean absolute error from 2018 to 2035 in ElecSim.

Running this simulation enabled us to see the effect on carbon emissions on the electricity grid over a long time period. For instance, does underestimating electricity demand mean that peaker power plants, such as reciprocal gas engines, are over utilized when other, less polluting power plants could be used?

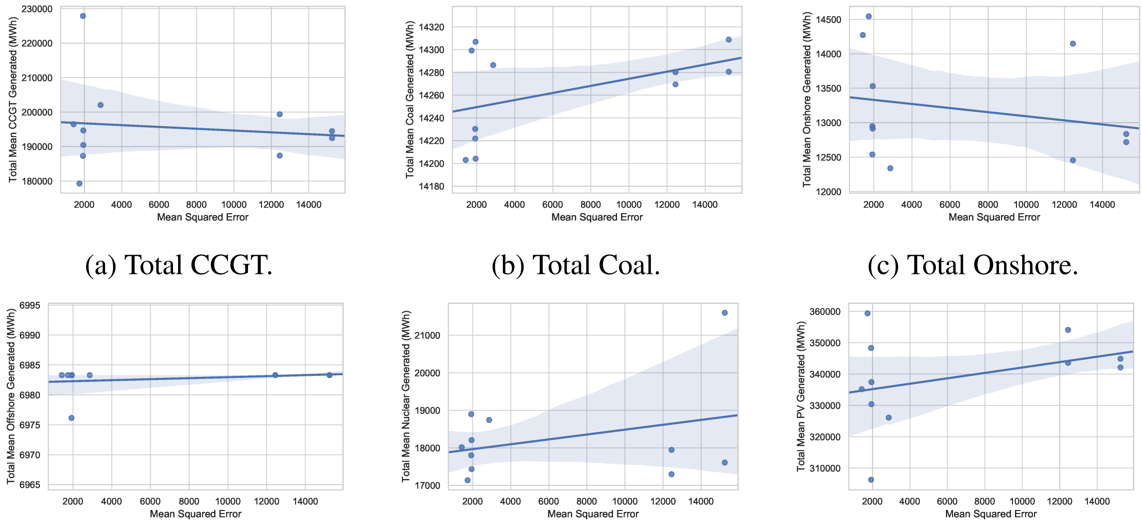
Mean Contributed Energy Generation

In this Section we display the mean electricity mix contributed by different electricity sources over the years 2018 to 2035.

Figure 5.19a displays the mean photovoltaic (PV) contributed between 2018 and 2035 vs. mean absolute error of the various online regressor models displayed in Figure 5.13. A positive correlation can be seen with PV contributed and mean absolute error. This is similar for coal and nuclear output, shown in Figures 5.19b and 5.19c respectively. However, as shown by Figure 5.19d, offshore wind reduces with mean absolute error. Figure 5.19e displays the mean reciprocal gas engine output vs mean absolute error between the same time period. Output for the reciprocal gas engine also increases with mean absolute error.

The reciprocal gas engine was expected to increase with times of high error. This is because, traditionally, reciprocal gas engines are peaker power plants. Peaker power plants provide power at times of peak demand, which cannot be covered by other plants due to them being at their maximum capacity level or out of service. It may also be the case, that with higher proportions of intermittent technologies, there is a larger need for these peaker power plants to fill in for times where there is a deficit in wind speed and solar irradiance.

It is hypothesized that coal and nuclear output increase to cover the predicted increased demands of the service. As these generation types are dispatchable, meaning operators can



(a) Total CCGT. (b) Total Coal. (c) Total Onshore.

(d) Total Offshore. (e) Total nuclear. (f) Total photovoltaics.

Fig. 5.20 Total technologies invested in vs. mean absolute error from 2018 to 2035 in ElecSim.

choose when they generate electricity, they are more likely to be used in times of higher predicted demand.

Photovoltaics may be used more with higher errors due to the times at which the errors were greatest. For example, during the day, where demand is higher, as is solar irradiance.

Total Energy Generation

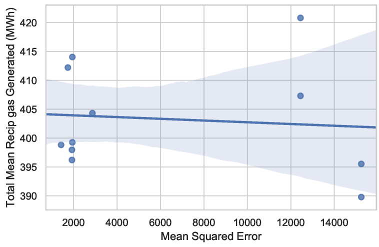
In this Section, we detail the difference in total technologies invested in over the time period between 2018 to 2035, as predicted by ElecSim.

CCGT, onshore, and reciprocal gas engines are invested in less over the time period, as shown by Figures 5.20a, 5.20d, 5.21a respectively. While coal, offshore, nuclear and photovoltaics all exhibit increasing investments.

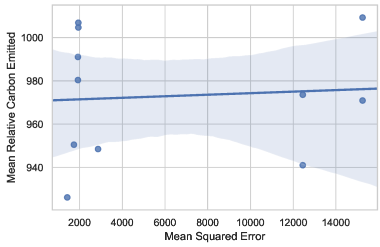
It is hypothesized that coal and nuclear increase in investment due to their dispatchable nature. While onshore, non-dispatchable by nature, become a less attractive investment when compared to the other technologies.

CCGT and reciprocal gas engines may have decreased in capacity over this time, due to the increase in coal. This could be because of the large consistent errors in prediction accuracy that meant that reciprocal gas engines were perceived to be less valuable.

Figure 5.21b shows an increase in relative mean carbon emitted with mean absolute error of the predictions residuals. The reason for an increase in relative carbon emitted could be due to the increased output of utility of the reciprocal gas engine, coal, and decrease in offshore output. Reciprocal gas engines are peaker plants and, along with coal, can be dispatched. By being dispatched, the errors in predictions of demand can be filled. It is therefore recommended that by improving the demand prediction algorithms, significant gains can be made in reducing carbon emissions.



(a) Total Reciprocal gas engine.



(b) Mean carbon emitted.

Fig. 5.21 a) Investments in reciprocal gas engine technologies vs. mean absolute error from 2018 to 2035 in ElecSim and d) mean carbon emissions between 2018 and 2035.

5.6.4 Discussion

From our results, it can be seen that different algorithms yield differing prediction accuracies. Online models can result in a decrease in 30% of prediction error on the best offline models. We calculated this by comparing the MAE for Extra Trees to the MAE for the Box-Cox regressor. We, therefore, recommend the use of online machine learning for predicting electricity demand in a day-ahead market.

Similar to our assumptions, the online learning algorithms were able to outperform the offline models. This is due to the non-stationary nature of the data. An online method is able to use the most up-to-date knowledge of the complex system of energy demand. For instance, a certain year may have a particularly warm winter when compared to previous years, reducing the amount of electricity used for heating.

However, contrary to our assumptions, the online linear regression techniques outperformed the online machine learning techniques. This may be due to their simpler nature and ability to learn from a smaller subset of new data as opposed to relying on a large historic subset. For the offline models, the best performing algorithms were the decision tree approaches such as extra trees and random forests. This is a similar outcome to our previous work, which showed that the best performing method for demand forecasting were random forests [125]. Contrary to our assumptions, however, the lasso and ridge regression outperformed the machine learning techniques support vector regression and multilayer perceptron. This may be due to the ability of feature selection by lasso and ridge regression, which only uses the most important features.

To the best of our knowledge, more work has been done using offline learning to predict electricity demand. This may be due to the additional complexity of running online algorithms, and a smaller number of available models to run in an online fashion.

In terms of computing power, finding the optimal input parameters, hyperparameters and models to use can be a large undertaking. This is due to the exponential growth of the number of choices that can be made. This can be an issue where accuracy is of importance, especially when the data changes over time, meaning it may be necessary to retest previous results. However, due to the financial and sustainability implications, we believe the trade-off between compute time and accuracy is balanced towards compute time. There are also large implications if the model were to break at a certain point in time. We, therefore, recommend the reliance on multiple well-performing models, as opposed to solely the best performing model at any one time.

For training time and prediction time, there is often a trade-off between training and predicting. For instance, the k-nearest neighbours is fast to train, but slow to sample from. Therefore stakeholders must make a decision based upon accuracy, speed of training and sampling.

Additionally, the impact on the broader electricity market has been shown to be significant. Principally, the investment behaviours of generation companies change as well as the dispatched electricity mix. The relative mean carbon emitted over this time period increases, due to an increase in the utilization of coal and reciprocal gas engines, at the expense of offshore wind.

5.6.5 Conclusion

In this work, we evaluated 16 different machine learning and statistical models to predict electricity demand in the UK for the day-ahead market. Specifically, we used both online and offline algorithms to predict electricity demand 24 hours ahead. We compared the ability for the offline models: lasso regression, random forests, support vector regression, for both online and offline learning: linear regression, multilayer perceptron and for just online learning: the Box-Cox transformation and the passive aggressive regressor, amongst others. The Box-Cox, as well as the passive aggressive regressors, were used as online learning algorithms, the multilayer perceptron and linear regression were used as both, whereas the rest were used as offline learning algorithms.

We measured the errors and compared these to each model as well as the national grid reserve. We found that through the use of an online learning approach, we were able to significantly reduce error by 30% on the best offline algorithm. We were also able to reduce our errors to significantly below the national grid's mean and maximum tendered reserve, thus significantly reducing the chances of blackouts.

In addition to this, we took these errors, or residuals, and perturbed the electricity market of the agent-based model ElecSim. This enabled us to see the impact of different error distributions on the long-term electricity market, both in terms of investment and in terms of the electricity mix.

We observed that with an increase in prediction errors, we get a higher proportion of electricity generated by coal, offshore, nuclear, reciprocal gas engines and photovoltaics. This could be due to the fact that more peaker and dispatchable plants are required to fill in for unexpected demand. In addition, a higher proportion of intermittent renewable energy sources leads to a higher use of peaker power plants to fill in the gaps of intermittency of wind and solar irradiance. However, by reducing the mean absolute error, we are able to significantly reduce the amount of reciprocal gas engines and coal usage.

In future work, we would like to trial a different selection of algorithms and statistical models and trial different inputs to the models, for instance, by providing the model with two months worth of historical data as dependent variables. Additionally, we would like to see the impact of predicting wind speed and solar irradiance to see how these impact the overall investment patterns and electricity mix.

Chapter 6

Carbon optimization

Prologue

Carbon taxes have been shown to be an efficient way to aid in a transition to a low-carbon electricity grid. In this work, we demonstrate how to find optimal carbon tax policies through a genetic algorithm approach, using the model developed, ElecSim. To achieve this, we use the NSGA-II genetic algorithm to minimize average electricity price and relative carbon intensity of the electricity mix. We demonstrate that it is possible to find a range of carbon taxes to suit differing objectives.

Our results show that we are able to minimize electricity cost to below £10/MWh as well as carbon intensity to zero in every case. In terms of the optimal carbon tax strategy, we found that an increasing strategy between 2020 and 2035 was preferable. Each of the Pareto-front optimal tax strategies are at least above £81/tCO2 for every year. The mean carbon tax strategy was £240/tCO2.

This Chapter is structured as follows: we introduce our work in Section 6.1. Section 6.2 covers examples of optimisations using genetic algorithms and different carbon strategies. Section 6.3 details the optimization techniques applied. We present our results in Section 6.4, and conclude in Section 6.5.

6.1 Introduction

In this work, we use the electricity market agent-based model ElecSim to find an optimum carbon tax policy [122]. Specifically, we use a genetic algorithm to find a carbon tax policy to reduce both average electricity price and the relative carbon density by 2035 for the UK electricity market. We compare this optimal strategy to the carbon tax policy of the UK British government.

Carbon taxes have been shown to quickly lower emissions and lower the costs to the public [211]. Carbon taxes are able to send clear price signals, as opposed to a cap-and-trade scheme, such as the EU Emissions Trading System, which has shown to be unstable [211].

In this work, we use the reference scenario projected by the UK Government's Department for Business & Industrial Strategy (BEIS) with model parameters calibrated by Kell *et al.* [50, 127]. This reference scenario projects energy and emissions until 2035. We undertake various carbon tax policy interventions to see how we can reduce relative carbon density whilst at the same time, reduce the average electricity price.

The parameter space we optimize over is the carbon tax price over a 17 year period from 2018 to 2035. The carbon price is used to influence the objectives of average electricity price and relative carbon intensity in 2035. Grid and random search are approaches which trial parameters at evenly distributed spaces and random spaces respectively. These approaches are often inefficient, however, and require an increased number of simulations due to their static nature. Genetic Algorithms, in contrast, use an evolutionary computing approach to find global optimal solutions faster. This is of particular importance in cases with a large number of parameters or in simulations which require a long compute time, which is the case for ElecSim.

In order to optimize over two potentially competing objectives, i.e. average electricity price and relative carbon intensity, we use the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [45]. The NSGA-II algorithm can approximate a Pareto frontier [162, 188]. A Pareto frontier is a curve in which there is no solution which is better than another along the curve for different sets of parameters. In this context, better means that a solution is closer to the optimal for a particular combination of objectives.

We find that the rewards of average electricity price and relative carbon intensity are not mutually exclusive. That is, it is possible to have both a lower average electricity price and a lower relative carbon price. This is due to the low short-run marginal cost of renewable technology, which has been shown to lower electricity prices [159].

The main contribution of this work is to explore carbon tax strategies using genetic algorithms for multi-objective optimization.

6.2 Literature review

Multi-objective optimization problems are commonplace. In this section, we review multiple applications that have used multi-objective optimization, as well as explore the literature which focus on finding optimal carbon tax strategies.

6.2.1 Examples of Optimization

Similar to our work, Ascione *et al.* use the NSGA-II algorithm to generate a Pareto front to optimize for two objectives: operating cost for space conditioning and thermal comfort [13]. The aim of their work is to optimize the hourly set point temperatures with a day-ahead planning horizon. A Pareto front is generated, which allows a user to select a solution according to their comfort needs and economic constraints. This work showed a reduction in operating costs by up to 56% as well as improved thermal comfort.

Gorzałczany *et al.* also apply the NSGA-II algorithm. However, they apply it to the credit classification problem [78]. The objectives optimized over were accuracy and interpretability when making financial decisions such as credit scoring and bankruptcy prediction. This technique was able to significantly outperform the alternative methods in terms of interpretability while remaining competitive or superior in terms of the accuracy and speed of decision making in comparison with the existing classification methods.

Ma *et al.* use the multi-objective artificial immune optimization algorithm for land use allocation (MOAIM-LUA model) [145]. They balance land use supply and demand based on the future dynamic demands from different land-use stakeholders in the region at the macro-level in Anlu County, China. The objectives to optimize were economic and ecological benefits. They found that for this application, they were able to obtain better solution sets than the NSGA-II algorithm.

In our work we use the NSGA-II algorithm to optimise average overhead and energy consumption of a condor system [126]. We use the genetic algorithm to trial different parameters of a Q-learning reinforcement learning algorithm, which acted as a job scheduler. We found that we were able to generate a Pareto-front which would allow stakeholders to select an optimum for their use case.

6.2.2 Carbon Tax Strategies

In this section, we explore different strategies employed in the literature to analyze the benefits and consequences of a carbon tax. To the best of our knowledge, we are the first to employ a multi-objective optimization algorithm to minimize average electricity price and relative carbon density.

Levin *et al.* use an optimization model to analyze market and investment impacts of several incentive mechanisms to support investment in renewable energy and carbon emission reductions [137]. Carbon tax was found to be the most cost-efficient method of reducing emissions.

Zhou *et al.* construct a social welfare model based on a Stackelberg game [215]. The differences and similarities between a flat carbon tax and an increasing block tariff carbon tax are analyzed using a numerical simulation. This work shows that an increasing block tariff carbon tax policy can significantly reduce tax burdens for manufacturers and encourage low-carbon production. In contrast to Zhou *et al.* we trial multiple different carbon tax strategies using a machine learning approach.

Li *et al.* use a hierarchical carbon market scheduling model to reduce carbon emissions [138]. Multi-objective optimization was applied to discover optimal behaviours for policymakers, customers and generators to minimize the costs incurred by these actors. Our work, however, focuses on the different strategies of carbon tax as opposed to optimal actor behaviour.

6.3 Optimization methods

Multi-objective optimization allows practitioners to overcome the problems with optimizing multiple objectives with classical optimization techniques, such as the genetic algorithm used in Chapter 4. Multi-objective optimization algorithms are able to generate Pareto-optimal solutions as opposed to converting the multiple objectives into a single-objective problem. A single-objective problem assumes that there is only a single optimum, and that other combinations are inferior. This may not be the case, as different solutions are superior for a different set of circumstances. A Pareto frontier is made up of many Pareto-optimal solutions which can be displayed graphically. A user is then able to choose between various solutions and trade-offs according to their wishes. The NSGA-II algorithm, a multi-objective genetic optimization algorithm, is able to generate a Pareto frontier in a single optimization run.

In the following sub-sections, we detail NSGA-II algorithm. For an overview of the standard Genetic Algorithm, please refer to Sub-Section 4.4.4

6.3.1 NSGA-II

NSGA-II is efficient for multi-objective optimization on a number of benchmark problems and finds a better spread of solutions than Pareto Archived Evolution Strategy (PAES) [132] and Strength Pareto EA (SPEA) [217] when approximating the true Pareto-optimal front [45].

The majority of multi-objective optimization algorithms use the concept of *domination* during population selection [29]. A non-dominated algorithm, however, seeks to achieve the Pareto-optimal solution. This is where no single solution should dominate another. An individual solution $\mathbf{x}^1$ is said to dominate another $\mathbf{x}^2$, if and only if there is no objective of $\mathbf{x}^1$ that is worse than objective of $\mathbf{x}^2$ and at least one objective of $\mathbf{x}^1$ is better than the same objective of $\mathbf{x}^2$ [16].

Non-domination sorting is the process of finding a set of solutions which do not dominate each other and make up the Pareto front. See Figure 6.1a for a visual representation, where f_1 and f_2 are two objectives to minimize and L1, L2 and L3 are dominated layers.

In this section, we define the processes used by the NSGA-II algorithm to determine which solutions to keep:

Non-dominated sorting

We assume that there are M objective functions to minimise, and that $\mathbf{x^1} = \{x_j^1\}$ and $\mathbf{x^2}$ are two solutions. $x_j^1 < x_j^2$ implies solution $\mathbf{x^1}$ is better than solution $\mathbf{x^2}$ on objective j. A solution $\mathbf{x}^1$ is said to dominate the solution $\mathbf{x}^2$ if the following conditions are true:

1. The solution $\mathbf{x}^1$ is no worse than $\mathbf{x}^2$ in every objective. I.e. $x_j^1 \leq x_j^2 \;\; \forall j \in \{1, 2, \ldots, M\}$.
2. The solution $\mathbf{x}^1$ is better than $\mathbf{x}^2$ in at least one objective. I.e. $\exists\; j \in \{1, 2, \ldots, M\} \;\; s.t. \;\; x_j^1 < x_j^2$.

Next, each of the solutions are ranked according to their level of non-domination. An example of this ranking is shown in Figure 6.1a. Here, f_1 and f_2 are the objectives to be minimised. The Pareto front is the first front. All of the solutions in the Pareto front are not dominated by any other solution. The solutions in layer 1, L1, are dominated only by those in the Pareto front, and are non-dominated by those in L2 and L3.

The solutions are then ranked according to their layer. For example, the solutions in the Pareto front are given a fitness rank (i_{rank}) of 1, solutions in L1 have an i_{rank} of 2.

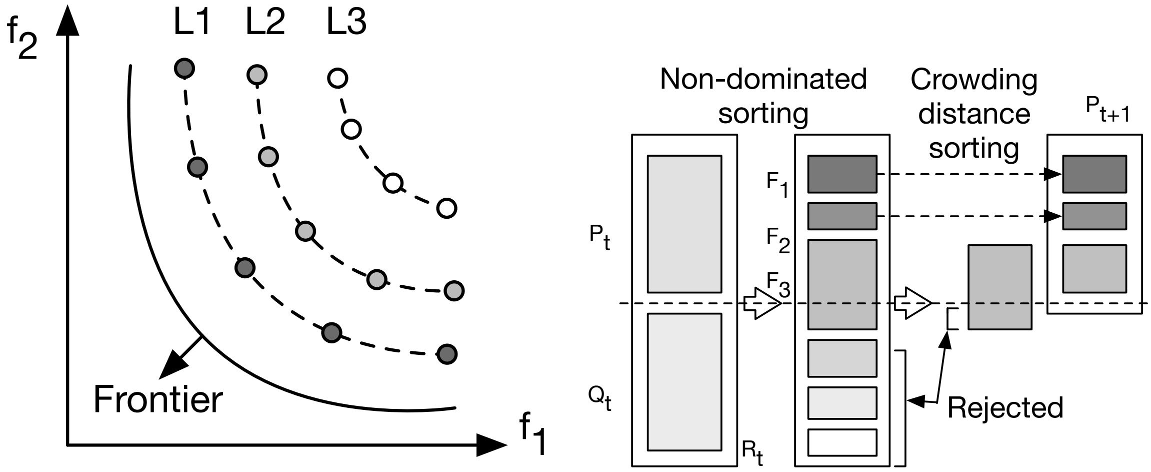


Fig. 6.1 a) Schematic of non-dominated sorting with solution layering b) Schematic of the NSGA-II procedure

Density Estimation

($i_{distance}$) is calculated for each solution. This is the average distance between the two closest points to the solution in question.

Crowded comparison operator

($\prec_n$) is used to ensure that the final frontier is an evenly spread out Pareto-optimal front. This is achieved by using the two attributes: (i_{rank}) and($i_{distance}$). The partial order is then defined as: $i \prec_n j$ if $(i_{rank} < j_{rank})$ or $((i_{rank} = j_{rank})$ and $(i_{distance} > j_{distance}))$ [45].

This order prefers solutions with a lower rank i_{rank}. For solutions with the same rank, the solution in the less dense area is preferred.

Main loop

Similarly to the standard GA, a population P_0 is created with random parameters. The solutions of P_0 are then sorted according to non-domination. The child population C_1' of size N is then created by binary tournament selection, recombination and mutation operators. In this case, tournament selection is the process of evaluating and comparing the fitness of various individuals within a population. In binary tournament selection, two individuals are chosen at random, the fitnesses are evaluated, and the individual with the better solution is selected [6].

Next, a new combined population is formed $R_t = P_t \cup C_t'$. R_t has a size of $2N$. R_t is then sorted according to non-domination. A new population is then formed P_{t+1}. Solutions are added from the sorted R_t in order of non-domination. Solutions are added until the size of P_{t+1} exceeds N. The solutions from the last layer are prioritised based on having the largest crowding distance [45].

This process is shown in Figure 6.1b, which is repeated until the termination condition is met. A termination condition could be: no significant improvement over X iterations or a specified number of iterations have been performed. The full procedure is detailed formally by Algorithm 2.

Algorithm 2 NSGA-II main loop [45]

$R_t = P_t \cup C_t'$ combine parent and child population
$\mathscr{F}$ = fast-non-dominated-sort (R_t)
  where $\mathscr{F} = (\mathscr{F}_1, \mathscr{F}_2, \ldots)$
$P_{t+1} = \emptyset$
while do $|P_{t+1} < N|$
  Calculate the crowding distance of $(\mathscr{F}_i))$
  $P_{t+1} = P_{t+1} \cup \mathscr{F}_i$
end while
Sort$(P_{t+1}, \prec_n)$ sort in descending order using $\prec_n$
$P_{t+1} = P_{t+1}[0:N]$ select the first N elements of P_{t+1}
Q_{t+1} = make-new-population(P_{t+1}) using
  selection, crossover and mutation to create
  the new population Q_{t+1}
$t = t + 1$

6.3.2 Carbon Optimization Application

In this section, we describe how the genetic algorithm is applied in our carbon optimization case. We use multi-objective optimization to find a solution which has both a low carbon emission and low average electricity price. The parameters that we adjust is the carbon tax between the years 2018 and 2035.

The mating steps work by, initially, taking the sets of carbon prices over the 17 year period (2018 to 2035) which have the best rewards (lowest relative carbon emissions and average electricity price). These carbon prices are then mated with a probability of 90%, creating child carbon prices. The children are mutated with a probability of 5%. Therefore, 5% of children have a carbon price which is not inherited from the parents. Over time, the mutations and inherited properties tend to a population with more desirable rewards.

6.3.3 Simulation Environment

In order to evaluate the different carbon strategies, we used ElecSim [122, 127]. For this work, we parametrized the model to data for the UK in 2018 to act as a digital twin of the UK electricity market. This includes the power plants in operation in 2018, and the funds available to their respective companies [63, 48]. ElecSim is validated by being instantiated by data from 2013 and projected forward to 2018, with a mean absolute scaled error (MASE) below or equal to 0.701 for all generator types [127].

The yearly income for each power plant is estimated for each generation company by running a merit-order dispatch electricity market ten years into the future. However, the expected cost of electricity ten years into the future is uncertain. We, therefore, use the reference scenario projected by BEIS and use the predicted costs of electricity calibrated by our previous work in Chapter 4 [50, 127].

6.3.4 Optimization

In this section, we detail the optimization approach taken. We modify the carbon tax each year, as we believe this is the most likely process taken by governments, giving generator companies and consumers the ability to understand market conditions during each year.

Non-parametric carbon policy

The optimization approach has two stages. First, we initialize the population of the NSGA-II algorithm P_0 with 18 attributes. These correspond to a separate carbon tax for each year, shown by Equation 6.1:

$$P_0 = \{a_1, a_2, \ldots, a_{18}\}, 0 \leq a_y \leq 250, \tag{6.1}$$

where P_0 is the first population, a_y is the attribute or carbon price in year y and a_1 is the carbon price in year 1, a_2 the carbon price in year two and so forth. The constraints of the algorithm are that each of the carbon prices are bound between the values of £0 and £250. This provides the optimization algorithm with the highest degree of freedom. The value £250 was chosen due to the relative costs of electricity, where £250 would be the upper bound for the cost of electricity. This high degree of freedom enables a high number of strategies to be trialled due to its non-parametric nature. This, however, comes with a large search space requiring a large number of iterations.

Linear carbon policy

To reduce the search space for the carbon strategy, we also trial a linear carbon strategy, of the form:

$$p_c = a_1 y_t + a_2, -14 \leq a_1 \leq 14, 0 \leq a_2 \leq 250, \tag{6.2}$$

where p_c is the carbon price, y_t is the year, a_1 is the gradient or first attribute and a_2 is the intercept or second attribute. The constraints of the optimisation problem are that a_1 is bound by -14 and 14, and a_2 by 0 and 250. These bounds are chosen to ensure that the carbon price does not exceed $\sim$£500 in the year 18 (2035) and is greater than about -£250, as well as ensuring that the carbon tax in the first year is greater than £0 but smaller than £250. The bounds for a_1 was chosen to make the mathematics simpler, whilst remaining in range.

6.4 Results

In this section, we explore the results of the optimizations, the optimum carbon strategies and the resultant electricity mixes.

6.4.1 Non-parametric carbon policy

Figure 6.2 displays the development of the genetic algorithm against the rewards, relative carbon density and average electricity price. Darker colours display higher generation numbers. The first generation shows a widespread in relative carbon density and average electricity price. However,

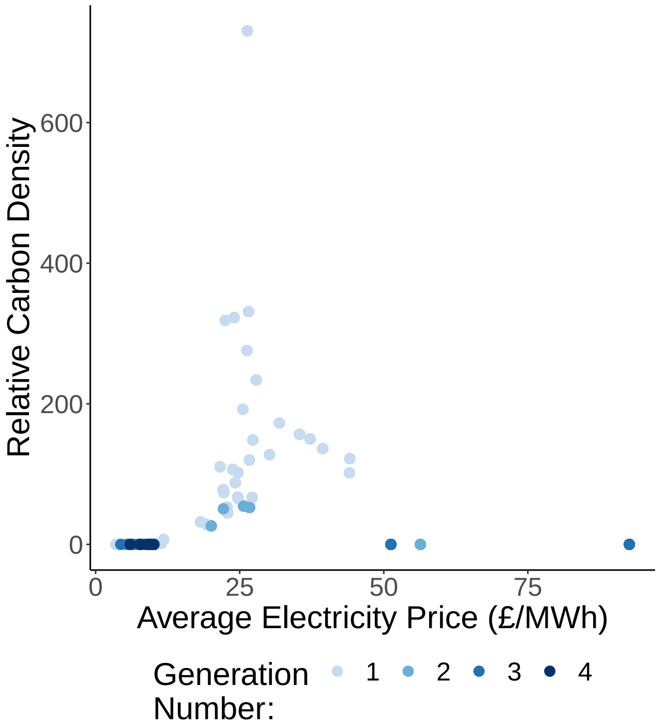


Fig. 6.2 Development of genetic algorithm rewards for non-parametric carbon tax policy results in 2035.

over successive generations, the solutions converge to a relative carbon density of 0 and an average electricity price under £10MW/h.

Strikingly, the rewards of relative carbon density and average electricity price are not mutually destructive. This could be due to the low short-run marginal cost of renewable energy which reduces both electricity prices and carbon emissions [159].

To understand the optimum carbon strategies, we visualized the parameters that produced the lowest average electricity prices in Figure 6.3. Specifically, we filtered for electricity prices under £5/MWh and displayed the results using a heat map. The darker colours represent a higher density of points.

Figure 6.3 displays a general trend, where carbon tax starts at ∼£100 until the year 2030, where it increases to ∼£200 by 2035. This may be due to the fact that a lower initial carbon tax of ∼£100 encourages investment in low-carbon technologies before the higher rate of ∼£200 comes into force. This higher rate of carbon tax would allow GenCos to outcompete higher carbon-emitting generators over the lifetime of the plants.

6.4.2 Linear carbon policy

Figure 6.4 displays the development of the genetic algorithm against the rewards: relative carbon density and average electricity price. Similarly to the non-parametric carbon policy shown in Figure 6.2, the first generation shows a wide spread of results. However, the spread is smaller than that of the linear carbon policy. This may be due to the fact that it is easier for the GenCos to predict the carbon policy, which increases confidence in the NPV calculations. The linear

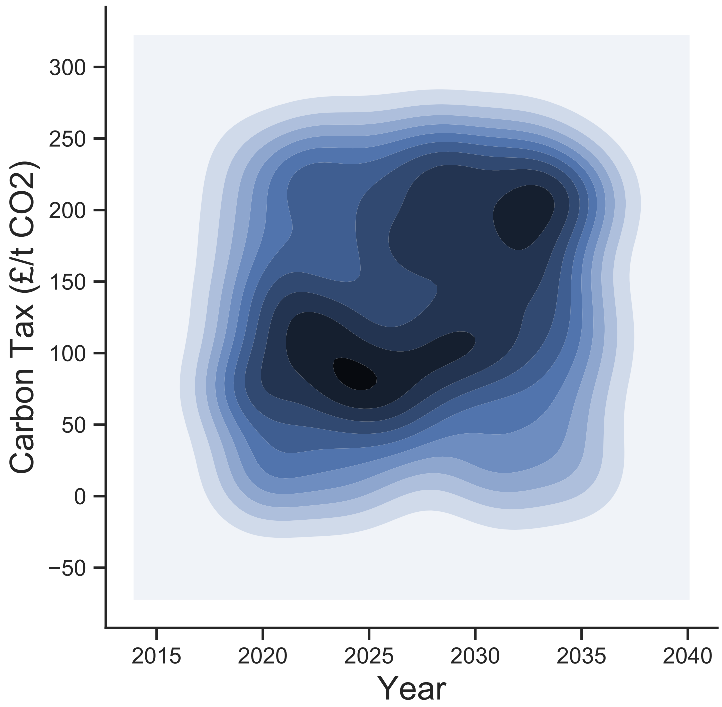


Fig. 6.3 Density plot of points with an average electricity price <£5/MWh for non-parametric carbon tax policy results in 2035.

carbon policy also converges to a relative carbon density of 0, and an average electricity price smaller than £10MW/h.

Figure 6.5 compares the distributions of average electricity price for both techniques. Both methods show improvements as the number of generations of the genetic algorithm increase. The linear policy, however, is able to more quickly converge to a low average electricity price, with a mode of ∼£5.4MW/h. The non-parametric policy has a number of poorer performing parameters, and Generation Number 4 has a bimodal distribution, with a mode of ∼£6.3MW/h.

Figure 6.6a displays the linear carbon policies which had an average electricity price under £4.5MW/h. There is no single 'optimum' carbon policy; a range of policies are able to achieve low carbon and a low average electricity price.

We explore the electricity mix generated of three different strategies shown in Figure 6.6b. We selected the highest, lowest, and the lowest flat carbon strategy to show a range of possible strategies.

Figure 6.7 displays the generated electricity mixes for each of the selected strategies. To generate these images, we ran 80 scenarios to capture the variability between scenarios.

Whilst there does not seem to be a significant difference between scenarios, with solar providing ∼60% of the electricity mix by 2035, there is an observable difference with the other generator types.

The 'highest' carbon strategy exhibits a higher uptake in nuclear, possibly due to the fact that nuclear becomes more competitive when compared to coal or gas. The 'lowest' carbon strategy shows a higher uptake in Combined Cycle Gas Turbines (CCGT) during the years of 2026 to 2031 as it outcompetes nuclear. The 'flat' carbon policy shows a higher percentage of

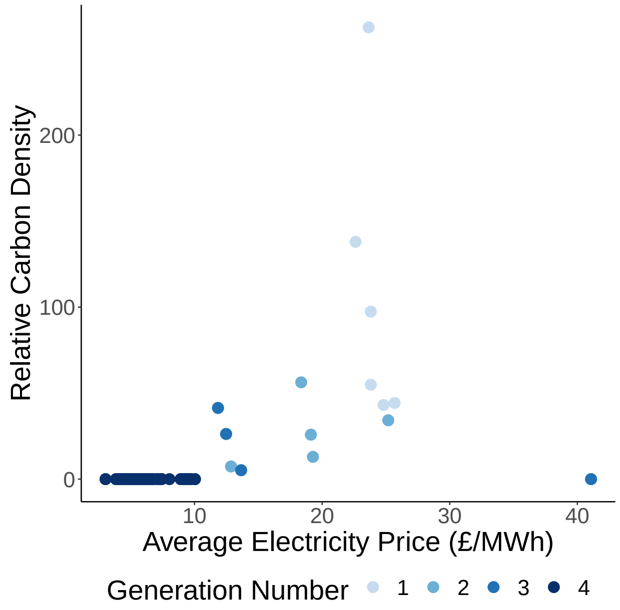


Fig. 6.4 Development of genetic algorithm rewards in 2035 for linear carbon strategy.

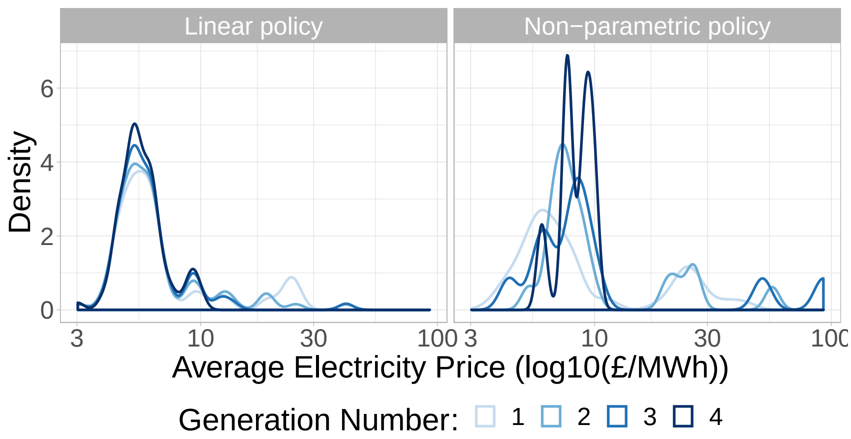
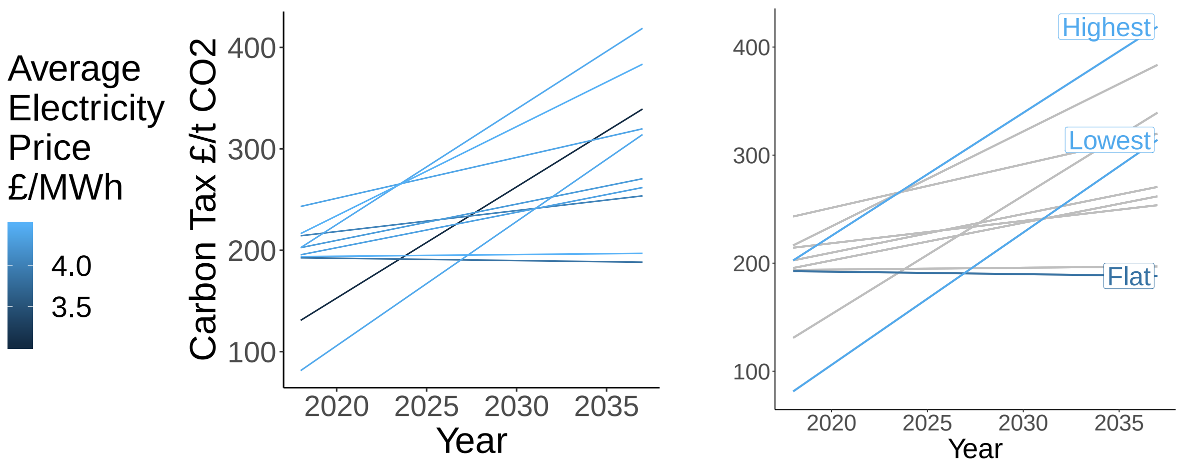


Fig. 6.5 Density plot of average electricity price in 2035 over generation number of genetic algorithm for both linear and non-parametric policy.



(a) All carbon policies.

(b) Highlighted policies.

Fig. 6.6 Linear carbon policies under £4.5MW/h visualised.

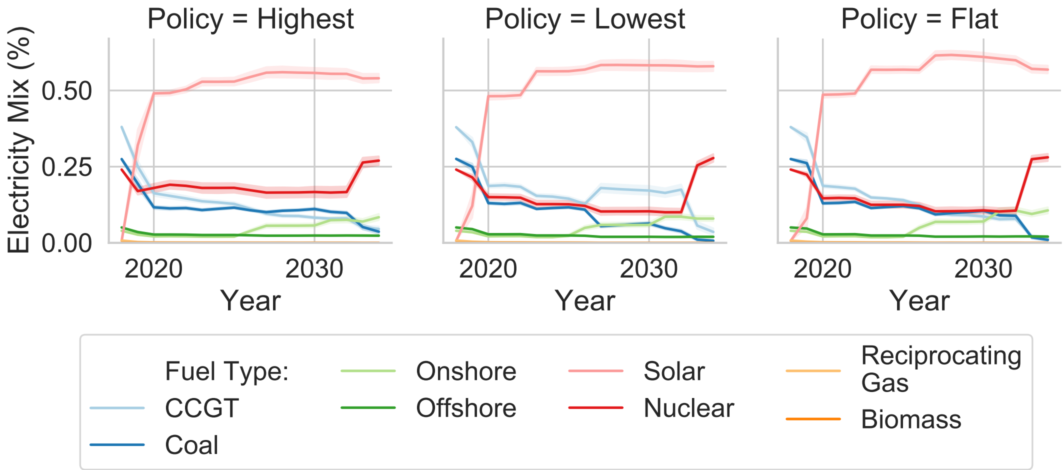


Fig. 6.7 Electricity mixes under selected linear carbon policies.

solar energy than any of the other scenarios, albeit with a lower percentage of nuclear. Onshore wind is shown to be consistent for these scenarios.

6.4.3 UK Government Policy

We compare our optimal carbon tax strategy to a scenario based on the UK Government's policy in this section from 2018 to 2034. Whilst it is not possible to know the future carbon tax strategy over such a long time horizon, we used a naive model approach to project a static carbon tax strategy. That is, the strategy is maintained at the current level of £18.08 throughout the projected horizon. We ran 40 simulations to capture the variance of the electricity mix. The work in this subsection is additional work to that which was published in [129].

Figure 6.8 displays the resultant electricity mix of this carbon tax strategy. A significant difference can be seen when compared to the optimal carbon strategy. 50% of the electricity mix is provided by nuclear energy by 2034. This is almost double that in the optimal carbon tax strategy.

Solar, the second largest source of electricity, provides 30% of electricity supply, with CCGT providing ∼15%. This is a marked difference to the electricity mix shown by Figure 6.7, where solar provides over 50% of electricity supply, followed by nuclear which provides ∼26%.

A larger variance can be seen in this scenario when compared to the optimal carbon tax. This may be because of the less defined differences between generator costs due to the lower carbon price, which does not distinguish so strongly between carbon emitting and non-carbon emitting generators.

Table **??** displays the average electricity price and relative carbon density of this scenario. As is expected, both average electricity price and relative carbon density are above that of the optimal carbon price scenario. This is because of the high short-run marginal cost of nuclear, and the carbon intensity of CCGT.

These results show the importance of carbon tax in deciding the electricity mix, where a difference is shown between high carbon taxes and low-carbon taxes. However, solar continues to do well without a carbon tax, as does nuclear, due to the high nuclear subsidy provided.

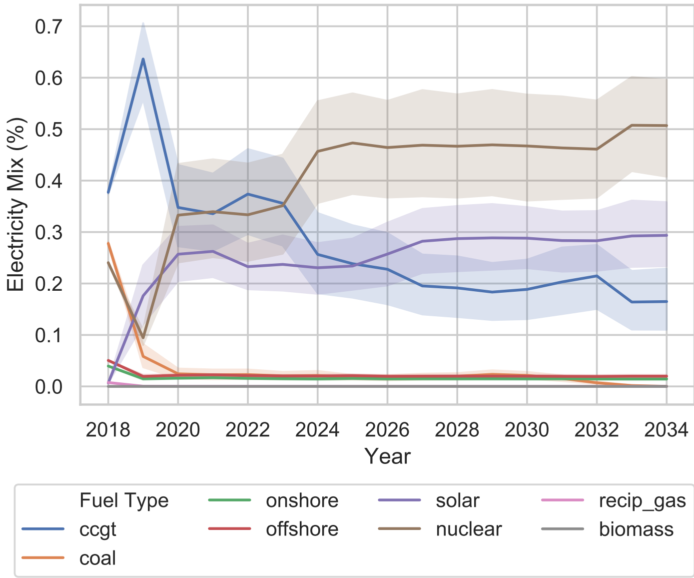


Fig. 6.8 Electricity mixes under UK Government's carbon tax.

Metric	Value
Average electricity price (£)	975.1
Relative carbon density	46.6

Table 6.1 Metrics from UK Government carbon tax policy.

6.5 Conclusion

In this work, we have demonstrated that it is possible to use the genetic algorithm technique NSGA-II to optimize carbon tax policy using an electricity market agent-based model.

We trialled a non-parametric carbon policy by allowing the genetic algorithm to optimize a carbon price for each year. These results showed us that a linear carbon tax might be appropriate. We then used a linear model as a carbon tax policy to reduce the total number of parameters for the genetic algorithm to optimize.

We were able to show that a range of linear carbon taxes were able to achieve both low average electricity price and a relative carbon intensity of zero in 2035. By exploring three different carbon tax policies, we saw that ∼60% of electricity consumption in the UK would be provided by solar. The difference between these 'optimal' carbon tax policies was largely shown by competition between CCGT, coal and nuclear.

This was largely due to the low short-run marginal cost of solar and nuclear energy, which means that they are often dispatched ahead of the fossil-fuel based generators. CCGT and coal, however, are useful for filling demand when there is low solar irradiance.

Additionally, we ran a carbon tax scenario based on that of the UK Government's. We found that an optimal carbon tax strategy had a much lower average electricity price due to the low short-run marginal cost of renewable energy. We also showed that we were able to achieve a low relative carbon density through a higher carbon tax. The majority of the electricity was provided by nuclear, which, in this scenario, had a high subsidy. Therefore, we believe that a lower carbon density, and lower average electricity price can be obtained without subsidies, but with a higher carbon tax.

In future work, we would like to try additional scenarios with varying future generation costs and calculate a sensitivity analysis to carbon taxes. In addition to this, we would like to model the uncertain reactions by consumers and generation companies with regards to carbon taxes. The linear carbon tax approach is an introductory approach which can be expanded upon.

Chapter 7

Reinforcement Learning in Electricity Markets

Prologue

Decentralized electricity markets are often dominated by a small set of generator companies who control the majority of the capacity. In this work, we explore the effect of the total controlled electricity capacity by any single or group of generator companies on the average electricity price. We demonstrate this through ElecSim. We develop an agent, representing a generator company, which uses a deep deterministic policy reinforcement learning algorithm to bid in a uniform pricing electricity market strategically. A uniform pricing market is one where all players are paid the highest accepted price. ElecSim is parameterized to the United Kingdom for the year 2018. This work can help inform policy on how to best regulate a market to ensure that the price of electricity remains competitive.

We find that capacity has an impact on the average electricity price in a single year. If any single generator company, or a collaborating group of generator companies, control more than $\sim$11% of generation capacity, prices begin to increase by $\sim$25%. The value of $\sim$25% and $\sim$11% may vary between market structures and countries. For instance, different load profiles may favour a particular type of generator or a different distribution of generation capacity. Once the capacity controlled by a generator company is higher than $\sim$35% of the total capacity, prices increase exponentially. The use of a market cap of approximately double the average market price has the effect of significantly decreasing this effect and maintaining a competitive market.

In Section 7.2 we review the literature, and explore other uses of RL in electricity markets. In Section 7.3 we introduce the agent-based model used and the DDPG algorithm. Section 7.4 explores the methodology taken for our case study. The results are presented in Section 7.5. We discuss and conclude our work in Sections 7.6 and 7.7 respectively.

7.1 Introduction

Under perfectly competitive electricity markets, generator companies (GenCos) tend to bid their short-run marginal costs (SRMC) when bidding into the day-ahead electricity market. However, electricity markets are often oligopolistic, where a small subset of GenCos provide the majority of the capacity to the market. Under these conditions, it is possible that the assumption that GenCos are price-takers does not hold. That is, large GenCos artificially increase the price of electricity to gain an increased profit using their market power. If they were price-takers, they would have to accept the competitive price set by the market.

Reduced competition within electricity markets can lead to higher prices to consumers, with no societal benefit. It is, therefore, within the interests of the consumer and that of government to maintain a competitive market. Low energy costs enable innovation in other industries reliant on electricity, and in turn, make for a more productive economy.

In this work, we explore the effect of total control over capacity on electricity prices. Specifically, we model different sizes of GenCos and groups of colluding GenCos, to bid strategically to maximize their profit using a reinforcement learning algorithm. This is in contrast to the strategy of bidding using the SRMC of their respective power plants, which would occur under perfect market conditions. To model this we use deep reinforcement learning (RL) to calculate a bidding strategy for GenCos in a day-ahead market. These GenCos are modelled as agents within the agent-based model, ElecSim [122, 127]. We use the UK electricity market instantiated on 2018 as a case study, similar to our work in [123]. That is, we model each GenCo with their respective power plants in the year 2018 to 2019. In total, we model 60 GenCos with 1085 power plants. It is possible, however, to generalise this approach and model to any other decentralized electricity market.

We use the deep deterministic policy gradient (DDPG) deep RL algorithm, which allows for a continuous action space [105]. Conventional RL methods require discretization of state or action spaces and therefore suffer from the curse of dimensionality [213]. As the number of discrete states and actions increases, the computational cost grows exponentially. However, too small a number of discrete states and actions will reduce the information available to the GenCos, leading to sub-optimal bidding strategies. Additionally, by using a continuous approach, we allow for GenCos to consider increasingly complex bidding strategies.

Other works have considered a simplified model of an electricity market by modelling a small number of GenCos or plants [58, 193]. We, however, model each GenCo as per the UK electricity market with their respective power plants in a day-ahead market. In addition, further work focuses on a bidding strategy to maximize profit for a GenCo. However, in our work, we focus on the impact that large GenCos, or colluding groups of GenCos, can have on electricity price.

Our approach does not require GenCos to formulate any knowledge of the data which informs the market-clearing algorithm or rival GenCo bidding strategies, unlike in game-theoretic approaches [201]. This enables a more realistic simulation where the strategy of rival GenCos are unknown.

7.2 Literature Review

Intelligent bidding strategies for day-ahead electricity markets can be divided into two broad categories: game-theoretic models and simulation. Agent-based models (ABMs) allow for the simulation of heterogenous irrational actors with imperfect information. Additionally, ABMs allow for learning and adaption within a dynamic environment [58]. Game-theoretic approaches may struggle in complex electricity markets where Nash equilibriums do not exist [201].

7.2.1 Game-theoretic approaches

Here, we explore game-theoretic approaches. Kumar *et al.* propose a Shuffled Frog Leaping Algorithm (SFLA) [199] to find bidding strategies for GenCos in electricity markets. SFLA is a meta-heuristic that is based on the evolution of memes carried by active individuals, as well as a global exchange of information among the frog population. They test the effectiveness of the SFLA algorithm on an IEEE 30-bus system and a practical 75-bus Indian system. A bus in a power system is a vertical line which several components are connected in a power system. For example, generators, loads, and feeders can all be connected to a bus. Kumar *et al.* find superior results when compared to particle swarm optimization and the genetic algorithm with respect to total profit and convergence with CPU time. They assume that each GenCo bids a linear supply function, and model the expectation of bids from rivals as a joint normal distribution. In contrast to their work, we do not require an estimation of the rivals bids.

Wang *et al.* propose an evolutionary imperfect information game approach to analyzing bidding strategies with price-elastic demand [201]. Their evolutionary approach allows for GenCos to adapt and update their beliefs about an opponents' bidding strategy during the simulation. They model a 2-bus system with three GenCos. Our work, however, models a simulation with 60 GenCos across the entire UK, which would require a 28-bus system model [21].

7.2.2 Reinforcement learning to model intelligence

Next, we explore reinforcement learning approaches used to make intelligent bidding decisions in electricity markets. RL is a suitable method for analyzing the dynamic behaviour of complex systems with uncertainties. RL can, therefore, be used to identify optimal bidding strategies in energy markets [212]. Simulations are often used to provide an environment for the reinforcement learning algorithm. In the following papers simulations are used as the environment.

Aliabadi *et al.* utilize an ABM and the Q-learning algorithm to study the impact of learning and risk aversion on GenCos in an oligopolistic electricity market with five GenCos [58]. They find that some level of risk aversion is beneficial, however excessive risk degrades profits by causing an intense price competition. Our work focuses on the impact of the interaction of many GenCos within the UK electricity market. In addition, we extend the Q-learning algorithm to use the DDPG algorithm, which uses a continuous action space.

Bertrand *et al.* use RL in an intraday market [22]. Specifically, they use the REINFORCE algorithm to optimize the choice of price thresholds. The REINFORCE algorithm is a gradient-based method. They demonstrate an ability to outperform the traditionally used method, the rolling intrinsic method, by increasing profit per day by 4.2%. The rolling intrinsic method accepts any trade, which gives a positive profit if the contracted quantity remains in the bounds of capacity. In our work, we model a day-ahead market and use a continuous action for price bids.

Ye *et al.* propose a novel deep RL based methodology which combines the DDPG algorithm with a prioritized experience replay (PER) strategy [213]. The PER samples from previous experience, but samples from the "important" ones more often [179]. The PER is a modification of the often used experience buffer, which is a buffer which stores previous transitions and samples uniformly. This helps to reduce the correlations between recent experiences. They use a day-ahead market with hourly resolution and show that they are able to achieve approximately 41%, 20% and 11% higher profit for the GenCo than the MPEC, Q-learning and DQN methods, respectively. In our work, we instead look at how to prevent GenCos (or sets of colluding GenCos) from forcing higher prices above market rates.

Zhao *et al.* propose a modified RL method, known as the gradient descent continuous Actor-Critic (GDCAC) algorithm [214]. This algorithm is used in a double-sided day-ahead electricity market simulation. Where in this case, a double-sided day-ahead market refers to GenCos selling their supply to distribution companies, retailers or large consumers. Their approach performs better in terms of participant's profit or social welfare compared with traditional table-based RL methods, such as Q-Learning. Our work also looks at improving on table-based methods by using function approximators.

7.3 Methodology

In this section, we describe the RL methodology used for the intelligent bidding process as well as the simulation model used as the environment.

7.3.1 Reinforcement Learning background

In RL an agent interacts with an environment to maximize its cumulative reward. RL can be described as a Markov Decision Process (MDP). An MDP includes a state-space $\mathscr{S}$, action space $\mathscr{A}$, a transition dynamics distribution $p(s_{t+1}|s_t,a_t)$ and a reward function, where $r : S \times \mathscr{A} \to \mathbb{R}$. At each time step an agent receives an observation of the current state which is used to modify the agent's behaviour.

An agent's behaviour is defined by a policy, π. π maps states to a probability distribution over the actions $\pi : \mathscr{S} \to \mathscr{P}(\mathscr{A})$. The return from a state is defined as the sum of discounted future reward $R_t = \sum_{i=t}^{T} \gamma^{(i-t)} r(s_i,a_i)$. Where γ is a discounting factor $\gamma \in [0,1]$. The return is dependent on the action chosen, which is dependent on the policy π. The goal in reinforcement learning is to learn a policy that maximizes the expected return from the start distribution $J = \mathbb{E}_{r_i,s_i \sim E, a_i \sim \pi}[R_1]$.

The expected return after taking an action a_t in state s_t after following policy π can be found by the action-value function. The action-value function is used in many reinforcement learning algorithms and is defined in Equation 7.1.

$$Q^{\pi}(s_t,a_t) = \mathbb{E}_{r_{i\geq t}, s_{i>t} \sim \mathscr{E}, a_{i>t} \sim \pi}[R_t|s_t,a_t]. \tag{7.1}$$

The action-value function defines the expected reward at time t, given a state s_t and action a_t when under the policy π.

7.3.2 Q-Learning

An optimal policy can be derived from the optimal Q-values $Q_*(s_t, a_t) = \max_\pi Q_\pi(s_t, a_t)$ by selecting the action corresponding to the highest Q-value in each state.

Many approaches in reinforcement learning use the recursive relationship known as the Bellman equation, as defined in Equation 7.2:

$$Q^\pi(s_t, a_t) = \mathbb{E}_{r_t, s_{t+1} \sim E}[r(s_t, a_t) + \gamma \mathbb{E}_{a_{t+1} \sim \pi}[Q_\pi(s_{t+1}, \pi(s_{t+1}))]]. \tag{7.2}$$

The Bellman equation is equal to the action which maximizes the reward plus the discount factor multiplied by the next state's value, by taking the action after following the policy in state s_{t+1} or $\pi(s_{t+1})$.

The Q-value can therefore be improved by bootstrapping. This is where the current value of the estimate of Q_π is used to improve its future estimate, using the known $r(s_t, a_t)$ value. This is the foundation of Q-learning [203], a form of *temporal difference* (TD) learning [192], where the update of the Q-value after taking action a_t in state s_t and observing reward r_t, which results in state s_{t+1} is:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \delta_t \tag{7.3}$$

where,

$$\delta_t = r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t) \tag{7.4}$$

$\alpha \in [0, 1]$ is the step size, δ_t represents the correction for the estimation of the Q-value function and $r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})$ represents the target Q-value at time step t.

It has been proven that if the Q-value for each state action pair is visited infinitely often, the learning rate α decreases over time step t, then as $t \to \infty$, $Q(s, a)$ converges to the optimal $Q_*(s, a)$ for every state-action pair [203].

However, it is often the case that Q-learning suffers from the curse of dimensionality. This is because Q-learning stores the Q-value function in a look-up table. This therefore requires the action and state spaces to be discretized. As the number of discretized states and actions increases, the computational cost increases exponentially, making the problem intractable. Many problems are naturally discretized which are well suited to a Q-learning approach, however this is not always the case.

7.3.3 Deep Deterministic Gradient Policy

It is not straightforward to apply Q-learning to continuous action spaces. This is because in continuous spaces, finding the greedy policy requires an optimization of a_t at every time step. Optimizing for a_t at every time step would be too slow to be practical with large, unconstrained function approximators and nontrivial action spaces [**?**]. To solve this, an actor-critic approach based on the deterministic policy gradient (DPG) algorithm is used [185].

The DPG algorithm maintains a parameterized actor function $\mu(s|\theta^{\mu})$ which specifies the current policy by deterministically mapping states to a specific action. The critic $Q(s,a)$ is learned using the Bellman equation as in Q-learning. The actor is updated by applying the chain rule to the expected return from the start distribution J with respect to the actor parameters:

$$\begin{aligned} \nabla_{\theta^{\mu}} J &\approx \mathbb{E}_{s_t \sim \rho^{\beta}}[\nabla_{\theta^{\mu}} Q(s,a|\theta^{Q})|_{s=s_t, a=\mu(s_t|\theta^{\mu})}] \\ &= \mathbb{E}_{s_t \sim \rho^{\beta}}[\nabla_a Q(s,a|\theta^{Q})|_{s=s_t, a=\mu(s_t)} \nabla_{\theta_{\mu}} \mu(s|\theta^{\mu})|_{s=s_t}] \end{aligned} \tag{7.5}$$

This is the policy gradient. The policy gradient is the gradient of the policy's performance. The policy gradient method optimizes the policy directly by updating the weights, θ, in such a way that an optimal policy is found within finite time. This is achieved by performing gradient ascent on the policy and its parameters π^{θ}.

Introducing non-linear function approximators, however, means that convergence is no longer guaranteed. Although these function approximators are required in order to learn and generalize on large state spaces. The Deep Deterministic Gradient Policy (DDPG) modifies the DPG algorithm by using neural network function approximators to learn large state and action spaces online.

A replay buffer is utilized in the DDPG algorithm to address the issue of ensuring that samples are independently and identically distributed. The replay buffer is a finite-sized cache, $\mathscr{R}$. Transitions are sampled from the environment through the use of the exploration policy, and the tuple (s_t, a_t, r_t, s_{t+1}) is stored within this replay buffer. $\mathscr{R}$ discards older experiences as the replay buffer becomes full. The actor and critic are trained by sampling from $\mathscr{R}$ uniformly.

A copy is made of the actor and critic networks, $Q'(s,a|\theta^{Q'})$ and $\mu'(s|\theta^{\mu'})$ respectively. These are used for calculating the target values. To ensure stability, the weights of these target networks are updated by slowly tracking the learned networks. Pseudo-code of the DDPG algorithm is presented in Algorithm 3.

7.3.4 Simulation

We utilized the long-term electricity market agent-based model, ElecSim [122, 127] discussed in Chapter 4. The model was run using a short term approach by only iterating through a single year (2018), composed of eight representative days, each of 24 time steps.

In this work we explore whether large GenCos, or group of GenCos, can manipulate the price of the electricity market through virtue of their size. We achieve this by allowing a subset of GenCos to bid away from their SRMC and allow them to learn an optimal bidding strategy for maximizing their income. The GenCo agents adopt a DDPG RL algorithm to select their bids. This is to explore whether large GenCos, or a group of GenCos can manipulate the price of the electricity market through market power. The remaining GenCos, which fall outside of this group, maintain a bidding strategy based upon their SRMC.

For the purpose of this work, we do not consider flow constraints within the electricity mix. This is because we model the entire UK with 1000+ generators, and many nodes and buses. This would make the optimization problem intractable for the purpose of our simulation, especially when considering the many episodes required for training. It takes $\sim$125 seconds

Algorithm 3 DDPG Algorithm [105]

Initialize critic network $Q(s,a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with random weights θ^Q and θ^μ
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q, \theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for `episode=1,M` **do**
    Initialize a random process $\mathcal{N}$ for action exploration
    Receive initial observation state s_1
    for `t=1,T` **do**
        Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the policy and exploration noise, $\mathcal{N}_t$
        Execute action a_t and observe reward r_t and new state s_{t+1}
        Store transition (s_t, a_t, r_t, s_{t+1}) in R
        Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
        Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
        Update critic by minimizing the loss:

$$L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$$

        Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s,a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu}\mu(s|\theta^\mu)|_{s_i}$$

        Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$

$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

    end for
end for

GenCo Groups	Capacity (MW)	Num. of Plants
Orsted	2738.7	11
Drax Power Ltd	4035.0	3
Scottish power	4471.5	49
Uniper UK Limited	6605.0	9
SSE	8390.7	130
RWE Generation SE	8664.0	11
EDF Energy	14763.0	14
{EDF Energy, RWE Generation SE}	23427.0	25
{EDF Energy, RWE Generation SE, SSE}	31817.7	155
{EDF Energy, RWE Generation SE, SSE, Uniper UK Ltd}	38422.7	164
{EDF Energy, RWE Generation SE, SSE, Uniper UK Ltd, Scottish Power}	42894.2	213
{EDF Energy, RWE Generation SE, SSE, Uniper UK Ltd, Scottish Power, Drax Power Ltd}	46929.2	216

Table 7.1 Groups of GenCos that used bidding strategies, number of plants and total electricity generating capacity.

to run a single year in the simulation, or episode with our current setup. By increasing the simulation time further, we would make the compute time intractable due to the many episodes required for reinforcement learning to learn an effective policy. Additionally, we must train several reinforcement learning policies to account for each GenCo and market cap. Therefore a simulation that takes ∼2 minutes to run, run 1000 times takes ∼33 hours to run, multiplied by 12 different GenCos takes ∼16 days, and with two market cap scenarios it would take ∼1 month.

7.4 Experimental Setup

To parameterize the simulation, we use data from the United Kingdom in 2018. This included 1085 electricity generators and power plants with their respective GenCos. The data for this was taken from the BEIS DUKES dataset [63]. The electricity load data was modelled using data from [gri]; offshore and onshore wind and solar irradiance data from [166]. It would be possible to adopt this approach to other decentralized markets in other countries.

By modelling bidding decisions as a RL algorithm, we hoped to observe the ability for RL to find the point at which market power artificially inflates electricity prices. To achieve this, we chose the six largest GenCos in the UK, as well as a smaller GenCo as a control. Groups of GenCos are modelled as a single GenCo with a single RL strategy for the purpose of this work. Table 7.1 displays the groups of GenCos, as well as individual GenCos, with their respective capacity and number of plants.

For the reinforcement learning problem we have the following tuple: (s_t, a_t, r_t, s_{t+1}), where (s_t, s_{t+1}) is the state at time t and $t+1$ respectively, a_t is the action at time t and r_t is the reward at time t. For our problem the state space is given by the tuple shown in Equation 7.6:

$$s_t = (H_i, D_i, p_{C02}, p_{gas}, p_{coal}, p_c) \tag{7.6}$$

where H_i is the segment hour to bid into at timestep i, D_i is the demand of the segment hour at timestep t, p_{gas} is the price of gas, p_{coal} the price of coal, p_{C02} is the carbon tax price, and p_c is the clearing price. We set the reward, r_t to be the average electricity price of that time step, p_{avg}.

For the action space, a_t, we modelled two scenarios. Where there was a price cap of £150/MWh and £600/MWh. Only these two values were chosen to reduce computational load. We chose £150/MWh as a reasonable price cap that may be introduced by a Government. This was roughly double the average accepted price in 2018, therefore allowed for higher prices in times of high demand or low supply. The 600/MWh was chosen to simulate an unbounded price cap. This enabled us to see the price that an equilibrium is reached within a market with agents with market power.

For this work, we assume that the action space a_t only bids price, and not how much capacity to bid on the market. We assume this to reduce the dimensionality of a_t, and simplify the training process.

In this work, we assume that the GenCo groups have no information about the generation capacity, marginal cost, bid prices or profits of other GenCos [58]. They learn the maximum profit that can be made through experience within a particular market. We assume this because in real-life GenCo groups have little information on their competitors sensitive bidding data. If they were to have perfect information on all their competitors they would be able to devise a perfect strategy which would always maximise their profit.

7.5 Results

In this section, we detail the results of the RL algorithm, and the effect that capacity has on average electricity price within the UK. Our approach could be generalised to any other decentralised electricity market in other countries.

Figures 7.1 and 7.2 show the rewards over a number of time steps for the unbounded and bounded cases respectively. Figure 7.1 shows a clear difference between agents which use the DDPG RL strategy and have a large capacity (green and yellow) compared to those which have a smaller capacity (dark purple). The axis in Figure 7.1 are much larger than those of 7.2, highlighting the effect of market power on an unbounded market.

The average electricity price for a capacity below 30,000MW, or $\sim 35\%$ of total capacity, remains stable between £70/MWh and £100/MWh. This range may be due to the stochasticity in calculating the weights for the DDPG algorithm. The average electricity price does not change over the time steps or training. We, therefore, hypothesize that there is no market power as long as an individual GenCo owns below $\sim$35% of total electrical capacity.

On the other hand, once the capacity of a GenCo or groups of GenCos is above 30,000MW, there is a significant increase in the average price for capacity. The average electricity price for capacity falls between the range of £170/MWh and £220/MWh.

Figure 7.3 displays the capacity controlled by the agents that use the RL strategy versus the average electricity price for the unbounded case. The color displays the number of steps. The step-change, as shown in Figure 7.1 can be seen clearly here, with agents with a capacity larger

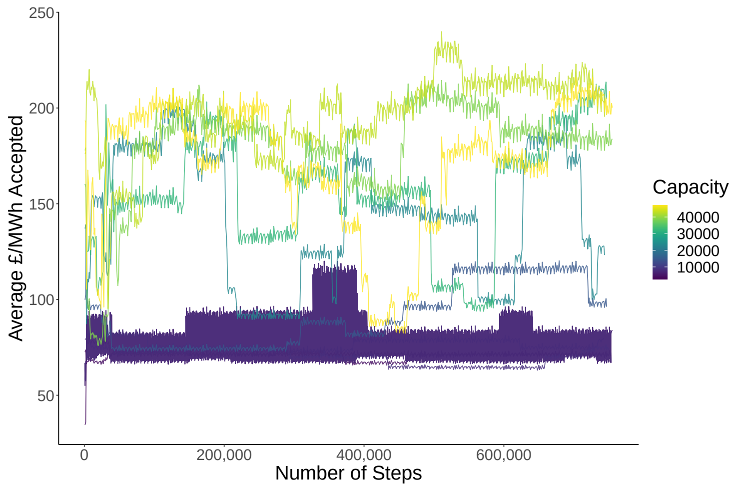


Fig. 7.1 Reward over time for different groups of GenCos, max bid = £600/MWh.

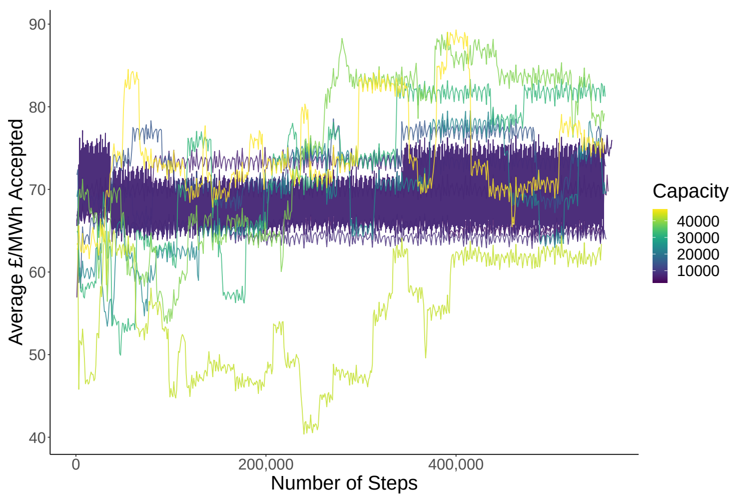


Fig. 7.2 Reward over time for different groups of GenCos, max bid = £150/MWh.

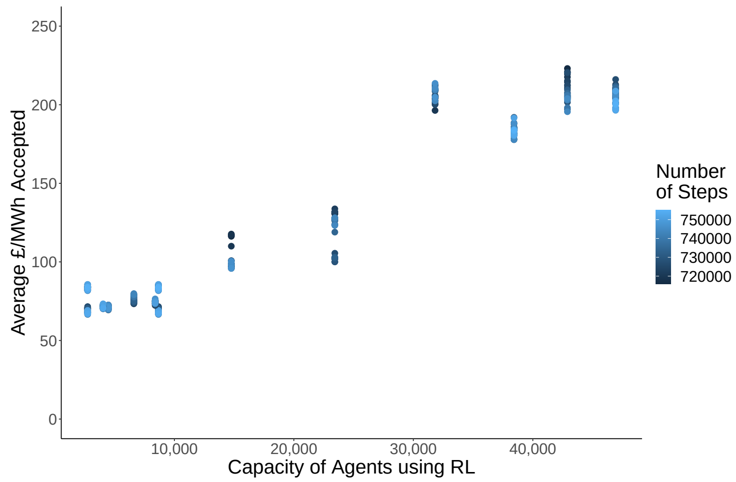


Fig. 7.3 Capacity of agents using RL vs. average electricity price accepted, for unbounded agents.

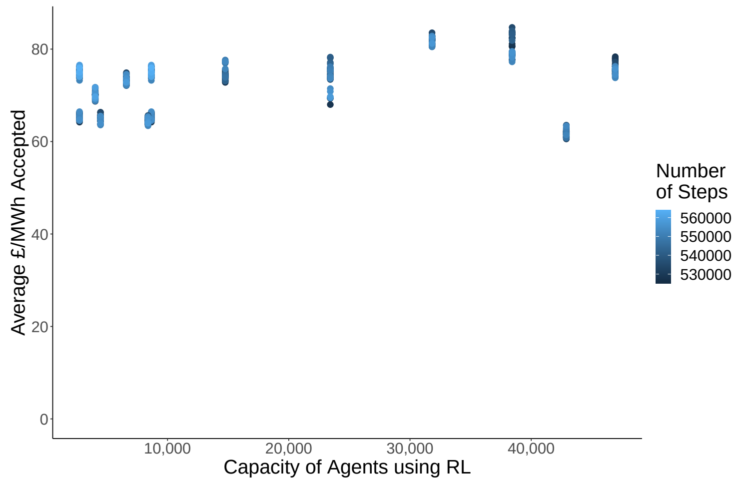


Fig. 7.4 Capacity of agents using RL vs. average electricity price accepted, for bounded agents.

than ∼25,000MW causing a step change in electricity price. Electricity prices seems to cluster below ∼10,000MW. However, after this point, the average electricity price begins to increase.

Figure 7.2 shows a cluster between ∼£60/MWh and ∼£80/MWh irrespective of the capacity of the agents. This is verified by Figure 7.4. This seems to suggest that setting a lower market cap reduces the ability for generators, irrespective of size, from influencing the electricity price.

Figures 7.5 and 7.6 display the actual bids made at the end of training within the electricity market for all of their power plants. The number of bids made by each GenCo changes dependent on the number of plants that they own, with the Orsted GenCo only making eleven bids per segment, and the largest group making 216 bids per segment. Figure 7.5 displays the uncapped scenario (£600/MWh) and 7.6 displays the capped scenario (£150/MWh).

Figure 7.5a shows the bids made by the largest group of GenCos as shown in Table 7.1. A bimodal distribution can be seen, where the group of GenCos tend to bid either the maximum or the minimum bid. We hypothesize that they bid the maximum amount as this ensures that the market price is artificially raised, and that they are able to utilize their market power. The minimum price is bid the rest of the time to ensure that generators bids are always accepted, regardless of whether the market price has been artificially raised or not in each respective clearing segment.

Figure 7.5b displays the bids of the small company with a market cap of £600/MWh. The small company also seems to have a bimodal distribution; however, bids the higher price more often. This may be due to the fact that it is able to influence the price at certain market segments, and the reward of the higher accepted reward outweighs the times in which it is not accepted on the market segments. Again, bidding low seems to be the strategy in which to take if the GenCo does not believe it will be able to influence the final price. As the market simulated is a uniform pricing market, having a £0 bid accepted does not mean that the GenCo will be paid £0. Rather, the GenCo will be paid the market clearing segment, which is set by the most expensive power plant accepted onto that market segment.

Figures 7.6a shows the bids made by the largest group of GenCos in each market segment. It seems to take a similar strategy to that of the large company in the uncapped scenario, as shown in Figure 7.5a. We believe, as similar in the uncapped scenario, that this is due to the market power that this group possesses. Being able to influence the market price enables the GenCo group to inflate the prices. It also takes a conservative strategy to bid the minimum price allowed, to ensure that the bid is accepted regardless of price.

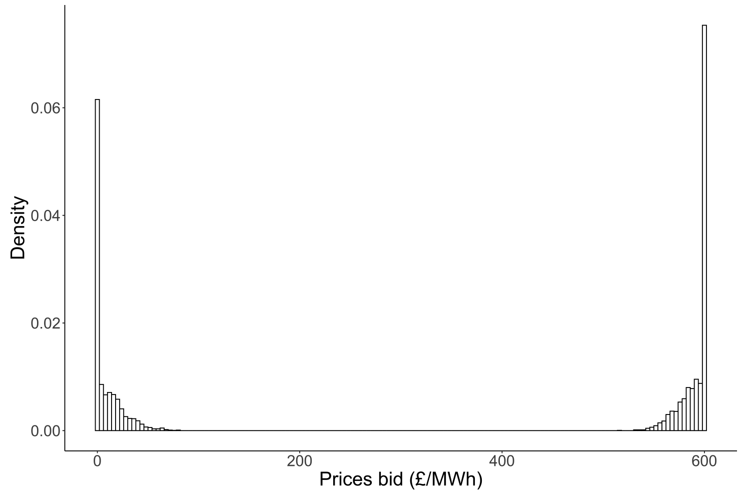
Figure 7.6b displays the strategy of the smallest company in the capped scenario. Here, it seems that the GenCo is unable to influence the price at all, and therefore bids £0/MWh for the majority of the time. This is similar to the expected strategy of GenCos, who tend to bid their short-run marginal cost to ensure that they do not miss out on potential profit. The short-run marginal cost can often change based upon fuel, carbon and generator type. However, for renewable energy it is near £0 and for fossil-fuel based plants it is near the cost of fuel and carbon at that point in time.

We ran a sensitivity analysis to observe the effects of the market cap on final average accepted bid price. The largest GenCo group used a strategy for this sensitivity analysis. Figure 7.7 displays the results. It seems that whilst the average accepted bid price increased with the capped bid level; there is a significant increase after a market cap of £190/MWh. This may be due to the case that the GenCos begin to outbid the SRMC bidding GenCos at this price point.

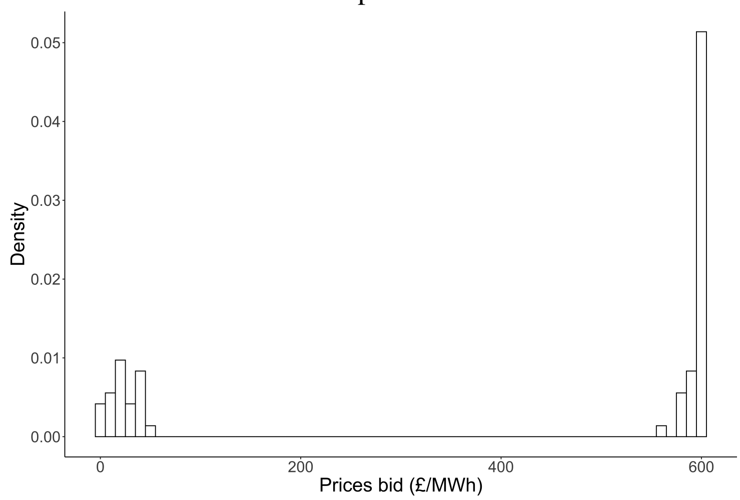
7.6 Discussion

Our results demonstrate the ability for GenCos to artificially increase the electricity price through market power in an uncapped market. Our results have shown that in an uncapped market, any single agent or groups of agents who make bids using the same strategy and information, should have less than $\sim$10,000MW. This defines the optimal capacity by any single GenCo to have a fair level of competition. After this, the electricity price begins to rise with the same outcome and welfare. It is also worth nothing that when the market is capped, the average accepted price does not simply become the capped price.

However, if there is an electricity market with a few large or colluding players, it is possible to remove their advantage through the introduction of a price cap. Our results show that whilst

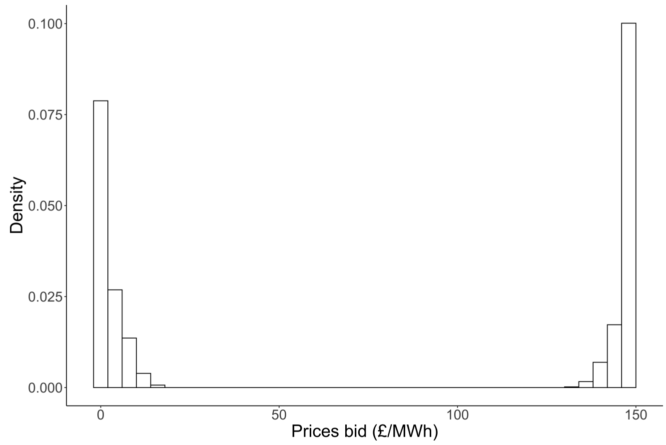


(a) Largest group of GenCos with a total controlled capacity of 46929.2MW with a market cap of £600/MWh.

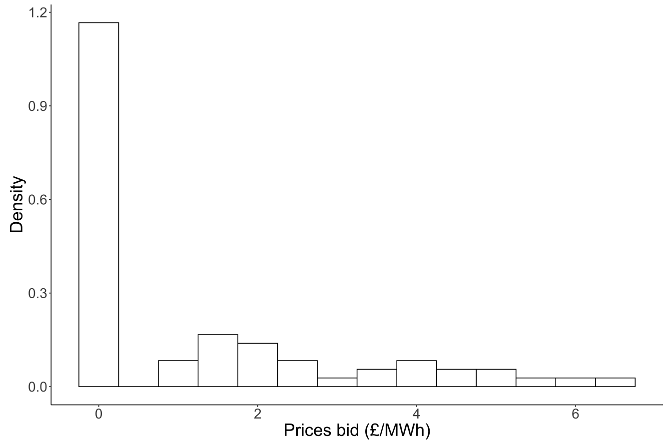


(b) Smallest company with a total controlled capacity of 2738.7MW with a market cap of £600/MWh.

Fig. 7.5 Bids made by generator companies with a market cap of £600/MWh.



(a) Largest group of GenCos with a total controlled capacity of 46929.2MW with a market cap of £150/MWh.



(b) Smallest company with a total controlled capacity of 2738.7MW with a market cap of £150/MWh.

Fig. 7.6 Bids made by generator companies with a market cap of £150/MWh.

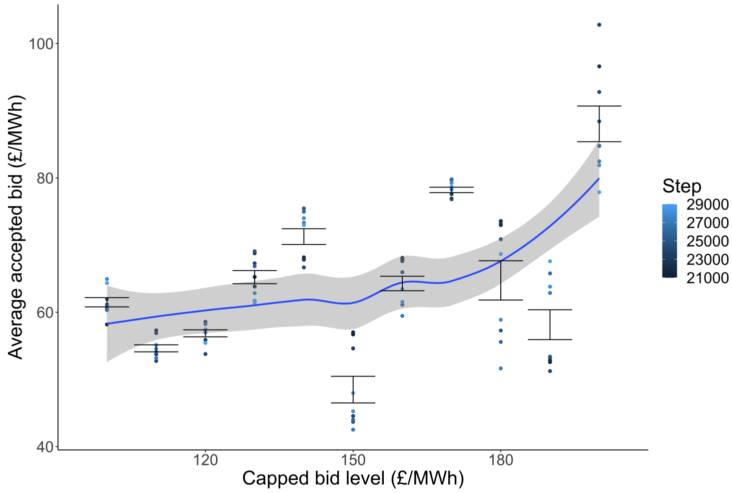


Fig. 7.7 Capacity of agents using RL vs. average electricity price accepted, for bounded agents.

average accepted bids increase with market cap level, the value does not increase significantly until £200 is reached.

This information and approach can help to inform government policy to ensure fair competition within electricity markets, as well as run the model for their own scenario. It is hypothesized that the findings in this work are generalizable to other decentralized electricity markets in other geographies due to their similar market structures. Whilst the figures presented here may not be the same; we hypothesize that the region of interest will be similar.

7.7 Conclusion

In this work, we used the deep deterministic policy gradient (DDPG) reinforcement learning method to make strategic bids within an electricity market. We utilized the agent-based model ElecSim to model the UK electricity market. We utilized the DDPG algorithm only for a certain subset of agents, from small individual generation companies (GenCos) to large groups of GenCos.

This enabled us to explore the ability for GenCos with a large capacity to artificially increase the price in the electricity market within the UK if they are in control of a sufficiently large generation capacity. Our results show that the optimum level of control of any single GenCo or groups of GenCo is below $\sim$10,000MW or $\sim$11% of the total capacity. Above this, prices begin to increase with no real additional benefit to the consumer. After $\sim$25,000MW, or $\sim$35% of the total capacity, the prices begin to increase substantially, to $\sim$£200, over triple the original cost without this market power. The introduction of a market cap of £150 reduces all market power and maintains electricity price at a reasonable level.

We found through a sensitivity analysis, that the average electricity price in the market over a year remains low with a price cap smaller than £190. However, after this level, the average electricity price begins to increase.

Our work has shown the ability for reinforcement learning to learn an optimal bidding strategy to maximize a GenCo's profit within an electricity market. The ability for GenCos to use their market power is also highlighted, and is dependent on electricity generation capacity of the respective GenCo.

In future work, we would like to enable GenCos to withhold the capacity on offer to the electricity market. This would enable further market power by reducing competition further. Additionally, we would like to assess the market power in different countries with different market structures and total electricity supply.

Chapter 8

Conclusion

8.1 Thesis summary

Test

8.2 Limitations

Test

8.3 Future research direction

Test

Appendix 1

Appendix 2

References

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