ElecSIM: Stochastic Open-Source Agent-Based Model to Inform Policy for Long-Term Electricity Planning

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ABSTRACT

Due to the threat of climate change, a transition from a fossil-fuel based system to one based on zero-carbon is required. However, this is not as simple as instantaneously closing down all fossil fuel energy generation and replacing them with renewable sources – careful decisions need to be taken to ensure rapid but stable progress. To aid decision makers, we present a new tool, ElecSIM, which is an open-sourced agent-based modelling framework used to examine the effect of policy on long term investment decisions in the electricity sector. ElecSIM allows non-experts to rapidly prototype new ideas, and is developed around a modular framework – which allows technical experts to add and remove features at will.

We review different techniques currently used to model long term electricity decisions, and use this to motivate why agent-based models will become an important strategic tool for policy makers. We provide motivational arguments as to why an open-source toolkit is required to model long-term electricity markets.

We compare actual electricity prices with our model and demonstrate that the modelling of stochasticity in the system improves performance by 52.5%

We demonstrate how effective a carbon tax is at encouraging a low-carbon electricity supply market and show how a £70 ($90) per tonne of carbon emitted would lead to an almost 100% renewable electricity energy market by 2050. An interesting note, however, is that starting with a low carbon tax and slowly increasing this by the year 2050 provides similar benefits to a lower, but consistent tax in the long run, due to the high capital costs and long operating periods of generators. This has the benefits of reducing costs as well as providing certainty to investors.

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1 INTRODUCTION

The world faces significant challenges from climate change and global warming [41]. A rise in carbon emissions increases the risk of severe impacts on the world such as rising sea levels, species extinction, heat waves and tropical cyclones [30]. The scientific literature concurs that the recent change in climate is anthropogenic, with 97% of peer reviewed articles of this view [15].

As shown by Figure 1, the electricity mix is dominated by high carbon emitting fuels such as coal and natural gas. Low-carbon solutions, such as nuclear, renewables and hydro, combine to produce less electricity than solely coal as a fuel source.

To achieve a low carbon energy infrastructure, and limit the effects of global warming, a transition in the electricity mix is required. Moving from a centralised and homogenous fossil fuel-based system to a distributed system based on renewable energy and batteries. Batteries are required due to the fact that most renewable sources are effected by conditions outside the control of the owners (e.g. time of day, wind speed and cloud cover). This leads to a need for electricity to be stored at times of low electricity demand and high renewable resources, and for the batteries to be discharged at times of high demand and low supply.

Such a transition needs to be performed in a safe and non-disruptive manner – it may be possible to close down all fossil fuel

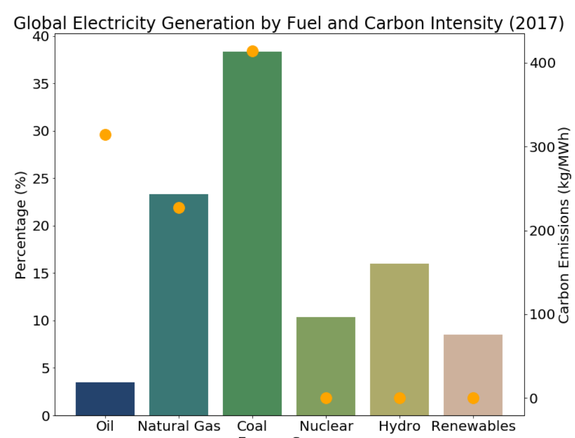


Figure 1: Global electricity generation sources and relative carbon emission intensity. [9, 17]

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 companies and homes. 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, long operating periods and high costs of power plants, investment decisions made today can have long term impacts on future electricity supply [12]. Governments, and society, therefore have a role in ensuring that the negative externalities of pollution and carbon emission are priced into electricity generation so that optimal decisions are made. Due to the absence of central control in electricity generation investment, other methods must be used to influence the independent players of the electricity market. Methods such as carbon taxes, policy and regulation can aid in the goals of reducing carbon emissions to limit global warming, as agreed in the Paris agreement [3].

A common method to understand and reduce risk and uncertainty, especially in electricity planning, is simulation and modelling. Simulation and modelling 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. Without simulation one would frequently make safer decisions to reduce risk.

Agent-based modelling (ABM) is a class of computational simulation models composed of autonomous, interacting agents. ABMs are a way of modelling the dynamics of a complex system [39]. Due to the numerous and diverse actors involved in the generation, distribution and sale of electricity in liberalised electricity markets, agent based models are well suited and increasingly being used in the literature [52].

In this paper, we present ElecSIM, an open-source agent-based model that simulates generation companies (GenCos) in an electricity market. ElecSIM models GenCos as multiple agents and electricity demand as a single aggregated agent, with a power exchange that facilitates trades between the two.

GenCos actively make bids for each of the power plants they own to match demand. Their bids are based on their costs to supply a single unit (1MWh) of electricity, known as their short run marginal cost (SRMC), which excludes capital and fixed costs. The power exchange links bids to supply based on merit-order, with priority to the cheapest bids first. GenCos then invest in power plants based on expected profitability of each option.

Through simulation we can evaluate many strategies in order to identify those most likely to achieve our goals of rapid but non-disruptive migration from fossil to renewable.

ElecSIM can be used by:

- **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.

A diagram showing the different players, who can influence them and how?

This paper details our model, ElecSIM. We contribute a new open-source framework, and test different scenarios with varying carbon taxes to provide advice to stakeholders. Section 2 is a literature review of the models currently used in practice. Section 3 details the model and assumptions made, and section 4 details how we validated our model, and displays performance metrics. Section 5 details our results, and explores ways in which ElecSIM can be used. We conclude the work and propose future work in section 6.

2 LITERATURE REVIEW

Live experimentation of physical processes is often not practical. The costs of real life experimentation can be prohibitively high, and it normally requires significant time in order to fully ascertain the long-term trends. There is also a risk that changes can have detrimental impacts, and therefore often leads to only minor tweaks being made [22]. These factors are particularly true for an electricity market, where decisions made can have long term impacts on energy mix, carbon emissions and investment decisions, with energy plants often having a lifetime of 25 years. A solution to this is simulation, which can be used for rapid testing and prototyping of ideas. Simulation is the substitution of a physical process with a computer model. The computer model is parametrised by real world data and phenomena. The user is then able to experiment using this model, and assess the likelihoods of outcomes under certain scenarios and input variables [37].

Electricity energy policy modelling is an example where simulation can be used. Real-life experimentation of energy policy is not always feasible due to the long times required to observe results and high risks associated with setting a sub-optimal policy which could radically alter business models and lead to blackouts in electricity supply. Decisions can have long-term impacts, such as producing an electricity market with many expensive and highly polluting coal power plants, they may have ramp-up times that are not suitable to accommodate the intermittent electrical flow of renewables. A number of different simulations and computer models have been used to aid policy makers and energy market developers in coming to informed conclusions:

Energy models can typically be classified as top-down macro-economic models or bottom-up techno-economic models [8]. 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 [25], for example MARKAL-MACRO [21] and LEAP [27]. Bottom-up models represent the energy sector in detail, and are written as mathematical programming problems [23]. They detail technology explicitly, and can include cost and emissions implications [25].

Tool name	Open Source	Long-Term Investment	Market	Stochastic Inputs	Country Generalisability
SEPIA	✓	x	✓	Demand	✓
EMCAS	x	✓	✓	Outages	✓
NEMSIM	?	✓	✓	x	x
AMES	✓	x	Day-ahead	x	x
PowerACE	x	✓	✓	Outages/Demand	✓
MACSEM	?	x	✓	x	✓
GAPEX	?	x	Day-ahead	x	✓
EMLab	✓	✓	Futures	x	✓
ElecSIM	✓	✓	Futures	✓	✓

Table 1: Features of electricity market agent based model tools.

It is possible to further categorise bottom-up models into optimisation and simulation models. Optimisation energy models minimise costs or maximise welfare from the perspective of a central planner, for instance a government [34]. A use-case would be a government that wants cheap, reliable and a low-carbon electricity supply by a specified date. An optimisation model would find the optimal mix of generators to meet this whilst taking into account the constraints such as space, resources and demand. Examples of optimisation models are MARKAL/TIMES [21] and MESSAGE [49]. MARKAL is possibly the most widely used general purpose energy systems model [45].

However, 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 in their own best interest [42]. Therefore, certain policy options which encourage changes must be used by a central planner to attain a desired outcome, for example carbon taxes or subsidies. It is proposed that these complex agents are modelled using agent-based simulation, which allows for the modelling of heterogeneous actors.

Agent-based simulation for electricity markets has received increasing attention in recent years.

There are numerous different mechanisms/markets for GenCos to sell electricity. These mechanisms can largely be split into pool markets and bilateral contracts. A pool market is a market in which bids and offers use supply and demand principles to set the price. Pool markets operators typically provide the function of matching buyers and sellers. Bilateral contracts are typically longer term markets where a GenCo will sell electricity to a demand company based on long-term contracts.

These mechanisms can be divided further into day-ahead markets and futures markets. Where day-ahead markets are markets where a buyer assesses how much energy it will need to meet demand the next day, and how much it is willing to pay for this volume, hour by hour [4]. The seller (GenCo), will decide how much electricity it can deliver and at what price, hour by hour. Futures markets is where electricity is traded as a commodity, where electricity is bought at a certain price, at either high or low demand at a day in the future.

A number of simulation tools have emerged which model these electricity markets, for example SEPIA [26] EMCAS [14], NEMSIM [7], AMES [51], PowerACE [48], [47], GAPEX [13] and EMLab [12].

However, by referring to Table 1, it can be seen that none of these suit the needs of an open source, long-term market model. The inclusion of stochastic input variables in ElecSIM allows for better performance.

Table 1 is made up of six columns. Tool name, whether the tool is open source or not, whether they model long-term investment in electricity infrastructure such as power plants and what markets they model. We also determine whether the model is generalisable to different countries or whether it is specific to a particular country’s regulatory structure. We determine how the stochasticity of real life is modelled in each tool.

SEPIA [26] is a discrete event agent based model 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 organization for coordinating and controlling of regular operations of the electric power system and market [52]. 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 where renewable energy runs intermittently. As can be seen by Table 1 it does not include long-term investment.

MACSEM [47] simulates a bilateral and pool market. It has been used to probe the effects of market rules and conditions by simulating and testing different bidding strategies. However, MACSEM does not model long term investment decisions or stochastic inputs.

As can be seen in Table 1, EMCAS [14] is a closed source agent-based framework. EMCAS investigates the interactions between physical infrastructures and economic behaviour of market participants. ElecSIM, however, focuses on purely the dynamics of the market, with an aim of providing a simplified, transparent, open source model of market operation, whilst maintaining robustness of results.

PowerACE [48] is also a closed source agent-based simulation of electricity markets that integrates short-term perspectives of daily electricity trading and long-term investment decisions. PowerACE models the spot market, forward market and a carbon market. A carbon market is a market where total carbon emissions within a region are capped. Companies receive emission allowances and are allowed to sell or buy additional allowances based on requirements. Similarly to ElecSIM, PowerACE initialises agents with all power plants in their respective country. However, as can be seen in Table 1 unlike ElecSIM, PowerACE does not take into account stochasticity

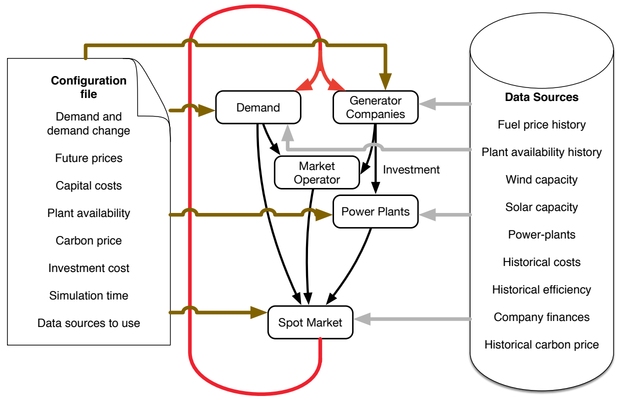


Figure 2: High level system overview demonstrating fundamental parts of ElecSIM.

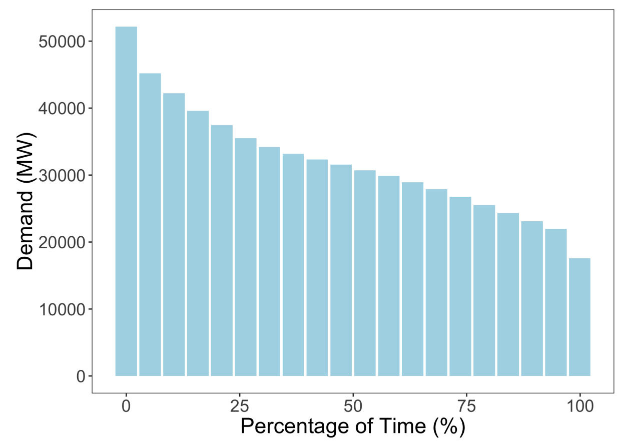


Figure 3: Example load duration curve in a single year.

of price risks in electricity markets which is of crucial importance to real markets [42].

EMLab [12] is also an agent-based modelling toolkit for the electricity market. EMLab models an endogenous European emissions trading scheme with a yearly time-step. Like PowerACE, EMLab models a carbon market, but they both differ from ElecSIM by not taking into account stochasticity in the electricity markets, such as outages, differing fuel prices within a year period and stochasticity in power plant operating costs. However, after correspondence with the authors, we were unable to run the current version of EMLab.

AMES [51] is an agent-based model specific to the US Wholesale Power Market Platform. GAPEX [13] is an agent-based framework for modelling and simulating power exchanges in MATLAB . GAPEX utilises an enhanced version of the reinforcement technique Roth-Erev to consider the presence of affine total cost functions. However, neither of these model the long-term dynamics that ElecSIM is designed for.

As can be seen from Table 1 none of the tools fill each of the characteristics we have defined. We therefore propose ElecSIM to fill the gaps that are not currently covered, which includes an open source, long-term stochastic investment model.

3 ELECSIM ARCHITECTURE

ElecSIM has been designed for ease of use to enable non-experts to rapidly test different policies, and the outcomes of various scenarios such as demand growth or fuel prices. The user is able to input exogenous variables such as fuel costs, carbon taxes, power plants, power plant costs, electricity demand and availability factors. This allows for the initialisation of different countries and scenarios to be tested.

3.1 High-Level Overview

ElecSIM is made up of four fundamental parts: The agents, which are split up into demand and generation company (GenCo) agents. The world in which these agents exist, and power plants which are owned by the GenCos. Finally, there exists a Power Exchange which acts as a market to match GenCo owned power plants with electricity demand.

A schematic of ElecSIM is displayed in Figure 2 which displays these four fundamental sections, and demonstrates how they interact.

3.1.1 Data parametrisation. To parametrise the world, two sources are used. A configuration file and a collection of data sources. The data sources contain information such as historical fuel prices, historical plant availability, wind and solar capacity, power plant costs, historical costs, historical efficiency, company finances and historical carbon price. This is data that does not change from scenario to scenario realisation, however can vary between countries.

The configuration file allows for rapid changes to test different hypothesis and scenarios. The configuration file points to the previously mentioned data sources. The configuration file enables the changing of demand growth and load duration curve, which is the shape of electricity demand over a year period. Future fuel and carbon prices, capital costs, plant availability, investment costs and simulation time. These data is used to calibrate the world, specifically generator companies and demand.

3.1.2 Demand Agent. The demand agent is a simplified representation of aggregated demand in a county. The demand is represented as a load duration curve. An example load duration curve is demonstrated in Figure 3. A load duration curve is an arrangement of all load levels in descending order of magnitude, where the lowest segment demand demonstrates baseload (ie. 100% of time). Each year, the demand agent multiplies the percentage of change in demand with each segment of the load duration curve. Therefore, whilst total demand changes, the load duration curve is assumed not to change between years.

As per [12], we modelled a load duration curve of the electricity demand for one year with 20 segments. 20 segments enabled us to capture the varying demand of electricity throughout the year to a high enough degree of accuracy, but also reduce computational complexity. This data is used by the Power Exchange to match supply with demand.

3.1.3 Generation Company Agents. The GenCos have two main functions. Investing in power plants and making bids to sell their

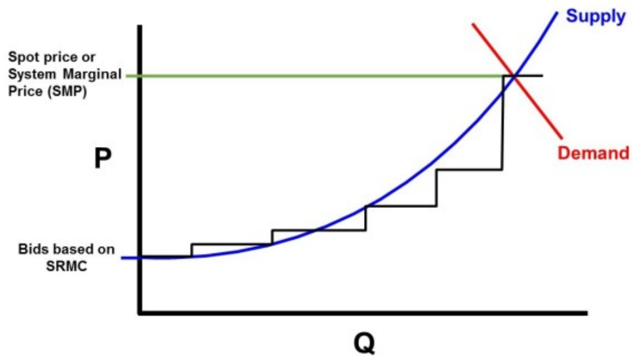


Figure 4: Power exchange clearing [5].

electricity each year for each of their power plants. We will first focus on the buying and selling of electricity using a Power Exchange, and then cover the investment algorithm for GenCos.

3.1.4 Electricity Market. Figure 4 displays the process for each segment of demand. The Power Exchange receives bids for every single power station in the modelled world from each of the GenCos. The final price paid to each of the GenCos is known as the spot price or the System Marginal Price (SMP). The spot price or SMP is the highest price that has been accepted to meet demand. This is paid to all generators regardless of their initial bid. For this reason, GenCos are motivated to bid their minimum profitable price to ensure that their bid is accepted. This minimum profitable price is known as the short run marginal cost (SRMC). The SRMC is the price that it costs a generator to sell a single unit of electricity.

3.1.5 Investment. Investment in power plants is made 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 to evaluating power plants which have a long lifetime. NPV is based upon the fact that current cash flow is worth more than future cash flow. This is due to the fact that money today can be invested and have a rate of return in the future. Meaning that, for example $50,000 today is worth more than $50,000.

Equation 1 displays 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 (cash inflow minus cash outflow) at time t.

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

A discount rate set by a firm's weighted average cost of capital (WACC) is often used. Where WACC is the rate that a company is expected to pay on average for its stock and debt. However, it is often believed that a higher rate should be selected to adjust for differing risk profiles, opportunity cost and rate of return desired.

Data is available for average WACC for power plants, and can be set in the configuration file. However, to account for differing risk profiles, opportunity costs, rate of return desired, and WACC based on companies' relative credit risk, we have sampled difference in discount rates from the mean WACC with a Gaussian distribution with a standard deviation of ±3%. Which was chosen to give sufficient variance between GenCos whilst remaining close to the mean set by the user.

To calculate the expected return per year, an understanding of future market conditions is required. Future market conditions are dependent on demand and costs that would be incurred by the GenCo based upon each prospective investment. We simplify this calculation by forecasting a single year in the future, and assuming that this year is representative of each year of a power plant's lifetime.

As in the real world, GenCos have imperfect information, and therefore must forecast expected demand, fuel prices, carbon price and electricity sale price. This achieved by fitting functions to historical data. Each GenCo is different in that they will use differing historical time periods of data to forecast in the future. The distribution of this is configurable in the configuration file, referred to in Figure 2.

Fuel price and carbon price is forecast using a linear regression. Demand, however, is first forecast using an exponential function, to take into account compounded growth. However, if a reasonable fit for historical demand data can not be found with optimisation linear regression is used.

These forecasted data is then used to simulate a market using the same electricity market algorithm that is detailed in Section 3.1.4. 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 life, and introduction of plants that are in construction or pre-development stages.

However, there may be scenarios where demand is forecast to grow significantly, and limited investments have, at this point, been made to meet demand at the point in the future to be modelled. The expected price, would therefore be that of lost load. Where lost load is defined as the price customers would be willing to pay to avoid a disruption in their electricity supply. To avoid GenCos from predicting that large profits will be made, and under the assumption that further power plant investments will be made by other GenCos, the lost load price is replaced with a predicted electricity price using a linear regression based on prices at lower points of the demand curve. These prices are predicted using a linear regression. If zero segments of demand is met (high demand or low demand), then the lost load price is used to encourage significant investment.

Once expected fuel prices, carbon price, discount rate, and expected sale price of electricity are all 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, or down payment, is set at 25%, but can be customised by the user in the configuration file. The GenCos then invest in the power plant with the highest NPV that they can afford with their cash, and this is repeated until they can no longer afford any more plants. We can reasonably make this assumption, as the NPV calculation provides information based upon which investments are worth more than money in a bank.

3.2 Power Plant Parameter Estimation

The estimation of power plant parameters is critical to electricity market models. Costs form an important element of markets and investment, and publicly available data 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.

We enable users to initialise costs relevant to their particular country. They can provide highly detailed costs, with the parameters shown in Table 2, or an average cost per MWh produced over the lifetime of a plant, also known as levelised cost of electricty (LCOE).

The parameters in Table 2 are explained here: 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 plant output, and variable operation & maintenance costs are those that do depend on generator output [38].

Parameters	Units	Notation
Efficiency	%	η
Operating Period	years	OP
Pre-development Period	years	P_D
Construction Period	years	C_D
Pre-development Cost	£/MW	P_C
Construction Cost	£/MW	C_C
Infrastructure	£	I_C
Fixed Operation and Maintenance	£/MW	F_C
Variable Operation and Maintenance	£/MW	V_C
Insurance Cost	£/MW	In_C
Connection Cost	£/MW	Con_C

Table 2: Parameter notation.

Precise data is often available only for specifically sized plants. Estimating the individual costs of power plants between two known capacities is achieved through linear interpolation of each parameter. Where the plant to be estimated falls outside of the range of known data points the closest data point is used. For example, the parameters of a $1,500$MW combined cycle gas plant (CCGT) are the same as a $1,200$MW CCGT plant if the $1,200$MW plant was the largest available data point.

If specific parameters are not known (those referred to in Table 2), then the LCOE can be used to for estimation, provided that these parameters are available for a single instance of each type of power plant. This is achieved through linear optimisation, with constraints available for each of the parameters. These constraints can be set by the user, enabling, for example, varying operation and maintenance costs per country as a fraction of the levelised cost of electricity.

In addition to cost parameters, the availability and capacity factors are required to fully parametrise power plants. Availability is the percentage of time that a power plant could possibly produce electricity over a given time period. Availability can be reduced by forced and planned outages. Historical data is also required, due to the fact that older plants have lower availability factors than newer plants.

Capacity factor is the actual electrical energy produced over a given time period divided by the maximum possible electrical energy it could have produced. In contrast to availability, capacity factor can be impacted by regulatory constraints, market forces and resource availability. For solar and wind, capacity factors can change significantly with time. Higher capacity factors are common for solar installations in the summer, and lower in winter for example.

3.3 Detailed Overview

ElecSIM is made up of two different agent types, GenCos (Generation Companies) and a Demand agent. GenCos can be initialised by the user. For example, to a desired country, or a toy-example. Each of the GenCos are initialised with their respective power plants. GenCos are given a randomized discount rate, which can be set by the user, around a mean of 10% for nuclear power plants [44] and 5.9% for all other generators [36].

3.3.1 Data Initialisation. ElecSIM's power generation costs are initialised using the UK government Department for Business, Energy and Industrial Strategy (BEIS) power plant generation report [18]. This contains information such as capital costs and operation and maintenance costs (F_C and V_C), including details such as insurance (In_C) and connection costs (Con_C). Where there are power plants of a size not included in this report, the parameters are linearly interpolated. Where the capacity of a power plant is larger or smaller than the data points in the report, the parameters are extrapolated by using the last known data point.

For historical power plants, we used historical costs of Levelised Cost of Energy (LCOE) [16]. Each parameter was scaled linearly from the modern LCOE calculated from the BEIS report, to attain the relevant historical LCOE. This was achieved by using linear optimisation, and therefore each parameter can be changed based on an individual user's country and dataset by modifying the constraints. As well as historical LCOE, historical plant efficiency was taken into account for gas and coal power plants [19].

When initialised, the variable operation and maintenance costs are selected from a uniform distribution, with the ability for the user to set maximum and minimum percentage increase from the BEIS report. A uniform distribution was chosen to capture the large deviations that can occur in variation of variable operation and maintenance, especially other a long time period. By doing this, the variance in costs between individual power plants for processes such as preventative and corrective maintenance, labour costs and skill, health and safety and chance are different per plant.

As per [12], we created a load duration curve of the electricity demand for one year with 20 segments. 20 segments enabled us

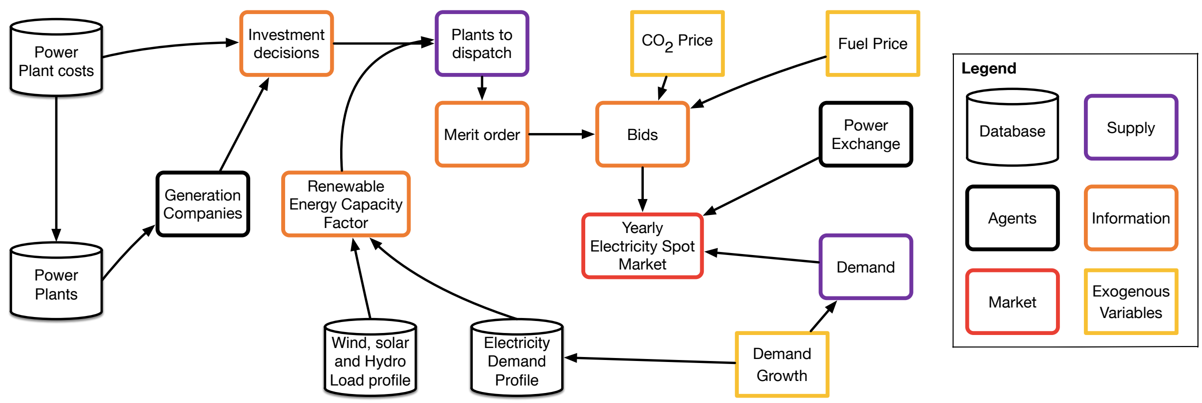


Figure 5: ElecSIM simulation overview

to capture the varying demand of electricity throughout a year to a high enough degree of accuracy, but also reduce computational complexity. To model the Intermittency of wind and solar power we allow them to contribute only a certain percentage of total capacity for each load segment based on empirical wind and solar capacity factors, relating demand to average capacity [12, 46, 50]. The requirement of storage to provide constant electricity from intermittent resources is an important issue. However, due to the fact that ElecSIM takes yearly time steps, we are unable to model short term variability in electricity demand. We also, do not model long-term storage due to its currently limited ability.

Whilst fuel price is controlled by the user, there is inherent volatility in fuel price in a single year. To take into account this variability, an ARIMA model was fit to historical gas and coal price data [1, 2]. The standard deviation of the residuals was used to model the precise price of fuel that a generation company will buy the fuel in a given year. This takes into account differences in hedging strategies and the process of luck between competing generation companies.

Outages are modelled by using availability data of gas, coal, photovoltaic, offshore and onshore power generators [10, 28, 38]. Plants bid a reduced percentage of their nameplate capacity based on their respective availability. Historical availabilities are modelled for older gas, coal and hydro power plants [6].

With historical power plants which have been refurbished, we sample their initialisation randomly between 15 years prior to initialisation year and the initialisation year.

Power plants are taken out of service if they have not sold any electricity in the past 7 years. We decided upon this due to the fact that power generators have high, sunk capital costs, which often have high demolition costs. We assume, therefore, that generator companies are willing to wait circa $\frac{1}{4}$ of their lives to see if a pay-out occurs due to the breakdown of competing power plants, increasing demand, or governmental support in the form of a carbon tax increase or reduction.

3.3.2 Spot Market. The buying and selling of electricity is modelled as a spot market, where each year, electricity is bought and sold in merit order. GenCos place bids for each of their plants at the respective short run marginal cost. We assume that generator companies do not have market power, however we set the lost load to be £6000 to encourage investment as per the recommendations of the UK government [11].

3.3.3 Investment. Investments are made on a yearly basis and are made purely on net present value calculations. The order in which GenCos invest in each simulated year is randomised as to not give certain generation companies an advantage.

Agents have imperfect information, and therefore fuel and carbon prices are predicted using linear regression, with a training period sampled uniformly from the previous 3 to 7 years. This allows us to model heterogeneity of GenCos. Demand is modelled through the use of an exponential function, so that compounded growth can be modelled. However, if a reasonable fit for the training data is not found, a linear regression is used.

GenCos only bid if they have 25% of the upfront capital costs, with the rest of the capital provided through equity and debt. The cost of equity and debt is modelled as a weighted average cost of capital (WACC), with values of 5.9% for non-nuclear power plants, and 10% for nuclear power plants [36, 44]. The WACC is used as the discount rate for net present value calculations [35]. Each GenCo is initialised with a slightly different discount rate based on a uniform distribution, with a ±3% standard deviation. This allows us to model the variability in discount rates that GenCos may have, based on different factors such as preference, risk strategies, and readiness for investors and lenders to supply capital.

The sale price of electricity in the future reference year is predicted by each generation company simulating the same merit-order market algorithm that is used for the spot market. They simulate the bids that they expect each of the power plants that are in operation to make, and use the demand predicted to match supply with demand. They then assess whether their investment option is likely to make a profit, ie. with a positive net present value. The power plant with the highest net present value is then invested in.

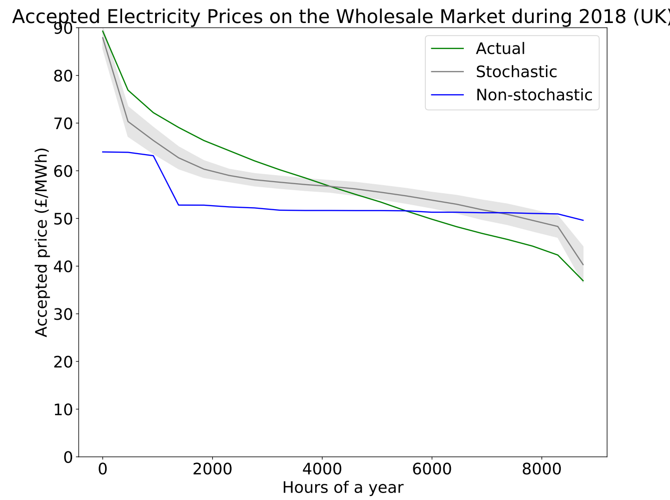


Figure 6: Price duration curve which compares real electricity prices to those paid in ElecSIM with and without stochasticity.

Figure	Nord Pool	ElecSIM	Non-Stochastic
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 3: Validation performance metrics.

4 VALIDATION AND PERFORMANCE

4.1 Validation

Validation of models is important to ascertain that the results output are accurate. However, it should be noted that these long-term simulations are not predictions of the future, rather possible outcomes based upon certain assumptions. Therefore, the results from ElecSIM should be analysed by taking into account the underlying assumptions of the model, and comparing inputs to outcomes.

Jager posits that a certain outcome or development path, captured by empirical data, might have developed in a completely different direction due to chance [32]. However, through observation, the processes that emerge from a model should be realistic and in keeping with expected behaviour [33].

We begin by comparing the price duration curve in the year 2018. Figure 6 shows the N2EX Day Ahead Auction Prices of the UK [24], the stochastic simulated electricity prices, and the non-stochastic electricity price throughout the year 2018. The variance of the simulated stochastic runs were achieved by making 40 runs and removing outliers.

Table 3 shows performance metrics of the stochastic and non-stochastic runs versus the actual price duration curve. It can be seen that stochastic implementation (ElecSIM), improves the mean absolute error (MAE) by 52.5%.

Therefore, the adding of stochasticity to fuel prices and variable operation & maintenance improves on previous attempts of a yearly step model.

By observing the processes that emerge from the long-term scenarios, we can see that carbon price and investment in renewable generation are positively correlated, and is what one would expect.

We found that the net present value (NPV) calculations are realistic, with onshore wind and Combined Cycle Gas Turbines (CCGT) the technologies that are most invested in. It is true, within the United Kingdom, that Onshore wind and CCGT power generators are the most cost effective, and heavy government subsidies are required for other generation types such as nuclear and coal.

4.2 Performance and Implementation

ElecSIM was built using python, this enabled us to lower barriers to entry and allow for users to integrate state-of-the-art machine learning and statistical packages in future work. We used project mesa as an open source agent based modelling framework for its ease of use [40].

We used Microsoft Azure Public Cloud. Utilising two virtual machines of 64 vCPU's each (D64 v3), which are built using Intel Broadwell E5-2673 v4 2.3GHz processor, and the Intel Haswell 2.4 GHz E5-2673 v3. They have a combined total of 256GB of memory

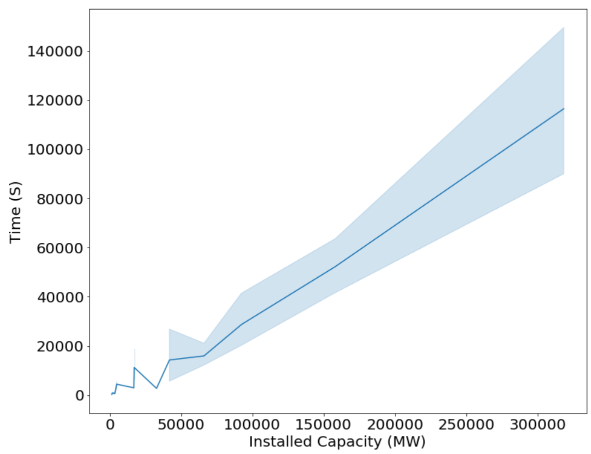


Figure 7: Run times of different country implementations

and use a Linux operating system. This enabled us to rapidly prototype different demand and carbon price scenarios, and produce multiple iterations to produce a variance.

Development and testing was done on a MacBook Pro with a quad-core 3.1GHz Intel Core i7 processor with 16 GB 1867 MHz DDR3 of RAM and a 500GB solid state drive (SSD).

The total disk size of ElecSIM, with all accompanying data, and external reports is 452MB. The memory used for a single run has a mean of circa 2GB.

5 SCENARIO TESTING

This section describes scenario runs using ElecSIM. Here, we vary the carbon tax and either grow or reduce total electricity demand. This was done to observe the effects of carbon tax policy on long-term investment.

We assume that carbon tax is set by the government, and not subject to market forces such as the EU Emissions Trading Scheme [20].

We run 16 different scenarios 8 times each, with demand increasing and decreasing by 1% per year and varying carbon prices. In this section we explore a decreasing demand of 1% a year. We chose this due to the increasing efficiency of homes, industry and technology, and due to the recent trend in the UK. Demand, however, did not display a large effect on the optimum carbon price. We select a burn-in period of 6 years, due to the fact that the majority of power plants take 6 years to go from investment to operation.

Table 6, in the appendix, displays the summary statistics of each run in full.

It can be seen from Figure 9a that a carbon tax of £10 per year does little to influence investment in low-carbon, renewable technology. With traditional, fossil fuel based generation, providing the majority of supply throughout each year. However, there is an increase in renewable technology over the years, starting from mean 15.85% market share in the year range 2019-2029, to 24.38% in the year range 2039-2050. However, a similar increase of renewable energy with a carbon tax of £0 can be seen, albeit at a lower mean by the year range 2039-2050 (22.29%).

The UK Government BEIS have predicted a carbon tax increasing from £18 to £200 by 2050. With carbon price increasingly linearly from 2030 to 2050. This models the EU ETS carbon price. We have approximated these assumptions in Figure 9c and modelled the results. Interestingly, the results show only a slight increase in low-carbon supply over the £20 carbon tax energy mix. This demonstrates the importance of long-term modelling, and understanding the long-term impacts that can result due to today's decisions.

It is hypothesised that a lower carbon tax early on changes the market dynamics for years to come, due to certain price structures, and therefore it takes a long time for renewable energy to recover.

Figure 9d shows that a carbon tax of £40 is sufficient in beginning to move towards a low-carbon economy, with backup fossil fuel generators.

However, by referring to Figure 8 it can be seen that to have 100% renewable, a carbon price of £70 is required.

These results show the importance of making difficult decisions as soon as possible to have the biggest effect on the energy mix for years to come.

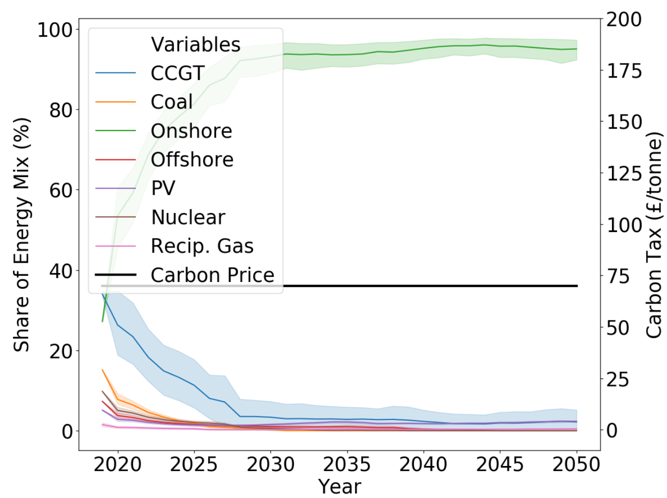
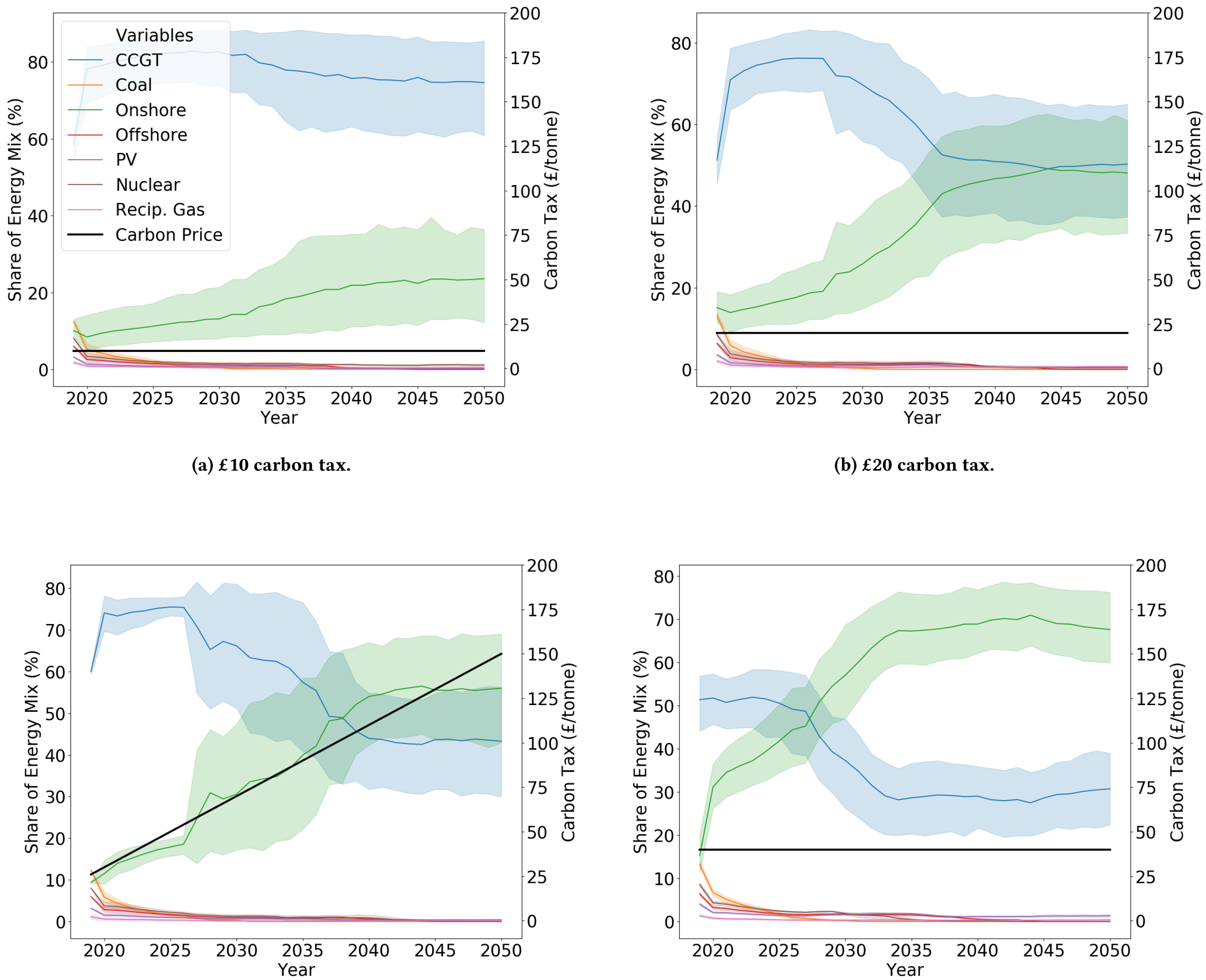


Figure 8: Demand decreasing by 1% per year with a carbon tax of £70.

6 CONCLUSIONS

The shift in electricity markets from a centrally controlled monopoly, to a liberalised market with many heterogeneous players has increased the need for a new type of modelling. We motivate that agent-based models can be used as a solution to this, by their ability to model many actors with individual properties.

Agent-based models are able to model imperfect information as well as heterogeneous actors. ElecSIM models imperfect information through forecasting of electricity demand and future fuel and



(a) £10 carbon tax.

(b) £20 carbon tax.

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

(d) £40 carbon tax.

Figure 9: Scenarios up to the year 2050, with varying carbon taxes and electricity demand decreasing 1% a year.

electricity prices. This leads to agents taking risk on their investments, and more realistically model market conditions.

We demonstrated that increasing carbon tax can lead to a significant increase in investment of low-carbon technologies such as onshore wind. However, an interesting result was that early decisions have a long impact on the future energy mix. The market can be significantly changed through investment decisions made many years previously.

Our future work includes comparing agent-learning techniques, using multi-agent reinforcement learning algorithms and artificial intelligence to allow agents to learn in a non-static environment. We propose the integration of a higher temporal and spatial resolution to model changes in daily demand, as well as capacity factors by region, and transmission effects.

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A RESEARCH METHODS

A.1 Parameters

Table 4: Modern power plant costs [18]

Type	Capacity	Year	η	OP	P_D	C_D	P_C	C_C	I_C	F_C	V_C	In_C	Con_C
CCGT	168.0	2018/20/25	0.34	25.0	3	3	60,000.0	700,000.0	13,600.0	28,200.0	5.0	2,900.0	3,300.0
	1200.0	2018/20/25	0.54	25.0	3	3	10,000.0	500,000.0	15,100.0	12,200.0	3.0	2,100.0	3,300.0
	1471.0	2018/20/25	0.53	25.0	3	3	10,000.0	500,000.0	15,100.0	11,400.0	3.0	1,900.0	3,300.0
Coal	552.0	2025	0.32	25.0	6	6	40,000.0	3,400,000.0	10,000.0	68,200.0	6.0	13,000.0	3,800.0
	624.0	2025	0.32	25.0	5	5	70,000.0	4,200,000.0	10,000.0	79,600.0	3.0	19,300.0	3,800.0
	652.0	2025	0.3	25.0	5	5	60,000.0	3,900,000.0	10,000.0	65,300.0	5.0	22,700.0	3,800.0
	734.0	2025	0.38	25.0	5	5	60,000.0	2,600,000.0	10,000.0	56,400.0	3.0	9,600.0	3,800.0
	760.0	2025	0.35	25.0	5	5	40,000.0	2,800,000.0	10,000.0	52,100.0	5.0	14,000.0	3,800.0
Hydro	0.033	2018/20/25	1.0	35.0	0	0	0.0	6,300,000.0	0.0	83,300.0	0.0	0.0	0.0
	1.046	2018/20/25	1.0	35.0	0	0	0.0	3,300,000.0	400.0	18,200.0	0.0	0.0	0.0
	11.0	2018/20/25	1.0	41.0	2	2	60,000.0	3,000,000.0	0.0	45,100.0	6.0	0.0	0.0
Nuclear	3300.0	2025	1.0	60.0	5	8	240,000.0	4,100,000.0	11,500.0	72,900.0	5.0	10,000.0	500.0
OCGT	96.0	2018/20/25	0.35	25.0	2	2	80,000.0	600,000.0	12,600.0	9,900.0	4.0	2,500.0	2,400.0
	299.0	2018/20/25	0.35	25.0	2	2	30,000.0	400,000.0	13,600.0	9,600.0	3.0	1,600.0	2,500.0
	311.0	2018/20/25	0.35	25.0	2	2	30,000.0	400,000.0	13,600.0	9,500.0	3.0	1,600.0	2,500.0
	400.0	2018/20/25	0.34	25.0	2	2	30,000.0	300,000.0	15,100.0	7,800.0	3.0	1,300.0	2,500.0
	625.0	2018/20/25	0.35	25.0	2	2	20,000.0	300,000.0	15,100.0	4,600.0	3.0	1,200.0	2,400.0
Offshore	321.0	2018	0.0	23.0	5	3	60,000.0	2,200,000.0	69,300.0	30,900.0	3.0	1,400.0	33,500.0
	321.0	2020	0.0	23.0	5	3	60,000.0	2,100,000.0	69,300.0	30,000.0	3.0	1,400.0	32,600.0
	321.0	2025	0.0	23.0	5	3	60,000.0	1,900,000.0	69,300.0	28,600.0	3.0	1,300.0	31,100.0
	844.0	2018	0.0	22.0	5	3	120,000.0	2,400,000.0	323,000.0	48,600.0	4.0	3,300.0	50,300.0
	844.0	2020	0.0	22.0	5	3	120,000.0	2,300,000.0	323,000.0	47,300.0	3.0	3,300.0	48,900.0
	844.0	2025	0.0	22.0	5	3	120,000.0	2,100,000.0	323,000.0	45,400.0	3.0	3,100.0	47,000.0
Onshore	0.01	2018	1.0	20.0	0	0	0.0	3,700,000.0	0.0	29,700.0	0.0	0.0	0.0
	0.01	2020	1.0	20.0	0	0	0.0	3,600,000.0	0.0	29,600.0	0.0	0.0	0.0
	0.01	2025	1.0	20.0	0	0	0.0	3,500,000.0	0.0	29,600.0	0.0	0.0	0.0
	0.482	2018	1.0	20.0	0	0	0.0	2,200,000.0	200.0	56,900.0	0.0	0.0	0.0
	0.482	2020	1.0	20.0	0	0	0.0	2,100,000.0	200.0	56,900.0	0.0	0.0	0.0
	0.482	2025	1.0	20.0	0	0	0.0	2,000,000.0	200.0	56,700.0	0.0	0.0	0.0
	20.0	2018	0.0	24.0	4	2	110,000.0	1,200,000.0	3,300.0	23,200.0	5.0	1,400.0	3,100.0
	20.0	2020	0.0	24.0	4	2	110,000.0	1,200,000.0	3,300.0	23,000.0	5.0	1,400.0	3,100.0
	20.0	2025	0.0	24.0	4	2	110,000.0	1,200,000.0	3,300.0	22,400.0	5.0	1,400.0	3,000.0
PV	0.003	2018	1.0	30.0	0	0	0.0	1,500,000.0	0.0	23,500.0	0.0	0.0	0.0
	0.003	2020	1.0	30.0	0	0	0.0	1,500,000.0	0.0	23,400.0	0.0	0.0	0.0
	0.003	2025	1.0	30.0	0	0	0.0	1,400,000.0	0.0	23,200.0	0.0	0.0	0.0
	0.455	2018	1.0	30.0	0	0	0.0	1,000,000.0	200.0	9,400.0	0.0	0.0	0.0
	0.455	2025	1.0	30.0	0	0	0.0	900,000.0	200.0	9,200.0	0.0	0.0	0.0
	1.0	2018	0.0	25.0	1	0	20,000.0	700,000.0	0.0	6,600.0	3.0	2,600.0	1,300.0
	1.0	2020	0.0	25.0	1	0	20,000.0	700,000.0	0.0	6,300.0	3.0	2,600.0	1,300.0
	1.0	2025	0.0	25.0	1	0	20,000.0	600,000.0	0.0	5,900.0	3.0	2,400.0	1,200.0
	4.0	2018	0.0	25.0	1	0	60,000.0	700,000.0	200.0	8,300.0	0.0	1,200.0	1,300.0
	4.0	2020	0.0	25.0	1	0	60,000.0	700,000.0	200.0	8,000.0	0.0	1,100.0	1,300.0
	4.0	2025	0.0	25.0	1	0	60,000.0	600,000.0	200.0	7,500.0	0.0	1,100.0	1,200.0
	16.0	2018	0.0	25.0	1	0	70,000.0	700,000.0	400.0	5,600.0	0.0	2,000.0	1,300.0
	16.0	2020	0.0	25.0	1	0	70,000.0	600,000.0	400.0	5,400.0	0.0	1,900.0	1,300.0
	16.0	2025	0.0	25.0	1	0	70,000.0	600,000.0	400.0	5,100.0	0.0	1,800.0	1,200.0
Recip. Engine (Diesel)	20.0	2018/20/25	0.34	15.0	2	1	10,000.0	300,000.0	2,200.0	10,000.0	2.0	1,000.0	-31,900.0
Recip. Engine (Gas)	20.0	2018/20/25	0.32	15.0	2	1	10,000.0	300,000.0	3,400.0	10,000.0	2.0	1,000.0	-31,900.0

Table 5: Sample of historic power plant costs [29, 31, 43]

Type	Capacity	Year	η	OP	P_D	C_D	P_C	C_C	I_C	F_C	V_C	In_C	Con_C
CCGT	168.0	1980	0.34	25	3	3	207,345	2,419,027	46,998	97,452	22	10,021	11,403
	168.0	1990	0.34	25	3	3	181,208	2,114,099	41,073	85,167	13	8,758	9,966
	168.0	2000	0.34	25	3	3	116,407	1,358,089	26,385	54,711	10	5,626	6,402
	168.0	2010	0.34	25	3	3	73,530	857,857	16,666	34,559	11	3,553	4,044
	1200.0	1980	0.54	25	3	3	59,102	2,955,138	89,245	72,105	31	12,411	19,503
	1200.0	1990	0.54	25	3	3	59,884	2,994,246	90,426	73,059	21	12,575	19,762
	1200.0	2000	0.54	25	3	3	49,674	2,483,747	75,009	60,603	21	10,431	16,392
	1200.0	2010	0.54	25	3	3	60,640	3,032,008	91,566	73,981	13	12,734	20,011
	1471.0	1980	0.53	25	3	3	92,000	4,600,023	138,920	104,880	10	17,480	30,360
	1471.0	1990	0.53	25	3	3	54,296	2,714,817	81,987	61,897	26	10,316	17,917
	1471.0	2000	0.53	25	3	3	49,310	2,465,515	74,458	56,213	21	9,368	16,272
	1471.0	2010	0.53	25	3	3	46,998	2,349,947	70,968	53,578	21	8,929	15,509
Coal	552.0	1980	0.32	25	6	6	118,041	10,033,488	29,510	201,259	22	38,363	11,213
	552.0	1990	0.32	25	6	6	41,766	3,550,192	10,441	71,212	2	13,574	3,967
	552.0	2000	0.32	25	6	6	51,429	4,371,538	12,857	87,687	3	16,714	4,885
	552.0	2010	0.32	25	6	6	43,411	3,689,957	10,852	74,016	10	14,108	4,124
	624.0	1980	0.32	25	5	5	183,851	11,031,076	26,264	206,176	15	41,497	9,980
	624.0	1980	0.32	25	5	5	188,476	11,308,571	26,925	211,362	11	42,541	10,231
	624.0	1990	0.32	25	5	5	62,458	3,747,483	8,922	70,042	5	14,097	3,390
	624.0	1990	0.32	25	5	5	65,126	3,907,588	9,303	73,034	3	14,699	3,535
	624.0	2000	0.32	25	5	5	80,033	4,802,002	11,433	89,751	3	18,064	4,344
	624.0	2000	0.32	25	5	5	80,882	4,852,979	11,554	90,704	3	18,256	4,390
	624.0	2010	0.32	25	5	5	84,549	5,072,973	12,078	94,816	3	19,084	4,589
	624.0	2010	0.32	25	5	5	81,834	4,910,056	11,690	91,771	5	18,471	4,442
	652.0	1980	0.3	25	5	5	161,344	10,487,387	26,890	175,596	16	61,041	10,218
	652.0	1990	0.3	25	5	5	54,542	3,545,235	9,090	59,359	4	20,635	3,454
	652.0	2000	0.3	25	5	5	68,516	4,453,581	11,419	74,568	2	25,922	4,339
	652.0	2010	0.3	25	5	5	67,915	4,414,497	11,319	73,914	4	25,694	4,301
	734.0	1980	0.38	25	5	5	249,766	10,823,198	41,627	234,780	16	39,962	15,818
	734.0	1990	0.38	25	5	5	87,920	3,809,903	14,653	82,645	7	14,067	5,568
	734.0	2000	0.38	25	5	5	118,072	5,116,482	19,678	110,988	5	18,891	7,477
	734.0	2010	0.38	25	5	5	132,370	5,736,075	22,061	124,428	5	21,179	8,383
	760.0	1980	0.35	25	5	5	160,182	11,212,746	40,045	208,637	8	56,063	15,217
	760.0	1990	0.35	25	5	5	55,208	3,864,573	13,802	71,908	4	19,322	5,244
	760.0	2000	0.35	25	5	5	65,705	4,599,358	16,426	85,580	8	22,996	6,241
	760.0	2010	0.35	25	5	5	77,393	5,417,570	19,348	100,805	3	27,087	7,352
Nuclear	3300.0	1980	1.0	60	5	8	516,790	8,828,507	24,762	156,975	21	21,532	1,076
	3300.0	1990	1.0	60	5	8	390,159	6,665,224	18,695	118,510	3	16,256	812
	3300.0	2000	1.0	60	5	8	378,998	6,474,560	18,160	115,120	15	15,791	789
	3300.0	2010	1.0	60	5	8	388,457	6,636,156	18,613	117,994	13	16,185	809
Offshore	321.0	1980	0.0	23	5	3	100,043	3,668,254	115,550	51,522	9	2,334	55,857
	321.0	1990	0.0	23	5	3	104,550	3,833,513	120,755	53,843	3	2,439	58,373
	321.0	2000	0.0	23	5	3	102,374	3,753,742	118,242	52,723	6	2,388	57,159
	321.0	2010	0.0	23	5	3	98,571	3,614,292	113,850	50,764	6	2,300	55,035
	844.0	1980	0.0	22	5	3	181,469	3,629,393	488,455	73,495	8	4,990	76,066
	844.0	1990	0.0	22	5	3	178,822	3,576,447	481,330	72,423	10	4,917	74,956
	844.0	2000	0.0	22	5	3	180,212	3,604,250	485,072	72,986	9	4,955	75,539
	844.0	2010	0.0	22	5	3	171,372	3,427,446	461,277	69,405	11	4,712	71,833
Onshore	20.0	1980	0.0	24	4	2	374,087	4,080,950	11,222	78,898	26	4,761	10,542
	20.0	1990	0.0	24	4	2	411,234	4,486,197	12,337	86,733	10	5,233	11,589
	20.0	2000	0.0	24	4	2	230,491	2,514,457	6,914	48,612	5	2,933	6,495
	20.0	2010	0.0	24	4	2	143,450	1,564,915	4,303	30,255	7	1,825	4,042
PV	16.0	1980	0.0	25	1	0	399,799	3,997,991	2,284	31,983	0	11,422	7,424
	16.0	1990	0.0	25	1	0	399,799	3,997,991	2,284	31,983	0	11,422	7,424
	16.0	2000	0.0	25	1	0	399,799	3,997,991	2,284	31,983	0	11,422	7,424
	16.0	2010	0.0	25	1	0	399,799	3,997,991	2,284	31,983	0	11,422	7,424

A.2 Scenario Runs

Table 6: Summary statistics for each scenario run.

Demand	Carbon Tax	Year Range	Low Carbon				Traditional Generation			
			mean	std	min	max	mean	std	min	max
Demand Decreasing 1% a Year	0	2019-2029	14.14	5.16	6.36	27.29	85.86	5.16	72.71	93.64
		2029-2039	16.95	11.19	6.2	52.52	83.05	11.19	47.48	93.8
		2039-2050	22.29	18.01	4.72	60.0	77.71	18.01	40.0	95.28
	10	2019-2029	15.85	8.82	8.8	41.0	84.15	8.82	59.0	91.2
		2029-2039	20.33	15.34	7.92	62.75	79.67	15.34	37.25	92.08
		2039-2050	24.38	17.17	8.79	61.87	75.62	17.17	38.13	91.21
	170 to 22	2019-2029	92.03	8.32	71.2	99.8	7.97	8.32	0.2	28.8
		2029-2039	99.66	0.11	99.11	99.82	0.34	0.11	0.18	0.89
		2039-2050	99.59	0.1	99.32	99.75	0.41	0.1	0.25	0.68
	26 to 174	2019-2029	24.84	11.32	11.01	65.78	75.16	11.32	34.22	88.99
		2029-2039	42.6	21.63	11.28	79.05	57.4	21.63	20.95	88.72
		2039-2050	56.42	15.48	31.63	81.72	43.58	15.48	18.28	68.37
	20	2019-2029	22.94	11.92	7.8	62.07	77.06	11.92	37.93	92.2
		2029-2039	40.52	21.73	7.04	73.0	59.48	21.73	27.0	92.96
		2039-2050	49.36	20.73	10.82	79.09	50.64	20.73	20.91	89.18
	40	2019-2029	48.16	12.28	32.61	82.35	51.84	12.28	17.65	67.39
		2029-2039	69.08	12.12	46.05	93.13	30.92	12.12	6.87	53.95
		2039-2050	70.61	10.82	52.5	91.98	29.39	10.82	8.02	47.5
	50	2019-2029	53.78	23.42	17.98	92.93	46.22	23.42	7.07	82.02
		2029-2039	68.41	20.18	29.54	96.29	31.59	20.18	3.71	70.46
		2039-2050	66.86	20.42	38.31	99.73	33.14	20.42	0.27	61.69
	70	2019-2029	83.62	13.16	41.29	99.41	16.38	13.16	0.59	58.71
		2029-2039	96.76	4.43	83.93	99.99	3.24	4.43	0.01	16.07
		2039-2050	97.63	3.58	87.8	99.94	2.37	3.58	0.06	12.2
Demand Increasing 1% a Year	0	2019-2029	14.87	9.9	6.73	45.59	85.13	9.9	54.41	93.27
		2029-2039	17.07	16.39	4.8	65.87	82.93	16.39	34.13	95.2
		2039-2050	17.54	20.0	3.83	67.95	82.46	20.0	32.05	96.17
	10	2019-2029	18.96	7.17	10.23	39.02	81.04	7.17	60.98	89.77
		2029-2039	23.44	16.47	8.89	61.96	76.56	16.47	38.04	91.11
		2039-2050	27.91	19.45	9.64	67.06	72.09	19.45	32.94	90.36
	170 to 22	2019-2029	92.09	9.29	67.32	99.8	7.91	9.29	0.2	32.68
		2029-2039	99.98	0.05	99.76	100.0	0.02	0.05	0.0	0.24
		2039-2050	100.0	0.0	100.0	100.0	0.0	0.0	0.0	0.0
	26 to 174	2019-2029	24.75	11.33	11.95	56.65	75.25	11.33	43.35	88.05
		2029-2039	39.28	20.39	10.87	73.41	60.72	20.39	26.59	89.13
		2039-2050	49.72	18.84	22.02	86.43	50.28	18.84	13.57	77.98
	20	2019-2029	26.32	16.01	8.08	83.77	73.68	16.01	16.23	91.92
		2029-2039	37.21	23.72	5.2	82.72	62.79	23.72	17.28	94.8
		2039-2050	45.79	26.31	7.5	88.24	54.21	26.31	11.76	92.5
	40	2019-2029	43.41	18.58	13.96	80.7	56.59	18.58	19.3	86.04
		2029-2039	61.79	29.18	14.83	92.44	38.21	29.18	7.56	85.17
		2039-2050	75.03	23.95	21.4	95.91	24.97	23.95	4.09	78.6
	50	2019-2029	64.64	23.56	16.96	99.22	35.36	23.56	0.78	83.04
		2029-2039	86.48	16.8	23.27	99.44	13.52	16.8	0.56	76.73
		2039-2050	91.18	9.17	65.77	99.78	8.82	9.17	0.22	34.23
	70	2019-2029	69.61	19.77	26.36	100.0	30.39	19.77	0.0	73.64
		2029-2039	89.07	13.79	31.57	100.0	10.93	13.79	0.0	68.43
		2039-2050	91.77	10.37	67.5	100.0	8.23	10.37	0.0	32.5