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

Anonymized

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.

Different techniques to model long term electricity decisions are reviewed, and we 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.

Actual electricity prices are compared with our model and we demonstrate that the modelling of stochasticity in the system improves performance by 52.5%

Using ElecSIM 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.

ACM Reference Format:
Anonymized. 2018. ElecSIM: Stochastic Open-Source Agent-Based Model to Inform Policy for Long-Term Electricity Planning. In *Proceedings of e-Energy '19: The Tenth International Conference on Future Energy Systems (e-Energy '19).* ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

The world faces significant challenges from climate change and global warming [27]. 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 [17]. The scientific literature concurs that the recent change in climate is anthropogenic, with 97% of peer reviewed articles of this view [7].

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 [4]. 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 [1].

A common method to understanding and reducing risk as well as reducing 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 [25]. Due to the numerous and diverse actors involved in the generation, distribution and sale of electricity in liberalised electricity markets, agent based models are increasingly being used [36].

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 (which can be expanded to include different types of demand such as industry, household and transport), 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
their short run marginal cost (SRMC), which excludes capital and fixed costs. The power exchange links bids
as merit-order dispatch. GenCos then invest in power plants based on expected profitability of each prospective power plant.

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.

e-Energy '19, June 25–28, 2019, Phoenix, AZ

ACM ISBN 978-1-4503-9999-9/18/06...$15.00
https://doi.org/10.1145/1122445.1122456

ElecSIM can be used by policy experts to test policy outcomes under different scenarios and provide quantitative advice to policy makers. They are able to modify a simple script to realise a scenario of their choose. It can also be used by energy market developers who can add things such as new energy sources policy types and storage types, allowing ElecSIM to adapt to a changing ecosystem.

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 [10]. 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 [23].

Energy models can typically be classified as top-down macro-economic models or bottom-up techno-economic models [3]. 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 [13], for example MARKAL-MACRO [9] and LEAP [15]. Bottom-up models represent the energy sector in detail, and are written as mathematical programming problems [11]. They detail technology explicitly, and can include cost and emissions implications [13].

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 [21]. 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 constraints such as space, resources and demand. Examples of optimisation models are MARKAL/TIMES [9] and MESSAGE [33]. MARKAL is possibly the most widely used general purpose energy systems model [30].

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 [28]. 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.

A number of simulation tools have emerged which model these electricity markets, for example SEPIA [14] EMCAS [6], NEMSIM [2], AMES [35], PowerACE [32], MACSEM [31], GAPEX [5] and EMLab [4]. By referring to Table 1, it can be seen that none of these suit the needs of an open source, long-term market model. We demonstrate that in addition to requiring a long-term electricity market model to be open source, 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, whether they model long-term investment in power plants and what markets they model. We determine how stochasticity is modelled in each tool. Finally, we determine whether the model is generalisable to different countries

The requirement for an open source toolkit is an important feature for reproducibility, transparency and lowering barriers to entry for electricity market models. It enables users to expand the model to their requirements, and rapidly prototype results. The modelling of long-term investment enables scenarios to emerge, and enable users to model investment behaviour. The classification of the type of market that is modelled enables a user to better understand the underlying dynamics of the model. We demonstrate that stochasticity improves results, and better models the physical world, whilst country generalisability is useful for different users to create realisations of their country of interest.

SEPIA [14] 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 [36]. 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 shown in Table 1, SEPIA does not include a long-term investment mechanism.

MACSEM [31] 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.

PowerACE [32] 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 of price risks in electricity markets which is of crucial importance to real markets [28].

EMLab [4] 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

Tool name	Open Source	Long-Term Investment	Market	Stochastic Inputs	Country Generalisability
SEPIA [14]	✓	×	✓	Demand	✓
EMCAS [6]	×	✓	✓	Outages	✓
NEMSIM [2]	?	✓	✓	×	×
AMES [35]	✓	×	Day-ahead	×	×
PowerACE [32]	×	✓	✓	Outages/Demand	✓
MACSEM [31]	?	×	✓	×	✓
GAPEX [5]	?	×	Day-ahead	×	✓
EMLab [4]	✓	✓	Futures	×	✓
ElecSIM	✓	✓	Futures	✓	✓

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

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 [35] is an agent-based model specific to the US Wholesale Power Market Platform. GAPEX [5] 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 policies and observe the outcomes of various scenarios such as demand growth. The user is able to input various exogenous variables
This allows for the initialisation of different countries and scenarios to be tested.

3.1 Overview

ElecSIM is made up of five fundamental parts: the agents, which are split up into demand and generation companies (GenCos); power plants, which are owned by the GenCos; a Power Exchange, which controls a spot market to match GenCo owned power plants with electricity demand; the world in which these agents and market exist; and the data for parametrisation.

A schematic of ElecSIM is displayed in Figure 1 which displays these five fundamental sections and demonstrates how they interact. The main components are discussed below:

3.1.1 Data parametrisation. To parametrise the world ElecSIM contains a configuration file and a collection of data sources. These 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.

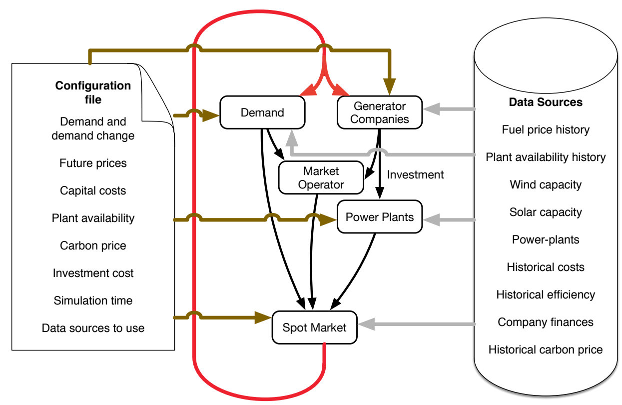


Figure 1: High level system overview demonstrating fundamental parts of ElecSIM.

The configuration file allows for rapid changes to test different hypothesis and scenarios, and points to previously mentioned data sources. The configuration file enables the changing of demand growth and shape, future fuel and carbon prices, capital costs, plant availability, investment costs and simulation time. These data is used to calibrate the world.

3.1.2 Demand Agent. The demand agent is a simplified representation of aggregated demand in a particular country. The demand is represented as a load duration curve.
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), and the highest segment represents peak demand. 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 between years, the ratio between each segment of the load duration curve is assumed not to change.

As per Chappin *et al.* [4], we modelled the load duration curve of the electricity demand for one year with twenty segments. Twenty segments enabled us to capture the varying demand of electricity throughout the year to a high enough degree of accuracy, whilst also reducing computational complexity.

3.1.3 Generation Company Agents. The GenCos have two main functions. Investing in power plants and making bids to sell their electricity each year for every one 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 used by GenCos.

The power exchange sorts bids in order of price
and accepts the lowest bids until supply meets demand. Once supply meets demand, the spot price or system marginal price (SMP) is paid to all generators regardless of their initial bid. It is for this reason that generators are motivated to bid their SRMC, to ensure that their generator is being utilised, and reducing the risk of over bidding and not being selected.

3.1.4 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 to evaluating power plants which have a long lifetime. A positive NPV means that the projected investment exceeds the anticipated costs, and is therefore profitable.

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

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

A discount rate set by a firm's weighted average cost of capital (WACC) is often used [22]. WACC is the rate that a company is expected to pay on average for its stock and debt. Therefore, if the income is higher than the WACC then the NPV is positive, and becomes a worthwhile investment. However, it is often believed that a higher rate than the WACC 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 a WACC based on companies' relative credit risk, we have sampled differences in discount rates from the mean WACC with a Gaussian distribution with a standard deviation of ±3%. This 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 of a power plant, 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 N years into the future, which can be selected by the user. We assume 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 is 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 1.

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

, This forecast data is then used to simulate a market N years into the future using the same electricity market algorithm that is detailed in Section **??**. 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.

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 N years into the future. The expected price, would therefore be calculated to be that of lost load. Where lost load is defined as the price customers would be willing to pay to avoid disruption in their electricity supply, and is typically much higher than average prices. 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 in the future, 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. If zero segments of demand are met (ie. total supply of generators is smaller than baseload), then the lost load price is used to encourage significant investment. If only a single segment of demand is met then the price of this demand segment is chosen. The lost load price can be configured in the configuration file.

Once expected fuel prices, carbon price, discount rate, and expected sale price of electricity are all forecast, 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, and this is repeated until they can no longer afford any more plants. We make this assumption as the NPV calculation provides information based upon risk profile and required rate of return.

3.2 Power Plant Parameters

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 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.

We enable users to initialise costs relevant to their particular country. They can provide highly detailed cost parameters, 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 electricity (LCOE).

The parameters in Table 2 are detailed 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. Variable operation & maintenance (V_C) costs are costs incurred in operating the plant that do depend on generator output [24].

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. (Whilst the unit of currency displayed is £, this can easily be changed to suit specific needs eg. $, €)

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. When the plant to be estimated falls outside of the range of known data points, the closest data point is used.

If specific parameters are not known (those referred to in Table 2), then the LCOE can be used for parameter 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 [34].

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, relating demand to average capacity. This is due to the fact that there is a correlation between demand and wind speed, as well as with solar irradiance. 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.

When initialised, the variable operation and maintenance costs are 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 variation of variable operation and maintenance, especially over 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 instant.

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

With historical power plants which have been refurbished, we sample their initialisation randomly between 15 years prior to the initialisation year and the initialisation year. This is done because there is rarely a comprehensive data set on when plants are refurbished. 15 years was chosen due to the fact that plants often have an operating period of 25 years, and therefore 15 years allowed for sufficient variance in results, whilst keeping plants in operation.

3.3 ElecSIM World

Figure 2 demonstrates the world and how it co-ordinates data and processes. It contains information on every GenCo, Power Exchange, and runs processes. The world also contains information on the year number and collects simulation data.

The World brings together power plant data and demand data. The investment decisions are based on future demand and power plant costs. The merit order bids are based upon the investment decisions made and power plant costs.

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 loan and dividend payments.

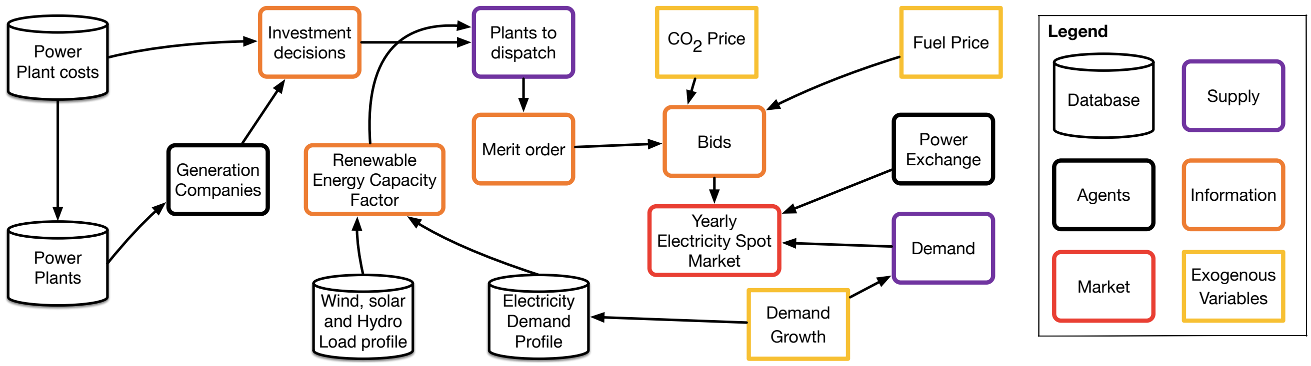


Figure 2: ElecSIM simulation overview

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, as well as looking at the general trends that emerge.

Jager posits that a certain outcome or development path, captured by empirical data, might have developed in a completely different direction due to chance [19]. However, through observation, the processes that emerge from a model should be realistic and in keeping with expected behaviour [20].

We begin by comparing the price duration curve in the year 2018. Figure 3 shows the N2EX Day Ahead Auction Prices of the UK [12], the stochastic simulated electricity prices, and the non-stochastic electricity price throughout the year 2018. 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 [12].

The variance of the simulated stochastic runs were achieved by calculating the runs 40 times. Outliers were removed as on a small number of occasions large jumps in prices at peak demand occurred which deviated significantly 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 (modelled load duration curve), therefore the results would be unreasonably skewed for the highest demand segment. However, we would expect these high prices to occur both in real life and in the model with a higher resolution price duration curve.

Figure 3 demonstrates very little variance in the non-stochastic case. This is because the majority of plants that set the spot price are combined cycle gas turbines (CCGTs). These CCGTs had little variance between one another as they were calibrated using the same data. 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 parametrise to the curve.

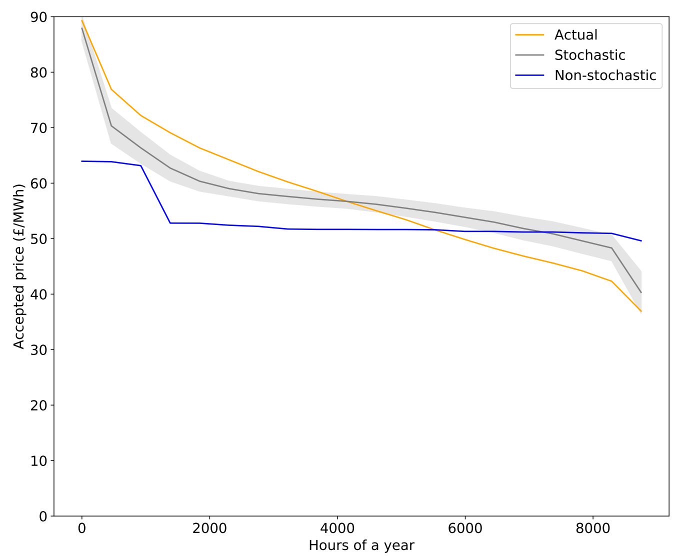


Figure 3: Price duration curve which compares real electricity prices to those paid in ElecSIM with and without stochasticity (2018).

Figure	N2EX Day Ahead	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.

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%.

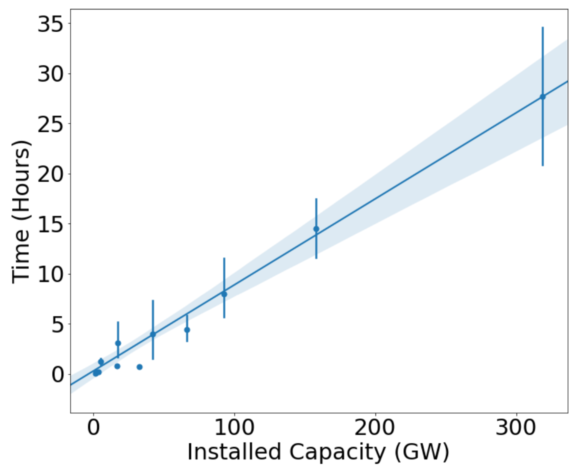


Figure 4: Run times of different sized countries.

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

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 processors, and the Intel Haswell 2.4 GHz E5-2673 v3. They have a combined total of 256GB of memory and use a Linux operating system.

The total disk size of ElecSIM is 199MB. The amount taken up by data and reports is 175MB, whilst the source code takes up 19.6MB. The memory used for a run 10 years into the future has a median of 57.1MB.

Figure 4 shows the running time for ElecSIM with varying installed capacity. We run the simulation with varying carbon taxes between 0, 20, 40 and £70 per tonne of CO_2. We varied demand between 2000MW and 320,000MW 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 generally linear time complexity with an increase in installed capacity leading to an increase in run time.

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.

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 [26].

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. We have approximated these assumptions in Figure 5a 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 5b 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 **??** 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.

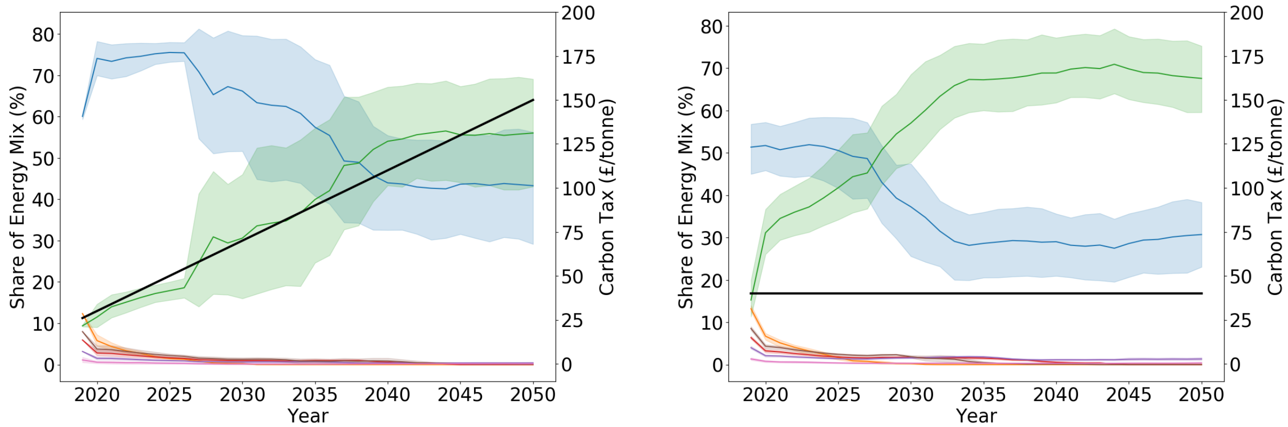
6 CONCLUSIONS

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 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.



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

(b) £40 carbon tax.

Figure 5: Scenarios up to the year 2050, with varying carbon taxes and electricity demand decreasing 1% a year.

REFERENCES

[1] 2015. Paris Agreement. *United Nations* 21 (2015), 1–23.
[2] David Batten and George Grozev. 2006. NEMSIM: Finding Ways to Reduce Greenhouse Gas Emissions Using Multi-Agent Electricity Modelling. *Complex Science for a Complex World* (2006), 227–252.
[3] Christoph Böhringer. 1998. The synthesis of bottom-up and top-down in energy policy modeling. *Energy Economics* 20, 3 (1998), 233–248. https://doi.org/10.1016/S0140-9883(97)00015-7
[4] Emile J.L. Chappin, Laurens J. de Vries, Joern C. Richstein, Pradyumna Bhagwat, Kaveri Iychettira, and Salman Khan. 2017. Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab). *Environmental Modelling and Software* 96 (2017), 421–431. https://doi.org/10.1016/j.envsoft.2017.07.009
[5] Silvano Cincotti, Giulia Gallo, and Lawrence Berkeley. 2013. The Genoa Artificial Power-Exchange The Genoa artificial power-exchange. January (2013). https://doi.org/10.1007/978-3-642-36907-0
[6] G. Conzelmann, G. Boyd, V. Koritarov, and T. Veselka. [n. d.]. Multi-agent power market simulation using EMCAS. *IEEE Power Engineering Society General Meeting, 2005* ([n. d.]), 917–922. https://doi.org/10.1109/PES.2005.1489271
[7] John Cook, Dana Nuccitelli, Sarah A Green, Mark Richardson, Bärbel Winkler, Rob Painting, Robert Way, Peter Jacobs, and Andrew Skuce. 2013. Environmental Research Letters Quantifying the consensus on anthropogenic global warming in the scientific literature Quantifying the consensus on anthropogenic global warming in the scientific literature. *Environ. Res. Lett* 8 (2013), 24024–7. https://doi.org/10.1088/1748-9326/8/2/024024
[8] Department for Business Energy & Industrial Strategy. 2016. Electricity Generation Costs. *Department for Business, Energy and Industrial Strategy* November (2016).
[9] Leslie G. Fishbone and Harold Abilock. 1981. Markal, a linearâĂŘprogramming model for energy systems analysis: Technical description of the bnl version. *International Journal of Energy Research* 5, 4 (1981), 353–375. https://doi.org/10.1002/er.4440050406
[10] Matthew Forshaw, Nigel Thomas, and A. Stephen McGough. 2016. The case for energy-aware simulation and modelling of internet of things (IoT). *Proceedings of the 2nd International Workshop on Energy-Aware Simulation - ENERGY-SIM '16* (2016), 1–4. https://doi.org/10.1145/2939948.2949688
[11] Maurizio Gargiulo and O Brian. 2013. Long-term energy models : Principles , characteristics , focus ,. *WIREs Energy and Environment* 2, April (2013). https://doi.org/10.1002/wene.62
[12] "Nord Pool Group". [n. d.]. "N2EX Day Ahead Auction Prices". ([n. d.]).
[13] Lisa M H Hall and Alastair R Buckley. 2016. A review of energy systems models in the UK : Prevalent usage and categorisation. *Applied Energy* 169 (2016), 607–628. https://doi.org/10.1016/j.apenergy.2016.02.044
[14] By Steven A Harp, Bruce F Wollenberg, and Tariq Samad. 2000. SEPIA: A Simulator for Electric Power Industry Agents. August (2000), 53–69.
[15] C.G. Heaps. [n. d.]. Long-range Energy Alternatives Planning (LEAP) system. ([n. d.]).
[16] IEA. 2015. Projected Costs of Generating Electricity. (2015), 215. https://www.oecd-nea.org/ndd/pubs/2015/7057-proj-costs-electricity-2015.pdf
[17] IPCC. 2014. Foreword, Preface, Dedication and In Memoriam. *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (2014), 1454. https://doi.org/10.1017/CBO9781107415416 arXiv:arXiv:1011.1669v3
[18] IRENA. 2018. *Renewable Power Generation Costs in 2017. IRENA - International Renewable Energy Agency.* 160 pages. https://doi.org/10.1007/SpringerReference_7300 arXiv:arXiv:1011.1669v3
[19] Wander Jager. 2006. Simulating consumer behaviour: a perspective. *Environmental Policy and Modelling in Evolutionary Economics* (2006), 1–28.
[20] Wander Jager. 2006. Stimulating the diffusion of photovoltaic systems: A behavioural perspective. *Energy Policy* 34, 14 (2006), 1935–1943. https://doi.org/10.1016/j.enpol.2004.12.022
[21] Dogan Keles, Patrick Jochem, Russell Mckenna, Manuel Ruppert, and Wolf Fichtner. 2017. Meeting the Modeling Needs of Future Energy Systems. *Energy Technology* (2017), 1007–1025. https://doi.org/10.1002/ente.201600607
[22] Stephen C Kincheloe. 1990. The Weighted Average Cost Of Capital - The Correct Discount. *The Appraisal journal.* 58, 1 (1990).
[23] Averill M Law and David W Kelton. 2000. *Simulation modeling and analysis; 3rd ed.* McGraw-Hill, New York, NY. http://cds.cern.ch/record/603360
[24] LeighFisher Ltd. 2016. Final Report: Electricity Generation Costs and Hurdle Rates.
[25] C. M. MacAl and M. J. North. 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation* 4, 3 (2010), 151–162. https://doi.org/10.1057/jos.2010.3
[26] David Masad and Jacqueline Kazil. 2015. Mesa: An Agent-Based Modeling Framework. *PROC. OF THE 14th PYTHON IN SCIENCE CONF* Scipy (2015), 53–60.
[27] Valérie Masson-Delmotte, Panmao Zhai, Hans-Otto Pörtner, Debra Roberts, Jim Skea, Priyadarshi R Shukla, Anna Pirani, Wilfran Moufouma-Okia, Clotilde Péan, Roz Pidcock, Sarah Connors, J B Robin Matthews, Yang Chen, Xiao Zhou, Melissa I Gomis, Elisabeth Lonnoy, Tom Maycock, Melinda Tignor, and Tim Waterfield. 2018. *IPCC Special Report 1.5 - Summary for Policymakers.* https://doi.org/10.1017/CBO9781107415324 arXiv:arXiv:1011.1669v3
[28] Dominik Möst and Dogan Keles. 2010. A survey of stochastic modelling approaches for liberalised electricity markets. *European Journal of Operational Research* 207, 2 (2010), 543–556. https://doi.org/10.1016/j.ejor.2009.11.007
[29] OWPB. 2016. Transmission Costs for Offshore Wind Final Report April 2016. April (2016), 25.
[30] Stefan Pfenninger, Adam Hawkes, and James Keirstead. 2014. Energy systems modeling for twenty- fi rst century energy challenges. *Renewable and Sustainable Energy Reviews* 33 (2014), 74–86. https://doi.org/10.1016/j.rser.2014.02.003
[31] Isabel Praça, Carlos Ramos, Zita Vale, and M Ascem. 2003. MASCEM : A Multiagent Markets. (2003).
[32] Werner Rothengatter. 2007. Assessment of the impact of renewable electricity generation on the German electricity sector An agent-based simulation approach. *Thesis* (2007).
[33] Leo Schrattenholzer. 1981. The energy supply model MESSAGE. *European Journal of Operational Research* December (1981). https://doi.org/10.1016/0377-2217(83)90165-0
[34] S. Stoft. 2002. *Power System Economics; Part 1. Power Market Fundamentals.* Vol. 2. http://www.lavoisier.fr/livre/notice.asp?id=OKLWRRAAOKOOWW
[35] Junjie Sun and Leigh Tesfatsion. 2007. Dynamic Testing of Wholesale Power Market Designs : An Open-Source Agent-Based Framework. *Computational Economics* 30, 3 (2007), 291–327. https://doi.org/10.1007/s10614-007-9095-1
[36] Zhi Zhou, Wai Kin Chan, and Joe H. Chow. 2007. Agent-based simulation of electricity markets: A survey of tools. *Artificial Intelligence Review* 28, 4 (2007), 305–342. https://doi.org/10.1007/s10462-009-9105-x

A RESEARCH METHODS

Table 4 shows a sample of modern power plant costs, and Table 5 displays a sample of historic power plant costs. The parameters for both of these tables are described in Table 2 and explained in Section 3.2

Table 6 displays summary statistics for each scenario run. It demonstrates the demand and whether it increases or decreases and by the percentage of change. Carbon tax price in £ per tonne of CO_2. Year range in which the summary statistics apply.

We then split the low carbon and traditional generation into two groups. Traditional generation contains gas, coal and nuclear power plants, whereas the low carbon group contains photovoltaic as well as offshore and onshore wind turbines. "mean" stands for the arithmetic mean, "std" stands for standard deviation, and min and max are the minimum and maximum values respectively.

A.1 Parameters

Table 4: Modern power plant costs [8]

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	3	3	60,000	700,000	13,600	28,200	5	2,900	3,300
	1200.0	2018/20/25	0.54	25	3	3	10,000	500,000	15,100	12,200	3	2,100	3,300
	1471.0	2018/20/25	0.53	25	3	3	10,000	500,000	15,100	11,400	3	1,900	3,300
Coal	552.0	2025	0.32	25	6	6	40,000	3,400,000	10,000	68,200	6	13,000	3,800
	624.0	2025	0.32	25	5	5	70,000	4,200,000	10,000	79,600	3	19,300	3,800
	652.0	2025	0.3	25	5	5	60,000	3,900,000	10,000	65,300	5	22,700	3,800
	734.0	2025	0.38	25	5	5	60,000	2,600,000	10,000	56,400	3	9,600	3,800
	760.0	2025	0.35	25	5	5	40,000	2,800,000	10,000	52,100	5	14,000	3,800
Hydro	0.033	2018/20/25	1.0	35	0	0	0	6,300,000	0	83,300	0	0	0
	1.046	2018/20/25	1.0	35	0	0	0	3,300,000	400	18,200	0	0	0
	11.0	2018/20/25	1.0	41	2	2	60,000	3,000,000	0	45,100	6	0	0
Nuclear	3300.0	2025	1.0	60	5	8	240,000	4,100,000	11,500	72,900	5	10,000	500
OCGT	96.0	2018/20/25	0.35	25	2	2	80,000	600,000	12,600	9,900	4	2,500	2,400
	299.0	2018/20/25	0.35	25	2	2	30,000	400,000	13,600	9,600	3	1,600	2,500
	311.0	2018/20/25	0.35	25	2	2	30,000	400,000	13,600	9,500	3	1,600	2,500
	400.0	2018/20/25	0.34	25	2	2	30,000	300,000	15,100	7,800	3	1,300	2,500
	625.0	2018/20/25	0.35	25	2	2	20,000	300,000	15,100	4,600	3	1,200	2,400
Offshore	321.0	2018	0.0	23	5	3	60,000	2,200,000	69,300	30,900	3	1,400	33,500
		2020	0.0	23	5	3	60,000	2,100,000	69,300	30,000	3	1,400	32,600
		2025	0.0	23	5	3	60,000	1,900,000	69,300	28,600	3	1,300	31,100
	844.0	2018	0.0	22	5	3	120,000	2,400,000	323,000	48,600	4	3,300	50,300
		2020	0.0	22	5	3	120,000	2,300,000	323,000	47,300	3	3,300	48,900
		2025	0.0	22	5	3	120,000	2,100,000	323,000	45,400	3	3,100	47,000
Onshore	0.01	2018	1.0	20	0	0	0	3,700,000	0	29,700	0	0	0
		2020	1.0	20	0	0	0	3,600,000	0	29,600	0	0	0
		2025	1.0	20	0	0	0	3,500,000	0	29,600	0	0	0
	0.482	2018	1.0	20	0	0	0	2,200,000	200	56,900	0	0	0
		2020	1.0	20	0	0	0	2,100,000	200	56,900	0	0	0
		2025	1.0	20	0	0	0	2,000,000	200	56,700	0	0	0
	20.0	2018	0.0	24	4	2	110,000	1,200,000	3,300	23,200	5	1,400	3,100
		2020	0.0	24	4	2	110,000	1,200,000	3,300	23,000	5	1,400	3,100
		2025	0.0	24	4	2	110,000	1,200,000	3,300	22,400	5	1,400	3,000
PV	0.003	2018	1.0	30	0	0	0	1,500,000	0	23,500	0	0	0
		2020	1.0	30	0	0	0	1,500,000	0	23,400	0	0	0
		2025	1.0	30	0	0	0	1,400,000	0	23,200	0	0	0
	0.455	2018	1.0	30	0	0	0	1,000,000	200	9,400	0	0	0
		2025	1.0	30	0	0	0	900,000	200	9,200	0	0	0
	1.0	2018	0.0	25	1	0	20,000	700,000	0	6,600	3	2,600	1,300
		2020	0.0	25	1	0	20,000	700,000	0	6,300	3	2,600	1,300
		2025	0.0	25	1	0	20,000	600,000	0	5,900	3	2,400	1,200
	4.0	2018	0.0	25	1	0	60,000	700,000	200	8,300	0	1,200	1,300
		2020	0.0	25	1	0	60,000	700,000	200	8,000	0	1,100	1,300
		2025	0.0	25	1	0	60,000	600,000	200	7,500	0	1,100	1,200
	16.0	2018	0.0	25	1	0	70,000	700,000	400	5,600	0	2,000	1,300
		2020	0.0	25	1	0	70,000	600,000	400	5,400	0	1,900	1,300
		2025	0.0	25	1	0	70,000	600,000	400	5,100	0	1,800	1,200
Recip. Engine (Diesel)	20.0	2018/20/25	0.34	15	2	1	10,000	300,000	2,200	10,000	2	1,000	-31,900
Recip. Engine (Gas)	20.0	2018/20/25	0.32	15	2	1	10,000	300,000	3,400	10,000	2	1,000	-31,900

Table 5: Sample of historic power plant costs [16, 18, 29]

Type	Capacity	Year	η	OP	P_D	C_D	P_C	C_C	I_C	F_C	V_C	Inc_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
		1990	0.34	25	3	3	181,208	2,114,099	41,073	85,167	13	8,758	9,966
		2000	0.34	25	3	3	116,407	1,358,089	26,385	54,711	10	5,626	6,402
		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
		1990	0.54	25	3	3	59,884	2,994,246	90,426	73,059	21	12,575	19,762
		2000	0.54	25	3	3	49,674	2,483,747	75,009	60,603	21	10,431	16,392
		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
		1990	0.53	25	3	3	54,296	2,714,817	81,987	61,897	26	10,316	17,917
		2000	0.53	25	3	3	49,310	2,465,515	74,458	56,213	21	9,368	16,272
		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
		1990	0.32	25	6	6	41,766	3,550,192	10,441	71,212	2	13,574	3,967
		2000	0.32	25	6	6	51,429	4,371,538	12,857	87,687	3	16,714	4,885
		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
		1980	0.32	25	5	5	188,476	11,308,571	26,925	211,362	11	42,541	10,231
		1990	0.32	25	5	5	62,458	3,747,483	8,922	70,042	5	14,097	3,390
		1990	0.32	25	5	5	65,126	3,907,588	9,303	73,034	3	14,699	3,535
		2000	0.32	25	5	5	80,033	4,802,002	11,433	89,751	3	18,064	4,344
		2000	0.32	25	5	5	80,882	4,852,979	11,554	90,704	3	18,256	4,390
		2010	0.32	25	5	5	84,549	5,072,973	12,078	94,816	3	19,084	4,589
		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
		1990	0.3	25	5	5	54,542	3,545,235	9,090	59,359	4	20,635	3,454
		2000	0.3	25	5	5	68,516	4,453,581	11,419	74,568	2	25,922	4,339
		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
		1990	0.38	25	5	5	87,920	3,809,903	14,653	82,645	7	14,067	5,568
		2000	0.38	25	5	5	118,072	5,116,482	19,678	110,988	5	18,891	7,477
		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
		1990	0.35	25	5	5	55,208	3,864,573	13,802	71,908	4	19,322	5,244
		2000	0.35	25	5	5	65,705	4,599,358	16,426	85,580	8	22,996	6,241
		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
		1990	1.0	60	5	8	390,159	6,665,224	18,695	118,510	3	16,256	812
		2000	1.0	60	5	8	378,998	6,474,560	18,160	115,120	15	15,791	789
		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
		1990	0.0	23	5	3	104,550	3,833,513	120,755	53,843	3	2,439	58,373
		2000	0.0	23	5	3	102,374	3,753,742	118,242	52,723	6	2,388	57,159
		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
		1990	0.0	22	5	3	178,822	3,576,447	481,330	72,423	10	4,917	74,956
		2000	0.0	22	5	3	180,212	3,604,250	485,072	72,986	9	4,955	75,539
		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
		1990	0.0	24	4	2	411,234	4,486,197	12,337	86,733	10	5,233	11,589
		2000	0.0	24	4	2	230,491	2,514,457	6,914	48,612	5	2,933	6,495
		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
		1990	0.0	25	1	0	399,799	3,997,991	2,284	31,983	0	11,422	7,424
		2000	0.0	25	1	0	399,799	3,997,991	2,284	31,983	0	11,422	7,424
		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