ElecSim: Monte-Carlo 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.

Different techniques to model long-term electricity decisions are reviewed and used to motivate why agent-based models will become an important strategic tool for policy. We motivate why an open-source toolkit is required for long-term electricity planning.

Actual electricity prices are compared with our model and we demonstrate that the use of a Monte-Carlo simulation in the system improves performance by 52.5%. Further, using ElecSim we demonstrate the effect of a carbon tax to encourage a low-carbon electricity supply. We show how a £40 ($50) per tonne of CO_2 emitted would lead to 70% renewable electricity by 2050.

CCS CONCEPTS

• **Computing methodologies → Modeling methodologies**; *Model verification and validation*; **Modeling methodologies**.

1 INTRODUCTION

The world faces significant challenges from climate change [26]. A rise in carbon emissions increases the risk of severe impacts on the world such as rising sea levels, heat waves and tropical cyclones [26]. A survey [7] showed that 97% of scientific literature concurs that the recent change in climate is anthropogenic.

High carbon emitting electricity generation sources such as coal and natural gas currently produce 65% of global electricity, whereas low-carbon sources such as wind, solar, hydro and nuclear provide 35% [3]. Hence, to bring about change and reach carbon-neutrality, a transition in the electricity mix is required.

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

ACM ISBN 978-1-4503-6671-7/19/06.
https://doi.org/10.1145/3307772.3330175

Due to the long construction times, operating periods and high costs of power plants, investment decisions can have long term impacts on future electricity supply [4]. Governments and society, therefore have a role in ensuring that the negative externalities of emissions are priced into electricity generation. This is most likely to be achieved via carbon tax and regulation to influence electricity market players such as generation companies (GenCos).

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

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

Agent-based modelling (ABM) is a class of computational simulation models composed of autonomous, interacting agents and model the dynamics of a system. Due to the numerous and diverse actors involved in electricity markets, ABMs have been utilised in this field to address phenomena such as market power [31].

This paper presents ElecSim, an open-source ABM that simulates GenCos in a wholesale electricity market. ElecSim models each GenCo as an independent agent and electricity demand. An electricity market facilitates trades between the two.

GenCos make bids for each of their power plants. Their bids are based on the generator's short run marginal cost (SRMC) [29], which excludes capital and fixed costs. The electricity market accepts bids in cost order, also known as merit-order dispatch. GenCos invest in power plants based on expected profitability.

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

The contribution of this paper is a new open-source framework with example scenarios of varying carbon taxes. We provide curated data, and improve realism via Monte-Carlo sampling. Section 2 is a literature review. Section 3 details the model and assumptions made, and Section 4 provides performance metrics and validation. Section 5 details our results. We conclude the 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 can require significant time in order to fully ascertain the long-term trends. There is also a risk that changes can have detrimental impacts and lead to risk-averse behaviour. These factors are true for electricity markets, where decisions can have long term impacts. Simulation, however, can be used for rapidly prototyping ideas. The simulation is parametrised by real world data and phenomena. Through simulation, the user is able to assess the likelihoods of outcomes under certain scenarios and parameters [24].

Energy models can typically be classified as top-down macro-economic models or bottom-up techno-economic models [2]. 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 [15], for example MARKAL-MACRO [10] and LEAP [17]. Bottom-up models represent the energy sector in detail, and are written as mathematical programming problems [11].

It is possible to further categorise bottom-up models into optimisation and simulation models. Optimisation energy models minimise costs or maximise welfare, defined as the material and physical well-being of people [21]. Examples of optimisation models are MARKAL/TIMES [10] and MESSAGE [35].

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 for their own best interest [27]. Policy options must therefore be used to encourage changes to attain a desired outcome. It is proposed that these complex agents are modelled using ABMs due to their non-deterministic nature.

Traditional centralised optimisation models are not designed to describe a system which is out of equilibrium. Optimisation models assume perfect foresight and risk neutral investments with no regulatory uncertainty. The core dynamics which emerge from equilibrium remain a black-box. For example, the model assumes a target will be reached, and does not provide information for which this is not the case. Reasons for this could be investment cycles which move the model away from equilibrium [4].

A number of ABM tools have emerged over the years to model electricity markets: SEPIA [16], EMCAS [6], NEMSIM [1], AMES [36], GAPEX [5], PowerACE [33], EMLab [4] and MACSEM [30]. Table 1 shows that these do not suit the needs of an open source, long-term market model. We will demonstrate that Monte-Carlo sampling of parameters is also required to increase realism.

There have been a number of recent studies using ABMs which focus on electricity markets, however they often utilize ad-hoc tools which are designed for a particular application [14, 23, 34]. ElecSim, however, has been built for re-use and reproducibility. The survey [37] cites that many of these tools do not release source code or parameters, which is a problem that ElecSim seeks to address.

Table 1 contains six columns: tool name, whether the tool is open source or not, whether they model long-term investment in electricity infrastructure, and the markets they model. We determine how the stochasticity of real life is modelled, and determine whether the model is generalisable to different countries.

Tool name	Open Source	Long-Term Investment	Market	Stochastic Inputs	Country Generalisability
SEPIA [16]	✓	×	✓	Demand	✓
EMCAS [6]	×	✓	✓	Outages	✓
NEMSIM [1]	?	✓	✓	×	×
AMES [36]	✓	×	Day-ahead	×	×
GAPEX [5]	?	×	Day-ahead	×	✓
PowerACE [33]	×	✓	✓	Outages Demand	✓
EMLab [4]	✓	✓	Futures	×	✓
MACSEM [30]	?	×	✓	×	✓
ElecSim	✓	✓	Futures	✓	✓

Table 1: Features of electricity market ABM tools.

An open source toolkit is important for reproducibility, transparency and lowering barriers to entry. It enables users to expand the model to their requirements and respective country. The modelling of long-term investment enables scenarios to emerge, and enable users to model investment behaviour. We demonstrate that the use of a Monte-Carlo method improves results.

SEPIA [16] is a discrete event ABM which utilises Q-learning to model the bids made by GenCos. SEPIA models plants as being always on, and does not have an independent system operator (ISO), which in an electricity market, is an independent non-profit organization for coordinating and controlling of regular operations of the electric power system and market [38]. SEPIA does not model a spot market, instead focusing on bilateral contracts. As opposed to this, ElecSim has been designed with a merit-order, spot market in mind. As shown in Table 1, SEPIA does not include a long-term investment mechanism.

EMCAS [6] is a closed source ABM. EMCAS investigates the interactions between physical infrastructures and economic behaviour of agents. However, ElecSim focuses on the dynamics of the market, and provides a simplified, transparent model of market operation, whilst maintaining robustness of results.

NEMSIM [13] is an ABM that represents Australia's National Electricity Market (NEM). Participants are able to grow and change over time using learning algorithms. NEMSIM is non-generalisable to other electricity markets, unlike ElecSim.

AMES [36] is an ABM specific to the US Wholesale Power Market Platform and therefore not generalizable for other countries. GAPEX [5] is an ABM framework for modelling and simulating power exchanges . GAPEX utilises an enhanced version of the reinforcement technique Roth-Erev [32] to consider the presence of affine total cost functions. However, neither of these model the long-term dynamics for which ElecSim is designed.

PowerACE [33] is a closed source ABM of electricity markets that integrates short-term daily electricity trading and long-term investment decisions. PowerACE models the spot market, forward market and a carbon market. Similarly to ElecSim, PowerACE initialises GenCos with each of their power plants. However, as can be seen in Table 1 unlike ElecSim, PowerACE does not take into account stochasticity of price risks in electricity markets [27].

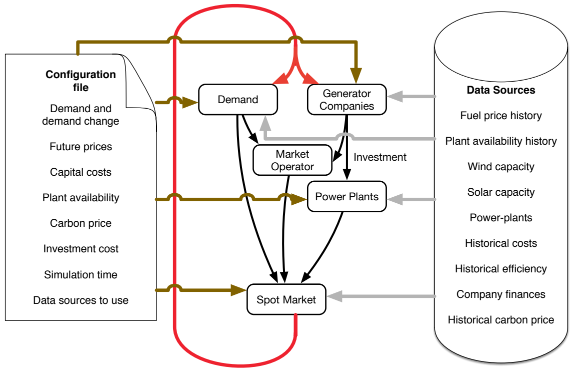


Figure 1: High level overview.

EMLab [4] is an open-source ABM toolkit for the electricity market. Like PowerACE, EMLab models an endogenous carbon market, however, they both differ from ElecSim by not taking into account stochasticity in the electricity markets, such as in outages, fuel prices and operating costs. After correspondence with the authors, however, we were unable to run the current version.

MACSEM [30] has been used to probe the effects of market rules and conditions by testing different bidding strategies. MACSEM does not model long term investments or stochastic inputs.

As can be seen from Table 1 none of the tools fill each of the characteristics we have defined. We therefore propose ElecSim to contribute an open source, long-term, stochastic investment model.

3 ELECSIM ARCHITECTURE

ElecSim is made up of five fundamental parts: the agents, which are split up into demand and GenCos; power plants; a Power Exchange, which controls a spot market to match power plants with electricity demand; and the data for parametrisation. A schematic of ElecSim is displayed in Figure 1 which demonstrates how they interact.

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.

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

Demand Agent. The demand agent is a simplified representation of aggregated demand in a country. The demand is represented as a load duration curve (LDC). An LDC is an arrangement of all load levels in descending order of magnitude. Each year, the demand agent changes each of the LDC segments proportionally.

As per Chappin *et al.* [4], we modelled the LDC of electricity demand with twenty segments. Twenty segments enabled us to capture the variation in demand throughout the year to a high degree of accuracy, whilst reducing computational complexity.

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

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

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

Equation 1 is the calculation of NPV, where t is the year of the cash flow, i is the discount rate, N is total number of periods, or lifetime of power plant, and R_t is the net cash flow at time t.

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

A discount rate set by a GenCo'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 to achieve a positive NPV, an income larger than the WACC is required. However, a higher WACC is often selected to adjust for varying risk profiles, opportunity costs and rates of return. To account for these differences we sample from a Gaussian distribution, giving us sufficient variance whilst deviating from the expected price.

To calculate the NPV, future market conditions must be considered. For this, each GenCo forecasts N years into the future, which we assume is representative of the lifetime of the plant. As in the real world, GenCos have imperfect information, and therefore must forecast expected demand, fuel prices, carbon price and electricity sale price. This is achieved by fitting functions to historical data. Each GenCo is different in that they will use differing historical time periods of data for forecasting.

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

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

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

Once this data has been forecasted, the NPV can be calculated. GenCos must typically provide a certain percentage of upfront capital, with the rest coming from investors in the form of stock

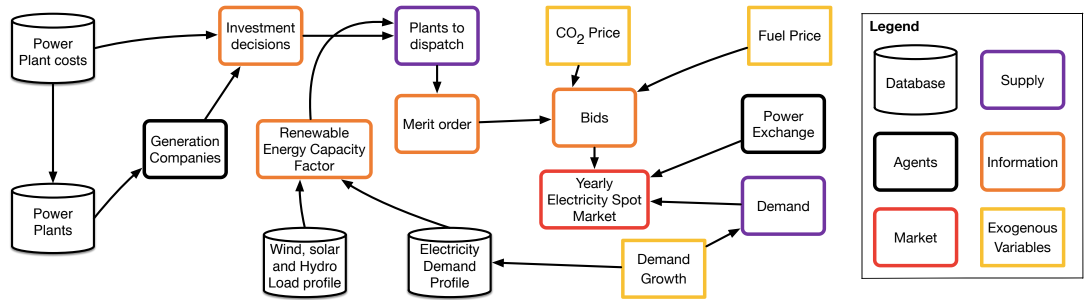


Figure 2: ElecSim simulation overview

and shares or debt (WACC). The percentage of upfront capital can be customised by the user in the configuration file. The GenCos then invest in the power plants with the highest NPV.

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

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

The parameters used to initialise the power plants are detailed in this section. Periods have units of years and costs in £/MW unless otherwise stated: Efficiency (η) is defined as the percentage of energy from fuel that is converted into electrical energy (%). Operating period (OP) is the total period in which a power plant is in operation. Pre-development period (P_D) and pre-development costs (P_C) include the time and costs for pre-licensing, technical and design, as well as costs incurred due to regulatory, licensing and public enquiry. The construction period (C_D) and construction costs (C_C) are incurred during the development of the plant, excluding network connections. The infrastructure costs (I_C) are the costs incurred by the developer in connecting the plant to the electricity or gas grid (£). Fixed operation & maintenance costs (F_C) are costs incurred in operating the plant that do not vary based on output. Variable operation & maintenance (V_C) costs are incurred in operating the plant that depend on generator output [25].

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

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

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

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

To model the intermittency of wind and solar power we allow them to contribute only a certain percentage of their total capacity (nameplate capacity) for each load segment. This percentage is based upon empirical wind and solar capacity factors. In this calculation we consider the correlation between demand and renewable resources. We are unable to model short-term storage due to ElecSim taking a single time-step per year.

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

Fuel price is controlled by the user, however, there is inherent volatility in fuel price. To take into account this variability, an ARIMA [9] model was fit to historical gas and coal price data. The standard deviation of the residuals was used to model the variance in price that a GenCo will buy fuel in a given year. This considers differences in chance and hedging strategies.

Figure 2 demonstrates the simulation and how it co-ordinates runs. The world contains data and brings together GenCos, the Power Exchange and demand. The investment decisions are based on future demand and costs, which in turn influence bids made.

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

4 VALIDATION AND PERFORMANCE

Validation. Validation of models is important to ascertain that the output is accurate. However, it should be noted that these long-term simulations are not predictions of the future, rather possible outcomes based upon certain assumptions. Jager posits that a certain outcome or development path, captured by empirical data, might have developed in a completely different direction due to chance. However, the processes that emerge from a model should be realistic and in keeping with expected behaviour [20].

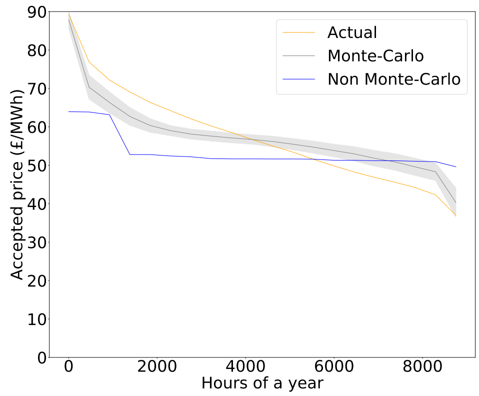


Figure 3: Price duration curve which compares real electricity prices to those paid in ElecSim (2018).

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 2: Validation performance metrics.

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 Monte-Carlo simulated electricity prices, and the non Monte-Carlo electricity price throughout the year 2018. Fuel prices varying throughout a year, as does V_C and WACC. WACC is sampled from a Gaussian distribution with a standard deviation of ±3%. V_C is sampled from a uniform distribution between 30% and 200% of the mean V_C price, whilst fuel price is sampled from the residuals of an ARIMA model fit on historical data. The N2EX Day Ahead Market is a day ahead market run by Nord Pool AS. Nord Pool AS runs the largest market for electrical energy in Europe, measured in volume traded and in market share [12].

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

Figure 3 demonstrates very little variance in the non-stochastic case. This is due to the fact that combined cycle gas turbines (CCGTs) set the spot price. These CCGTs have little variance between one another as they were calibrated using the same dataset. By adding stochasticity of fuel prices and operation and maintenance prices, a curve that more closely resembles the actual data occurs. The stochastic curve, however, does not perfectly fit the real data, which may be due to higher variance in fuel prices and historical differences in operation and maintenance costs between power plants. One method of improving this would be fitting the data used to parametrise to the curve.

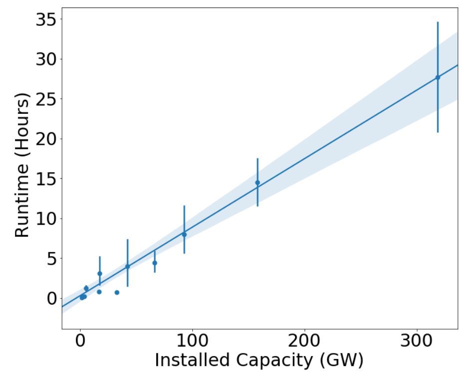


Figure 4: Run times of different sized countries.

Table 2 shows performance metrics of the stochastic and non-stochastic runs versus the actual price duration curve . The stochastic implementation, improves the mean absolute error (MAE) of the non-stochastic case by 52.5%.

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, as would be expected. The highest NPV calculations were for onshore wind and CCGT plants. This is realistic for the United Kingdom, where subsidies are required for other forms of generation such as coal and nuclear.

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 total of 256GB of memory and use a Linux operating system. The total disk size of ElecSim is 5.8MB. The memory used for a 10 year run has a median of 57.1MB.

Figure 4 shows the running time for ElecSim with varying installed capacity. We varied demand between 2GW and 320GW to see the effect of different sized countries on running time. The makeup of the electricity mix was achieve through stratified sampling of the UK electricity mix. The results show a linear time complexity.

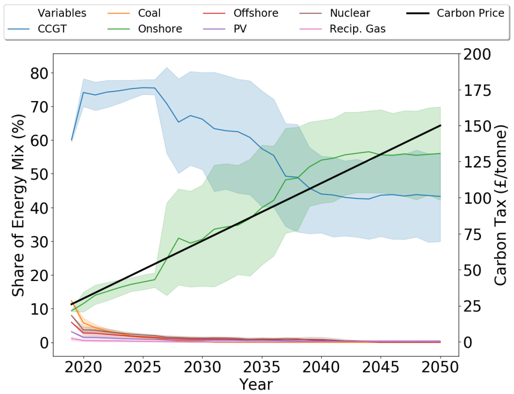
5 SCENARIO TESTING

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

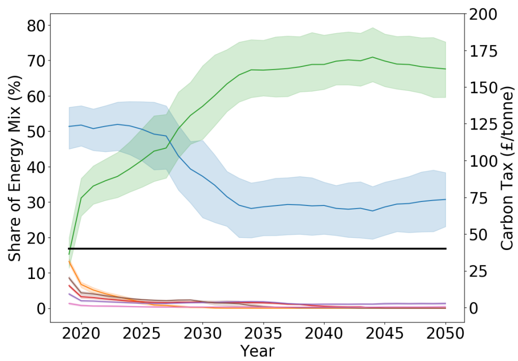
For the first scenario run displayed, we have approximated the predictions by the UK Government, where carbon tax increases linearly from £18 to £200 by 2050 [8]. Figure 5a demonstrates a significant increase in gas turbines in the first few years, followed by a decrease, with onshore wind increasing.

Figure 5b displays a run with a £40 carbon tax. This run demonstrates a higher share of onshore wind than in the previous scenario.

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



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



(b) £40 carbon tax

Figure 5: Scenarios with varying carbon taxes and decreasing demand (-1%/year)

6 CONCLUSIONS

Liberalised electricity markets with many heterogenous players are suited to be modelled with ABMs. ABMs 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 model market conditions more realistically.

We demonstrated that increasing carbon tax can lead to an increase in investment of low-carbon technologies. We showed that early decisions have a long-term impact on the energy mix.

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. This will allow us to model that demand is met at all times and not just on average. We propose the modelling of collusion between GenCos.

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A RESEARCH METHODS

Table 3 shows a sample of modern power plant costs, and Table 4 displays a sample of historic power plant costs. The parameters for both of these tables are explained in Section 3

Table 5 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 is in £ per tonne of CO_2, and also the 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.

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 3: 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	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

Table 4: Sample of historic power plant costs [18, 19, 28]

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

Table 5: Summary statistics for each scenario run.