Long-Term Electricity Market Agent Based Model Validation using Genetic Algorithm based Optimization

ABSTRACT

Electricity market modelling is often used by governments, industry and agencies to explore the development of various scenarios over differing timeframes. Optimization based solutions have been the dominant approach for analysing energy policy. However, these types of models have certain limitations such as the need to be interpreted in a normative manner, and assumption that the electricity market remains in equilibrium throughout.

The aim of this paper is to validate our agent-based modelling framework to increase confidence in its ability to be used in policy and decision making.

Our framework is able to model heterogenous agents with imperfect information. The model uses a rules-based approach to approximate the underlying dynamics of a real life, decentralised electricity market. We use the UK as a case-study, however our framework is ~~generalisable to other countries.~~ We increase the temporal granularity of the model by selecting representative days of electricity demand and weather using a K-means clustering approach.

We show that our modified framework, ElecSim, is able to adequately model the transition from coal to gas observed in the UK between 2013 and 2018. We are also able to simulate a future scenario to 2035 similarly to the UK Government, Department for Business and Industrial Strategy (BEIS). However, we show a more realistic increase in nuclear power over this time period.

Through this work, we show that agent-based models are a viable technique to simulate decentralised electricity markets.

CCS CONCEPTS

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

KEYWORDS

agent-based modelling, simulation, energy market simulation, energy models, policy, long-term, validation, genetic algorithm, optimisation

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1 INTRODUCTION

Impacts on natural and human systems due to global warming have already been observed, with many land and ocean ecosystems having already changed. A rise in carbon emissions increases the risk of severe impacts on the world such as rising sea levels, heat waves and tropical cyclones [33]. A study by Cook *et al.* demonstrated that 97% of scientific literature concurred that recent global warming was anthropogenic [8]. Limiting global warming requires limiting the total cumulative global anthropogenic emissions of CO_2 [33].

Global carbon emissions from fossil fuels, however, have significantly increased since 1900 [5]. Fossil-fuel based electricity generation sources such as coal and natural gas currently provide 65% of global electricity. Low-carbon sources such as solar, wind, hydro and nuclear, however, provide 35% [6]. To halt this increase in CO_2 emissions, a transition of the energy system towards a renewable energy system is required.

However, such a transition needs to be performed in a gradual and non-disruptive manner. This ensures that there are no electricity shortages or power cuts that would cause damage to businesses, consumers and the economy.

To ensure such a transition, energy modelling is often used by governments, industry and agencies to explore possible scenarios under different variants of government policy, future electricity generation costs and energy demand. These energy modelling tools aim to mimic the behaviour of energy systems through different sets of equations and data sets to determine the energy interactions between different actors and the economy [32].

Optimization based solutions have been the dominant approach for analysing energy policy [7]. However, the results of these models should be interpreted in a normative manner. For example, how investment and policy choices should be done, under certain assumptions and scenarios. However, the processes which emerge from an equilibrium model remain a black-box, making it difficult to fully understand the dynamics that lead to certain processes [7].

In addition to this, optimization models do not allow for endogenous behaviour to emerge from typical market movements, such as investment cycles [7, 18]. By modelling these naturally occurring behaviours, policy can be designed that is robust against movements away from the optimum/equilibrium. Thus, helping policy to become more effective in the real world.

The work presented in this paper builds on the agent-based model (ABM), ElecSim, developed by Kell *et al.* [27]. Agent-based models differ from optimization models by the fact that they are

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able to explore what-if questions regarding how a sector could develop under different prospective policies, as opposed from determining optimal trajectories. ABMs are particularly pertinent in decentralised electricity markets, where a centralised actor does not dictate investments made within the electricity sector. ABMs have the ability to closely mimic the real world by, for example, modelling irrational agents, in this case Generation Companies (GenCos) with incomplete information in uncertain situations [16].

There is a desire to validate the ability of energy-models to make long-term predictions. Validation increases confidence in the outputs of a model and leads to an increase in trust amongst the public and policy makers. Energy models, however, are frequently criticised for being insufficiently validated, with the performance of models rarely checked against historical outcomes [4].

In answer to this we postulate that ABMs can provide accurate information to decision makers in the context of electricity markets. We increase the temporal granularity of the work by Kell *et al.* [27] and use genetic algorithms to tune the model to observed data. This enables us to understand the parameters required to observe certain phenomena, as well as use these fitted parameters to make inferences about the future.

We measure the accuracy of projections of our improved ABM with those of the UK Government's Department for Business, Energy and Industrial Strategy (BEIS) for the UK electricity market between 2013 and 2018. In addition to this, we compare our projections from 2018 to 2035 to those made by BEIS in 2018 [12].

We use a genetic algorithm approach to find an optimal set of price curves predicted by generation companies (GenCos) that adequately model observed investment behaviour in the real-life electricity market in the United Kingdom. Similar techniques can be employed for other countries of various sizes [27].

Similarly to Nahmmacher *et al.* we demonstrate how clustering of multiple relevant time series such as electricity demand, solar irradiance and wind speed can reduce computational time by selecting representative days [34]. In this context, representative days are a subset of days that have been chosen due to their ability to approximate the weather and electricity demand in an entire year. Distinctly to Nahmacher *et al.* we use a K-means clustering approach [15] as opposed to a hierarchical clustering algorithm described by Ward [26]. We chose the K-means clustering approach due to previous success of this technique in clustering time series [28].

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

We show in this paper that agent-based models are able to adequately mimic the behaviour of the UK electricity market under the same specific scenario conditions. Concretely, we show that under an observed carbon tax strategy, fuel price and known exogenous demand, the model ElecSim closely matches the observed electricity mix between 2013 and 2018.

In addition to this, we compare our projections to those of BEIS from 2018 to 2035. To achieve this we use the same genetic algorithm optimisation technique as during our cross-validation stage. Our model demonstrates that we are able to closely match the projections of BEIS. Our model, however, exhibits a more realistic step change in nuclear output than that of BEIS. This is because, whilst BEIS projects a gradual increase in nuclear output, our model projects that nuclear output will grow instantaneously at a single point in time as a new nuclear power plant comes online.

Through the addition of an increased temporal granularity, using a K-means clustering approach to select a subset of representative days with relation to wind speed, solar irradiance and electricity demand to approximate an entire year, we have provided an accurate framework to allow policy makers, decision makers and the public explore the effects of policy on investment in electricity generators.

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

2 LITERATURE REVIEW

In this section we cover how other energy models tackle the problem of validating energy models, the difficulties inherent in validating these models and describe our approach.

Beckman *et al.* state that questions frequently arise as to how much faith one can put in energy model results. This is due to the fact that the performance of these models as a whole are rarely checked against historical outcomes [4].

The model OSeMOSYS [23] is, however, validated against the similar model MARKAL/TIMES through the use of a case study named UTOPIA. UTOPIA is a simple test energy system bundled with ANSWER, a graphical user interface packaged with the MARKAL model generator [24, 35]. Hunter *et al.* use the same case study to validate their model Temoa [24]. In these cases, MARKAL/TIMES is seen as the "gold standard". In this paper, however, we argue that the ultimate gold standard should be real-world observations, as opposed to a hypothetical scenario.

The model PowerACE demonstrate that realistic prices are achieved by their modelling approach, however do not indicate success in modelling GenCo investment over a prolonged time period [38].

Under the definition by Hodges *et al.* [20] long-range energy forecasts are not validatable [9]. Under this definition, validatable models must be observable, exhibit constancy of structure in time, exhibit constancy across variations in conditions not specified in the model and it must be possible to collect ample data [20].

Whilst it is possible to collect data for energy models, the data covering important characteristics of energy markets are not always measured. Furthermore, the behaviour of the human population and innovation are neither constant nor entirely predictable. This leads to the fact that static models cannot keep pace with global long-term evolution. Assumptions made by the modeller may be challenged in the form of unpredictable events, such as the oil shock of 1973 [9].

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

Work by Koomey *et al.* expresses the importance of conducting retrospective studies to help improve models [30]. In this case, a model can be rerun using historical data in order to determine how much of the error in the original forecast resulted from structural problems in the model itself, or how much of the error was due to incorrect specification of the fundamental drivers of the forecast [30].

A retrospective study published in 2002 by Craig *et al.* focused on the ability of forecasters to accurately predict electricity demand from the 1970s [9]. They found that actual energy usage in 2000 was at the very lowest end of the forecasts, with only a single exception. They found that these forecasts underestimated unmodelled shocks such as the oil crises which led to an increase in energy efficiency.

Hoffman *et al.* also developed a retrospective validation of a predecessor of the current MARKAL/TIMES model, named Reference Energy System [22], and the Brookhaven Energy System Optimization Model [2]. These were studies applied in the 70s and 80s to develop projections to the year 2000. This study found that the models had the ability to be descriptive, but were not entirely accurate in terms of predictive ability. They found that emergent behaviours in response to policy had a strong impact on forecasting accuracy. The study concluded that forecasts must be expressed in highly conditioned terms [21].

Schurr *et al.* argued against predicting too far ahead in energy modelling due to the uncertainties involved [41]. However, they specify that long-term energy forecasting is useful to provide basic information on energy consumption and availability which is helpful in public debate and in guiding policy makers.

Ascher concurs with this view and states that the most significant factor in model accuracy is the time horizon of the forecast; the more distant the forecast target the less accurate the model. This can be due to unforeseen changes in society as a whole [17].

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

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

3 IMPLEMENTATION DETAILS

ElecSim is made up of five distinct sections: 1) power plant data; 2) scenario data; 3) the time-steps of the algorithm; 4) the power exchange; 5) the investment algorithm. ElecSim has been previously published [27], however, amendments have since been made to the model in the form of efficiency improvements to decrease compute time as well as increase the granularity of time-steps from yearly to representative days. Representative days, in this context, are a subset of days which when scaled up to 365 days can adequately represent a year.

In this paper we initialised the model to a scenario of the United Kingdom as an example, however, the model is generalisable to any country. In this section we detail the modifications made to ElecSim for this paper. Further details of the design decisions of ElecSim are shown in [27]

3.1 Selecting Representative Days

In previously published work, ElecSim modelled a single year as 20 time-steps for solar irradiance, onshore and offshore wind and electricity demand [27]. Similarly to findings of other authors, this relatively low number of time-steps led to an overestimation of the uptake of intermittent renewable energy resources (IRES) and an underestimation of flexible technologies [19, 31]. This is due to the fact that the intermittent nature of renewable energy could not be accurately modelled in such a small number of time-steps.

To address this problem, whilst maintaining a tractable compute time, we approximated a single year as eight, proportionally weighted, representative days. Each representative day consisted of 24 equally separated time-steps, which model hours in a day.

Similarly to Nahmmacher *et al.* we used a clustering technique to split similar days of weather and electricity demand into separate groups. We then selected the historic day that was closest to the centre of the cluster, known as the medoid [34]. Distinctly to Nahmmacher, however, we used the k-means clustering algorithm [15] as opposed to the Ward's clustering algorithm [26]. This was due to previous success of the k-means algorithm to cluster time-series into relevant groups [29]. These days were scaled proportionaly to the number of days within their respective cluster to approximate a total of 365 days.

To measure the validity of the optimum number of days we used a technique similar to Poncelet *et al.* [13, 37]. We trialled the number of clusters against three different metrics: correlation (CE_{av}), normalised root mean squared error (*nRMSE*) and relative energy error (REE_{av}).

REE_{av} is the average value over all the considered time series $p \in P$ compared to the actual average value. *nRMSE* is measured as the normalised root mean squared error between the actual duration curve and representative duration curve. In this context, the duration curve can be constructed by sorting the capacity factor and electrical load data from high to low. The final metric used is the correlation between the different time series. This is used due to the fact that wind and solar output influences the load within a single region, solar and wind output are correlated, as well as offshore and onshore wind levels within the UK. This is referred to as the average correlation error (CE_{av}). Further details are shown seen in the work by Poncelet *et al.* [37].

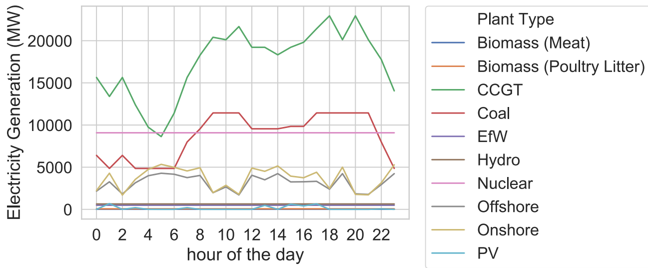

Figure 1: Example of a single day of dispatched supply.

We found that for each of these metrics, the accuracy of the approximation did not significantly increase after 8 days. We therefore selected 8 days as a compromise between accuracy and tractability for the model, ElecSim.

3.2 Integrating higher temporal granularity

To integrate the additional temporal granularity of the model, extra time-steps were taken per year. In this case, we chose 8 days of 24 time-steps each, leading to 192 time-steps per year.

GenCos make bids at the beginning of every time-step and the Power Exchange matches demand with supply in merit-order dispatch using a uniform pricing market. An example of electricity mix in a single representative day is shown in Figure 1.

Figure 1 displays the high utilization of low marginal-cost generators such as nuclear, wind and photovoltaics. At hour 19, an increase in offshore wind leads to a direct decrease in CCGT. In contrast to this, a decrease in offshore and onshore between the hours of 8 and 12 lead to an increase in dispatch of coal and CCGT. This is behaviour which one would expect to prevent blackouts and meet demand at all times. This process has enabled us to more closely match fluctuations in IRES.

4 PROBLEM FORMULATION

For GenCos to adequately make investments, they must formulate an expectation of future electricity prices over the lifetime of a plant. Future electricity prices are a function of demand and supply, and with renewable electricity generator costs falling, future prices are uncertain [25].

Due to the uncertainty of future electricity prices over the horizon of the lifetime of a power plant we have set future electricity prices as an exogenous variable that can be set by the user in ElecSim.

To gain an understanding of expected electricity prices that lead to particular scenarios we use a genetic algorithm optimisation approach. This enables us to understand the range of future electricity prices that lead to certain scenarios developing.

4.1 Genetic Algorithms

Genetic Algorithms (GAs) are a type of evolutionary algorithm. In this section we detail the genetic algorithm used in this paper.

Initially, a population P_0 is generated for generation 0. Each of these populations are evaluated for their fitness. A subset of these individuals $C_{t+1} \subset P_t$ are chosen for mating. This subset is selected proportionally to their fitness. With 'Fitter' individuals having a higher change of reproducing to create the offspring group C'_{t+1}. C'_{t+1} have characteristics dependent on the genetic operators: crossover and mutation. The genetic operators are an implementation decision [3].

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

Algorithm 1 Genetic algorithm [3]

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

4.2 Cross-validation

To verify the accuracy of the underlying dynamics of ElecSim, the model was initialised to the year 2013 and allowed to develop until 2018. We used a genetic algorithm to find the optimum price duration curve predicted by the GenCos 10 years ahead of the year of the simulation. This predicted price duration curve was used to model expected rate of return of prospective generation types.

The genetic algorithm's objective was to reduce the error of simulated and observed electricity mix in the year 2018 by finding a suitable price curve predicted by the GenCos.

4.2.1 Scenario. For this experiment, we initialised ElecSim with parameters known in 2013. For example, ElecSim was initialised with every power plant and respective GenCo that was in operation in 2013 using the BEIS DUKES datatset [14]. The funds available to each of the GenCos was taken from publicly released official company accounts at the end of 2012 [11].

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

The data for the observed EU Emission Trading Scheme (ETS) price between 2013 and 2018 was taken from [39]. Fuel prices for each of the fuels were taken from [10]. The electricity load data was modelled using data from [1]. There were three known significant coal plant retirements in 2016. These were removed from the simulation at the beginning of 2016.

4.2.2 Optimisation problem. The price duration curve was modelled linearly as shown by Equation 1. In this case, y is the cost of electricity, m is the gradient, x is the demand of the price duration curve and c is the intercept.

$$y = mx + c \tag{1}$$

Equation 2 details this optimisation formally.

$$\min_{m,c} \sum_{o \in O} \left(\frac{|A_o - f_o(m,c)|}{||O||} \right) \tag{2}$$

Where $o \in O$ refers to the average percentage electricity mix during 2018 for wind (both offshore and onshore generation), nuclear, solar, CCGT, and coal. A_o refers to observed electricity mix percentage for the respective generation type in 2018. $f_o(m,c)$ refers to the simulated electricity mix percentage for the respective generation type also in 2018. The input parameters to the simulation are m and c from Equation 1. $||O||$ refers to the cardinality of the set.

4.3 Scenario analysis

In addition to verifying the ability for ElecSim to mimic observed investment behaviour over 5 years, we compared ElecSim's long-term behaviour to that of the UK Government's Department for Business, Energy and Industrial Strategy (BEIS) [12]. This scenario shows the projections of generation by technology for all power producers from 2018 to 2035 for a reference scenario.

4.3.1 Scenario. We initialised the model to 2018 as in [27]. The scenario for development of fuel prices and carbon prices were matched to that of the BEIS reference scenario [12].

4.3.2 Optimisation problem. The optimisation approach taken was a similar process to that discussed in Sub-Section 4.2, namely using a genetic algorithm to find the optimum expected price duration curve. However, instead of using a single expected price duration curve for each of the agents for the entire simulation, we used a different expected price duration curve for each year, leading to 17 different curves. This enabled us to model the non-static dynamics of the electricity market over time.

In addition to optimising for multiple expected price duration curves, we also optimised for a nuclear subsidy, S_n, and uncertainty in the expected price parameters m and c, named σ_m and σ_c respectively. Where σ is the standard deviation in a normal distribution.

This enabled us to model the different expectations of future price curves between the independent GenCos. The addition of a nuclear subsidy as a parameter is due to the likely requirement for Government to provide subsidies for new nuclear [40].

A modification was made to the reward algorithm for the long-term scenario case. Rather than using the discrepancy between observed and simulated electricity mix in the final year (2018) as the reward, a summation of the error metric for each simulated year was used. This is detailed formally in Equation 3.

$$\min_{m \in M, m \in C} \sum_{y \in Y} \sum_{o \in O} \left(\frac{\left|A_{y_o} - f_{y_o}(m_y, c_y)\right|}{||O||} \right) \tag{3}$$

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

5 RESULTS

Here we present the results of the problem formulation of Sections 4.2 and 4.3. Specifically, we compare the ability of our model to that of BEIS in the context of a historical cross-validation between 2013 and 2018 of the UK electricity market. We also compare our ability to generate scenarios up to 2035 with that of BEIS.

5.1 Cross-validation

Figure 2 shows the output of ElecSim under the cross-validation scenario, BEIS' projections and the observed electricity mix between 2013 and 2018 explained in Sub-Section 4.2.

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

Both ElecSim and BEIS were able to model the fundamental dynamics of this shift from coal to gas as well as the increase in renewables. Both models, however, underestimated the magnitude of the shift from coal to gas. This could be due to unmodelled behaviours such as consumer sentiment towards highly polluting coal plants, a prediction from industry that gas would become more economically attractive in the future or a reaction to The Energy Act 2013 which aimed to close a number of coal power stations over the following two decades [36].

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

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

We display the error metrics to evaluate our models 5 year projections in Table 1. Where MAE is mean absolute squared error, MASE is mean absolute scaled error and RMSE is root mean squared error.

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

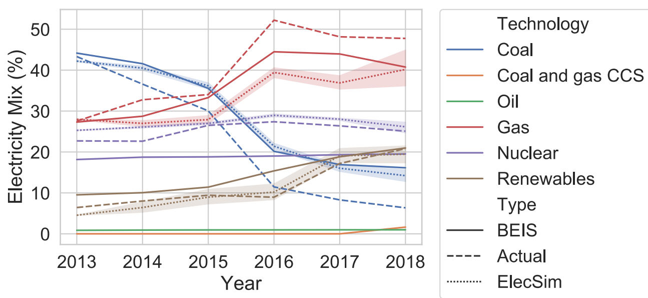

Figure 2: Comparison of actual electricity mix vs. ElecSim vs. BEIS projections and taking three coal power plants out of service.

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

Table 1: Error metrics for time series forecast from 2013 to 2018

Figure 3 displays the optimal predicted price duration curve (PPDC) found by the genetic algorithm. This price curve was used by the GenCos to achieve the results shown in Figure 2.

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

The optimal predicted price duration curve (PPDC) closely matches the simulated fit in 2018, shown by Figure 3. However, the PPDC has a slightly higher peak price and lower baseload price. This could be due to the fact that there is a predicted increase in the number of renewables with a low SRMC. However, due to the intermittency of renewables such as solar and wind, higher peak prices are required to generate in times of low wind and sun output.

To generate Figure 4, we run 40 scenarios with the PPDC to observe the final, simulated electricity mix. The error bars are computed based on a Normal distribution 95% confidence interval.

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

5.2 Scenario analysis

In this section we discuss the results of the analysis of the BEIS reference scenario. Specifically, we created a scenario that mimicked

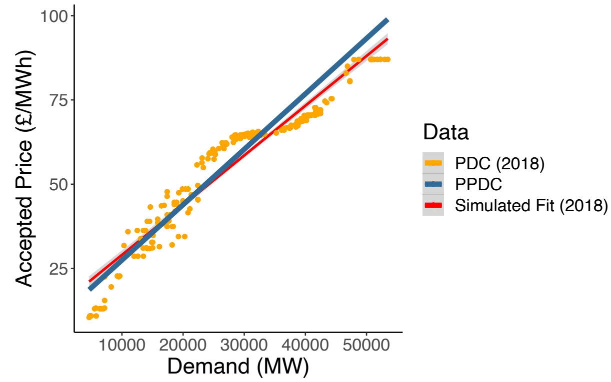

Figure 3: Predicted price curve for investment for most accurate run against simulated run in 2018.

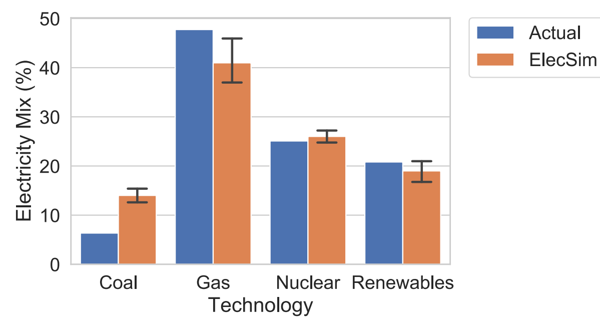

Figure 4: Electricity generation mix simulated by ElecSim from 2013 to 2018 compared to observed electricity mix in 2018.

that of BEIS in ElecSim and optimised a number of parameters using a genetic algorithm to match this scenario.

Figure 5 displays the electricity mix projected by both ElecSim and BEIS. To generate this image we run 60 scenarios under the optimal collection of predicted price duration curves, nuclear subsidy and uncertainty in predicted price duration curves.

The optimal parameters were chosen by choosing the parameter set with the lowest mean error per electricity generation type and per year throughout the simulation, as shown by Equation 3.

Figure 6 displays the optimal, average predicted price duration curves (PPDCs) per year of the simulation, shown in blue. These are compared to the price duration curve simulated in 2018, as per Figure 3. The optimal nuclear subsidy, S_n, was found to be $\sim$ £120, the optimal σ_m and σ_c were found to be 0 and ~ 0.0006 respectively

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

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

A significant difference, however, is the step-change in nuclear power in 2033. This led to an almost equal reduction in natural

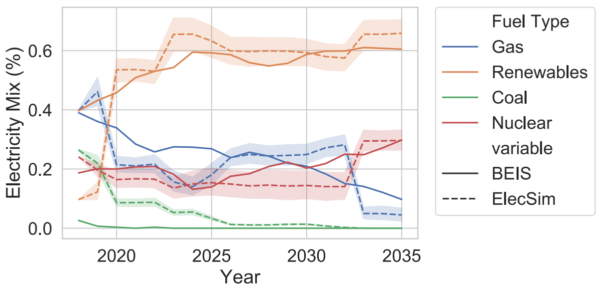

Figure 5: Comparison of ElecSim and BEIS' reference scenario from 2018 to 2035.

gas during the same year. In contrast, BEIS project a continuously increasing share of nuclear.

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

Figure 6 exhibits the price curves required to generate the scenario show in Figure 5. The majority of the price curves are similar to the simulated price duration curve of 2018 (red line). However, there are some price curves which are significantly higher and significantly lower than the predicted price curve of 2018. These cycles in predicted price duration curves may be explained by investment cycles typically exhibited in electricity markets [18].

In this context, investment cycles reflect a boom and bust cycle over long timescales. When electricity supply becomes tight relative to demand, prices rise to create an incentive to invest in new capacity. Price behaviour in competitive markets can lead to periods of several years of low prices (close to short-run marginal cost) [42].

As plants retire or demand increases, the market becomes tighter until average prices increase to a level above the threshold for investment in new power generators. At this point investors may race to bring new plants on-line to make the most out of the higher prices. Once adequate investments have been made, the market returns to a period of low prices and low investment until the next price spike [18].

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

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

6 CONCLUSION

In this paper we have demonstrated that it is possible to use agent based models to simulate liberalised electricity markets. Through cross-validation we are able to show that our model, ElecSim, is able to accurately mimic the observed, real-life scenario in the UK between 2013 and 2018.

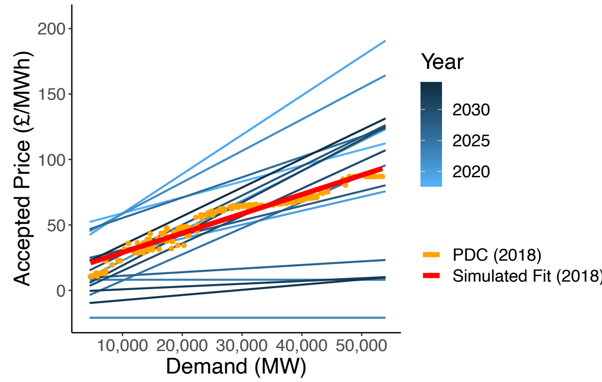

Figure 6: Comparison between optimal price duration curves and simulated price duration curve in 2018.

In addition to this, we were able to compare our long-term scenario to that of the UK Government, Department for Business, Energy & Industrial strategy. We show that we are able to mimic their reference scenario, however, demonstrate a more realistic increase in nuclear power.

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

We used a genetic algorithm to find the parameters that most closely matched the scenarios that we compared. The parameters found were realistic, providing confidence in the underlying dynamics of ElecSim.

In future work we would like to evaluate further scenarios to provide advice to stakeholders, integrate multi-agent reinforcement learning techniques to better model agents in both investment and bidding strategies and model different countries.

In addition to this, a method of dealing with the non-validatable nature of electricity markets, as per the definition of Hodges *et al.* is to vary input parameters over many simulations and look for general trends [20]. This could be achieved using ElecSim through the analysis of a reference case, and a limited set of scenarios which include the most important uncertainties in the model structure, parameters, and data, i.e. alternative scenarios which have both high plausibility and major impacts on the outcomes.

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