Validating the long-term electricity market model ElecSim

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Abstract

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1. Introduction

To limit the effects of climate change, a transition from a fossil-fuel based energy system to one based on low-carbon, renewable energy is required. The report by the Intergovernmental Panel on Climate Change detailed that reaching and sustaining zero global anthropogenic CO_2 would halt anthropogenic global warming on multi-decadal time scales [1].

The Paris Agreement was a declaration signed in 2015 by 195 state parties to plan and regularly report on the contribution made to mitigate global warming [2]. Based on this commitment, policy makers require quantitive advice on interventions to aid in the mitigation of climate change and limit global average temperatures to well below 2°C.

The decarbonization of electricity generation is of strategic importance for this goal due to the fact that low-carbon electricity can enable reductions in CO_2 emissions in industry, transport and building sectors [3].

However, there remain a number of uncertainties in the technological transition to a low-carbon energy supply. Examples of these uncertainties are investor behaviour, future prices of electricity generation and storage, domestic and international policy, energy efficiency and electricity demand. To successfully create effective policies an increase in understanding of these uncertainties and how they interact is required.

Energy modelling is a method that allows policy makers to increase their understanding of policy decision outcomes under a wide range of scenarios. Agent-based modelling (ABM) is a simulation technique that allows for heterogeneous agents to interact and can lead to effects on the aggregated level of the total system, a phenomenon called "emergence" [4]. Traditional models for analysing electricity systems, such as centralised optimisation models do not account for the heterogeneous nature of electricity investors and are, to some extent, based on obsolete assumptions [5].

In this paper we motivate that agent-based models are a valid way of complimenting existing models to provide advice to decision makers. We show that the model ElecSim [6] can be validated over a 5 year period, starting from the year 2013 and ending in the year 2018, with a root mean squared error of ~ 0.045 and a standard deviation of ~ 0.16. 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 [7]. However, distinctly to Nahmacher *et al.* we use a K-means clustering approach [8] as opposed to a hierarchical clustering algorithm described by Ward [9].

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. However, similar techniques can be employed for other countries of various sizes [6]. We are able to model the transitional dynamics of the electricity mix in the United Kingdom as shown in Figure 4, where there was an ~ 88% drop in coal use, ~ 44% increase in Combined Cycle Gas Turbines (CCGT), ~ 111% increase in wind energy and increase in solar from near zero to ~ 1250MW.

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. However, under the definition by Hodges *et al.* [10] long-range energy forecasts are not validatable

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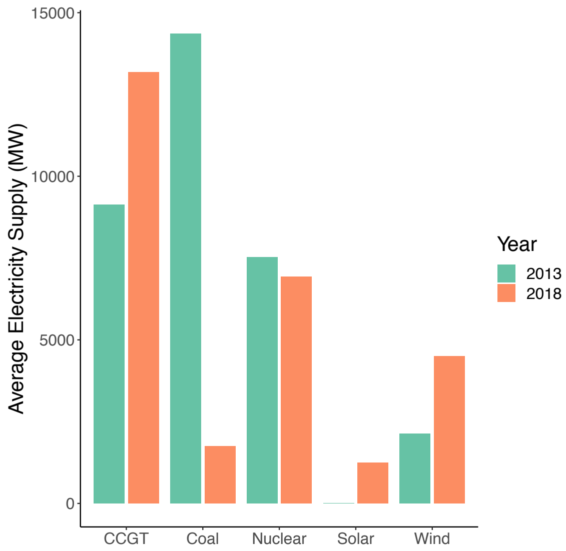

Figure 1: Electricity generation transition from 2013 to 2018 in the United Kingdom.

[11]. 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 [10].

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 or 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.

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 lead to a change in human behaviour. Thus avoiding the original scenario that was predicted.

A retrospective study published in 2002 by Craig *et al.* focused on the ability for forecasters to accurately predict electricity demand from the 1970s [11]. They found that actual energy usage in 2000 was at the very lowest end of the forecasts, with only one exception. They found that these forecasts underestimated unmodelled shocks such as the oil crises which lead to increased energy efficiency.

Hoffman *et al.* also developed a retrospective validation of a predecessor of the current MARKAL/TIMES model named Reference Energy System [12], and the Brookhaven Energy System Optimization Model [13]. These were applied in the 70s and 80s to develop projections to the Year 2000 . They found that the models were able 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. They concluded that forecasts must be expressed in highly conditioned terms [14].

Schurr *et al.* argued against looking too far ahead in energy modelling due to the uncertainties involved [15]. 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 guiding policy makers.

Work by Koomey *et al.* expresses the importance of conducting retrospective studies to help improve models [16]. For example, 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 and how much from incorrect specification of the fundamental drivers of the forecast [16].

Ascher concludes that the most significant factor in model accuracy is the time horizon of the forecast, with the more distant the forecast target, the less accurate, due to unforeseen changes in society as a whole [17].

It is for the reasons described in this section that this paper focuses on a relatively short-term (5 year) horizon window when choosing to validate the model.

- Energy systems modelling to help transition to low-carbon energy systems (Paris Agreement)
- Application of quantitive analysis to policy
- Use of agent-based models to model heterogeneous actors
- Optimum policy interventions for a smooth transition
- Requirement to validate model using historical data
- Prediction of electricity prices to understand optimal decisions
- Confidence in model under certain scenarios

2. Material and methods

- Reproducible data

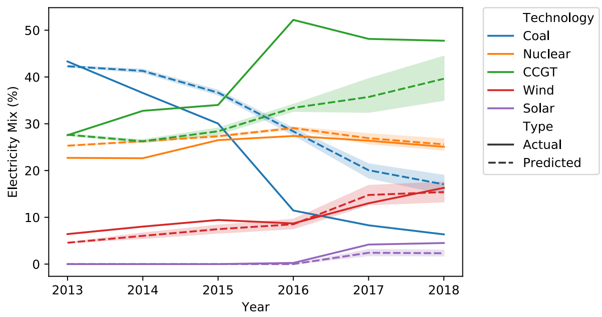

Figure 2: Electricity generation transition from 2013 to 2018 in the United Kingdom.

- Summarize previously published results
- Modifications of previous results for this paper

3. Calculations

- Practical development

4. Results

Technology	MAE	MASE	RMSE	SD
CCGT	6.42	0.59	7.94	5.27
Coal	9.3	0.4	10.79	10.83
Nuclear	3.05	1.52	3.16	1.38
Solar	0.59	0.43	0.97	1.23
Wind	1.36	0.24	1.58	4.56

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

- Clear and concise results

5. Discussion

- Significance of work
- Avoid discussion of public work

6. Conclusion

- Main conclusions

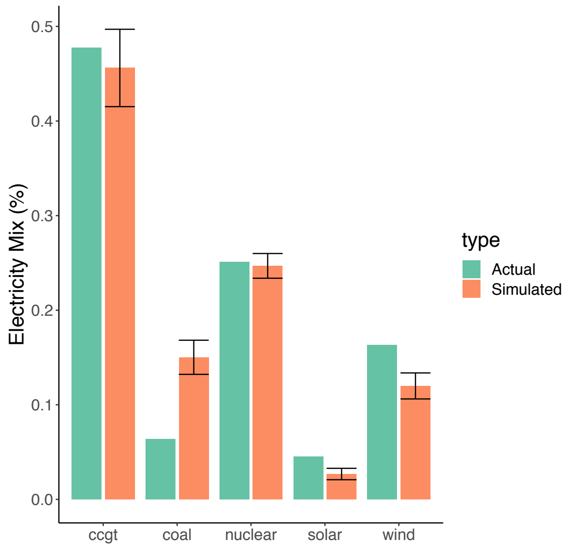

Figure 3: Electricity generation transition from 2013 to 2018 in the United Kingdom.

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