Validating the long-term electricity market model ElecSim

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Abstract

Keywords: Long-term energy modelling, model validation, Machine learning, Optimization

1. Introduction

To limit the effects of climate change, a transition from a fossil-fuel based 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 for a 5 year period, starting from the year 2013 until the year 2018, with a mean absolute percentage error of XX% and a standard deviation of XX. 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. We accurately capture 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) and a ~ 111% increase in wind energy.

- 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

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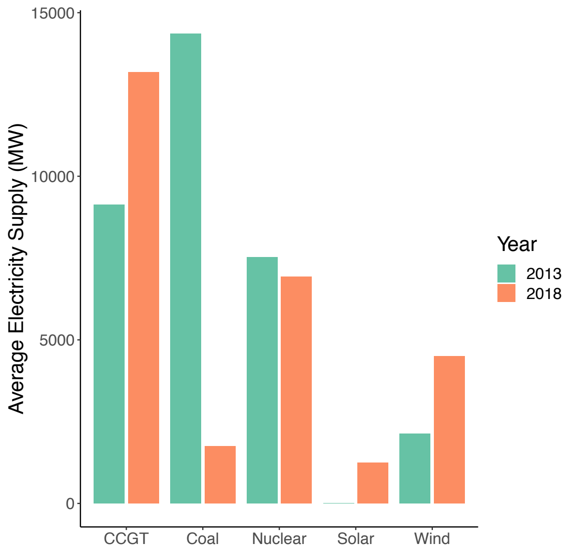

Figure 1: Electricity generation transition from 2013 to 2018 in the United Kingdom.

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

3. Calculations

- Practical development

4. Results

- Clear and concise results

5. Discussion

- Significance of work
- Avoid discussion of public work

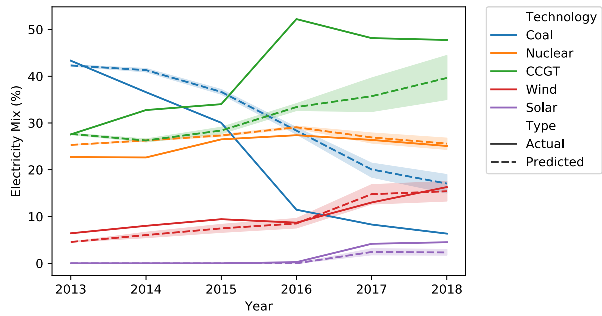

Figure 2: Electricity generation transition from 2013 to 2018 in the United Kingdom.

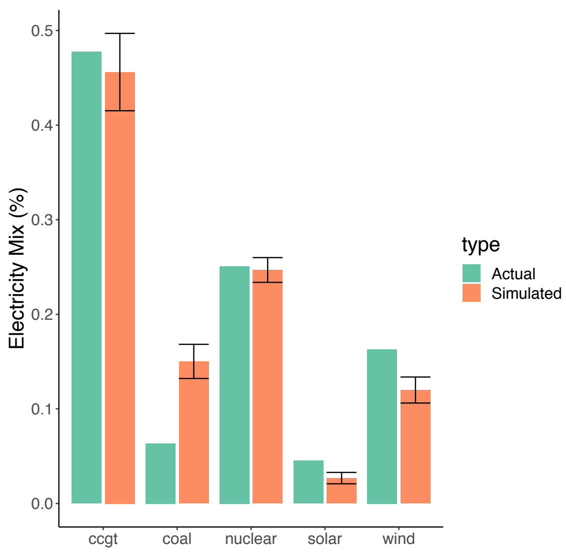

Figure 3: Electricity generation transition from 2013 to 2018 in the United Kingdom.

6. Conclusion

- Main conclusions

7. Funding Sources

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