Validating the long-term electricity market model ElecSim

Alexander J. M. Kell, A. Stephen McGough, Matthew Forshaw

School of Computing, Newcastle University, Newcastle-upon-Tyne, United Kingdom

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 root mean squared error of $\sim$ 0.045 and a standard deviation of $\sim$ 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. We accurately capture the transitional dynamics of the electricity mix in the United Kingdom as shown in Figure 4, where 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.

- 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 heteroge-

Email address: a.kell2@newcastle.ac.uk (Alexander J. M. Kell)

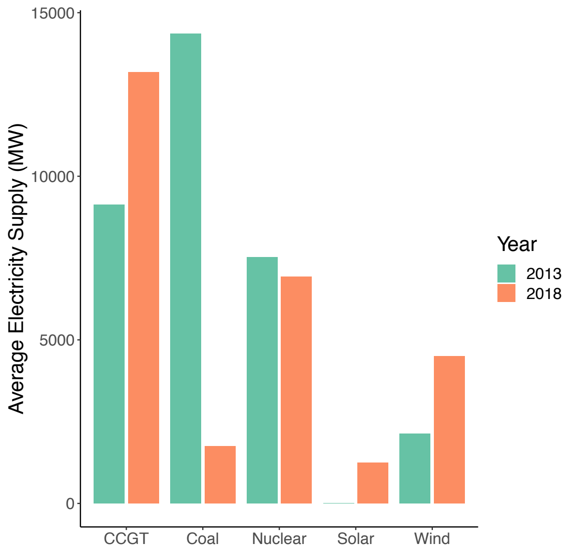

Figure 1: Electricity generation transition from 2013 to 2018 in the United Kingdom.

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

3. Calculations

- Practical development

4. Results

- Clear and concise results

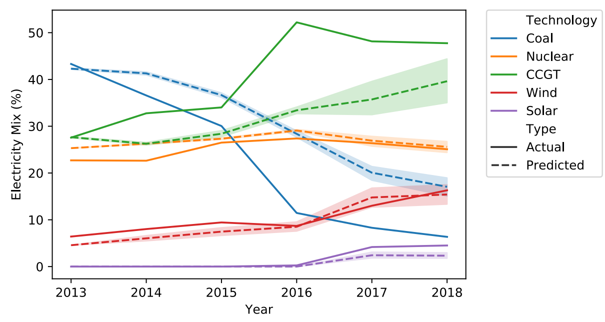

Figure 2: Electricity generation transition from 2013 to 2018 in the United Kingdom.

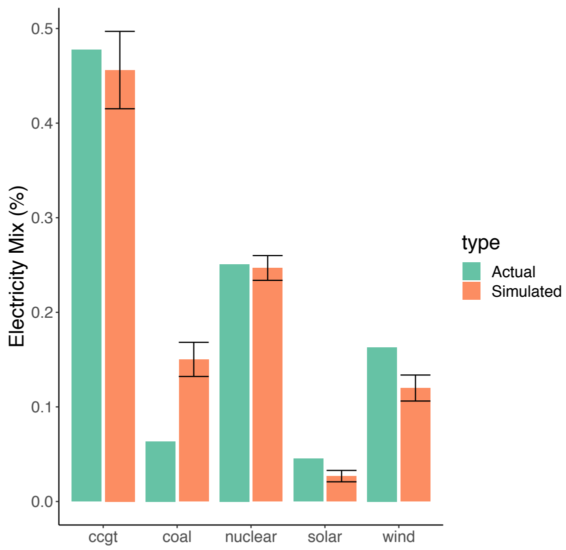

Figure 3: Electricity generation transition from 2013 to 2018 in the United Kingdom.

Technology	MAE	MASE	RMSE	SD
CCGT	6.42	0.592	7.941	5.266
Coal	9.303	0.397	10.791	10.831
Nuclear	3.055	1.519	3.161	1.375
Solar	0.592	0.428	0.969	1.226
Wind	1.357	0.244	1.579	4.563

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

5. Discussion

- Significance of work
- Avoid discussion of public work

6. Conclusion

- Main conclusions

7. Funding Sources

This work was supported by the Engineering and Physical Sciences Research Council, Centre for Doctoral Training in Cloud Computing for Big Data [grant number EP/L015358/1].

References

[1] V. Masson-Delmotte, P. Zhai, H. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, T. Waterfield, IPCC Special Report 1.5 - Summary for Policymakers, IPCC, 2018.

[2] Paris Agreement, United Nations 21 (2015) 1–23.

[3] P. Salas, The Effects of Uncertainty in the Technological Transitions of the Power Sector (March) (2017).
URL `https://www.repository.cam.ac.uk/bitstream/handle/1810/265885/Thesis_Pablo_Salas.pdf?sequence=1&isAllowed=y`

[4] a. Epstein, Joshua M., Generative Social Science: Studies in Agent-Based Computational Modeling /, course book. Edition, Princeton University Press,, Princeton, N.J. :.

[5] P. Ringler, D. Keles, W. Fichtner, Agent-based modelling and simulation of smart electricity grids and markets - A literature review, Renewable and Sustainable Energy Reviews 57 (2016) 205–215.

[6] A. Kell, M. Forshaw, A. S. Mcgough, ElecSim : Monte-Carlo Open-Source Agent-Based Model to Inform Policy for Long-Term Electricity Planning, The Tenth ACM International Conference on Future Energy Systems (ACM e-Energy) (2019) 556–565.

[7] P. Nahmmacher, E. Schmid, L. Hirth, B. Knopf, Carpe diem: A novel approach to select representative days for long-term power system modeling, Energy 112 (2016) 430–442. doi:10.1016/j.energy.2016.06.081.
URL `http://dx.doi.org/10.1016/j.energy.2016.06.081`

[8] E. Forgy, Cluster analysis of multivariate data: Efficiency versus interpretability of classification, Biometrics 21 (3) (1965) 768–769.

[9] J. H. W. Jr., Hierarchical grouping to optimize an objective function, Journal of the American Statistical Association 58 (301) (1963) 236–244. arXiv:https://www.tandfonline.com/doi/pdf/10.1080/01621459.1963.10500845, doi:10.1080/01621459.1963.10500845.
URL `https://www.tandfonline.com/doi/abs/10.1080/01621459.1963.10`