The impact of online machine-learning methods on long-term investment decisions in electricity markets

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

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

Abstract

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1. Introduction

The integration of higher proportions of intermittent renewable energy sources (IRES) in the smart grid will mean that the forecasting of electricity demand will become increasingly important. This is due to the fact that supply must mean demand at all times and that IRES are less predictable than dispatchable energy sources such as coal and combined cycle gas turbines (CCGTs) [1].

Typically, peaker plants, such as reciprocal gas engines, are used to fill fluctuations in demand, that hadn't been previously planned for. These peaker plants are typically expensive to run and have higher greenhouse gas emissions than their non-peaker counterparts [2].

To reduce reliance on peaker plants, it is helpful to know how much electricity demand there will be in the future, so that more efficient plants can be used to meet this demand. To aid in this, machine learning and statistical techniques have been used to accurately predict demand based on a number of different factors and data sources, such as weather, day of the week and holidays [3, 4, 5, 6].

Whilst various studies have looked at how to best predict electricity demand at various time horizons [7], the impact that the differing methods used have on a long-term electricity market have been studied to a lesser degree. In this paper, we compare a number of machine learning and statistical techniques to forecast 24 hours ahead to simulate a day-ahead market.

In addition to this, we use the long-term agent-based model, ElecSim [8, 9], to simulate the impact of different forecasting methods on long-term investments, power plant usage and carbon emissions from the year 2018 to 2035 in the United Kingdom.

To compare the impact of different methods we trial both online and offline machine learning and statistical techniques. Online learning methods are able to learn from novel data whilst maintaining what was learnt from previous data. This type of statistical modelling is useful for non-stationary datasets, and time-series data where recalculation of a model would take a prohibitive amount of time.

2. Literature Review

- Literature review on online machine learning and different impacts on long-term investment decisions (look for things directly similar to this work)

3. Material

- Introduce online learning, machine learning and ElecSim.
- Should I introduce theory behind machine learning techniques? If so, just the most successful?

4. Methods

- Use of hyperparameter tuning, talk about time taken to train/query models.
- Talk about ML methods used
- Talk about residuals
- Talk about sampling from residuals and placing these errors on the day-ahead market.

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

5. Results

- Results of offline learning, online machine learning shown. Include residuals and MAE,MAPE,MASE etc

- Results of the residuals on the output of ElecSim until 2035.

6. Discussion

- Discuss the impact of this on the electricity market and global economy. Make suggestions.

7. Conclusion

- Summary of work and future work.

8. Funding Sources

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