WHAT MACHINE LEARNING CAN TELL US ABOUT THE DRIVERS OF ELECTRICITY PRICES: THE CASE OF GERMANY

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Overview

In explaining the dynamics of electricity prices, a variety of economic modeling approaches is available in the literature. However, the existing models diverge not only in the choice of the functional form and the underlying assumptions but importantly also in their views on the key drivers of the power prices. The ongoing energy transition with the structural changes in demand and supply sides, caused by the rising penetration of renewables and the expansion of carbon-related restrictions, adds further to the complexity and calls "historical" insights into question. This study proposes a hybrid approach for modeling power prices based on machine learning (ML) algorithms, underpinned by economic insights.

Methods

We determine the top predictors of electricity prices and proceed to compare and assess the accuracy of alternative ML-based models, in predicting the power prices of Germany in the years 2016 to 2021. We investigate possible biases stemming from the ongoing energy transition and assess the degree to which historical information is relevant and should be retained for predicting future power prices.

Results

First, we determine the top 5 drivers of the electricity prices in Germany and show how the ranking of these variables with respect to their importance may change between different feature selection techniques, but that the members of the list stay the same. Next, we provide various statistics on the performance of the models and find the superiority of ensemble models for predictions. We find the prediction error to be the largest for the year 2021, during which Europe experienced unprecedentedly high energy prices. Thus, we find that despite the advantages of an ML-based approach and our ability to overcome interpretability issues, the inability to extrapolate beyond the historically observed range of values calls for further improvements in the modeling methodology.

Conclusions

Germany has been going through a rapid energy transition. The increase in the share of renewables in the energy system has led to increased fluctuations and hence, uncertainty in the electricity prices. Combining ML with economic insights, we offer a hybrid methodology to identify the key drivers of power prices. Comparing various setups, we find ensemble models to offer the best performance, but shocks, such as the energy price spikes seen in 2021 pose a threat to the accuracy of the predictions.

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