ECONOMETRIC ANALYSIS OF RESERVE ENERGY DEMAND.

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Overview

The necessity to decrease greenhouse gas emissions requires to increase the share of low-carbon technologies in the power mix, intermittent renewable energy sources representing a significant share. In addition, the electrification of heating and transports, among others, may increase peak demand or modify the load curve. In this context, the evolution of reserve needs may represent an important challenge for the power system. The evolution of reserve capacity needs in this context has been studied extensively in the literature (Hirth & Ziegenhagen, 2015). However, reserve energy needs have been little studied. This work focuses on establishing the relationship between reserve energy demand and the main drivers of imbalances, namely forced outages of power plants, demand and generation forecast errors (De Vos, et al., 2019). To that end, autoregressive models with exogenous variables are estimated.

Methods

We consider a data sample from 2016 to 2019. It is split into 24 independent samples, one for each hour of the day (Hinman & Hickey, 2009), (Weron & Misiorek, 2008). The data samples are cleaned for missing observations, measurement errors and outliers. The presence of unit roots at seasonal and the zero frequency is also investigated. The results presented in this paper concern the 15th hour of the day, where no unit root was found for any variable.
To investigate the link between secondary reserve (or aFRR) energy demand and the drivers of imbalances, autoregressive models with explanatory variables are estimated for each hour of the day separately (Ketterer, 2014), (Kyritsis, Andersson, & Serletis, 2017). Explanatory variables are load, wind and solar forecast errors as well as daily and monthly dummies. Models with load, wind and solar generation are also estimated to see if they can approximate the behaviour of their forecast errors.

Results

The results show that estimating the model for 2019 yield better results than in the period 2016-2019. They also show that the difference between the models with load, wind and solar and the ones with their forecast errors is relatively small.
In the model for upward aFRR, only wind generation is significant, apart from dummies. However, if we remove daily dummies, load becomes significant with a negative coefficient. It highlights the fact that in average, upward average aFRR is higher during week-ends. Thus, the negative effect of load allows greater levels of upward aFRR during weekends because load is lower for these days. Even if not significant, the coefficient of solar is negative. This sign can be explained by the fact that upward aFRR is higher during winter than during summer. Thus, the decreasing effect of solar is greater during summer, allowing higher levels of upward aFRR during this season. In addition, solar forecast errors represent a smaller share of solar generation during summer because it is less uncertain than the rest of the year.

Conclusions

The model estimated on 2019 data show that the impact of wind and solar generation on upward aFRR is small compared to one of load. This may be the results of the relatively low penetration rate of wind and solar. Upward aFRR is the highest during winter, when load and wind are high and solar is low. Future upward aFRR during winter might increase with the share of wind, as the positive coefficient of wind suggest.
It is also the period when the availability of conventional generation as a share of load is the lowest. It might mean that the liquidity of the intraday market is more limited during this period, reducing the possibility to balance forecast errors and thus increasing reserve energy demand in real-time.

References

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