THE EFFECT OF OFFSHORE WIND CAPACITY EXPANSION ON UNCERTAINTIES IN GERMANY'S DAY-AHEAD WIND ENERGY FORECASTS

David Schönheit, TU Dresden, Chair of Energy Economics, +49 351 463 39766, david.schoenheit@tu-dresden.de
Dominik Möst, TU Dresden, Chair of Energy Economics, +49 351 463 39770, dominik.moest@tu-dresden.de

Overview

Germany has seen rising onshore wind capacities in the past two decades, with a total installed capacity of around 56 GW at the end of 2018. At the same time around 5.6 GW of offshore wind parks were installed, with substantial capacities starting to be added in 2013. These large capacities make substantial contributions to the renewable energy generation. Large, additional wind offshore parks are supposed to be completed or fully commissioned in 2019. Until 2025, the total offshore wind capacity in Germany will almost reach 12 GW.[1]

Wind energy forecasts are subject to uncertainties due to errors in wind speed forecasts. This affects day-ahead decisions of power plant operators, e.g. unit commitment of conventional power plants, which take into account forecasts for renewable energy generation, at hand at the time of decision. Wind energy is characterized by variability and limited predictability. Additionally, it affects the power system at all hours of the day and does not necessarily coincide with load. Offshore wind turbines are consolidated to a higher degree due to large-scale wind parks. Generally, oceanic conditions and large hub heights result in high wind speeds for offshore wind turbines. Because of the cubic relation between wind speed and power output, wind speed forecast errors cause greater deviations in output at medium to high wind speeds, compared with low wind speeds. This could mean that offshore wind speed deviations have a greater effect on wind energy forecast errors, even when compared to onshore wind speed deviations of equal magnitude.

This paper analyzes forecast and actual wind speeds at a high geographical resolution from the ECMWF database, in particular the publicly available CAMS Near-real-time and ERA5 datasets.[2] The resulting deviations are used to evaluate (i) if differences exists in wind speed forecast errors for onshore and offshore locations and (ii) if offshore capacity expansion introduces greater uncertainty into aggregated wind energy forecasts due to higher wind speeds, greater consolidation of offshore wind capacities and possibly larger wind speed forecast errors.

Methods

First, a descriptive statistical analysis is conducted to evaluate location-specific differences in deviations between forecast and actual wind speeds. The deviations are evaluated regarding systematic deviations, average magnitude of deviations, variation of deviations and magnitude of extreme deviations.

The second part develops a machine learning-based Extremely Randomized Trees (Extra Trees) model to transform wind speeds, combined with location-specific capacities and capacity-weighted hub heights, into aggregated amounts of generated wind energy. The trained model is utilized to translate all available forecast and actual wind speed time series into wind energy, based on different cases of installed capacities. This is done for (i) a base case, using the actual installed capacity at the end of 2018, (ii) a case with an additional 5 GW of offshore wind energy and (iii) a case with an additional 5 GW of onshore wind energy. The resulting time series are used to compare deviations between forecast aggregated wind energy and actual aggregated wind energy. The distributions of deviations are compared across the three cases to evaluate if offshore capacity expansion leads to higher deviations in aggregated wind energy forecasts.

Results

The greater geographical consolidation of offshore wind capacities, due to large wind turbines and high accumulation of turbines into wind parks, translates into a higher capacity affected by forecast errors simultaneously.

[1] Capacities are obtained from a self-compiled dataset, with information on planned offshore power plants. The dataset is based on online databses of the federal state offices, agencies and ministries of Germany as well as The Wind Power and 4C Offshore.
[2] Note that this analysis contains modified Copernicus Atmosphere Monitoring Service Information and modified Copernicus Climate Change Service Information [2016-2018]. Neither the European Commission nor ECMWF is responsible for any use that may be made of the information it contains.

Further, wind speeds are, on average, higher offshore than onshore. The results indicate that offshore locations are subject to wind speed forecast deviations with greater standard deviations and higher average magnitudes. Additionally, the magnitude of large deviations is greater at offshore than onshore locations.

The comparison of actual amounts of wind energy, obtained from the ENTSO-E Transparency Platform, and results based on the trained Extra Trees model indicate that this is a viable method to transform geographically highly-resolved wind speed time series, in combination with location-specific capacities and capacity-weighted hub heights, into aggregated wind energy, without knowledge of power curves or other wind turbine characteristics. Based on a preliminary evaluation, the developed model's output shows smaller deviations from the ENTSO-E values than capacity factors available from EMHIRES and Renewables Ninja.

The results from the Extra Trees model suggest that the expansion of offshore wind capacity increases the frequency of medium to high forecast errors, namely deviations in the range of 1-5 GW, more substantially than the expansion of onshore wind capacity. The forecast error distribution under onshore expansion, however, shows heavier tails and consequently more frequent extreme deviations. This phenomenon likely stems from similar wind speed forecast errors that simultaneously affect many onshore locations and possibly from near-shore locations, which are characterized by the highest wind speed uncertainties in terms of magnitude and variability.

Conclusions

Taking into consideration the planned German offshore wind parks, which will add substantial capacities in the coming years, day-ahead markets will likely be subject to greater uncertainties regarding available wind energy. Extreme events, however, do not seem to increase with the expansion of offshore capacities. In addition to the more centralized feed-in of offshore wind energy at few nodes in the grid, the greater magnitude and variability of forecast errors of offshore wind speeds have to be accounted for when planning the integration of intermittent renewable energy.

Future research should validate the model's performance on longer time spans. Furthermore, bottom-up, fundamental modeling of wind power feed-in could serve as an additional performance benchmark for the Extra Trees model, whose advantage lies in the decreased effort to compile data.

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