Adv. Sci. Res., 20, 81–84, 2023
https://doi.org/10.5194/asr-20-81-2023

Advances in Science & Research
Open Access Proceedings

EMS Annual Meeting: European Conference for Applied Meteorology and Climatology 2022

Decentralized forecasting of wind energy generation with an adaptive machine learning approach to support ancillary grid services

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Published: 17 July 2023

Abstract. We report on an approach to distributed wind power forecasting, which supports wind energy integration in power grid operation during exceptional and critical situations. Forecasts are generated on-site the wind power plant (WPP) in order to provide blackout-robust data transmission directly from the WPP to the grid operator. An adaptively trained forecasting model uses locally available sensor data to predict the available active power (AAP) signal in a probabilistic fashion. A forecast generated off-site based on numerical weather prediction (NWP) is deposited and combined on-site the WPP with the locally generated forecast. We evaluate the performance of the method in a case study and find that the locally generated forecast significantly improves forecast reliability for a short-term horizon, which is highly relevant for enabling power reserve provision from WPPs.

1 Introduction

The volatility of wind power generation poses a challenge to grid operators when integrating it into the power grid. Obtaining grid-supporting services from wind power plants (WPPs) requires a reliable knowledge about the available active power (AAP) signal. Accurate forecasts, especially the nowcasting time horizon, hence play a crucial role, as they enable and allow for a more accurate planning of ancillary services like frequency containment reserve (FCR) and frequency restoration reserve (FRR) provision (Gomes et al., 2020). Probabilistic forecasts play an important role, since they allow an estimation of the uncertainty and reliability of the prediction (Späth et al., 2015) and they have the potential to improve human decision making, e.g, by taking less risky decisions (Möhrlen et al., 2022). One can predict the minimal AAP with certain levels of reliability, depending on the chosen percentile. A conservative choice (small percentile) of the power setpoint of a WPP is more reliable, whereas a more progressive choice (large percentile) predicts more control reserve with reduced reliablity. A useful tool for evaluation and the choice of an adequate percentile are *reliability lines*, i.e. is the ratio of the observed frequency of the AAP being larger than a forecast quantile q_α and the predicted frequency $1-\alpha$, which reads

$$r(\alpha) = \frac{p(P_{\mathrm{obs}} \geq q_\alpha)}{1-\alpha}. \tag{1}$$

To ensure blackout-robust availability of forecast data to the grid operator we suggest a two-fold setup: From a central computing server a probabilistic power forecast (hereafter called off-site component p_{off}) is distributed to the WPP. This forecast is derived from 7 different regional and global NWP models from different national and international weather services – each model serves as one ensemble member. On-site, an adaptive machine learning based forecasting system improves the NWP forecast ensemble in the nowcasting time horizon using data from local sensors (hereafter called on-site component p_{on}; see Sect. 2). The NWP forecast is calculated for single turbine locations based on various meteorological variables, where turbine-specific power curves are used to transfer wind speed to power. Each model is bias corrected with turbine specific observations of mainly wind and power data leading to typical error metrics of from 1 to $2\,\mathrm{m\,s^{-1}}$ RMSE for wind speed. In this study we used the most recent NWP data available. Experiments with a time lag of

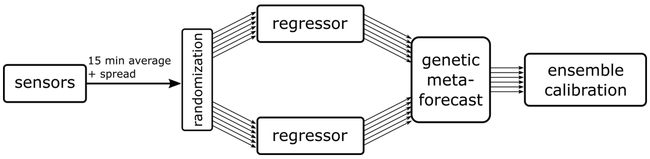

Figure 1. The process chain of the local forecasting model. Groups of arrows represent ensembles of scenarios.

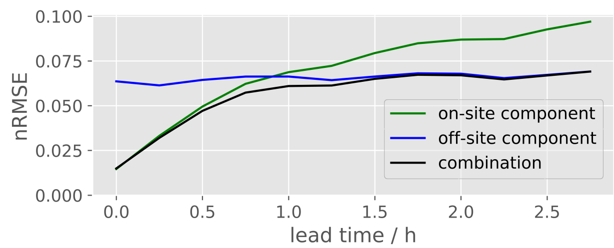

Figure 2. Root mean squared error (nRMSE) over leadtime, normalized to the installed power. Shown are on- and off-site component (each as stand-alone) as well as the final combination of both components.

up to 24 h showed a minor impact on the presented findings and are not reported here. Based on these data we then produce an hourly forecast of the different curtailments by using specific information of the turbine control strategy. We consider external factors (storm and icing shut down), regulatory curtailments (bat and bird protection, shadow and nighttime curtailment) and other losses (maintenance shut down, cable losses and others) to compile a forecast of the actual AAP for each turbine, which can then readily be aggregated, e.g. to WPP level.

This setup enables a blackout-robust forecast delivery via the WPP telecontrol interface to the grid operator, which is available as long as the WPP itself is available. The blackout-robust forecast transmission in combination with a special control mode of the WPP designed to support the grid operator in critical situations with FCR and an adjustable frequency setpoint has been validated in a field testing (Holicki et al., 2022; Abels et al., 2023).

2 Local model

Wind speed time series exhibit non-stationarity on short time scales already. Forecasting wind power generation therefore requires adaptive models, which are continuously improved upon sequentially arriving new data. The local model trains on a sliding window with a width of 24 h of local sensor data: wind speed from the nacelle anemometer, temperature at hub height and the technically available active power (AAP). The wind direction is estimated from the nacelle azimuth angle, which is corrected to account for misalignments among the turbines. Wind power generation can be viewed as a stochastic process. Following this perspective we generate data-based forecast ensembles by treating the input variables for the forecast models as stochastic variables, that are aggregated over 15 min bins. The input data scenarios (observation scenarios) are randomized using the variance and the mean of the time series in each bin. The ensemble spread hence represents the fluctuation of the data w.r.t. the time resolution. Figure 1 shows a sketch of this process.

The on-site component of the forecast is generated on hardware available in the WPP. It is therefore necessary to use only little computational resources (the set-up is designed to run on a Raspberry Pi type hardware). We use two very simple regression methods for the short-term forecast: The *ensemble persistence model* continues the distribution of the latest observations, modified with a lag-dependent weight factor. The probability density function (PDF) of the predicted variable y is constructed like

$$p(t+\mathrm{d}t, y) \propto \int_{-\infty}^{t} \mathrm{d}s\, p(s, y)\, e^{-|t-s|/\xi}, \tag{2}$$

where ξ is the temporal correlation length of the time series, that is obtained from a fit to past observations. Furthermore we use *gradient boosted tree regression* following an interval ansatz as described in Schicker et al. (2017) and Papazek et al. (2020).

The regressor outputs are then combined via genetic optimization w.r.t. their performances in earlier forecast cycles ("genetic metaforecast"). To this end an archive with 24 h of past forecasts and corresponding observation data is continuously updated. The combination weights are lead-time dependent such that the combined predictor reads

$$y_{\mathrm{meta}}(t) = \sum\nolimits_{m \in \{\mathrm{regressors}\}} w_m(t - t_0)\, y_m(t), \tag{3}$$

where t_0 is the first time stamp in the forecast. The weight functions $w_m(t-t_0)$ are normalized polynomials, whose parameters are subject to the genetic optimization procedure w.r.t. to the root mean square error (RMSE). This evolution is a Markov chain, which is tuned to not produce the optimal solution in each iteration. The solution candidates sluggishly follow the local minima of the cost function, and the termination criterion depends on the local density of agents in solution space. This way the weight evolution is robust against fluctuations and outliers in the data.

The forecast ensemble generated on-site $p_{\mathrm{on}}(t, y)$ is then combined with the off-site component $p_{\mathrm{off}}(t, y)$ like

$$p(t, y) = (f(t)\, p_{\mathrm{on}}(t, y)) * ((1 - f(t))\, p_{\mathrm{off}}(t, y)), \tag{4}$$

where $f(t) \propto e^{-t/\gamma}$ is a lead-time dependent relaxation function, that smoothly connects the two components. The combined ensemble is then calibrated using Ensemble Copula Coupling, as in Späth et al. (2015).

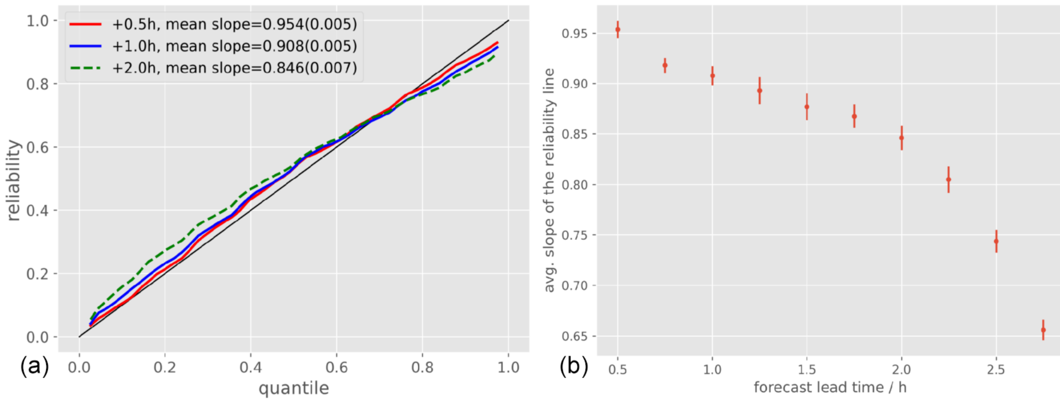

Figure 3. **(a)** Reliability lines for different forecast horizons (1/2, 1, 2 h). The x-axis of the plots shows the prediction quantile and the y-axis the relative frequency with which the actual AAP is below or equal the respective prediction quantile. The diagonal represents the ideal reliability. **(b)** The mean slopes of the reliability lines over lead time.

3 Performance evaluation

As a case study, the forecasting system was subjected to a long-term test for a single WPP with 22 turbines and a total installed power of 51.9 MW over a period from June to December 2022. We find that, depending on the forecast horizon, the availability of up-to-date measurement data has a major impact on the forecast quality. Compared to the off-site generated forecast, these data lead to a significant improvement in a time horizon of up to 2 h, whereas for forecast horizons larger than one hour, the consideration of the off-site component improves compared to the on-site component alone (see Fig. 2). The relevant time-horizon depends on the actual use case at the grid operators control centre and in case of a grid restoration process, this includes the horizons of less than one hour for taking actions to a few hours for planning purposes.

In the left panel of Fig. 3 the reliability lines of the forecast of the minimal AAP at lead times 1/2, 1 and 2 h are shown. The diagonal indicates ideal reliability. In order to assess the average reliability of a prediction, the mean slope of the reliability line is determined from a fit. In the right panel of Fig. 3 these mean slopes of the reliability lines are plotted over the forecast lead time. For lead times up to 2 h the reliability is very high and then drops, where the off-site component becomes dominant in the forecast. We conjecture, that the on-site component strongly improves upon forecast reliability for lead times where observation data has the largest impact. The improvement in forecast quality due to this forecast set-up occurs exactly in the time window that has the greatest relevance for short term decision making in grid operation, e.g. during exceptional or critical situations.

4 Conclusion and outlook

In this article we have described a distributed power forecasting procedure for short time horizons (nowcast) of the first few hours that consists of an off-site component (from a central computing server) and an on-site component (to be generated at the WPP). This setup provides the grid operator with valuable information about the AAP and hence enables the provision of power reserve from WPPs. Data delivery directly via the WPPs telecontrol interface ensures blackout-robust forecast transmission. To our knowledge, it is the first time such a forecasting system has been designed and tested that allows, also in case of a wide-spread blackout, to combine NWP forecast data with actual sensor data and to deliver the forecast to the grid operators control centre to support grid operation. Furthermore, the incorporation of most recent observation data improves the forecast quality and ensures a high level of reliability of the predicted AAP signal. From our point of view, a research entity could consider further research building on the results of our case study, e.g. by comparing different forecasting methods or by investigating whether the on-site improvements to the power forecast depend on parameters such as location (wind farm size, climate zone, terrain complexity, height above ground, ...) or season or time-of-day, to name just a few possible parameters.

Code availability. The software code used to generate these data is not publicly accessible as it is property of WRD Wobben Research and Development GmbH.

Data availability. The data presented here is not publicly accessible as it is property of WRD Wobben Research and Development GmbH.

Author contributions. LH contributed Conceptualization, Methodology, Investigation, Project administration, Software development to the presented research. Software development was conducted by LH, MD and GS. MD contributed Validation

and Investigation and ML Supervision and Resources. All authors wrote and reviewed the paper.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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Special issue statement. This article is part of the special issue "EMS Annual Meeting: European Conference for Applied Meteorology and Climatology 2022". It is a result of the EMS Annual Meeting: European Conference for Applied Meteorology and Climatology 2022, Bonn, Germany, 4–9 September 2022. The corresponding presentation was part of session: OSA2.3: Energy meteorology.

Financial support. The presented research has been carried out in the joint research project "SysAnDUk" (Ancillary services provided by distributed generators to support grid operators in critical situations and during system restoration) (FKZ 03EI4004A) (Becker et al., 2020, 2021) funded by the German Federal Ministry for Economic Affairs and Climate Action.

Review statement. This paper was edited by Sven-Erik Gryning and reviewed by two anonymous referees.

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