Short-term wind power forecasting with responses transformation for taking into account wind turbine operational state

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Abstract - The amount of electricity production provided by wind farms is increasing globally. In this regard, the accurate and reliable wind power forecasting for ensuring efficient operation of wind farms as part of energy systems is becoming crucial issue. The most rarely considered among the possible methods for prediction errors reducing is changing of the prediction responses and the individual wind turbines power aggregation method: forecasting at the turbine level, at the groups of turbines and at the wind farm level. There is no consensus yet on which approach is most effective. Also, the issue of taking into account the wind turbines operational state is not adequately covered in reported studies on the wind power forecasting. And the observations corresponding to the switched-off state of turbines are most likely considered as outliers. In this paper the effect of spatial smoothing within a wind farm is investigated and the evaluation of the response selection and individual turbines power aggregation approaches effectiveness in terms of the wind farm output prediction is performed. And finally, a new technique for taking into account the number of switched-off wind turbines based on response transformation for short-term wind power forecasting at the turbine groups and wind farm levels is proposed.

WIND TURBINES POWER AGGREGATING APPROACHES

Three main approaches for wind power forecast (WPF) response selection and the individual wind turbines power aggregating can be distinguished:

- **The wind farm level (P)** forecast which is aggregation of all wind farm turbines power to obtain a response, training one model for whole wind farm and the total wind farm power prediction;
- **The wind turbines groups level (G)** forecast which is aggregation of the turbines power by group, training the model for each group, power prediction for each group and aggregation of all groups forecasts to obtain the wind farm total power output prediction;
- **The turbine level (T)** forecast which is the model training for each turbine, prediction of power output for each turbine and aggregation of all turbines forecasts to obtain the wind farm total power output prediction.

There is no consensus yet on which approach is most effective.

PROPOSED RESPONSE TRANSFORMATION TECHNIQUE

This paper proposes a new technique for taking into account wind turbines operational state for WPF at the turbine groups and wind farm level based on response transformation (RT).

It is proposed to transform the responses by recalculating the actual wind turbines measured power into the possible available turbines power, based on the number of units with available switch-on operational state. Calculation of available power is carried out according to the relation:

$$\boldsymbol{P_{av}} = \boldsymbol{P} \cdot \frac{\boldsymbol{K}}{\boldsymbol{K_{av}}}, \qquad (1)$$

where $\boldsymbol{P_{av}}$ – available power, kW; $\boldsymbol{P}$ – measured power, kW; $\boldsymbol{K}$ – number of turbines in group or farm; $\boldsymbol{K_{av}}$ – number of available turbines.

The response transformation according to this ratio is performed for the training sample. The inverse relationship is used to adjust the forecasted available power values to the actual power of turbines group or wind farm.

CASE STUDY

Experimental setup

The real-world wind farm with total installed capacity of 98.8 MW was considered as the object of the study. The numerical weather prediction (NWP) data on wind speed, wind direction, temperature, humidity and atmospheric pressure were used to train the models and make forecasts. In this work, short-term forecasts for 24 hours ahead were performed. The total number of observations in the considered data set is 6343.

In this study 9 simulations were carried out to determine the most effective WPF strategy. The descriptions are shown in Table I. In all cases, the forecast result is the total output power of the whole wind farm. In this work the gradient boosting over decision trees algorithm (GBDT) is used as a regression model. The regression model hyperparameters are determined during each simulation using Bayesian optimization.

Table I. – Simulations for comparing WPF strategies

Label	WPF level	$\boldsymbol{K_{av}}$ as feature	RT
1P	Farm	No	No
2G	Groups	No	No
3T	Turbines	No	No
4TS	Farm	Yes	No
5TS	Groups	Yes	No
6TS	Turbines	Yes	No
7PRT	Farm	No	Yes
8GRT	Groups	No	Yes
9TRT	Turbines	No	Yes

The following metrics are used to assess the accuracy and reliability of the obtained forecasts:

$$\boldsymbol{NRMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{e_i}{P_{inst}}\right)^2} \cdot 100\%. \qquad (2)$$

$$\boldsymbol{NMAE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|e_i|}{P_{inst}} \cdot 100\%. \qquad (3)$$

$$\boldsymbol{EICP_{20}} = \frac{1}{N}\sum_{i=1}^{N} c_i \cdot 100\%, \qquad (4)$$

$$\boldsymbol{SS} = \left(1 - \frac{NRMSE_{eval}}{NRMSE_{ref}}\right) \cdot 100\%, \qquad (5)$$

Results and discussion

Table II presents the results of assessing the accuracy and reliability of compared WPF strategies. It also illustrates the time spent training the models in each simulation in relative units.

Table II. – Accuracy and reliability of WPF strategies evaluation

Label	SS, %	NRMSE, %	NMAE, %	EICP_20, %	T, pu
1P	0.0	14.2	10.2	85.3	1.0
2G	7.6	13.1	9.5	86.5	1.5
3T	7.2	13.2	9.6	87.0	16.4
4PS	1.6	14.0	10.0	85.3	1.1
5GS	10.6	12.7	9.3	89.1	1.7
6TS	7.6	13.1	9.5	87.6	20.9
7PRT	3.1	13.7	9.5	86.4	1.0
8GRT	13.4	12.3	8.8	89.4	1.5
9TRT	11.0	12.6	9.0	88.6	16.5

The following conclusions can be drawn based on the obtained results.

1. The use of the turbine level (**3T**) and group level (**2G**) WPF strategies reduced the forecast error comparing to wind farm level (**1P**). Training individual models for each took approximately 10 times more time than training models for each group of turbines.
2. The use of available turbines number as a feature (**4PS**, **5GS** and **6TS**) increases the WPF accuracy for all wind turbines power aggregating approaches. The best skill score for this types of simulation is **10.6%** and corresponds to group level WPF (**5GS**).
3. The proposed RT technique also proves its effectiveness for all WPF levels. The highest efficiency is achieved for turbine groups level WPF strategy with skill score **13.4% (8GRT)**. It is also worth noting that using RT reduces the training time of one regression model by about 10% comparing to additional features.
4. The best skill score of **13.4%** corresponds the use of turbine groups WPF strategy and response transformation based on turbine availability data (**8GRT**).

Based on the forecast errors outlier analysis using Fig.1 it can be judged that the overall error decrease was largely achieved by eliminating gross errors. Only a small number of observations displayed in shades of yellow and red (about 15 pcs.) on Fig.2 corresponds to an error of more than 35 MW.

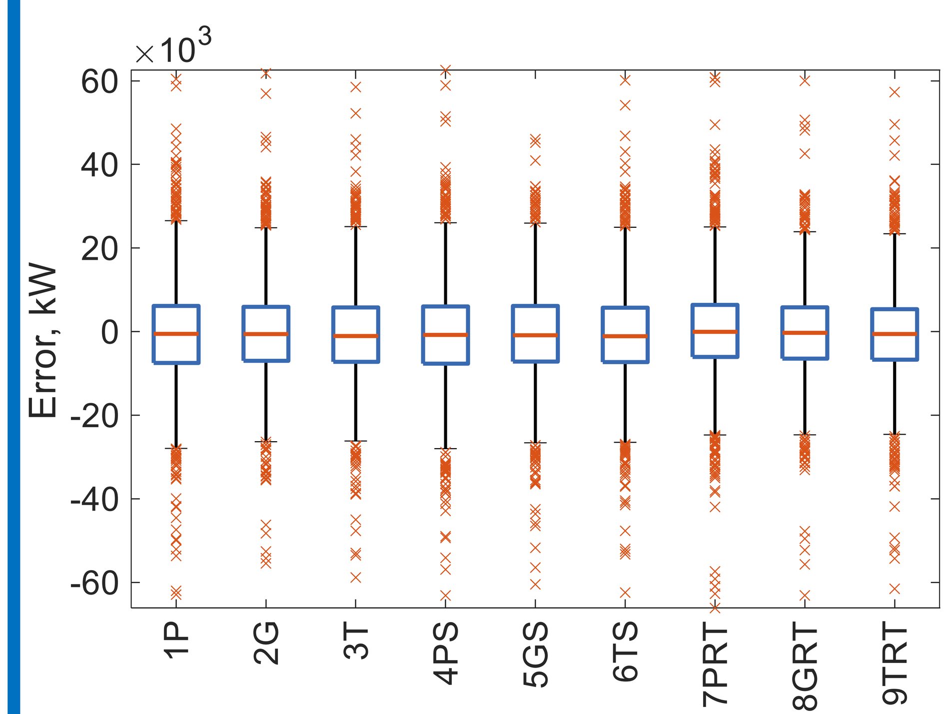

Fig.1. WPF strategies errors boxplot

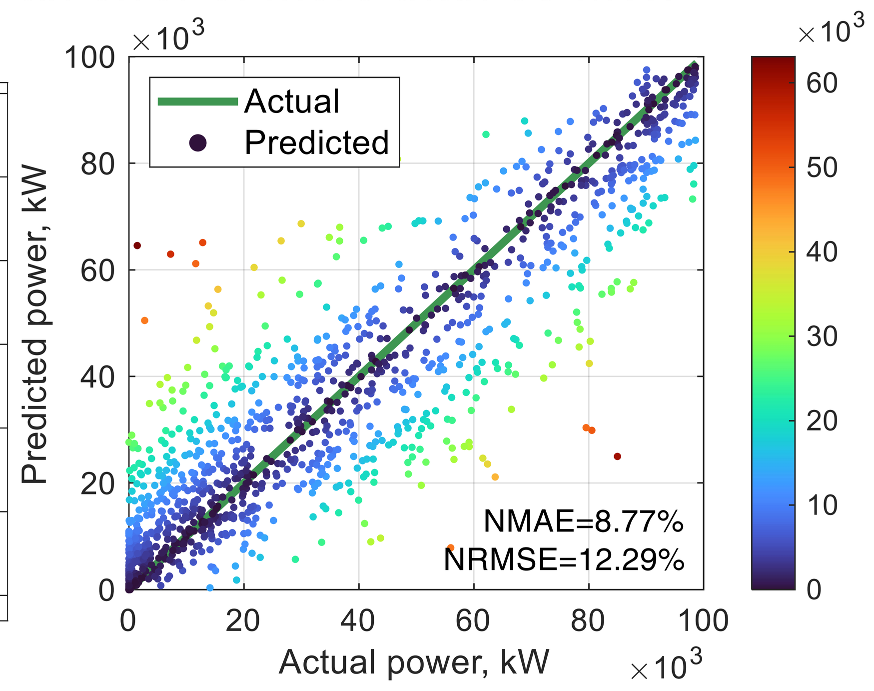

Fig.2. 8GRT simulation prediction error scatter diagram

CONCLUSIONS

Based on the experiments results, it was found out that the lowest prediction error is achieved by the use of the turbines groups level WPF approach. The NRMSE skill score for turbine groups WPF strategy was 7.6% for conducted experiments.

It was also discovered that wind turbines operational state utilization can reduce the forecast error, both as a predictor and as mean for response transformation. A greater effect was achieved with proposed response transformation technique. The NRMSE skill score for turbine groups WPF strategy with availability-based response transformation was **13.4%**.