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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.

Key words. Wind power forecast, aggregated forecast, data preprocessing, wind turbine operational state, response transformation, machine learning.

1. Introduction

The amount of electricity production provided by renewable energy sources is increasing globally. A significant share of this amount comes from wind farms. In this regard, the accurate and reliable wind power forecasting (WPF) for ensuring efficient operation of wind farms as part of energy systems is becoming crucial issue. The solution to this problem is required for power systems regimes planning, the wind farms participation in the electricity markets, as well as the power system automatic and dispatch control. A particularly urgent need for accurate and reliable WPF arises in power systems with a large share of installed wind power capacity, weak links with neighboring power systems and sufficiently low active power reserves.

The wind power forecasting problem usually comes down to determining the regression model and its parameters using a training set of predictors (wind speed, wind direction, etc.) and responses (wind farm power output). The resulting model should enable to determine the predictive value of the response forecast based on forecasted predictors.

As a rule, the increase of WPF efficiency can be achieved due to:

- The data preprocessing, which usually includes the training set outlier detection and elimination [1],[2];
- The feature transformation for relevance increasing, most often achieved with data normalization or standardization, also wavelet transforms are widely used [3]-[5];
- The feature selection providing the determination of the most relevant predictors (including among transformed ones), also reducing the regression model size and training time [4]-[7];
- The regression model determination (in the last decade, increasing preference has been given to machine learning models) [5],[7]-[9];
- The model hyperparameters optimization, that is the selection of the parameters that are set before training process [6],[10].

The response selection is the most rarely considered way to increase the wind power forecast efficiency while building regression models. Commonly the wind farm total power output is used as a response. This approach uses the spatial smoothing effect reported in some research [11],[12] to be a way to improve overall model accuracy and reduces the computational costs of training individual models for each turbine. However, spatial smoothing in some cases leads to a decrease in the correlation between the initial weather data and the wind farm total power output due to the very different location conditions of each wind turbines even at the same wind farm. Turbines can be located at a considerable distance from each other (up to 10 km or more), and may also be subject to shading effects in relation to each other or landscape elements. These facts can reduce the accuracy and reliability of WPF at farm level [13]. A number of studies consider an approach based on the limited use of spatial smoothing by combining turbines into groups within one wind farm [11],[14].

2. Wind turbines power aggregating approaches

Based on the results of previously reported studies, three main approaches for wind power forecast response selection and the individual wind turbines power aggregating can be distinguished [11-14]:

- The wind farm level 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 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 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.

The choice of one approach or another can have a significant impact on the way the wind turbine operational state is considered while training models and after that subsequently obtaining predictions. The issue of taking into account the wind turbines operational state is not adequately covered in reported studies on the WPF. The observations corresponding to the switched-off state of turbines are most likely considered as outliers and excluded from training samples and even from test samples. The outlier detection is usually performed using a wind turbines power curve obtained from pairs of wind speed and power measurements [15].

A significant number of outlier points are fall in the region with power values close to zero, occurring along the entire wind speed axis. And particularly these points can be associated with the turbine switched-off state associated with maintenance, failure or the control system malfunction. Given the number of these points, it is quite difficult to explain them by power or wind speed measuring devices failures. This type outlier detection can be carried out only at the individual turbines power curve level. An observation with an incomplete set of available turbines will correspond to reduced power for the certain value of wind speed at the wind farm level or turbines group level. Depending on the chosen methods for outlier detection, this observation can be included in the training dataset, which will lead to the regression model distortion due to the inconsistency between wind speed and available turbine power.

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.

3. Proposed response transformation technique

For these individual turbines power aggregating approaches 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.

As it was performed in works of other researches taking into account the wind turbine operational state in the training set for the turbine level WPF is carried out by excluding observations with unavailable turbine state as outliers. In this case, the predicted turbine power is equal to zero if the planned turbine operational state is switched-off.

The use of the proposed approach requires the wind turbines operational state data, which is often inaccessible. This lack of this information can be addressed utilizing an empirical expression to determine the turbines operational state based on the measured wind speed and the measured power for each turbine:

$$\begin{aligned} \boldsymbol{V} &> \Delta_{\boldsymbol{u}} \cdot (\boldsymbol{1} + \Delta\boldsymbol{V}) \cdot \boldsymbol{V_{cut-in}} \\ \boldsymbol{P} &< \Delta_{\boldsymbol{u}} \cdot \boldsymbol{P_{tres}} \cdot \sqrt{\boldsymbol{3}\Delta\boldsymbol{I^2} + \Delta\boldsymbol{U^2} + \Delta\boldsymbol{P^2}} \cdot \boldsymbol{P_{rated}} \end{aligned}, \qquad (2)$$

где $\boldsymbol{V}$ – measered wind speed, m/s; $\Delta\boldsymbol{V}$ – wind speed measuring devices error, which is assumed to be 0.02; $\Delta_{\boldsymbol{u}}$ – correction factor for unaccounted errors, which is taken equal to 1.1; $\boldsymbol{V_{cut-in}}$ – the turbine cut-in wind speed, m/s; $\boldsymbol{P}$ – the turbine measuered power, kW; $\boldsymbol{P_{tres}}$ – threshold turbine power for determining the switched-off state, which is taken equal to 0.05; $\Delta\boldsymbol{I}$ – current transformer error, which is assumed to be 0.05, and taking into account possible initial magnetization at low current increases by three times; $\Delta\boldsymbol{U}$ – voltage transformer error, which is assumed to be 0.05; $\Delta\boldsymbol{P}$ – power measurement error, which is assumed to be 0.05; $\boldsymbol{P_{rated}}$ – the wind turbine rated power.

4. Case study

A. Data description

The real-world wind farm with total installed capacity of 98.8 MW was considered as the object of the study. Wind farm is located at Rostov region (Russia). There are 26 Vestas V126-3.80 wind turbines installed at the wind farm. The installed capacity of each unit is 3.8 MW. The cut-in wind speed is 3 m/s.

The initial data set included SCADA measurements of each turbine's power and wind speed at nacelle height. This data was used to determine the condition of the turbines. 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.

B. Experimental methodology

In this study 9 simulations were carried out to determine the most effective WPF strategy. These experiments vary the wind turbines power aggregating approaches (wind farm level, group level and turbine level), whether or not the available turbines number is used as a feature, and whether the proposed response transformation based on turbines availability is performed. In all cases, the forecast result is the total output power of the whole wind farm.

The turbines grouping was carried out using simplified approach based on the geographical location proximity, determined by connection of turbines to feeders.

The descriptions and labels for WPF forecasting strategies simulations comparing are shown in Table I.

Table I. – Simulations for comparing WPF strategies

Label	Forecast level	Availability as feature	Availability based response transformation
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

One general regression model is built for the wind farm level WPF. One model for each group of turbines is built for the group level WPF. And individual model for each turbine is trained for the wind turbine level.

In this work the gradient boosting over decision trees algorithm (GBDT) is used as a regression model [16]. This machine learning method produces fairly accurate regression models with a quite low computational cost, which is an important factor since training time increases in proportion to the number of turbines for turbine-level forecast simulations.

The regression model hyperparameters are determined using Bayesian optimization [17],[18]. The foloowin parameters were optimized: the number of models in ensemble, learn rate, minimum number of leaf node observations, maximal number of splits within one regression tree and number of predictors to select at random for each split.

All observations are assumed to be an independent and identically distributed random variables since the 24 hours WPF is performed during simulations and no lag features is used. This assumption allows to randomly select the test data set observations and to use a standard 5-fold cross-validation with random dataset divisions.

20% of observations (1268 obs.) are removed from the original data set and used to evaluate metrics for WPF strategies comparison. The remaining observations (5075 obs.) are used to train and validate models during hyperparameters optimization. Bayesian optimization performs a directed search of various hyperparameter configurations, while minimizing the average value of the quadratic loss function obtained using cross-validation..

5 models were trained at each iteration of Bayesian optimization because cross-validation was used. A total of 60 hyperparameter optimization iterations are performed. Also, another model is trained on a whole training and validation set with the obtained hyperparameters.

Thus, in total, within each simulation the following number of regression models is trained:

- for the wind farm level WPF – 361 models;
- for the level of turbine groups WPF – 1444 models;
- for turbine level –9386 models.

The models were trained in parallel using 12 processes.

The wind farm level WPF without taking into account the wind turbines operational state is considered as a reference experiment.

The experiments were carried out using MATLAB software package. Statistics and Machine Learning Toolbox was used to perform machine learning models training and hyperparameters optimization [19].

C. Evaluation metrics

The following nomenclature is used for describing metrics to assess the WPF accuracy and reliability:

$\boldsymbol{P_{inst}}$ – wind farm installed capacity, kW;

$\boldsymbol{N}$ – number of observations in test sample;

$\boldsymbol{P_i}$ – actual measured output power for $\boldsymbol{i}$-th observation, kW;

$\boldsymbol{\hat{P}_i}$ – forecasted output power for $\boldsymbol{i}$-th observation, kW;

$\boldsymbol{e_i}$ – forecast error for $\boldsymbol{i}$-th observation, kW.

The forecast error is determined according to the formula:

$$\boldsymbol{e_i = P_i - \hat{P}_i}. \tag{3}$$

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

Normalized to rated power root mean square error (*NRMSE*) is a quadratic metric. The greater the error value, the greater this error square contribution to the metric value. The following expression is used to evaluate this parameter:

$$\boldsymbol{NRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{e_i}{P_{inst}}\right)^2} \cdot 100\%}. \tag{4}$$

Normalized to rated power mean absolute error (*NMAE*) sums up all absolute errors linearly. All considered errors make a proportional contribution to the metric. It can be calculated using:

$$NMAE = \frac{1}{N}\sum_{i=1}^{N}\frac{|e_i|}{P_{inst}} \cdot 100\%. \qquad (5)$$

Normalized to total amount of actual values sum of absolute errors (*NSAE*) indicates the total electrical energy forecast error, since the numerator and denominator use the active power sum averaged over the same time interval. The following formula is used to calculate this metric:

$$NSAE = \frac{\sum_{i=1}^{N}|e_i|}{\sum_{i=1}^{N}P_i} \cdot 100\%. \qquad (6)$$

Error interval coverage probability for +-20% of rated power interval (*EICP_20*) is used as a metric to evaluate the resulting forecasts reliability. This value shows the share of errors that are in the +-20% range of the wind farm installed capacity. This metric is close to the *PICP* metric, but does not require prediction intervals calculation and is easier to understand. This metrics is calculated using:

$$EICP_{20} = \frac{1}{N}\sum_{i=1}^{N} c_i \cdot 100\%, \qquad (7)$$

where c_i is determined using

$$c_i = \begin{cases} 1, if\ |e_i| < 0.2 \cdot P_{inst} \\ 0, otherwise. \end{cases} \qquad (8)$$

The *NRMSE* metric is used as a main in this work to compare the effectiveness of WPF strategies. The skill score (*SS*) is used to estimate the effectiveness of considered strategy comparing to the reference. It can be calculated as:

$$SS = \left(1 - \frac{NRMSE_{eval}}{NRMSE_{ref}}\right) \cdot 100\%, \qquad (9)$$

where $NRMSE_{eval}$ – *NRMSE* value for evaluated WPF tecnique, %; $NRMSE_{ref}$ – *NRMSE* value for reference WPF tecnique, %. In this study, the simulation labeled 1P is used as a reference.

D. *Results and discussion*

In accordance with the experimental methodology, the series of simulations for wind power forecasting was performed.

Table II presents the results of assessing the accuracy and reliability of compared WPF strategies. The table presents the metrics described in the previous section. It also illustrates the time spent training the models in each simulation in relative units, using the time spent training the models in **1P** simulation as the base. The following conclusions can be drawn based on the obtained results.

1. The **1P**, **2G** and **3T** simulations comparison reveals that turbine level and group level WPFs reduce the forecast error. The **2G** and **3T** simulation results are approximately the same in terms of skill score, 7.6% and 7.2%, respectively. Moreover, training individual models for each turbine in simulation **3T** took approximately 10 times more time than training models for each group of turbines in experiment **2G**.
2. The results analysis for simulations **4PS**, **5GS** and **6TS** related to the use of available turbines number as a feature indicates that this strategy increases the WPF accuracy for all wind turbines power aggregating approaches. The most effective use of this feature was for the turbine groups level forecast **5GS**. The skill score for this simulation is 10.6%.
3. It can be concluded based on the results for **7PRT**, **8GRT** and **9TRT** simulation related to proposed response transformation technique that these strategies are superior among other considered. Proposed approach also proves its effectiveness for all WPF levels. The highest efficiency is achieved for turbine groups level forecasting strategy **8GRT** with skill score 13.4%. It is also worth noting that using response transformation reduces the training time of one regression model by about 10% comparing to additional features.
4. The best skill score of 13.4% among the performed experiments corresponds to the **8GRT** experiment, which used the turbine groups strategy and response transformation based on turbine availability data.

Table II. – Accuracy and reliability of WPF strategies evaluation

Label	SS, %	NRMSE, %	NMAE, %	EICP_20, %	Train time, 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 WPF strategies errors boxplot is shown at Fig. 1. The plot shows that for all simulations errors median highlighted by orange lines coincide and are close to zero. The upper and lower box boundaries indicating the 25th and 75th percentile of errors highlighted in blue are also close. But these lines are slightly closer to each over for **5GS**, **8GRT** and **9TRT** simulations. Based on the forecast errors outlier analysis, indicated by orange crosses, it can be judged that the overall error decrease was largely achieved by eliminating gross errors. This errors probably arose due to lack of wind turbines operational state taking into account.

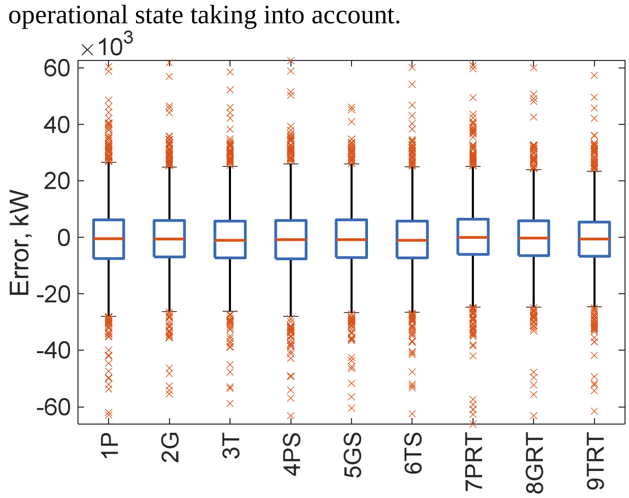

Fig.1. WPF strategies errors boxplot

A significant part of the test sample observations are indicated in blue and light blue and are concentrated along the diagonal line. For such observations, the forecast error is close to zero or less than 15 MW. Approximately 15 percent of observations are concentrated in the 15-35 MW error range and are appeared in shades of green. And only a small number of observations displayed in shades of yellow and red (about 15 pcs.) corresponds to an error of more than 35 MW.

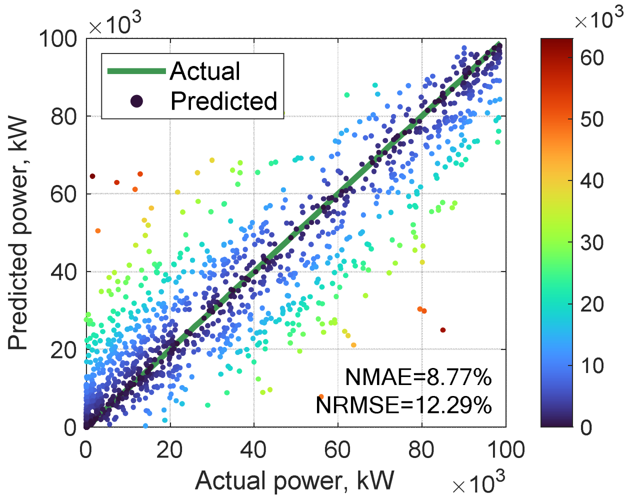

Fig.2. 8GRT simulation scatter diagram

5. Conclusions

In this research a number of computational experiments to compare the efficiency of considered approaches were performed. These experiments included evaluation of:

- The response selection and the of individual turbines power aggregating approaches,
- The wind turbines operational state utilization as a feature while building the regression models;
- The wind turbines operational state utilization for response transformation while building the regression models.

Based on the experiments results, it was found out that for the considered data set the lowest prediction error and highest prediction reliability is achieved by the use of the turbines groups level WPF approach. Most likely, this result is traceable to the spatial smoothing effect. In comparison with turbine level WPF this effect smooths individual turbine power fluctuations without loss of relevance between predictors and responses due to similar turbines behavior. And on the contrary for the wind farm level WPF turbines power aggregations do not lead to excessive smoothing and loss of relevance between predictors and responses because of different behavior of distant turbines. 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 response transformation. The *NRMSE* skill score for turbine groups WPF strategy with availability-based response transformation was 13.4%.

In this paper the effect of spatial smoothing within a wind farm was examined and the effectiveness of response selection and individual turbines power aggregation techniques for wind farm WPF was evaluated. A new methodology based on response transformation is proposed for taking into account the wind turbines operational state while performing the turbine groups and the wind farm levels WPF.

Further research will be focused at the improving of the wind turbines grouping approach by assessing the wind turbine generation time series similarity. Also, further investigation will involve outlier identification methods comparison and enhancement for turbine level, turbines groups level and wind farm level WPF.

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