Development and implementation of a methodology for the optimization of wind power forecasting

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Abstract: In this work, a methodology for the optimization of wind power forecasting is developed and implemented. The main idea is to combine three Wind Power Forecasting (WPF) models in order to minimize the forecast error. The available data include historical potential power and three WPF models' predictions from the case study Pestera wind farm in Romania, as well as relevant meteorological parameters from the same location. Two weather parameters that are most correlated with the WPF errors - wind speed and temperature - are used in weather class definition. Various approaches to combination weights are taken and later compared – the use of one vs two weather parameters, randomized vs chronological data partition. A performance comparison shows that a model based on the weighted combination method with the use of two weather parameters and the randomized data partition outperforms all individual WPF models as well as other combination approaches. The overall Normalized Mean Absolute Error decreased by over one percentage point, which stands for 10,1% improvement for the individually best performing model and 16,3% improvement in case of the weakest model. In monetary terms, WPF improvements cause a decrease in mispredictions in day-ahead energy markets and in the case of the Pestera wind fam with the installed capacity of 90MW, allowed for imbalances penalties and opportunity cost savings of over € 57 000 in less than two months.

Keywords: wind power forecasting, combined forecasting, correlation of weather parameters and forecast errors

I. INTRODUCTION

Nowadays, all around the world, the power sector is going through a significant change, aiming at achieving a clean, sustainable and reliable electricity market. Power system transformation is a complex process that requires a lot of actions at multiple levels: creation of local, national and global policy, establishment of operational and planning practices, major investments in innovation as well as the use of already existing efficient, smart and environment-friendly technology options. Renewable energy is already contributing to this transition to a great and growing extent. According to the Renewables 2017 Global Status Report[1], wind energy covered 10.4% of EU demand in 2016, proving to play an important role in power supply. The Global Wind

[1] Global Wind Energy Council, "Global Wind Energy Outlook 2016 - Opening up New Markets for Business," 2016, http://files.gwec.net/files/GlobalWindEnergyOutlook2016.

Energy Council in their latest Outlook 2016[2] presents the advanced scenario, where global wind installations are foreseen to reach 5,806 GW by 2050.

Together with the continuous increase of wind power penetration rates, there comes the challenge of integration of this intermittent source into the electricity grid. Wind power brings many challenges to the electricity market, particularly utility operators, generating companies and regulators. The uncertainty and variability of wind hinders power generation scheduling and dispatch decisions as well as it affects trading performance on the electricity markets. Wind power forecasting (WPF) is therefore identified as an essential tool to deal with the progressively growing global wind power installations. WPF can be of great use in multiple applications: generation and transmission maintenance planning, determination of operating reserve requirements, unit commitment, economic dispatch, energy storage optimization (e.g., pumped hydro storage), and energy trading[3].

Many attempts have been made to improve WPF and therefore decrease the issues that the uncertain and discontinues nature of wind brings. Usually, a number of alternative predictions is considered. A single forecast may not always provide satisfactory results, while a combined forecast using several individual ones might yield better results. Ideally, the combined final stage forecast ought to represent an improvement as compared to the individual one, or at least be equal to the best performing prediction[4]. Combination of several forecasts takes advantage of the fact that each prediction model exhibits strengths and weaknesses in different situations[5]. The concept of originally proposed in 1969 by Bates and Granger[6], where they proved that a combined set of forecasts can generate lower mean-square error than either of the forecasts individually. The purpose of the following work is to address and answer the following research questions:

- What are the impacts of different weather parameters on WPFs errors?
- What is the performance of various WPF models in different weather classes?
- What is the optimal combination of WPF models for each weather class to minimize the absolute error between the combined forecasts and the measurement?

II. METHODOLOGY

In order to develop and apply the methodology described below, data from the Pestera wind farm in Romania, covering the period from 12/04/2016 to 31/05/2017, were provided by EDP Renewables. The wind farm is composed of 30 operational units with the cumulative installed capacity of 90MW. Apart from the

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[2] REN21, "RENEWABLES 2017 GLOBAL STATUS REPORT," 2017, http://www.ren21.net/wp-content/uploads/2017/06/17-8399_GSR_2017_Full_Report_0621_Opt.pdf.

[3] C Monteiro et al., "Wind Power Forecasting," *Information Sciences* 11, no. 4 (2009): 762–767, https://doi.org/10.1016/B978-0-8155-2047-4.10007-9.

[4] Ismael Sánchez, "Adaptive Combination of Forecasts with Application to Wind Energy," *International Journal of Forecasting* 24, no. 4 (October 2008): 679–93, https://doi.org/10.1016/j.ijforecast.2008.08.008.

[5] Ceyda Er Koksoy et al., "Improved Wind Power Forecasting Using Combination Methods," in *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)* (IEEE, 2015), 1142–47, https://doi.org/10.1109/ICMLA.2015.60.

[6] J. M. Bates and C. W. J. Granger, "The Combination of Forecasts," *The OR Society* 20, no. 4 (1969): 451, https://doi.org/10.2307/3008764.

historical potential power from the farm (assuming 100% availability), data from the following three WPF models is used:

- Kernel Density Estimation model 1 (KDE150)
- Kernel Density Estimation model 2 (KDE250)
- Analog-based model (ANLG50)

In order to identify the parameters that mostly impact power production (so as to reduce the range of parameters to be analyzed in the subsequent steps), the meteoblue[7] global weather simulation archive is used. Historical weather simulation data, i.e. wind speed and direction, temperature, relative humidity as well as mean sea level pressure, are taken for the exact location of the Pestera wind farm, covering the same period as the WPF data.

In the following methodology, 85% of data is used to set up the model and 15% to assess the quality of the combined WPFs. The proposed methodology is divided into three stages: Analysis, Setup and Operation.

i. Analysis

The first step of the analysis stage is the identification of the errors (i.e. deviations between forecasted and actual power generation) of the different WPF models for the case study wind farm. The second step of the analysis stage consists of the identification of the most relevant weather parameters in terms of their impact on the WPFs' errors. For that purpose, the correlation between time series of weather parameters measured at the wind farm and time series of WPF errors are studied. The Pearson product-moment correlation coefficient, which provides a measure of the linear correlation between two variables, is used. This coefficient (ρ) is calculated as follows:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where cov is the covariance of two variables and $\sigma_X \sigma_Y$ is the product of their standard deviations.

ii. Setup

The proposed methodology is based on the conditional weighted combination of WPF models. This is a classical linear regression model for combined forecasting in which the time-varying combination weights are a function of relevant meteorological variables. The approach is to evaluate the performance of the several WPF models available for the wind farm for different weather classes. These classes are defined by ranges of the relevant meteorological parameters identified in the analysis stage. The use of a single weather parameter will be compared to the use of the two most relevant weather parameters in the definition of weather classes.

It is assumed that the several WPF models perform differently for each weather class, i.e. some models may be more accurate for certain weather classes than others. The definition of the combination weights for the different weather classes will reflect these differences in the accuracy of the models, by providing extra weight to the most accurate models in each class. A criterion to select the optimal combination of WPF models for each weather class is to minimize the least square error between the combined forecast and the measurements.

[7] Meteoblue, "Weather History+," accessed April 23, 2018, https://www.meteoblue.com/en/historyplus.

iii. Operation

The operation (running and validation) of the Combined Wind Power Forecast (CWPF) model developed in the previous stages based on 85% of forecasted and measured data, uses as inputs:

- the remaining 15% of the WPF's results and meteorological parameters available
- the optimal combination of WPFs for each weather class, as identified in the model setup stage
- the actual power output of the wind farm

III. RESULTS

In order to assess the accuracy of the available WPF models, the Normalized Mean Absolute Error (NMAE) was calculated. First, the MAE was determined with the use of the following formula:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \qquad (2)$$

As the name suggests, MAE is an average of the absolute errors, where y_i is the prediction, x_i is the true value and n is the number of readings. Then, MAE was normalized to the installed capacity of the wind farm. Table 1 summarizes the results of the NMAE calculations for each model separately.

Table 1 Normalized Mean Absolute Error of WPF models

WPF model	**Normalized Mean Absolute Error [%]**
NMAE_KDE250	10.504867
NMAE_KDE150	10.53881
NMAE_ANLG50	11.284863

The following step consisted of the calculation of the Pearson product-moment correlation coefficient according to equation (1). The results of these calculations allow also for an identification of the parameters that mostly impact WPF errors. As can be seen in Figure 1, the highest correlation between the WPF erorrs and weather parameters is for the **wind speed** and **temperature** and for the further analysis, only these two will be considered.

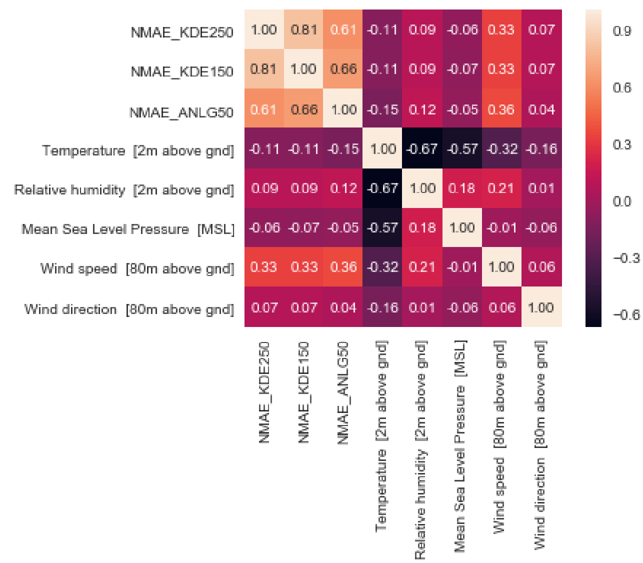

Figure 1 Matrix of WPF errors' Pearson product-moment correlations

In order to carry out a comparison between the use of one parameter and the use of two parameters, firstly only wind speed will be considered for the weather classes definition. In this case, 27 weather classes were defined (divided evenly) and the randomized partition of data was applied in order to arrive at a reasonable distribution of readings throughout all the weather classes. In the case of the use of two weather parameters, a matrix of wind speed and temperature ranges was defined. The choice of scopes of wind speed ranges was based on the number of readings available for particular values. E.g. for wind speeds lower than 4m/s or higher than 10m/s the amount of available data is smaller than for the range between 4 and 10m/s. In the case of the temperature, no such state has been identified, therefore the division is even. Again, the randomized partition of data was applied to obtain a sound distribution of readings throughout the weather classes.

In order to arrive at the optimal combination of the available models, for each defined weather class (range), a linear regression was applied, minimizing the least square error between the forecast models and the historical potential power. For the purpose of model training, 85% of the available data was used, partitioned randomly.

The running and validation of the Combined Wind Power Forecast obtained in the setup stage were performed with the use of the remaining 15% of the available data for the case study wind farm, as well as the selected meteorological parameters – wind speed and temperature - for the corresponding period. In order to plot NMAE for the different weather classes, for each class the NMAE was calculated according to the formula:

$$NMAE_{class} = \frac{\sum_{i=1}^{n} |y_i - x_i| \cdot Power(i)}{Total\ Power} \qquad (3)$$

where y_i is the forecast, x_i is the true value and Power(i) is the average power for the respective class. Figure 2 and Figure 3 illustrate the NMAE values for each weather class of both cases – use of one and two weather parameters respectively (the weather classes in which there were no corresponding readings for the model to be trained were omitted in the graph, therefore there are only 24 classes in the first case and 27 in the second). The green line in the graphs illustrates the validated and tested Combined Wind Power Forecast and it is visible that, in general, it performs better than each of the individual forecasts in both cases.

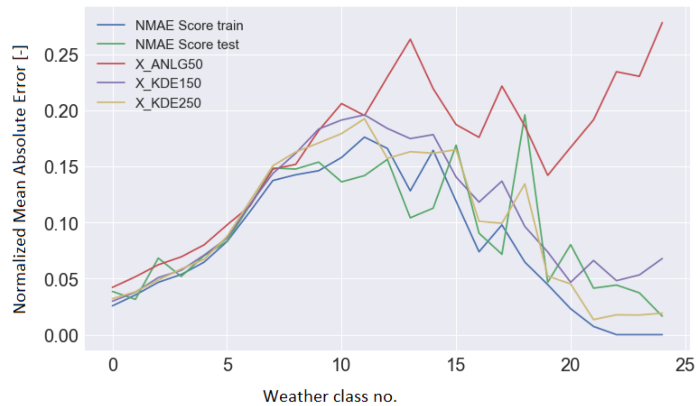

Figure 2 Case of the use of one parameter only (wind speed): Normalized Mean Absolute Error of the trained (blue) and tested (green) Combined Wind Power Forecast, as well as of three models individually (red, purple, yellow)

Table 2 Case of the use of one parameter only (wind speed): Number of readings used in the train and test models

Weather class no.	0	1	2	3	4	5	6	7	8
No. of readings (train)	154	409	684	870	1127	1240	1254	1135	819
No. of readings (test)	18	46	76	97	126	138	140	127	91
Weather class no.	9	10	11	12	13	14	15	16	17
No. of readings (train)	472	228	144	63	34	36	25	20	16
No. of readings (test)	53	26	17	8	4	4	3	3	2
Weather class no.	18	19	20	21	22	23	24	25	26
No. of readings (train)	9	12	14	7	2	2	0	1	0
No. of readings (test)	2	2	2	1	1	1	0	1	0

Below each graph illustrating the NMAE of the individual and combined forecasts for both cases, the respective table with the number of readings used in the train and test models is presented (Table 2and Table 3). They are here particularly important to properly analyze the results presented in the graphs (again, the weather classes in which there were no corresponding readings for the model to be trained were omitted in the graph, therefore there are only 24 classes in the first case and 27 in the second). When analyzing the two graphs, in both cases it is visible that the combined model performed the best in the weather classes for which the number of available readings was the highest. In the case of weather classes with a few readings only, the performance of the Combined Wind Power Forecast is considerably poorer.

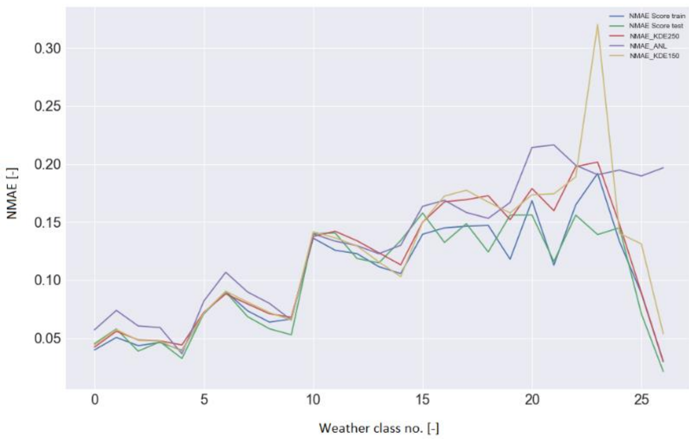

Figure 3 Case of the use of two parameters (wind speed and temperature): Normalized Mean Absolute Error of the trained (blue) and tested (green) Combined Wind Power Forecast, as well as of three models individually (red, purple, yellow)

Table 3 Case of the use of two parameters (wind speed and temperature): Number of readings used in the train and test models

Weather class no.	[	2	3	4	5	6	7	8	9	10	11	12
No. of readings (train)	126	452	782	572	97	192	540	868	551	133	242	669
No. of readings (test)	23	80	139	102	18	34	96	154	98	24	43	119
Weather class no.	13	14	15	16	17	18	19	20	21	22	23	24
No. of readings (train)	855	436	90	198	444	411	147	31	121	175	123	33
No. of readings (test)	151	78	16	36	79	73	27	6	22	31	22	6
Weather class no.	25	26	27	28	29	30	31	32	33	34	35	
No. of readings (train)	0	79	36	0	0	0	28	0	0	0	0	
No. of readings (test)	0	14	7	0	0	0	6	0	0	0	0	

In order to present a selected cut of the time-series, illustrating the individual WPF models together with the combined one, the data partition in the train/test models had to be changed from randomized to chronological. The reason is that the combined model can only be presented with the use of the 15% test data. In the case of the randomized partition, the data would not present the continuous time-series, but rather a random distribution of points. The weather classification applied here was exactly the same as in the similar case of the randomized data partition. The chronological partition method is not really applicable here, as the distribution of readings throughout the weather classes is constrained due to the little data available: if data from several years were used, the model could be trained with a certain number of years and then tested for the following years. Here, the 15% of data are all from the similar weather season and therefore there are many weather classes without any readings. However, this distribution allows for a graphical illustration of a time-series. Figure 4 presents the NMAE of the combined model as well as of the individual WPF models, for a randomly selected continuous 72h of operation. Is it notable that, even for a casually chosen period of time, the combined model in general performs better than the singular models.

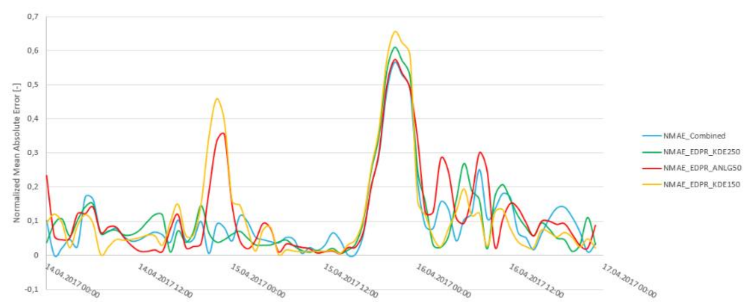

Figure 4 Time-series illustration of NMAE of the combined model as well as individual WPF models, for a randomly selected continuous 72h of operation

IV. RESULTS

Table 4 summarizes the NMAE of the three different approaches followed to arrive at the Combined Wind Power Forecast:

1) Randomized data partition with the use of one weather parameter only – wind speed

2) Randomized data partition with the use of two weather parameters – wind speed and temperature
3) Chronological data partition with the use of two weather parameters – wind speed and temperature

All three approaches are then compared to the individual WPF models and the improvement over the individually best performing model (KDE250) as well as over the worst performing model (ANLG50) is determined. It is visible that in the best case (2), the overall NMAE has decreased by over one percentage point, which stands for 10,1% improvement in comparison with the individually best performing model (KDE250) and 16,3% improvement in the case of the weakest model (ANLG50

Table 4 Summary of Combined Wind Power Forecast improvements

	WPF model	Normalized Mean Absolute Error [%]	Improvement over individually best performing model (KDE250)	Improvement over individually worst performing model (ANLG50)
Individual forecasts	NMAE_KDE250	10,505		
	NMAE_KDE150	10,539		
	NMAE_ANLG50	11,285		
1) 1 weather parameter (randomized data partition)	NMAE_Combined (test)	10,022	4,59%	11,19%
2) 2 weather parameters (randomized data partition)	NMAE_Combined (test)	9,442	10,11%	16,33%
3) 2 weather parameters (chronological data partition)	NMAE_Combined (test)	9,519	9,38%	15,64%

V. IMPLICATIONS

From the analysis of the results of the NMAE calculations, one can claim that the difference between the combined and the individual models does not seem large and significant. However, in the case of wind power predictions, the consequences of mispredictions and resulting over- or under-productions can be very costly. Wind generation imbalances penalties in day-ahead energy markets are usually settled using the current market price[8]. Therefore, even small decreases in WPF errors may bring visible positive monetary benefits.

In order to estimate the possible savings from the improved Combined Wind Power Forecast, the results

[8] C. Brunetto and G. Tina, “Wind Generation Imbalances Penalties in Day-Ahead Energy Markets: The Italian Case,” *Electric Power Systems Research* 81, no. 7 (2011): 1446–55, https://doi.org/10.1016/j.epsr.2011.02.009.

from the model with the chronological data partition were used. In this case, the test data (15% of the available data) covered the period from 12.04.2017 - 16:00:00 until 31.05.2017 - 23:00:00, with hourly readings. Firstly, the difference in the over-estimated production and the under-estimated production resulting from using the improved combined WPF, in comparison to the individual WPF models, was determined.

Table 5 Combined Wind Power Forecast - Resulting change in under- and over production

	Change in underproduction [MWh]:	Change in overproduction [MWh]:
KDE250	571,79	-2156,13
KDE150	797,05	-2243,68
ANLG50	-1530,57	-1360,13

Table 5 presents the differences in mispredictions, comparing the Combined Wind Power Forecast with the individual WPF models. What is interesting to notice is that underproduction increased in comparison with the first two models (KDE250 and KDE150), however overproduction decreased by a significantly higher amount. In other words, the combined model compensates the overestimation trend of the individual forecasts, but has a higher tendency to underestimate (except for the case of the ANLG50 model). The compensations in the overestimation are larger than the underestimations, hence the overall error is smaller. It is important to further analyze this outcome, taking into account the actual monetary value of these differences in mispredictions.

To arrive at a reasonable assessment of the cost difference, the historical data of the electricity market price in Romania for April and May 2017 were used (see Table 6)[9]. If the generated wind power is less than what it was scheduled for (underproduction), the wind power producer incurs an imbalance penalty. This penalty is determined as the wind power producer is obliged to purchase the shortfall from the real-time market, which usually has higher prices[10]. Therefore, possible penalties were assumed, depending on the misprediction type. In case of underproduction, the penalty of 130% of electricity market price was adopted for every MWh of imbalance, while for overproduction the opportunity cost was equated to the market price.

Table 6 Historical data of electricity market price in Romania[11]

Month	Price [€/MWh]
April 2017	38,03
May 2017	42,54

Table 7 presents the results of the estimation of the wind generation imbalances penalties. It is evident that the improved Combined Wind Power Forecast model

[9] Andreea Paul, "Prețurile La Energie Electrică În România Ating Recorduri Istorice În August 2017 – INACO," 2017, https://inaco.ro/preturile-la-energie-electrica-in-romania-ating-recorduri-istorice-in-august-2017/.

[10] Desmond W H Cai, Sachin Adlakha, and K Mani Chandy, "Optimal Contract for Wind Power in Day-Ahead Electricity Markets," accessed May 10, 2018, https://pdfs.semanticscholar.org/99a2/604f9eafd599b5e70fa1b6cedd42fb8116cf.pdf.

[11] Andreea Paul, "Prețurile La Energie Electrică În România Ating Recorduri Istorice În August 2017 – INACO," 2017, https://inaco.ro/preturile-la-energie-electrica-in-romania-ating-recorduri-istorice-in-august-2017/.

brings monetary benefits. For the case study Pestera wind farm in Romania, having the installed capacity of 90MW, the calculations resulted in savings of over € 57 000 in less than two months.

Table 7 Summary of the estimations of wind generation imbalances penalties

WPF model	Cumulated penalty for the period of 12/04/2017 - 31/05/2017
KDE250	€ 504 031,16
KDE150	€ 495 431,11
ANLG50	€ 581 507,77
Combined	€ 446 488,16

VI. CONCLUSIONS

The following are the main conclusions that can be withdrawn from the results:

- Weighted combination as a function of two relevant weather parameters resulted in greater improvements, in comparison to the use of one parameter.
- Randomized data partition provided better data distribution over defined weather classes and therefore better results than chronological partition.
- Larger scope of historical training data could result in better-trained model and consequent superior improvements.
- The improved Combined Wind Power Forecast model brings monetary benefits. The calculations for the given case study wind farm resulted in savings of over € 57 000 in less than two months.

VII. LIMITATIONS

In the course of the study, certain limitations were acknowledged. First of all, the sample size of the analyzed data was narrow, especially for the occasionally occurring high wind speeds. This limitation caused the trained model to be worse-trained in certain weather classes and the improvements for those classes were poor or unreliable. Secondly, two of the available individual WPF models – KDE250 and KDE150 - demonstrated high correlation between one another. The reason for that was that both models were based on the same physical Kernel Density Estimation method. The combination of WPF models with lower correlation could result in better improvements. Finally, the meteorological parameters used in the analysis were taken from one point location, chosen based on the numerical mean the of wind turbines' locations distributed over a certain area. This averaging could have caused slight miscalculations. Besides, the use of weather historical measurements instead of historical simulation data could lead to potential further improvements of training the model.

VIII. FUTURE RESEARCH SUGGESTIONS

As for the future research, it is suggested to follow the methodology with the use of larger sample size, in order to arrive at well-trained models for each of the defined weather classes. Additionally, it is advised to verify the methodology with the use of less correlated WPF models. Moreover, after seeing the improvement resulting from passing from a single weather parameter to two in weather class definition, even if seemingly the second had no significant correlation with the forecast errors, there is the potential for improvement by using a third weather parameter in the definition of the weather classes, or even a forth.

The results presented in this paper prove the high potential of Combined Wind Power Forecast model. The improvements over the individual WPF models, brought by their combination, are evident and therefore further research is highly recommended.

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