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Analyzation and optimization of different wind power infeed combination forecasts

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1 Introduction

As a result of the energy transition, renewable energy sources (RES) have become a significant part of gross electricity generation in Europe. The growth of volatile generation goes along with increasing uncertainty and thus, becomes a major challenge for market participants such as TSO, DSO and direct marketers. Using RES infeed forecasts (IF) for the day-ahead Congestion Forecast ensures that the expected consumption is covered in advance. Furthermore, by predicting the infeed level from RES, IF are a key element in building the market value of RES with direct impact on the market value of the day-ahead forecast. With decreasing forecasting quality, the costs per MWh in the intraday trading and for the balancing energy increases. As demonstrated, a reliable and uniform IF is essential for various market participants. Sufficiently accurate IFs are already being offered by a large number of providers, using different approaches, methods and information sources leading to distinct results. So far, there is no forecasting model that dominates the other models in all respects.

2 Forecast Combination

The idea of making the optimal use of individual IF is to combine them. This could cause positive and negative IF errors that compensate each other thus improving the forecasting quality. Thereby, the weighting of individual providers has a decisive influence on the quality of the combined forecast (CoF) and thus on safe network operations as well as on profits of energy traders and producers. [1] Although combining forecasts is already a well-known method for improving forecast accuracies with a wide range of approaches such as the Bayesian methods, it is still underdeveloped. [2] This abstract focus on a development of a multi-level hybrid concept and a comparison of seven different methods for an optimized CoF. This includes methods of descriptive statistics as well as heuristic methods. Those are based on studies already carried out by the authors in [1,3] and show huge improvements between 4 – 6 % and 2 – 2 % compared to the provider forecasts. Through dynamic and optimal weightings $\boldsymbol{w}$ and the combination of the provider time series $\boldsymbol{P}_{\mathrm{pro}}$ according to equation (1), the deviation of the overall CoF $\boldsymbol{p}_{\mathrm{c}}$ to the actual infeed is minimized.

$$\boldsymbol{p}_{\mathrm{c}} = \boldsymbol{P}_{\mathrm{pro}} \cdot \boldsymbol{w} \tag{1}$$

The methods continuously consider the fluctuations in the IF quality of individual providers. Firstly, weights for 3 providers IF are determined and compared using particle swarm optimization (PSO), genetic algorithm (GA), the least square method (LSM) and the Energy Minimization Method (Emin) according to [1,3]. Additionally, a simple multiple linear regression (MLR) is used to determine weights for the provider IFs, that simultaneously represents the current network operator combination forecast.

Secondly, various hybrid model combinations are used to investigate if a combination of the results of the individual methods can lead to an optimization of the overall result.

3 Results

In order to compare and evaluate the developed methods, the extrapolated actual infeed and provider forecasts of a German transmission system operator for the year 2018 are used. The simple methods (PSO, GA, LSM, Emin, MLR) obtain the best results with a data base of 3 months and a forecast horizon for the weightings of 3 months. Thus, the weightings remain static for 3 months. A dynamic daily weighting resulted in worse results. However, two hybrid methods (Hybrid RMSE, Hybrid NNRMSE) can convince with a dynamic linking of the results of the simple methods for each day. According to [1], the first hybrid method combines the simple methods based on their forecast accuracy in the previous month. The second hybrid method uses neural networks to forecast a forecast error for each simple method. Subsequently, the methods are weighted according to the level of their expected error.
Table 1 shows the results of the simple methods in comparison to the hybrid methods.

Table 1 Results and comparison of the combination forecast methods

Jul.-Oct. 2018	PSO	GA	LS	Emin	MLR	Hybrid RMSE	Hybrid NNRMSE
total RMSE	3.58	**3.51**	3.53	3.59	3.53	**3.51**	3.52
min RMSE	0.59	**0.51**	0.58	0.57	0.58	0.56	0.55
max RMSE	9.19	9.04	9.16	**8.69**	9.16	**8.94**	9.10

In order to assess the quality of the forecast, the normalized RMSE is used related to the installed wind power. According to the total and the minimum RMSE, the GA achieves the best results. Therefore, the hybrid models can only achieve equally good (Hybrid RMSE) or worse (Hybrid NNRMSE) results. However, Hybrid RMSE shows better forecast accuracy at the maximum RMSE. This combined with the best total RMSE can be rated as being successfully, as large deviations are particularly critical for any forecast applications. The improvement between the current network operator forecast and the Hybrid RMSE method is very small at 0.52 %, but the maximum RMSE has been improved by 2.42 %. In Comparison to the best provider forecast an improvement of 4.18 % can be achieved.

4 Conclusion

The developed methods continue to improve the forecast quality compared to the previous network operator forecast and the best provider forecast. Thus, they provide a good initial point for minimizing system security interventions and avoid significant costs. Overall, the improvements are not as high as at the beginning of our project with the test data from 2014/2015. An assumption is, provider forecasts have already been optimized in the meantime and thus, their quality does not seem to fluctuate so extremely anymore. Furthermore, the results show that LS and MLR give the same results, although LS uses the quadratic error and MLR uses only the simple error. This also shows that the deviations between the extrapolated actual infeed and the provider forecasts in 2018 are located in the smaller error range.

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