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RESEARCH ARTICLE

Improved Short-Term Wind Power Forecasts: Low-Latency Feedback Error Correction Using Ramp Prediction and Data From Nearby Farms

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ABSTRACT This paper shows that the short-term wind power forecasts of a target farm can be significantly improved by using ramp predictions and information from nearby farms. To do this, we first obtain benchmark wind power forecasts from Scipher.Fx by Utopus Insights, Inc, which is owned by Vestas Wind Systems. Second, we build a low-latency feedback error correction model that predicts the forecast error at a given look-ahead time based on a novel ramp predictor, the last known forecast errors, and optionally, the last known forecast errors from nearby farms. The predicted forecast error is then combined with the benchmark wind power forecast to obtain the improved forecasts. The novel ramp predictor is constructed using the benchmark wind power forecast and optionally, measured data over a defined time window, to improve the less accurate wind power forecasts during ramp events. The ramp predictor also improves forecast accuracy for longer look-ahead times by a second mechanism which we detail. The nearby farm selection algorithm is based on two approaches: 1) Correlation analysis of historical data, and 2) Feature selection based on Shapley additive explanations feature importance values. Our approach was tested on 17 wind farms in Europe and the results showed that the ramp predictor can decrease the average relative normalized mean-absolute error of 10 minutes to 6 hours look-ahead forecasts by 3.61%. Additional improvements from nearby farms can be as high as 2.54% for some look-ahead times depending on the availability of data from upwind farms.

INDEX TERMS Wind power forecasting, feedback error correction, machine learning, XGBoost, wind power ramp prediction, correlation analysis, nearby farm selection.

NOMENCLATURE

SYMBOLS

k	Timestamp.
l	Look-ahead time.
$P^{\mathrm{e}}_{k,l}$	The error in benchmark forecast power of look-ahead time l at timestamp k.
$\hat{P}^{\mathrm{e}}_{k,l}$	The predicted power forecast error of look-ahead time l at timestamp k.
$P^{\mathrm{f}}_{k,l}$	The forecast power of look-ahead time l at timestamp k.
$P^{\mathrm{m}}_{k,l}$	The measured power of look-ahead time l at timestamp k.
$P^{\mathrm{i}}_{k,l}$	The improved power forecast of look-ahead time l at timestamp k.
$R_{k,l}$	The ramp predictor of look-ahead time l at timestamp k.

ACRONYMS/ ABBREVIATIONS

XGBoost	Extreme gradient boosting.
NWP	Numerical weather prediction.
SHAP	Shapley additive explanations.
nMAE	Normalized mean-absolute error.

I. INTRODUCTION

The variable and uncertain nature of wind and solar power generation places a premium on the accuracy of generation forecasts. Balancing authorities, responsible for maintaining

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the balance between load and generation within their territory, may impose imbalance penalties on the owners of these resources if the output of their plant varies too much from their forecast [1], [2].

Accurate wind power forecasts reduce or eliminate the imbalance penalties that wind resource owners must pay. Greater forecast accuracy also enables the independent system operator to enhance market efficiency and improve the operational reliability of the bulk power system. A more detailed account of the benefits of improved wind power forecast accuracy can be found in [1].

Given these insights, it is evident that more accurate wind power forecasts are essential for the future power grid. A range of wind power forecasting methods has been proposed in the literature [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25] and are categorized into physical models and data-driven models. Physical models use numerical weather prediction (NWP), which shows a good performance for forecast horizons from several hours up to six days [7], [8], [9], [10]. Data-driven models can be further divided into statistical and machine learning models. Statistical models include auto-regressive integrated moving average, auto-regressive moving average, coupled auto-regressive and dynamic system [11], [12], and Markov models [7], [13], [14]. Machine learning models include support vector machine [8], feed-forward neural networks [8], [10], [12], [15], [16], [17], [18], [19], recurrent neural networks such as long short-term memory networks [20], [21], [22] and decision trees such as extreme gradient boosting (XGBoost) [10], [23], [24], [25], [26].

One state-of-the-art wind power forecasting product is called Scipher.Fx by Utopus Insights, Inc, New York, USA [27], which is owned by Vestas Wind Systems, Aarhus, Denmark. Vestas is the largest installer of wind turbines in the world with over 100 GW capacity [28] and Scipher.Fx provides forecasts for many of these installations as well as those of other turbine manufacturers. This paper focuses on improving the accuracy of Scipher.Fx by using a feedback error correction based on a novel approach to ramp event prediction. We also demonstrate further improvements to forecast accuracy by including data from nearby farms. Real-time access to low-latency data from multiple geographically distributed sensors is key to successfully implementing our approach.

We first established benchmark wind power forecasts using Scipher.Fx and noted a degradation in forecast accuracy during periods when power generation is rapidly changing, that is, during ramp periods. A ramp period is characterized by a large variation in wind power output observed at a wind farm (or at a portfolio of wind farms) over a short period of time (up to a few hours) [29]. To improve forecast accuracy during ramp periods, we constructed a novel ramp predictor using the benchmark wind power forecasts (Section IV).

We then demonstrate significant forecast accuracy improvements from the ramp predictor for look-ahead times

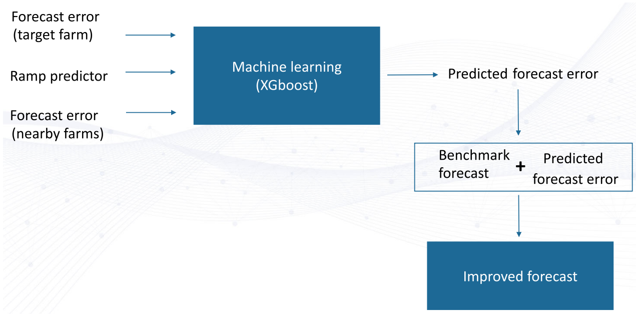

FIGURE 1. Feedback error correction approach.

from 10 minutes to 6 hours. For look-ahead times between 10 minutes and 3 hours 30 minutes, much of the improvement comes from an improved prediction of ramp events. However, for look-ahead times between 3 hours 30 minutes and 6 hours, an additional improvement is obtained. This is because the benchmark wind forecasts for look-ahead times beyond 3 hours 30 minutes are obtained using only NWP models compared to the measurement data and NWP-based machine learning models used for look-ahead times up to and including 3 hours 30 minutes. NWP based models results in more accurate forecasts after a certain look-ahead time but unfortunately, this transition point varies for different wind farms and is computationally difficult to calculate it for each farm. Our ramp predictor smooths the transition into the only NWP-based forecasts by significantly improving the accuracy of the NWP-based forecasts.

Finally, we demonstrate that forecasts at a target farm can be further improved by using data from nearby farms that are upwind in the prevailing wind direction. For each target farm and forecast look-ahead times, optimum selection of nearby farms depends on the location with respect to the target farm and the prevailing wind speed and direction. We automate the selection process through either a correlation analysis of the historical data or feature selection and Shapley additive explanations (SHAP) feature importance values (Section V) [30].

Our feedback error correction approach, as shown in Fig. 1, uses the last known forecast errors of the target wind farm, a novel ramp predictor, and optionally, the last known forecast errors from nearby farms to predict the forecast error of the target farm for the given look-ahead time. The predicted forecast error is then combined with the benchmark forecast to obtain the improved forecast. Note that the ramp predictor is constructed using the benchmark forecast; training the benchmark model again to include the ramp predictor would be computationally costly compared to training the feedback error correction model.

The rest of the paper is structured as follows: Section II describes wind power forecasting, while Section III is devoted to the proposed feedback error correction approach. The construction of the ramp predictor and methods for selection of nearby farms are presented in Section IV and Section V, respectively. Section VI explains details of the implementation of feedback error correction and Section VII presents the improved forecast results. Section VIII concludes the paper.

II. WIND POWER FORECASTING

A. BENEFITS OF IMPROVED WIND POWER FORECASTS

The economic and reliability benefits of improved wind power forecast accuracy are discussed for various scenarios in [1]. The benefits depend on the mix of conventional generation resources, the existence of battery energy storage systems, and wind penetration levels. Some of the important findings are as follows. The cost savings from improved forecasts are higher for systems with high penetration of renewable energy sources, but the savings further depend on the mix of conventional generation resources. For example, cost savings are greater in a coal-dominated system than in a natural gas-dominated system because of the savings from high startup and shutdown costs. Improved wind power forecasts provide significant monetary benefits for both the independent system operator and the wind farm owners depending on the market structure and the operational practice.

B. SCIPHER.FX POWER FORECASTING SOFTWARE

Scipher.Fx is a proprietary wind forecasting SaaS (software as a service) by Utopus Insights, Inc [27] and is used as the benchmark in this paper. Forecasts are produced by two distinct machine learning models. The first model, for shorter look-ahead times, uses measurement data from a target farm and NWP data for the target farm location as predictors. The second model, for longer look-ahead times, uses only NWP data as a predictor. The NWP models are better than the measurement-based models beyond a certain forecast horizon but it is computationally difficult to exactly calculate this transition point because it varies for different wind farms. It is important to note that, for this work, the second model was used for look-ahead times longer than 3 hours 30 minutes.

C. XGBOOST

One of the state-of-the-art machine learning algorithms used for wind power forecasting is XGBoost, which is a gradient boosting decision tree approach first proposed by Tianqi Chen in 2015 [26]. Our feedback error correction model is implemented using XGBoost as it is capable of providing quality solutions without a high computational burden.

III. FEEDBACK ERROR CORRECTION

Our feedback error correction approach is illustrated in Fig. 1. The main objective of the algorithm is to predict the error of the benchmark forecast for a given look-ahead time. The machine learning model for prediction of the forecast error uses the last known forecast errors, a novel ramp predictor (Section IV), and last known forecast errors from nearby farms (Section V) as predictors. The predicted forecast error is then simply added to the benchmark forecast to improve the accuracy. This approach allows us to gain the benefits of the ramp predictor with less computational burden compared to having to retrain our benchmark wind power forecast model to incorporate the ramp predictor. Another great advantage of this ''post-processing approach'' is that it can be applied to any given benchmark forecast, independently of its modeling approach.

We formulate the problem as follows: The error in forecast power $P^{\mathrm{e}}_{k,l}$ of look-ahead time l at timestamp k, is calculated by subtracting the measured power P^{m}_{k} from the forecast power $P^{\mathrm{f}}_{k,l}$ as shown below:

$$P^{\mathrm{e}}_{k,l} = P^{\mathrm{f}}_{k,l} - P^{\mathrm{m}}_{k}. \tag{1}$$

Note that the measured power here corresponds to the forecast-for-time (i.e., time for which the forecast is generated) which is forecast-at-time plus the look-ahead time.

The predicted forecast error $\hat{P}^{\mathrm{e}}_{k,l}$ is then used to obtain the improved forecast $P^{\mathrm{i}}_{k,l}$ using:

$$P^{\mathrm{i}}_{k,l} = P^{\mathrm{f}}_{k,l} + \hat{P}^{\mathrm{e}}_{k,l}. \tag{2}$$

IV. RAMP PREDICTION

A wind energy ramp tool and metric [31] was initially used to evaluate the performance of our benchmark forecast during different ramp conditions. We defined a ramp event as a change of 30% rated capacity or higher over a 3h time window. This preliminary analysis showed that the wind power forecasts are less accurate during ramp periods, which led the authors to speculate that the forecast could be improved if we could better inform the forecasting model about probable ramp events. This section first explains the ramp events, second discusses existing methods of predicting ramp events, and finally presents the proposed ramp predictor.

A. A RAMP EVENT

A ramp event is a large variation in wind power output that is observed on a wind farm (or in a portfolio) within a short period of time (up to a few hours), thus typically characterized by magnitude and duration [29], [32]. A positive value for the magnitude can correspond to an upward ramp while a negative value is a downward ramp. A classification of a ramp event often involves specification of a start time, direction, magnitude and duration, but more sophisticated approaches have been demonstrated [32], [33], [34], [35], [36].

B. BRIEF REVIEW OF RAMP PREDICTION APPROACHES

There are two main strategies for predicting ramp-events. The first is to detect ramps from a time series of wind power or wind speed forecasts according to a given ramp-event definition [37]. The second strategy is to use regression to predict ramp-events from historical data [38], [39]. According to [38], the ramp capture rate was less than 50% for most cases.

Given these insights, our approach to feedback error correction does not forecast the magnitude or the time of ramp events. Instead, a continuous variable that we call the *ramp predictor* informs the feedback error controller about

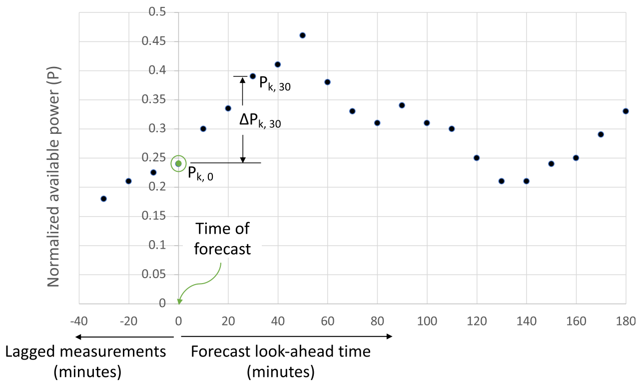

FIGURE 2. Graphical illustration of the ramp predictor.

potential ramps happening within a predefined window. This approach has not been previously discussed in the literature.

C. PROPOSED RAMP PREDICTOR

The ramp predictor used in our approach to feedback error correction is graphically illustrated in Fig. 2. It consists of a series of values obtained by subtracting the last known power value from measured and/or forecast values in a defined time window. The mathematical formulation is as follows: The ramp predictor for look-ahead time l at timestamp k defined by $R_{k,l}$ is constructed using the benchmark wind power forecasts (for some look-ahead times, the last few known measured power values are also included) over a time window, as shown by:

$$R_{k,l} = \left[\Delta P_{k,1}, \ldots \Delta P_{k,f}, \ldots \Delta P_{k,F}\right], \tag{3}$$

where $\Delta P_{k,f}$ is the power difference from the measured or forecast at f in the time window with the measured power $P_{k,0}$ at the current timestamp k, given by:

$$\Delta P_{k,f} = P_{k,f} - P_{k,0}. \tag{4}$$

The time window brackets the look-ahead time, and the beginning and end of the time window depend on the chosen look-ahead time as explained in Section VI.

V. SELECTION OF NEARBY FARMS

Changes in wind power at a chosen target farm will be correlated in time with changes at nearby farms. In particular, changes in power at the target farm will lag similar changes at nearby farms that are upwind of the target farm. Thus our error correction approach uses power generation data from nearby farms as a predictor to improve the forecast accuracy for a target farm.

We demonstrate the value of this approach in a simple model which uses data from nearby farms that are upwind in the prevailing wind direction. We found that the machine learning model, when fed all available data from all nearby farms considered in the test portfolio, was not capable of extracting meaningful information for forecast correction from all the features [40]. Manual selection of nearby farms based on prevailing wind direction and the geographic

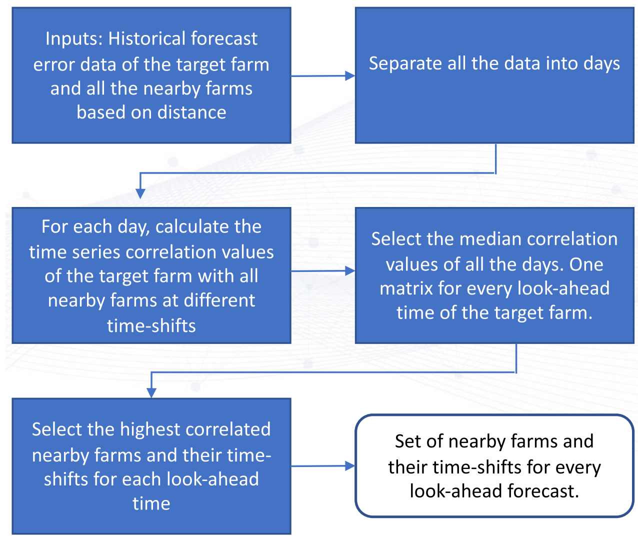

FIGURE 3. Selection of nearby farms based on correlation values.

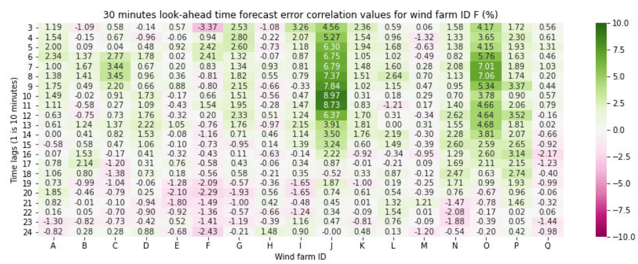

FIGURE 4. Correlation values for 30-minute look-ahead time forecast error for the farm ID: F (%).

locations showed the expected correlations in forecast error with respect to the target farm. Manual selection of time-shifts (the differences between timestamps at a nearby farm and a target farm) also demonstrated the expected correlations between geographic locations on prevailing wind direction and speed. We therefore explored and compared two methods for automated feature selection.

A. METHOD 1: CORRELATION ANALYSIS

A correlation analysis is used to select the nearby farms for each target farm and the corresponding time-shift of the data, which may be different for each look-ahead time.

Our approach shown in Fig. 3 is as follows: First we create the forecast error correlation matrices for each look-ahead time of the target farm with different time shifts of the nearby farms' forecast error. The correlation is computed for each day of the training dataset and only the median values are shown in the matrices. Fig. 4 shows the 30-minute look-ahead time correlation matrix for a target farm (ID: F). The correlation values are smaller when we use forecast error compared to if we had used measured power but the same end result is obtained.

Second, we extract the most correlated nearby farms along with the time-shifts of their highest correlated values (i.e., lags) for each look-ahead time of the target farm. To be

TABLE 1. Selected nearby farms for the target farm ID F with the chosen time-shifts (i.e., lags).

Look-ahead time	Nearby farm 1 (1 = 10 minutes lag)	Nearby farm 2 (1 = 10 minutes lag)
10 minutes	6, 7, 8	6, 7, 8
20 minutes	7, 8, 9	Not used
30 minutes	6, 7, 8	Not used
1 hour	1, 2, 3	0, 1, 2
1.5 hours	0, 1	0, 1, 2
2 hours	0, 1	Not used
2.5 hours	0, 1	Not used
3 hours	0, 1, 2	Not used
3.5 hours	1	Not used

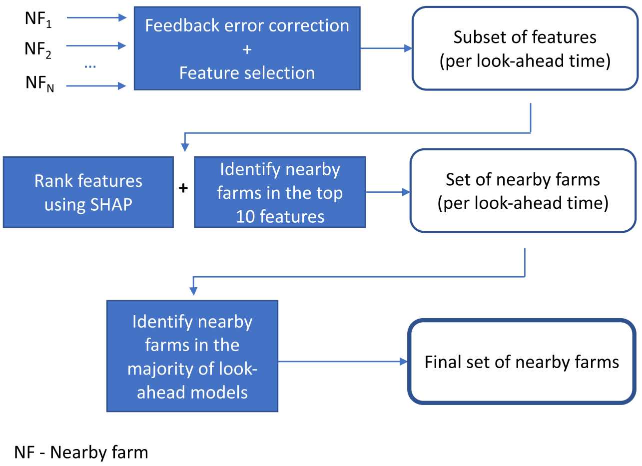

FIGURE 5. Selection of nearby farms based on feature selection.

selected as a nearby farm, a farm must exceed a threshold for minimum correlation value and also fall within a certain range of the highest correlation value of all the farms. Table 1 lists selected lags (the correlation time-shift between each nearby upwind farm and the target farm) for various look-ahead times for two nearby farms that were selected based on the correlation values displayed in Fig. 4. In order to maximize the information from nearby farms ±1 lags have been added to the chosen nearby farm's optimum lag. Note that the shorter the look-ahead time, the longer the selected optimum lag time. This is expected, since at time of forecast, smaller look-ahead times at the target farm correlate maximally with conditions at the nearby farm that are farther in the past.

B. METHOD 2: FEATURE SELECTION BASED ON SHAP FEATURE IMPORTANCE VALUES

To successfully utilize the information coming from nearby farms, we used a well-known method for feature selection based on feature importance using SHAP values [30]. The method shown in Fig. 5 works as follows: For a given portfolio with N farms and for each target farm in the portfolio, the machine learning model using information from all farms in the portfolio is trained using a feature selection algorithm based on SHAP feature importance values. The feature selection algorithm recursively eliminates the least important features until no further improvements in the predictions are achieved or until a minimum number of features (user-defined) is reached. The results from this method determine the optimal subset of nearby farms that actively provide predictive value to improve forecast accuracy.

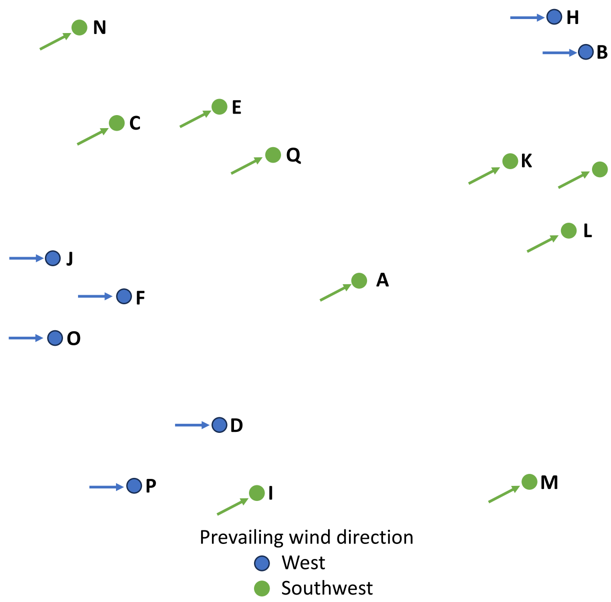

FIGURE 6. Prevailing wind direction of all the wind farms in the test portfolio.

TABLE 2. Time windows of the ramp predictor used for different look-ahead times.

Look-ahead time	Start of the time window	End of the time window
10 minutes	-30 minutes (measured data)	2 hours 10 minutes (Look-ahead time + 2 hours)
20 minutes	-30 minutes (measured data)	2 hours 20 minutes (Look-ahead time + 2 hours)
30 minutes	0 Forecast-at-time	2 hours 30 minutes (Look-ahead time + 2 hours)
1 hour to 3 hours 30 minutes	Look-ahead time - 30 minutes	Look-ahead time + 2 hours
3 hours 30 minutes to 6 hours	2 hours 30 minutes	Look-ahead time + 2 hours

VI. IMPLEMENTATION

This section summarizes the implementation details of the proposed approach.

A. DATA PREPARATION

The dataset used in this paper consists of available and actual wind power time-series and meteorological data such as wind speed for 17 wind farms in Europe over two years (from September 1, 2019 to August 31, 2020). These farms were selected from a portfolio of over 200 farms based primarily on the quality and availability of data. Fig. 6 shows the prevailing wind directions of the 17 selected wind farms.

TABLE 3. Hyper-parameters of the XGBoost model.

n_estimators	1000
max_depth	5
learning_rate	0.01
subsample	1
colsample_bytree	0.8

B. TRAINING

The target variable of the machine learning model is forecast error while the last known forecast errors, the ramp predictor and the last known forecast errors from nearby farms are the input predictors as shown in Fig. 1. Python XGBoost library is used for the training, which requires each input predictor to be a column in a python dataframe. We generate one XGBoost model for each look-ahead time. The time windows of the ramp predictor used in this paper are summarized in Table 2. The hyper-parameters used in this work, shown in Table 3, are found from experimentation.

C. TESTING

During forecast-at-time, we feed in the last known forecast errors, ramp predictor and forecast errors from nearby farms into the trained XGBoost model to predict the target forecast error of the given look-ahead time. This forecast error is then additively combined with the benchmark forecast to obtain the improved forecast.

VII. TEST RESULTS AND DISCUSSION

Applying our feedback error correction method, we find an average relative improvement in normalized mean-absolute error (nMAE) of 3.71% for all look-ahead times for the 17 wind farms in the test portfolio. This result was obtained by training the algorithm once on a historical dataset spanning one full year. As would be expected, the forecast accuracy increased with the length of the historical dataset used for training. Training with datasets covering periods of 6 months yielded roughly 70% of the accuracy improvement obtained by training with a dataset covering a full year. The results discussed below were obtained with 1 year of historical data, but our simulations demonstrated additional gains in forecast accuracy with more frequent training on longer datasets.

With only the ramp predictor and forecast errors from the target farm as predictors (Fig. 1), our trained error correction model generated forecasts with significantly improved accuracy. Fig. 7 shows the relative improvement in nMAE for look-ahead times from 10 minutes to 6 hours for each of the 17 wind farms in our test portfolio. The relative improvement, averaged over all look-ahead times and all wind farms is 3.61%. (Monthly re-training with two years of historical data increases this relative improvement in forecast accuracy to 4.03%). A large increase in this relative improvement is observed for look-ahead models for 3 hours 30 minutes and longer - out to at least 6 hours. As discussed in Section II-C, these longer look-aheads are provided by machine learning models that rely solely on NWP data. The implementation of

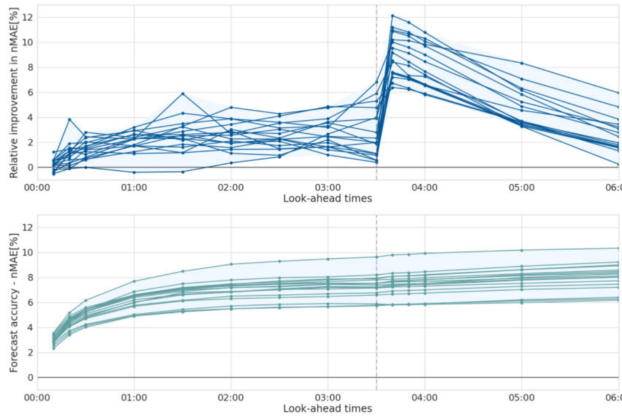

FIGURE 7. Relative improvement in nMAE [%] and the final forecast accuracy for each farm in the test portfolio from using the ramp predictor.

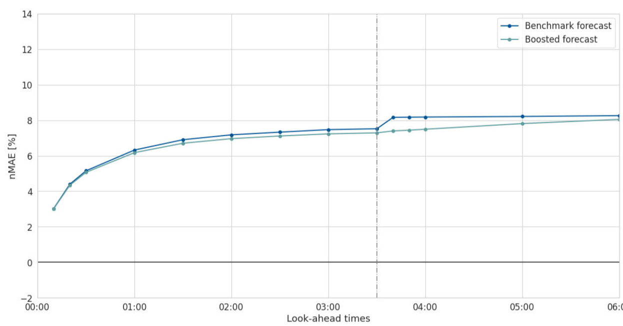

FIGURE 8. Comparison of the overall nMAE [%] for the benchmark forecast and the improved forecast using the ramp predictor.

the ramp predictor in our feedback error correction method corrects the errors of the NWP-based forecast models, resulting in a large improvement in the forecast accuracy at 3 hours 30 minutes and longer. Note that NWP-based forecast models provide more accurate forecasts beyond a certain look-ahead time but unfortunately, calculating this look-ahead time is computationally difficult as it changes with the wind farm. The efficacy of this correction is evident in Fig. 8, where the nMAE of the benchmark wind power forecasts increases smoothly and gradually as the look-ahead time increases to 3 hours 30 minutes, with a steeper increase in nMAE with the switch to the "NWP only" model for longer look-ahead times. In contrast, the corrected forecast shows very little increase in nMAE that can be attributed to the transition to the NWP-based forecast model.

Additional improvements in forecast accuracy were achieved by adding the forecast errors from nearby farms as predictors for error correction (Fig. 1). As can be seen in Fig. 9, the information from nearby farms had a positive impact on the forecast accuracy in most farms present in the test portfolio, with an average relative improvement in nMAE of 0.11%. For one farm, the positive effect was notable, with a 2.54% relative improvement in nMAE for the look-ahead time of 2 hours. In few instances, adding information from nearby farms negatively impacted the forecast accuracy, with

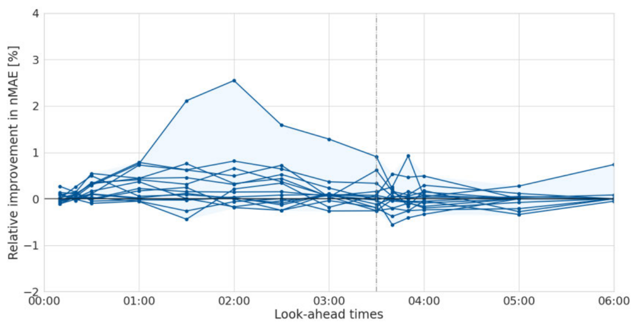

FIGURE 9. Additional relative improvement in nMAE [%] from adding information from nearby farms.

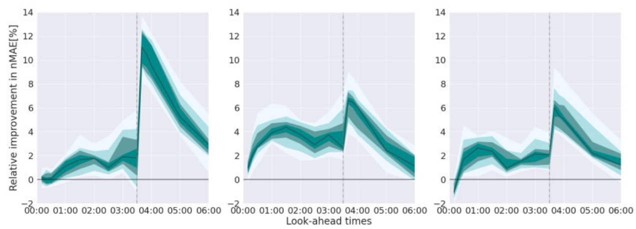

FIGURE 10. Relative improvement in nMAE [%] per ramp condition: no ramp event (left), ramp up event (middle), and ramp down event (right).

one farm experiencing a decrease in nMAE of 0.56%. The observed positive and negative effects of adding information from nearby farms are intrinsically related to the relative positions of the farms in the test portfolio: target farms with one or more upwind farms from the prevailing wind direction will benefit from adding information from those farms, while farms with no good upwind farms might experience accuracy degradation.

Lastly, to quantify the improvements of the proposed approach during several ramp conditions, the wind energy ramp tool and metric function described in Section IV was applied to separate the results into three categories: 1) no ramp event, 2) ramp-up event, and 3) ramp-down event. The same definition of ramp event was used, i.e., a 30% change in rated capacity or higher in a 3h time window. Fig. 10 illustrates the relative improvements in nMAE achieved by implementing the feedback error correction method proposed in this paper in each ramp event category. As can be seen in Fig. 10, the application of the feedback correction error method produces an overall positive effect on forecast accuracy during all ramp conditions. During the no-ramp event conditions, a significant relative improvement in nMAE is observed for look-ahead times above 3 hours and 30 minutes. In this case, the main added value of the ramp predictor comes from the fact that it contains the last known measurement data at the wind farm's site. This allows the machine learning model to calibrate the forecasts from the NWP models to the actual production levels of the wind farm, thus considerably reducing the error of the NWP forecasts. The applied methodology also allowed an improvement in nMAE during ramp-up conditions, especially for shorter look-ahead times, a direct result of the ramp predictor allowing the model to better recognize the potential future variations of power production and thus improve forecast accuracy. The improvements during ramp-down events are overall smaller and has a slight increase in nMAE for very short look-ahead times (10 and 20 minutes ahead). These results indicate that the ramp predictor could provide more valuable information to detect ramp-up events than ramp-down events.

VIII. CONCLUSION

We have presented a feedback error correction approach to improve short-term wind power forecasts for look-ahead times up to 6 hours using a ramp predictor and data from nearby farms.

The results show an average 3.6% relative decrease in nMAE for the 10 minutes to 6 hours look-ahead forecasts, with a competitive overall accuracy of 6.6% nMAE. Most of this improvement is due to the implementation of a novel ramp predictor, which only uses information from the target farm and improves the response of our feedback error correction to the onset of ramp events, as demonstrated by an enhanced decrease in average nMAE during ramp-up and ramp-down events, periods with typically higher imbalance penalties for stakeholders. Additional improvement in forecast accuracy for target farms is achieved by leveraging information from nearby farms located upwind from the prevailing wind direction.

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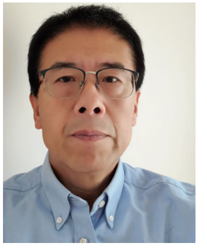

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