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Machine learning forecasts of Scandinavian numerical weather prediction wind model residuals with control theory for wind energy

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Abstract

The quality of wind data from the numerical weather prediction significantly influences the accuracy of wind power forecasting systems for wind parks. Therefore, an in-depth investigation of these wind data themselves is essential to improve wind power generation efficiency and maintain grid reliability. This paper proposes a novel framework based on machine learning for concurrently analyzing and forecasting predictive errors, called residuals, of wind speed and direction from a numerical weather prediction model versus measurements over a while. The performance of the framework is testified by a wind farm inside the Arctic. It is demonstrated that the residuals still contain significant meteorological information and can be effectively predicted with machine learning and the linear autoregression works well for multi-timesteps predictions of overall, East–West, and North–South wind speeds residuals by comparing the four forecast learning algorithms' performance. The predictions may be applied to correct the NWP wind model, making quality feedback improvements for inputs for wind power forecasting systems.

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Keywords: Autoregressive forecast; Machine learning; Residual analysis; Statistical inference; Wind energy; Feedback

1. Introduction

Wind energy is one of the crucial resources for the development and utilization of renewable energy. The wind itself is the natural energy source of wind turbines. The quality of wind resources, especially wind speed, in the wind farm is the most critical factor affecting the power generation efficiency and performance [1]. The distinction between wind energy and conventional electricity generation lies in the variability and uncertainty of wind, significantly impacting grid operations.

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The effective wind model for a site should understand the historical wind characteristics and be able to predict the wind temporally based on these characteristics. It is served as the input of a wind power forecast model. Quantitatively and accurately analyzing and forecasting the wind power is essential to effectively achieve wind turbine control parameter optimization settings, which are beneficial to ameliorate the status quo of low power generation efficiency of some wind power stations and improve operational management and economic benefits. The forecasting methods combined wind from Numerical Weather Prediction (NWP) physical and historical wind power data machine learning modelings provide an attractive approach to improving wind forecast accuracy [2]. In this hybrid model, the wind data generated by the NWP and the ensemble learning algorithm are major factors influencing its performance.

It is vital to understand when and to what extent forecast errors occur in wind power engineering [3]. When prediction errors occur, power system operators must quickly take corresponding measures to restore the power balance between supply and demand. It is estimated that wind generation prediction error costs can reach as much as 10% of the total wind generator energy income [2]. Many factors affect the error of wind prediction and its distribution. The main factors are wind data quality, weather conditions, power curves, prediction algorithms, and parameters of models [4]. Among them, wind data from NWP is considered one of the most fundamental contributions to prediction errors. In particular, wind speed is at the top of the list with a significant effect due to the cubic relationship between wind speed and wind power. Wind direction has a relatively small impact on prediction uncertainty, while other weather parameters' influence is subtle. So, detailed comprehension of wind from NWP, both in speed and direction perspectives, is essential to lower wind forecasts errors and lead to better inputs for wind power prediction models.

The mainstream of wind residual research is the direct analysis of wind energy errors [5,6]. P. Higgins et al. [7] investigated the influence of wind power forecast errors on the carbon constraint energy market and found the impart is double-edged. J. Duan et al. [8] used the prediction error to correct the previously predicted wind speed to reach the well-performed recurrent neural networks with decompositions to forecast wind.

However, this analysis is usually purely data-driven and lacks a physical basis. The statistical analysis of residuals centers on probabilistic modeling and there is a scarcity of statistical inference and hypothesis testing for the residuals as time series [9]. Meanwhile, they typically only focus on the persistence model residuals and neglect residuals analysis from different algorithms. Moreover, a little research considers both wind speed and direction residuals and predicts them based on machine learning.

The residuals of the vector of wind velocity from the NWP wind model are the research objective of this study. This means we not only investigate wind speed predictive errors but also consider an indirect way of reflecting the wind direction residuals by modeling them with East–West and North–South wind speeds.

The main contributions of this paper can be summarized as follows:

Unlike traditional approaches to enhance the resolution of numerical weather by reducing the forecast scale. This paper utilizes machine learning prediction for the wind speed and direction residuals from the NWP. Furthermore, predictions can be used to correct the NWP wind model, enabling quality improvements as feedback for inputs of wind power prediction systems through control theory persperctive.

2. Scandinavian numerical weather prediction for wind

Due to weather measurement complexity and expense, the vast majority of global wind data comes from NWP models. The NWP model is a sophisticated atmospheric computational fluid dynamics model that splits the Earth's surface into grids [10]. The grid's spatial resolution defines how meteorological processes are simulated with different accuracy levels, which also restricts the quality of predictions. In wind engineering, it has been proven that different types of NWPs yield different accuracy and computational efficiency for wind evaluation [11].

There are four steps to conducting an NWP wind modeling: 1. Observation, 2. Assimilation producing the analysis, 3. Prognosis, 4. Post-processing [12]. To start an NWP model, the initial state of the atmosphere should be inputted. Owing to the messy weather data and inherent complexity of weather phenomena and computational fluid dynamics, assimilation or reanalysis should be done to make the wind data consistent with the physical equations assumed by the model. The commonly used assimilation method in wind energy is Measure–Correlate–Predict (MCP), which helps determine the long-term wind statistics of a site. The NWP model computes the atmosphere state into the future; this is called the prognosis. The process takes the current values of all variables into a grid with high resolution and calculates the values for ahead time step based on corresponding physical rules. Then, sub-grid processes can be done for different usage purposes. As the resolution increases, more memory and computing power are needed, so there is a trade-off in computing availabilities and resolutions.

There are two categories of errors: model inherent errors and input errors. The first one is caused by the failure of describing real physical phenomena. Noteworthy, in wind predictions, sometimes the errors tend to cancel each other out [12] and lead to an acceptable predictive result.

The Scandinavian weather institutions use an NWP model named MEPS (Meteorological cooperation on operational Ensemble Prediction System). It is an ensemble forecasts model and a unique combination of having three national (Norway, Sweden, and Denmark) meteorological services sharing operational model simulations, 24/7 monitoring, infrastructure, expertise, and model development [13]. Ref. [13] presents in detail a numerical weather model applied to Scandinavia and analyzes the model's predictive performance in forecasting temperature, precipitation, wind, and extreme weather. They find that the AROME-MetCoOp model improves wind, temperature, and precipitation forecasts compared to the European Centre for Medium-Range Weather Forecasts. In areas with a complex topography (e.g., the Norwegian mountains), the high-resolution model adds considerable value to temperature and wind forecasts. And it can also better simulate high wind speeds and precipitation. The model initiates at 00, 06, 12, and 18 UTC, and its predictive results for the next 66 h are available after around 1 h 15 min of computing.

3. Methodology

In classical time series analysis, the AutoRegressive model (AR) is a statistical approach to time series that uses the previous periods of a variable to predict its current period and assumes that they have a linear relationship [14]. The current period value equals a linear combination of one or several prior period values, plus a constant term, plus a random error. It is defined as in (1):

$$X_t = \sum_{i=1}^{k} \rho_i X_{t-i} + c + \varepsilon_t \tag{1}$$

where ρ_i is the slope of X_{t-i}, c is a constant, ε_t has a mean of zero and its standard deviation is assumed to be constant for any t.

Similarly, the concept of autoregression can be extended and avoid assumptions of linear autoregression, such as in (2):

$$X_t = f\left(X_{t-1}, X_{t-2}, \ldots, X_{t-p}\right) + \varepsilon \tag{2}$$

The nonlinear autoregression can be modeled with machine learning algorithms. In this research, we choose four representative machine learning algorithms to perform autoregression of the residual time series of the wind velocity. Viz. Linear Regression (LR) based on attribute selection, Back Propagation Neural Network (BPNN), Support Vector Regression (SVR), and Reduced-Error Pruning TREE (REPTREE). The reason for choosing these relatively basic algorithms is according to Ref. [15], the advanced learning algorithms do not deliver on their superiority for univariate time-series predictions.

LR Based on Attribute Selection: The LR algorithm is a basic supervised machine learning algorithm because of its comparative simplicity and known features. It uses a least-squares function to pattern the relationship between the independent and dependent variables [16]. One of LR biggest challenges is to select independent variables that have a significant linear relationship to the dependent variable. Heuristic algorithms can address this problem. We conduct an attribute selection M5 method to remove the attribute with the smallest standardized coefficient until improvement in error estimates given by the Akaike information criterion is not observed. The M5 model is a decision tree learner for regression, used to predict the numeric dependent variable's values. It can simulate many attributes, with up to hundreds of dimensionalities [17]. The Akaike I information criterion is an estimator of the out-of-sample prediction error. It estimates the relative volume of information lost with a given model: the less information missing from a model, the higher its quality [18].

Neural Networks (NN): NN is a bionic algorithm inspired by biological neural networks. The concept of neural network modeling has a broad scope of applications in energy modeling [19]. MultiLayer Perceptrons (MLP) with backpropagation algorithms are the most widely used neural networks, shorten as BPNN. BPNN generally consists of three layers: an input layer, a hidden layer, and an output layer. Each layer is composed of neurons that are connected to neurons in the previous layer by connection weights. These weights are adjusted according to the backpropagation in the training stage. Besides, a bias term is provided to introduce a threshold for neuron activations. The input data is fed to the network through the input layer, transmitted to the hidden layer along with the weights, and added to the threshold to generate inputs for neurons in the output layer. The output is then created by the activation function [20].

SVR is an application of Support Vector Machine (SVM) to regression problems. SVM is a classifier defined as a margin's maximizer in the feature space, and its learning strategy is to convert the margin's maximization to a convex quadratic programming problem [21]. It finds optimal separating hyperplane between classes by concentrating training cases that the support vectors that lie at the edge of class distributions and the other training cases are discarded. When the number of variables increases, the mapping's dimensionality to higher dimensions grows exponentially, which makes it challenging to compute, so the kernel function is required. Like SVM, SVR is trying to find a hyperplane that minimizes the distances of all data, mapped by the kernel function.

The decision tree is a popular learning algorithm due to its understandability and simplicity [22]. REPTREE is a rapid and competitive decision tree learning approach that constructs decision trees based on information gain or variance reduction. It is a useful decision tree pruning method that places a new validation set to correct the tree for avoiding overfitting problems. It creates a relatively simplified decision tree by traversing all subtrees and replacing each subtree with a leaf node and then comparing the old and new decision trees with data from the validation set. If the new tree performs better than the old one, it is employed until the entire decision tree's performance is no longer improved [23].

3.1. Forecasts and predictive evaluation

Three metrics in evaluating forecasts for wind speed residuals modeled with varying algorithms. Namely, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Directional Accuracy (MDA). The first two are error magnitude metrics for regression analysis, and the third is an error direction index, which is widely used in econometrics but rarely in energy science. RMSE is a metric to measure regression quality, especially in machine learning regression since many regression algorithms use Mean Square Error (MSE) as their loss function in the training process. Nevertheless, it is sensitive to outliers because of squared error calculations. MAPE has advantages in interpretability over RMSE. Meanwhile, it gives a heavier penalty on negative errors due to absolute operations. So, it is beneficial to consider both metrics simultaneously. MDA compares prediction directions (upward or downward) to the actual direction and it is independent of the amount of increase or decrease in the time series [24].

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y(t) - \hat{y}(t))^2} \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|y(t) - \hat{y}(t)|}{\frac{1}{n}\sum_{t=1}^{n} y(t)} \tag{4}$$

$$MDA = \frac{1}{n}\sum_{t=1}^{n}\mathbf{1}_{sgn\left(y(t)-\hat{y}(t)\right)} \tag{5}$$

where $y(t)$ is wind velocity residual time series, $\hat{y}(t)$ denotes its forecasting time series, and $\mathbf{1}_{\mathrm{sgn}(.)}$ denotes the indicator function.

4. Experimental results and discussions

4.1. Experimental study setup

An Arctic wind site surrounded by hills and fronts a fjord is our case study's target. The wind site offers the measured wind speed and direction data. The modeling wind data computed by the Scandinavian MEPS are with 2.5 km resolution, which is regarded as the mesoscale resolution in wind research. Both datasets are from 0:00 1st January 2017 to 23:00 31st December 2017 with one-hour temporal resolution. The entire annual data are divided into four quarterly datasets with sizes of 2160, 2184, 2208, and 2208. We use the first three quarterly data as the training set and the last quarterly data as the forecasting testing set.

It is well known that the NWP wind model is not perfect [25], so it can be determined that its prediction residuals are not white noise or random walk without any meaningful information. This also indicates that the NWP wind speed and direction forecast model does not fully extract actual physical properties in regression analysis. Thus, it is possible to optimize the NWP model by further forecasting the corresponding wind velocity residual series.

In vector analysis, the wind speed is the scalar value of the wind velocity vector. East–West and North–South wind speeds are the East–West and North–South scalar values of the wind velocity vector, both of which can reflect this vector's size and direction. These three variables can comprehensively describe the wind as a vector. We define the East–West wind speed (u), North–South wind speed (v), and wind velocity vector ($\boldsymbol{V}$) in (6), (7), and (8):

$$u = p \times \sin\theta \tag{6}$$

$$v = p \times \cos\theta \tag{7}$$

$$\boldsymbol{V} = \{p, u, v\} \tag{8}$$

The residual of the NWP model is defined as the difference between the measured wind velocity and wind velocity predicted by NWP. Their abbreviations are *P, u, v* (measured overall, East–West and North–South wind speed); P_N, u_N, v_N (overall, East–West and North–South wind speed computed by NWP model); *RP, Ru, Rv* (residual overall, East–West, and North–South wind speed calculated by measured data minus correspond NWP data).

A multi-step autoregressive forecast for these wind velocity residual series by employing several machine learning algorithms. The results of forecasts from different algorithms and steps are analyzed in detail. Furthermore, we suggest that the actual wind velocity can be expressed in (9). The forecasts can serve as critical corrections to upgrade the NWP wind velocity predictive model for practical usage and environmental research of wind sites. The forecasts can serve as critical corrections to upgrade the NWP wind velocity predictive model for practical usage and environmental research of wind sites.

$$\boldsymbol{V} = \boldsymbol{V}_{NWP} + \boldsymbol{V}_{Residual} + \boldsymbol{\varepsilon} \tag{9}$$

To determine the number of prior period variables in autoregressive predictions, the autocorrelation plots for *RP*, *Ru,* and *Rv* are drawn. There is a significant autocorrelation of these time series over a full day from these plots. As mentioned above, the NWP model is operated every 6 h, so the most recent variable included in autoregressive models is the one beyond 6 h. Given that the winds have an apparent daily similarity phenomenon [26], we also include the one hour after a day (25 h later) corresponding to the model's forecast time. In summary, the predictive model is represented by (10):

$$\boldsymbol{R_t} = \boldsymbol{f}\left(\boldsymbol{R_{t-6},} \boldsymbol{R_{t-7,}} \ldots, \boldsymbol{R_{t-25}}\right) + \boldsymbol{\varepsilon} \tag{10}$$

Moreover, since the NWP provides weather forecasts for the upcoming 66 h, we also undertake 66 time-step predictions for wind velocity residual series to complement the wind information from NWP in wind engineering.

4.2. Wind velocity residuals forecasts

For the linear regression with M5 attribute selection, the regression model for *RP*, *Ru,* and *Rv* are with 8, 11, and 12 variables, respectively. For machine learning algorithms, the grid search is made to tune algorithm parameters and the best performance-related parameters are chosen in these models. For the performance metrics of different 1 to 66 time-steps ahead forecasting approaches tested in the fourth quarter residual data, it is observed that MDA and MAPE are not correlated with the forecast steps, so their means and Coefficients of Variation (CV) (defined as the standard deviation divided by the mean.) are calculated and displayed in Table 1. Table 1 left part shows that the forecast error of REPTREE is bidirectional and fluctuates with forecasting steps because it has the minimum average MDA and maximum CV. The other three algorithms accumulated more bias in forecast directions. For MAPE comparison, SVR has the smallest average MAPE in *RP*, *Ru,* and *Rv* predictions. Generally, LR and REPTREE have similar MAPE and BPNN shows the worst performance in terms of MAPE. Compared to *Ru* and *Rv*, forecasts of *RP* have higher MAPE, which indicates larger absolute errors exist in the forecasts.

The RMSE for various algorithms corresponding to each forecast step is illustrated in Fig. 1. Generally, almost all RMSE increases with forecast steps. Within six hours, each algorithm shows quite steady RMSE, which also

Table 1. Average and CV of MDA and MAPE for forecast algorithms.

MDA	LR	BPNN	SVR	REPTREE	**MAPE**	LR	BPNN	SVR	REPTREE
RP (Mean)	49.882	50.279	49.892	18.000	*RP* (Mean)	5.100	9.708	4.591	7.833
Ru (Mean)	50.163	50.141	49.803	13.556	*Ru* (Mean)	2.801	2.506	1.681	1.687
Rv (Mean)	49.766	49.983	49.827	19.304	*Rv* (Mean)	1.957	4.774	1.757	2.870
RP (CV)	0.017	0.022	0.018	0.144	*RP* (CV)	0.163	0.362	0.200	0.563
Ru (CV)	0.017	0.020	0.017	0.968	*Ru* (CV)	0.068	0.313	0.130	0.326
Rv (CV)	0.021	0.020	0.021	0.265	*Rv* (CV)	0.330	0.156	0.250	0.031

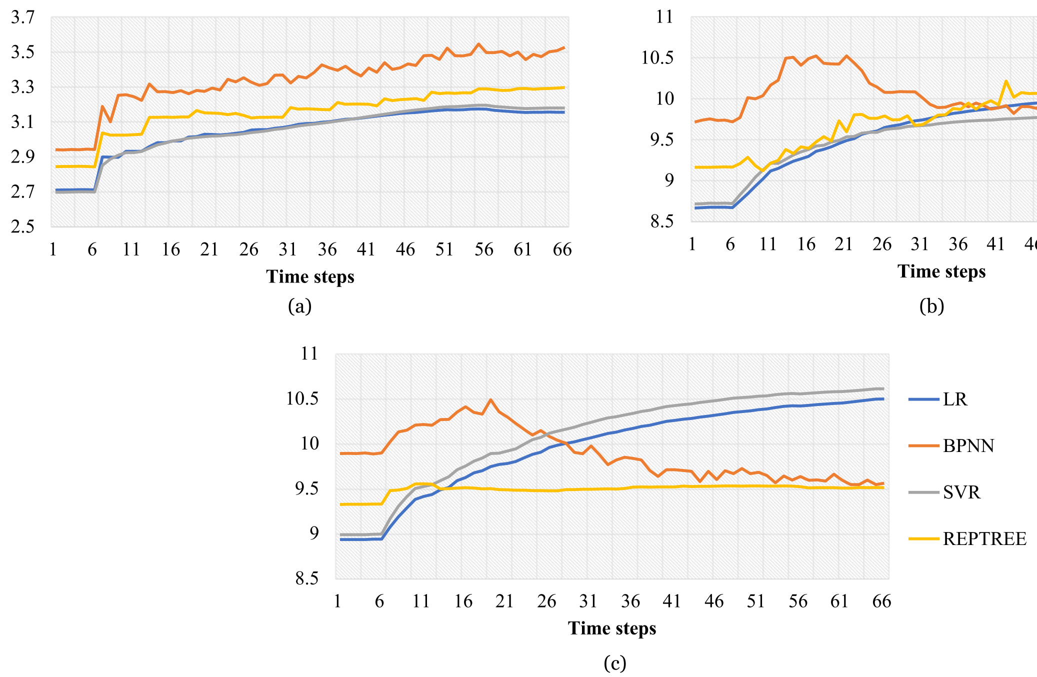

Fig. 1. The RMSE of residuals forecasts. ((a), (b), and (c) are related to the forecasting RMSE of *RP, Ru,* and *Rv,* respectively).

indicates from a side that larger data corrections are made in each NWP model update. LR and SVR give the best performance for all residuals within six hours. However, their superiority over REPTREE diminishes as the forecast time grows, especially in *Rv* forecast. Meanwhile, the intrinsic characteristics of *Ru* and *Rv* are more difficult to model with learning methods since their RMSE are generally higher than the one of *RP.* Especially, the RMSE curves of BPNN are contradictory to physical laws in (b) and (c) because as the forecast step increases, so does the number of model iterations, which results in more predicted values from the previous step involved in the next forecast, causing a decrease in overall model performance. This anomaly may be explained as errors in BPNN models cancel each other out in iterations.

It is intuitively clear from Fig. 1 that no single algorithm outperforms the other algorithms for all data and forecast steps. Moreover, BPNN and REPTREE models in *RP* and *Ru* forecasts that are underperforming are excluded. We use a Friedman test [27] to check the difference in RMSE of the other different algorithms. The p-values corresponding to tests for *RP*, *Ru,* and *Rv* are 0.3248, 0.0267, and smaller than 0.0001, respectively. This means LR and SVR are statistically the same in forecasts of *RP* and *Ru*. Besides, it is still challenging to determine the most suitable algorithm for *Rv*.

The 66 h, starting from 24:00 31st December 2017, ahead of residual predictions by the four algorithms are shown in Fig. 2. BPNN gives dramatic vibrations in predictions, and in contrast, REPTREE provides a selection of predictions among only a few fixed values. Considering all the above and the simplicity and interpretability and computational time, LR is a reasonable approach for multi-step predictions of NWP wind velocity residual series and delivers rapid and relatively accurate corrections to the NWP wind velocity model. A plausible explanation is

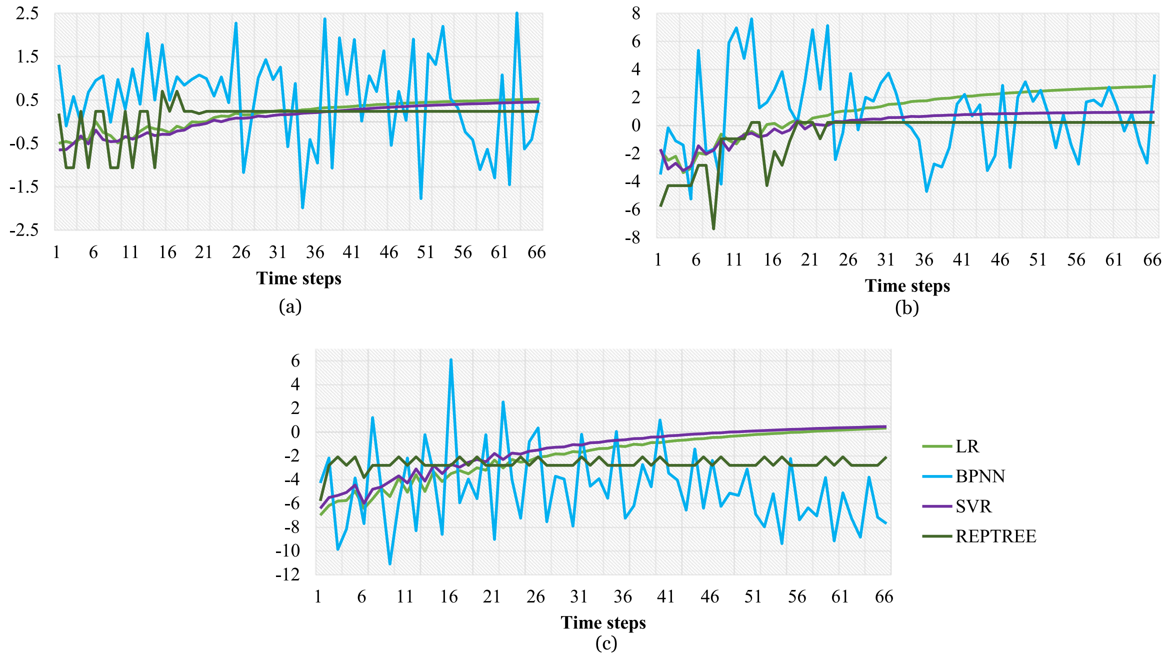

Fig. 2. The 66 h ahead of residuals predictive values by various algorithms. ((a), (b), and (c) are related to predictions of *RP, Ru,* and *Rv,* respectively).

that most of the actual wind speed and direction characteristics are already collected by NWP models, and classical autoregressive models can well capture the remaining wind features.

5. Conclusion

The autoregression combined with machine learning algorithms enables compelling multi-step predictions of these NWP wind velocity residuals. Linear autoregression is proven to achieve fast and competitive forecasts with rigorous statistical approaches. The superiority of the statistical method for machine learning is further demonstrated by the fact that the residual series are considerably stochastic and sophisticated algorithms resulting in overfitting. These forecasts complement the wind data from the current updating NWP to significantly optimize the input data quality for wind energy utilization systems.

In future works, we hope to combine the proposed wind residuals analytical and predictive framework with the NWP wind model with higher resolution to obtain more accurate wind data.

CRediT authorship contribution statement

Hao Chen: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Qixia Zhang:** Writing – review & editing. **Yngve Birkelund:** Comments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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