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A data-driven multi-model methodology with deep feature selection for short-term wind forecasting

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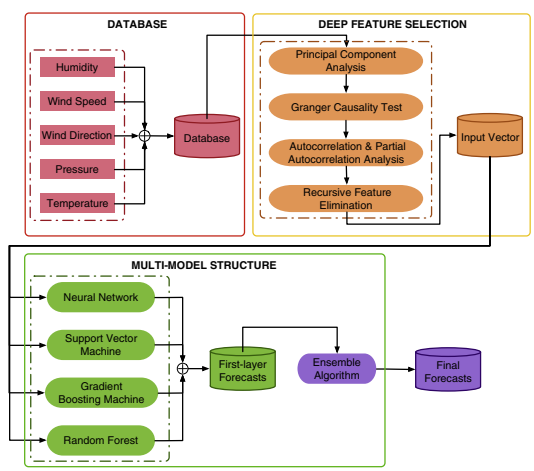
HIGHLIGHTS

- An ensemble model is developed to produce both deterministic and probabilistic wind forecasts.
- A deep feature selection framework is developed to optimally determine the inputs to the forecasting methodology.
- The developed ensemble methodology has improved the forecasting accuracy by up to 30%.

GRAPHICAL ABSTRACT



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ABSTRACT

With the growing wind penetration into the power system worldwide, improving wind power forecasting accuracy is becoming increasingly important to ensure continued economic and reliable power system operations. In this paper, a data-driven multi-model wind forecasting methodology is developed with a two-layer ensemble machine learning technique. The first layer is composed of multiple machine learning models that generate individual forecasts. A deep feature selection framework is developed to determine the most suitable inputs to the first layer machine learning models. Then, a blending algorithm is applied in the second layer to create an ensemble of the forecasts produced by first layer models and generate both deterministic and probabilistic forecasts. This two-layer model seeks to utilize the statistically different characteristics of each machine learning algorithm. A number of machine learning algorithms are selected and compared in both layers. This developed multi-model wind forecasting methodology is compared to several benchmarks. The effectiveness of the proposed methodology is evaluated to provide 1-hour-ahead wind speed forecasting at seven locations of the Surface Radiation network. Numerical results show that comparing to the single-algorithm models, the developed multi-model framework with deep feature selection procedure has improved the forecasting accuracy by up to 30%.

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1. Introduction

Renewable energy resources, particularly wind and solar energy, have become a primary focus in government policies, academic research, and the power industry. Among various renewables, wind energy is considered as one of the most promising alternatives [1]. However, the variable and uncertain nature of the wind resource may affect the economic and reliable operations of the power system [2], especially with the increasing penetration levels of wind power [3]. Therefore, it is important and desired to improve the accuracy of the wind speed forecasting (WSF) or wind power forecasting (WPF) that is used in power system scheduling. Different forecasting models have been developed in the literature, and they can be generally classified into three groups [4]: (i) physical models that are usually based on numerical weather prediction (NWP) models; (ii) statistical methods, most of which are intelligent algorithms based on data-driven approaches; and (iii) hybrid physical and statistical models.

NWP models simulate the physics of the atmosphere utilizing physical laws and boundary conditions. There exist a variety of challenges by directly adopting NWP models for wind forecasting, such as the accuracy, spatial and temporal resolutions, domain and hierarchical importance of the physical processes. Based on the domain coverage, the NWP models could be divided into limited area models (LAMs) and global models (GMs) [5]. Several GMs [6–8] have been developed to fulfill different forecasting needs, such as the Global Forecast System (GFS) and the Integrated Forecast Model (IFS). LAMs normally produce higher-resolution forecasts than GMs. Different LAMs have been developed for forecasting at different domains, some of which include the High-Resolution Limited Area Model (HIRLAM) [9], ALADIN [10], the Fifth-Generation Mesoscale Model (MM5) [11], and High Resolution Rapid Refresh (HRRR) [12].

Statistical models are trained using historical data and usually outperform NWP models in very short-term forecasting (within one-hour ahead) [13]. Both linear and non-linear methods have been widely applied to wind forecasting. Linear models, such as autoregressive moving average (ARMA) methods [14,15], Box-Jenkins methods [16], Kalman filter [17], and Markov Chain models [18,19], are most widely used in the literature. Artificial neural networks (ANN) and support vector machine (SVM) are the two most popular nonlinear methods for wind forecasting. Ghorbani et al. [20] forecasted one-hour ahead wind speed with ANN model combined with genetic expression programming. It was found that this model could significantly improve the forecast accuracy compared to the selected benchmark models. Chitsaz [21] adopted multi-dimensional wavelets as the activation functions in the ANN models to improve the forecasting accuracy. Li and Shi [22] comprehensively compared different ANN models in wind speed forecasting and concluded that the ANN models performed inconsistency with different conditions. Zhou et al. [23] developed three SVM methods with three kernels, and found that the SVM model performed better than the persistence approach for the test cases. Decision trees of many forms have also been used extensively as nonlinear methods for wind power forecasting. Troncoso et al. [24] proposed several regression tree models that could achieve competitive results with less computational time compared to other benchmark models. More research about wind forecasting with ANN and SVM algorithms has been done in [25–28].

Considering the spatial and temporal complexity of wind forecasting, it is challenging to develop a single algorithm that performs the best for all forecasting scenarios. An alternative way to reduce the risk of bad forecasts and improve the overall accuracy is hybriding multiple characteristically different algorithms, which is also known as 'ensemble forecasting'. Hybrid methods have been shown in the literature to produce more accurate forecasts than any of the individual forecasting models [29]. These hybrid or ensemble models can be divided into four categories: (i) data pre-processing based ensemble approaches; (ii) model-optimized ensemble approaches; (iii) data post-processing based ensemble approaches; and (iv) weighting-based ensemble approaches [30]. More information about the hybrid models could be found in [31–33]. For most studies, only two or three algorithms are blended with linear or non-linear weighting strategies. In addition, most models are tested with no more than two datasets, which is generally not enough to convincingly conclude that hybrid models are better than individual models, given the large differences in forecasting accuracy exhibited by the same algorithms at different sites. In this paper, a novel two-layer multi-model forecasting methodology is developed, which utilizes multiple characteristically different machine learning algorithms with different kernels in both layers. The developed methodology is validated with the data collected from seven Surface Radiation (SURFRAD) network locations to provide 1-h-ahead wind forecasting.

One of the major components of the developed multi-model forecasting model is a deep feature selection framework, which can select the most suitable inputs to the forecasting model. Full-dimension features will not only increase the computation time but also decrease the forecasting accuracy. A well-designed feature selection process plays a key role in wind forecasting. Different feature selection methods have been used in the literature. Liu et al. [34] utilized the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis, along with the Granger causality test to quantitatively analyze the relation between wind speeds and other variables on different lags. Kou et al. [35] used the sequential forward greedy search approach to determine the length of historical wind speed data as the inputs. Li et al. [36] developed a conditional mutual information-based feature selection approach to determine a small set of wind power and wind speed as input features. However, most of the existing feature selection methods present two major issues: (i) linear methods, such as ACF and PACF analysis, only consider the linear relations between time series; and (ii) nonlinear methods always take a continuous feature subset as a factor but do not analyze the individual lags.

To bridge the gap discussed above in wind forecasting, this paper develops a data-driven multi-model methodology with a deep feature selection process for short-term wind forecasting. The main contributions of this paper are as follows:

(1) An ensemble model for WSF is developed to automatically blend multiple single-algorithm models with different kernels being able to generate both deterministic and probabilistic forecasts.
(2) A deep feature selection framework is developed to optimally determine the input vector to the forecasting methodology.

The remainder of the paper is organized as follows. Section 2 describes the developed deep feature selection procedure and the individual algorithms employed in the two-layer hybrid model. Section 3 presents the results of deep feature selection, deterministic and probabilistic wind forecasts at multiple studied locations. Section 4 gives the conclusions and future work.

2. Multi-model wind forecasting with deep feature selection

Due to the nonlinear and non-stationary characteristics of wind speed, it is challenging to develop a generic model based on a single machine learning algorithm that can produce the best forecasts at different spatial and temporal scales. In this paper, a data-driven

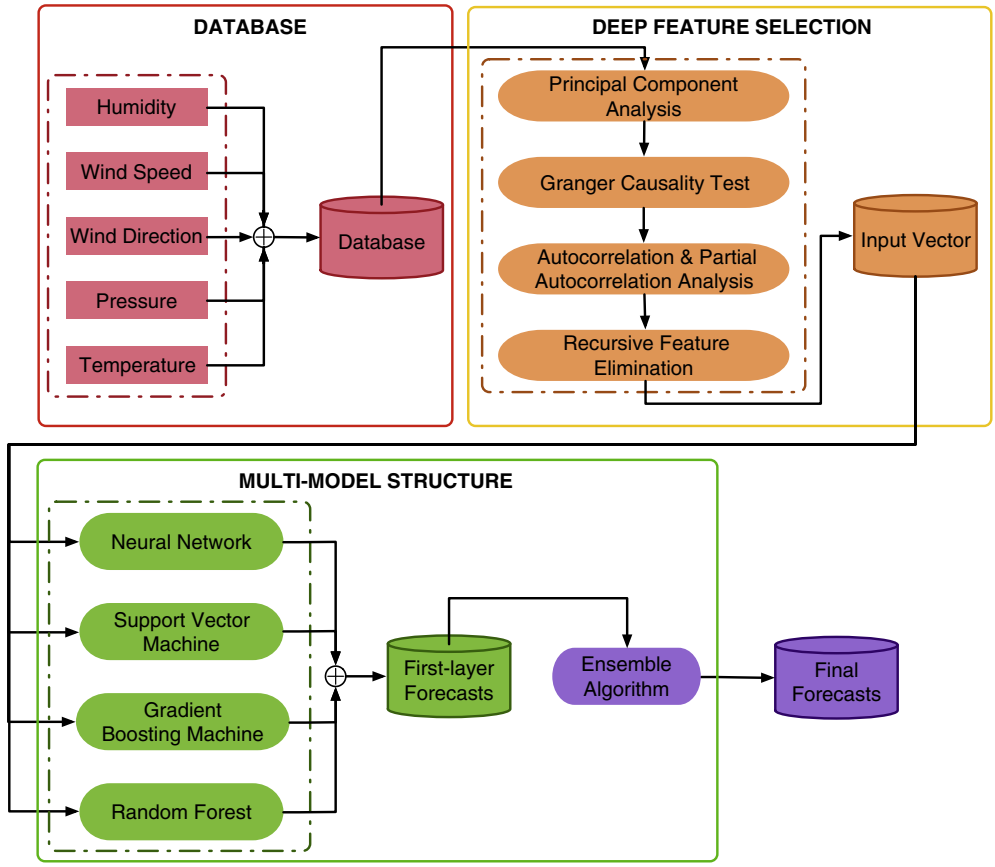


Fig. 1. The overall framework of the ensemble forecasting model.

multi-model wind forecasting methodology with deep feature selection is developed. The developed methodology is illustrated in Fig. 1, with a two-layer forecasting structure. First, features extracted from the data variables are determined by a deep feature selection procedure and serve as inputs to the model. Four independent feature selection methods are included in the procedure and implemented sequentially. The first layer machine learning models are built based on the selected feature combination. These models forecast wind speed or wind power as the output. A blending model is developed in the second layer to combine the forecasts produced by different algorithms from the first layer, and to generate both deterministic and probabilistic forecasts. Parameters of these models are optimally tuned by the grid search technique. Machine learning algorithms have distinctive advantages. For instance, ANN algorithms are adaptive by choosing different learning functions and loss functions, but have overfitting issues when the training data set is not long enough. SVM is efficient to train and can provide relatively accurate results, but they are memory-intensive and hard to tune. Tree ensemble algorithms like random forest and gradient boosting machine can avoid overfitting issues. The developed blending model is expected to integrate the advantages of different algorithms by canceling or smoothing the local forecasting errors.

2.1. Deep feature selection

The performance of a data-driven model highly depends on its inputs. There are several variables in one data set, such as wind speed, humidity, etc. Each variable has several lags, which are different features that need to be selected. The selected features will serve as inputs to the machine learning models. A comprehensive feature selection as illustrated in Fig. 2 is developed with the aim of improving the forecasting accuracy by selecting optimal feature combinations. Four different approaches are employed to select the most suitable input variables, which are: (i) principal component analysis (PCA); (ii) Granger causality test (GCT); (iii) autocorrelation analysis (ACF) and partial autocorrelation analysis (PACF); and (iv) recursive feature elimination (RFE).

2.1.1. Principal component analysis (PCA)

The data used for WPF or WSF usually contains a large number of variables, which may lead to high computational cost and may also decrease the prediction accuracy due to the extraneous information. To reduce the risk of over-fitting and inaccurate forecasts, PCA is applied to determine the major factors that contribute to the prediction [37]. The substance of PCA is the linear transformation. By using PCA, the observation matrix, X, is transformed into covariance matrix $\sum$. The contribution rate (CR) and the cumulative contribution (CC) of the ith principal component are, respectively, computed by:

$$CR_i = \frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j} \tag{1}$$

$$CC_i = \frac{\sum_{j=1}^{i} \lambda_i}{\sum_{j=1}^{p} \lambda_j} \tag{2}$$

where λ_i is the eigenvalue corresponding to the ith principal component, and p is the number of parameters.

2.1.2. Granger causality test (GCT)

PCA can reduce the variable dimension, but not all of the remaining variables are useful for the forecasting. To further explore correlations between the remaining variables and the wind

speed series, GCT is conducted. GCT is a statistical hypothesis test first proposed by Clive W.J. Granger [38]. GCT has been widely applied in econometrics, and recently also in WPF or WSF. The efficiency of GCT in WPF or WSF feature selection has been proved in the literature [34,39,40].

The overall process of GCT is described in the green dash rectangular of Fig. 2. The prerequisite to conduct GCT is to ensure the testing time series be stationary [41]. To this end, the Augmented Dickey-Fuller unit root test (ADF) [42] is chosen as the stationary test approach in this paper. The null hypothesis of the ADF test is 'the testing time series does not have unit root', which means the series is non-stationary. If the test statistic is smaller than the critical value, the proposed null hypothesis is rejected, which means the series is stationary and thus GCT can not be implemented directly. To further ensure the long-term relationship between two variables, the Johansen cointegration test (JCT) is also applied.

If the testing series is stationary or is validated to have stable relationship, GCT can be carried out. The unrestricted model and restricted model for the testing are, respectively, described as [38]:

$$x_1^u(t) = \sum_{j=1}^{l} \alpha_j x_1(t-j) + \sum_{j=1}^{p} \beta_j x_2(t-j) + \varepsilon(t) \tag{3}$$

$$x_1^r(t) = \sum_{j=1}^{l} \alpha_j x_1(t-j) + \varepsilon(t) \tag{4}$$

where $\{x_1\}$ and $\{x_2\}$ are testing variables, $\varepsilon(t)$

Table 6
Results of parameter tuning at the BND site.

Model	Search range	Selected value
SVR_li	$C \in [1:100]$	$C = 1$
SVR_poly	$C \in [1:100]; degree \in [1:5]$	$C = 3; degree = 3$
ANN	$n_l \in [1:5]; n_o \in [1:50]; decay \in [0.01:1]$	$n_l = 1; n_o = 36; decay = 0.04$
GBM	$n.trees \in [50:1500]; \lambda \in 0.1^{[1:4]}; int.depth \in [1:10]; n.ob \in 5^{[1:10]}$	$n.trees = 650; \lambda = 0.01; int.depth = 9; n.ob = 5$
RF	$mtry \in [1:100]$	$mtry = 7$

performance of the forecasting model is much worse than that with all fifteen features combined, as illustrated in Fig. 7.

3.3. Model selection and parameter tuning

The developed multi-model framework includes multiple individual models in the first layer and also several models in the second layer. Different algorithms are tested in both layers. The parameters are optimized to improve the forecasting performance of these single-algorithm models. In this paper, the grid search

Table 7
1-h-ahead forecasting NMAE of single-algorithm models without feature selection.

Models	BND	TBL	DRA	FPK	GCM	PSU	SXF
P	**4.05**	**4.27**	**5.25**	**4.28**	**4.13**	**5.78**	**3.91**
SVR_li	5.26	5.04	6.65	5.18	5.42	7.13	4.93
SVR_poly	5.04	4.90	6.17	4.93	5.06	6.86	4.86
ANN	5.35	5.96	6.23	5.29	5.65	6.90	4.73
GBM_g	4.95	4.82	6.02	4.80	4.82	6.68	4.78
GBM_l	5.01	4.80	6.23	4.94	4.96	6.67	4.93
RF	5.32	4.93	6.51	5.31	5.58	7.51	5.25

Note: The best NMAE values of the component models are in boldface. P represents the persistence model.

Table 8
1-h-ahead forecasting NRMSE of single-algorithm models without feature selection.

Models	BND	TBL	DRA	FPK	GCM	PSU	SXF
P	**5.65**	**6.60**	**7.36**	**5.91**	**5.68**	**8.27**	**5.42**
SVR_li	7.76	8.37	9.88	7.92	8.09	9.90	6.95
SVR_poly	7.05	7.62	8.58	6.81	6.72	9.33	6.51
ANN	7.27	8.09	8.47	6.94	7.05	9.37	6.30
GBM_g	6.78	7.77	8.06	6.59	7.01	9.24	6.37
GBM_l	6.79	7.71	8.86	6.68	6.67	9.42	6.52
RF	7.36	7.21	9.10	7.35	7.46	10.04	7.11

Note: The best NRMSE values of the component models are in boldface. P represents the persistence model.

Table 9
NMAE of the developed multi-model forecasting without feature selection.

Models	BND	TBL	DRA	FPK	GCM	PSU	SXF
P	**4.05**	**4.27**	**5.25**	**4.28**	**4.13**	**5.78**	**3.91**
E_SVM_li	4.32	5.28	5.44	4.45	6.04	6.03	4.05
E_SVM_poly	*4.20*	*4.54*	*5.36*	*4.31*	*5.14*	*5.84*	*4.01*
E_GBM	4.26	4.58	5.49	4.37	5.81	6.11	4.19
E_RF	4.26	4.60	5.66	4.33	5.34	6.09	4.22

Note: The smallest NMAE at each location is in boldface. The best ensemble model is in italic.

Table 10
NRMSE of the developed multi-model forecasting without feature selection.

Models	BND	TBL	DRA	FPK	GCM	PSU	SXF
P	**5.65**	**6.60**	**7.36**	**5.91**	**5.68**	**8.27**	**5.42**
E_SVM_li	6.20	8.96	7.51	6.29	9.21	8.52	5.61
E_SVM_poly	*5.77*	*7.22*	*7.36*	6.05	*7.08*	*8.16*	*5.49*
E_GBM	5.95	7.29	7.58	6.00	8.23	8.48	5.72
E_RF	5.85	7.52	7.63	*5.92*	7.53	8.46	5.74

Note: The smallest NRMSE at each location is in boldface. The best ensemble model is in italic.

Table 11
NMAE of the developed multi-model forecasting with deep feature selection.

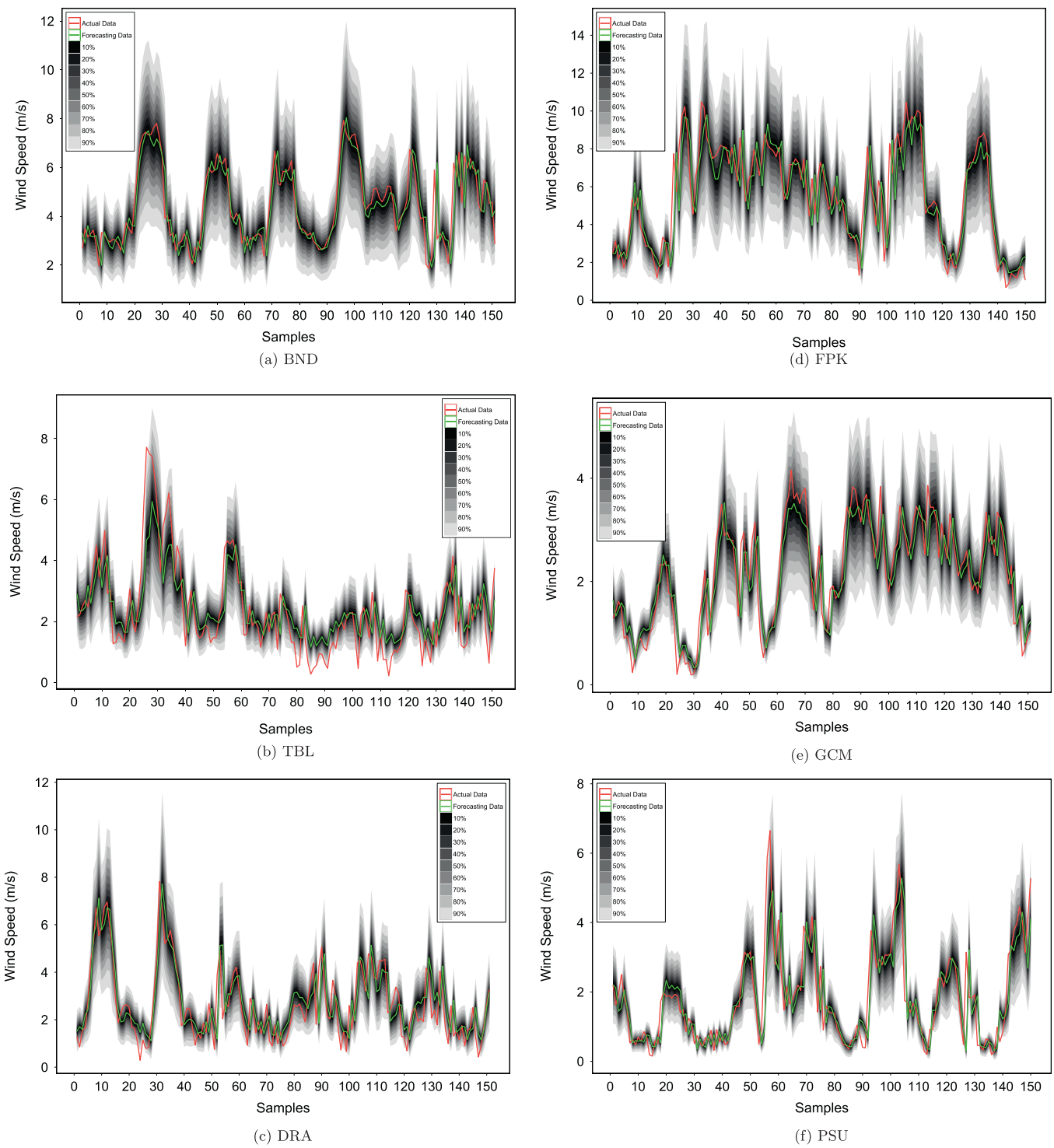
Models	BND	TBL	DRA	FPK	GCM	PSU	SXF
P	4.05	4.27	5.25	4.28	**4.13**	5.78	3.91
E_SVM_li	4.05	4.61	*5.20*	*4.19*	4.76	*5.72*	*3.84*
E_SVM_poly	**3.93**	**4.12**	*5.21*	**4.08**	**4.13**	**5.70**	**3.76**
E_GBM	4.13	4.40	**5.18**	*4.20*	4.54	*5.77*	*3.82*
E_RF	4.21	4.51	5.30	*4.22*	4.54	5.86	*3.87*

Note: The smallest NMAE at each location is in boldface. Other NMAEs smaller than persistence model are in italic.

Table 12
NRMSE of the developed multi-model forecasting with deep feature selection.

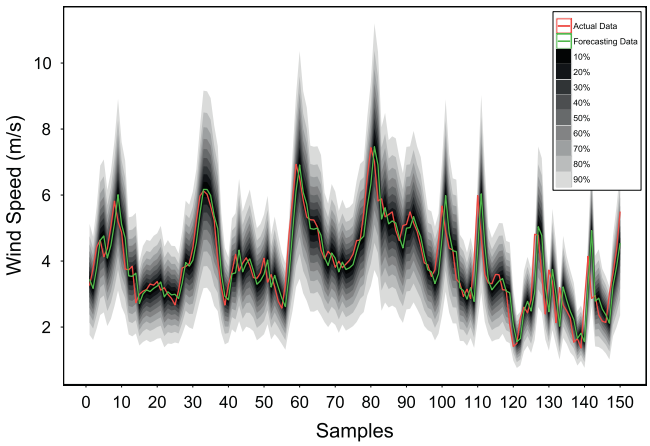
Models	BND	TBL	DRA	FPK	GCM	PSU	SXF
P	5.65	6.60	7.36	5.91	5.68	8.27	5.42
E_SVM_li	5.69	8.12	7.36	*5.82*	7.91	*8.10*	*5.35*
E_SVM_poly	**5.43**	**6.17**	**7.24**	**5.64**	**5.67**	**8.09**	**5.21**
E_GBM	5.83	6.93	**7.24**	*5.81*	6.65	*8.11*	*5.31*
E_RF	5.85	7.02	*7.30*	*5.77*	6.47	*8.20*	*5.34*

Note: The smallest NRMSE at each location is in boldface. Other NRMSEs smaller than persistence model are in italic.



(a) BND (d) FPK (b) TBL (e) GCM (c) DRA (f) PSU

Fig. 9. Deterministic forecasting from the multi-model framework with confidence intervals



(g) SXF

Fig. 9 (*continued*)

method is used to determine the optimal parameters that generate the minimum forecasting error.

For SVR, the linear (SVR_li) and polynomial (SVR_poly) models are selected in the first layer. The sole parameter of SVR_li to tune is the cost (C). For SVR_poly, there are two parameters to be determined: polynomial degree (*degree*) and cost (C).

For ANN, different learning algorithms and activation functions are tested. The selected models employ the feed-forward back propagation as the learning function, and the sigmoid function as the activation function. The most important parameters for ANN models are the hidden layer number (n_l), neurons in each layer (n_o), and weight decay parameter (*decay*).

For the GBM models, different loss functions are utilized. Two GBM models are selected in the first layer using Gaussian (GBM_g) and Laplacian (GBM_l) loss functions. Four parameters, i.e., the number of trees to fit (*n.trees*), the learning rate (λ), the maximum depth of variable interactions (*int.depth*), and the minimum number of observations in the terminal nodes (*n.ob*) need to be tuned.

The RF model in this paper only has one parameter to be optimized. It is the number of variables randomly sampled as candidates at each split (*mtry*). One example of parameters optimization results is listed in Table 6.

3.4. Deterministic results of the multi-model forecasting

In order to evaluate the forecasting accuracy of the developed framework, two error criteria are utilized: the normalized mean absolute error (*NMAE*) and the normalized root mean square error (*NRMSE*). They are defined by:

$$NMAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_i - y_i}{y_{max}}\right| \tag{15}$$

$$NRMSE = \frac{1}{y_{max}}\sqrt{\frac{\sum_{i=1}^{n}(f_i - y_i)^2}{n}} \tag{16}$$

where f_i is the forecasted wind speed, y_i is the actual wind speed, y_{max} is the maximum actual wind speed, and n is the sample size.

Tables 7–12 summarize the results of different models based on these two evaluation metrics. Tables 7 and 8, respectively, list the *NMAE* and *NRMSE* of component single-algorithm models that are trained without the feature selection procedure. Tables 9 and 10 show the evaluation results of the developed two-layer multi-model framework without the feature selection procedure. Tables 11 and 12 illustrate the results of the developed framework with the feature selection procedure.

As shown in Tables 7 and 8, none of the single-algorithm models performs better than the persistence method. Without considering the persistence model, no single-algorithm model is always most accurate at all seven locations. For example, GBM_g is the most accurate model at BND, and GBM_l performs the best at TBL. In addition, models with non-linear kernels are generally more accurate than those with linear-kernels. For instance, the SVR_poly model always outperforms the SVR_li models.

Comparing Tables 9 and 10 with Tables 7 and 8, the proposed multi-model forecasting framework with different blending algorithms outperforms the single-algorithm models. Even without the feature selection procedure, the two-layer models have improved the accuracy of the component models by up to 23.8% based on *NMAE* and 25.6% based on *NRMSE*. For the blending algorithms, the models with non-linear blending algorithms have better performance than the models with linear blending algorithms. This shows that the forecasts produced from the first-layer models exhibit a non-linear relationship with the actual wind speed. The model with the polynomial-kernel SVM algorithm is the most accurate model among all the ensemble models.

The results of the developed hybrid models in conjunction with the deep feature selection procedure are listed in Tables 11 and 12. Comparing the same hybrid models as shown in Tables 9 and 10, the deep feature selection has improved the forecasting accuracy by up to 21.86% and 19.92% based on *NMAE* and *NRMSE*, respectively. Similar to the models without feature selection, the SVM with polynomial kernel is the best performing algorithm among all hybrid algorithms. Comparing the developed multi-model framework with deep feature selection with the single-algorithm models, the multi-model forecasting model has improved the accuracy by up to 30.87% and 30.03% based on *NMAE* and *NRMSE*, respectively. In addition, this best hybrid model is performing better than the persistence forecasts at all seven locations.

3.5. Probabilistic results of the multi-model forecasting

In addition to deterministic forecasts, the developed multi-model methodology can also produce probabilistic forecasts. Fig. 9 provides an example of the deterministic forecasts along with the confidence intervals in the form of fan chart, at all seven locations. The confidence bands are calculated based on the component models. The colors of the intervals fade with the increasing confidence level, ranging from 10% to 90% in a 10% increments. The intervals are symmetric around the deterministic forecasting curves with a changing width. When the wind speed fluctuates within a small range, the confidence bands are narrow, as shown by hours 0–20 at the BND site and hours 40–50 at the DRA site. When there is a significant ramp, the uncertainty of the forecasts is increased and the bands tend to be broader, as shown by hours 20–35 at the BND site. This further proves the necessity of probabilistic forecasting.

To quantify the probabilistic forecasting accuracy, two metrics are used: reliability and sharpness. Reliability is the correct degree of a probabilistic forecasting [52], which can be assessed by the hit percentage [53]. Sharpness is the uncertainty conveyed by the probabilistic forecasts, which can be computed as the average interval size of different confident levels [54]. These two metrics are visualized by the reliability diagram and δ-diagram. In our case, the reliability diagrams of all seven locations are depicted in Fig. 10. The black solid line represents the ideal probability of the forecasts. The probabilistic forecasting produced by the developed multi-model framework is under-confident at BND and SXF, and over confident at TBL, GCM, PSU, and DRA. The reliability of the probabilistic forecasts at FPK is the best due to the smallest devia-

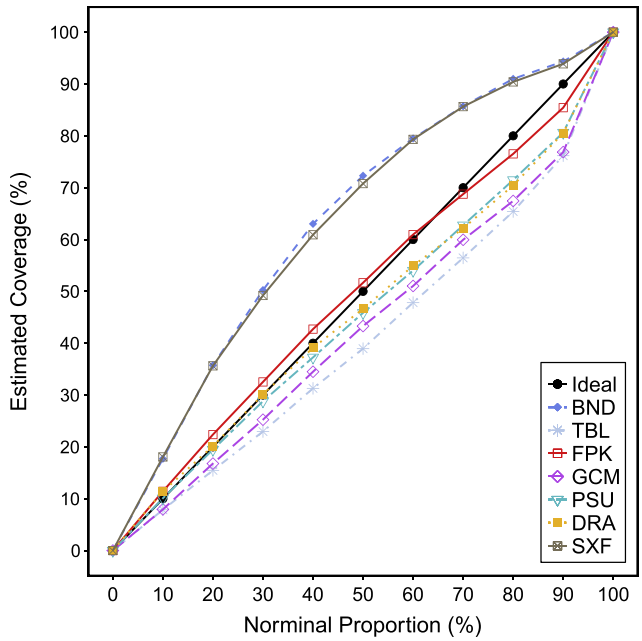


Fig. 10. Reliability diagram for the probabilistic forecasting results at seven locations.

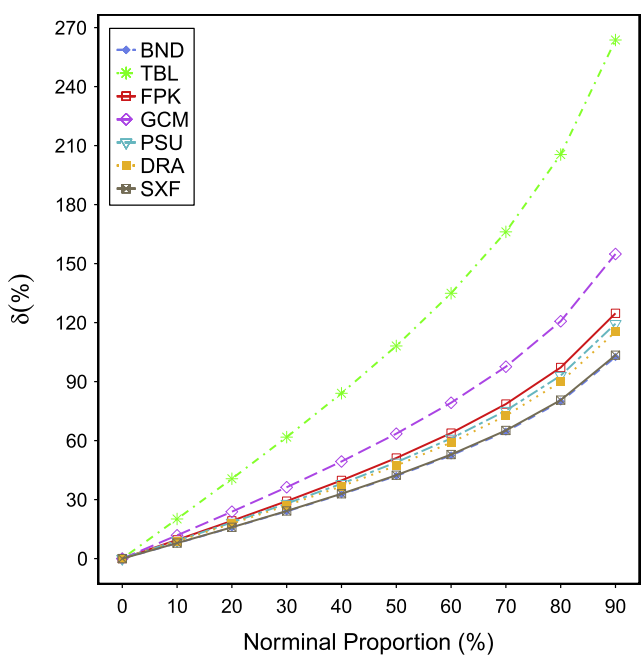


Fig. 11. δ-diagram for the probabilistic forecasting results at seven locations.

tion to the ideal line. Similarly, Fig. 11 depicts the δ-diagrams of the probabilistic forecasting at all seven location. Except for TBL, the model shows a consistent sharpness over different locations. The high sharpness of the probabilistic forecasts at TBL is mainly due to the frequent ramps of wind speed.

4. Conclusion

In this paper, a novel two-layer hybrid WPF/WSF methodology in conjunction with deep feature selection was developed. The framework consists of multiple single machine learning algorithms in the first layer and blending algorithms in the second layer. Several algorithms such as ANN, SVM, GBM, and RF with different kernels were tested and tuned in both layers. A deep feature selection framework was also developed to optimally determine the most suitable input combinations for the forecasting models. In the deep feature selection framework, the PCA, GCT, ACF, PACF, and RFE methods were adopted and implemented in an optimized sequence to take advantage of each method. The multi-model wind forecasting methodology was evaluated using data from seven SURFRAD locations. Both the hybrid algorithms and the feature selection approach were found to significantly improve the 1-h-ahead forecasting performance. The developed multi-model methodology outperformed the benchmark models by up to 30.87% and 30.03% at the 1-h-ahead forecasting horizon based on *NMAE* and *NRMSE*, respectively. Also, probabilistic forecasting produced by the developed method quantified the uncertainty of the forecasts along with the deterministic forecasting.

The developed enhanced deterministic and probabilistic wind forecasting could benefit power system operators, energy traders, and wind plant owners from different perspectives. The system operators can apply the improved forecasts in the real time security constrained unit commitment and real time security constrained economic dispatch to (i) start up/shut down generators in response to fluctuations; (ii) reduce the utilization of fast acting but expensive units; (iii) decrease the reserve levels; and (iv) reduce the wind curtailment. Overall, the improved wind forecasts would be helpful in reducing the operation costs and increasing the system reliability. The forecasts can also be used to determine the charge and discharge schedule of energy storage in a microgrid system with distributed wind generators and energy storage.

The potential future work is to validate the effectiveness of the developed multi-model framework with different time horizons in short-term forecasting. Additionally, other variables, such as temperature and humidity, can also be forecasted by first-layer models and blended by the second-layer algorithms.

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