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AdaBoosting Neural Network for Short-Term Wind Speed Forecasting Based on Seasonal Characteristics Analysis and Lag Space Estimation

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Abstract: High accurary in wind speed forcasting remains hard to achieve due to wind's random distribution nature and its seasonal characteristics. Randomness, intermittent and nonstationary usually cause the portion problem of the wind speed forecasting. Seasonal characteristics of wind speed means that its feature distribution is inconsistent. This typically results that the persistence of excitation for modeling can not be guaranteed, and may severely reduce the possibilities of high precise forecasting model. In this paper, we proposed two effective solutions to solve the problems caused by the randomness and seasonal characteristics of the wind speed. (1) Wavelet analysis is used to extract the robust components of time series and reduce the influence of randomness. (2) Based on the energy distribution about the extracted amplitude and associated frequency, seasonal characteristics of wind speed are analyzed based on self-similarity in periodogram under scales range generated by wavelet transformation. Thus, the original dataset is reasonably divided into subsest which can effectively reflect the seasonal distribution characteristics of wind speed. In addition, two strategies are given to optimal model structure and improve the forecasting accuracy: (1) The forecasting model's lag space is approximately estimated by the Lipschitz quotient to improve the generality ability of the feedforward neural network. (2) The forecasting accuracy and model robustness are further improved by the wavelet decomposition combined with AdaBoosting neural network. Finally, experimental evaluation based on the dataset from National Renewable Energy Laboratory (NREL) is given to demonstrate the performance of the proposed approach.

Keywords: Wind speed forecasting, seasonal characteristics analysis, wavelet analysis, lipschitz quotient.

Notation

Db4: Daubechies wavelet of order 4

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NREL: National Renewable Energy Laboratory

RMSE: Root mean square error

RSD: Relative standard deviation

SCA: seasonal characteristics analysis

WT: wavelet transformation

1 Introduction

Wind energy, as a typical renewable, inexhaustible and free energy resource, has been considered as an optimal solution to solve the problems caused by the traditional energy [Wang, Song, Liu et al. (2016)]. Wind energy production requires accurate and reliable wind power forecasting which in turn is closely related to wind speed forecasting. Up to date, precise short-term wind speed forecasting unfortunately remains a challenging issue due to wind's randomness and intermittent nature [Shao, Wei, Deng et al. (2016)]. Usually, randomness and nonstationary can cause the portion problem of the wind speed forecasting [Grilli and Shumchenia (2015)].

(1) In the literature, numerical weather prediction [Abd-Elaal, Mills and Ma (2018)] hydrological evaluation methods [Honti, Scheidegger and Stamm (2014)], probabilistic model [Dowell and Pinson (2016)] and neural network (NN) [Chang, Lu, Chang et al. (2017)], etc. have all been considered to analyze the uncertainty effects in climate change and wind power penetration. Du et al. [Du, Wang, Wang et al. (2016)] discussed the significant characteristics of the randomness in wind power system output, and figured out that the potential influence factors which can influence the power capacity credit on different output levels. Roy [Roy (2013)] gave a comprehensively and quantitatively description for the randomness of wind speed to evaluate the outputs variability. In order to reduce the potential influence on power system operation from the randomness of the wind speed, Ding et al. [Ding, Hu and Song (2012)] utilized the stochastic optimization method to optimize the gird plant scheduling. Wavelet analysis as a powerful time-frequency analysis method can capture the local feature of the any time series are widely used in short-term wind speed forecasting and used to reduce the negative influence caused by randomness.

(2) Aiming at the assessing the statistical characteristics and modeling the uplift capacity, Shademan et al. [Shademan, Barron, Balachandar et al. (2014)] utilized the numerical simulation of wind speed loading of the full panel to analyze the effects of the lateral gap spacing and seasonal distribution pattern. The experiments denoted that two bottom panels experience larger mean wind loading compared to the top panels. This benefits the analysis of the wind speed's seasonal distribution pattern and model configuration.

Neural network with its strong nonlinear mapping modeling ability is currently the most widely used method in the short-term wind speed or wind power forecasting. Recently, many studies indicated that the analysis method in combined with NN can significantly improve the forecasting accuracy of the short-term wind speed. Kavousi-Fard et al. [Kavousi-Fard, Khosravi, Nahavandi et al. (2016)] proposed a fuzzy-based approach in combination with NN optimized by the lower upper bound estimation to capture the uncertainty of the wind power and improve the forecasting accuracy. Meng et al. [Meng, Ge, Yin et al. (2016)] used the wavelet packet decomposition, crisscross optimization algorithm and artificial NNs to develop a new hybrid approach for short-term wind speed forecasting. The forecasting result indicated that the NN in combined with WT etc has the minimum mean absolute percentage error regardless of one-step, three-step or five-step prediction. Analogy, Ren et al. [Ren, Suganthan, Srikanth et al. (2015)] used the empirical mode decomposition-based to capture the stationary feature of wind speed, and combined with NN to establish the short-term model with high forecasting accuracy. Theoretically, although the feedforward NN with a single hidden layer can approximate any complex function, only the proper model architecture is beneficial to the acquisition of forecasting model with high accuracy. Our previously work [Wei, Shao, Deng et al. (2015)] indicated that the proper model structure selection can eliminate the unreasonable trend of data as well as feature extraction without loss of data characteristics. In addition, the forecasting accuracy can be further improved based on two following issues:

(1) Persistence of excitation for modeling. The training samples need to contain the sufficient features that they can be used to help improve the accuracy of the forecasting model. More precisely, more data sets or larger training sample sizes may be not conducive to the establishment of high-precision model unless they have enough effective features for training.

(2) Model lag estimation. The *curve-fitting* degree and *cut-off* distribution are usually selected as the principle to evaluate the model order. Lipschitz condition, Akaike Information Criterion and Bayesian Akaike Information Criterion are the most widely used methods to evaluate the model order. However, its significant drawback is that the outlined criteria are independent with the forecasting modeling. Based on the previous discussion, two following strategies are given:

(1) Seasonal characteristics analysis for persistence of excitation. The inputs of the neural network must be continuously energized, i.e. the input variables must be able to fully energize all model's modes. Periodicity detection based on WT is conducive to extract the repetitive, stable and periodic characteristics of the wind speed time series. This obviously benefits that the various modes of the NN are continuously energized, and the spectrum of the training sample contains the pre-established model's spectrum;

(2) Lag space evaluation for model lag estimation. The nonlinear mapping between the input-output is helpful to reflect the logical relationship between the historical input data and the current output data, and it is helpful to establish the feedforward NN with high generalization ability. Lipschitz quotients as a powerful measure method are used to calculate the proper delay of the chosen model.

The rest of this paper is organized as follows. The proposed approach includes the seasonal characteristics analysis (SCA) and lag space estimation etc. is given in Section 2. In Section 3, experimental evaluation is given to verify the performance of the proposed approach, and this paper is concluded in Section 4.

2 Proposed approach

The main objective of this paper is to propose a robust forecasting model with high accuracy by properly analyzing seasonal characteristics and lag space in wind resource, etc. The processing steps in general are specified as follows:

Step 1: Detect the irrelevant data and noisy to improve the sample quality. The irrelevant data and noisy will be effectively detected based on the WT.

Step 2: WT is used to decompose the original signal, extract the stationary component and reflect the similar frequency feature with respect to wind speed.

Step 3: Satisfy the persistence of excitation for NN, and ensure that the training sample contains enough seasonal characteristics used for testing. The proper subsets division is generated based on the different seasonal characteristics.

Step 4: Lag space estimation and model robustness enhancement. Lipschitz quotient and AdaBoosting NN are used to reflect the appropriate model structure and enhance the model robustness, respectively.

Experimental evaluation based on the dataset from NREL in 2004 is given to evaluate the performance of the proposed approach. The processing flow of this paper is stated in Fig. 1.

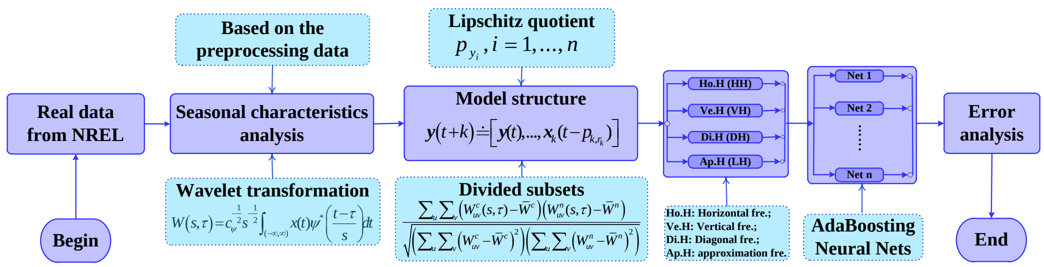

Figure 1: The processing flow

Firstly, WT is given to detect the wind variation pattern and capture the seasonal characteristics in different seasons. Secondly, wavelet decomposition is used to estimate the approximate frequency and extract the stationary component of wind speed to reduce the influence of the uncertainty in wind resources. Thirdly, Lipschitz quotient is used to estimate the lag space, reflect the model lag between the output power and the historical wind speed and power, and then promote the architecture configuration. Fourthly, AdaBoosting NN is utilized to promote the model configuration and enhance the model robustness. Finally, experimental comparison based on the dataset from NREL in 2004 is given to evaluate the performance of the proposed approach.

2.1 Seasonal characteristics analysis

WT composes of discrete and continuous wavelet transformation, which can be used to capture the distribution of the wind speed in different seasons based on the multi-frequency bands with multi-resolutions along with time. WT can detect the wind variation pattern and capture the seasonal feature in different seasons [Duo-Neng, Zhong-Xi, Zheng et al. (2016); Shao, Wei, Deng et al. (2016)]. Morlet function is dedicated to the meteorological time series analysis because its waveform shape is close to the analyzed signal [Megahed, Moussa, Elrefaie et al. (2008); Shao, Deng, Cui et al. (2016)]. The continuous wavelet transformation is defined by

$$W(s,\tau)=c_{\psi}^{-\frac{1}{2}}s^{-\frac{1}{2}}\int_{(-\infty,\infty)}x(t)\psi^{*}\left(\frac{t-\tau}{s}\right)\mathrm{d}t \tag{1}$$

where $x(t)$ is the given time series, and ψ^{*} denotes the complex conjugate operator with respect to mother function $\psi(t)\in L_2(R)$. The admissibility condition is defined by $c_{\psi}=\int_{(-\infty,\infty)}\frac{|\psi(\omega)|^2}{|\omega|^2}\mathrm{d}\omega<\infty$, where $\psi(\omega)$ is the Fourier transformation related to $\psi(t)$. $W(s,\tau)$ is the wavelet coefficient, and τ is the translation parameter associated to time t. s is a scale factor refer to $x(t)$, which is used for the frequency measurement. The similarity of the seasonal characteristics with respect to $x(t)$ can be captured based on the scale s along with the time t. The similarity among the different seasonal characteristics in periodogram will be higher if the corresponding $W(s,\tau)$ is larger. The Pearson correlation coefficient $r_{W(s,\tau)}$ is applied to accurately reflect the correlation with respect to $\{W(s,\tau)\}_{m\times n}$ in different seasons, which is defined b

$$r_{W(s,\tau)}=\frac{\sum_u\sum_v\left(W_{uv}^{c}(s,\tau)-\bar{W}^{c}\right)\left(W_{uv}^{n}(s,\tau)-\bar{W}^{n}\right)}{\sqrt{\left(\sum_u\sum_v\left(W_{uv}^{c}-\bar{W}^{c}\right)^2\right)\left(\sum_u\sum_v\left(W_{uv}^{n}-\bar{W}^{n}\right)^2\right)}} \tag{2}$$

where $W_{uv}^{c}(s,\tau)$ is the wavelet coefficient matrices at the current month, and $W_{uv}^{n}(s,\tau)$ is the ones about the next month. $\bar{W}^{c}$ and $\bar{W}^{n}$ are the mean related to the matrix elements. Technically, $r_{W(s,\tau)}$ is a statistical parameter used to show whether and how strongly pairs of given matrices $\{W(s,\tau)\}_{m\times n}$ are related. The months will be properly divided based on the relationship between the self-similar coefficient r_{SS} and the correlation coefficient $r_{W(s,\tau)}$. Taking into account the requirement of the persistence of excitation in NN, training sample should contain various variation types of pattern used for the modeling and useful information for testing. In chronological order, the proper subsets division in each season is generated based on the similarity and periodicity between the different seasonal characteristics.

2.2 Randomness analysis and model lag estimation

Lipschitz quotient [He and Asada (1993)], wavelet decomposition and AdaBoost technique [Shao, Deng, Cui et al. (2016)] are used to estimate the model lags space, reduce the influence from the randomness and non-stationary. Model order is generally treated as the maximum lag to reflect the intrinsic relations between the output and the historical data. Lipschitz quotient is a powerful measure method with computational efficiency used to calculate the proper delay based on the chosen model, which is given by

$$L_{ij,i\neq j}^{n_a n_b}=\frac{\left|y_i(t)-y_j(t)\right|}{\left|x_i(t)-x_j(t)\right|},i,j=1,\ldots,N \tag{3}$$

$L_{ij,i\neq j}^{n_a n_b}$ is essentially defined as the absolute ratio of the Euclidean distance between the output $y(t)$ and input $z(t)$, and it can be rewritten as [Sragner and Horvath (2014)]

$$L_{ij,i\neq j}^{n_a n_b}=\frac{\left|y_i(t)-y_j(t)\right|}{\sqrt{\frac{1}{3(n_b+1)}\sum_{q=1,\ldots,n_b} z(i,q,n_k)+\frac{1}{n_a}\sum_{p=1,\ldots,n_a}\left\|y(i-p)-y(j-p)\right\|^2}} \tag{4}$$

where $z(i,q,n_k)=\left\|z(i-q-n_k)-z(j-q-n_k)\right\|^2$. The optimal order related to Eq. (4) can be defined by $L^{n_a n_b}=\left[\prod_{k=1,\ldots,p} L^{n_a n_b}(k)\sqrt{n_a+3(n_b+1)}\right]^{1/p}$, where $L^{n_a n_b}(k)$ is the k-th largest Lipschitz quotient $L_{ij,i\neq j}^{n_a n_b}$. $\sqrt{n_a+3(n_b+1)}$ is the number of the input variables. WT can decompose the wind speed into wavelet packets and recursively generate the new frequency to reflect the similar frequency feature refer to wind speed. This is conductive to reduce the influence from the wind speed's randomness and non-stationary. Wavelet packet $\left\{d_{level-n}^{j,n}\right\}$ decomposition and reconstruction method are illustrated as $d_{level-n}^{j,2n}=\sum_k \eta_{k-2l} d_k^{j-1,n}$, $d_{level-n}^{j,2n+1}=\sum_k \mu_{k-2l} d_k^{j-1,n}$, and

$d_{level-n}^{j-1,n}=\sum_k\left(\tilde{\eta}_{k-2l} d_{level-n}^{j,2n}+\tilde{\mu}_{k-2l} d_{level-n}^{j,2n+1}\right)$

where η and μ are the wavelet filter coefficients related to low and high frequency, respectively. $\tilde{\eta}$ and $\tilde{\mu}$ are the corresponding wavelet coefficients associated to the reconstructed wavelet. Model robustness can be significantly improved through AdaBoosting method using the multiple NNs' learning abilities. Moreover, the model optimization technique is processed based on our preliminary version [Wei, Shao and Deng (2015)] to avoid the over-fitting issue in model learning process.

2.3 Model performance

The validation of the model results is used to evaluate the produced error in short-term wind speed forecasting. The proposed approach in this paper is mainly based on the multi-layered perceptron with one hidden layers NN using the Levenberg-Marquardt optimization method. Two performance criteria are used in this paper: Root mean square error (RMSE), Relative standard deviation (RSD), and they respectively defined by

$$\text{RMSE}=\sqrt{\frac{\sum_{t=1}^{n}\left(\boldsymbol{y}_{tf}-\hat{\boldsymbol{y}}_{tr}\right)^2}{\sum_{t=1}^{n}\boldsymbol{y}_{tf}^2}},\quad \text{RSD}=\sqrt{\frac{\sum_{t=1}^{n}\left(\boldsymbol{y}_{tf}-\hat{\boldsymbol{y}}_{tr}\right)^2}{n}}$$

where $\boldsymbol{y}_{tf}$ and $\hat{\boldsymbol{y}}_{tr}$ are observation vector and forecasting vector, respectively. RMSE and RSD represent regular and relative bias between the real and forecasting sample, respectively.

3 Experimental evaluation

3.1 Data description

The sample used for experimental evaluation is downloaded from the National Renewable Energy Laboratory (NREL) at: http://www.nrel.gov/electricity/transmission/. The sample contains two variables: wind speed (M/S) and netpower (MW). The site number of the utilized sample is 06996, and the sampling frequency is 10 min/point. In order to effectively reflect the seasonal characteristics of wind speed trend in a whole year, the sample size is 26352×1 (only the wind speed) from January 1, 2004 to December 31, 2004 is selected for analysis. In this section, the verification steps corresponding to the proposed approach are given in detail:

Step 1: Detect the irrelevant data and noisy to improve the sample quality. The irrelevant data and noisy will be effectively detected based on the principles that the true signal's distribution density will gradually decrease while noisy data's amplitude increase.

Step 2: Decompose the processed wind speed to derive the accurate analysis. Time-frequency analysis method WT is used to decompose the original signal and reflect the similar frequency feature with respect to wind speed. Meanwhile, WT can avoid the wind speed's local transient feature which maybe propagated over time. For instance, Daubechies (Db) wavelet of order 4 (Db4) encodes the constants and linear components. Db4 is dedicated to the analysis of the meteorological time series because it can perform appropriate trade-off ability between wavelength and smoothness.

Step 3: The proper subsets division is generated to effectively reflect the seasonal characteristics of the wind speed and satisfy the persistence of excitation for NN used for testing, which is mainly divided by the similarity and periodicity between the different seasonal characteristics.

Step 4: Lag space estimation and model robustness enhancement. Lipschitz quotient is applied to investigate the proper lag space to reflect the appropriate model structure. AdaBoosting NN is used to enhance the model robustness by utilizing the multi-network's learning abilities. Experimental evaluation based on the dataset from NREL is given to evaluate the performance of the proposed approach.

3.2 Seasonal characteristics analysis

Usually, wind speed has a continuous spectrum to reflect the periodically change and external climates conditions. However, it is still a challenge issue to estimate the change period of the wind speed due to the complicated meteorological interaction. The seasonal characteristics of wind speed can be effectively derived based on the scalogram percentage of energy distribution. Wind speed's trend and seasonality can be sufficiently reflected based on self-similarity related to the WT coefficient in periodogram. Note that, the energy distribution of the signal and noise is different, so wavelet filter method is used to improve the SCA accuracy. SCA results about July are intuitively displayed in Fig. 2.

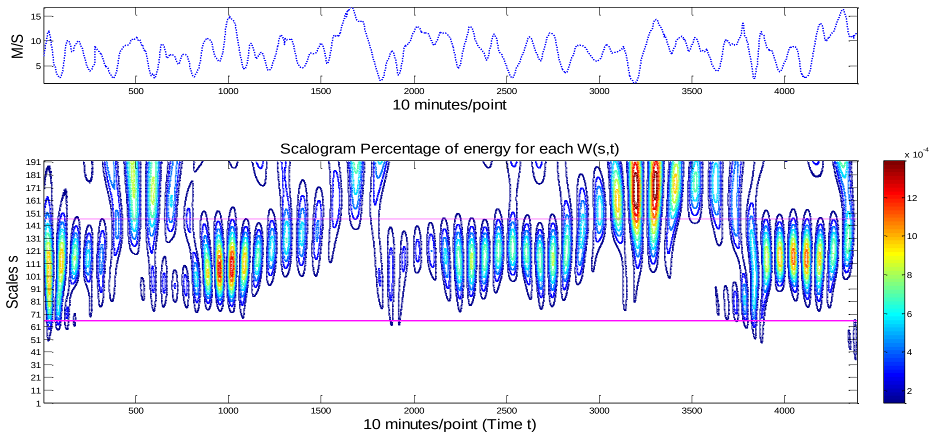

Figure 2: Seasonal characteristics analysis (July)

Table 1: Statistical results

Season	Months	median $W(s,\tau)$	μ	σ	r_{SS}	$r_{W(s,\tau)}$	
Spring	March	-0.0194	0.1507	4.1324	-0.1167	Mar. vs Apr.	-0.1192
	April	-0.1125	0.2631	5.4016	-0.1473	Apr. vs May.	-0.2041
	May	-0.1981	0.2347	5.3180	-0.0214	May. vs Jun.	-0.1309
Summer	June	-0.0988	0.0814	4.2341	-0.0225	Jun. vs Jul.	-0.5526
	July	1.1494	0.2619	3.5559	-0.1920	Jul. vs Aug.	-0.3147
	August	0.1367	0.2008	3.7416	-0.0627	Aug. vs Sep.	-0.2303
Autumn	September	0.0778	0.1801	3.8877	-0.2208	Sep. vs Oct.	-0.0235
	October	0.0878	0.2285	3.1071	0.2644	Oct. vs Nov.	0.0335
	November	-0.2399	0.2437	3.3770	0.0206	Nov. vs Dec.	0.0973
Winter	December	-0.5107	0.4225	4.5610	0.0404	Dec. vs Jan.	0.1155
	January	-0.4444	0.3639	4.3104	-0.0545	Jan. vs Feb.	-0.1478
	February	0.5799	0.1179	4.1928	0.3189	Feb. vs Mar.	-0.3224

where median $W(s,\tau)$, μ, σ and r_{SS} are the median value, expectation, variance and self-similar coefficient related to wavelet coefficient matrices $\{W(s,\tau)\}_{m\times n}$. The proper subsets division is generated based on the similarity between the different seasonal characteristics. The months in different seasons are divided into the following subsets in Tab. 2.

Table 2: Divided subsets based on SCA

Seasons	Subsets	Months	Considered order
Spring	1	March	8
	2	April & May	7
Summer	3	June, July & August	10
Autumn	4	September	7
	5	October	10
	6	November	9
Winter	7	December & January	5
	8	February	9

Based on the SCA of the wind speed, two seasonal distributions are reflected. Wind speed distribution in July is local periodicity and seasonal, which is obviously the type of distinguish seasonal characteristics. Half day (about 67 points) is approximately treated as the minimum period under scales 1-256 along with time. The other one distribution of the wind speed is seasonal but no obvious periodicity along with time, for instance, November is a typical month with the outlined seasonal characteristics. The *vertical-axis* is essentially about the scale s in Fig. 3, which represents the pseudo-frequencies estimated by matlab inline function 'scal2frq'. The estimated frequencies 66 and 146 can be approximately treated as the 'true' frequency to investigate the seasonal characteristics. There are two seasonal distribution pattern based on WT spectrum:

(1) The ones related to seasons with half-day of periodic, which is seasonal and local periodicity such as summer and winter;

(2) The other one associated to the seasons is seasonal but no obvious periodicity along with time, such as the autumn and spring. The statistical results related to the wavelet coefficient matrices $\{W(s,\tau)\}_{m\times n}$ is given to accurately analyze the wind speed's seasonal characteristics, given in Tab. 1.

The months are merged into one subset if the self-similar coefficient r_{SS} is smaller than the correlation coefficient $r_{W(s,\tau)}$ related to the last and next month. In particular, June, July and August are merged into one subset due to $r_{W(s,\tau)} > r_{SS}$. This indicates that these months have a higher similarity about seasonal characteristics than the self-similarity in each month. Based on the outlined discussion, larger sample may not benefit the establishment of the high-accuracy model unless the training sample contains the sufficient seasonal characteristics information used for testing. Wind speed's seasonal characteristics will be sufficiently reflected in the wind speed forecasting process.

3.3 Experiments

The improper lag space cannot reflect the appropriate model structure, based on the identified inputs and outputs, the proper lag space structure associated to model order

$p_y, p_{i,r_i} \in \{J_i\}_{i=1}^{k} \subseteq N$ can be accurately estimated. These model orders will be treated as the considered order in (6) based on the curve trend. More precisely, the order is selected as the model order when it is greater or equal to the knee-point where the matrix order index $L_{ij,i\neq j}^{n_a n_b}$ flattens out along with curve trend. The estimated result for model order is shown in Tab. 3 and Fig. 3.

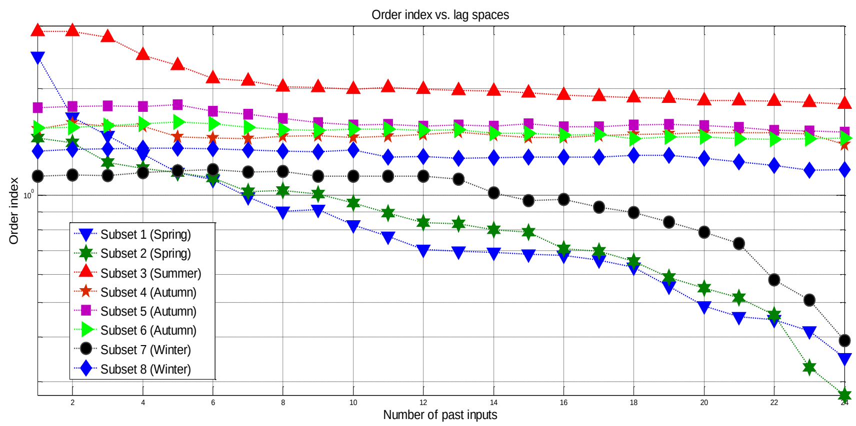

Figure 3: Model order estimation

Daubechies (Db) wavelets as one typical type of the orthogonal wavelet are usually to represent the wind speed's complicated feature. Db4 is dedicated to the analysis of the wind speed because it can carry out appropriate trade-off ability between wavelength and smoothness. Db4 at the resolution level-2 [Shao, Deng, Cui et al. (2016)] is selected as the wavelet decomposition method to reduce the influence from the uncertainty and non-stationary in wind speed. Adaboosting NN using Levenberg-Marquardt learning algorithm is used to promote the model configuration, enhance the model robustness and improve the wind speed forecasting accuracy by utilizing the multi-individual NN's learning abilities. This paper proposes the 24-steps (i.e. 4 h) ahead forecasting for wind speed in short-term. 60%, 20% and 20% of each subset are respectively selected as the training sample, verification sample and testing sample based on the model optimization strategy. The experimental results are validated through the cross-validation based on the forecasting results in each subset. The forecasting results are given in Tab. 3 and Fig. 4.

Table 3: Forecasting results

Seasons	Error	FMSCA	DS	FMNSCA	PRA
Spring	RMSE	0.1303	1	0.1198	0.1181
	RSD	0.5337		0.5435	0.5361
	ET	59.89		20.45	109.42
	RMSE		2	0.1275	0.1274
	RSD			0.5045	0.5043
	ET			29.32	151.83
Summer	RMSE	0.1397	3	0.1397	0.1384
	RSD	0.5426		0.5426	0.5376
	ET	67.17		67.17	366.75
Autumn	RMSE	0.1205	4	0.1344	0.1332
	RSD	0.4938		0.5004	0.4958
	ET	44.76		14.94	77.09
	RMSE		5	0.1319	0.1325
	RSD			0.4428	0.4447
	ET			23.55	128.02
	RMSE		6	0.1316	0.1239
	RSD			0.6622	0.6238
	ET			22.22	110.92
Winter	RMSE	0.1149	7	0.1063	0.1083
	RSD	0.4888		0.5641	0.5751
	ET	23.46		15.24	70.81
	RMSE		8	0.1332	0.1321
	RSD			0.5446	0.5402
	ET			23.80	129.48

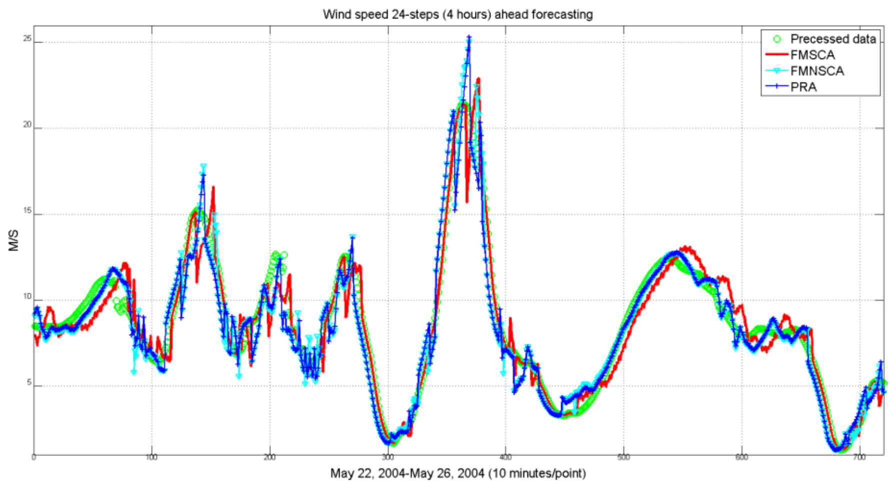

Figure 4: Forecasting results

where DS represents the divided subsets in Tab. 3, and ET indicates the time cost in seconds. FMSCA represents the forecasting methods based on the subsets generated by the traditional division in the whole season, and it utilizes the wavelet decomposition but without SCA and AdaBoosting NN. PRA indicates the proposed approach based on the divided subsets generated by SCA, which includes the uncertainty measurement, randomness evaluation, wavelet decomposition, SCA and AdaBoosting NN. FMNSCA is the PRA without AdaBoosting NN. Note that, the forecasting results using the FMSCA and FMNSCA is same with each other due to the same subsets. The forecasting result about the May 22-26, 2004 is shown in Fig. 4. Six individual networks using the Levenberg-Marquardt technique compose of the AdaBoosting NN, each of which contains three layers, input layer, hidden layer and output layer. The numbers of the input layers have been given in Tab. 2 according to the estimated model order, and the output layer contains only one neuron associated to the wind speed. Empirical equation $n_{hidden} = \sqrt{n_{input} + 1} + \alpha$ is used to estimate the number of the hidden layer, where n_{hidden} and n_{input} are the number of hidden and input layers nodes, respectively, and α is a constant with interval [1, 10]. Learning rate and convergence goal are 0.01 and 0.001, respectively. Tansig and purelin are chosen as the activation function of the hidden layer and output layer in NN. The forecasting results from 1-h to 12-h ahead are given in Tab. 4 and Fig. 5, respectively.

Table 4(a): Forecasting results using proposed approach

Seasons	Error	DS	1-h	2-h	3-h	4-h	5-h	6-h
Spring	RMSE	1	0.0209	0.0576	0.0930	0.1384	0.1741	0.2030
	RSD		0.0951	0.2617	0.4221	0.6281	0.7898	0.9206
	ET		88.68	92.11	90.87	89.29	89.06	83.46
	RMSE	2	0.0429	0.1132	0.1915	0.2491	0.2868	0.3072
	RSD		0.1703	0.4489	0.7583	0.9856	1.1341	1.2137
	ET		119.51	118.37	119.19	122.65	121.74	123.65
Summer	RMSE	3	0.0545	0.1060	0.1617	0.2103	0.2441	0.2740
	RSD		0.2122	0.4121	0.6286	0.8173	0.9482	1.0641
	ET		232.95	224.54	224.25	224.16	239.43	236.30
Autumn	RMSE	4	0.0518	0.1052	0.1710	0.2292	0.2854	0.3190
	RSD		0.1937	0.3929	0.6377	0.8533	1.0608	1.1866
	ET		62.85	62.95	62.88	62.95	62.89	62.85
	RMSE	5	0.0243	0.0651	0.1112	0.1540	0.1971	0.2360
	RSD		0.0822	0.2194	0.3740	0.5173	0.6611	0.7906
	ET		80.91	80.53	80.46	80.45	80.33	80.33
	RMSE	6	0.0447	0.0899	0.1459	0.2067	0.2426	0.2833
	RSD		0.2303	0.4589	0.7393	1.0403	1.2150	1.4124
	ET		74.36	74.25	75.34	75.05	69.92	75.08
Winter	RMSE	7	0.0269	0.0647	0.1045	0.1404	0.1707	0.1979
	RSD		0.1439	0.3454	0.5562	0.7454	0.9043	1.0455
	ET		57.89	57.55	57.63	57.37	57.31	57.38
	RMSE	8	0.0255	0.0709	0.1303	0.1867	0.2340	0.2542
	RSD		0.1046	0.2903	0.5335	0.7637	0.9546	1.0333
	ET		82.22	80.95	81.15	81.60	81.09	79.82

Table 4(b): Forecasting results using proposed approach

Seasons	Error	DS	7-h	8-h	9-h	10-h	11-h	12-h
Spring	RMSE	1	0.2179	0.2215	0.2246	0.2314	0.2401	0.2411
	RSD		0.9845	1.0023	1.0184	1.0484	1.0889	1.0929
	ET		89.02	89.11	89.55	89.26	89.25	89.03
	RMSE	2	0.3298	0.3498	0.3534	0.3492	0.3477	0.3401
	RSD		1.3022	1.3806	1.3938	1.3770	1.3704	1.3395
	ET		117.66	111.26	117.63	115.74	117.85	117.68
Summer	RMSE	3	0.2949	0.3123	0.3255	0.3365	0.3382	0.3417
	RSD		1.1453	1.2127	1.2638	1.3062	1.3124	1.3255
	ET		234.43	235.62	235.29	234.46	235.36	235.66
Autumn	RMSE	4	0.3502	0.3753	0.4072	0.4311	0.4549	0.4789
	RSD		1.2981	1.3890	1.5043	1.5890	1.6712	1.7521
	ET		60.00	62.85	62.87	58.54	59.01	59.08
	RMSE	5	0.2666	0.2796	0.2962	0.3046	0.3071	0.3136
	RSD		0.8923	0.9344	0.9889	1.0154	1.0223	1.0424
	ET		80.21	80.11	80.31	80.19	77.60	80.06
	RMSE	6	0.3132	0.3322	0.3552	0.3691	0.3943	0.4085
	RSD		1.5540	1.6383	1.7397	1.7917	1.8945	1.9421
	ET		74.51	75.48	70.76	75.83	79.97	75.60
Winter	RMSE	7	0.2185	0.2363	0.2502	0.2599	0.2697	0.2767
	RSD		1.1520	1.2433	1.3140	1.3624	1.4114	1.4456
	ET		57.28	57.36	57.12	54.38	56.90	57.14
	RMSE	8	0.2793	0.2914	0.3064	0.3271	0.3327	0.3401
	RSD		1.1308	1.1745	1.2286	1.3042	1.3185	1.3397
	ET		82.93	79.93	81.14	79.84	79.73	80.92

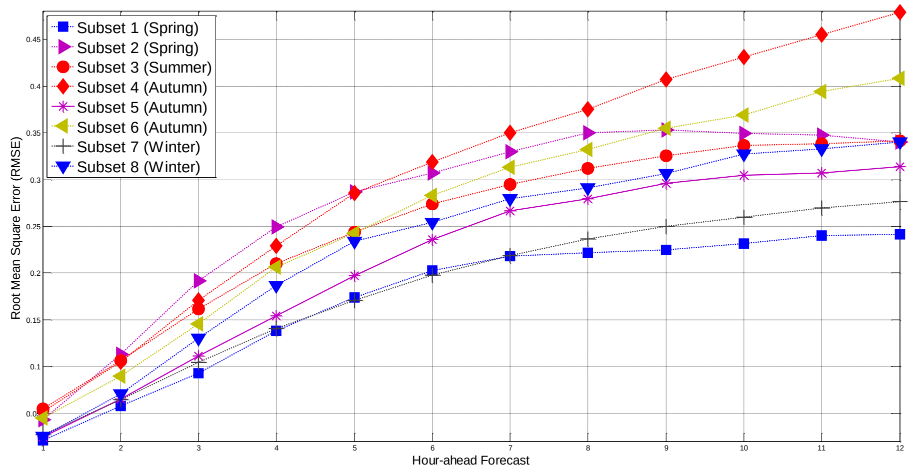

Figure 5: Wind speed hour-ahead forecast using proposed approach

Based on the outlined discussion about the experimental results, two conclusions are given:

(1) The forecasting accuracy based on the reasonable model structure and proper samples will be significantly improved based on the subsets with high similarity in seasonal characteristics. For instance, although FMSCA's model architecture is same as the FMNSCA's, its forecasting accuracy is still lower than the results generated by FMNSCA and PRA in general due to the insufficient seasonal characteristics analysis.

(2) The forecasting accuracy based on the reasonable model is still easily susceptible to the samples with non-uniform feature distribution. For instance, based on the statistical results, FMNSCA's and PRA's forecasting accuracy are higher than FMSCA on RMSE but still slightly lower than the ones based on the subsets in autumn.

(3) The forecasting performance deteriorates and the forecasting accuracy decreases along with the increment of the forecasting-steps. Typically, the small error in wind speed forecasting means the big errors in wind power forecasting. This indicates the forecasting model should have the ability of the error correction, dynamical feedback and adaptive adjustment in combination with the proposed approach in this paper.

As a conclusion, PRA can improve the forecasting accuracy related to the short-term wind speed though the approximate seasonal characteristics analysis and proper uncertainty measurement.

4 Conclusion

This paper attempted to establish a high accuracy and reliable wind speed forecasting method, taking into account wind's seasonal characteristics and lag space. Firstly, the similarity among the different seasonal characteristics of wind speed is investigated based on self-similarity in periodogram to effectively reflect the wind speed's Seasonal distribution characteristics by properly dividing the original dataset into subsets. Secondly, the model lag space is approximately evaluated to construct the reasonable model structure. Thirdly, wavelet analysis and AdaBoosting NN are utilized to estimate the approximate frequency of wind speed and promote the model configuration. This enhances the model robustness and improves the forecasting accuracy. Experimental evaluation using the dataset from NREL in 2004 was conducted to verify the effectiveness of the proposed approach. Wavelet analysis and seasonal characteristics analysis benefit the analysis of the wind speed's randomness and optimal neural network's structure, respectively. AdaBoosting neural network and lag space estimation can be used to promote the model's configuration and show the confidence in high-accuracy forecasting of short-term wind speed. In our further work, the dynamical model with ability of error correction and adaptive adjustment in combination with the proposed approach in this paper will be considered.

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Reference

Abd-Elaal, E. S.; Mills, J. E.; Ma, X. (2018): Numerical simulation of down burst wind flow over real topography. *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 172, pp. 85-95.

Chang, G.; Lu, H.; Chang, Y.; Lee, Y. (2017): An improved neural network-based approach for short-term wind speed and power forecast. *Renewable Energy*, vol. 105, pp. 301-311.

Ding, H.; Hu, Z.; Song, Y. (2012): Stochastic optimization of the daily operation of wind farm and pumped-hydro-storage plant. *Renewable Energy*, vol. 48, pp. 571-578.

Dowell, J.; Pinson, P. (2016): Very-short-term probabilistic wind power forecasts by sparse vector autoregression. *IEEE Transactions on Smart Grid*, vol. **7**, no. 2, pp. 763-770.

Du, C.; Wang, X.; Wang, X.; Shao, C. (2016): Comprehensive value assessment of wind power by layer. *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1238-1247.

Duo-Neng, L.; Zhong-Xi, H.; Zheng, G.; Xi-Xiang, Y.; Xian-Zhong, G. (2016): Permissible wind conditions for optimal dynamic soaring with a small unmanned aerial vehicle. *Computer Modeling in Engineering & Sciences*, vol. 111, no. 6, pp. 531-565.

Grilli, A. R.; Shumchenia, E. J. (2015): Toward wind farm monitoring optimization: assessment of ecological zones from marine landscapes using machine learning algorithms. *Hydrobiologia*, vol. 756, no. 1, pp. 117-137.

He, X.; Asada, H. (1993): A new method for identifying orders of input-output models for nonlinear dynamic systems. *American Control Conference, IEEE*, pp. 2520-2523.

Honti, M.; Scheidegger, A.; Stamm, C. (2014): The importance of hydrological uncertainty assessment methods in climate change impact studies. *Hydrology and Earth System Sciences*, vol. 18, no. 8, pp. 3301.

Kavousi-Fard, A.; Khosravi, A.; Nahavandi, S. (2016): A new fuzzy-based combined prediction interval for wind power forecasting. *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 18-26.

Megahed, A.; Moussa, A. M.; Elrefaie, H.; Marghany, Y. (2008): Selection of a suitable mother wavelet for analyzing power system fault transients. *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*, pp. 1-7.

Meng, A.; Ge, J.; Yin, H.; Chen, S. (2016): Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm. *Energy Conversion and Management*, vol. 114, pp. 75-88.

Ren, Y.; Suganthan, P.; Srikanth, N. (2015): A comparative study of empirical mode decomposition-based short-term wind speed forecasting methods. *IEEE Transactions on Sustainable Energy*, vol. 6, no. 1, pp. 236-244.

Roy, S. (2013): Power output by active pitch-regulated wind turbine in presence of short duration wind variations. *IEEE Transactions on Energy Conversion*, vol. 28, no. 4, pp. 1018-1025.

Shademan, M.; Barron, R. M.; Balachandar, R.; Hangan, H. (2014): Numerical simulation of wind loading on ground-mounted solar panels at different flow configurations. *Canadian Journal of Civil Engineering*, vol. 41, no. 8, pp. 728-738.

Shao, H.; Wei, H.; Deng, X.; Xing, S. (2016): Short-term wind speed forecasting using wavelet transformation and AdaBoosting neural networks in Yunnan wind farm. *IET Renewable Power Generation*, vol. 11, no. 4, pp. 374-381.

Shao, H.; Deng, X.; Cui, F. (2016): Short-term wind speed forecasting using the wavelet decomposition and AdaBoost technique in wind farm of East China. *IET Generation, Transmission & Distribution*, vol. 10, vol. 11, pp. 2585-2592.

Sragner, L.; Horvath, G. (2014): Improved model order estimation for nonlinear dynamic systems. *International Journal of Computing*, vol. 2, no. 2, pp. 93-100.

Wang, J.; Song, Y.; Liu, F.; Hou, R. (2016): Analysis and application of forecasting models in wind power integration: a review of multi-step-ahead wind speed forecasting models. *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 960-981.

Wei, H.; Shao, H.; Deng, X. (2015): Using a model structure selection technique to forecast short-term wind speed for a wind power plant in North China. *Journal of Energy Engineering*, vol. 142, no. 1.