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Review

Current status of wind energy forecasting and a hybrid method for hourly predictions

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ABSTRACT

Generating accurate wind energy and/or power forecasts is crucially important for energy trading and planning. The present study initially gives an extensive review of recent advances in statistical wind forecasting. Numerous prediction methods for varying prediction horizons from a few seconds to several months are listed. Then in the light of accurate results in the literature, the present study combines the adaptive neuro-fuzzy inference system (ANFIS) and an artificial neural network (ANN) for 1 h ahead wind speed forecasts. The performance results show the mean absolute percentage errors (MAPE) of 2.2598%, 3.3530% and 3.8589% at three different locations for daily average wind speeds.

Contents

1. Introduction

Fossil fuel usage is being planned to be restricted and alternative renewable energy resources such as solar, wind, biomass and geothermal are having a growing part in the energy production. The wind energy, which is one of the most popular clean resources, has significant advantages and is widely used around the world. Nevertheless, due to chaotic nature of the wind, generating accurate wind energy forecasts stays problematic. Improving the predictions is in high demand and developing superior forecasting models is a subject of intense research [1–14].

The study initially provides an extensive review of recent studies in statistical wind speed and power forecasting in Section 2. It reviews the intensive effort for more accurate predictions and shows the recent improvements owing to the advanced machine learning techniques. The review focuses on statistical prediction methods. It differs from most of the surveys in extent by tabling prediction errors with respect to the forecast horizon. Detailed tables present recent obtained results along with the method used or developed. Study groups the prediction methods in four categories as pre-processing, non-hybrid, hybrid and post-processing. The review also lists the previous studies by their prediction horizons.

Section 3 gives a hybrid method. The adaptive neuro-fuzzy inference system (ANFIS) and the feed-forward artificial neural network (FNN) techniques are chosen to be combined in an adaptive way. This combination can be one of the most accurate candidates for hourly predictions in the light of literature review. And the method gives markedly low prediction errors in terms of three different error measures.

2. Literature review

The recent advances in wind energy and power prediction are reviewed in this section. This section gives the current methods

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with their reported accuracies and identifies enduring challenges in terms of forecast accuracy for different prediction horizons. Wind blows randomly and by definition it is not possible to predict its speed exactly. Accuracy of predictions and performance of the prediction methods are critically important for usage of wind energy. Results on the performance of methods in literature depend on the target location and tested data. And determining the ultimate best approach is difficult. The goal of this survey is twofold. The first is to reveal the range of prediction error in respect to the horizon obtained by the latest methods. And secondly, to list the approaches or techniques that can be favorable for a specific predication horizon.

In general, if historical data are preprocessed for a specific location and for a given prediction horizon, predictions improve. The reported studies show that hybrid methods combining several techniques mostly outperform the non-hybrid methods. Vast variety of methods and ongoing researches for different prediction horizons together with corresponding errors are demonstrated in Tables 1–3.

Table 1 lists the prediction errors of recent studies along with their horizons. Table compares the prediction errors in terms of different error measures including the mean absolute percentage error (MAPE), the mean absolute error (MAE), the mean squared error (MSE) and the root mean square error (RMSE) values. Studies are grouped by whether wind speed or power data are used. Table 1 reveals that wind power forecasting might be more accurate than the wind speed forecasting. The table includes the previous studies which report both the prediction error and horizon clearly. Also the references using non-conventional error measures are excluded since they are not comparable.

Table 2 presents the vast variety of methods employed in forecasting. The abbreviation list of method names is given alongside the table. The methods are classified as "hybrid" if they combine different techniques. The methods are put into separate groups when they are used for preprocessing or post-processing. Both pre and post-processing improve the predictions in general. In preprocessing, input data are manipulated, for example wind speeds are extrapolated to a hub height, or data are decomposed into representative components such as wavelet or principal components. In post-processing, the output data are classified to render the results or modified according to other available predictions such as from the numerical weather forecasts.

In Table 3, the previous studies are grouped by their prediction horizons as very short-term, short-term, medium-term, long-term and very long-term. The very short-term predictions cover a period from a few seconds to 30 min, the short-term predictions are from 30 min to 6 h, the medium-term predictions are from 6 h to 24 h, the long-term predictions are from 24 h to 72 h and the very long-term predictions are for 72 h and longer. This classification is made in regard to the drop in prediction accuracy and the focus of different business sectors. The review shows that most of the studies tackle with the short-, medium- and long-term forecasts. However, being accurate for these terms is particularly difficult. And if a prediction horizon inside any of these terms increases, the accuracy characteristically gets down. Table 3 gives the list of prediction horizons along with a reference list.

Wide variety of methods are being used and developed for predictions. The studies reviewed here are arranged by their horizon from very-short to long-term. *For the very short-term predictions*, a new artificial neural network (ANN)-Markov chain (MC) model is described in [15]. For wind speed predictions, study investigates data patterns of different time scales. A set of data of 175 min is used for examining the accuracy of the proposed model and predicting the wind speeds up to 7.5 s ahead. The MAPE values for the ANN-MC model are obtained as 3.14%, 8.03% and 11.33% for 2.5, 5 and 7.5 s ahead predictions, respectively. Errors show that abrupt behavior of wind reduces the accuracy in this horizon. Another time series model that is integrating the concepts of structural breaks and the Bayesian inferences is introduced in [16]. This approach, however, gives 0.165 MAE and 2.266 MAE for 1 min and 1 h ahead forecasts, respectively.

By deriving the optimal loss functions from different error models, a uniform model of ν-support vector regression in connection with the general noise model (N-SVR) is investigated in [17]. Study compares three different N-SVR models, namely ν-SVR, GN-SVR

Table 1
Errors in recent studies against the prediction horizon.

Refs.	Input data	Prediction Horizon	Error
[15]	Wind speed	2.5-s 5-s 7.5-s	3.14% MAPE 8.03% MAPE 11.33% MAPE
[16]	Wind speed	1-min 1-h	0.165 MAE 2.266 MAE
[17]	Wind speed	10-min 1-h	3.79% MAPE 12.40% MAPE
[18]	Wind speed	10-min 30-min 1-h 2-h	8.01% MAPE 15.99% MAPE 23.85% MAPE 34.70% MAPE
[19]	Wind power	10-min 12-h	70.25 MAE 101.26 MAE
[20]	Wind speed	15-min (Site 1) 30-min (Site 2)	7.75% MAPE (Site 1) 9.84% MAPE (Site 2)
[21]	Wind speed	15-min	11.5% MAPE
[22]	Wind power	1-h	4.3678 NMAE
[23]	Wind speed	30-min 60-min 90-min	1.61% MAPE 3.33% MAPE 5.08% MAPE
[24]	Wind power	1-h	3.513% MAPE
[25]	Wind speed	1-h 3-h 5-h	0.051 RMSE 0.074 RMSE 0.100 RMSE
[26]	Wind power	1–6 h 24-h	Between 2.70 and 7.82 MAE 8.64 MAE
[27]	Wind power	3-h	3.75% MAPE
[28]	Wind speed	4-h	5.71% MAPE
[29]	Wind power	6-h	13.02% MAPE (Ave.)
[30]	Wind speed Wind power	24-h	Around 2.65 m/s MAE (WS) Around 0.19% NMAE (WP)
[31]	Wind power	1–24 h	Range from 8.96% to 11.66% MAPE
[32]	Wind power	24-h	5.41% MAPE
[33]	Wind speed	24-h	21.61% MAPE (Exp.1) 22.93% MAPE (Exp.2) 19.83% MAPE (Exp.3)
[34]	Wind power	24-h	23.73% MAPE (Ave.)
[35]	Wind speed Wind power	24-h	Around 1.85 m/s MAE Around 69 kW MAE
[36]	Wind power	24-h Weekly	11.91% MAPE (Ave.) 15.38% MAPE (Ave.)
[37]	Wind power	48-h	3.0 MAE (Ave.)
[38]	Wind power	12-h 84-h	12.41 MAE 11.62 MAE
[39]	Wind power	48-h	8.90 NMAE
[41]	Wind speed Wind power	72-h	1.66 MAE (WS) 146.50 MAE (WP)
[42]	Wind power	5-day	0.096 sMAPE (Station A) 0.069 sMAPE (Station B)
[44]	Wind speed	Quarter-yearly	15.32% MAPE

Table 2
Methods used in the literature.

Preprocessing		Hybrid		Non-Hybrid		Post-processing	
MLP	[15]	ANN+MC	[15]	Bayesian	[16,73]	MC	[15]
EWT	[20]	ARIMA+ELM+SVM+LSSVM	[20]	N-SVR	[17]	ANN	[31]
IMF	[22]	EMD-ELM	[22]	DNN	[18]	DF	[35]
HHT	[22]	EMD-LSSVM	[22]	AR	[19]	SVM	[36]
EMD	[22,23]	FEEMD+MLP	[23]	VAR	[19]	k-NN	[38]
WPD	[23]	FEEMD+ANFIS	[23]	Mycielski	[19,78]	k-ANN	[49]
WD	[23,33]	ACO+PCO	[24]	RNN	[21,57,74]	GM	[69]
FEEMD	[23]	ARIMA-BP	[25]	MDN	[41]		
MI	[27]	Bagging-BP	[25]	LRNN	[42]		
PSO	[32,46,48]	WT-BP	[25]	RSVM	[46]		
ABC	[33]	WT+ANFIS+EPSO+MI	[27]	MLP	[49,56]		
PCA	[28,38,39,46]	SC+ESN+GA	[28]	ANN	[47,48,54,62,67,68,76]		
GA	[28,51,86]	WT+ANFIS+SVM+GS	[29]	ANFIS	[54,56,60,61,70,72]		
PSR	[30,38]	PSR+SVR	[30]	ITSM	[55]		
BT	[38]	Neuro-fuzzy+ANN	[31]	Elman N	[56]		
K-Means	[39]	PSO+ANFIS	[32]	ARMA	[57]		
FFT	[43]	WD+ABC	[33]	MLFFN	[50,56]		
SVR	[44]	KF+ANN	[34]	IRR-MLP	[58]		
WT	[27–29,36,43,45,53,55,63,69]	NWP+LL	[35]	LAP-MLN	[58]		
		WT+FA+FF+SVM	[36]	DRNN	[58]		
		PCA+RNN	[37]	NF	[59]		
		MLP+k-NN	[38]	MS	[64]		
		Dynamic clustering+LR	[39]	MC	[65]		
		WRF+WindSim+LR	[40]	FARMA	[66]		
		WT+FFT	[43]	FTDNN	[66]		
		SVR+SIA+ERNN	[44]	SVM	[67]		
		WT+FA	[45]	BT	[67]		
		GA+PSVM	[51]	RF	[67]		
		GA+BP	[52]	k-NN	[67]		
		WT+ANN	[53,63]	GP	[75]		
		WT+CT+GM	[69]	BP	[77]		
		BCD+SVR	[71]	RBF	[77]		
		MM5+ANN	[82]	ADALINE	[77]		
		NWP+KF+ARMA+NNs+FIS	[83]	*f*-ARIMA	[79]		
		NNs+FL	[84]	Eta	[80]		
				WT	[81]		
				ACLMS	[85]		
				TSK	[86]		

Abbreviations: ABC: Artificial Bee Colony Algorithm, ACLMS: Augmented Complex Least Mean Square Algorithm, ACO: Ant Colony Optimization, ADALINE: Adaptive Linear Element, ANFIS: Adaptive Neuro Fuzzy Inference System, ANN: Artificial Neural Networks, AR: Auto-Regressive, ARIMA: Auto-Regressive Integrated Moving Average, ARMA: Auto-Regressive Moving Average, BCD: Bayesian Clustering by Dynamics, BP: Back Propagation, BT: Boosting Tree, CT: Chaotic Time series, DF: Data Fusion, DNN: Deep Neural Networks, DRNN: Diagonal Recurrent Neural Network, ELM: Extreme Learning Machine, EMD: Empirical Mode Decomposition, EPSO: Evolutionary Particle Swarm Optimization, ERNN: Elman Recurrent Neural Networks, ESN: Echo State Networks, EWT: Empirical Wavelet Transform, FA: Fuzzy ARTMAP, *f*-ARIMA: Fractional ARIMA, FARMA: Functional ARMA, FEEMD: Fast Ensemble Empirical Mode Decomposition, FF: Firefly, FFT: Fast Fourier Transform, FIS: Fuzzy Inference System, FL: Fuzzy Logic, FTDNN: Focus Time-Delay Neural Network, GA: Genetic Algorithm, GM: Grey Model, GP: Gaussian Process, GS: Grid Search, HHT: Hilbert-Huang Transform, IMF: Intrinsic Mode Function, IRR-MLP: Infinite Impulse Response Multilayer Perceptron, ITSM: Improved Time Series Method, KF: Kalman Filter, k-NN: k-Nearest Neighbor, LAP-MLN: Local Activation Feedback Multilayer Network, LL: Lazy Learning, LR: Linear Regression, LRNN: Layer Recurrent Neural Networks, LSSVM: Least Square Support Vector Machine, MC: Markov Chain, MDN: Mixture Density Neural Networks, MI: Mutual Information, MLFFN: Multi-layer Feed-Forward Neural Network, MLP: Multi-Layer Perceptron Network, MM5: Fifth Generation Mesoscale Model, MS: Markov-Switching Approach, NF: Neuro-Fuzzy, NNs: Neural Networks, N-SVR: Noise model based ν-Support Vector Regression, NWP: Numerical Weather Prediction, PCA: Principal Component Analysis, PSO: Particle Swarm Optimization, PSR: Phase Space Reconstruction, PSVM: Piecewise Support Vector Machine, RBF: Radial Basis Function, RF: Random Forest Algorithm, RNN: Recurrent Neural Networks, RSVM: Reduced Support Vector Machine, RVM: Relevance Vector Machine, SC: Spectral Clustering, SIA: Seasonal Index Adjustment, SVM: Support Vector Machine, SVR: Support Vector Regression, TSK: Takagi, Sugeno and Kang Fuzzy Model, VAR: Vector Auto-Regressive, WD: Wavelet Decomposition, WPD: Wavelet Packet Decomposition, WRF: Weather Research and Forecast Model, WT: Wavelet Transform.

and BN-SVR, for 10 min and 1 h ahead wind speed predictions based on four different indicators i.e. MAE, MAPE, RMSE and SEP (standard error of prediction). The results are examined using the wind speed records from artificial data sets and the real-world data. 3.79% MAPE and 12.40% MAPE are reported for 10 min and 1 h ahead predictions.

Goal of [18] is to extract the hidden rules of wind speed patterns by the deep neural networks (DNNs). Neural networks are one of the most employed class of prediction methods in wind energy prediction [13]. Study finds 8.01%, 15.99%, 23.85% and 34.70% MAPEs for 10 min, 30 min, 1 h and 2 h ahead predictions, respectively. Neural network methods are diverse in configuration and implementation difficulty. Although, the DNN model is found to be beneficial in case of insufficient training data, in this setting its test errors are can be considered to be high. Another study in [19] presents a comparison of the forecasting methods, which are wind power prediction tool (WPPT), generalized WPPT (GWPTT), Mycielski, auto-regressive (AR), vector auto-regressive (VAR), with 10 min forecasting intervals for 72 steps ahead. The results show that the time series models (AR or VAR) perform best for 10 min ahead forecasting and GWPPT is more accurate for 12 h ahead forecasting than the others in all cases.

A study in [20] reports a hybrid method and uses the empirical wavelet transform (EWT) as a preprocessing step to obtain the number of relevant modes of wind speed data automatically. The study combines the auto-regressive integrated moving average (ARIMA), the extreme learning machine (ELM), the support vector machine (SVM) and the least square support vector machine (LSSVM). Then, the Gauss process regression (GPR) model is utilized to connect the forecasting engines and improve wind speed forecasting. The study shows that combination of different methods can improve the accuracy of multi-step predictions.

Table 3
Prediction horizons.

Very short-term (a few seconds-30 min)		Short-term (30 min–6 h)		Medium-term (6–24 h)		Long-term (24–72 h)		Very long-term (72 h and longer)	
1-s	[86]	40-m	[16,22,49]	7-h, …, 24-h	[30,31,37,38]	25-h, …, 48-h	[37,38]	73-h, …, 83-h	[38]
2.5-s	[15]	50-m	[49]	8-h	[81]	36-h	[59]	5-day	[42]
5-s	[15,86]	1-h	[16–18,22–26,30,31,38,48–51,53,54,56,71,73,75,77,85]	9-h	[57]	48-h	[37–39,57,79,82]	Weekly	[36,43]
7.5-s	[15]	90-m	[23]	12-h	[19,30,31,37,38,56,65]	48-h,…,72-h	[38]	Monthly	[43,45]
10-s	[67]	2-h	[18,22,26,30,31,37,38,49,51]	16-h	[81]	72-h	[38,40,41,45,57,58]	Quarter-yearly	[43,44]
20-s	[67]	3-h	[25–27,30,31,37,38,49,51–53,56,57,85]	24-h	[12,21,30–38,40,45,52,54,56,57,62,63,79,81]			Half-yearly	[43]
30-s	[67]	4-h	[26,28,30,31,37,38,49,51]					Yearly	[43]
40-s	[67]	5-h	[25,26,30,31,37,38,51]						
50-s	[67]	6-h	[26,29–31,37,38,51,56,57,85]						
1-m	[16,67]								
2.5-m	[70]								
5-m	[60,61,68]								
10-m	[17–19,49,54,64,65,68]								
15-m	[20,21,68]								
20-m	[22,49,68]								
30-m	[16,18,20,23,49,50,68]								

A study using the recurrent neural network (RNN) conducts a comparative analysis of the wind speed forecasting accuracy with the univariate and multivariate ARIMA models in [21]. The results indicate that multivariate models are more accurate than univariate models and the RNNs outperform the ARIMA models and give 11.5% MAPE for 15 min ahead wind speeds. Another method based on the Hilbert-Huang transform (HHT) and the Hurst analysis for multi-scale wind power forecasting is introduced in [22]. In this, the Hurst analysis is utilized to determine the fractal characteristics of the time-frequency components of the data. Three different time scales are defined as the micro-, meso- and macro-scale. Then, the ELM and the LSSVM are separately used to generate predictions from 10 min to 24 h. The results give 4.3678 NMAE (normalized MAE) for 1 h (6-step) ahead wind power forecasting. Results also shows an accuracy improvement gained by preprocessing.

For the short-term predictions, different data decomposition and hybrid prediction methods are investigated in [23]. Hybrid models consist of the decomposition algorithms and the ANN based forecasting methods for prediction horizons of 30, 60 and 90 min. The proposed fast ensemble empirical mode decomposition multi-layer perceptron (FEEMD-MLP) and (FEEMD-ANFIS) models are compared with the other hybrid models. The results show that the combining the decomposing algorithms with the artificial neural networks to predict wind speed time series is effective and the MLP (multi-layer perceptron) has better performance than ANFIS. By combining different methods and employing pre-processing, study obtains accurate predictions with 1.61%, 3.33% and 5.08% MAPEs for 30, 60 and 90 min predictions, respectively.

For 1 h ahead forecasts, a new hybrid approach, called HAP, is proposed in [24]. It uses the wind power data. The approach consists of the ant colony optimization (ACO) and the particle swarm optimization (PSO) based on swarm intelligence. The HAP model has a low MAPE of 3.513% and it is found to be better than the ACO and PSO. Another study selects three ensemble methods, ARIMA-BP, WT-BP and Bagging BP, for comparison in [25]. These ensemble forecasting methods are compared with two non-ensemble methods for 1, 3 and 5 h ahead wind speed forecasting. The RMSE errors are found to be 0.051, 0.074 and 0.100 for 1, 3 and 5 h ahead predictions, respectively. The wavelet transform (WT) is used in the study, which is one of the most common pre-processing methods in literature. WT allows analyzing scale and frequency separately. While one scale corresponds to minute-to-minute change of wind speed, another can correspond to day-to-day change. Accordingly, an appropriate scale can be beneficial to increase the forecast accuracy for associated horizon.

Rapid changes in wind speed (i.e. ramps) can reduce the prediction accuracy significantly. A location's ramp behavior can be decisive in forecast performance. Ramp's magnitude, duration, direction and occurrence frequency are important in evaluation of ramp behavior. In [26], wind power ramp forecasting for varying horizons ranging from 1 h to 24 h is investigated. The swinging door algorithm is used for extracting ramps from data. The results show a correlation between the ability of ramp forecasting and the accuracy of wind power predictions.

A new hybrid evolutionary-adaptive methodology, called HEA, is tested for 3 h ahead wind power predictions, using wind power data of the previous 12 h recorded with 15 min intervals in [27]. This study combines the mutual information (MI), WT, evolutionary particle swarm optimization (EPSO) and ANFIS. The study compares the results with eight other previously published methods. Using the HEA methodology, the average values of the error measures MAPE and NMAE are obtained as 3.75% and 1.51%, respectively. Results suggest a promising method in terms of accuracy for 3 h ahead predictions.

Another study integrates the spectral clustering (SC), echo state network (ESN) and genetic algorithm (GA) for 4 h ahead predictions with 15 min intervals in [28]. This study attempts to combine the WT and the principal component analysis (PCA) for wind speed data preprocessing and uses the SC to group similar samples. An ESN model that can predict wind speeds over short periods is constructed. The GA is used to optimize the ESN parameters in the procedure. The study shows 5.71% MAPE for 4 h ahead predictions. Since errors mostly soars to 10% MAPE for 6 h, this error range suggests that 4 h ahead predictions may be preferred for reliable planning in practice.

For the medium-term predictions, recent studies mostly concentrate on hybrid methods. For instance, a new hybrid forecasting method composed of the WT, the ANFIS, the SVM and the grid search (GS) algorithm (denoted as WT+ANFIS+SVM+GS) for 6 h ahead wind power forecasting is introduced in [29]. The results reveal that the model's error in terms of MAPE is in the range between 12.16% and 13.83%. Another hybrid method, named as PSR-SVR$_{GA}$, for 1–24 h ahead wind speed forecasts is developed in [30]. It uses the time delay coordinates (TDC) model and the phase space reconstruction (PSR) procedure for feature selection. The GS is used to tune the SVR parameters. For wind power forecasting, a hybrid method is reported in [31] that combines the neuro-fuzzy and the ANN models. The ANN is used to improve the predictions of the neuro-fuzzy wind power forecasting. The improved model is used for 1–24 h ahead wind power forecasting. The MAPE values found to be in a range from 8.96% to 11.66%. The method gives low errors for 24 h ahead predictions while its accuracy drops for shorter horizons.

For the long-term predictions, a hybrid approach is developed in [32]. It is based on the combination of the PSO and the ANFIS and used for 1 day ahead predictions with a time-step of 15 min. The study reports a surprisingly low MAPE value of 5.41% for 1 day ahead wind power predictions for four selected days. However, in contrast to previous studies, the method's average performance over a longer period of time is not provided.

Another study examines a hybrid model combining the wavelet decomposition (WD) and the artificial bee colony (ABC) algorithm together with the relevance vector machine (RVM), called WABCRVM, in [33]. This model uses the WD to decompose wind speed data and utilizes the ABC to select the appropriate kernel parameters of the RVM model. The MAPE values of the proposed model are found to be between 19.83% and 22.93% for 24 h ahead predictions. Another hybrid method is reported in [34] that is a combination of the Kalman filter (KF) and the ANN, called KF+ANN. The results show that the MAPE values of the training forecasts are 16.52% and 8.10% for selected Iraqi and Malaysian locations for daily wind speed predictions, respectively. The MAPE values of the testing forecasts are found to be 36.17% and 11.29% for the same sites. A novel framework combined multiple forecasting models and adaptive machine learning techniques for 1 day ahead wind power forecasting in [35]. The prediction outputs are merged with the lazy learning (LL) algorithm as a post-processing approach.

Another study presents a novel hybrid method for wind power forecasting in [36]. It is a combination of a preprocessing approach (WT) and the fuzzy ARTMAP (FA) network. The FA method is optimized using a technique called firefly (FF) algorithm. Also, the SVM classifier is applied to minimize the wind power forecasting errors obtained from the WT+FA+FF combination. The proposed hybrid model is denoted as WT+FA+FF+SVM. The MAPE values are 9.95%, 12.19%, 12.07% and 13.44% for daily forecasts while they are 13.46%, 15.13%, 14.22% and 18.71% for weekly forecasts. The average MAPEs of the four tested seasons for daily and weekly forecasts are 11.91% and 15.38%, respectively. The comparison indicates a significant improvement in daily and weekly MAPEs. The average MAPE improvements obtained by the proposed model for daily and weekly forecasts are around 53% and 38%, respectively.

For the very long-term predictions, a new forecasting model based on the resource allocating network (RAN) is proposed recently and applied for wind power forecasting in [37]. The phase space reconstruction (PSR) and PCA for 48 h ahead predictions with 1 h steps is used. The proposed model is compared with the AR, persistence and adaptive wavelet neural network (AWNN) models. The results give 3.0 average MAE value and 6.0 average RMSE value for 48 h ahead prediction.

A data-mining approach is used in [38] for varying prediction horizons between 1 and 84 h ahead wind farm power predictions. The short- and long-term prediction models are created with the rapid update cycle (RUC) model and the North American Mesoscale (NAM) model, respectively. Five data-mining algorithms, SVM$_{reg}$, MLP, RBF, C-R tree and random forest (RF), are utilized to construct a prediction model for wind power. Then, the MLP algorithm is selected for training all twelve prediction models. Finally, the integrated model composed of the MLP and k-NN algorithms is obtained for short- and long-term power predictions. The MAE values of the integrated model are in the range from 9.67 to 12.72 for 1–12 h ahead and from 6.22 to 16.72 for 3–84 h ahead wind power predictions.

A case study uses a combination of the dynamic clustering and linear regression for 48 h ahead wind power forecasting in [39] for Turkey. The numerical weather predictions (NWPs) are taken from three different sources, i.e. the Global Forecast System (GFS), European Centre for Medium Range Weather Forecasts (ECMWF) and Turkish Met Office (DMI) and data are merged with regression to generate predictions. The results demonstrate that the NMAE values vary between 8.90% and 16.32% for 48 h predictions. In [40], the weather research and forecast model (WRF) and WindSim, a computational fluid dynamics model, are coupled for 72 h ahead wind speed and direction forecasts. The results are compared for the wind power output generated at 36 different turbines. The results show that daily wind power generation errors per turbine vary between 90 kW and 350 kW.

Another study reports an ensemble approach based on the mixture density neural networks (MDN) for forecasting of the wind speed and wind power in [41]. In [42], the layer recurrent neural network (LRNN) is utilized to forecast the wind speed and power for 5 days ahead. The results indicate that the MASE value is 0.096 with 5 min measurements and 0.069 on average with 10 min measurements for 5 day ahead forecasts.

Goal of [43] is to understand the fluctuating nature of wind speed using the wavelet and the fast Fourier transform techniques. The daily mean values of wind speed from nine different meteorological stations are utilized to examine the wind nature. In [44], a hybrid method integrating the SVR with the seasonal index adjustment (SIA) and the Elman recurrent neural network (ERNN) methods, named as PMERNN and PAERNN, for 3 months ahead wind speed forecasting is presented. The results show a MAPE of 15.32% on average for three different sites.

According to studies reviewed above, for a few seconds to a few minutes ahead predictions, MAPE values vary in a range from 1.61% to 15.99%; 1 h ahead prediction errors are reported in a range between 3.33% and 23.85%, while 24 h ahead prediction errors are reported in a range between 11.91% and 23.73%. Six hour ahead prediction errors are reported approximately 13%. Additionally, in some studies, for the very long-term, i.e., weekly, monthly, quarter yearly, etc., prediction errors are obtained around 15%. Wildly varying errors above show insufficient understanding of the typical degree of error for a given horizon (one step ahead period). For a prediction horizon less than 4 h, in general, a MAPE value can be expected to be between 2% and 6%; for 6–12 h ahead predictions, it is typically between 10% and 15%; for 12–24 h predictions, it rises to a range between 15% and 20%. For 24–72 h, it can increase up to 25% and after 72 h, MAPE value reduces back to 15% level.

Nevertheless some regions might be less predictable. In this case, a comparison with persistence predictions must be provided to claim superiority of a proposed approach. It can also be said that a region's energy production depends on not only seasonal wind speed averages but also its wind behavior predictability.

3. The proposed hybrid method

A vast number of different hybrid methods can be proposed by combining any number of exiting methods. In the light of recent studies and their results for different prediction horizons, we have realized that for 1 h ahead wind speed predictions, combination of the adaptive neuro-fuzzy inference system (ANFIS) and the feed-forward artificial neural network (FNN) can be an effective approach [23,31,32,83,87]. Our motivation for this section is that this simple combination can be one of the most accurate candidates to benefit for 1 h ahead predictions. For longer horizons, combination of more methods together with a preprocessing (e.g. wavelet decomposition) may be favorable. Fig. 1 illustrates main steps of the ANFIS+FNN combination.

In combination, an adaptive weighted technique is used. The Sugeno type fuzzy system is employed in ANFIS with 5 generalized bell-shaped membership functions and run for 20 epochs. The feed-forward network is adopted with 30 hidden layers and 50 epochs. For each prediction, last 180 days of data are employed in learning in both methods. All simulations are run in Matlab. The feed-forward network is trained with the Levenberg-Marquardt algorithm. The genfis1 function of Matlab is used in the ANFIS. Both the ANFIS and the FNN are trained to learn the relation between two consecutive hours. For example, to predict wind speed for time 13:00, last 180 days of data recorded at 12:00 and 13:00 are fed to methods and the ANFIS and FNN structures are accordingly constructed. Then obtained parameters and network architectures are used to predict wind speed at 13:00 of the next day (in single input - single output manner). For each hourly prediction, learning is repeated. In some days, wind fluctuates with significant ramps. In those days, if a method predicts a wind speed smaller than zero, it is set to be zero.

To improve the one hour ahead predictions, both wind speed predictions obtained from the ANFIS and FNN are combined as

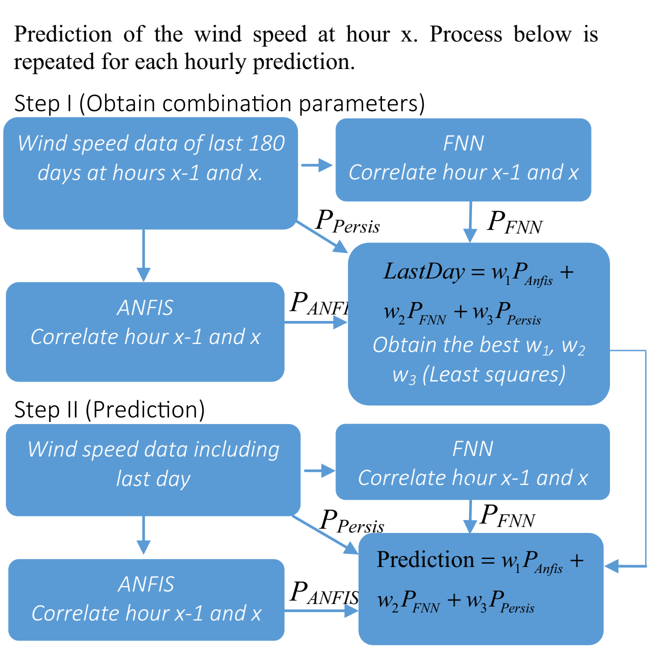

Fig. 1. Diagram of the proposed method.

$$P_{new} = w_1 P_{Anfis} + w_2 P_{FNN} + w_3 P_{Persis}$$

where P_{persis} is the persistence data (i.e. last hour's measurement), w_1, w_2 and w_3 are weights which are calculated with the least squares method considering last 30 days. The least squares problem is solved by the backslash operator of Matlab. For each hourly wind speed predictions, new weight parameters are calculated again and then used for predictions. In multi-step predictions, the persistence data are not available and therefore they are not used in combination.

In this study, the input data is collected from three different sites namely, Amasra, Bandırma and Selçuk, which are located in Turkey. Data cover a period of two years consists of 2013 and 2014. All predictions are made for the year 2014. Mid-month of each season, January, April, July and October are selected for testing. Error values are given as average over a period of month. The prediction results are evaluated with three error criteria, i.e., mean absolute error (MAE), mean square error (MSE) and mean absolute percentage error (MAPE). They are computed by formulas:

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N} |\hat{p}_t - p_t|$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{t=1}^{N} (\hat{p}_t - p_t)^2$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{t=1}^{N} \left|\frac{\hat{p}_t - p_t}{p_t}\right| \times 100$$

where p_t is the wind speed measurement at the time period t, $\hat{p}_t$ is the prediction made for the same period and N is the number of predictions. In MAPE calculations, if the measured data record is zero or missing, at this point the MAPE value is not calculated and the rest of the values are used in averaging.

Fig. 2 illustrates the generated daily wind speed predictions for Amasra and Selçuk on February 14, 2014. Obtained daily average MAPEs are 3.3647% and 3.1736% for Amasra and Selçuk, respectively. Fig. 3 shows MAE, MSE and MAPE performances of daily average predictions. All predictions are made with 1 h ahead intervals for 24 h during a month. Predictions are generated hourly for a period of a month and averaged for comparison. Fig. 3 shows that errors can fluctuate monthly and seasonally but the proposed method is consistently accurate. The results also show that the combined method performs better than the individual FNN and ANFIS models for eleven out of twelve cases.

At Amasra site, all results of the combined method in terms of MAE, MSE and MAPE outperform the FNN and the ANFIS. The MAE values of the combined method for Amasra are 0.2371, 0.1775, 0.1913 and 0.1413 for January, April, July and October, respectively. The MSE values of the combined method are 0.1060, 0.0459, 0.0534 and 0.0329 while the MAPE values are 4.0279%, 3.5892%, 3.4032% and 2.3919%, for January, April, July and October, respectively, as listed in Table 4.

For Bandırma site, the combined method is worse than ANFIS in one case only. The MAE values of the combined method are 0.0856, 0.1021, 0.1342 and 0.1493, respectively, for January, April, July and October. The MSE values are 0.0150, 0.0263, 0.0276 and 0.0394; while the MAPE values are found to be 2.2518%, 2.2225%, 2.1567% and 2.4082%.

The results of the combined method again show better performances than the FNN and the ANFIS in Selçuk. The MAE values of the combined method are 0.0721, 0.0818, 0.0637 and 0.0923, the MSE values are 0.0155, 0.0106, 0.0067 and 0.0207 and the MAPE values are obtained as 4.1635%, 3.6185%, 2.7607% and 4.9832% for January, April, July and October, respectively.

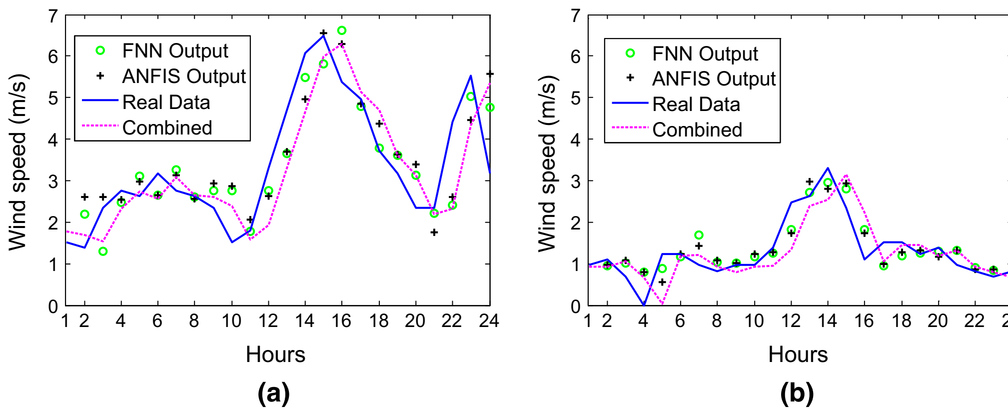

Fig. 2. Daily wind speed predictions for (a) Amasra and (b) Selçuk on 14 February 2014. Calculated daily average MAPEs are 3.3647% and 3.1736% for Amasra and Selçuk, respectively.

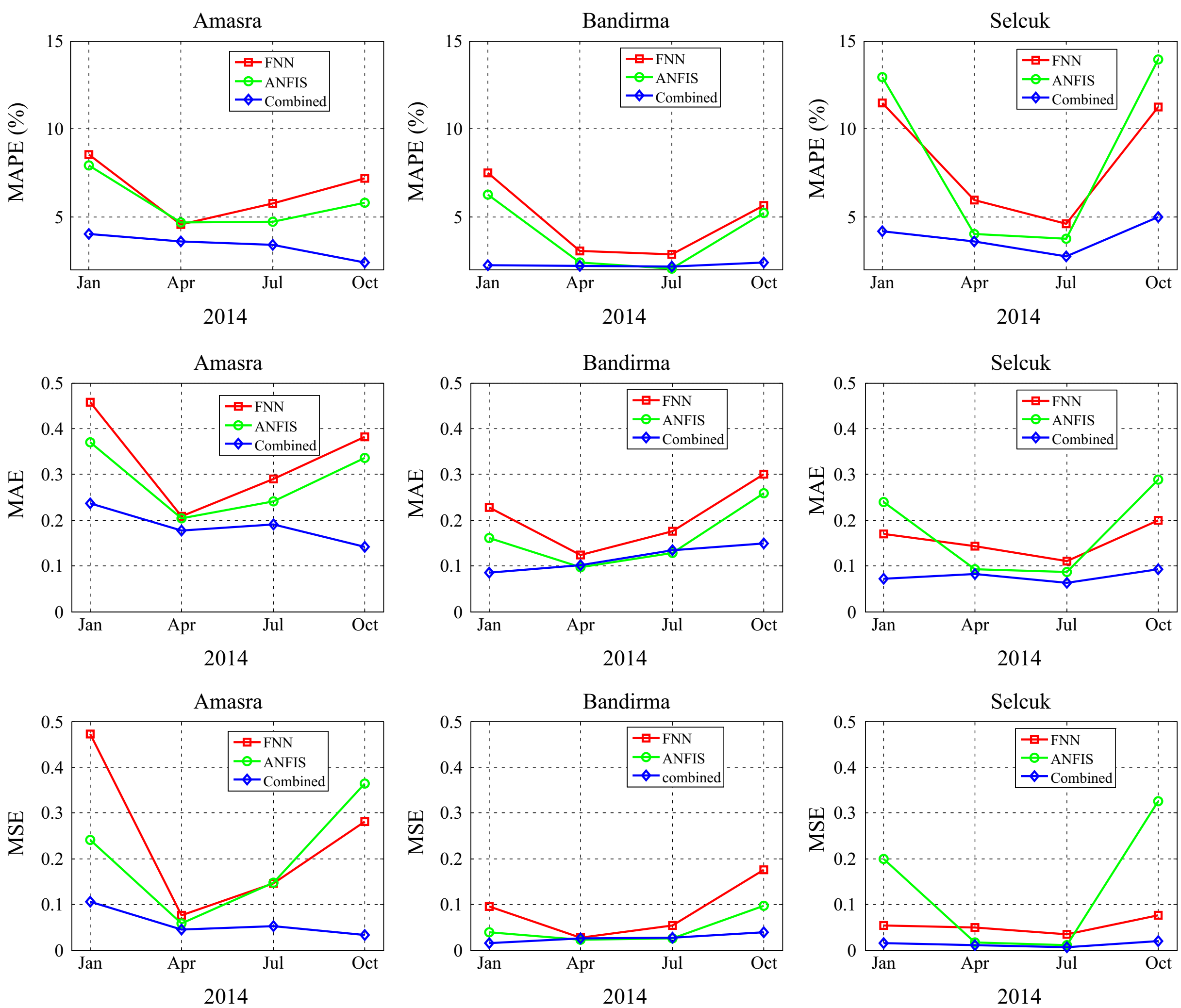

Fig. 3. Comparison between the proposed method and individual FNN and ANFIS results based on MAPE, MAE and MSE values at Amasra, Bandırma and Selçuk locations. The red lines with square symbols are FNN, the green lines with circle symbols are ANFIS and the blue lines with diamond symbols are combined method predictions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The combined method gives particularly low error values for Bandırma compared to the other two sites based on MAPE. Four month average of MAPE is found as 2.2598% in Bandırma. Nevertheless combined method gives 3.3530% and 3.8589% MAPE errors for Amasra and Selçuk, respectively. According to MAE, Selçuk has the lowest average MAE of 0.0774, Amasra and Bandırma have 0.1868 and 0.1178, respectively. Finally, based on MSE, Selçuk has better result by 0.0133 on average MSE compared with Amasra and Bandırma, which have 0.0595 and 0.0270, respectively. Also in all twelve cases the combined method gives a smaller MAPE error

Table 4
Prediction errors of the proposed hybrid method at three test locations. Predictions are made for 24 h with 1 h ahead intervals (prediction horizon is 1 h). Error values are calculated according to daily average wind speed values. Table shows twelve test cases.

			MAE	MSE	MAPE
Amasra	January	FNN	0.4574	0.4730	8.5465
		ANFIS	0.3701	0.2411	7.9288
		Combined	0.2371	0.1060	4.0279
	April	FNN	0.2085	0.0763	4.5676
		ANFIS	0.2036	0.0583	4.6852
		Combined	0.1775	0.0459	3.5892
	July	FNN	0.2899	0.1462	5.7507
		ANFIS	0.2408	0.1479	4.7155
		Combined	0.1913	0.0534	3.4032
	October	FNN	0.3814	0.2809	7.1823
		ANFIS	0.3364	0.3643	5.7991
		Combined	0.1413	0.0329	2.3919
	Average	Combined	0.1868	0.0595	3.3530
Bandırma	January	FNN	0.2274	0.0951	7.5116
		ANFIS	0.1610	0.0389	6.2772
		Combined	0.0856	0.0150	2.2518
	April	FNN	0.1239	0.0277	3.0753
		ANFIS	0.0976	0.0229	2.3969
		Combined	0.1021	0.0263	2.2225
	July	FNN	0.1753	0.0538	2.8611
		ANFIS	0.1279	0.0263	2.0702
		Combined	0.1342	0.0276	2.1567
	October	FNN	0.3005	0.1752	5.6340
		ANFIS	0.2587	0.0971	5.2028
		Combined	0.1493	0.0394	2.4082
	Average	Combined	0.1178	0.0270	2.2598
Selçuk	January	FNN	0.1699	0.0543	11.4667
		ANFIS	0.2389	0.1993	12.9387
		Combined	0.0721	0.0155	4.1635
	April	FNN	0.1429	0.0503	5.9426
		ANFIS	0.0934	0.0176	4.0174
		Combined	0.0818	0.0106	3.6185
	July	FNN	0.1112	0.0353	4.6196
		ANFIS	0.0865	0.0116	3.7555
		Combined	0.0637	0.0067	2.7607
	October	FNN	0.1990	0.0769	11.2329
		ANFIS	0.2893	0.3251	13.9459
		Combined	0.0923	0.0207	4.9832
	Average	Combined	0.0774	0.0133	3.8589

compared to the persistence outputs for 1 h ahead predictions. The predictions outperform the persistence predictions by 5% MAPE on average.

Furthermore, the same hybrid approach is applied with multi-step manner for 24 h ahead forecasts again creating predictions with 1 h intervals. In this case, error values significantly soars up to a MAPE value around 25% for the test locations. This combined method is found to be inaccurate for 24 h ahead forecasts.

4. Conclusion

The literature review discloses the present-day challenges. The prediction accuracy goes particularly down after six hours and error rises up to 15% MAPE for between 6 and 24 h ahead predictions and a value lower than 10% seems to be quite challenging. When the prediction horizon extends to a few days, this error continues to rise. For between 24 and 72 h ahead predictions, obtaining a MAPE value lower than 15% for wind speed predictions stays also as a challenging task. To overcome these challenges, extracting a bit of meaningful information can be precious. Processing all available (meteorological, topological, power system) data with best hybrid methods might be necessary to obtain the most meaningful data correlation between past and future along with site specific pre- and post-processing steps.

Sudden changes in wind speed (i.e. ramps) are mostly not treated well. Some studies show that ramps may increase the error in predictions significantly and locations having frequent ramps require devising new ramp prediction techniques. Also some reports show that some tested regions give unexpectedly large prediction errors. This suggests that wind predictability behavior of a region can be as important as its energy potential. Even if this site has a vast energy potential, connecting it to the regional grid efficiently and trading this energy profitably depend on prediction performance. For a best predicting system and a much better energy planning, regional grid system might be adapted for 4 h ahead predictions. Since, after 4 h, error is expected to start to escalate using existing techniques. The review also suggests that a method should also be reliable as well as accurate. A method giving errors mostly within a known range and staying mostly lower than an upper error bound can be more valuable in practice than a method extremely accurate for only a short period of time, although having identical average error.

The present review shows that wind speed/power prediction methods combining and benefiting from different approaches are frequently more accurate. Combination of several methods are favorable for forecast horizons longer than 6 h. But a priori combination is not evident and tests are required. Also the preprocessing of data for a specific target site and for a particular prediction horizon improves the prediction accuracy. Post-processing of predictions with other available data can also improve the accuracy of predictions. Nevertheless, some studies are lack of a comparison with the persistence predictions. Any newly proposed method must outperform the persistence data.

Recent studies also show that predicting the wind power can give more accurate results compared to the wind speed predictions, since power curve of a wind turbine may inhibit the errors close to the cut-in and the cut-off wind speeds. Interestingly, a region in terms of wind power can be more predictable when the wind turbine with a particular power curve is selected carefully.

In the light of recent studies, the study has combined the ANFIS and the FNN techniques. They are combined in an adaptive way as described in the study. Accurate predictions with 2.2598%, 3.3530% and 3.8589% MAPE errors at three tested locations are obtained. These predictions also have outperformed the persistence predictions in all twelve cases by 5% MAPE on average.

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References

[1] Liu H, Tian HQ, Li YF. Four wind speed multi-step forecasting models using extreme learning machines and signal decomposing algorithms. Energy Convers Manage 2015;100:16–22.
[2] Lydia M, Kumar SS, Selvakumar AI, Kumar GE. Linear and non-linear autoregressive models for short-term wind speed forecasting. Energy Convers Manage 2016;112:115–24.
[3] Li P, Guan X, Wu J. Aggregated wind power generation probabilistic forecasting based on particle filter. Energy Convers Manage 2015;96:579–87.
[4] Hu X, Martinez CM, Yang Y. Charging, power management, and battery degradation mitigation in plug-in hybrid electric vehicles: a unified cost-optimal approach. Mech Syst Signal Process 2016. http://dx.doi.org/10.1016/j.ymssp.2016.03.004.
[5] Colak I, Sagiroglu S, Yesilbudak M. Data mining and wind power prediction: a literature review. Renew Energy 2012;42:241–7.
[6] Wu YK, Hong JS. A literature review of wind forecasting technology in the world. In: Power Tech. Lausanne: IEEE; 2007. p. 504–9.

[7] Tascikaraoglu A, Uzunoglu M. A review of combined approaches for prediction of short-term wind speed and power. Renew Sustain Energy Rev 2014;34:243–54.
[8] Gallego-Castillo C, Cuerva-Tejero A, Lopez-Garcia O. A review on the recent history of wind power ramp forecasting. Renew Sustain Energy Rev 2015;52:1148–57.
[9] Foley AM, Leahy PG, Marvuglia A, McKeogh EJ. Current methods and advances in forecasting of wind power generation. Renew Energy 2012;37:1–8.
[10] Jung J, Broadwater RP. Current status and future advances for wind speed and power forecasting. Renew Sustain Energy Rev 2014;31:762–77.
[11] Zhang Y, Wang J, Wang X. Review on probabilistic forecasting of wind power generation. Renew Sustain Energy Rev 2014;32:255–70.
[12] Soman SS, Zareipour H, Malik O, Mandal P. A review of wind power and wind speed forecasting methods with different time horizons. In: North American power symposium (NAPS). p. 1–8.
[13] Ata R. Artificial neural networks applications in wind energy systems: a review. Renew Sustain Energy Rev 2015;49:534–62.
[14] Kavousi-Fard A, Khosravi A, Nahavadi S. A novel fuzzy multi-objective framework to construct optimal prediction intervals for wind power forecast. In: Proceedings of the international joint conference neural networks (IJCNN). p. 1015–9.
[15] Pourmousavi Kani SA, Ardehali MM. Very short-term wind speed prediction: a new artificial neural network-Markov chain model. Energy Convers Manage 2011;52:738–45.
[16] Jiang Y, Song Z, Kusiak A. Very short-term wind speed forecasting with Bayesian structural break model. Renew Energy 2013;50:637–47.
[17] Hu Q, Zhang S, Xie Z, Mi J, Wan J. Noise model based on ν-support vector regression with its application to short-term wind speed forecasting. Neural Netw 2014;57:1–11.
[18] Hu Q, Zhang R, Zhou Y. Transfer learning for short-term wind speed prediction with deep neural networks. Renew Energy 2016;85:83–95.
[19] Croonenbroeck C, Ambach D. A selection of time series models for short- to medium-term wind power forecasting. J Wind Eng Ind Aerodyn 2015;136:201–10.
[20] Wang J, Hu J. A robust combination approach for short-term wind speed forecasting and analysis – combination of the ARIMA (Autoregressive Integrated Moving Average), ELM (Extreme Learning Machine), SVM (Support Vector Machine) and LSSVM (Least Square SVM) forecasts using a GPR (Gaussian Process Regression) model. Energy 2015;93:41–56.
[21] Cao Q, Ewing BT, Thompson MA. Forecasting wind speed with recurrent neural networks. Eur J Oper Res 2012;221:148–54.
[22] Liang Z, Liang J, Zhang L, Wang C, Yun Z, Zhang X. Analysis of multi-scale chaotic characteristics of wind power based on Hilbert–Huang transform and Hurst analysis. Appl Energy 2015;159:51–61.
[23] Liu H, Tian HG, Li YF. Comparison of new hybrid FEEMD-MLP, FEEMD-ANFIS, Wavelet Packet-MLP and Wavelet Packet-ANFIS for wind speed predictions. Energy Convers Manage 2015;89:1–11.
[24] Rahmani R, Yusof R, Seyedmahmoudian M, Mekhilef S. Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting. J Wind Eng Ind Aerodyn 2013;123:163–70.
[25] Ren Y, Suganthan PN, Srikanth N. Ensemble methods for wind and solar power forecasting – a state-of-the-art review. Renew Sustain Energy Rev 2015;50:82–91.
[26] Zhang J, Florita A, Hodge BM, Freedman J. Ramp forecasting performance from improved short-term wind power forecasting. In: Proceedings of the ASME 2014 international design engineering technical conferences and computers and information in engineering conference (IDETC/CIE '14).
[27] Osorio GJ, Matias JCO, Catalao JPS. Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information. Renew Energy 2015;75:301–7.
[28] Liu D, Wang J, Wang H. Short-term wind speed forecasting based on spectral clustering and optimized echo state networks. Renew Energy 2015;78:599–608.
[29] Haque AU, Mandal P, Nehrir HM, Bhuiya A, Baker. A hybrid intelligent framework for wind power forecasting engine. In: Proceedings of the electrical power and energy conference (EPEC '14). p. 184–9.
[30] Santamaría-Bonfil G, Reyes-Ballesteros A, Gershenson C. Wind speed forecasting for wind farms: a method based on support vector regression. Renew Energy 2016;85:790–809.
[31] Katsigiannis YA, Tsikalakis AG, Georgilakis PS, Hatziargyriou ND. Improved wind power forecasting using a combined neuro-fuzzy and artificial neural network model. In: Advances in artificial intelligence. Berlin Heidelberg: Springer; 2006. p. 105–15.
[32] Pousinho HMI, Mendes VMF, Catalao JPS. A hybrid PSO-ANFIS approach for short-term wind power prediction in Portugal. Energy Convers Manage 2011;52:397–402.
[33] Fei S, He Y. Wind speed prediction using the hybrid model of wavelet decomposition and artificial bee colony algorithm-based on relevance vector machine. Electr Power Energy Syst 2015;73:625–31.
[34] Shukur OB, Lee MH. Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA. Renew Energy 2015;76:637–47.
[35] Vaccaro A, Mercogliano P, Schiano P, Villacci D. An adaptive framework based on multi-model data fusion for one-day-ahead wind power forecasting. Electr Power Syst Res 2011;81:775–82.
[36] Haque AU, Nehrir HM, Mandal P. A hybrid intelligent model for deterministic and quantile regression approach for probabilistic wind power forecasting. IEEE Trans Power Syst 2014;29:1663–72.
[37] Han L, Romero CE, Yao Z. Wind power forecasting based on principle component phase space reconstruction. Renew Energy 2015;81:737–44.
[38] Kusiak A, Zheng H, Song Z. Wind farm power prediction: a data-mining approach. Wind Eng 2009;12:275–93.
[39] Ozkan MB, Karagoz P. A novel wind power forecast model: statistical hybrid wind power forecast technique (SHWIP). IEEE Trans Ind Inform 2015;11:375–87.
[40] Efe B, Mentes S, Unal Y, Tan E, Unal E, Ozdemir T, et al. 72 hr forecast of wind power in Manisa, Turkey by using the WRF model coupled to WindSim. In: Proceedings of the International conference on renewable energy research and applications (ICRERA '12). p. 1–6.
[41] Men Z, Yee E, Lien FS, Wen D. Short-term wind speed and power forecasting using an ensemble of mixture density neural networks. Renew Energy 2016;87:203–11.
[42] Olaofe ZO. A 5-day wind speed & power forecasts using a layer recurrent neural network (LRNN). Sustain Energy Technol Assess 2014;6:1–24.
[43] Alam MM, Rehman S, Al-Hadhrami LM, Meyer JP. Extraction of the inherent nature of wind speed using wavelets and FFT. Energy Sustain Dev 2014;22:34–47.
[44] Wang J, Qin S, Zhou Q, Jiang H. Medium-term wind speeds forecasting utilizing hybrid models for three different sites in Xinjiang, China. Renew Energy 2015;76:91–101.
[45] Haque AU, Mandal P, Meng J, Negnevitsky M. Wind speed forecast model for wind farm based on a hybrid machine learning algorithm. Int J Sustain Eng 2015;34:38–51.
[46] Kong X, Liu X, Shi R, Lee KY. Wind speed prediction using reduced support vector machines with feature selection. Neurocomputing 2015;169: 449–56.
[47] Cadenas E, Rivera W. Short term wind speed forecasting in La Venta, Oaxaca, Mexico, using artificial neural networks. Renew Energy 2009;34:274–8.
[48] Jursa R, Rohrig K. Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models. Int J Forecast 2008;24:694–709.
[49] Kusiak A, Zheng H, Song Z. Short-term prediction of wind farm power: a data mining approach. IEEE Trans Energy Convers 2009;24:125–36.
[50] Hong YY, Chang HL, Chiu CS. Hour-ahead wind power and speed forecasting using simultaneous perturbation stochastic approximation (SPSA) algorithm and neural network with fuzzy inputs. Energy 2010;35:3870–6.
[51] Shi J, Yang Y, Wang P, Liu Y, Han S. Genetic algorithm-piecewise support vector machine model for short term wind power prediction. In: Proceedings of the 8th world congress on intelligent control and automation (ICA '10). p. 2254–8.
[52] Weidong X, Yibing L, Xingpei L. Short-term forecasting of wind turbine power generation based on genetic neural network. In: Proceedings of the eighth world congress on intelligent control and automation (ICA '10). p. 5943–6.
[53] Wang L, Dong L, Hao Y, Liao X. Wind power prediction using wavelet transform and chaotic characteristics. In: Proceedings of the World non-grid-connected wind power and energy conference (WNWEC '09). p. 1–5.
[54] Wu YK, Lee CY, Tsai SH, Yu SN. Actual experience on the short-term wind power forecasting at Penghu-from an island perspective. In: Proceedings of the International conference on power system technology (PST '10). p. 1–8.
[55] Liu H, Tian HQ, Chen C, Li YF. A hybrid statistical method to predict wind speed and wind power. Renew Energy 2010;35:1857–61.
[56] Giorgi MGD, Ficarella A, Tarantino M. Error analysis of short term wind power prediction models. Appl Energy 2011;88:1298–311.
[57] Senjyu T, Yona A, Urasaki N, Funabashi T. Application of recurrent neural network to long-term-ahead generating power forecasting for wind power generator. In: IEEE PES power systems conference and exposition. p. 1260–5.
[58] Barbounis TG, Theocharis JB, Alexiadis MC, Dokopoulos PS. Long-term wind speed and power forecasting using local recurrent neural network models. IEEE Trans Energy Convers 2006;21:273–84.
[59] Xia J, Zhao P, Dai Y. Neuro-fuzzy networks for short-term wind power forecasting. In: Proceedings of the International conference on power system technology (PST '10). p. 1–5.
[60] Johnson PL, Negnevitsky M, Muttaqi KM. Short term wind power forecasting using adaptive neuro-fuzzy inference systems. In: Australasian universities power engineering conference (AUPEC '07). p. 1–6.
[61] Negnevitsky M, Johnson P. Very short term wind power prediction: a data mining approach. In: 2008 IEEE power and energy society general meeting-conversion and delivery of electrical energy in the 21st century. p. 1–3.
[62] Catalao JPS, Pousinho HMI, Mendes VMF. An artificial neural network approach for short-term wind power forecasting in Portugal. In: Proceedings of the 15th international conference on intelligent system applications to power systems (ISAPS '09). p. 1–5.
[63] Catalao JPS, Pousinho HMI, Mendes VMF. Short-term wind power forecasting in Portugal by neural networks and wavelet transform. Renew Energy 2011;36:1245–51.
[64] Pinson P, Madsen H. Probabilistic forecasting of wind power at the minute time-scale with Markov-switching autoregressive models. In: Proceedings of the 10th international conference on probabilistic methods applied to power systems (PMAPS '08). p. 1–8.
[65] Carpinone A, Langella R, Testa A, Giorgio M. Very short-term probabilistic wind power forecasting based on Markov chain models. In: Proceedings of the 11th

international conference on probabilistic methods applied to power systems (PMAPS '10). p. 107–12.
[66] Vargas L, Paredes G, Bustos G. Data mining techniques for very short term prediction of wind power. In: Bulk power system dynamics and control (iREP)-VIII, 2010 iREP symposium. p. 1–7.
[67] Kusiak A, Zhang Z. Short-horizon prediction of wind power: a data driven approach. IEEE Trans Energy Convers 2010;25:1112–22.
[68] Blonbou R. Very short-term wind power forecasting with neural networks and adaptive Bayesian learning. Renew Energy 2011;36:1118–24.
[69] An X, Jiang D, Liu C, Zhao M. Wind farm power prediction based on wavelet decomposition and chaotic time series. Expert Syst Appl 2011;38:11280–5.
[70] Potter CW, Negnevitsky M. Very short-term wind forecasting for Tasmanian power generation. IEEE Trans Power Syst 2006;21:9656–972.
[71] Fan S, Liao JR, Yokoyama R, Chen L, Lee W-J. Forecasting the wind generation using a two-stage network based on meteorological information. IEEE Trans Energy Convers 2009;24:474–82.
[72] Riahy GH, Abedi M. Short term wind speed forecasting for wind turbine applications using linear prediction method. Renew Energy 2008;33:35–41.
[73] Miranda MS, Dunn RW. One-hour-ahead wind speed prediction using a Bayesian methodology. In: Power engineering society general meeting. p. 1–6.
[74] Kariniotakis GN, Stavrakakis GS, Nogaret EF. Wind power forecasting using advanced neural networks models. IEEE Trans Energy Convers 1996;11:762–7.
[75] Mori H, Kurata E. Application of Gaussian process to wind speed forecasting for wind power generation. In: Proceedings of the International conference sustainable energy technologies (ICSET '08). p. 956–9.
[76] Alexiadis MC, Dokopoulos PS, Sahsamanoglou HS. Wind speed and power forecasting based on spatial correlation models. IEEE Trans Energy Convers 1999;14:836–42.
[77] Li G, Shi J. On comparing three artificial neural networks for wind speed forecasting. Appl Energy 2010;87:2313–20.
[78] Hocaoglu FO, Fidan M, Gerek ON. Mycielski approach for wind speed prediction. Energy Convers Manage 2009;50:1436–43.
[79] Kavasseri RG, Seetharaman K. Day-ahead wind speed forecasting using *f*-ARIMA models. Renew Energy 2009;34:1388–93.
[80] Lazic L, Pejanovic G, Zivkovic M. Wind forecasts for wind power generation using the Eta model. Renew Energy 2010;35:1236–43.
[81] Khan AA, Shahidehpour M. One day ahead wind speed forecasting using wavelets. In: Proceedings of the power systems conference and exposition (PSCE '09). p. 1–5.
[82] Salcedo-Sanz S, Perez-Bellido AM, Ortiz-Garcia EG, Portilla-Figueras A, Prieto L, Paredes D. Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction. Renew Energy 2009;34:1451–7.
[83] Ramirez-Rosado IJ, Fernandez-Jimenez LA, Monteiro C, Sousa J, Bessa R. Comparison of two new short-term wind-power forecasting systems. Renew Energy 2009;34:1848–54.
[84] Sideratos G, Hatziargyriou ND. An advanced statistical method for wind power forecasting. IEEE Trans Power Syst 2007;22:258–65.
[85] Mandic DP, Javidi S, Goh SL, Kuh A, Aihara K. Complex-valued prediction of wind profile using augmented complex statistics. Renew Energy 2009;34:196–201.
[86] Damousis IG, Alexiadis MC, Theocharis JB, Dokopoulos PS. A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Trans Energy Convers 2004;19:352–61.
[87] Hu X, Li S, Yang Y. Advanced machine learning approach for lithium-ion battery state estimation in electric vehicles. IEEE Trans Transport Electrific 2015;99:1–10. http://dx.doi.org/10.1109/TTE.2015.2512237.